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Cargo Consolidation, Routing, and Location Optimization to Reduce Traffic Congestion by Minimizing Commercial Heavy Vehicle Trips

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16. Abstract

Commercial heavy vehicles, given their frequency of acceleration and deceleration, impact the traffic stream more than passenger cars, leading to greater congestion on the roads. Mixed-cargo shipments, or cargo consolidation, is an operational strategy that has gained traction in many industries because it reduces transportation costs while increasing asset utilization, such as making use of all the available capacity. This practice achieves cost reductions and increased asset efficiency by reducing the number of trips that are needed to deliver the same volume of products among different companies. However, its implementation is far from optimal since it is often carried out by intuition and rudimentary operations, leaving substantial opportunity for process improvements. As part of this project, both a survey and interviews were conducted to understand the industry cargo shipment practices, with responses favoring the use of cargo consolidation adoption. This work developed a methodology to optimize the consolidation of cargo, the routing of shipments of commercial heavy vehicles, the location of logistics distribution centers (namely depots) to minimize distance, and the number of commercial heavy vehicle trips, while also increasing the utilization of transportation assets such as commercial heavy vehicles. This optimization methodology delivers positive impacts on traffic congestion with the reduction of distance traveled and decrease in the number of commercial heavy vehicle trips, which translates to fewer vehicle miles (kilometers) traveled. The methodology was tested using publicly available data pertaining to real-world private-sector operations.

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Executive Summary

This work provided real-world insights into the empirical and modeling impacts of cargo consolidation on congestion. The contributions of this work include:

1. A robust methodology of data fusion and analytics that offers real-world data on private-sector operations without confidentiality issues.
2. Comprehensive information on current insights and status of cargo consolidation practices in the private and public sectors through a literature review, a survey, and direct interviews.
3. An optimization methodology—and model—for cargo consolidation that focuses on the minimization of distances and vehicles/trips, and calculates the optimal location of a depot, offering significant benefits in terms of impacts on traffic.
4. An algorithm that provides improved solutions to the cargo consolidation strategy and that allows for the expansion of the application in larger scenarios.
5. An additional methodology step that minimizes depot location based on spherical distances, which in turn supplies additional benefits for distance—and traffic—reduction.

Results show that the cargo consolidation model could achieve initial annual benefits of 172,170 vehicle-kilometers less congestion, which is roughly 107,000 vehicle-miles, while the algorithm could yield 72,797 vehicle-kilometers less congestion, which in turn is roughly 45,233 vehicle-miles. These reductions in congestion stemmed from a small set of 20 clients in the area of analysis (i.e., Houston) for two commodities: wood and metal. The latter offers insight into the potential benefits of cargo consolidation practices when using optimization and heuristics tools for operation design.

In addition, the quantitative benefits of the model, algorithm, and location optimization steps were estimated using the single-demand (i.e., nonconsolidated cargo) scenario as a benchmark. It is important to note that this baseline scenario is also a model-optimized scenario for nonconsolidated cargo. In the real world, this is not common since companies generally perform routing operations without any optimization tools. Thus, the benefits estimated in this work may represent the lower bound of the actual benefits range when implementing this methodology in real-world operations.

Future research should look at improving the optimization model and the algorithm by adding features such as cargo sequence and methodology steps to match route paths to road capacities and transit, affording a more accurate estimate of the impacts of cargo consolidation practices. The latter could help determine the specific roads that serve a given market or commodity; assess needs versus road capacities; and facilitate planning, maintenance, and infrastructure design and investments.

Objective

The purpose of this project aligns with the pillars established by the National Institute for Congestion Reduction (NICR) by developing a methodology for reducing congestion while simultaneously lowering the number of trips and total distance required to meet market demand. The NICR pillars “Battling Congestion Using Innovative Mobility Platforms,” “Battling Congestion on the Freeway Corridor,” and “Urban and Rural Traffic Management in the Age of Big Data” are covered in this project through the development of a methodology that consolidates cargo and lowers trip distance, number of trips, and consequently congestion. To achieve this goal, the project developed a survey and a methodology aimed at lowering the number of commercial heavy trucks on the road while improving truck capacity to consistently move the same commodity volumes as needed by the market.

The goals of this project were as follows:

1. Optimize commercial truck trips, resulting in traffic reduction and improved travel reliability.
2. Develop different scenarios and evaluate improvements in transit and congestion.
3. Focus on mixed-cargo consolidation from different locations and companies as an approach for reducing, or optimizing, the number of trucks on the road.

Literature Review

The literature review gives background information on the impact of congestion related to cargo movement and presents solutions and models for reducing congestion. A commercial vehicle's impact on congestion can be equivalent to the impact of several cars depending on the truck dimensions, engine power and truck weight, geometric design, and prevalent traffic. One significant factor that affects the efficiency of heavy freight transportation is the presence of numerous road restrictions related to the weight and dimensions of the cargo being transported.

One possible solution to reduce congestion is through the consolidation of cargo movement. To achieve this goal while simultaneously reducing transport costs with the use of consolidation services, the current transportation structure of the client must be analyzed. Suppliers are assigned to certain warehouses regarding a transportation enterprise's terminal network providing services for consolidation. In the case of direct transportation, the vehicles must travel many kilometers/miles to convey a single tiny item or pallet. For such enterprises, medium and large cargos are not cost-effective; nevertheless, direct and consolidation methods can be combined to achieve the best outcomes (Łukasik et al., 2021). Table 1 contains a set of cargo consolidation strategies.

Table 1. Identified Cargo Consolidation Strategies

Multi-stop Consolidation	Inventory or Temporal Consolidation	Terminal or Facility Consolidation
Small load shipments are picked up and dropped off along a multi-stop route by the same vehicle, allowing combined large loads to optimize the capacity of the container or truck. Some operational difficulties, such as how to route trucks and allocate shipments to trucks or containers, must be considered to solve this issue.	Current shipments are retained while future shipments are processed. Waiting for one or more periods allows the complete combined cargo to be shipped using one container or one truck, saving numerous separate less-than-truckload (LTL) costs. Two fundamental operational issues in this area are (1) when to dispatch a vehicle so that service requirements are met, and (2) how large the dispatch quantity should be so that the economies of scale are realized.	Small shipments from various facilities are transported over long distances to the transshipment center to be consolidated into bigger shipments. To optimize system performance, several tactical and operational decisions on hub placements, hub service areas, and vehicle routing are required (Deng, 2013).

Shipments are often transported within their preestablished transportation network, which includes fixed hubs, hub service areas, and transit frequency. Cargo or passengers from various origins are consolidated in hubs before being shipped to intermediate hubs and/or destinations. Another application of freight consolidation is the vendor managed inventory (VMI) practice. Vendors handle downstream warehouse or client inventories, delivery, and their own inventory. Transportation costs and traffic can be considerably reduced by integrating inbound and outgoing shipments (Deng, 2013).

Survey and Interviews

To gain insights on the state and practice of cargo consolidation in the real world, the research team developed a survey that included the private and public sectors to obtain the views and opinions from professionals in both sectors. Additionally, a total of four interviews with large distributors and shipping companies were held to understand the thought process that goes into shipments, how they approach mixed-cargo shipments, and whether any optimization is attempted.

The private-sector survey revealed that implementing cargo consolidation techniques can be important for businesses by offering cost savings, enhanced operational efficiency, sustainability benefits, and traffic congestion mitigation. Companies can strategically use cargo consolidation techniques to enhance the efficiency of their supply chains, cut down on transportation expenses, and boost overall operational performance. A few companies are already using cargo consolidation strategies, and they noted that minimized shipping costs, increased efficiency, quicker transit time, and better shipment scheduling are the major benefits that made them consider it. In addition, respondents reported that finding the right partner, cost, distribution requirement, product features, and distribution network are key considerations for effective consolidation. Also, short lead times, finding the right carrier/partner, and system complexity are some of the major challenges they face when implementing consolidation strategies.

Overall, most private-sector respondents felt that in the next 5 to 10 years, it will be moderately/very important to employ cargo consolidation, rerouting, and optimization strategies to reduce traffic congestion and transportation costs.

In the public-sector survey, most respondents felt that traffic congestion is extremely/very important for their agency plan, and many felt that bottlenecks, traffic incidents, work zones, bad weather, and commercial heavy vehicle impacts are the major causes of traffic congestion. They also felt that geometric improvements to roads and intersections, cargo consolidation, access management, and traffic signal timing optimization are the best methods to alleviate traffic congestion.

Nonetheless, most of the agencies noted that they are not willing to collaborate on the implementation of cargo consolidation strategies and felt that it is only moderately beneficial to implement those strategies to help alleviate traffic congestion because doing so may prove to be a challenge in public and private partnerships.

The interviews were held with two large distributors and two shipping companies. Based on the responses, the research team observed that freight optimization has become an integral component of the thought process in planning shipments for both standard cargo and mixed cargo. Large distributors and shipping companies increasingly rely on freight optimization tools to make informed decisions that align with economic goals while adhering to evolving environmental standards and expectations. The researchers concluded from the interviews that most, if not all, of the companies use optimization models for their freight shipments for both standard shipments and mixed-cargo operations.

Methodology

The methodology of the technical part of this work comprised three main elements:

1. Data assessment and dataset production: Focused on assessing available data sources and the activities needed to produce and build the final dataset for the analysis.
2. Model and algorithm development: Focused on developing the mathematical and programming model, as well as the heuristic (algorithm) for routing and location optimization.
3. Design of experiment: Focused on designing the application of the model and algorithm to evaluate their performance and benefits. This included the sampling design.

Data Assessment and Dataset Production

The project team attempted to obtain data from private-sector companies; however, confidentiality issues arose that jeopardized the progress of the project. Therefore, the team developed a methodology for assessing and retrieving available data pertaining to private-sector operations. This methodology allowed the researchers to overcome confidentiality issues and the dependance on companies' data availability constraints, while also providing a close-to-reality dataset on which to build validation scenarios for the model and algorithm.

Based on this new methodology, and after assessing several areas in terms of total demand for two identified commodities and establishment locations, the team selected Houston, Texas, as the study case. A total of 58 specific clients that had demand for both of the identified products were selected for the analysis.

This 58-client plus 2-supplier set (namely the master dataset), including location, commodities, and corresponding demand tonnage, was used as the basis for the development and application of the model and algorithm.

Model and Algorithm Development

The project team used a combination of methodologies to develop the cargo consolidation optimization (and improvement) method. First, the team developed an exact mathematical optimization model. However, because these types of operations (cargo consolidation, routing, and location) comprise large instances, this type of optimization falls in the non-deterministic polynomial-time hardness (NP-hard) problem classification, which involves problems that cannot be solved at mathematical optimality for large instances. Therefore, the team also developed a heuristic (algorithm) as part of the overall method. More specifically, the mathematical model optimizes small instances and serves as a benchmark for the performance of the heuristic, while the heuristic allows the applicability of this method in large-scale operations while preserving a high level of effectiveness.

The model was implemented using Lingo software. For that purpose, several linear programming versions of this model were developed.

Mathematical, Programming Model – Location

The location of logistics activity centers/distribution centers is an additional improvement to the optimization methodology. The objective of the location step is to minimize the total distance from all clients to the new center. For that purpose, the research team used the Haversine formula (Agramanisti Azdy & Darnis, 2020) to calculate the (spherical) distance between depot(s) and each client. This location optimization step was implemented using Excel Solver.

Heuristic, Algorithm

The heuristic developed in this work follows the k-nearest neighbor (KNN) technique (Taunk et al., 2019), with distance and capacity constraints. The algorithm identifies the closest client to the depot and then evaluates distance and capacity conditions. When either of these is not met, the algorithm saves the client for subsequent iterations. When these conditions are within constraints, the algorithm either publishes (issues) the route if conditions are equal to the threshold or adds the client to the route list and continues searching for the next closest client (i.e., nearest neighbor), and then evaluates conditions accordingly. The algorithm was coded and executed in Python.

Design of Experiment (DoE)

The research team designed the application of the model and algorithm to evaluate their performance and benefits. For this purpose, the researchers developed different scenarios to evaluate improvements in transit and congestion stemming from cargo consolidation optimization. The latter included the sampling design given the constraints of model optimization as an NP-hard problem type. The sampling process consisted of generating three 20-client subsamples extracted from the 58-client sample. The team used uniform distribution to select the three 20-client subsamples. These subsamples were then used for all steps of the DoE to make all results comparable. Figure 1 shows the complete DoE in more detail.

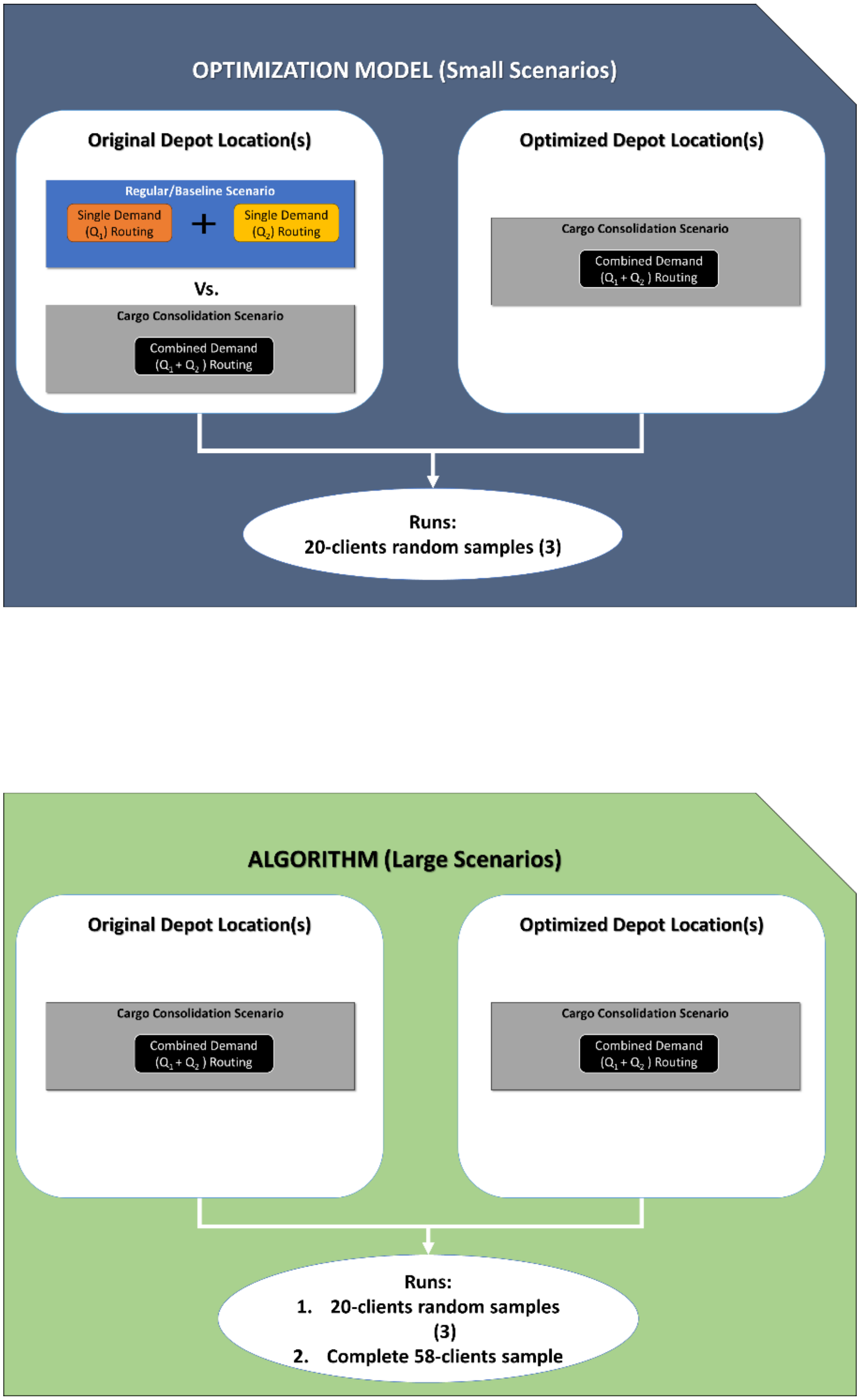


Figure 1. Experiment model design.

Results

Based on the DoE, the model was first run for single-demand (i.e., regular operations) scenarios for both commodities (wood and metal) separately using the three 20-client subsamples and the original depot location.

Then, the model was run for the combined demand or cargo consolidation scenario. Again, the values of all demands (separate and combined for all clients) were at a daily level. For model runs, a vehicle capacity of 18 tons was used with a maximum range (i.e., autonomy) of 400 km. Table 2 compares the results between single-demand and cargo consolidation runs.

Table 2. Results Comparison – Single-Demand versus Cargo Consolidation

		Single-Demand Model	Cargo Consolidation (CC) Model	CC Model Improvement
RS1	Volume (tons)	39.3	39.3	
	Distance (km)	818.3	460.2	43.76%
	No. Trucks/Trips	3	3	0.00%
RS2	Volume (tons)	27.6	27.6	
	Distance (km)	1347	677	49.74%
	No. Trucks/Trips	4	2	50.00%
RS3	Volume (tons)	29.8	29.8	
	Distance (km)	818	431	47.31%
	No. Trucks/Trips	3	2	33.33%
Average %	***Distance (km)***	994.4	522.7	***46.94%***
	No. Trucks/Trips	3.3	2.3	***27.78%***
Average Nominal	***Distance (km)***			***–471.7***
	No. Trucks/Trips			***–1.0***

Results show that the cargo consolidation model offers substantial benefits in both measures: distance and truck trips. The average cargo consolidation improvement on needed distance from the algorithm is 29%, with 19% fewer trips needed to meet client demand. The fewer trips translate to roughly 300 km and 0.7 trips/vehicles less every day than separate nonconsolidated operations. As in the case of the model, the benefits increase to 72,797 vehicle-kilometers less congestion (299.2 km × 0.7 vehicles of improvement), which is roughly 45,233 vehicle-miles. Both the model and the algorithm provide significant improvement on cargo consolidation versus the single-demand nonconsolidated operation. However, the model affords greater benefits than the algorithm. Table 3 shows the difference between improvements by the algorithm versus the model. This difference can be deemed the algorithm's deviation from optimality (right-hand column).

Table 3. Results Comparison – Cargo Consolidation Improvement, Model versus Algorithm

		Cargo Consolidation Improvement		Algorithm's Deviation from Optimality
		Model	Algorithm	
RS1	Distance	43.76%	15.43%	−50.38%
	No. Trucks/Trips	0.00%	0.00%	0.00%
RS2	Distance	49.74%	34.38%	−30.56%
	No. Trucks/Trips	50.00%	25.00%	−50.00%
RS3	Distance	47.31%	37.67%	−18.31%
	No. Trucks/Trips	33.33%	33.33%	0.00%
Average	***Distance***	46.94%	29.16%	−33.08%
	No. Trucks/Trips	27.78%	19.44%	−16.67%

The average suboptimality gap is 33% in distance and a little less than 17% in the number of trips. In any case, the algorithm consistently provides significant improvements over the single-demand nonconsolidated routing.

The next step in the DoE was to minimize the total—depot—distance from all clients. The result of this model for the new optimized depot location yielded the following latitude and longitude: 29.78859344, −95.39668513. This location provided a total—summed—distance for all 58 clients of 1,587 km. The original spherical total distance was 1,748 km, which would then represent a one-way (as-the-crow-flies) improvement of 161 km. Figure 2 shows the optimized location of the depot (black factory icon highlighted in green circle) and the original depot locations (maroon factory icons highlighted in red circles).

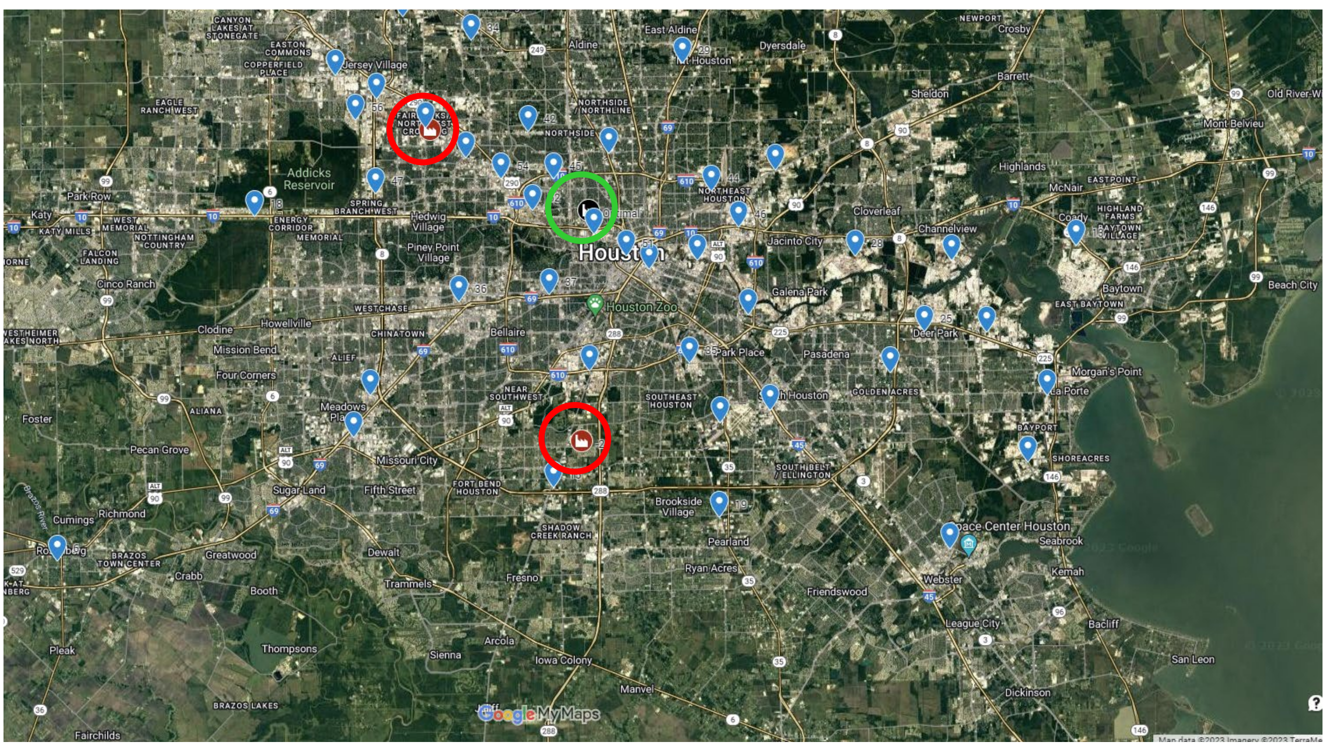


Figure 2. Optimized and original depot/supplier locations – Houston, Texas.

A new distance matrix was calculated based on this optimized location, and then the model and algorithm were implemented again with the same three 20-client samples and the complete 58-client dataset. When comparing the optimized location single-demand model with the cargo consolidation algorithm (Table 4), the benefit is larger for the optimized location than for the original location (Table 2).

Table 4. Results Comparison – Single-Demand Model versus Cargo Consolidation Algorithm (Optimized Location)

		Single-Demand Model	Cargo Consolidation Algorithm	CC Algorithm Improvement
RS1	Volume (tons)	39.3	39.3	
	Distance (km)	806.9	611.6	24.20%
	No. Trucks/Trips	3	3	0.00%
RS2	Volume (tons)	27.6	27.6	
	Distance (km)	1288	838.3	34.91%
	No. Trucks/Trips	4	3	25.00%
RS3	Volume (tons)	29.8	29.8	
	Distance (km)	806	569.6	29.33%
	No. Trucks/Trips	4	2	50.00%
Average %	***Distance (km)***	967.0	673.2	***29.48%***
	No. Trucks/Trips	3.7	2.7	***25.00%***
Average Nominal	***Distance (km)***			***−293.8***
	No. Trucks/Trips			***−1.0***

In the case of the optimized location, the average suboptimality gap remains close to the previous values, with 35.88% deviation in distance and 16.67% in number of trucks/trips (Table 5).

Table 5. Results Comparison – Cargo Consolidation Improvement, Model versus Algorithm (Optimized Location)

		Improvement from Cargo Consolidation		Algorithm Deviation from Optimality
		Model	Algorithm	
RS1	Distance	47.38%	24.20%	−44.05%
	No. Trucks/Trips	0.00%	0.00%	0.00%
RS2	Distance	49.77%	34.91%	−29.57%
	No. Trucks/Trips	50.00%	25.00%	−50.00%
RS3	Distance	47.27%	29.33%	−34.02%
	No. Trucks/Trips	50.00%	50.00%	0.00%
Average	**Distance**	48.14%	29.48%	−35.88%
	No. Trucks/Trips	33.33%	25.00%	−16.67%

These last results show additional benefits by optimizing depot locations. However, these benefits may not seem large, possibly because location optimization is performed based on spherical distances and not on actual routing distances, as the model and algorithm consider.

Chapter 1. Introduction

Shipments via truck, ship, train, and plane—often known as road, maritime, rail, and air shipments—are the four basic modes of transportation in logistics. Among these, over-the-road transportation is the most popular, widely used, and in-demand mode of transportation because of its cost and versatility. More products in the United States are transported by trucks than by railway, water, and air freight (Kong et al., 2021).

Almost everything manufactured, purchased, or consumed in the United States is transported by truck at some point. Although the number of heavy vehicles in the traffic stream is limited, their impact is significant. Traditional transportation plans merely analyze and calculate route selection for larger goods using the following weight values: road length, road width, and transportation cost. The turning direction at road crossings, on the other hand, is an essential factor for large trucks. Al Eisaeia et al. (2017) noted, “Due to the operational characteristics (e.g. acceleration/deceleration, maneuverability) and physical specifications (e.g. length, size) of heavy vehicles, they impose negative impacts on surrounding traffic.” In addition to increased air and noise pollution, these negative effects include a decrease in road safety and a rise in traffic congestion. Due to the existence of traffic lights—where heavy trucks must slow down at a red light, halt, and then resume accelerating—the negative effects caused by large vehicles are amplified on arterial highways. Most transportation literature and transportation impact models treat congestion as a cost factor, comprised of time delay and operating expense since it affects the efficiency of logistics operations by increasing trip time and uncertainty.

