

Strategic Inbound Logistics Planning:
A Cross-Business Approach to Hub Location and Supplier Pickup Scheduling

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ABSTRACT

In large companies, inbound logistics is often managed independently by different business divisions. This fragmented approach leads to repetitive pickups at suppliers, inefficient route planning, underutilized vehicles, and high transportation costs. This capstone, developed in collaboration with a multinational industrial company, proposes two distinct methodologies: (i) locate optimally located consolidation hubs, (ii) create an optimization heuristic to coordinate pickups at suppliers. The first model uses historical shipment data, including trip frequency and cargo weight, to develop a facility location model using the p-median approach and identify the optimal number and location of consolidation hubs. The second model incorporates demand variability to simulate a 100-year time horizon and create a heuristic to find the optimal pickup schedule. The results reveal that placing three consolidation hubs, located in Shanghai, Qingdao, and Guangzhou, can reduce distance travelled by approximately 50%. In addition, increasing pickup frequency at suppliers improves full truckload utilization but reduces flexibility and increases reliance on spot trucks. An optimal balance is achieved at 80% contracted truck utilization. This capstone shows how a data-driven, cross-divisional approach to inbound logistics can reduce inefficiencies, improve transportation planning, and enable a more scalable and cost-effective supply chain.

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1 INTRODUCTION

1.1 Motivation

In supply chain management, operating in silos frequently results in inefficiencies and increased cost. According to the Association for Supply Chain Management (ASCM), siloed operations create fragmented processes, delayed decision-making, and a lack of visibility across the supply chain (ASCM, 2024). Reducing silos within organizations, through supplier volume consolidation, is critical for achieving supply chain optimization and resiliency. Consolidating supplier volumes can reduce costs, enhance inventory control, and lower supply chain risks (Felicio & Sharma, 2018). By working with fewer, more reliable suppliers, organizations can negotiate better pricing, streamline procurement processes, and build stronger, more consistent relationships (Spendflo, 2024). Effective consolidation requires strategic management practices; without a disciplined approach, supply chain operations are prone to mismanagement (Nelson Miller Group, 2024).

Furthermore, studies have highlighted how inefficiencies across global supply chains raise operational costs, with expedited freight options significantly impacting profitability due to their higher costs compared to standard shipping. Port congestion, poor coordination, and infrastructure bottlenecks hinder the consistent export of full container loads, leading to routing delays and unpredictable transit times (Notteboom, 2006; U.S. Department of Transportation, 2022). Increased variability in lead times has been linked to a rise in safety stock requirements (Panditrao & Adiraju, 2014) and an increase in stockouts (Bagchi et al, 1986). These issues not only raise freight costs but also reduce the predictability and reliability of international shipments.

Several companies have implemented consolidation strategies to address inefficiencies, optimize transportation, and mitigate risks, offering valuable insights into the practical relevance of these approaches. A prominent example is General Electric (GE) Gas Power, a major manufacturer of gas and steam turbines. GE operates within a global supply chain, sourcing components internationally and transporting them to U.S. manufacturing and assembly sites. To address the high complexity of their freight network, GE developed a multi-period, multi-commodity network flow model. This system incorporates consolidation and storage options at intermediate nodes, optimizing shipments while maintaining assembly timelines and reducing costs (Camur et al., 2023). This approach demonstrates how tailored consolidation strategies can enhance supply chain performance in industries with high transportation volumes and intricate logistics.

In the oil and gas sector, consolidation efforts are often tied to mergers and acquisitions aimed at streamlining supply chains and boosting resilience. A case study for this practice is ExxonMobil's acquisition of Pioneer Natural Resources, a strategic move designed to consolidate assets, reduce operational redundancies, and optimize supply chain networks (MarketWatch, 2024). Such efforts highlight how consolidation not only reduces inefficiencies but also creates opportunities for integrated operations and improved resource utilization.

1.2 Problem Statement

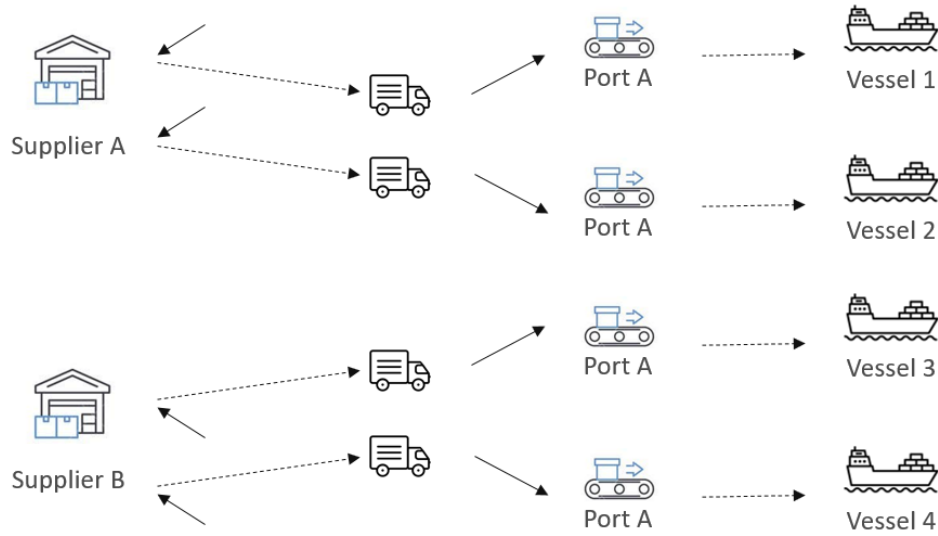
Managing inbound logistics cost-effectively and consistently remains a central challenge for industrial firms operating large, complex supply chains. In this paper, we define inbound logistics as the flow of goods originating from suppliers and moving toward manufacturing sites.

Irregular pick-ups at supplier locations often result in low truckload utilization, high transportation costs, and an inconsistent flow of goods. These disruptions increase reliance on expensive spot market trucking, which limits the ability to ship efficiently using full container loads. As a result, companies face greater variability in transit times and broader downstream inefficiencies.

Spot market trucking refers to the ad hoc hiring of trucks on short notice, typically at a higher cost compared to contracted trucks, which operate on pre-defined schedules and offer more cost-effective and predictable service. Full container load (FCL) shipping means that a container is filled entirely by one shipper's cargo, enabling better cost efficiency and reliability. Less-than-container load (LCL) refers to cargo that does not fill a full container and is consolidated with shipments from other shippers, typically resulting in longer lead times, increased handling, and higher per-unit transportation costs.

Figure 1 illustrates this common problem, where multiple trucks visit the same supplier several times a day with no coordination. Goods are then transported directly to the port for international shipment, traveling in less-than-container loads.