Congestion Problem

Traffic congestion is a global phenomenon that is expected to worsen in the future. If ignored, traffic congestion could negatively impact the competitiveness of a country (Kesuma et al., 2019). Because large trucks are heavier than passenger cars and take up a lot of space, these heavy vehicles have a significant impact on traffic, especially during rush hour. Congestion also results in increased travel time and uncertainty. The travel time/distance between customers and distribution centers is an important component that influences congestion. As traffic congestion worsens, the number of vehicles required to provide a certain level or service and complete the tour also increases, forming a vicious cycle between the number of vehicles and congestion. Therefore, reducing the number of commercial heavy vehicles reduces their negative effect on traffic flow.

Solution Illustration: Cargo Consolidation and Truck Sharing

The trucking industry contributes more than 84% of revenue in the U.S. commercial transportation sector. However, the U.S. trucking industry is very fragmented and this fragmentation hinders the efficiency of cargo transportation. An estimated 20% of the trucks on the road are traveling empty. This reduced efficiency causes traffic congestion, a hike in shipping prices, and greenhouse gas emissions. Cargo consolidation, or truck sharing, is one way to attain better efficiency in cargo transportation, which in turn helps avoid traffic congestion (Liu & Zhao, 2019). Figure 3 depicts the consolidation of less-than-truckload (LTL) shipments into full truckload (FTL) before delivering to the receiver.

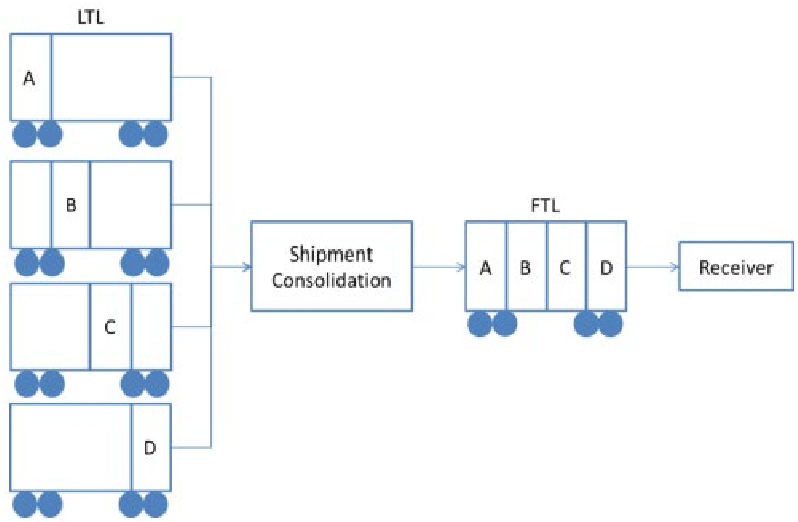
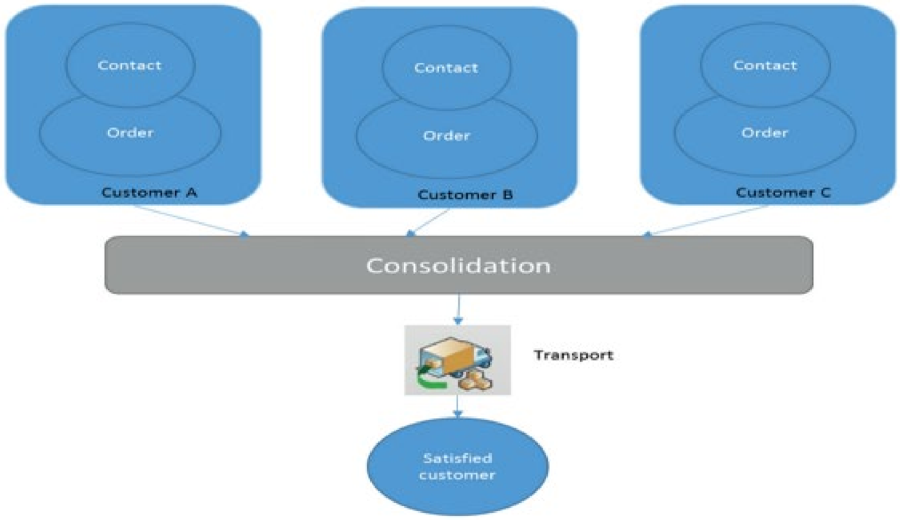


Figure 3. Principle of shipment consolidation.

Freight consolidation not only helps reduce traffic congestion but can also benefit everyone who uses LTL shipping because it makes logistics more efficient. As the freight loads of different companies are combined in the same truck, these companies no longer need to pay for empty truck space and, as a result, businesses can avoid heavy logistics costs.

The number of online marketplaces for freight-matching is on the rise since the concept and goal of freight-matching is to connect truck drivers and shippers based on request/need. However, the working principle behind freight-equipment matching is more complicated than hailing an Uber in real life because of the sizes and types of freights and trucks. It is difficult and time-consuming for carriers to search shippers' demand information online and to identify freight consolidation options. Therefore, online marketplaces need effective freight consolidation algorithms.

Consolidation shipping allows for combining individual LTL shipments from various shippers into one full container shipment. These consolidation strategies decrease transportation costs and reduce congestion. Figure 4 depicts the consolidation of shipments from various customers.



Source: Adapted from (Łukasik et al., 2021)

Figure 4. Cargo consolidation.

Even though cargo consolidation helps decrease traffic congestion, some challenges exist. Because of the increased complexity, for example, not all carriers are willing to carry consolidated shipments. Moreover, these shipments take more time because they require more planning and coordination than truckload (TL) shipments. Thus, a mechanism must be created for optimizing cargo consolidation and shipment routing via commercial heavy vehicles while maximizing transportation asset utilization.

The purpose of this project aligns with the pillars established by the National Institute for Congestion Reduction (NICR) by developing a methodology for reducing congestion while simultaneously lowering the number of trips and total distance required to meet market demand. The NICR pillars "Battling Congestion Using Innovative Mobility Platforms," "Battling Congestion on the Freeway Corridor," "Incentivizing Transit in the Face of Innovative Alternatives," and "Urban and Rural Traffic Management in the Age of Big Data" are covered in this project through the development of a methodology that consolidates cargo and lowers trip distance, number of trips, and consequently congestion. To achieve this goal, the project developed a survey and a methodology aimed at lowering the number of commercial heavy trucks on the road while improving truck capacity to consistently move the same commodity volumes as needed by the market.

The goals of this project were as follows:

1. Optimize commercial truck trips, resulting in traffic reduction and improved travel reliability.
2. Develop different scenarios and evaluate improvements in transit and congestion.
3. Focus on mixed-cargo consolidation from different locations and companies as an approach for reducing, or optimizing to a certain degree, the number of trucks on the road.

This report is comprised of details related to the literature review, survey and interview results, methodology that includes the data assessment and dataset produced for the analysis, developed model and algorithm, and design of experiment (DoE). The literature review section focuses on strategies for mixed-cargo transport aimed at reducing the number of commercial trucks on roads and the related impacts on congestion and cost savings. The survey and interview section presents results related to the questions developed to understand current cargo consolidation practices among private-sector companies and public-sector entities, along with how they can potentially reduce cargo congestion. The methodology section discusses data sources considered for the methodology and the production of the master dataset that formed the foundation of the model and algorithm; manufacturer establishment data and commodity volume databases were the primary sources considered to trace the movement of cargo. A description of the model and algorithm developed in this project is then presented, as well as how the variables are incorporated. Finally, a discussion of the results and takeaways from the project make up the last section of the report.

Chapter 2. Literature Review

With the rapid advancement of economic globalization and regionalization, industry supply chains in all industries are becoming increasingly sophisticated, and the transportation network is becoming increasingly perplexing. As a result, the requirements for cargo transport have changed significantly—namely, first meeting customers' expectations, and second achieving prompt and efficient cargo delivery.

Bulk freight transportation is an important aspect of the transportation business. It has long been recognized that the various techniques of transferring bulk—bulk storage, bulk unloading, and bulk transportation—all have serious environmental consequences in ports and cities. As a result, containers have quickly advanced as a safe and efficient means of transportation. Furthermore, bulk transportation can lower the overall cost of logistics by reducing the trade gap between container shipping lines and the cost of transportation for cargo owners. A variety of road restrictions connected to the weight and dimensions of the item being transported significantly impact how efficiently large loads are moved. The primary goal of cargo delivery optimization is frequently characterized as minimizing delivery resources in terms of sustainability requirements. This goal can be met if the cargo delivery system is a logistics system based on the consolidation of all delivery process stakeholders intended to ensure the continuity of material flows as well as related information and financial flows.

A commercial vehicle's impact on congestion can be equivalent to the impact of several cars depending on the truck dimensions, engine power and truck weight, geometric design, and prevalent traffic conditions (Transportation Research Board [TRB], 2000). One significant factor that affects the efficiency of heavy freight transportation is a number of road restrictions related to the weight and dimensions of the cargo being transported.

To deal with the increase in heavy vehicle traffic, proper management approaches must be established, taking into account the negative effects of heavy vehicles on adjacent traffic. Implementing alternative heavy vehicle restriction strategies is a standard method of controlling heavy vehicle movements (Al Eisaeia et al., 2017).

Consolidation enables the transportation of smaller goods (e.g., placed on a few pallets) from far locations at a reasonable cost. Because time and price are the most critical concerns nowadays, cargo consolidation is a good solution to reduce traffic congestion. The flow of commodities ensures the smooth operation of cities and regions; however, heavy vehicles, due to their size, speed of movement, and frequency of stops, present significant problems in road traffic. Furthermore, heavy vehicles are known to contribute to traffic congestion, increased noise, and environmental degradation. Since these obstacles remain, cargo consolidation in road transport is the future of knowledge-based transportation. Cargo consolidation is the merging of several different shipments into a single cargo, which enables cost optimization (Łukasik et al., 2021).

Cargo Consolidation Strategies

To achieve the goal of reducing traffic congestion while decreasing transport costs via consolidation services, the current transportation structure of the client must be analyzed. Suppliers are assigned to certain warehouses regarding a transportation enterprise's terminal network providing services for consolidation. In the case of direct transportation, the vehicles must travel many kilometers/miles to convey a single tiny item or pallet. For such enterprises, medium and large cargos are not cost-effective; nevertheless, direct and consolidation methods can be combined to achieve the best outcomes (Łukasik et al., 2021).

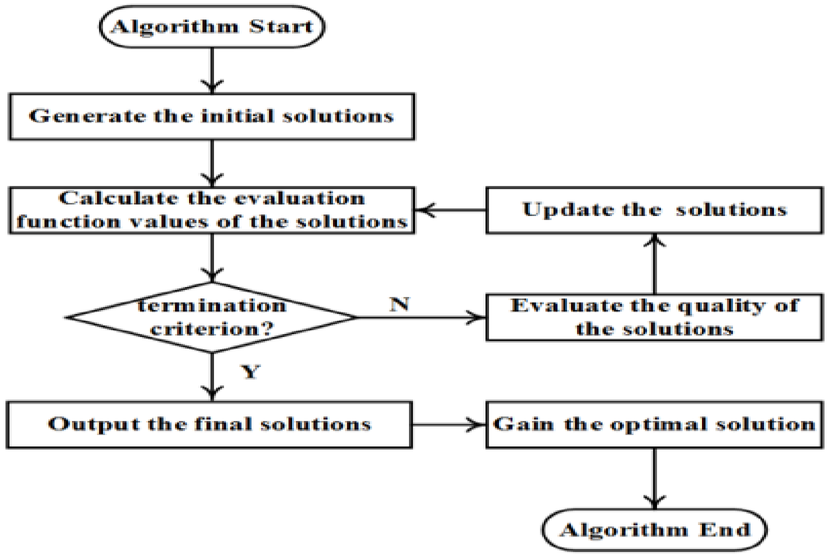
Consolidation strategies can be achieved in three ways (Hall, 1987; Higginson & Bookbinder, 1994; Ghiani et al., 2004). The first is the vehicle or multi-stop consolidation (over stops), in which small load shipments are picked up and dropped off along a multi-stop route by the same vehicle, allowing combined large loads to optimize the capacity of the container or truck. Some operational difficulties, such as how to route trucks and allocate shipments to trucks or containers, must be considered to solve this issue. The second is inventory or temporal consolidation (across time), in which current shipments are retained while future shipments are processed. Waiting for one or more periods allows the complete combined cargo to be shipped using one container or one truck, saving numerous separate LTL costs. Two fundamental operational issues in this area are (1) when to dispatch a vehicle so that service requirements are met, and (2) how large the dispatch quantity should be so that the economies of scale are realized. The third consolidation approach is terminal or facility consolidation (over space), in which small shipments from various facilities are transported over long distances to the transshipment center to be consolidated into bigger shipments. To optimize system performance, several tactical and operational decisions on hub placements, hub service areas, and vehicle routing are required (Deng, 2013).

Shipments are often transported within their preestablished transportation network, which includes fixed hubs, hub service areas, and transit frequency. Cargo or passengers from various origins are consolidated in hubs before being shipped to intermediate hubs and/or destinations. Another application of freight consolidation is the vendor managed inventory (VMI) practice. Vendors handle downstream warehouse or client inventories, delivery, and their own inventory. Transportation costs and traffic can be considerably reduced by integrating inbound and outgoing shipments (Deng, 2013).

Optimization Models in the Literature

Optimization models are developed to mathematically describe the multimodal transportation freight routing planning problem. Optimal solutions can be obtained by entering practical transportation data into optimization models and then solving them using exact solution methods (e.g., column generation method and branch-and-bound method) or approximate solution methods (e.g., genetic algorithm and Tabu Search algorithm) (Sun et al., 2015).

The genetic algorithm is the most well-known and widely used heuristic algorithm. Understanding the genetic algorithm can assist in capturing the essence of the heuristics. To improve the performance of specific heuristic algorithms, the coefficient modification method and combinatorial optimization methods can be used in the updating step. Figure 5 depicts a heuristic algorithm flowchart.



Source: Adapted from Sun et al. (2015)

Figure 5. Common flowchart of the heuristic algorithms.

Heuristic Algorithm for the Truckload and Less-Than-Truckload Problem

A heuristic algorithm to route the private trucks and to select less-than-truckload carriers by minimizing a total cost function is proposed in Chu (2005). The author introduces both the mathematical model and the heuristic algorithm to solve the less-than-truckload and truckload problem. In many sectors, such as lumber, wood, petroleum, stone, clay, and glass products, transportation costs amount to a fifth or even a quarter of the average sales price. Extensive experimental results show that the heuristic algorithm that was developed obtains the optimal or near-optimal solutions in an efficient way in terms of both time and accuracy.

The mathematical model was designed based on five assumptions:

1. One warehouse system is considered; all trucks start there as the origin and return to the same place.
2. The requirements of all the customers are known and cannot exceed the truck capacity.
3. Each customer is served by one truck (private or LTL). The requirements of all the customers must be met.
4. The model is restricted to delivering only.
5. The total cost of operating truck fleet = fixed cost (salary, insurance, truck depreciation) + variable cost (fuel).

Heuristic Algorithm for Vehicle Routing Problem

The vehicle routing problem (VRP) is a significant and difficult subject in combinatorial optimization, which is an active research field in supply chain management. VRP aims to reduce overall routing costs in terms of fleet size and/or total miles. Finding the ideal VRP solution is NP-hard (non-deterministic polynomial-time hardness), and an exhaustive search is impractical even with a reasonable number of nodes. To find the best solution in large-scale situations where reaction time is critical, sophisticated, precise algorithms like branch-and-bound and column generation are developed, but they still have a high computing burden. Because heuristics design makes extensive use of expert intuition, it is an excellent candidate for integration with machine learning and, as a result, automation and augmentation (Gao et al., 2020).

VRP is defined using a directed graph G = (N, A). With service time windows and vehicle capacity constraints, the goal of VRP is to identify one or more Hamiltonian cycles (a cyclic tour that visits each vertex precisely once) (Gao et al., 2020).

The Neighborhood Search framework is used to iteratively search the neighborhood of the current solution, and the local minimum is then used as a replacement. In this sense, the solution will eventually converge to something close to optimal. A well-designed heuristics operator H produces improved exploration effectiveness and converging efficiency.

This simple definition of heuristics leads to a limited local scope and exploration possibilities. In more complex VLNS (Very Large Neighborhood Search) frameworks, the neighborhood is defined implicitly by a pair of destroying and repairing operators. The destroy operator destroys a portion of the current solution by deleting a number of nodes from the routes. The repair operator rebuilds the destroyed solution by gradually reintroducing the removed nodes.

Heuristic Algorithms for Solving the Generalized Vehicle Routing Problem

An expansion of VRP is the generalized vehicle routing problem (GVRP). The goal of GVRP is to create the best delivery or collection routes from a given depot to as many predetermined, mutually exclusive, and exhaustive node sets as possible while considering capacity constraints (clusters). GVRP may be thought of as a specific kind of location-routing issue for which there are several methods, most of which are heuristics (Pop et al., 2011).

Pop et al. (2011) presented two integer linear programming formulations for GVRP with $O(n^2)$ binary variables and $O(n^2)$ constraints, where *n* is the number of customers divided into a given number of clusters. They also proposed an integer programming formulation for GVRP with a polynomially increasing number of binary variables and constraints.

GVRP involves finding the lowest overall cost tours that start and end at the depot while ensuring that (a) each cluster is visited exactly once, (b) the entering and leaving nodes of each cluster are the same, and (c) the total of all demands for any tour (route) does not exceed the vehicle's capacity. When there is no known way to identify an optimal solution within the given restrictions (of time, space, etc.), or at all, heuristics are frequently utilized. For the traditional VRP, several families of heuristic algorithms have been put forth. The two primary categories of these are classical heuristics and metaheuristics. The majority of commonly used conventional building and improvement techniques fall within the first class. These techniques undertake a relatively restricted investigation of the solution space and typically result in high-caliber solutions in a fair amount of time.

Heuristic-Based Ant Colony Optimization for Vehicle Routing Problem

A new and effective hybrid metaheuristic method for large-scale vehicle routing problems based on the decomposition technique combines the strengths of the well-known Nearest Neighbor Search and Tabu Search into a two-stage procedure. The Nearest Neighbor Search is used in the first stage to build initial routes, and the Tabu Search is used in the second stage to optimize intra- and inter-routes.

Vehicle routing is an NP-complete (non-deterministic polynomial-time) combinatorial optimization problem. Among the many proposed approaches, metaheuristic algorithms seem promising for tackling NP issues. As a result, a modified ant colony optimization (ACO) is proposed to address a form of VRP known as capacitated vehicle routing problem (CVRP), which requires minimizing the overall routing distance by each vehicle as well as the total service time on the customer nodes. The explored CVRP is considered a two-phase problem, with customer/vehicle assignment and makespan minimization phases. In the clustering phase, a modified ACO with a semi-greedy heuristic in the state transition rule is applied. Meanwhile, during the makespan minimization phase, an NEH (Nawaz-Enscore-Ham) heuristic is used to update the visiting customers' order of each vehicle.

However, CVRP must meet the following constraints:

- Every route starts and ends at the depot.
- Each customer must be visited only once.
- The total demand from customers on the route cannot exceed the capacity limit of vehicles.
- The traveling time of every route by the fleet cannot be over the duration limit.

The experimental findings show that the proposed approach, as per Chen et al. (2012), is suitable for tackling CVRP-type issues.

Shipment Consolidation Using Mixed-Integer Linear Program (MILP)

Verseput (2016) discussed a new MILP model for shipment consolidation. Individual shipments of the same origin-destination (O-D) pair are combined in one order to achieve cost savings since the combined total weight will fall at a lower cost/kilogram rate. Thus, consolidation is optimized per unique O-D pair. It is assumed that the cheapest carrier and transport mode can be chosen so that one cost rate table always applies to a certain O-D pair. Here, both consolidation policies and an MILP solution are considered and results are compared.

Redesigned Benders Decomposition Approach for Large-Scale In-Transit Freight Consolidation Operations

In Hanbazazah et al. (2018), the authors developed a mixed-integer programming formulation for a multi-period freight consolidation problem that involves multiple products, suppliers, and potential consolidation points.

Third-party logistics (3PL) providers pick up the products from the suppliers on given shipment dates and deliver them to the customers within the delivery time frame. All products picked up are first delivered to intermediate gateways before being delivered to the customer. A 3PL company usually has more than one gateway that offers flexibility pertaining to shipment cost and consolidation options. Thus, the routing decisions must be made for two legs: from suppliers to gateways and from gateways to the final customer. The first leg decision involves assigning the shipment to a particular gateway and selecting the transportation mode. The consolidation-related decisions are made at the gateway. In the second leg, the carrier ships the products, either as consolidated shipments or to minimize shipment costs without violating the constraints set by the delivery time windows. When a shipment is not consolidated, it is forwarded to the customer in a more expensive way.

The authors formulated the in-transit freight consolidation problem as a mixed-integer programming problem and developed a Blenders decomposition-based solution approach that provides a significant scale-up in the performance of the solver. The decomposition replaces a large number of integer "freight consolidation" variables with a small number of continuous variables, which reduces the size of the problem in terms of both the number of variables and constraint without impacting the optimality.

Genetic Algorithm for the Freight Consolidation Problem

In Zhang et al. (2011), a detailed design of the genetic algorithm for the freight consolidation problem is proposed. In this genetic algorithm, shipping routes for various shipments and loading items into containers with varying sizes and costs must be considered. This model is used where different shipments are to be consolidated with the objective of minimizing the total cost (container transportation costs plus parcel delivery costs). Considering the hardness of the problem, Zhang et al. designed and implemented a genetic algorithm approach to solve it. The effectiveness of the algorithm was verified and tested using a large number of test cases. Extensive experimental results and comparison data show that the approach is far more suitable than the existing CPLEX 11.0, both in terms of quality and computation time (applicable for medium- to large-size shipments).

For mathematical formulation, Zhang et al. (2011) considered various attributes for various objects. Some of the important attributes mentioned are shipping route, price, capacity, and weight limitation.

Optimal Route Planning Based on Artificial Intelligence

An enormous traffic problem is being caused by the logistics sector. Using techniques such as big data analysis or artificial intelligence to minimize traffic by optimizing travel routes, lowering fuel consumption, and efficiently dispatching cars is one method to approach this issue. Even if the quickest road is not necessarily the best one, navigation devices on the market today can plan routes. Many navigation systems rely on their calculations of trip time on the current speed limit or length of the road; however, other factors such as the increase in traffic during rush hour or current weather conditions may cause traffic congestion and prolong journey time. Therefore, choosing the ideal course necessitates considering several factors. Since idle driving due to poor travel routes consumes fuel and reduces transportation efficiency, innovative methods are needed to make logistics trucks' transit routes more effective (Hu et al., 2020).

Using an adaptation matrix to calculate the shortest or best routes is one method for determining the optimal route (Hu et al., 2020). This method uses maps as part of its computation. Because there may be barriers between two places on the map, the shortest path may not always be the best option. Matrix calculations are used to determine the best path between two points, with a focus on dynamic path planning. Ant colony optimization may be used to find the best way across a certain region, and the technique can successfully address problems with dynamic path planning to find the best overall path.

Artificial intelligence may be used to create an ideal route identification system for logistics vehicles. Currently, existing route planning systems only take time and distance into account; however, to provide the best route, route planning must take more variables into account. As a result, Hu et al. (2020) included further information in the calculations, such as the history of traffic jams and the current weather. Big data analysis can also be used to extract features on each route throughout various periods. Then, to conduct the best route computation, a multilayer perceptron (MLP) model is developed and eventually Dijkstra's algorithm is used based on vehicle speed (Hu et al., 2020).

Cargo transport is rapidly expanding and will continue to grow in the near future. However, issues such as road congestion, negative environmental impacts from commercial heavy vehicles, and low utilization of truck capacity make cargo transportation less efficient. To address these issues, cargo consolidation appears to be a promising approach because it will significantly reduce LTL shipments. This literature review presented different cargo consolidation and optimization models used to analyze previous work performed and to determine which model to utilize in this study.

Chapter 3. Survey and Interviews

To address some of the challenges and issues stated in the introduction, surveys for both the private and public sectors were developed to obtain views and opinions from professionals in those sectors. Additionally, a total of four interviews with large distributors and shipping companies were held to understand the thought process that goes into shipments, how they approach mixed-cargo shipments, and whether any optimization is attempted.

Survey

Private-Sector Survey

The objective of the private-sector survey was to understand current cargo consolidation practices among private-sector companies and their potential to ease traffic congestion. For this, the research team identified target participants among private-sector professionals who are involved in cargo transportation, logistics service providers, freight forwarders, and other stakeholders involved in cargo consolidation and optimization efforts.

Next, the research team developed a set of well-defined questions including a mix of closed-ended (i.e., multiple choice) and open-ended (i.e., open text) questions that aligned with the survey objectives. Also included were Likert-scale questions to allow respondents to rate their agreement or disagreement with a statement on a scale, typically ranging from strongly agree to strongly disagree.

With this survey, the research team sought to obtain insights from private freight companies and professionals regarding cargo consolidation and optimization models that help reduce traffic congestion and benefit everyone who uses LTL shipping to make logistics more efficient. Appendix A contains a copy of the survey.

Private-Sector Survey Results

The data results from the survey were analyzed, and visualizations were plotted using Tableau.

The survey was taken by 25 professionals, 16 of whom completed the survey. The 25 professionals included distributors, freight carriers, freight forwarders, manufacturers, non-government organizations (NGOs), and retailers. The 16 survey respondents included five manufacturers, one retailer, three NGO representatives, one 3PL/4PL individual, and six others (consultant, hospitality operator, etc.), as shown in Figure 6.

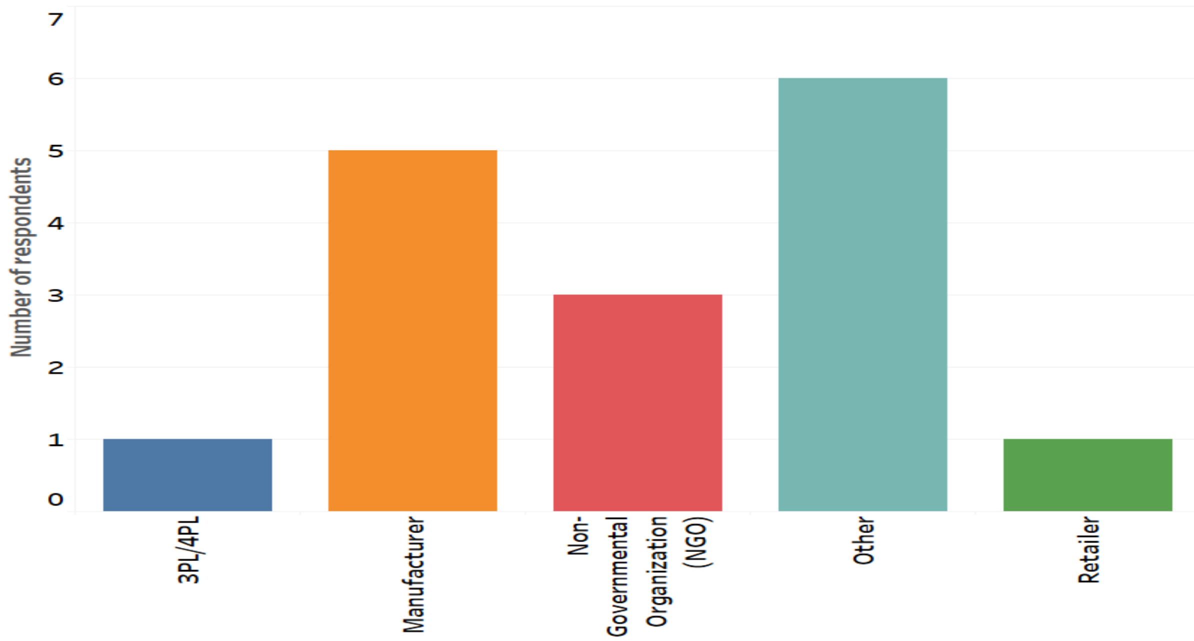


Figure 6. Private-sector organization type.

Figure 7 shows that the majority of respondents were from companies located in the United States, while a couple were from Europe and other regions.

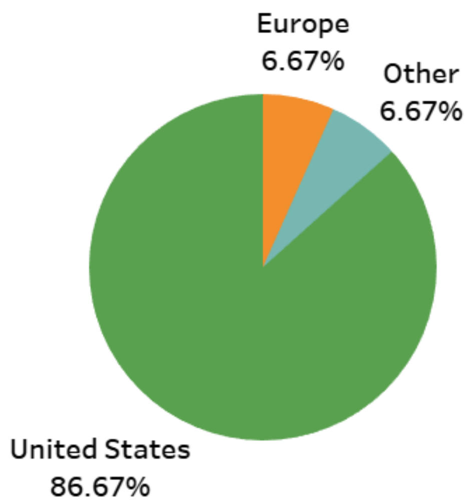


Figure 7. Location of private-sector companies.

Following is a presentation of the private-sector survey questions followed by a summary of the responses.

Survey Question 1: Is your company currently using cargo consolidation strategies?

A few of the companies are currently using cargo consolidation strategies to optimize their logistics operations and improve supply chain efficiency, but the majority are not implementing them yet, as shown in Figure 8.

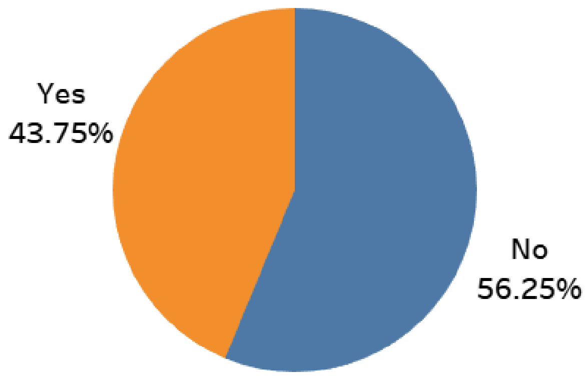


Figure 8. Proportion of companies using cargo consolidation strategies.

Survey Question 2(a): What internal factors/benefits made your company consider cargo consolidation? (1 = most important and 8 = least important)

Figure 9 shows that among the companies that are currently using cargo consolidation strategies, according to the weighted averages, the majority are using them because of minimized shipping costs (especially when shipping larger volumes of goods), increased efficiency (due to streamlined logistics operations, reduced handling and processing time, and optimized transportation routes), quicker transit time, and better shipment scheduling.

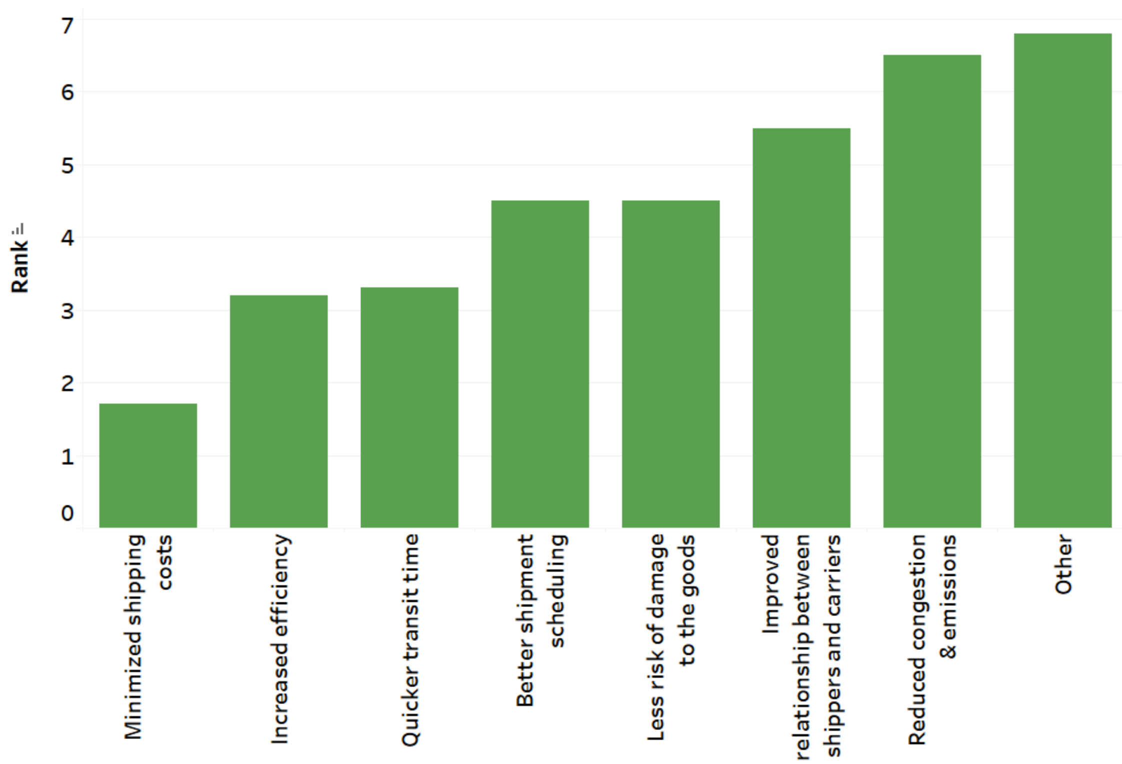


Figure 9. Internal benefits that made companies consider cargo consolidation.

Survey Question 2(b): What benefits are important for your company to consider cargo consolidation? (1 = most important and 8 = least important)

According to the weighted averages, the companies that are currently not utilizing cargo consolidation strategies reported that minimized shipping costs, quicker transit time, less risk of damage to the goods, and increased efficiency are the major factors that would cause them to consider implementing consolidation strategies, as shown in Figure 10.

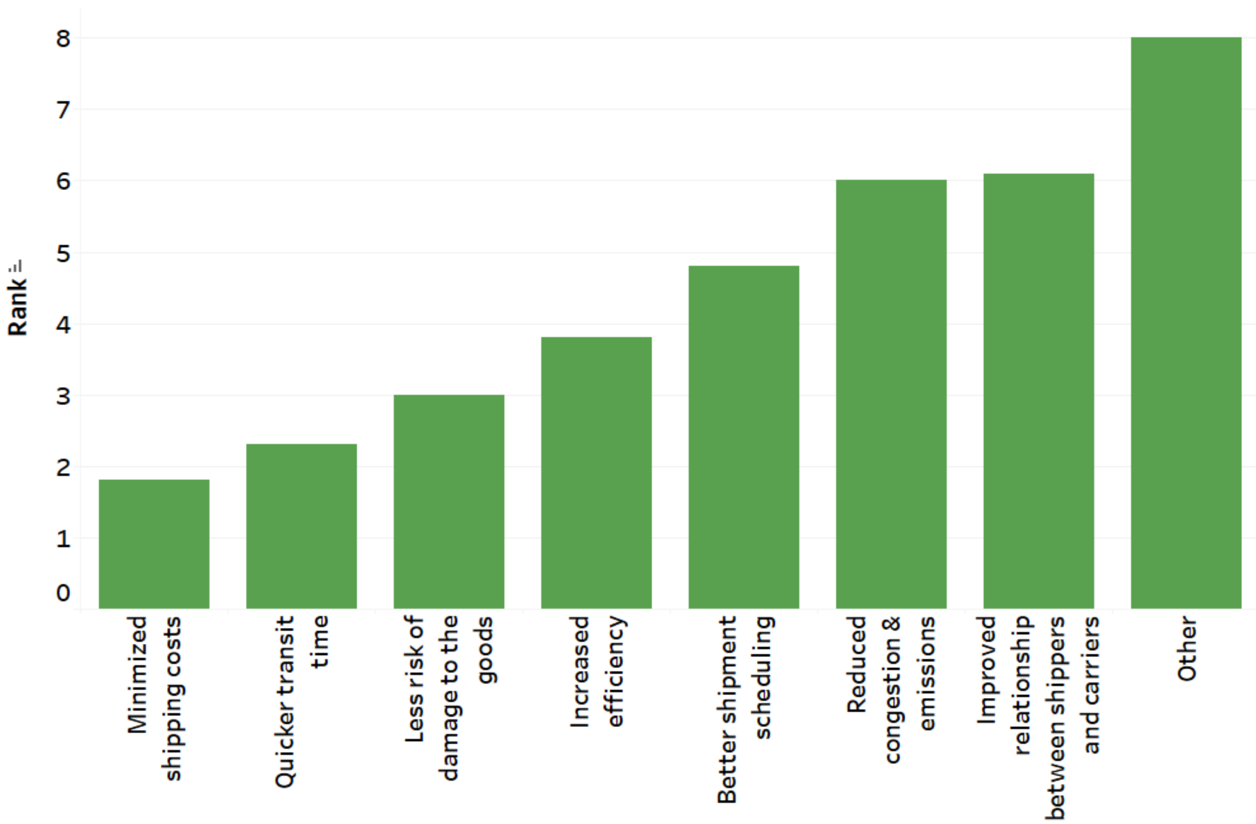


Figure 10. Benefits that are important for companies to consider cargo consolidation.

Survey Question 3: In your opinion, what are the key considerations for effective cargo consolidation? (1 = most important and 8 = least important)

Effective cargo consolidation requires careful consideration of various factors. As Figure 11 shows, respondents revealed that finding the right partner, cost, distribution requirement (demand to be delivered), product features, and distribution network (distances between supply chain nodes) are some of the key considerations, according to the weighted averages, for effective cargo consolidation.

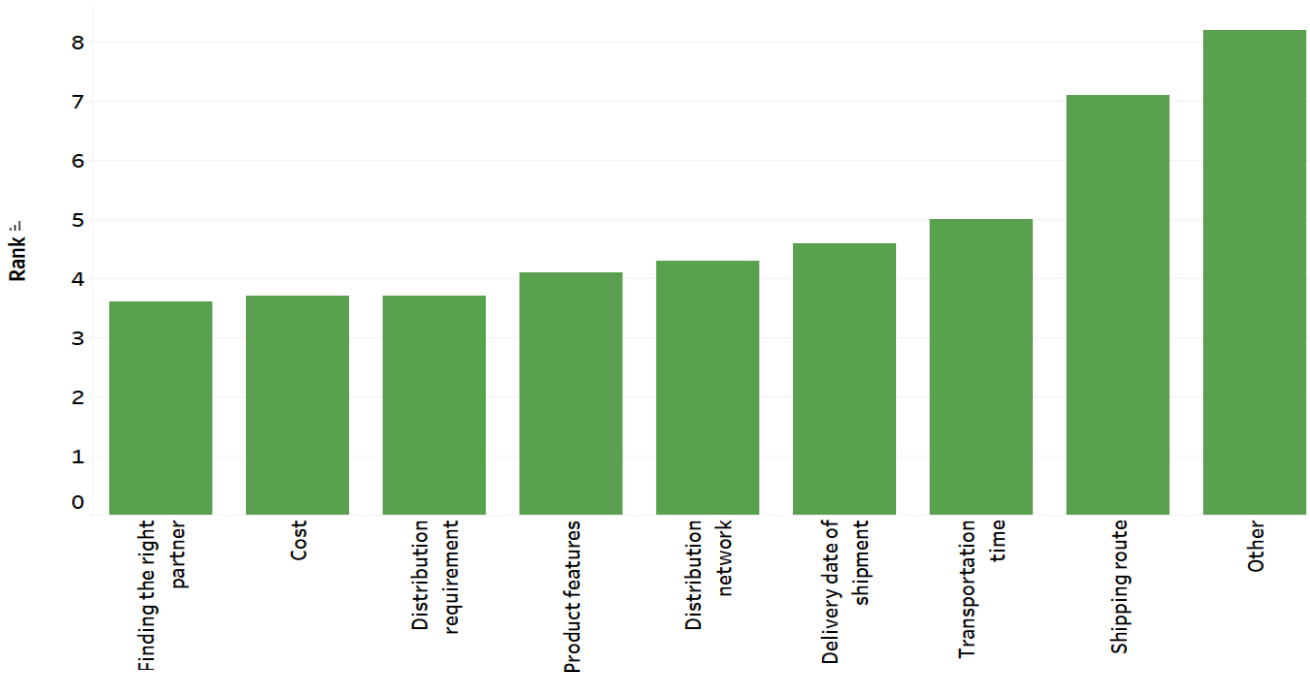


Figure 11. Key considerations for effective cargo consolidation.

By carefully evaluating these considerations, companies can implement cargo consolidation strategies that are cost-effective, efficient, and aligned with their supply chain requirements.

Survey Question 4: What challenges does/might your company face when implementing cargo consolidation?

Implementing cargo consolidation strategies presents several challenges for companies. Figure 12 shows that short lead times, finding the right carrier/partner, and system complexity are some of the major challenges companies are facing when implementing consolidation strategies.

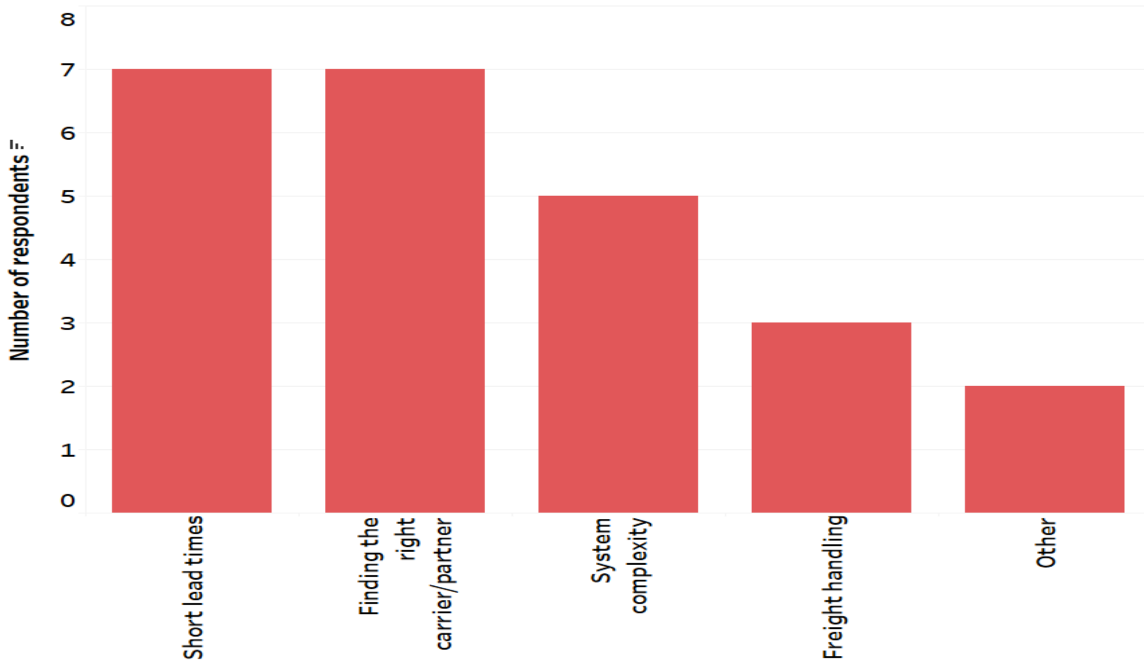


Figure 12. Challenges faced by companies when implementing cargo consolidation.

Survey Question 5: When would you prefer to use cargo consolidation services?

Cargo consolidation services are preferred by companies in situations where they can result in cost savings, increased effectiveness, improved sustainability, better customer service, streamlined logistics operations, flexibility in transportation modes, improved supplier collaboration, and customization of shipments.

The majority of respondents revealed that they would prefer to use these services when buying from multiple suppliers, when shipping few products from time to time, and when implementing sustainability goals, as shown in Figure 13.

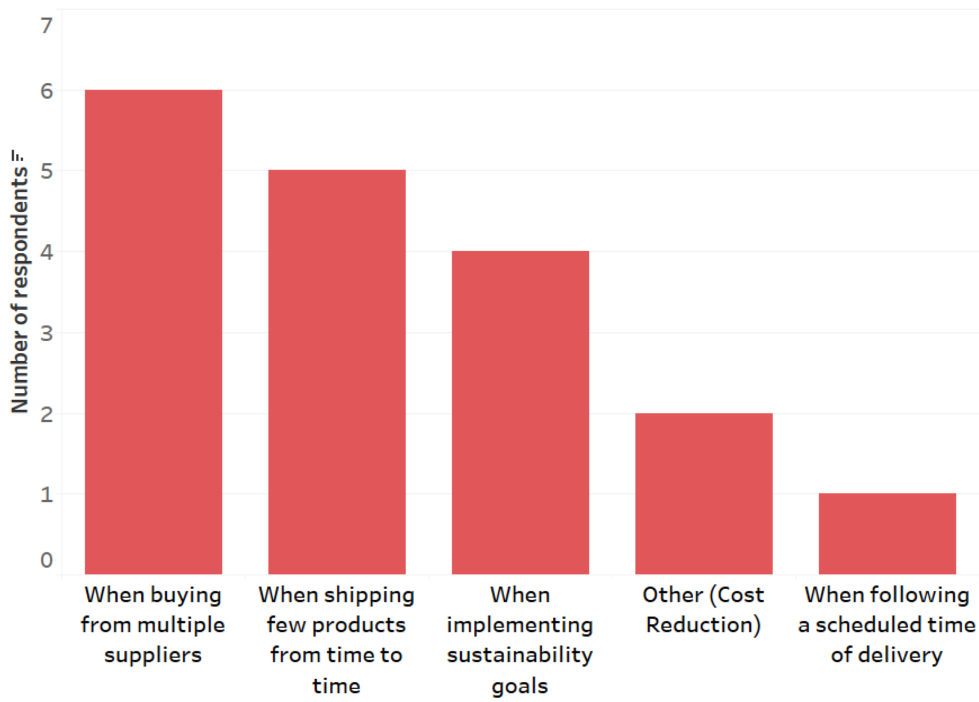


Figure 13. Preferred time to use cargo consolidation services.

Survey Question 6: Presently, how beneficial do you think it is to implement cargo consolidation strategies (combining multiple LTL shipments that are traveling in the same vicinity into one full truckload shipment) for the alleviation of traffic congestion?

Figure 14 shows that most respondents in the private sector felt that it is very/moderately beneficial to implement cargo consolidation strategies for alleviating traffic congestion.

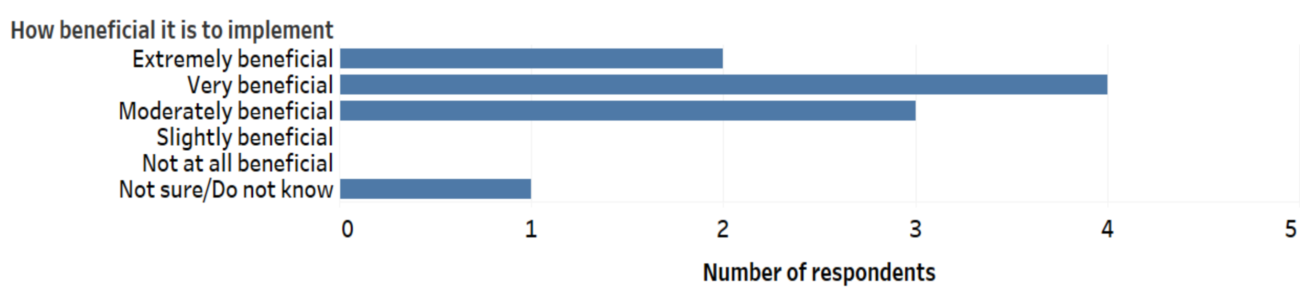


Figure 14. Private-sector opinion on how beneficial it is to implement cargo consolidation strategies.

Survey Question 7: Within five to ten years, how important will it be in your opinion to employ cargo consolidation, rerouting, and optimization strategies to reduce traffic congestion and transportation costs?

In the next five to ten years, it is likely that strategies like cargo consolidation, rerouting, and optimization will continue to be important considerations for people in the private sector when it comes to lowering traffic congestion and transportation costs. Figure 15 shows that most of the respondents felt that it is moderately/very important to employ these techniques.

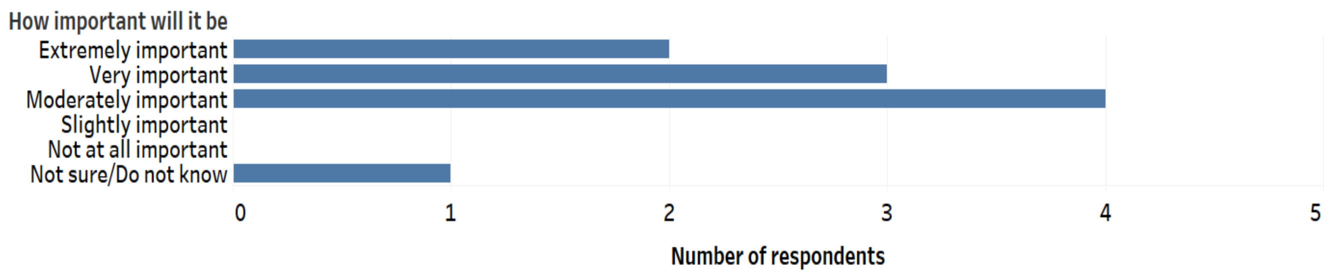


Figure 15. Importance of employing cargo consolidation strategies within five to ten years.

Overall, implementing cargo consolidation techniques in the private sector can be important for businesses by offering cost savings, enhanced operational efficiency, sustainability benefits, and traffic congestion mitigation. Companies can strategically use cargo consolidation techniques to enhance the efficiency of their supply chains, cut down on transportation expenses, and boost overall operational performance.

Public-Sector Survey

The objective of the public-sector survey was to understand current cargo consolidation practices among the public sector and their potential to ease traffic congestion. For this, the research team identified target participants among public-sector professionals who are involved in cargo transportation, logistics service providers, freight forwarders, and other stakeholders involved in cargo consolidation and optimization efforts.

Next, the research team developed a set of well-defined questions including a mix of closed-ended (i.e., multiple choice) and open-ended (i.e., open text) questions that aligned with the survey objectives. Also included were Likert-scale questions to allow respondents to rate their agreement or disagreement with a statement on a scale, typically ranging from strongly agree to strongly disagree.

With this survey, the research team sought to obtain insights from public freight companies and professionals regarding cargo consolidation and optimization models that help reduce traffic congestion and benefit everyone who uses LTL shipping to make logistics more efficient. Appendix B provides a copy of the survey.

Public-Sector Survey Results

The data results from the survey were analyzed, and visualizations were plotted using Tableau.

The survey was taken by 21 professionals, 9 of whom completed the survey. These professionals were from metropolitan planning organizations, state departments of transportation (DOTs), government agencies, USDOT, and local governments. Of the nine who completed the survey, two were from state DOTs, two were from a U.S. government agency, two were academics/researchers, one was from local government, and two indicated being from “other,” as shown in Figure 16.