FIGURE 1. INEFFICIENT SUPPLIER PICKUPS DUE TO LACK OF COORDINATION



To explore this problem, this capstone is guided by a set of key research questions. **First**, we examine how to define the appropriate composition of contract and spot trucks for a transportation lane, and whether a consistent ratio of the two can be optimized for different types of supplier cities and shipment profiles. **Second**, we evaluate how the product mix in a city, measured by business division overlap and average load size, affects this optimal ratio. **Third**, we explore whether increasing the allowable delay between supply readiness and truck dispatch (i.e., extending the pickup window) improves consolidation opportunities and reduces the number of spot trucks needed.

By answering these questions, our study provides insights into balancing cost and service across inbound lanes, improving truckload consolidation, and designing resilient pickup schedules that support regular and efficient full container load shipments.

1.3 Case Study: Multinational Industrial Company

To explore the research questions outlined in the previous section, this paper examines the inbound logistics operations of a multinational industrial company that recently transitioned into a standalone entity. The company comprises three major business divisions and twelve specialized units, each responsible for distinct logistics and transportation activities. Historically, these units have functioned independently, limiting opportunities for cross-divisional coordination.

Our partnership with the company provides access to rich operational data and a unique opportunity to investigate how shared supplier networks and shipment patterns can inform more integrated logistics planning. Specifically, the study uses this real-world context to evaluate how consolidation hubs and scheduling impact efficiency, truckload utilization, and transportation cost. The case enables analysis of whether product mix and supplier overlap affect the ideal composition of contract and spot trucking strategies, and how extending pickup windows might enable better load consolidation across divisions.

1.3.1 Partner Company Context

The partner company operates on a global scale, with manufacturing sites located in the United States, Europe, and India. These sites serve as the primary destinations for shipments originating from a globally dispersed supplier base. Some destinations are shared across all three business divisions, while others serve only one or two. The geographical distribution of these destinations is illustrated in Figure 2.

FIGURE 2. GLOBAL OPERATION OF PARTNER COMPANY



The company sources from 186 suppliers across China to fulfill demand at 102 global destinations. In 2024 alone, approximately 22,000 shipments were dispatched, totaling 312 million kilograms of cargo. Despite this scale, coordination across business units remains limited. Eight supplier origins are shared by all three divisions, and 21 origins are common to two divisions, revealing potential for load consolidation

and coordinated pickups. Figure 3 illustrates the supplier base in China and color codes the quantity of divisions that source at these sites.

FIGURE 3. SUPPLIER OVERLAP ACROSS BUSINESS DIVISIONS



Legend: ● Sourced by all 3 business divisions ● Sourced by 2 divisions ● Exclusive to 1 division

Many supplier locations are repeatedly visited by different business units, often within the same week, creating inefficiencies in freight movement. By examining these patterns, this study evaluates whether consolidated operations, both in terms of creating consolidation facilities and shared pickup schedules, can improve the balance between contract and spot market reliance, increase truckload utilization, and enhance the resilience of the logistics network.

This real-world case forms the empirical foundation for testing consolidation strategies and developing frequency schedules in high-overlap supplier cities. The analysis serves not only as a proof of concept for coordinated freight planning but also as a contribution to broader insights into the structural levers, such as hub location, supplier mix, and schedule design, that enable consistent, full-container-load movements within a complex inbound logistics system.

1.4 Hypotheses

Based on industry practices and a preliminary understanding of the partner company's logistics network, this study formulates the following hypotheses to guide the analysis of inbound freight consolidation.

1. **Contract trucking should dominate the mode mix in an optimized network.**

Contract rates are generally lower and less volatile compared to spot market rates. Moreover, they offer greater scheduling stability, which is essential for consistent full-container-load (FCL) movements. Therefore, we hypothesize that a cost-efficient and resilient network will exhibit a higher proportion of contract trucks relative to spot trucks.

2. **Cities with a high share of heavy products require significantly more trucks to achieve desirable consolidation.**

When product weight per shipment is high, the number of full truckloads needed increases even if the shipment frequency remains stable. We hypothesize that the required truck capacity scales non-linearly with average product weight, especially in cities serving multiple business units.

3. **Extending the pickup window reduces the reliance on spot trucks.**

A longer permissible pickup window provides greater flexibility to aggregate shipments across days and business units. This flexibility enables better load consolidation, which we hypothesize leads to a reduction in spot truck usage, particularly in high-volume or high-overlap cities.

4. **Supplier overlap across business divisions is positively correlated with consolidation potential.**

Locations where multiple business units share the same or nearby suppliers offer greater scope for volume pooling. We expect to find that such cities can achieve higher average truck utilization and lower shipment variability than cities dominated by a single business unit.

5. **The effectiveness of a consolidation hub is sensitive to its proximity to supplier clusters.**

Strategically located hubs closer to dense supplier regions are more likely to facilitate high utilization rates and reduce the total distance traveled. We hypothesize that optimal hub locations will align with regions showing high supplier density and divisional overlap.

2 STATE OF THE PRACTICE

In this chapter, we discuss the relevant existing literature regarding freight consolidation, facility locations, and scheduling. This review synthesizes existing knowledge on mode selection strategies, contract versus spot market dynamics, consolidation hub placement, and the role of pickup flexibility in improving load utilization. By anchoring our study in these established frameworks and empirical findings, the literature review provides the theoretical foundation for our methodological choices and identifies gaps that this paper seeks to address.

2.1 Freight Consolidation

Freight consolidation is the practice of combining multiple smaller shipments into a single, larger load, typically by grouping cargo that originates from or is destined for the same geographic region (Hall, 1987). There are 3 main types of freight consolidation:

1. **Inventory consolidation:** holding items that have been produced over time and transporting them as a single load. Shipments are held until a minimum load size is met or transported on pre-determined scheduled days (Hall, 1987).
2. **Vehicle consolidation:** picking up and dropping off shipments at different locations. These movements are known as “milk runs” and reduce the total number of trucks required to service locations (Hall, 1987).
3. **Terminal consolidation:** brings multiple shipments from multiple origins to a single terminal where they are sorted and loaded into a staging area or new vehicle according to their destination (Hall, 1987).

2.1.1 Key Drivers of Freight Consolidation

One of the key drivers for inbound freight consolidation is **container utilization** (LCL vs. FCL). Container utilization, particularly the distinction between less-than-container-load (LCL) and full container load (FCL) shipments, plays a critical role in determining the efficiency and cost of inbound freight operations. By aggregating multiple less-than-container-load (LCL) shipments into full container loads (FCL), firms can optimize the use of available container space (Matikka, 2016). This approach minimizes the reliance on partially filled containers and contributes to lower per-unit transportation costs, as freight charges are generally applied per container or shipment rather than based on cargo volume.

Consequently, consolidation reduces shipment frequency and leads to more cost-effective freight operations.

Another key driver is the type of **transportation rate**, namely, spot, contracted, or dedicated, which has a substantial impact on cost stability, service reliability, and strategic logistics planning (Caplice, 2021). **Dedicated trucking** involves the exclusive use of assets, either through private fleets or third parties. This procurement strategy is common for consistent, high-volume lanes, offering maximum reliability but risks underutilization when there is no inventory backhaul. **Contracted rates** are negotiated annually through request-for-proposal (RFP) processes, locking in prices for specific lanes over a set period. These agreements provide pricing stability without guaranteeing volume or capacity, making them well-suited for moderately predictable demand. **Spot rates**, by contrast, are negotiated per shipment in real time and are typically used when contract carriers reject loads. Though highly flexible, spot trucking is the most expensive option due to its rate volatility and short-term nature. (Scott, 2015).