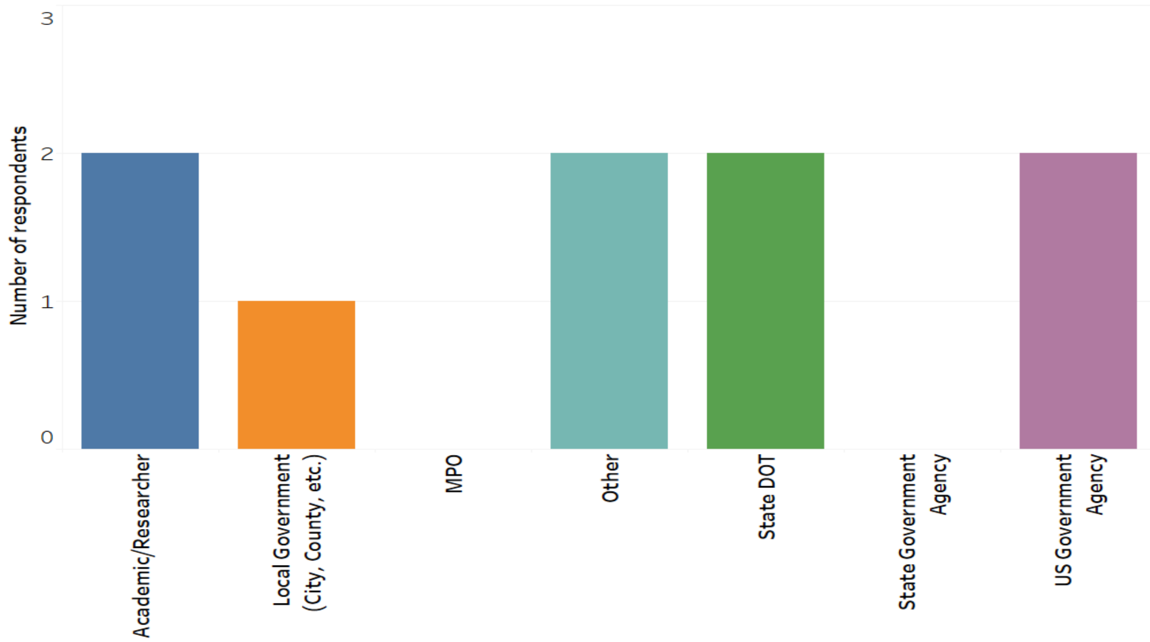


Figure 16. Public-sector organization type.

Figure 17 shows that the majority of survey respondents were from agencies located in the United States, while only a couple were from Europe and Asia.

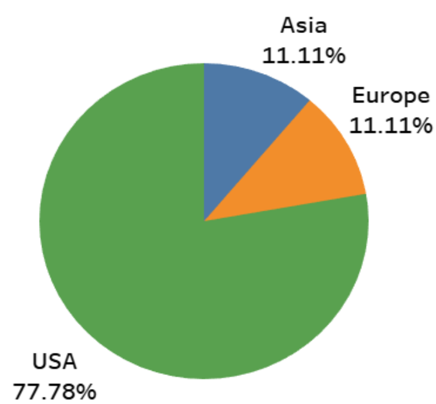


Figure 17. Location of public-sector agencies.

Following is a presentation of the public-sector survey questions followed by a summary of the responses.

Survey Question 1: How important is traffic congestion to your agency plans?

Traffic congestion is an important consideration for public agencies when planning transportation systems and urban development. Figure 18 indicates that most of the public-sector respondents felt that traffic congestion is extremely/very important for their agency plan.

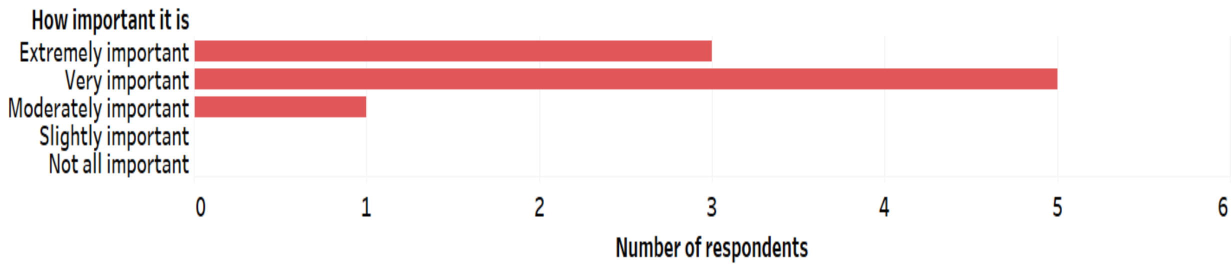


Figure 18. Importance of traffic congestion to agency plans.

Survey Question 2: From your agency's perspective, what is the main cause of traffic congestion? (1 = most important and 8 = least important)

According to the public agencies surveyed, there are many potential causes of traffic congestion, and these causes can change based on a particular situation. Figure 19 shows that bottlenecks, traffic incidents, work zones, bad weather, and commercial heavy vehicle impacts are the major causes of traffic congestion, according to the weighted averages.

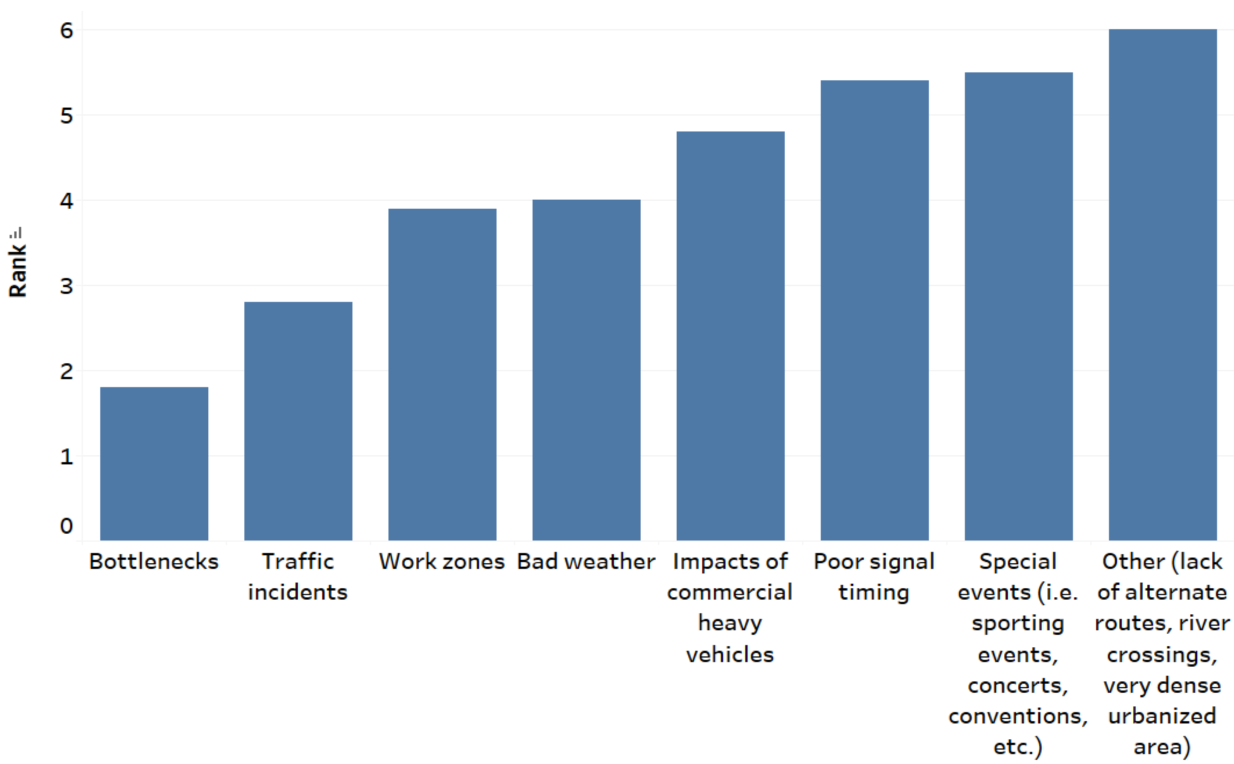


Figure 19. Main causes of traffic congestion.

Survey Question 3: Please rank the following methods to alleviate traffic congestion. (1 = most important and 8 = least important)

Public agencies employ a variety of methods to alleviate traffic congestion. Figure 20 shows that geometric improvements to roads and intersections, cargo consolidation, access management, and traffic signal timing optimization are the most used methods, according to the weighted averages.

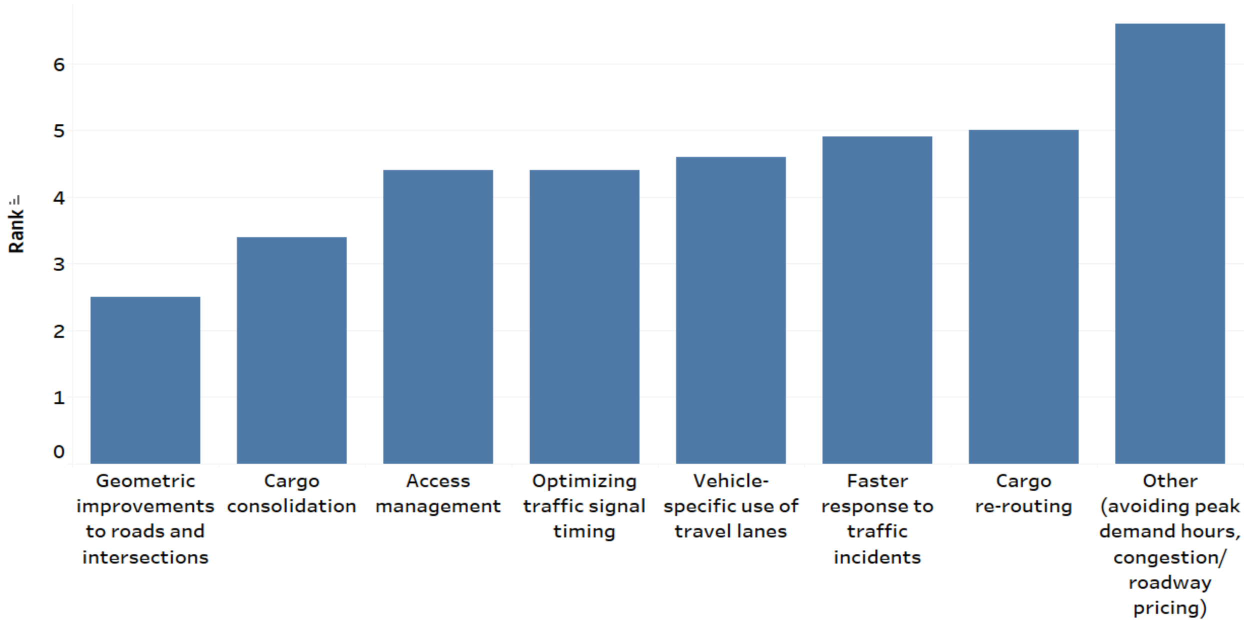


Figure 20. Methods to alleviate traffic congestion.

Survey Question 4: What does your agency use as mobility measures to track congestion?

Various mobility measures are used by public organizations to track traffic and evaluate the effectiveness of the transportation network. These measures typically involve gathering and studying information about traffic volumes, travel speeds, travel times, and other relevant variables. Most of the agencies use volume-to-capacity ratio, travel delay, travel time index, and average travel speed as mobility measures to track congestion, as per Figure 21.

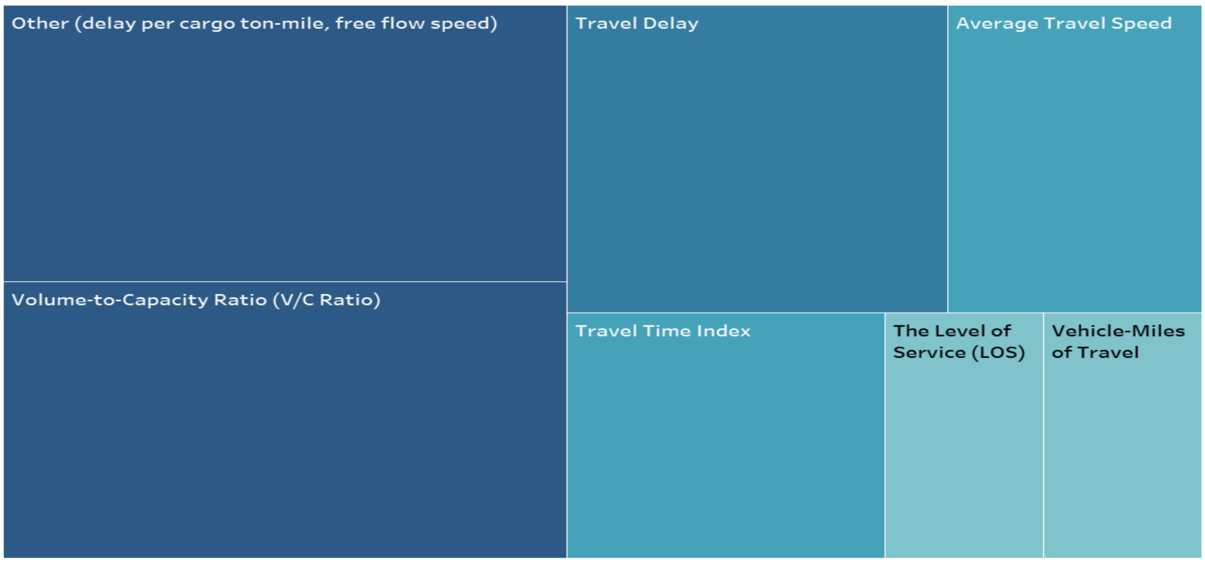


Figure 21. Mobility measures used to track congestion.

Survey Question 5: What does your agency use as reliability measures to track congestion?

Reliability measurements are frequently used by public agencies to monitor traffic and evaluate the effectiveness of transportation systems. A few of the agencies use level of travel time reliability and 95th percentile travel time as reliability measures to track congestion. However, as Figure 22 shows, most of the agencies do not know or are not using any reliability measures to track congestion.

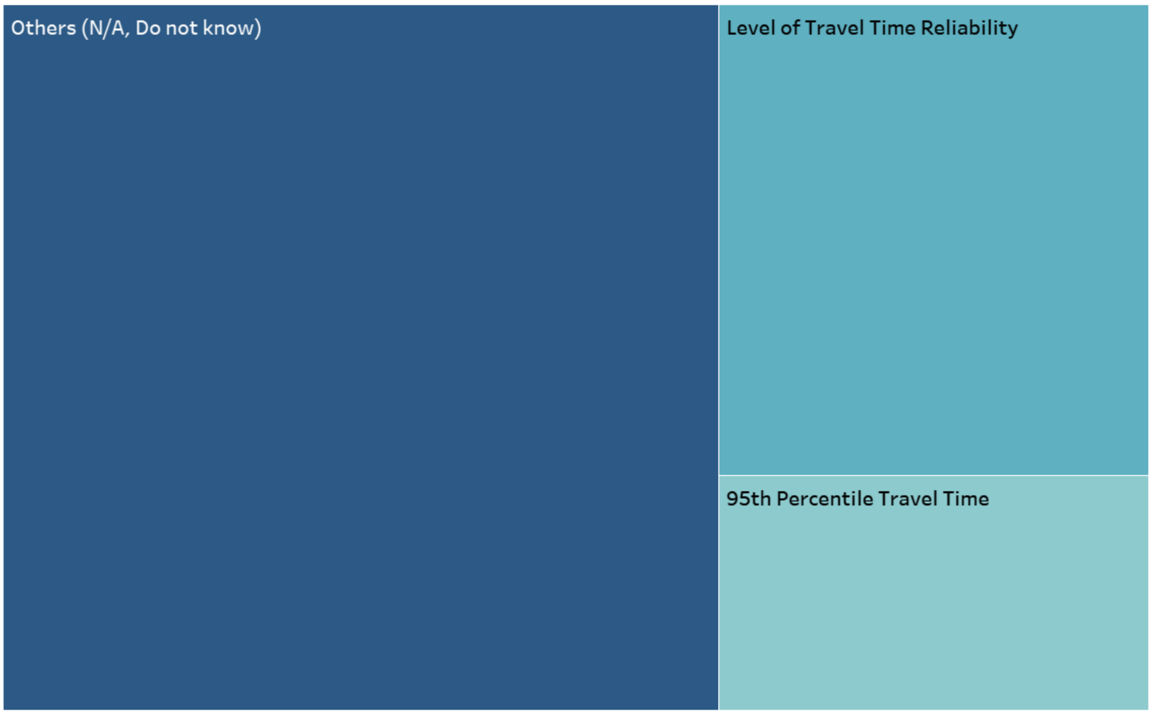


Figure 22. Reliability measures used to track congestion.

Survey Question 6: Would your agency be willing to collaborate on the implementation of cargo consolidation strategies to reduce traffic congestion?

In order to implement cargo consolidation strategies intended to lessen traffic congestion, public agencies frequently seek collaborations and partnerships with various stakeholders, including companies, shippers, logistics providers, and other relevant organizations. Figure 23 reveals that most of the agencies are not willing to collaborate on the implementation of cargo consolidation strategies to reduce traffic congestion.

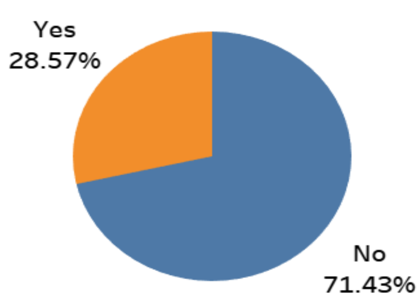


Figure 23. Agency willingness to collaborate.

Survey Question 7: Presently, how beneficial do you think it is to implement cargo consolidation strategies (combining multiple LTL shipments that are traveling in the same vicinity into one full truckload shipment) for the alleviation of traffic congestion?

According to the survey results, most of the public-sector respondents felt that it is moderately beneficial to implement cargo consolidation strategies for alleviating traffic congestion, as shown in Figure 24.

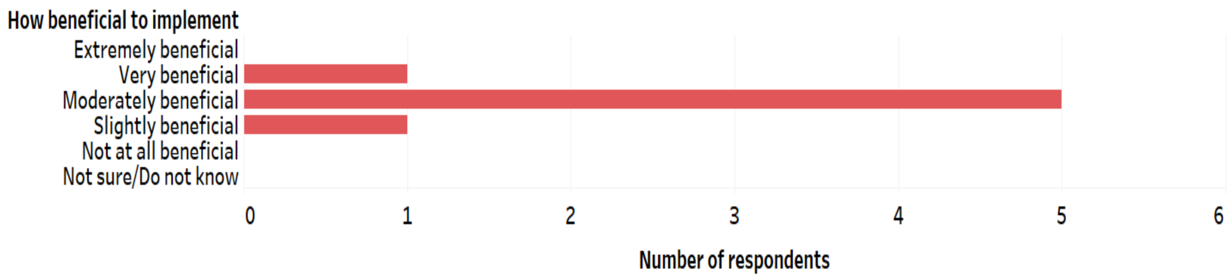


Figure 24. Public-sector opinion on how beneficial it is to implement cargo consolidation strategies.

Discussion of Survey Responses

Cargo transport is rapidly expanding and will continue to grow in the near future. However, issues such as road congestion, negative environmental impacts from commercial heavy vehicles, and low utilization of truck capacity make cargo transportation less efficient. To address these issues, cargo consolidation appears to be a promising approach because it will significantly reduce LTL shipments. In this study, the results of the public- and private-sector surveys were analyzed to determine which methods to utilize.

As observed from the private-sector survey, only a few companies are already using cargo consolidation strategies, and they reported that minimized shipping costs, increased efficiency, quicker transit time, and better shipment scheduling were the major benefits that made them consider it. In addition, finding the right partner, cost, distribution requirement, product features, and distribution network are the key considerations for effective consolidation. Moreover, short lead times, finding the right carrier/partner, and system complexity are some of the major challenges faced when implementing consolidation strategies.

Overall, most of the private-sector respondents felt that in the next five to ten years, it will be moderately/very important to employ cargo consolidation, rerouting, and optimization strategies to reduce traffic congestion and transportation costs.

In the public-sector survey, most of the respondents reported that traffic congestion is extremely/very important for their agency plan, and many felt that bottlenecks, traffic incidents, work zones, bad weather, and commercial heavy vehicle impacts are the major causes of traffic congestion. They also felt that geometric improvements to roads and intersections, cargo consolidation, access management, and traffic signal timing optimization are the best methods to alleviate traffic congestion.

Nonetheless, most of the agencies are not willing to collaborate on the implementation of cargo consolidation strategies and felt that it is only moderately beneficial to implement those strategies for alleviating traffic congestion because doing so may prove to be a challenge in public and private partnerships.

Interviews

Interview 1—Large Distributor 1

The research team held an interview on August 21, 2023, with a large distributor to delve into the factors influencing the planning of shipments, especially in the context of mixed cargos and whether any optimization is used for these activities.

A pivotal concern highlighted during the discussion was the company's geographical/supply chain location and congestion. Interestingly, the overall cost did not emerge as a primary concern for the company. The company prioritized reliability and customer service, valuing on-time shipments, proper documentation, and ease of booking confirmation. Occasionally, the company opted for higher freight rates, recognizing the trade-off for heightened reliability and superior customer service.

The company emphasized the need for infrastructural enhancements, including containers, chassis, cranes, and related equipment. In addition, the company mentioned that optimization techniques are utilized in the planning process for mixed cargo shipments and are being used by the company for regular shipments as well.

Interview 2—Large Distributor 2

On August 28, 2023, the research team conducted an interview with a second large distributor to explore the factors influencing the planning of shipments, especially in the context of mixed cargos and whether any optimization is used for these activities.

One of the factors that emerged as pivotal was the distribution center network, and the company emphasized the importance of effective network planning and optimization as far as cargo shipments are concerned. The company directly works with regional distribution centers from the import freight sector, making infrastructure at ports, throughput capacity, and port productivity critical determinants. Continuous evaluation of port capacity, drayage capacity, and drayage transportation is imperative to meet network requirements, considering factors like weather, labor strikes, and unforeseen conditions that necessitate adaptability without disrupting freight flow. Therefore, port flexibility and reliability are also paramount in the decision-making process.

The company strategically calculates the shortest distance between the port of entry and the end network and then optimizes for lowest cost by considering the mode choice selection for each commodity and its rate per a certain mode of transportation.

The company confirmed that it uses network and freight optimization to determine cargo and mixed cargo shipments, and it optimizes for minimized costs and shortest distance; however, the interviewee also mentioned that the company's priority is service first, with cost consideration as a secondary factor.

Interview 3—Shipping Company 1

The research team held an interview with a major shipping company on August 30, 2023, to delve into the factors influencing the planning of shipments, especially in the context of mixed cargos and whether any optimization is used for these activities.

Numerous considerations impact the company's planning of shipments, encompassing geographical location and available logistics capacity for each freight mode. The presence of multiple available options for the company is deemed very advantageous because it fosters competitiveness and facilitates lower rates.

In practice, the company orchestrates the transportation of various commodities to and from major ports—each serving a distinct purpose. According to the company, to attract more shippers and create a competitive environment, the ports must entice carriers with resources and incentives, enhancing service offerings and sailings while maintaining competitive labor unit costs on terminal fees. The availability of drayage carriers, chassis, and an adequate labor force for timely vessel loading is crucial since any shortfall in these elements can disrupt the customer supply chain.

That said, the company has a supply chain network simulation model with a built-in optimizer, and this is being utilized for planning of cargo and mixed cargo shipments. The company's entire network is included in this model, and timely delivery is one of the most important factors considered as the optimization is run.

Interview 4—Shipping Company 2

On September 7, 2023, the research team conducted an interview with a second large distributor to explore the factors influencing the planning of shipments, especially in the context of mixed cargos and whether any optimization is used for these activities.

During the interview, one of the major factors for shipment planning was highlighted as the supply chain network and the company's proximity to its customers. The company also places significant emphasis on evaluating landed costs, transit times, and the reliability of connecting routes when making decisions. Meeting customer demands for data analytics and predictability also factors into the planning, along with considerations of budget, alternatives, and potential routes. A critical focus for this company is the last mile.

The company uses a Transportation Management System (TMS) for managing its logistics, and the TMS comes with an optimizer for freight movements that takes into account minimized delivery times and costs.

Discussion of Interview Responses

From the interviews, the researchers observed that the planning of shipments for large distributors and shipping companies involves a sophisticated and strategic thought process driven by various considerations. Geographical logistics play a crucial role, where the proximity of ports to distribution centers and end destinations is meticulously evaluated. This thought process extends beyond mere distance, encompassing factors such as transportation infrastructure, road networks, and accessibility. Large distributors and shipping companies also engage in a comprehensive analysis of the characteristics of the cargo they handle. This includes considerations for the nature of the products, their storage requirements, and any regulatory constraints associated with their transportation. Furthermore, the choice of transportation modes—whether maritime, rail, road, or air—is a critical decision influenced by factors like transit times, cost efficiency, and specific requirements of the shipped goods.

In recent years, freight optimization has become an integral component of the thought process in planning shipments for both standard cargo and mixed cargo, as was observed in the four interviews. The complexity of modern supply chain operations demands a more dynamic approach to logistics. Freight optimization leverages advanced algorithms and data analytics to enhance the efficiency of cargo transportation. It involves evaluating various factors, including route planning, carrier selection, and cargo consolidation, with the goal of minimizing costs, reducing transit times, and maximizing overall operational efficiency.

This strategic use of technology not only streamlines logistics processes but also contributes to sustainability efforts by minimizing environmental impacts. Large distributors and shipping companies increasingly rely on freight optimization tools to make informed decisions that align with economic goals while adhering to evolving environmental standards and expectations. The researchers concluded from these interviews that most, if not all, of these companies use optimization models for their freight shipments for standard shipments as well as mixed cargo operations.

Chapter 4. Methodology

The methodology of the technical part of this work comprised the following three main elements:

1. Data assessment and dataset production—Focused on assessing available data sources and the activities needed to produce and build the final dataset for the analysis.
2. Model and algorithm development—Focused on developing the mathematical and programming model, as well as the heuristic (algorithm) for routing and location optimization.
3. Design of experiment—Focused on designing the application of the model and algorithm to evaluate their performance and benefits. This included the sampling design.