Finally, **lead time** considerations are a critical driver of inbound logistics performance, as they shape the effectiveness of freight consolidation and inventory planning. Predictable lead times allow businesses to maintain a steady flow of inventory into distribution centers or production facilities, reducing the need for excess safety stock and enabling consistent product availability. Regular shipments enhance lead time reliability by minimizing the delays and disruptions often associated with smaller, fragmented loads. This stability improves a company's ability to meet demand, reduces the risk of stockouts and backorders, and enhances overall responsiveness to market changes (Lilly, 2016).

2.1.2 Benefits and Challenges of Freight Consolidation

One of the most notable advantages of freight consolidation is **economies of scale**, where larger shipments result in lower per-unit freight costs. For example, UPS charges significantly less per pound for larger packages. A 1-pound package from Cambridge to Manhattan costs approximately USD 20, while a 15-pound package costs USD 45 (equivalent to USD 3 per pound)¹. This pattern applies broadly across different modes of transportation, including full truckload (FTL) versus less-than-truckload (LTL) and full container loads (FCL) compared to less-than-container loads (LCL) (Ford, 2001).

In addition to lowering per-unit shipping costs, freight consolidation reduces **administrative overhead** by decreasing the number of individual shipments. Fewer shipments mean less time spent on

¹ Shipping rates for UPS 3 Day Select® retrieved from the official UPS website on May 4, 2025.

documentation, customs processing, and brokerage fees, all of which contribute to overall cost savings (Ford, 2001).

Consolidated shipments are also **faster and more reliable**. Full truckloads (FTL) and full container loads (FCL) experience fewer stops, less handling, and reduced risk of damage, leading to shorter transit times and increased shipment integrity (Ford, 2001). These advantages support a more resilient supply chain by improving operational efficiency, ensuring product availability during high-demand periods, and shortening total cycle times.

However, freight consolidation also results in a set of challenges. One drawback is the **potential delay** incurred while waiting for enough cargo to accumulate before dispatch. In some cases, shipments may need to be routed through a central hub, increasing **travel distance** and total cost (Ford, 2001). Additionally, effective consolidation requires **coordination** across suppliers, transport providers, and systems. Establishing the necessary processes and digital infrastructure can be time-consuming and complex (Ford, 2001).

Overall, while consolidation provides substantial cost and efficiency benefits, businesses must weigh these advantages against potential delays, increased distances, and coordination costs to determine the best approach for their operations.

2.2 Facility Selection for Consolidation Hubs

Hall (1987) identifies two primary approaches to terminal assignment within freight consolidation: n-terminal-closest and n-terminal-best-nearby. These models are particularly relevant in networks involving large shipment volumes and a wide geographic dispersion of suppliers and destinations. The n-terminal-closest method assigns high-volume suppliers to the nearest terminal, emphasizing proximity to reduce transportation costs. In contrast, the best-nearby approach incorporates destination alignment, assigning lower-volume suppliers based on downstream routing efficiencies rather than solely geographic closeness. These models highlight the importance of balancing shipment volume, terminal location, and destination in designing effective consolidation strategies.

This section reviews literature on facility location models, specifically through the lens of the n-terminal-closest approach as defined by Hall (1987).

2.2.1 Facility Location Modeling

Facility location modeling plays a central role in designing efficient hub-and-spoke transportation networks. Manzini et al. (2006) designed a mixed-integer linear programming (MILP) framework to optimize supply chain configurations involving multiple actors, including production plants, distribution centers, and customer locations. Their approach identifies optimal hub locations that minimize total transportation costs while maintaining service efficiency. In this context, suppliers are typically assigned to consolidation hubs based on factors such as geographic proximity, transportation cost, and logistical constraints. The literature emphasizes that strategic hub placement and supplier assignment are essential to achieving cost-effective and high-performance supply chain operations.

Mixed-Integer Linear Programming (MILP) has been widely recognized as a powerful optimization tool in supply chain management, particularly for addressing complex decision-making problems involving both continuous and discrete variables. MILP is especially well-suited for modeling scenarios that require selecting among discrete options, such as facility locations or supplier allocations, while simultaneously minimizing costs or maximizing service levels across a network. Nemhauser and Wolsey (1988) emphasized the flexibility and rigor of MILP in handling multi-echelon logistics challenges, including facility placement, inventory distribution, and transportation network optimization.

In the context of hub location and supplier assignment, MILP has been employed to model constraints such as capacity limits, fixed operating costs, and varying demand requirements. Its ability to integrate these operational factors into a unified framework makes it an essential method for generating solutions that are both efficient and implementable in real-world supply chain environments.

2.2.2 P-Median Model

Median-based models represent a fundamental class of discrete facility location problems, primarily aimed at minimizing the demand-weighted average distance between service facilities and the demand nodes they serve. These models are widely applied in distribution and logistics planning, where transportation distance acts as a key determinant of cost and service efficiency (Daskin, 2008).

Among these models, the p-median involves selecting p facility locations from a set of candidates to minimize the total weighted distance between demand points and their assigned facilities. This approach is particularly relevant for the design of supply chain networks, including the placement of warehouses, distribution centers, and consolidation hubs, where minimizing overall transportation costs is a central objective.

A notable strength of the p-median model is its capacity to account for both demand intensity and geographic distance, often favoring facility placement in high-demand areas to reduce aggregate logistics costs. This characteristic distinguishes it from covering models, which focus on ensuring all demand points fall within a specified service radius, and from center models, which seek to minimize the maximum (worst-case) distance between a demand node and its assigned facility (Daskin, 2008).

2.3 Scheduling with Heuristic Modeling and Simulation

Supply chain segmentation serves as a foundational framework for developing differentiated scheduling strategies based on supplier characteristics. By classifying suppliers according to dimensions such as supply variability, risk exposure, and profit contribution, organizations can align scheduling policies with operational requirements. As outlined by McKinsey & Company (2017), segmentation enables targeted decision-making while maintaining manageable complexity. To support the formulation of such segment-specific scheduling approaches, the following sections examine relevant literature on **heuristic modeling** and **simulation**, which are widely used for addressing complex scheduling problems under uncertainty and constraints.

2.3.1 Heuristic Modeling

Heuristic methods have been widely employed in the literature to address complex logistics problems, particularly in cases where exact optimization methods are computationally infeasible. As defined by Pearl (1984), “heuristics are strategies using readily accessible, though loosely applicable, information to control problem-solving in human beings and machines” (Pearl, 1984, p. 6).

In supply chain and transportation applications, heuristics are valued for their ability to handle constraints such as delivery time windows, vehicle capacities, and routing order requirements with reduced computational demand.

Common heuristic techniques include savings algorithms, clustering methods, and the sweep algorithm (Ballou, 2007). Notably, Ballou and Chowdhury (1991) extended vehicle routing models by integrating mode and carrier selection into a cost-based heuristic, illustrating the potential of hybrid approaches in generating practical logistics solutions.

While no standard heuristic model exists for supplier pickup scheduling, the literature provides a foundation of adaptable strategies that inform the development of customized solutions.

2.3.2 Simulation

Simulation is a key methodological tool for analyzing dynamic systems under uncertainty. It involves constructing computational models that replicate real-world operations over time, allowing researchers to evaluate performance across a range of scenarios and use them to make informed decisions (Law & Kelton, 2007). A major strength of simulation lies in its ability to incorporate stochastic elements, including randomness and uncertainty, making it particularly suitable for supply chains with inherent variability.

In modeling systems with uncertain inputs, probability distributions are commonly employed to represent random variables such as shipment weights, inventory levels, and demand fluctuations. The choice of distribution depends on the nature of the variable and the availability of historical data. When data is limited and all outcomes are assumed equally likely, a **discrete uniform distribution** can provide a simple yet valid approximation. However, in cases where variability follows more structured patterns, other distributions are often more appropriate. For example, the **normal distribution** is frequently used for modeling continuous variables with symmetric variability around a mean, such as lead times or daily demand. The **exponential distribution** is suitable for modeling the time between independent events, such as arrival times or machine failures. The **triangular distribution** is often used when limited data exists, but expert estimates of minimum, maximum, and most likely values are available. These distributions enable the generation of synthetic data that reflects real-world variability, supporting robust scenario analysis and decision-making under uncertainty (Law & Kelton, 2007).

2.4 Synthesis of Literature

The existing literature provides valuable insights into specific components of inbound logistics optimization, including consolidation strategies, facility location modeling, transportation mode selection, and scheduling. While these studies offer strong conceptual and methodological foundations, they tend to address these elements in isolation. To the best of our knowledge, no existing study has integrated freight consolidation dynamics, mode allocation (contract vs. spot), pickup window flexibility, and supplier overlap within a unified framework to assess their combined impact on inbound supply performance.

This gap highlights an opportunity to advance the field by developing an integrated, data-driven approach that reflects the interdependencies among these components. To address this, our study develops an integrated methodological framework that combines facility location modeling, supplier segmentation, and pickup scheduling using real-world industry data.

3 METHODOLOGY

3.1 Overview

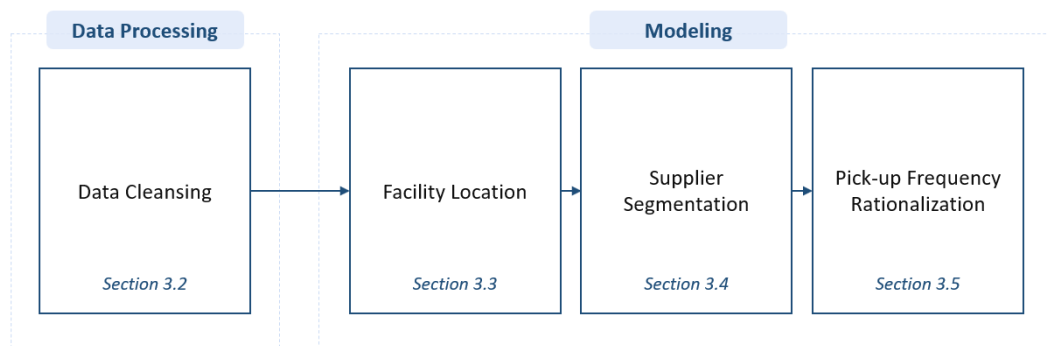
To address the proposed research questions regarding the optimal allocation of contract and spot trucking, the influence of supplier city shipment profiles, and the impact of pickup window flexibility on consolidation, we drew insights from the literature review to develop a structured, multi-phase methodology.

We grounded the analysis on the operational context of the case study company described in Section 1.3, leveraging real-world shipment data to evaluate alternative inbound logistics strategies.

In the first phase, we cleansed and consolidated shipment records from all business divisions into a unified and standardized dataset. We then generated facility location scenarios based on historical shipment frequency, weight, and distance traveled, identifying optimal consolidation hubs across China. In the next phase, we segmented suppliers based on trip frequency, shipment weight, and hub assignment, classifying them into distinct profiles. From this analysis, we selected three high-priority cities to evaluate hypotheses related to pick-up scheduling strategies.

Figure 4 presents an overview of the methodological framework.

FIGURE 4. METHODOLOGY OVERVIEW



3.2 Data

Data cleansing represented a critical preparatory step in this study to ensure the accuracy, consistency, and usability of the dataset. This process involved consolidating, standardizing, and validating data sourced from multiple business divisions, while addressing key issues such as duplicate supplier records, incomplete geographic information, and inconsistent data formats. The cleaned dataset formed a robust foundation for the subsequent phases of analysis.

3.2.1 Data Collection and Preparation

To begin the study, we collected shipment data from three separate databases, each corresponding to a different business division. Although the level of data completeness varied across divisions, all datasets included the minimum required information for our analysis: cargo weight, supplier source city, destination city, and release date.

After data consolidation, we took four essential steps to transform the raw files into a clean and well-structured dataset: (i) supplier name standardization, (ii) data structure optimization, (iii) geographic refinement, and (iv) temporal processing.

The summary statistics presented in Table 1 illustrate the extent of data refinement during the cleansing phase. Division 1 experienced the most reduction, with 86.7% of records removed, indicating significant initial inconsistencies or redundancies. In contrast, Division 2 saw only a 0.3% reduction, suggesting high data quality from the outset. Division 3 underwent a moderate reduction of 55.3%, reflecting partial refinement. Overall, 68.9% of records were removed across all divisions, underscoring the scale of consolidation required to produce a clean and unified dataset. In addition, the number of unique suppliers was reduced by 20.1% following harmonization, reflecting our efforts to standardize supplier identifiers and eliminate duplicates across divisions.

TABLE 1. DATA CLEANSING OVERVIEW

Dataset	Raw Count	Cleansed Count	Reduction (%)
Division 1	34,669	4,608	86.7%
Division 2	2,867	2,857	0.3%
Division 3	31,036	13,873	55.3%
Overall Records	68,572	21,338	68.9%
Suppliers (harmonized)	304	243	20.1%

After completing the data cleansing process, the dataset was significantly enhanced in terms of consistency, accuracy, and relevance. By standardizing supplier and city names, we improved uniformity across records, reduced ambiguity, and ensured consistent data interpretation. By correcting erroneous country-city mismatches through geospatial validation, we ensured the data accuracy necessary for reliable geographic analysis. Additionally, by applying country and time-based filters, we aligned the dataset with the study's objectives, retaining only the most relevant data points.