Data Assessment and Dataset Production

The research team attempted to obtain data from private-sector companies; however, confidentiality issues arose that jeopardized the progress of the project. Therefore, the team developed a methodology for assessing and retrieving available data pertaining to private-sector operations. This methodology allowed the researchers to overcome confidentiality issues and the dependance on companies' data availability constraints, while also providing a close-to-reality dataset on which to build validation scenarios for the model and algorithm.

In the data assessment and dataset production, manufacturing establishment data were selected to determine the share of commodities traveling through Texas roads. The data were obtained from the U.S. Department of Homeland Security (DHS) Geospatial Management Office and were in a geodatabase format for mapping. This dataset is comprised of point data containing information on manufacturing establishments across the country. Specific information in this dataset includes employment numbers, company address, and North American Industry Classification System (NAICS) codes and descriptions. For this project, the data were filtered to only display Texas. Commodity volumes were not included in this dataset, prompting the team to search for additional supplemental sources.

Different data source options were explored to match establishments with their respective commodity volumes. The team set out to find manufacturing commodity totals by city or county. The U.S. Census typically contains information with a resolution up to the city level; however, a different source option was chosen since commodity volumes were not available to that degree of granularity. The Commodity Flow Survey and Freight Analysis Framework (FAF) contain commodity volume estimates, with FAF providing data for specific Texas regions, also known as FAF Zones, that can be matched closer with Texas establishments. FAF categorizes its commodities using the Standard Classification of Transported Goods, while establishment data from the DHS Geospatial Management Office are categorized using the NAICS. Both of these code standards are comparable to one another and guided researchers in pairing establishments to commodity and its tonnage value.

To determine the approximate tonnage share contributed by each establishment, establishment employment numbers were summed together according to commodity type, resulting in total employment values by commodity. An employment percentage of each establishment was derived from the employment number divided by total employment by commodity type. This percentage was then used to distribute tonnage value across all establishments that match commodity types.

Once tonnage was allocated to each establishment, the team selected the two top commodities for the final dataset. These two commodities are wood and metal, the consolidation of which also makes sense in the real world due to similarities in some of their distribution operations. The commodity tonnage was stated in daily values in the final dataset.

After assessing several areas in terms of total demand for both commodities and establishment locations, the team selected Houston, Texas, as the study case. A total of 58 specific clients that had demand for both products were identified and selected for the analysis. Figure 25 shows the geographic distribution of client nodes (blue location icon) and supplier nodes (maroon factory icon highlighted in red circle).

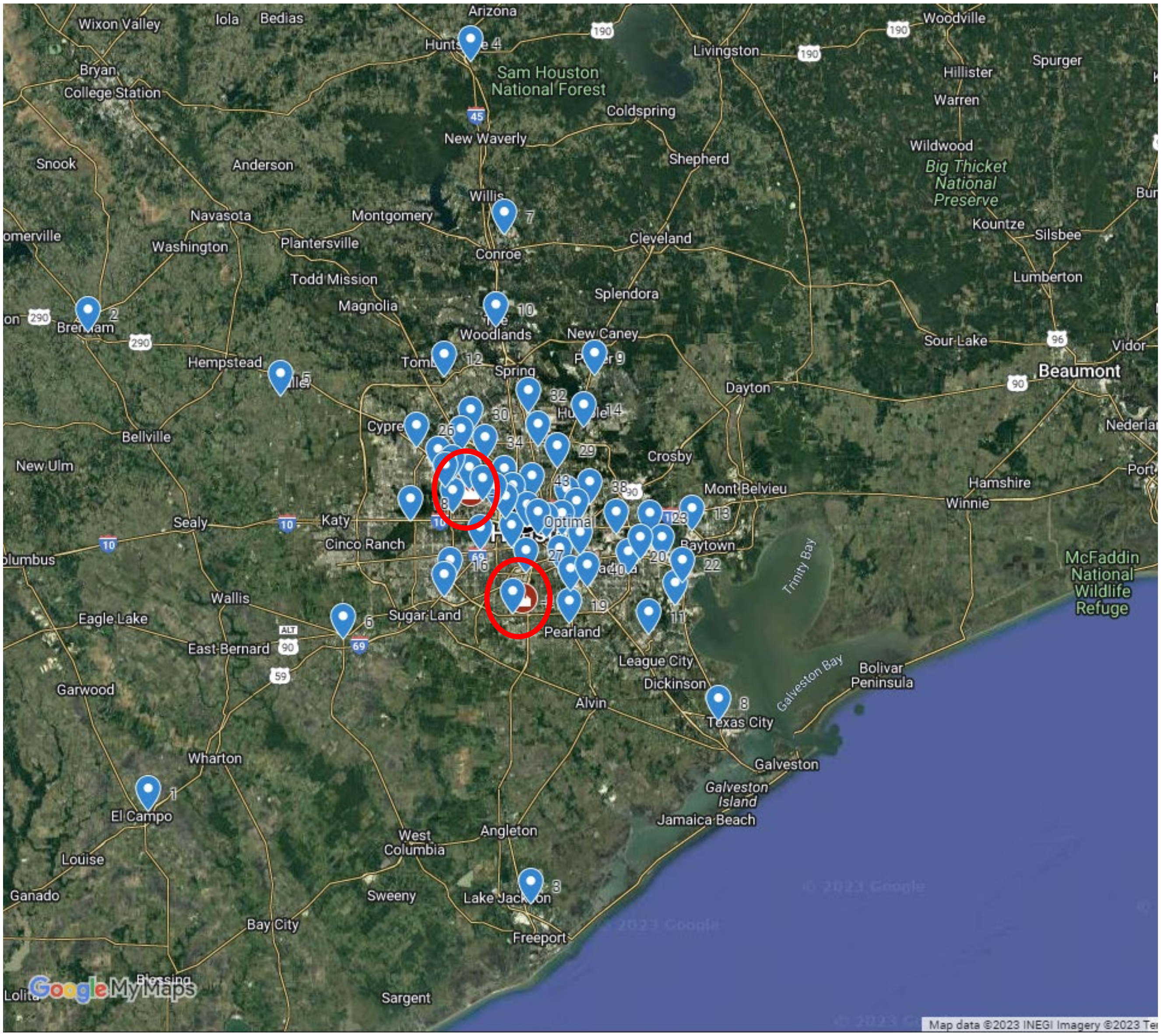


Figure 25. Geographic distribution of selected client and supplier nodes—Houston, Texas.

This 58-client plus 2-supplier set (namely master dataset) including location, commodities, and corresponding demand tonnage was used as the basis for the development and application of the model and algorithm. This allowed a close-to-reality analysis without any confidentiality issues based on a new methodology to fuse and merge publicly available data.

Model and Algorithm Development

The project team used a combination of methodologies to develop the cargo consolidation optimization (and improvement) method. First, the project team developed an exact mathematical optimization model. However, because these types of operations (cargo consolidation, routing, and location) comprise large instances, this type of optimization falls in the NP-hard problem classification, which involves problems that cannot be solved at mathematical optimality for large instances. Therefore, the project team also developed a heuristic (algorithm) as part of the overall method. More specifically, the mathematical model optimizes small instances and serves as a benchmark for the performance of the heuristic, while the latter allows the applicability of this method in large-scale operations while preserving a high level of effectiveness.

Mathematical, Programming Model—Routing

The routing model assumptions are as follows:

- Two supplier nodes, a and b, each supplies a single product/commodity.
- Clients demand products, at different quantities, from each node.
- Vehicles departing from depot a are partly loaded and then head to depot b to complete loading of all cargo/demand for assigned client nodes.
- The vehicle then travels along a certain path until it reaches client node j_k, $(b, j_1, j_2, j_3, \ldots j_i, \ldots j_k)$. Then, the vehicle returns to depot b.

Consequently, the model specifies the following:

The cumulative loads to be delivered up to the point j_k of the path are given by:

$$U_{dv}(j_k) = \sum_{j \in P(a, j_k)} d_{ja} + \sum_{j \in P(a-b, j_k)} d_{jb} \tag{1}$$

P(b, j_k) denotes the nodes along that path.

After a vehicle visits node j_k, its net load (D_{jkv}) is:

$$D_{j_k v} = D(0) - U_{dk}(j_k) \tag{2}$$

where D(0) represents the initial, full load after departing the last depot (b), and d_{ja} and d_{jb} denote client node demands of product supplied by depot a and b, respectively.

Notations

G = Asymmetric Graph; *G* = (*T*, *A*)
a = Depot a
b = Depot b
I = J = Set of client nodes
T = Set of nodes; $T = [N \cup \{0, n+1\}]$
A = Set of arcs linking any pair of nodes, (*i,j*) or (*a,j*), or (*a,b*) or $(b,j) \in A$
V = Total number of vehicles; *v* = {1,2… *V*}
y_{ij} = Distance of traveling from node *i* to node *j*
d_{ia} = Product demand of node *i, i = 1, …, N* from depot *a*
d_{ib} = Product demand of node *i, i = 1, …, N* from depot *b*

D(0) = Initial, full load after departing the last depot (b)
Q = Capacity of vehicle
MD = Maximum distance for any vehicle *v*

Decision Variables

D_{iv} = The load remaining to be delivered by vehicle *v* when departing from node *i*

$$x_{ijv} = \begin{cases} 1\ if\ vehicle\ v\ travels\ from\ i\ to\ j \\ 0\ otherwise \end{cases}$$

$$z_{abv} = \begin{cases} 1\ if\ vehicle\ v\ travels\ from\ a\ to\ b \\ 0\ otherwise \end{cases}$$

d_{ia}, d_{ib}, Q, y_{ij} ≥ 0

$$Min\ \sum_{v=1}^{V} \sum_{i=0}^{N} \sum_{j=0}^{N} y_{ij} x_{ijv} + \sum_{v=1}^{V} y_{ab} z_{abv} \tag{3}$$

S.T.

$$\sum_{v=1}^{V} \sum_{i=0}^{N} X_{ijv} = 1 \qquad \forall\ j = 1, \ldots, N \tag{4}$$

$$\sum_{j=1}^{N} X_{0jv} \leq 1 \qquad \forall\ v = 1, \ldots, V \tag{5}$$

$$\sum_{i=0}^{N} X_{ijv} - \sum_{i=0}^{N} X_{jiv} = 0 \qquad \forall\ j = 1, \ldots, N\ and\ \forall\ v = 1, \ldots, V \tag{6}$$

$$D_{iv} \leq Q \qquad \forall\ j = 1, \ldots, N\ and\ \forall\ v = 1, \ldots, V \tag{7}$$

$$D_{0v} \leq Q \qquad \forall\ v = 1, \ldots, V \tag{8}$$

$$D_{0v} = \sum_{i=1}^{N} \sum_{j=1}^{N} X_{ijv} d_{ia} + \sum_{i=1}^{N} \sum_{j=1}^{N} X_{ijv} d_{ib} \quad \forall\ v = 1, \ldots, V \tag{9}$$

$$D_{jv} = D_{iv} - d_{ja} - d_{jb} \qquad \forall\ i, j = 1, \ldots, N\ and\ \forall\ v = 1, \ldots, V \tag{10}$$

$$\sum_{i=0}^{N} \sum_{j=0}^{N} y_{ij} X_{ijv} \leq MD \qquad \forall\ v = 1, \ldots, V \tag{11}$$

The objective function (3) minimizes total distance of travel. Constraint (4) secures single visits for each node, and (5) ensures a sole vehicle per trip. Restriction (6) makes sure that the same vehicle arrives and departs from each node; (7) ensures that the load on vehicle *v*, at node *i*, does not exceed vehicle capacity. Similarly, (8) ensures that the total load on vehicle *v*, when departing from the starting node, is lower than vehicle capacity. Constraint (9) ensures that the total node demand for a route is placed on the vehicle *v*, at the starting (last of the two) depot. Restriction (10) makes sure that the load of the vehicle decreases by the same demand quantity to be delivered (d_{ja} + d_{jb}) when client node *j* is visited by the vehicle *v*. Finally, constraint (11) ensures the maximum autonomy/distance for any vehicle *v*.

The model was implemented using Lingo software. For that purpose, several linear programming versions of this model were developed. More details are given in the results section.

Mathematical, Programming Model—Location

The location of logistics activity centers/distribution centers is an additional improvement in the optimization methodology. The objective of the location step is to minimize the total distance from all clients to the new center. For that purpose, the project team used the Haversine formula (Agramanisti Azdy & Darnis, 2020) for calculating the (spherical) distance between depot(s) and each client.

Haversine formula:

$$d = 2r\, sin^{-1}\left(\sqrt{sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + cos\,\varphi_1\, cos\,\varphi_2\, sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \quad (12)$$

Where:

ϕ_1 = Latitude of origin point in radians (rad)
λ_1 = Longitude of origin point in radians
ϕ_2 = Latitude of destination point in radians
λ_2 = Longitude of destination point in radians

The decision variables are then:

ϕ_b = Latitude of optimal depot location (origin point) in radians
λ_b = Longitude of optimal depot location (origin point) in radians

Then the objective function is simply:

$$Min\ \sum_{i=1}^{I} d_{b,i} \quad (13)$$

S.T.

$-1.5708 \leq \phi_b \leq 1.5708$ rad
$-3.1416 \leq \lambda_b \leq 3.1416$ rad

This location optimization step was implemented using Excel Solver.

Heuristic, Algorithm

The heuristic developed in this work follows the k-nearest neighbor (KNN) technique (Taunk et al., 2019), with distance and capacity constraints. Figure 26 shows the algorithm logic starting from the data input (gray box on the left).

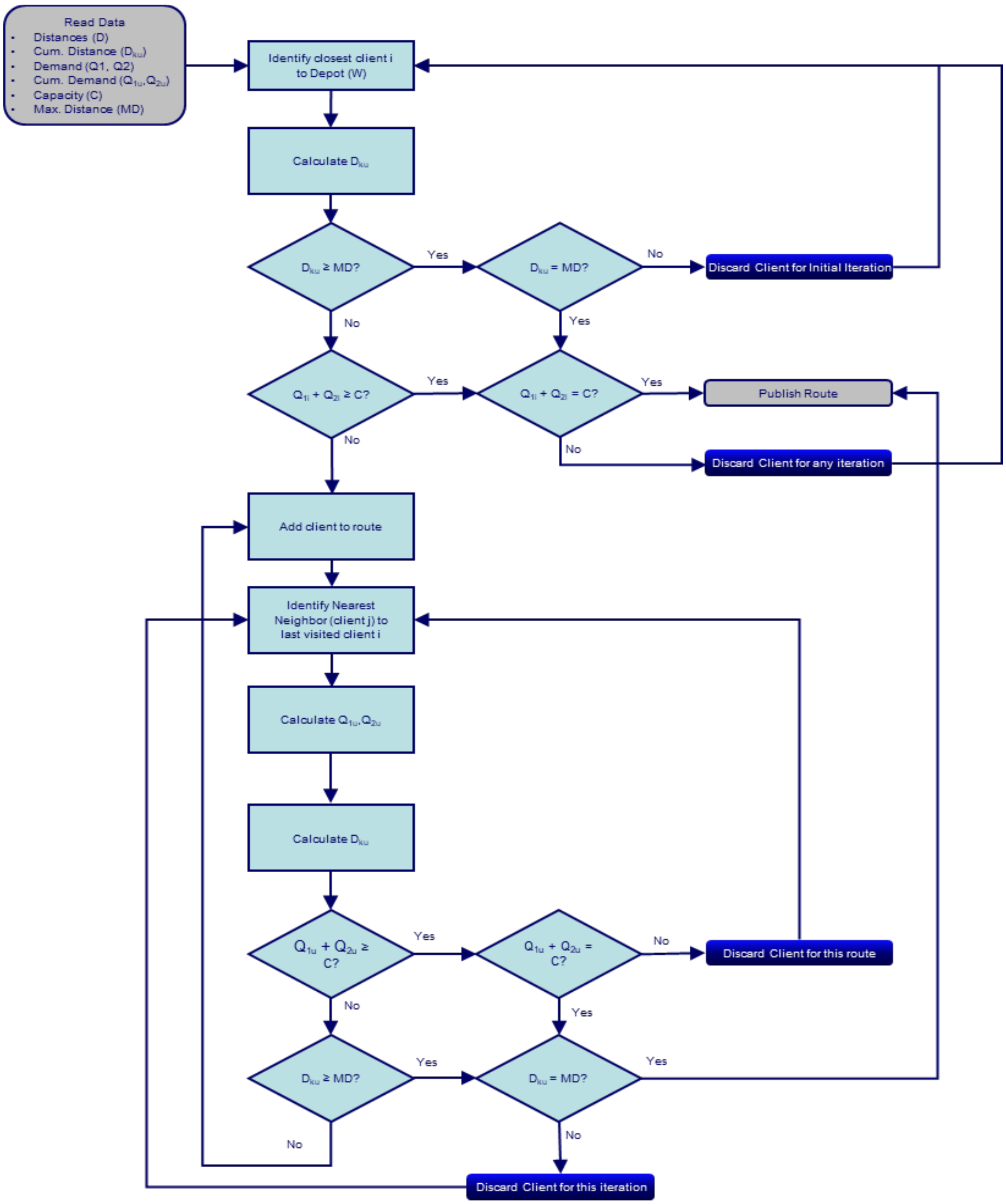


Figure 26. Algorithm logic.

The algorithm identifies the closest client to the depot and then evaluates distance and capacity conditions. When either of these is not met, the algorithm saves the client for subsequent iterations. When these conditions are within constraints, the algorithm either publishes (issues) the route if conditions are equal to the threshold or adds the client to the route list and continues searching for the next closest client (i.e., nearest neighbor), and then evaluates conditions accordingly.

The algorithm final step “publish route,” represented by the right-hand gray box in Figure 26, issues a single route per iteration. Thus, multiple iterations of the algorithm must be run until all clients are served or discarded. The algorithm was coded and executed in Python.

Design of Experiment

The research team designed the application of the model and algorithm to evaluate their performance and benefits. For this purpose, the researchers developed different scenarios to evaluate improvements in transit and congestion stemming from cargo consolidation optimization. The latter included the sampling design given the constraints of model optimization as an NP-hard problem type. The sampling process consisted of generating three 20-client subsamples extracted from the 58-client sample. The team used uniform distribution to select the three 20-client subsamples. These subsamples were then used for all steps of the Design of Experiment (DoE) to make all results comparable. Figure 27 shows the complete DoE in more detail.

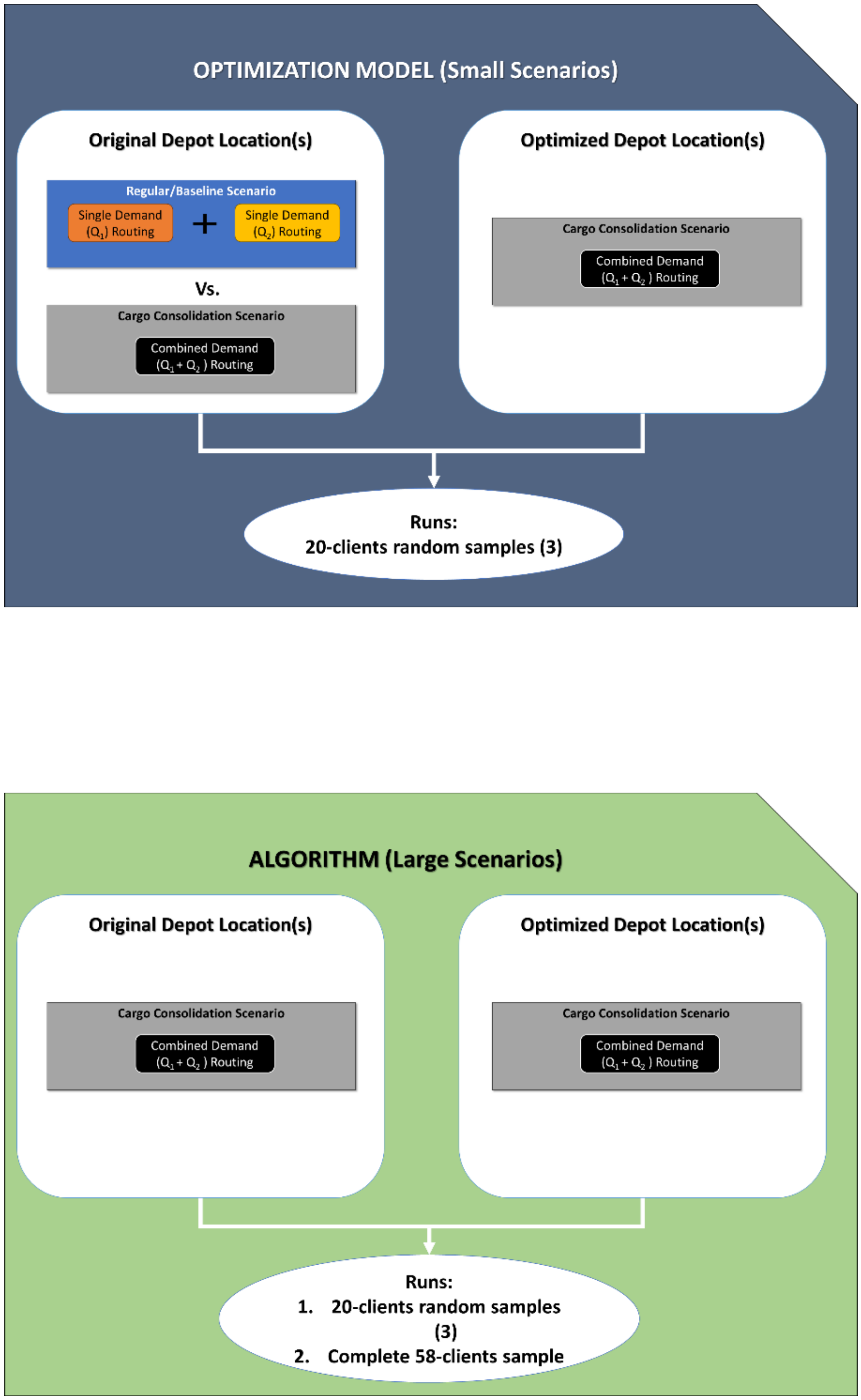


Figure 27. Experiment model design.

The upper box in the diagram shows the model application using the three 20-client subsamples. Larger instances would not be feasible to solve optimally given the properties of the NP-hard classification problems; thus, the model was not implemented with the complete 58-client sample.

The optimization model was then executed in single-demand scenarios for both commodities: wood and metal (Q1 and Q2). This was for the regular type of independent operations without cargo consolidation practices. Then, the model was run in the cargo consolidation, or combined demand, scenario. The comparison between these two yielded the optimized benefits of cargo consolidation versus regular operations in terms of distance, truck trips, and consequently congestion. These first applications were done considering the originally identified depots' locations.

Then, the model calculated the optimal location of a depot by minimizing spherical distances. Using this optimal location, the model was run in the combined, or cargo consolidation, scenario. This did not yield optimal routing, but rather close-to-optimal[1] in terms of location.

The lower box in Figure 27 shows the algorithm application. Both the original depot location and optimized location were evaluated on the cargo consolidation or combined demand scenario. However, this time the algorithm was run not only on the three 20-client samples but also on the complete 58-client sample.

This DoE not only allows for comparing the direct benefits of cargo consolidation in terms of distance, number of trucks/trips, and vehicle utilization but also provides a good benchmark for the algorithm performance and its benefits in large instances (i.e., greater than 20-client scenarios).

[1] Close-to-optimal because the scenarios were run with a 20-client subsample and not the entire sample used to calculate optimal location.

Chapter 5. Results

Based on the DoE, the model was first run for single-demand (i.e., regular operations) scenarios for both commodities (wood and metal) separately using the three 20-client subsamples and the original depot location. Then, the model was run for the combined demand, or cargo consolidation, scenario. Again, the values of all demands (separate and combined for all clients) were at the daily level.

For model runs, a vehicle capacity of 18 tons was used with a maximum range (i.e., autonomy) of 400 km. For illustration purposes, Figure 28, Figure 29, and Figure 30 show the final routes for random sample 1 (RS1); the last depot b is highlighted with the blue circle. Similar figures pertaining to random samples 2 and 3 can be found in Appendix D.

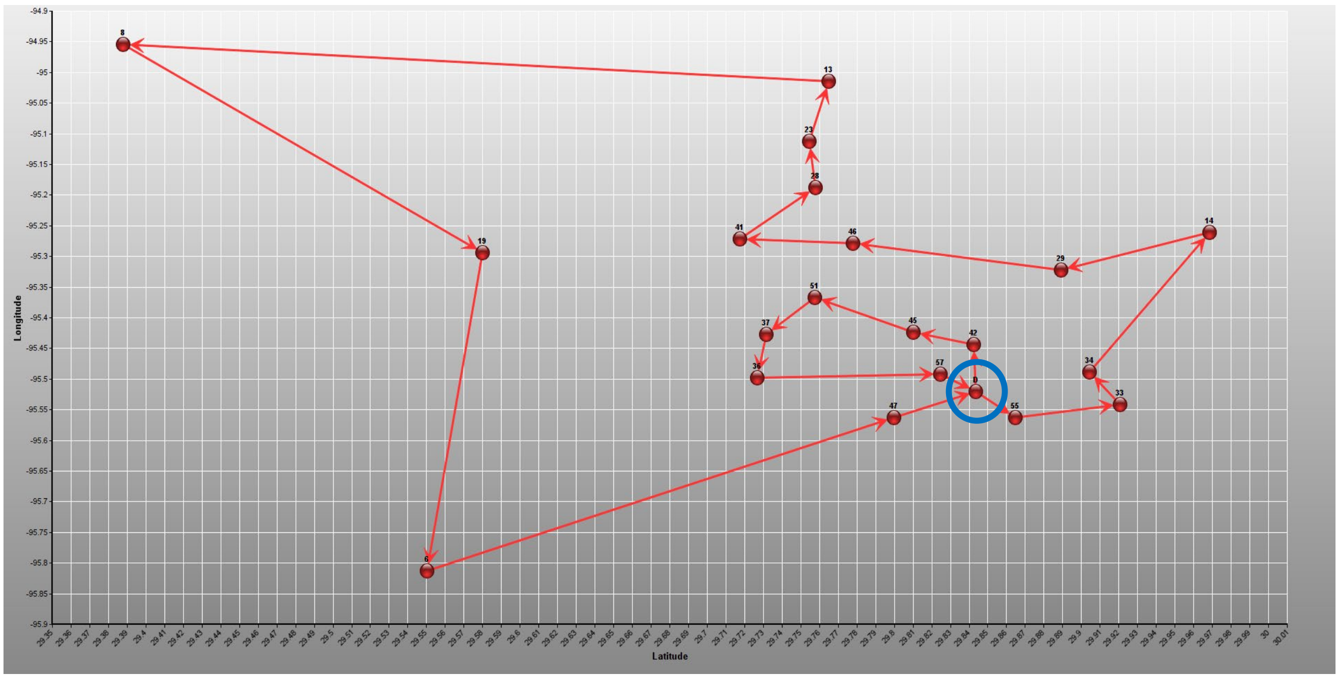


Figure 28. Single-demand routing wood – RS1.