3.2.2 Pre-Processing

During the pre-processing stage, we transformed and aggregated the data into the required structure for the modeling phase. This included grouping information at the city and weekly levels, as well as incorporating additional parameters to ensure all necessary inputs were available for running the optimization and simulation models effectively:

- **Supply Aggregation at City Level:** We aggregated supplier data at the city level across all business divisions, allowing the model to treat each city as a single supply node.
- **Distance Matrix Calculation:** We calculated geodesic distances, the shortest possible distance between two points on the surface of a curved shape, between each supplier city and every port under consideration. This distance matrix served as a core input for the facility location model.
- **Weekly Supply Aggregation:** We calculated weekly supply volumes for each city by summing up the weights of all shipments scheduled for release during the same week. This provided a consistent, time-based demand structure to support pickup frequency and truckload optimization.
- **Mapping Ports as Potential Hub Locations:** We mapped and indexed all relevant port locations as potential consolidation hubs, generating the candidate locations required by the p-median facility location model.
- **Demand Weight Assignment for p-Median:** We assigned each city's total weekly shipment weight as the demand input in the p-median formulation, capturing the relative importance of each node in the network.

3.3 Facility Location

To identify the most effective consolidation hubs within the current supply network, we applied an integrated modeling approach combining the facility location problem, mixed-integer linear programming (MILP), and the p-median model, as outlined in Section 2.2. This integrated approach ensured both mathematical rigor and practical relevance in identifying optimal hub locations tailored to the partner company's logistics needs.

To systematically evaluate hub placement within the inbound supply network, we adopted a quantitative modeling approach grounded in the facility location problem. We used historical shipment volume data from supplier cities in China to define supply nodes and considered all major Chinese ports as potential consolidation hubs. Our objective was to minimize the total volume-weighted distance between suppliers and assigned hubs, with geodesic distance serving as a proxy for transportation cost.

We formulated the problem as a mixed-integer linear programming (MILP) model, enabling the assignment of supplier nodes to hub locations under standard facility location constraints. Given the absence of a predefined number of hubs or fixed candidate locations, we employed a p-median to determine both the optimal number and location of hubs. This approach is particularly well suited for greenfield network design scenarios, where facility siting decisions must be made from a continuous set of possibilities.

The following subsections present an overview of the model structure, define the key parameters and decision variables, outline the mathematical formulation, and describe the optimization tools used for implementation.

3.3.1 Model Overview

We considered a set of supplier cities, denoted by I , where $i = 1, 2, 3, \dots$, and a set of potential hub locations, denoted by J , where $j = 1, 2, 3, \dots$. Each hub location could either be opened or closed, $Y_{ij} \in \{0, 1\}$. The Euclidean Distance between each supplier city $i \in I$ and potential hub $j \in J$ was represented as d_{ij} , and each supplier was associated with an annual shipment volume h_i , which served as the weight for that flow.

Our primary objective was to minimize weighted distances, $h_i d_{ij} Y_{ij}$ (used as a proxy of transportation cost), by optimizing the flows of goods from cities in China to ports in China (door-to-port) such that all supply was absorbed by the hubs and only one hub was assigned to a city.

3.3.2 Parameters and Variables

The parameters and variables from the model are described in Table 2.

TABLE 2. PARAMETERS AND VARIABLES – FACILITY LOCATION

Parameters	Description
I	Set of supplier cities
J	Set of potential hub locations
P	Number of hubs to be opened
d_{ij}	Distance between supplier city i and hub location j
h_i	Flow volume or demand weight associated with supplier city i
Decision Variables	Description
$X_j \in \{0, 1\}$	Equals 1 if a hub is opened at location $j \in J$; 0 otherwise
$Y_{ij} \in \{0, 1\}$	Equals 1 if supplier node $i \in I$ is assigned to hub $j \in J$; 0 otherwise

Assumption: All hub locations are assumed to have unlimited capacity.

3.3.3 Model Formulation

We designed an objective function to minimize the distance between supplier city and potential hub locations, based on the open hubs and the weighted demand at the origin.

Objective Function:

$$\text{Min} \sum_{j \in J} \sum_{i \in I} h_i d_{ij} Y_{ij} \quad (1)$$

Subject to:

Each supplier is assigned to one hub:

$$\sum_{j \in J} Y_{ij} = 1 \quad \forall i \in I \quad (2)$$

Suppliers can only be assigned to open hubs:

$$\sum_{j \in J} Y_{ij} - X_j \leq 0 \quad \forall i \in I, \forall j \in J \quad (3)$$

Open exactly P hubs (as determined by the p -median model):

$$\sum_{j \in J} X_j = P \quad (4)$$

Binary decision variables:

$$X_j \in \{0,1\} \quad \forall j \in J \quad (5)$$

$$Y_{ij} \in \{0,1\} \quad \forall i \in I, \forall j \in J \quad (6)$$

The constraints define a classic p -median facility location problem, where each supplier must be assigned to exactly one hub, ensuring full and exclusive coverage (Constraint 2). However, suppliers can only be assigned to open hubs, preventing allocations to inactive facilities (Constraint 3). Our model also requires that exactly P hubs be opened, aligning with a predetermined number of facilities to be selected (Constraint 4). Constraints 5 and 6 specify that the decision variables are binary: X_j equals 1 if hub j is open and 0 otherwise (Constraint 5), while Y_{ij} equals 1 if supplier i is assigned to hub j and 0 otherwise (Constraint 6). These binary constraints ensure that both hub openings and supplier assignments are discrete, yes/no decisions. Together, these constraints formed the foundation for optimizing hub locations to minimize total distances while ensuring feasible supplier assignments.

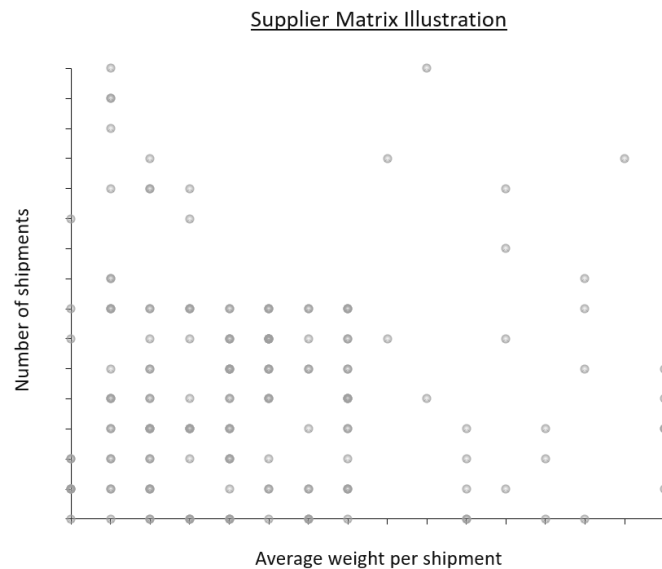
3.3.4 Tools Utilized

To develop and implement the facility location model, we applied a combination of Python libraries to support transportation network analysis, with specific emphasis on optimization, geospatial computation, and data visualization. We used Pandas for data cleaning and aggregation, and Gurobi to solve complex route optimization problems. Using Geopy, we calculated geodesic distances, and with Folium, along with its plugins, we created interactive map visualizations. To model maritime logistics, we leveraged SCGraph, specifically the `marnet_geograph` module and `GeoGraph` class, which supports real-world network construction and queries. Together, these tools provided a robust, reproducible framework for our end-to-end analysis.

3.4 Supplier Segmentation

To understand how supplier cities aligned with business divisions across the proposed hubs and to identify which city should be prioritized to test the proposed hypothesis, we created a supplier segmentation matrix. We based the segmentation on the average weight per shipment and the total number of shipments. A scatter plot, shown in Figure 5, illustrates the rationale behind the supplier segmentation and how it supports decision-making.

FIGURE 5. SUPPLIER MATRIX



After plotting the supplier cities, we used the matrix to classify suppliers into four main quadrants, presented in Figure 6:

- **High Potential for Consolidation:** Suppliers with a high number of shipments that have high potential for consolidation of trips and contribute highly to total inbound logistics cost.
- **Strategic Contributors:** Suppliers with both a high number of shipments and a high average weight per shipment. These suppliers have a significant impact on the supply chain and should have tailored rules.
- **Low Priority:** Suppliers with a low number of shipments and a low average weight per trip. These suppliers have a minimal impact on the overall supply chain.
- **High Performers:** Suppliers with low shipment frequency but high average shipment weight.

FIGURE 6. SUPPLIER CLASSIFICATION



For this project, we selected three high-potential supplier cities to test the proposed hypotheses related to pickup scheduling and consolidation strategies. We identified these cities based on shipment volume, frequency, and their strategic relevance within the network. By focusing on a targeted subset, we conducted a more detailed analysis of how pickup window flexibility and supplier overlap impact mode allocation and overall logistics performance.

3.4.1 Model Overview

To create the supplier matrix classification, we considered two key dimensions: the total number of shipments per year (s_i) and the average weight per shipment (w_i) for each supplier city $i \in I$. We segmented cities into four categories based on whether their values fall above or below the predetermined thresholds, $\bar{s}$ and $\bar{w}$. This framework enabled a structured evaluation of supplier behavior and highlighted key differences in shipment patterns across cities. The resulting classification supports strategic decision-making around supplier prioritization and consolidation opportunities.

3.4.2 Parameters and Variables

The parameters and variables used for the supplier segmentation are described in Table 3.

TABLE 3. PARAMETERS AND VARIABLES – SUPPLIER SEGMENTATION

Parameters	Description
I	Set of supplier cities
s_i	Number of shipments from supplier city i over one year.
w_i	Average weight per shipment for city i
$\bar{s}$	Threshold for a high number of shipments
$\bar{w}$	Threshold for high average weight per shipment
Decision Variable:	$C_i \in \{0, 1\}$ {Low Priority, High Performers, High Potential, Strategic Contributors} for each city $i \in I$

3.4.3 Model Formulation

We used the segmentation model to categorize each supplier city based on defined thresholds for shipment frequency and average weight per shipment. This classification provides a structured foundation for prioritizing supplier engagement and designing tailored logistics strategies.

Classification rules:

$$C_i = \begin{cases} \text{Low Priority} & \text{if } s_i < \bar{s} \text{ and } w_i < \bar{w} \\ \text{High Performers} & \text{if } s_i < \bar{s} \text{ and } w_i \geq \bar{w} \\ \text{High Potential} & \text{if } s_i \geq \bar{s} \text{ and } w_i < \bar{w} \\ \text{Strategic Contributors} & \text{if } s_i \geq \bar{s} \text{ and } w_i \geq \bar{w} \end{cases} \quad (7)$$

We classified cities with both low shipment volume ($s_i < \bar{s}$) and low average shipment weight ($w_i < \bar{w}$) as Low Priority, since their overall impact on logistics performance and cost is minimal. Cities with low shipment volume but high average weight ($s_i < \bar{s}$, $w_i \geq \bar{w}$) were labeled High Performers, as they ship in large, efficient loads but with low frequency. We identified High Potential cities as those with frequent shipments but lighter loads ($s_i \geq \bar{s}$, $w_i < \bar{w}$), indicating opportunities to reduce costs through load consolidation and improved scheduling. Finally, cities with both high shipment frequency and high average weight ($s_i \geq \bar{s}$, $w_i \geq \bar{w}$) were designated as Strategic Contributors, as they represent the largest share of inbound logistics volume and are key targets for optimization and cost-saving initiatives.

3.4.4 Tools Utilized

To carry out the supplier segmentation analysis, we used a combination of Microsoft Excel and Microsoft Power BI. Excel was primarily used for preliminary data organization, validation, and calculation of key metrics such as average shipment weight and annual shipment counts per supplier city. After cleaning and structuring the data, we leveraged Power BI to build a dynamic supplier matrix that visually segments cities based on the defined thresholds. Power BI's interactive capabilities and advanced visualization tools were particularly effective for identifying patterns and communicating insights. By combining Excel's flexibility and Power BI's analytical power, we ensured a streamlined and transparent approach to data-driven classification.

3.5 Optimal Pick-Up Frequency

To design the optimal pickup frequency for the prioritized cities, we designed a model to evaluate and optimize weekly full truckload (FTL) operations over a one-year period. The objective was to balance truck utilization while minimizing the expiration of supply due to delayed pickups. We structured the methodology in two main phases: a deterministic analysis using historical shipment data to establish baseline performance, followed by a stochastic analysis that incorporated variability through sampling to assess the robustness of the scheduling approach under uncertainty.

Phase 1, **deterministic analysis**, used fixed historical inputs to simulate weekly supply pickup operations across a full calendar year for a selected city. Weekly supply data, aggregated from daily records, represents the total quantity (in kilograms) requiring pickup.

We assumed a truck capacity of 26,000 kg, with the operational constraint that supply had to be picked up within a two-week window to avoid contractual penalties. The simulation tested fleet sizes ranging from 1 to 50 trucks per week. Each scenario assumed a constant number of available trucks, with unused trucks allowed if demand was low. We classified any unpicked supply past the two-week window as expired and converted it into equivalent truckloads to estimate spot-trucking needs. For each fleet size, we tracked truck utilization and expired supply over the year.

Moreover, we conducted a sensitivity analysis by varying the pickup window to four and six weeks, providing insights into how operational flexibility impacted the system performance.

Phase 2, **stochastic analysis**, captured uncertainty to understand system behavior through variable demand. In this phase, we generated 100 synthetic weekly supply profiles based on the distribution of the historical data.

To ensure realistic supply scenarios, we first assessed the skewness of historical supply data. In moderately skewed cases, we applied a square-root transformation to approximate normality, then sampled from a truncated normal distribution. We subsequently squared the sampled values to return to the original scale. For highly skewed data, we used a uniform distribution as a more appropriate alternative.