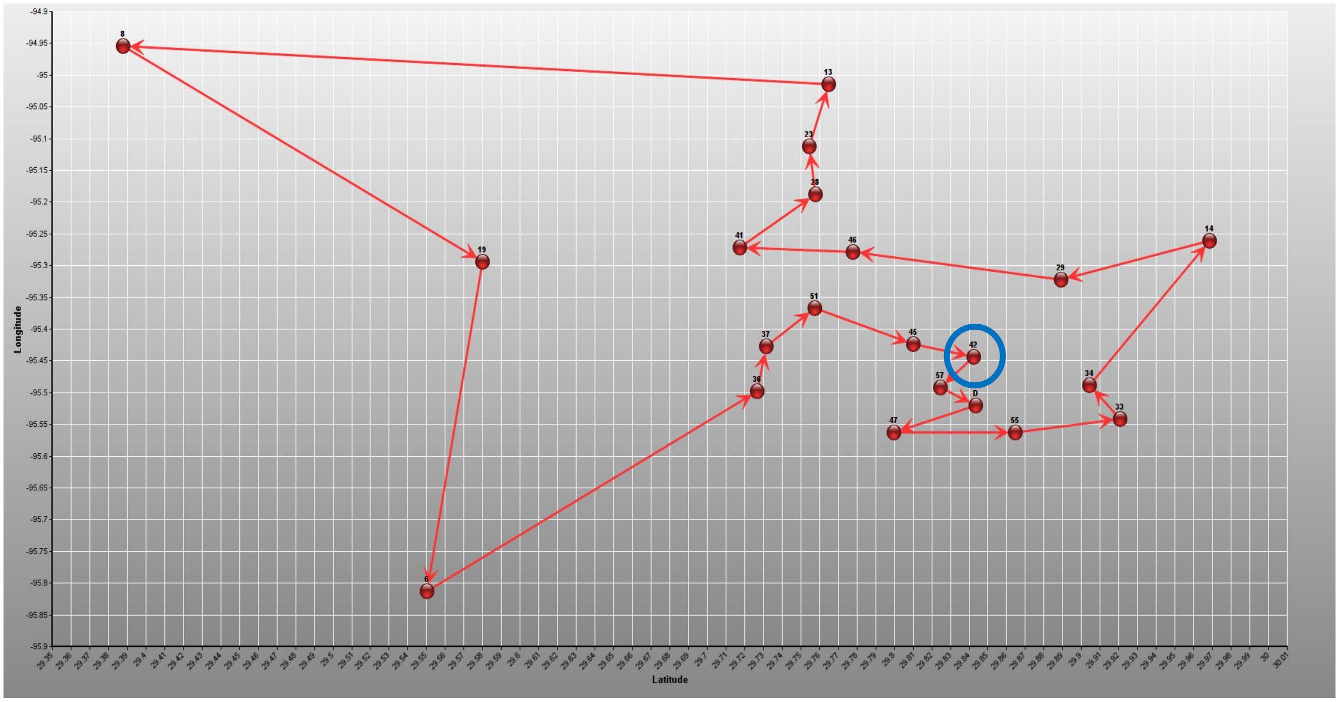


Figure 29. Single-demand routing metal – RS1.

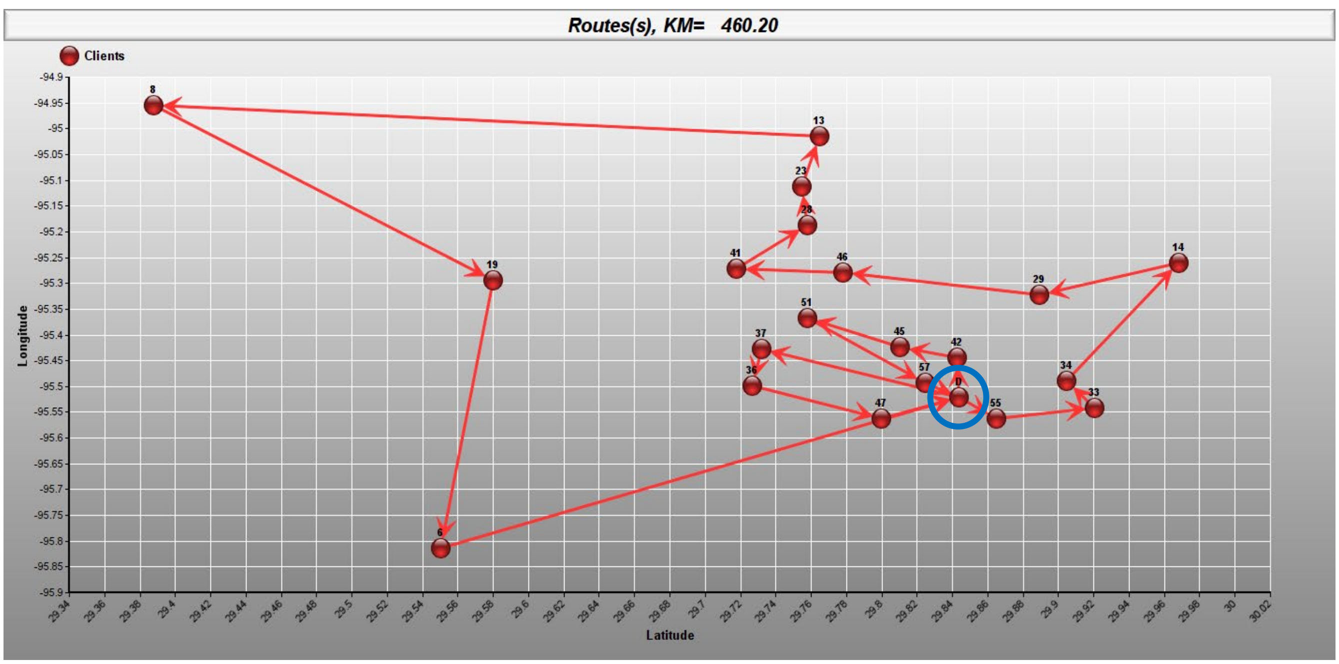


Figure 30. Cargo consolidation routing – RS1.

Table 6 compares the results between single-demand and cargo consolidation runs.

Table 6. Results Comparison – Single Demand versus Cargo Consolidation

		Single-Demand Model	Cargo Consolidation Model	CC Model Improvement
RS1	Volume (tons)	39.3	39.3	
	Distance (km)	818.3	460.2	43.76%
	No. Trucks/Trips	3	3	0.00%
RS2	Volume (tons)	27.6	27.6	
	Distance (km)	1347	677	49.74%
	No. Trucks/Trips	4	2	50.00%
RS3	Volume (tons)	29.8	29.8	
	Distance (km)	818	431	47.31%
	No. Trucks/Trips	3	2	33.33%
Average %	***Distance (km)***	994.4	522.7	***46.94%***
	No. Trucks/Trips	3.3	2.3	***27.78%***
Average Nominal	***Distance (km)***			***–471.7***
	No. Trucks/Trips			***–1.0***

Results show that the cargo consolidation model provides substantial benefits in both measures: distance and truck trips. Specifically, on average, cargo consolidation decreases needed distance by practically 47% while saving almost 28% of the trips needed to meet client demand. In nominal values, cargo consolidation represents 471 km and one trip/vehicle less. Note that these are daily values considering only two companies in a small sample. When extrapolating these numbers to yearly values, assuming the same small samples, the benefits increase to 172,170 vehicle-kilometers less congestion, which is roughly 107,000 vehicle-miles.

The algorithm was then run for the combined demand, or cargo consolidation, scenario using the same three 20-client subsamples and the same original depot location. Once more, the values of all demands were at the daily level, and a vehicle capacity of 18 tons with a maximum range (i.e., autonomy) of 400 km was also used. Table 7 shows the comparison results of the single-demand model versus cargo consolidation algorithm.

Table 7. Results Comparison – Single-Demand Model versus Cargo Consolidation Algorithm

		Single-Demand Model	Cargo Consolidation Algorithm	CC Algorithm Improvement
RS1	Volume (tons)	39.3	39.3	
	Distance (km)	818.3	692.0	15.43%
	No. Trucks/Trips	3	3	0.00%
RS2	Volume (tons)	27.6	27.6	
	Distance (km)	1347	883.9	34.38%
	No. Trucks/Trips	4	3	25.00%
RS3	Volume (tons)	29.8	29.8	
	Distance (km)	818	509.9	37.67%
	No. Trucks/Trips	3	2	33.33%
Average %	***Distance (km)***	994.4	695.3	***29.16%***
	No. Trucks/Trips	3.3	2.7	***19.44%***
Average Nominal	***Distance (km)***			***–299.2***
	No. Trucks/Trips			***–0.7***

This time results show that the cargo consolidation algorithm also provides benefits in both measures: distance and truck trips. The average cargo consolidation improvement on needed distance from the algorithm is 29%, with 19% fewer trips needed to meet client demand. The latter translates to roughly 300 km and 0.7 trips/vehicles less every day compared to separate nonconsolidated operations. As in the case of the model, the benefits increase to 72,797 vehicle-kilometers less congestion (299.2 km × 0.7 vehicles of improvement), which is roughly 45,233 vehicle-miles.

Both the model and the algorithm provide significant improvement on cargo consolidation versus the single-demand nonconsolidated operation. However, the model offers greater benefits than the algorithm. This was expected due to the reasons stated throughout the literature review, introduction, and DoE related to the nature—and capabilities—of optimization methods (i.e., the model) versus heuristics (i.e., the algorithm). Specifically, the model provides mathematically optimized solutions—in other words, the best possible solution(s)—but it is not practical (sometimes unfeasible) in larger instances or scenarios. The algorithm, on the other hand, does not guarantee optimality rather than improvements, but it is applicable to larger scenarios. Thus, it is important to develop both—first as options to solve different scenario sizes and second as a benchmark system to estimate the algorithm performance.

Table 8 shows the difference between improvements provided by the algorithm and the model. This difference can be deemed as the algorithm's deviation from optimality (right-hand column).

Table 8. Results Comparison – Cargo Consolidation Improvement, Model versus Algorithm

		Cargo Consolidation Improvement		Algorithm's Deviation from Optimality
		Model	Algorithm	
RS1	Distance	43.76%	15.43%	−50.38%
	No. Trucks/Trips	0.00%	0.00%	0.00%
RS2	Distance	49.74%	34.38%	−30.56%
	No. Trucks/Trips	50.00%	25.00%	−50.00%
RS3	Distance	47.31%	37.67%	−18.31%
	No. Trucks/Trips	33.33%	33.33%	0.00%
Average	**Distance**	46.94%	29.16%	−33.08%
	No. Trucks/Trips	27.78%	19.44%	−16.67%

The average suboptimality gap is 33% in distance and a little less than 17% in the number of trips. In any case, the algorithm consistently provides significant improvements over the single-demand nonconsolidated routing.

After these initial runs with the original depot locations, the methodology included optimizing the depot location. For this purpose, the model to minimize the total—depot—distance from all clients was implemented. As previously stated, this model used the Haversine formula, which provides spherical distances between depots and each client. The result of this model for the new optimized depot location yielded the following latitude and longitude: 29.78859344, −95.39668513. This location provided a total—summed—distance for all 58 clients of 1,587 km. The original spherical total distance was 1,748 km, which would then represent a one-way (as-the-crow-flies) improvement of 161 km. Figure 31 shows the optimized location of the depot (black factory icon highlighted in green circle) and the original depot locations (maroon factory icons highlighted in red circles).

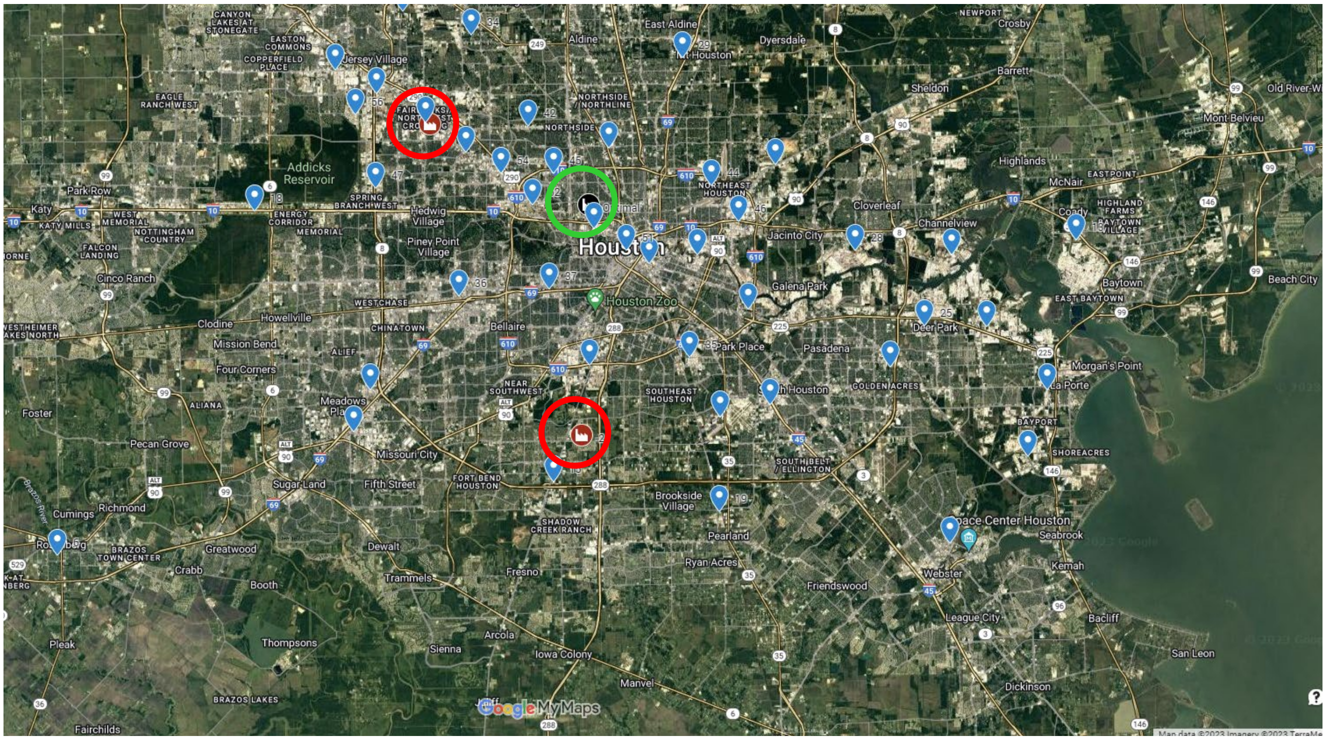


Figure 31. Optimized and original depot/supplier locations – Houston, Texas.

A new distance matrix was calculated based on this optimized location, and then the model and algorithm were implemented again with the same three 20-client samples and the complete 58-client dataset. The complete dataset allowed for comparing benefits of the new optimized coordinates versus the previous original depot location. As before, a vehicle capacity of 18 tons was used, with a maximum range (i.e., autonomy) of 400 km. For illustration purposes, Figure 32, Figure 33, and Figure 34 show the final routes for random sample 1 (RS1); the optimal depot location is highlighted with the blue circle. Similar figures pertaining to random samples 2 and 3 can be found in Appendix E.

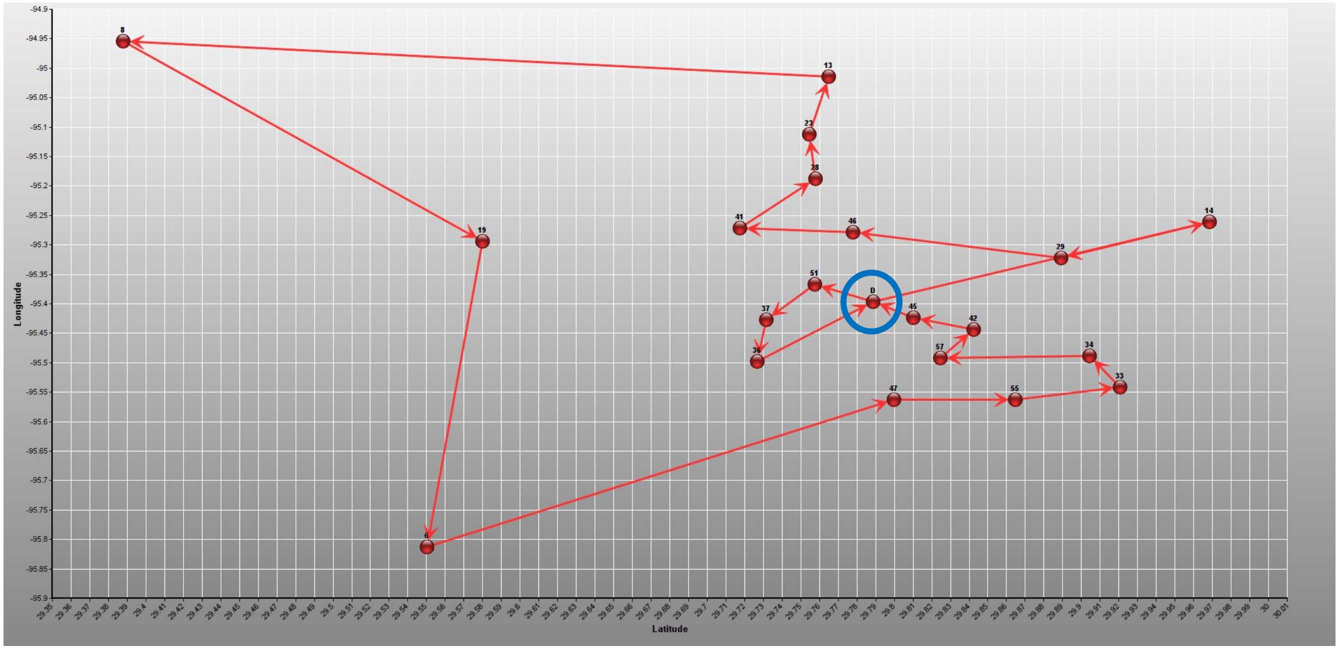


Figure 32. Single-demand routing wood – RS1 optimal location.

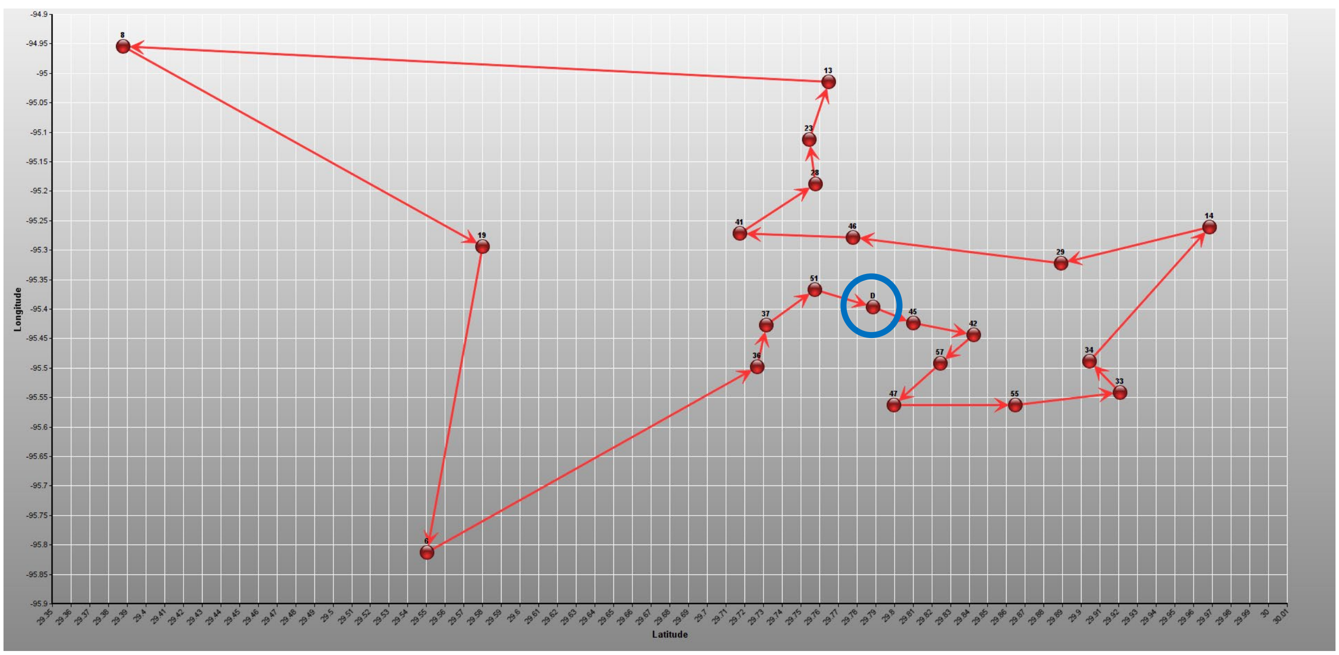


Figure 33. Single-demand routing metal – RS1 optimal location.

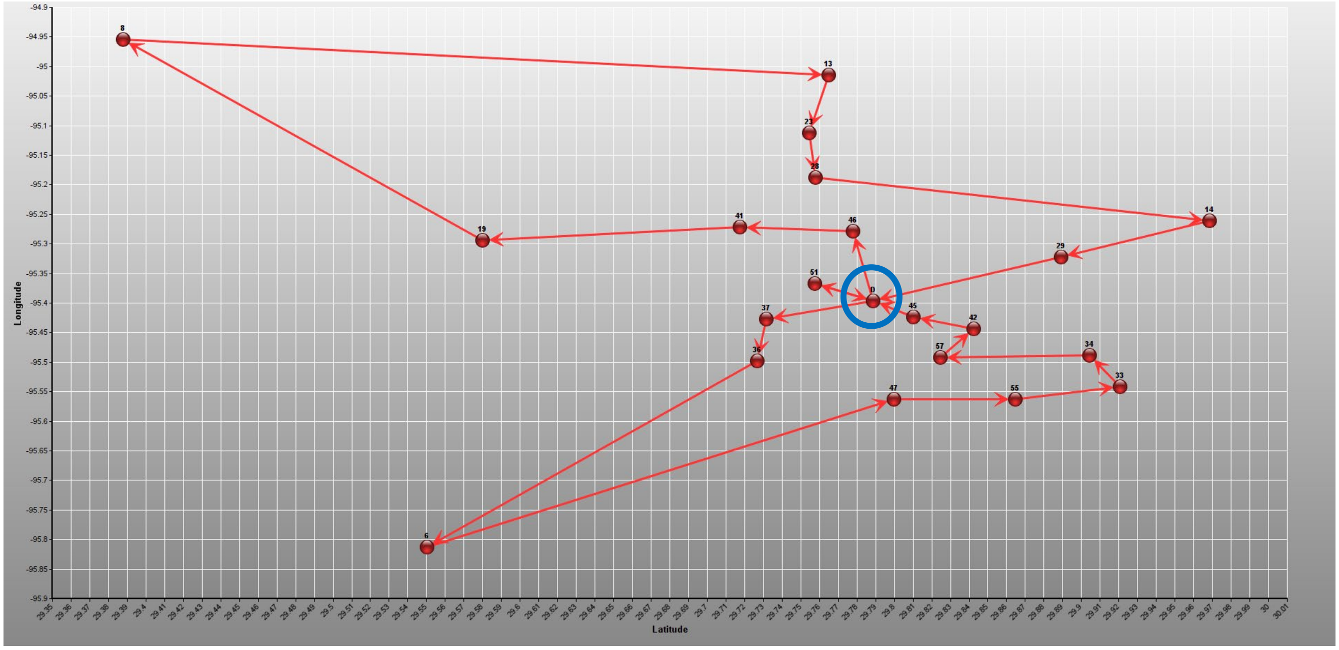


Figure 34. Cargo consolidation routing – RS1 optimal location.

Table 9 compares the results between the original depot and optimized locations for all scenarios.

Table 9. Results Comparison – Original versus Optimized Locations (All Scenarios)

		Single Demand		Original vs. Optimized Improvement	Cargo Consolidation		Original vs. Optimized Improvement	Cargo Consolidation		Original vs. Optimized Improvement
		Original Depot Loc.	Optimized Depot Loc.		Original Depot Loc.	Optimized Depot Loc.		Original Depot Loc.	Optimized Depot Loc.	
		Model	Model		Model	Model		Algorithm	Algorithm	
RS1	Distance (km)	818.3	806.9	1.39%	460.2	424.6	7.74%	692.047	611.645	11.62%
	No. Trucks/Trips	3	3	0.00%	3	3	0.00%	3	3	0.00%
RS2	Distance (km)	1347	1288	4.38%	677	647	4.43%	883.858	838.296	5.15%
	No. Trucks/Trips	4	4	0.00%	2	2	0.00%	3	3	0.00%
RS3	Distance (km)	818	806	1.47%	431	425	1.39%	509.897	569.589	−11.71%
	No. Trucks/Trips	3	4	−33.33%	2	2	0.00%	2	2	0.00%
Average %	***Distance (km)***	994.4	967.0	***2.41%***	522.7	498.9	***4.52%***	695.3	673.2	***1.69%***
	No. Trucks/Trips	3.3	3.7	***−11.11%***	2.3	2.3	***0.00%***	2.7	2.7	***0.00%***
Average Nominal	***Distance (km)***			***−27.5***			***−23.9***			***−22.1***
	No. Trucks/Trips			***0.3***			***0.0***			***0.0***

Table 9 shows that the optimized location provides additional—average—benefits in terms of distance reductions. Also, when comparing the single-demand model with the cargo consolidation algorithm (Table 10), the benefit is larger for the optimized location than for the original location (Table 7).