For each of the 100 sampled profiles, we repeated the same simulation process from the deterministic phase across the full range of fleet sizes. This process allowed us to evaluate performance variability under different demand scenarios. Finally, we aggregated key performance metrics, including average truck utilization and average spot trucking needs, across all simulations to visualize trade-offs.

3.5.1 Model Overview

We considered a single city c observed over a set of weeks $w = 1, 2, \dots$. In each week w , we observed a new quantity of supply S_w (in kg) becoming available for pickup. We stored this supply in a backlog queue Q_w , where each entry $i \in Q_w$ was characterized by its age a_i , measured in weeks since availability.

Each week, we made a fixed number of trucks t available with a capacity of $C_{\text{truck}} = 26,000\text{kg}$. We required all supply to be picked up within a maximum window of L weeks to avoid expiration. At each week w , we divided supply into two sets:

- M_w : mandatory pickups (aged $a_i = L$)
- R_w : regular pickups (aged $a_i < L$)

The total weight of these sets is given by $W_{m,w}$ and $W_{\text{reg},w}$, respectively, and their sum forms the total available weight for pickup $W_{\text{avail},w}$. The actual used truck capacity is denoted $C_{\text{used},w}$, and the number of trucks deployed is $T_{\text{used},w}$, where $T_{\text{used},w} \leq t$. We recorded any expired supply as E_w , and additional spot trucks required in week w , as $T_{\text{spot},w}$.

Our objective with the model was to evaluate the effect of different weekly truck capacities $t \in \{1, 2, \dots, 50\}$ on key performance indicators, including:

- Average weekly truck utilization $U(t)$
- Total expired supply $E_{\text{total}}(t)$
- Annual spot trucking needs

We solved the model in two stages. First, we conducted a deterministic analysis that simulated operations using historical supply data, with fixed values of S_w . Then, we performed a stochastic analysis using 100 sampled supply profiles based on the distribution of S_w , which enabled us to evaluate performance under demand uncertainty.

3.5.2 Parameters and Variables

The parameters and variables from the model are described in Table 4.

TABLE 4. PARAMETERS AND VARIABLES – OPTIMAL PICK-UP FREQUENCY

Parameters	Description
w	Week index
c	City index
t	Number of trucks per week
Q_w	Backlog queue at week w
a_i	Age (in weeks) of backlog entry i
C_{truck}	Full truck capacity (26,000 Kg)
L	Maximum pick-up window (in weeks)
E_w	Expired supply in week w (in Kg)
M_w, R_w	Mandatory and regular pickup sets at week w
W_{m_w}	Total mandatory weight in week w
W_{reg_w}	Total regular weight in week w
W_{avail_w}	Total available weight for pickup
$C_{planned_w}$	Planned pickup capacity in week w
C_{used_w}	Used truck capacity in week w
U_w	Weekly truck utilization
T_{used_w}	Trucks used in week w
T_{spot_w}	Spot trucks required due to expire in week w
$U(t)$	Average utilization for configuration t
$E_{total}(t)$	Total expired supply across the year
$T_{annual}(t)$	Annual trucks used
$T_{capacity}(t)$	Annual truck capacity (52 weeks $\times t$)
$U_{annual}(t)$	Annual truck utilization
W	Number of weeks in the year

3.5.3 Model Formulation

This sub-section outlines the mathematical framework we used to simulate weekly supply pickups under varying fleet sizes. We developed a model that operates in discrete time steps (weekly) and evaluates performance across both deterministic (historical) and stochastic (sampled) supply conditions.

Framework:

Backlog aging:

$$a_i \leftarrow a_i + 1 \quad (8)$$

Expired Supply for week w:

$$E_w = \Sigma (weight_i) \text{ for all } i \in Q_w \text{ where } a_i > L \quad (9)$$

Mandatory Pick-ups (aged out) and Regular Pick-ups (within window):

$$M_w = \{ i \in Q_w \mid a_i \geq L \} \quad (10)$$

$$R_w = \{ i \in Q_w \mid a_i < L \} \quad (11)$$

The total available supply for pickup in week w was computed as:

$$W_{m_w} = \Sigma weight_i \in M_w \quad (12)$$

$$W_{reg_w} = \Sigma weight_i \in R_w \quad (13)$$

$$W_{avail_w} = W_{mand_w} + W_{reg_w} \quad (14)$$

Planned weekly capacity:

$$C_{planned_w} = t \times C_{truck} \quad (15)$$

Capacity used:

$$C_{used_w} = C_{planned_w} \text{ if } W_{m_w} \geq C_{planned_w}; \text{ else } C_{used_w} = W_{m_w} + \min(W_{reg_w}, C_{planned_w} - W_{m_w}) \quad (16)$$

Truck utilization:

$$U_w = C_{used_w} / C_{planned_w} \quad (17)$$

Trucks used:

$$T_{used_w} = \text{ceil}(C_{used_w} / C_{truck}) \quad (18)$$

Estimation of Spot trucks:

$$T_{spot_w} = \text{ceil}(E_w / C_{truck}) \quad (19)$$

Average Annual utilization:

$$U(t) = (1 / W) \times \Sigma U_w \text{ over all weeks} \quad (20)$$

Total Expired supply in the year:

$$E_{total(t)} = \Sigma E_w \text{ over all weeks} \quad (21)$$

Total number of contracted Trucks used in the year:

$$T_{annual(t)} = \Sigma T_{used_w} \text{ over all weeks} \quad (22)$$

Total number of contracted Trucks in the year:

$$T_{capacity(t)} = W \times t \quad (23)$$

Annual Contracted truck utilization in the year:

$$U_{annual(t)} = T_{annual(t)} / T_{capacity(t)} \quad (24)$$

We structured the simulation as a discrete weekly process over a defined planning horizon. For each city c , we added the supply for each week w to a backlog queue Q_w , where each entry i carried a weight and an age a_i . At the beginning of every week, we aged all backlog entries by one unit as described in Equation (8). If the age of any entry exceeded the maximum allowed pickup window L , its weight contributed to the expired supply E_w , as defined in Equation (9). We then split the backlog into two categories: mandatory pickups M_w , which included entries where $a_i \geq L$, and regular pickups R_w , where $a_i < L$, as shown in Equations (10) and (11).

We calculated the total weight available for pickup in week w by summing the mandatory and regular weights, resulting in W_{avail_w} (Equations 12, 13, 14). Given a weekly truck plan of t trucks, the total planned pickup capacity was determined by Equation (15), where each truck has a capacity of $C_{truck} = 26,000$ kg. If the total mandatory weight W_{m_w} exceeded the planned capacity, it was capped at $C_{planned_w}$; otherwise, the remaining capacity was used to pick from the regular backlog. This decision rule is formalized in Equation (16).

We then calculated the actual utilization of truck capacity in week w as the ratio of used to planned capacity, U_w , as shown in Equation (17). Based on the used capacity C_{used_w} , we estimated the number of trucks required using Equation (18). Any picked-up weight was removed from the backlog, and the remaining weight became the rolled-over backlog Q_{w+1} for the next week. If there was any expired supply E_w , we estimated additional spot trucks using Equation (19) to account for the missed logistics opportunity.