Table 10. Results Comparison – Single-Demand Model versus Cargo Consolidation Algorithm (Optimized Location)

		Single-Demand Model	Cargo Consolidation Algorithm	CC— Algorithm Improvement
RS1	Volume (tons)	39.3	39.3	
	Distance (km)	806.9	611.6	24.20%
	No. Trucks/Trips	3	3	0.00%
RS2	Volume (tons)	27.6	27.6	
	Distance (km)	1288	838.3	34.91%
	No. Trucks/Trips	4	3	25.00%
RS3	Volume (tons)	29.8	29.8	
	Distance (km)	806	569.6	29.33%
	No. Trucks/Trips	4	2	50.00%
Average %	***Distance (km)***	967.0	673.2	***29.48%***
	No. Trucks/Trips	3.7	2.7	***25.00%***
Average Nominal	***Distance (km)***			***–293.8***
	No. Trucks/Trips			***–1.0***

In the case of the optimized location, the average suboptimality gap remains close to the previous values, at 35.88% deviation in distance and 16.67% in number of trucks/trips (Table 11).

Table 11. Results Comparison – Cargo Consolidation Improvement, Model versus Algorithm (Optimized Location)

		Improvement from Cargo Consolidation		Algorithm Deviation from Optimality
		Model	Algorithm	
RS1	Distance	47.38%	24.20%	–44.05%
	No. Trucks/Trips	0.00%	0.00%	0.00%
RS2	Distance	49.77%	34.91%	–29.57%
	No. Trucks/Trips	50.00%	25.00%	–50.00%
RS3	Distance	47.27%	29.33%	–34.02%
	No. Trucks/Trips	50.00%	50.00%	0.00%
Average	**Distance**	48.14%	29.48%	–35.88%
	No. Trucks/Trips	33.33%	25.00%	–16.67%

These last results show additional benefits from optimizing depot locations. However, these benefits may not seem large, possibly because location optimization is performed based on spherical distances and not on actual routing distances, as the model and algorithm consider.

Chapter 6. Conclusion

This work provided real-world insights into the empirical and modeling impacts of cargo consolidation on congestion. The contributions of this work include:

1. A robust methodology of data fusion and analytics that offers real-world data on private-sector operations without confidentiality issues.
2. Comprehensive information on current insights and status of cargo consolidation practices in the private and public sectors through a literature review, a survey, and direct interviews.
3. An optimization methodology—and model—for cargo consolidation that focuses on the minimization of distances and vehicles/trips, and calculates the optimal location of a depot, offering significant benefits in terms of impacts on traffic.
4. An algorithm that provides improved solutions to the cargo consolidation strategy and that allows for the expansion of the application in larger scenarios.
5. An additional methodology step that optimizes depot location based on spherical distances, which in turn supplies additional benefits for distance—and traffic—reduction.

Results show that the cargo consolidation model could achieve initial annual benefits of 172,170 vehicle-kilometers less congestion, which is roughly 107,000 vehicle-miles, while the algorithm could yield 72,797 vehicle-kilometers less congestion, which in turn is roughly 45,233 vehicle-miles. These reductions in congestion are only for 20 clients in the area of analysis (i.e., Houston) for two commodities: wood and metal. The latter provides an idea of the potential benefits of cargo consolidation practices when using optimization and heuristics tools for operation design.

In addition, the quantitative benefits of the model, algorithm, and location optimization steps are estimated using the single-demand (i.e., nonconsolidated cargo) scenario as a benchmark. This baseline scenario is also a model-optimized scenario for nonconsolidated cargo. In the real world, this is not common since companies generally perform routing operations without any optimization tools. Thus, the benefits estimated in this work may represent the lower bound of the actual benefits range when implementing this methodology in real-world operations.

Future research should look at improving the optimization model and the algorithm by adding features such as cargo sequence and methodology steps to match route paths to road capacities and transit to estimate the impacts of cargo consolidation practices more accurately. The latter could help determine the specific roads that serve a given market or commodity; assess needs versus road capacities; and facilitate planning, maintenance, and infrastructure design and investments.

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Appendix A – Private-Sector Survey

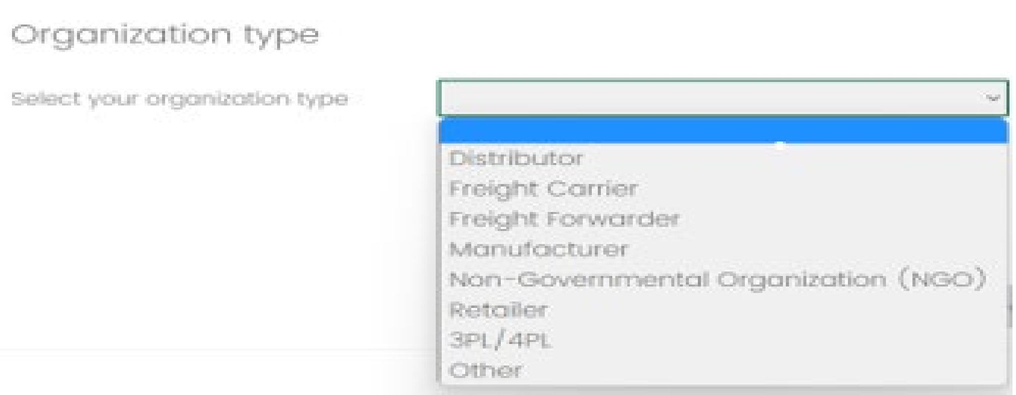
Introduction
The Supply Chain Innovation Lab at the Monica Wooden Center for Supply Chain Management & Sustainability at the University of South Florida is conducting research for the National Institute for Congestion Reduction (NICR) to optimize the consolidation of cargo and the routing of shipments via commercial heavy vehicles to maximize the utilization of transportation assets. Consolidation shipping allows us to combine individual less-than-truckload (LTL) shipments from various shippers into one full container shipment. The research objective is to identify the cargo consolidation and optimization models that help to reduce traffic congestion and benefit everyone who uses LTL shipping as it makes logistics more efficient. The survey will take approximately 5 minutes to complete, and your contribution is greatly appreciated.

Participation in the survey is completely voluntary. Survey responses will be retained for the life of the project and stored on password-protected computers. The results of this survey may be published; however, published results will be confidential and anonymized. Your name and your organization's name will not be associated with any publication of results. The data will be stored for up to five years after the results have been published. At that point, all data will be deleted.

If you have any questions about your rights as a research participant, please contact the USF IRB at (813) 974-5638 or contact by email at RSCH-IRB@usf.edu. If you have questions regarding the research, please contact the researcher via email at sozkul@usf.edu or by telephone at (813) 974-2530.

<u>**Consent to Take Part in This Survey**</u>
By clicking “Accept” below, I agree that:
(1) I have fully read or have had read and explained to me this informed consent form describing this project and associated survey; and
(2) I understand that I am being asked to participate in this survey. I understand the risks and benefits, and I freely give my consent to participate in the research outlined in this form under the conditions indicated.

- Accept
- Decline



If you selected "Other," please enter your organization type:

Please provide your contact information if you would like to receive a summary of the results of the survey (optional).

Name

Organization name

Email

Phone

Mixed-cargo shipments combine multiple less-than-truckload (LTL) shipments of different products, typically from different companies, that are traveling in the same vicinity into one full truckload shipment. This practice achieves cost reductions and increased asset efficiency by reducing the number of trips that are needed to deliver the same volume of products among different companies.

Instructions

Please answer the survey questions to the best of your abilities and complete the survey by March 27, 2023.
Survey Length – The survey will take approximately 5 minutes to complete and will be available online until March 27, 2023. Your progression through the survey will be tracked by a "progress bar" at the top of the screen indicating the percent complete.
Required Responses – All items require a response. If you are unsure of a response to a particular item, please indicate N/A for "not applicable."
Moving Within the Survey – Where it is allowable, you will be able to move back and forth within the survey. Please use the "Back" and "Next" buttons within the survey itself for this purpose.
Saving the Survey – The survey will automatically save any responses you make. When you get to the last page of the survey, do not click "Next" until you are completely finished with the Survey. Once you click the "Next" button on the last page, you will be unable to change your responses.

Please select the region where your company is located.

- ○ United States
- ○ Europe
- ○ Latin America
- ○ Asia
- ○ Other

Survey Questionnaire:

1. Is your company currently using cargo consolidation strategies?

- ◯ Yes
- ◯ No

If yes is selected

2. What internal factors/benefits made your company consider cargo consolidation?

Please rank the following factors ("1" being the most important and "8" being the least important)
Please drag and drop each factor in the ranking order

- Minimized shipping costs
- Quicker transit time
- Less risk of damage to the goods
- Increased efficiency
- Better shipment scheduling
- Improved relationship between shippers and carriers
- Reduced congestion & emissions
- Other, please specify

If No is selected

2. What benefits are important for your company to consider cargo consolidation?

Please rank the following factors ("1" being the most important and "8" being the least important)
Please drag and drop each factor in the ranking order

- Minimized shipping costs
- Quicker transit time
- Less risk of damage to the goods
- Increased efficiency
- Better shipment scheduling
- Improved relationship between shippers and carriers
- Reduced congestion & emissions
- Other, please specify

3. In your opinion, what are the key considerations for effective cargo consolidation?

Please rank the following factors ("1" being the most important and "9" being the least important)
Please drag and drop each factor in the ranking order

Finding the right partner
Distribution network (distances between supply chain nodes)
Distribution requirement (demand to be delivered)
Product features (i.e. weight/volume, perishability, fleet and vehicle capacity)
Cost
Delivery date of shipment
Transportation time
Shipping route
Other, please specify

4. What challenges does/might your company face when implementing cargo consolidation? (Select all that apply)

- ☐ Finding the right carrier/partner
- ☐ System complexity
- ☐ Freight handling
- ☐ Short lead times
- ☐ Other, please specify

5. When would you prefer to use cargo consolidation services? (select all that apply)

- ☐ When shipping few products from time to time
- ☐ When buying from multiple suppliers
- ☐ When following a scheduled time of delivery
- ☐ When implementing sustainability goals (reducing the carbon footprint with fewer trucks)
- ☐ Other, please specify

6. Presently, how beneficial do you think it is to implement cargo consolidation strategies (combining multiple LTL shipments that are traveling in the same vicinity into one full truckload shipment) for the alleviation of traffic congestion?

- ◯ Extremely beneficial
- ◯ Very beneficial
- ◯ Moderately beneficial
- ◯ Slightly beneficial
- ◯ Not at all beneficial
- ◯ Not sure/Do not know

7. Within five to ten years, how important will it be in your opinion to employ cargo consolidation, re-routing, and optimization strategies to reduce traffic congestion and transportation costs?

- ◯ Extremely important
- ◯ Very important
- ◯ Moderately important
- ◯ Slightly important
- ◯ Not at all important
- ◯ Not sure/Do not know

If you have any documentation related to cargo re-routing and consolidation that may be useful to this research, please feel free to share the corresponding links in the text box below.

This concludes the survey. Click the “Back” button to review or revise your responses. If you are satisfied with your responses click the “Next” button to submit your responses.

Thank you for your participation in this survey. Your response is very important to this research.

Appendix B – Public-Sector Survey

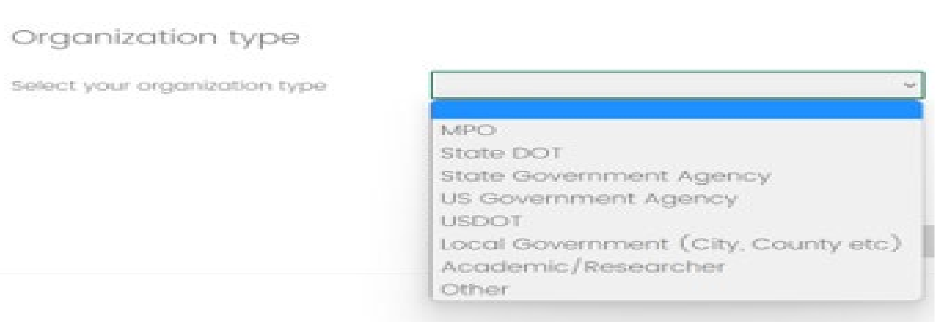
Introduction
The Supply Chain Innovation Lab at the Monica Wooden Center for Supply Chain Management & Sustainability at the University of South Florida is conducting research for the National Institute for Congestion Reduction (NICR) to optimize the consolidation of cargo and the routing of shipments via commercial heavy vehicles to maximize the utilization of transportation assets. Consolidation shipping allows us to combine individual less-than-truckload (LTL) shipments from various shippers into one full container shipment. The research objective is to identify the cargo consolidation and optimization models that help to reduce traffic congestion and benefit everyone who uses LTL shipping as it makes logistics more efficient. The survey will take approximately 5 minutes to complete, and your contribution is greatly appreciated.

Participation in the survey is completely voluntary. Survey responses will be retained for the life of the project and stored on password-protected computers. The results of this survey may be published; however, published results will be confidential and anonymized. Your name and your organization's name will not be associated with any publication of results. The data will be stored for up to five years after the results have been published. At that point, all data will be deleted.

If you have any questions about your rights as a research participant, please contact the USF IRB at (813) 974-5638 or contact by email at RSCH-IRB@usf.edu. If you have questions regarding the research, please contact the researcher via email at sozkul@usf.edu or by telephone at (813) 974-2530.

__Consent to Take Part in This Survey__
By clicking "Accept" below, I agree that:
(1) I have fully read or have had read and explained to me this informed consent form describing this project and associated survey; and
(2) I understand that I am being asked to participate in this survey. I understand the risks and benefits, and I freely give my consent to participate in the research outlined in this form under the conditions indicated.

- Accept
- Decline



If you selected "Other," please enter your organization type:

Please provide your contact information if you would like to receive a summary of the results of the survey (optional).

Name

Organization name

Email

Phone

Mixed-cargo shipments combine multiple less-than-truckload (LTL) shipments of different products, typically from different companies, that are traveling in the same vicinity into one full truckload shipment. This practice achieves cost reductions and increased asset efficiency by reducing the number of trips that are needed to deliver the same volume of products among different companies.

Instructions
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Survey Length – The survey will take approximately 5 minutes to complete and will be available online until March 27, 2023. Your progression through the survey will be tracked by a "progress bar" at the top of the screen indicating the percent complete.
Required Responses – All items require a response. If you are unsure of a response to a particular item, please indicate N/A for "not applicable."
Moving Within the Survey – Where it is allowable, you will be able to move back and forth within the survey. Please use the "Back" and "Next" buttons within the survey itself for this purpose.
Saving the Survey – The survey will automatically save any responses you make. When you get to the last page of the survey, do not click "Next" until you are completely finished with the Survey. Once you click the "Next" button on the last page, you will be unable to change your responses.

Please select the region where your company is located.

- ○ United States
- ○ Europe
- ○ Latin America
- ○ Asia
- ○ Other

Survey Questionnaire:

1. How important is traffic congestion to your agency plans?

- ○ Extremely important
- ○ Very important
- ○ Moderately important
- ○ Slightly important
- ○ Not at all important

2. From your agency's perspective what is the main cause of traffic congestion?

Please rank the following factors ("1" being the primary cause and "8" being the least cause)
Please drag and drop each factor in the ranking order

- Impacts of commercial heavy vehicles
- Work zones
- Traffic incidents
- Bad weather
- Bottlenecks
- Special events (i.e. sporting events, concerts, conventions, etc.)
- Poor signal timing
- Other, please specify ____

3. Please rank the following methods to alleviate traffic congestion ("1" being the most important and "8" being the least important)

Please drag and drop each factor in the ranking order

Geometric improvements to roads and intersections
Cargo consolidation (combining multiple Less Than Truckload shipments into one full truckload shipment)
Vehicle-specific use of travel lanes (i.e. Truck-only toll (TOT) lanes)
Cargo re-routing (directing along a different route)
Access management (set of techniques that control several elements of a street, such as the spacing, design, and operation of driveways)
Faster response to traffic incidents
Optimizing traffic signal timing
Other, please specify

4. What does your agency use as mobility measures to track congestion? (Select all that apply)

- [ ] Volume-to-Capacity Ratio (V/C Ratio)
- [ ] The Level of Service (LOS)
- [ ] Travel Time Index
- [ ] Travel Delay
- [ ] Percent of Congested Travel
- [ ] Average Travel Speed
- [ ] Vehicle-Miles of Travel
- [ ] Other, please specify

5. What does your agency use as reliability measures to track congestion? (Select all that apply)

- [ ] Buffer Index
- [ ] Planning Time Index
- [ ] Level of Travel Time Reliability
- [ ] 95th Percentile Travel Time
- [ ] Other, please specify

6. Would your agency be willing to collaborate on the implementation of cargo consolidation strategies to reduce traffic congestion?

- ○ Yes
- ○ No

7. Presently, how beneficial do you think it is to implement cargo consolidation strategies (combining multiple LTL shipments that are traveling in the same vicinity into one full truckload shipment) for the alleviation of traffic congestion?

- ○ Extremely beneficial
- ○ Very beneficial
- ○ Moderately beneficial
- ○ Slightly beneficial
- ○ Not at all beneficial
- ○ Not sure/Do not know

If you have any documentation related to cargo re-routing and consolidation that may be useful to this research, please feel free to share the corresponding links in the text box below.

This concludes the survey. Click the “Back” button to review or revise your responses. If you are satisfied with your responses click the “Next” button to submit your responses.

Thank you for your participation in this survey. Your response is very important to this research.

Appendix C – Interview Protocol

Interview Protocol Guide[2]
The USF Supply Chain Innovation Lab at the University of South Florida (USF) is conducting research on evaluating factors influencing planning of shipments, especially in the context of mixed cargos and whether any optimization is used for these activities.

Opening
Introductions
Overview of purpose of the study
Confidentiality assurance

Firm Data
What types of goods does the firm manufacture/make/process/ship?
Where are the firm's major manufacturing/processing/logistics facilities located?
What commodities does the firm import/export? From where?

Initial Question: GRAND TOUR
What is the current thought process/planning that goes into shipments, and how does your company approach mixed cargo shipments? Also, is optimization used for these activities?

Additional Questions
Have you ever considered using optimization (if company is not using optimization)?
What are some challenges in making this a successful operation?

Wrap Up
Is there anything we have not discussed yet that impacts this topic?

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[2] The Interview Protocol Guide is based on recommendations by McCracken, Grant (1988). *The Long Interview*. Newbury Park, CA: Sage Publications.

Appendix D – Final Routes for Random Samples 2 and 3 (*Original* Depot Locations)

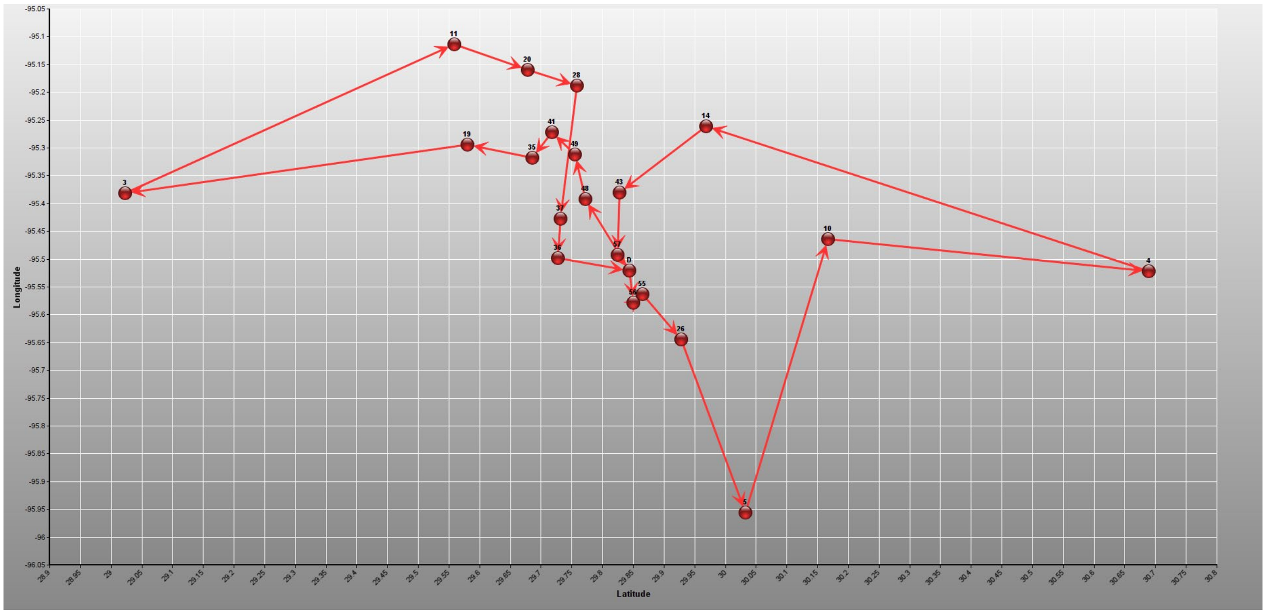

Figure 35. Single-demand routing wood – RS2 original depot location.

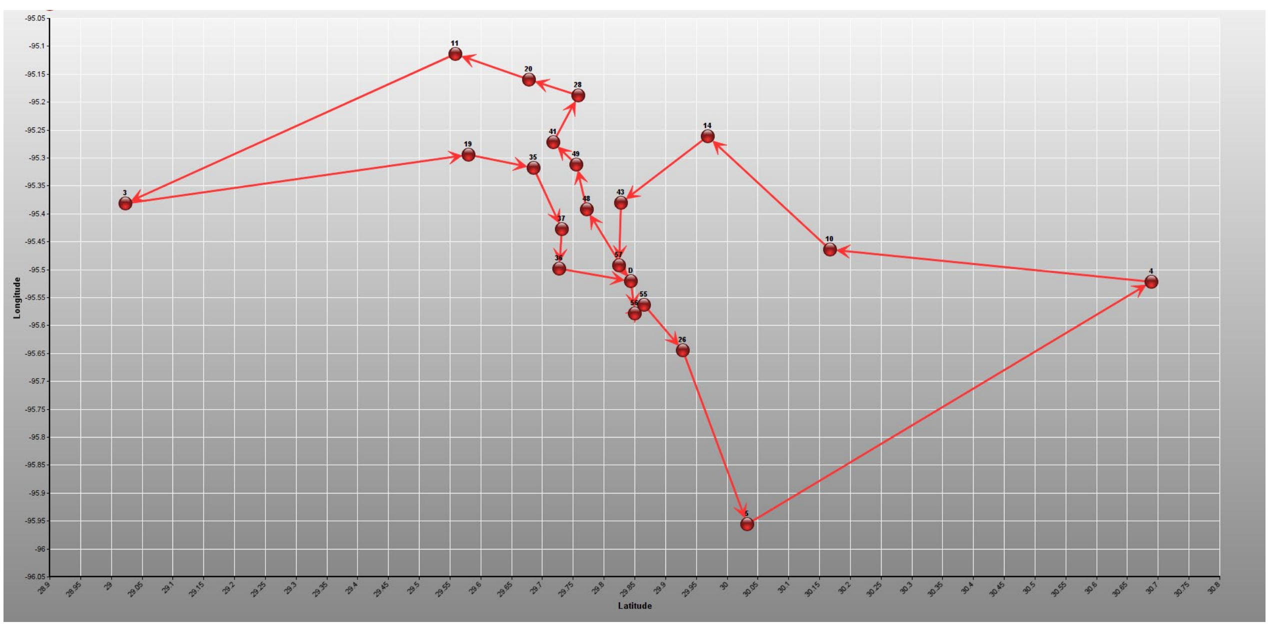

Figure 36. Single-demand routing metal – RS2 original depot location.

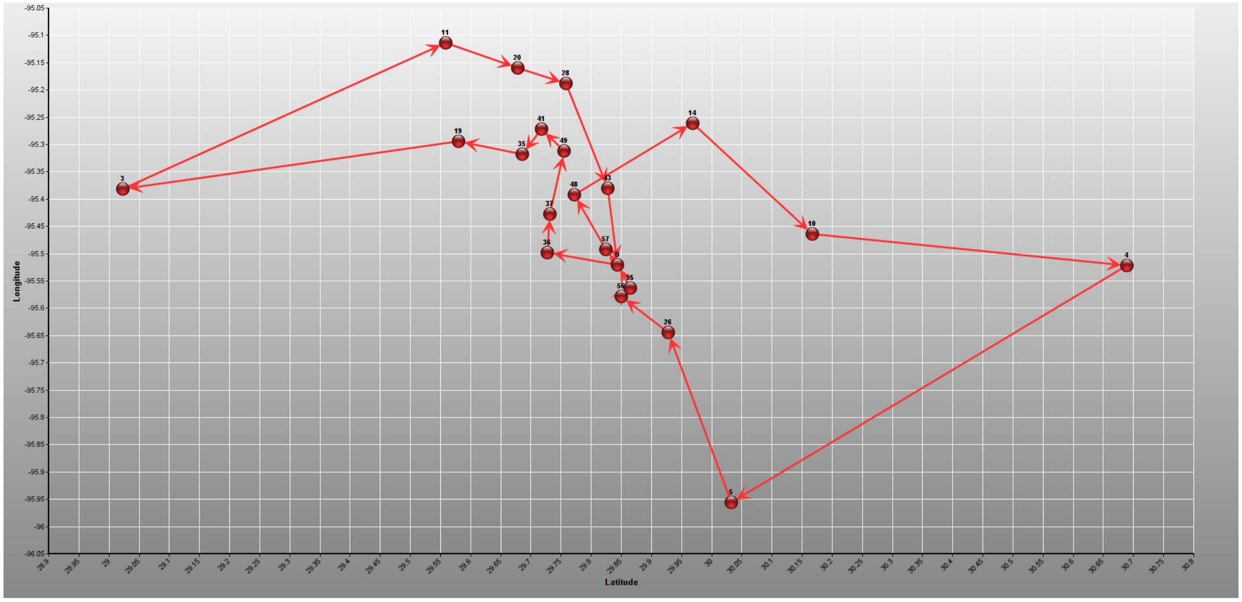

Figure 37. Cargo consolidation routing – RS2 original depot location.

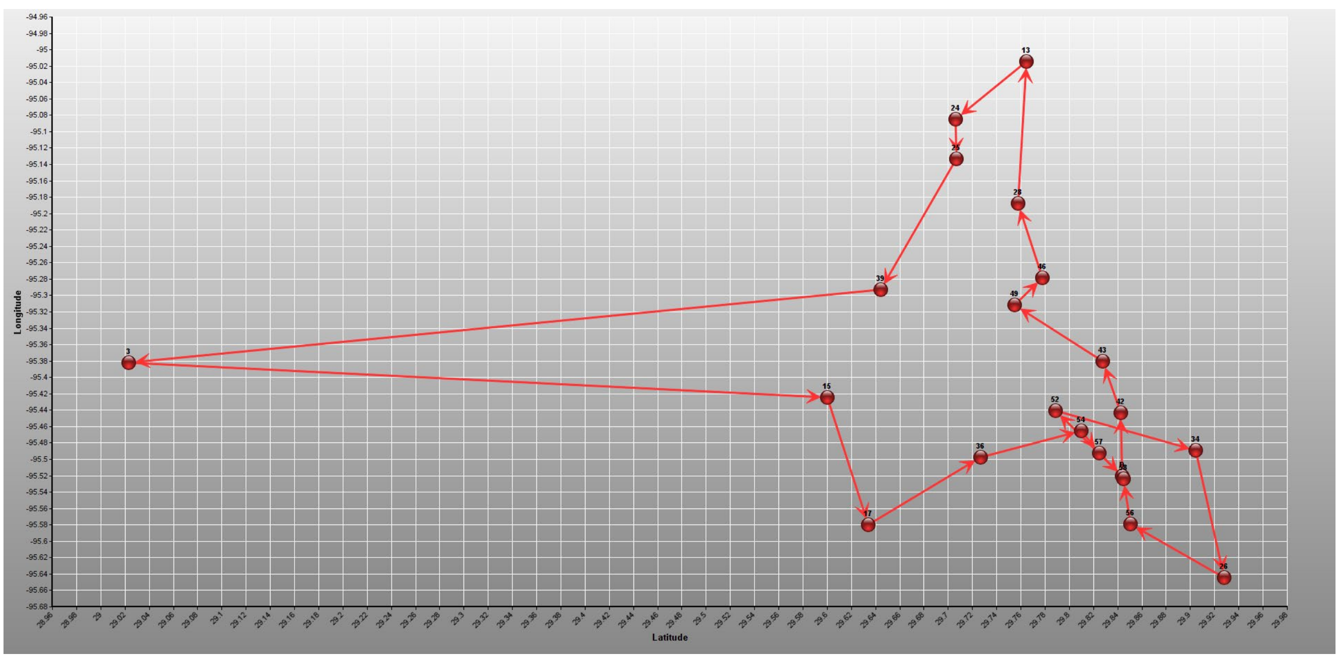

Figure 38. Single-demand routing wood – RS3 original depot location.

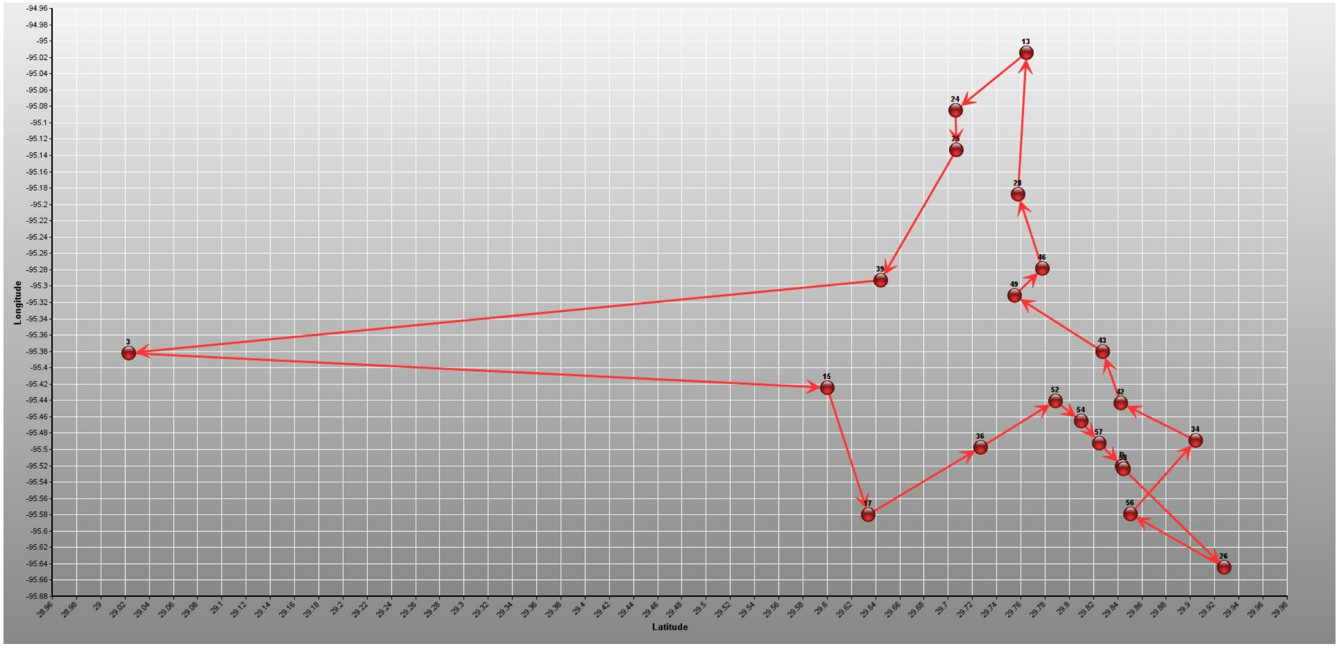

Figure 39. Single-demand routing metal – RS3 original depot location.

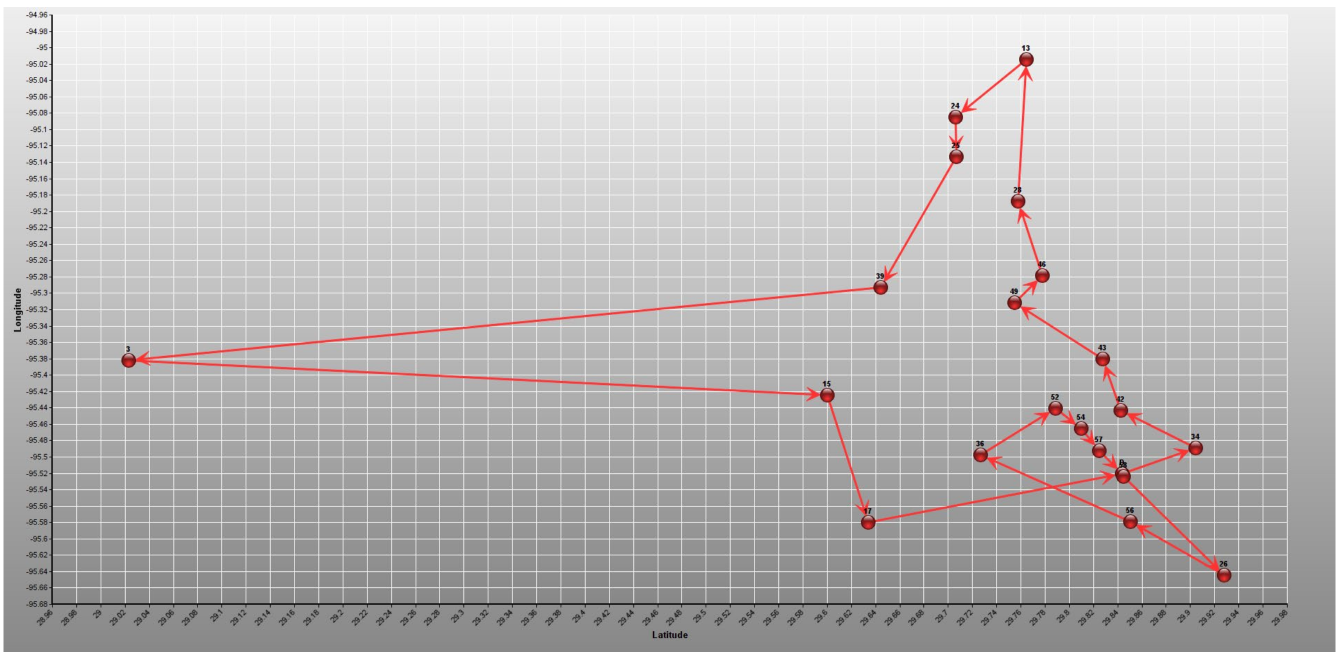

Figure 40. Cargo consolidation routing – RS3 original depot location.

Appendix E— Final Routes for Random Samples 2 and 3 (*Optimal* Depot Location)

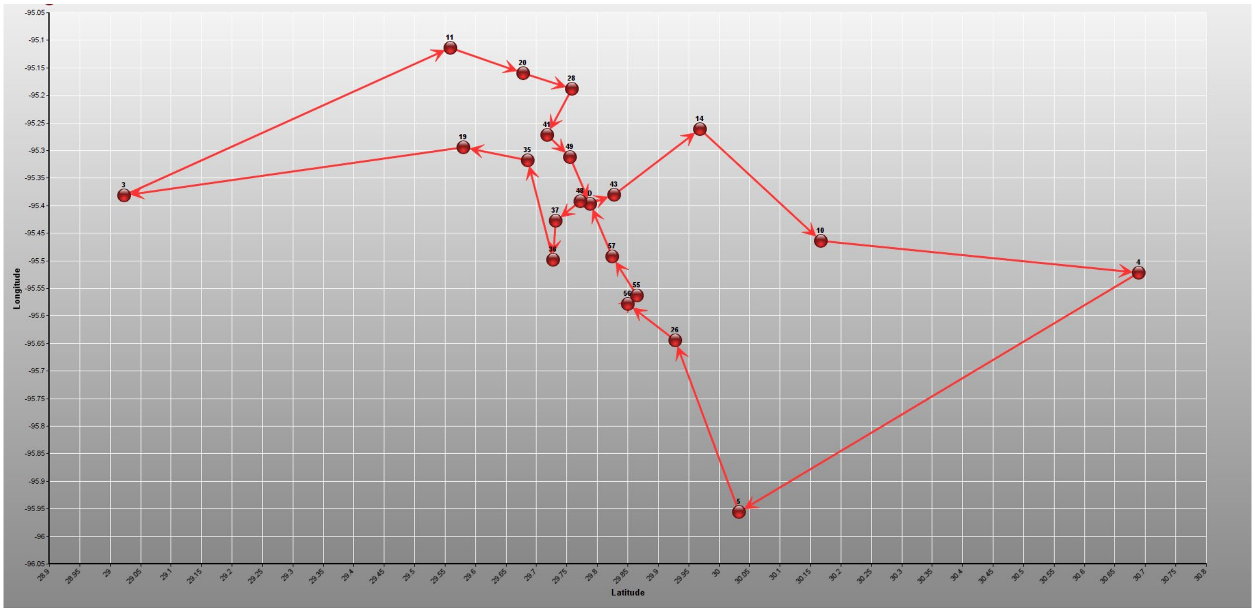

Figure 41. Single-demand routing wood – RS2 optimal depot location.

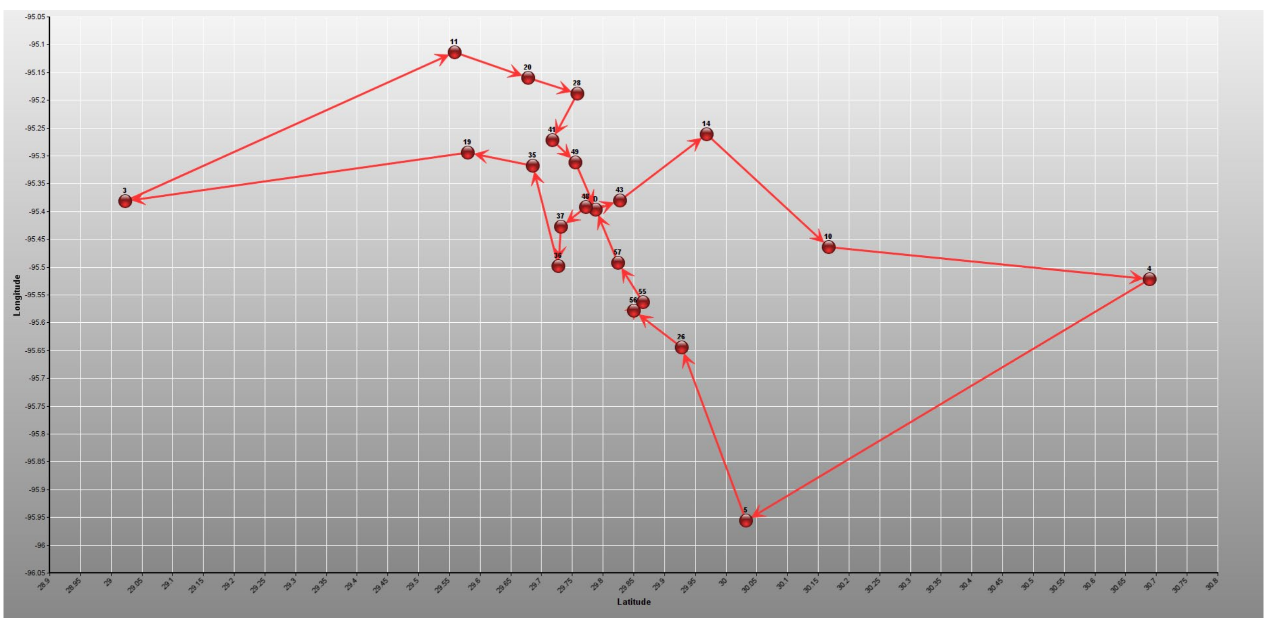

Figure 42. Single-demand routing metal – RS2 optimal depot location.

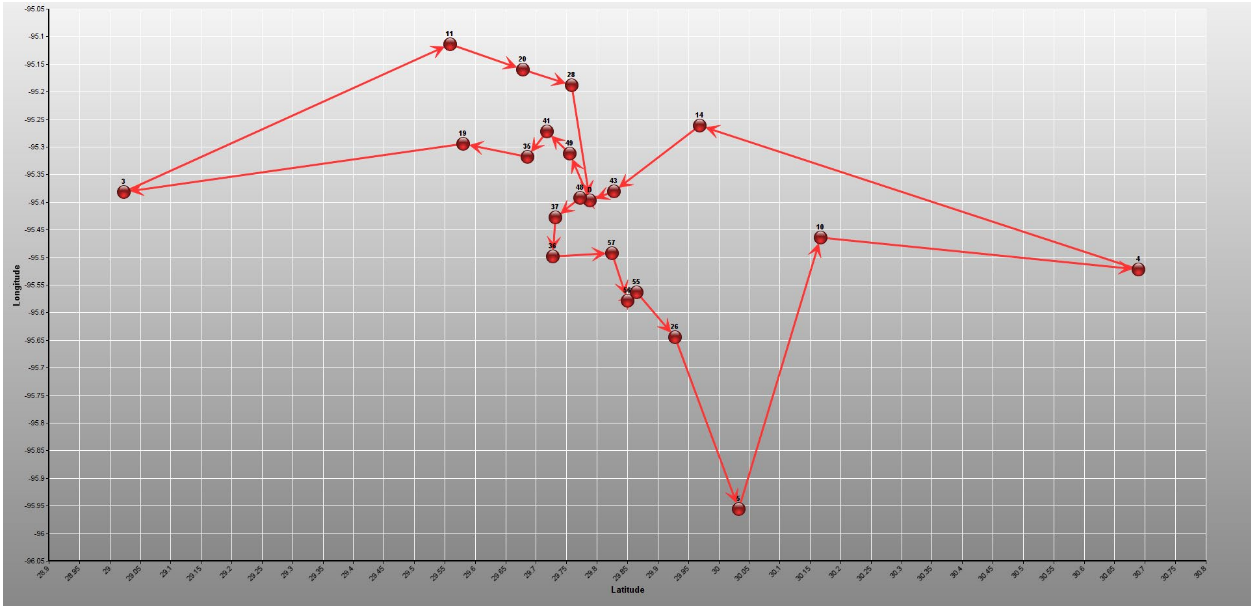

Figure 43. Cargo consolidation routing – RS2 optimal depot location.

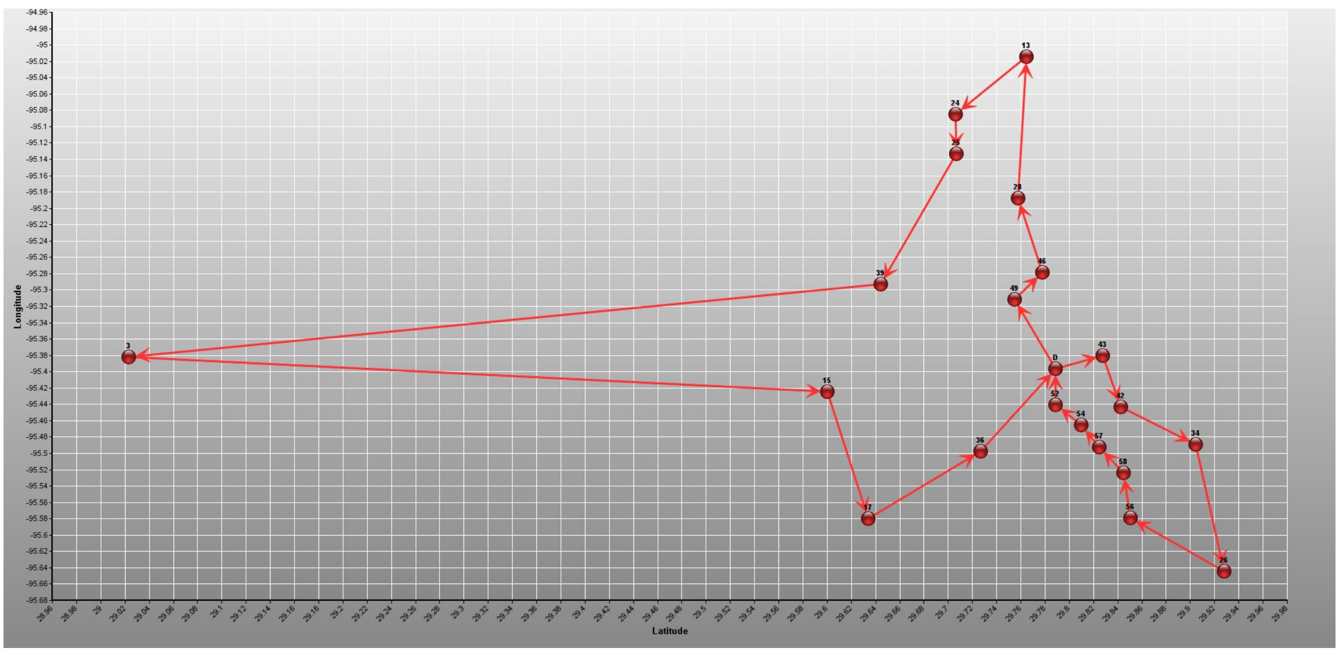

Figure 44. Single-demand routing wood – RS3 optimal depot location.

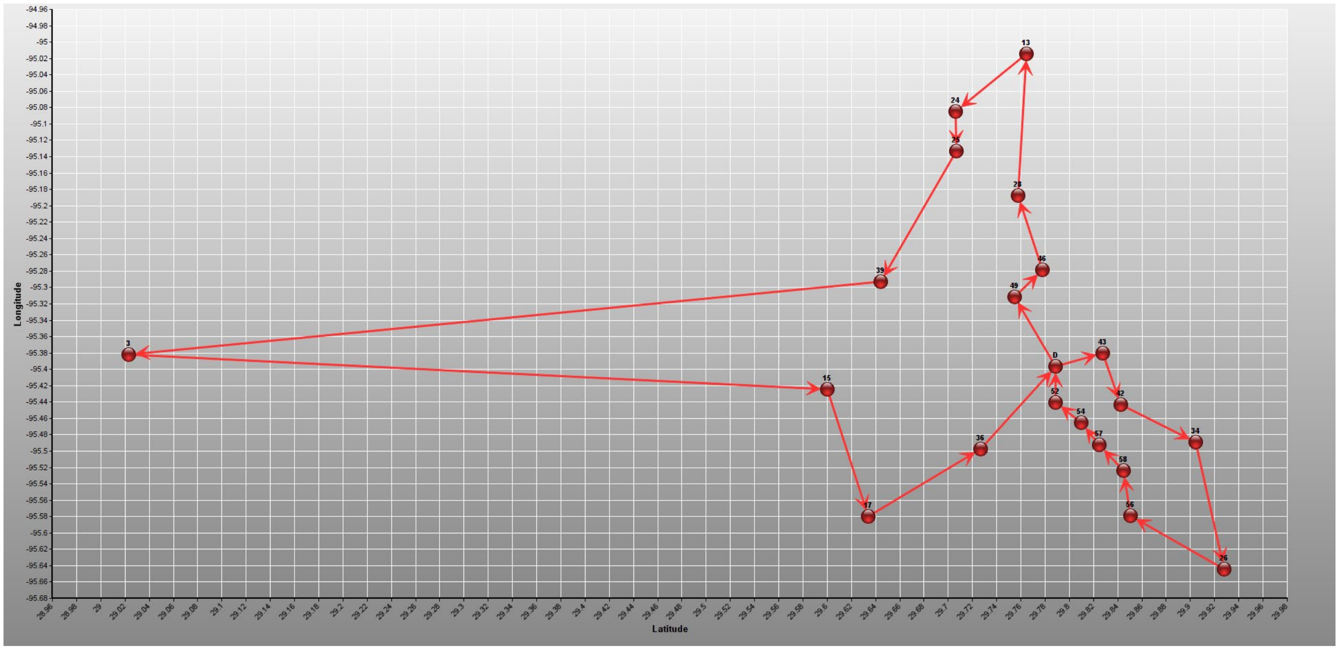

Figure 45. Single-demand routing metal – RS3 optimal depot location.

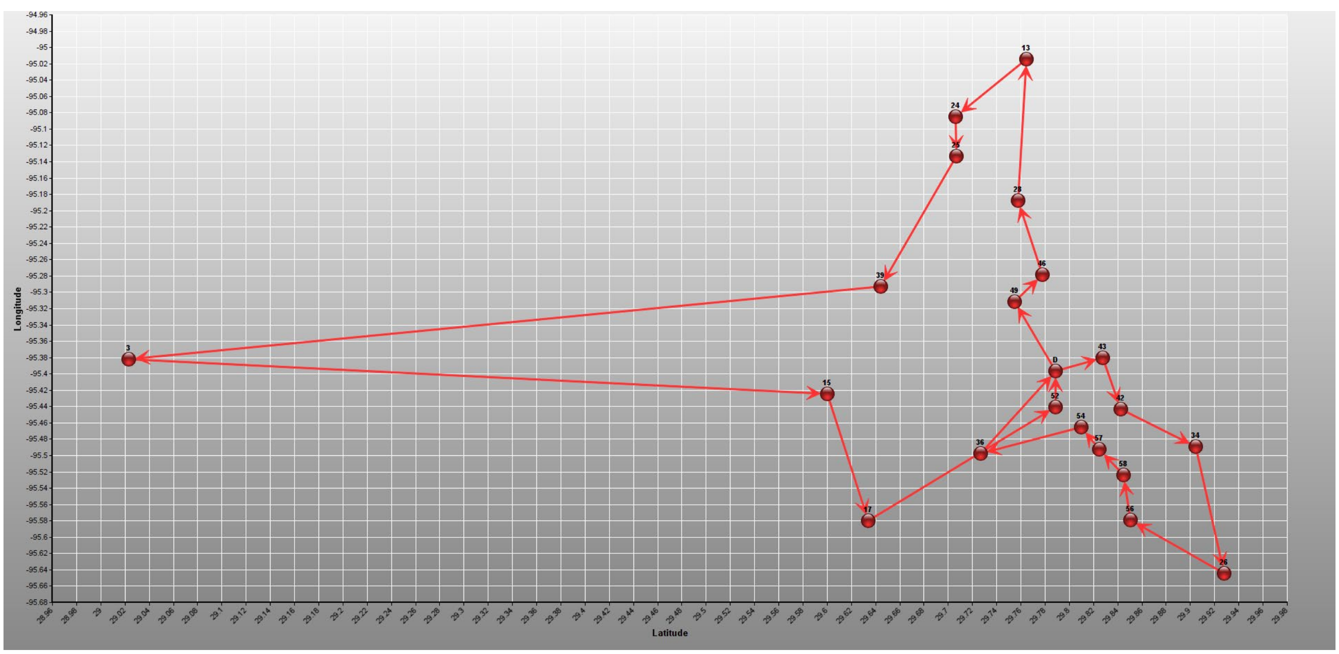

Figure 46. Cargo consolidation routing – RS3 optimal depot location.

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