We repeated this simulation process for multiple values of t , allowing for the generation of annual summary metrics. These include average weekly utilization $U(t)$ (Equation 20), total expired supply $E_{total}(t)$ (Equation 21), total trucks used annually $T_{annual}(t)$ (Equation 22), total planned truck capacity $T_{capacity}(t)$ (Equation 23), and annual truck utilization $U_{annual}(t)$ (Equation 24). Finally, we used these metrics to compare truck plans and identify the most efficient weekly frequency for minimizing backlog and maximizing asset usage.

3.5.4 Tools Utilized

To conduct the analysis, we used a focused set of Python libraries designed for efficient data processing and statistical evaluation. We leveraged Pandas to clean, organize, and manipulate the data, and used NumPy to support fast numerical computations and an array of operations. For statistical analysis, we applied functions from `scipy.stats`, enabling hypothesis testing, correlation calculations, and the derivation of key summary statistics.

4 RESULTS & DISCUSSION

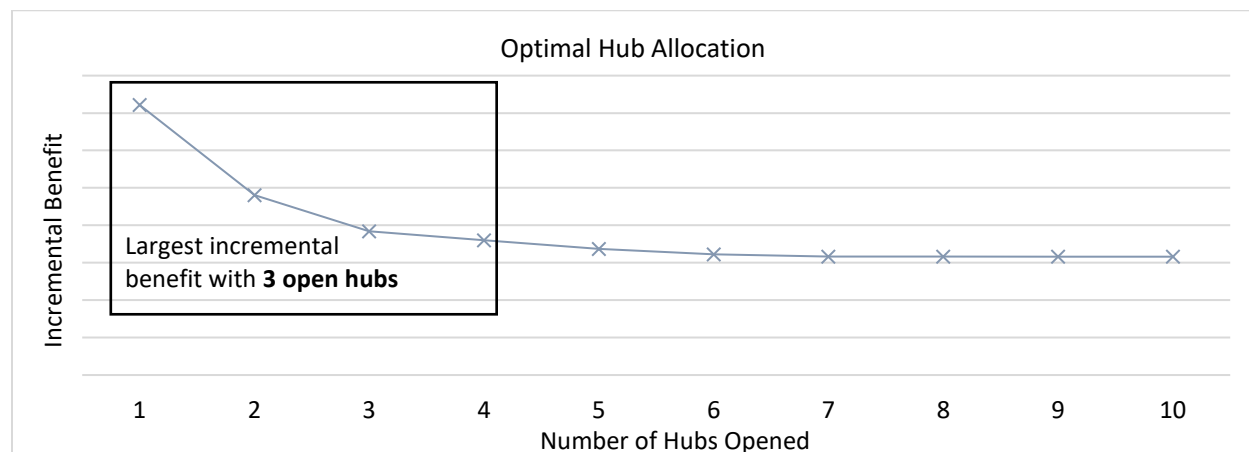
In this chapter, we present the results of our study. The facility location analysis was performed considering all ports to determine the optimal number and location of consolidation hubs. The supplier segmentation was later performed to define the three prioritized cities used to test the proof of concept for the pickup frequency rationalization.

4.1 Facility Location Results

The facility location scenario model evaluates potential hub locations for consolidating cargo before transportation out of China. The objective is to consolidate cargo from suppliers near each hub, regardless of the destination, and then segregate and consolidate shipments at the hub for consistent deliveries out of the port. Potential hub locations were first selected considering all ports in China and all supplier nodes, resulting in a total of 106 potential locations. The scope was subsequently narrowed to include only port locations as candidate consolidation sites, as all cargo is exported from ports, making inland consolidation sites impractical for the partner company. Moreover, for simplicity, real estate costs were not considered in this model. Once candidate locations were identified, the model was run using cargo weight, distance, and optimization through the P-Median model.

The results of the model are illustrated in Figure 7, which shows that the incremental benefit of adding additional hubs decreases over time. The optimal number of hubs recommended is three, as the benefit reaches a plateau shortly thereafter, with little to no marginal improvement. Opening three hubs located in Shanghai, Qingdao, and Guangzhou improves the objective function by 68%.

FIGURE 7. ELBOW CHART



The facility location model provided clear insights into optimal hub placement, highlighting Shanghai as the prime single-hub location and recommending Qingdao and Guangzhou as additional hubs for maximum efficiency. This approach enhances cargo consolidation, reduces transportation costs, and ensures consistent shipments to the port, contributing to an optimized supply chain network. The results of the model are shown in Figure 8.

FIGURE 8. OPTIMAL MODEL



The network design map above highlights the regional structure of the supplier network and how it connects to the three main export ports: Shanghai, Qingdao, and Guangzhou. Each port can strategically serve as a consolidation hub for suppliers located in its surrounding region, with shipment flows grouped accordingly.

In the northeast, Qingdao receives a high volume of shipments from nearby cities like Shenyang, reinforcing its role as the main gateway for suppliers in that region. In the central and eastern region, Shanghai acts as a strong consolidation hub, receiving consistent shipments from multiple surrounding cities, which confirms its importance both in volume and accessibility. In the southwest, cities like Chengdu feed into Guangzhou, forming a distinct regional flow despite the longer transport distances involved.

This regional breakdown reflects a well-structured supply network, where each port supports a specific geographic cluster. It also supports a more localized logistics strategy, where port selection and supplier location are closely aligned, reducing complexity and enabling more efficient transport planning across the network.

The summary statistics of the behavior of each hub are displayed in Table 5.

TABLE 5. HUB LEVEL RESULTS

Consolidation Hub	Suppliers Served	Total Annual Cargo (in million KG)	Average Weekly Cargo (in million KG)	Average Distance from Supplier (in KM)	Average Weekly Inbound Trucks
Shanghai	33	140.08	2.69	134	104
Qingdao	34	101.03	1.94	238	75
Guangzhou	29	40.80	0.78	833	30

The consolidation hub in Shanghai handles the highest total and weekly supply, supported by a moderate supplier count and the shortest average distance, resulting in the highest average inbound truck volume. In contrast, the Port of Guangzhou manages the lowest supply levels and truck activity, despite having a relatively high average supplier distance. The Port of Qingdao strikes a balance, with the highest number of suppliers, moderate distances, and a strong supply volume, making it a significant hub with steady inbound truck movement.

4.2 Supplier Segmentation

In this section, we present the results of our supplier segmentation, which defined the main suppliers that would be used as proof of concept for the Pick-up Frequency Rationalization (results discussed in section 4.3). First, suppliers were grouped by their respective cities² and segregated according to their hub allocation described in section 4.1. Second, supplier cities were plotted across a scatter plot of average weight per shipment and total number of shipments. Lastly, suppliers were segmented according to the methodology described in section 3.3.2.

² Oversized trips have been removed from the study as they have specific transportation and do not have consolidation capabilities.

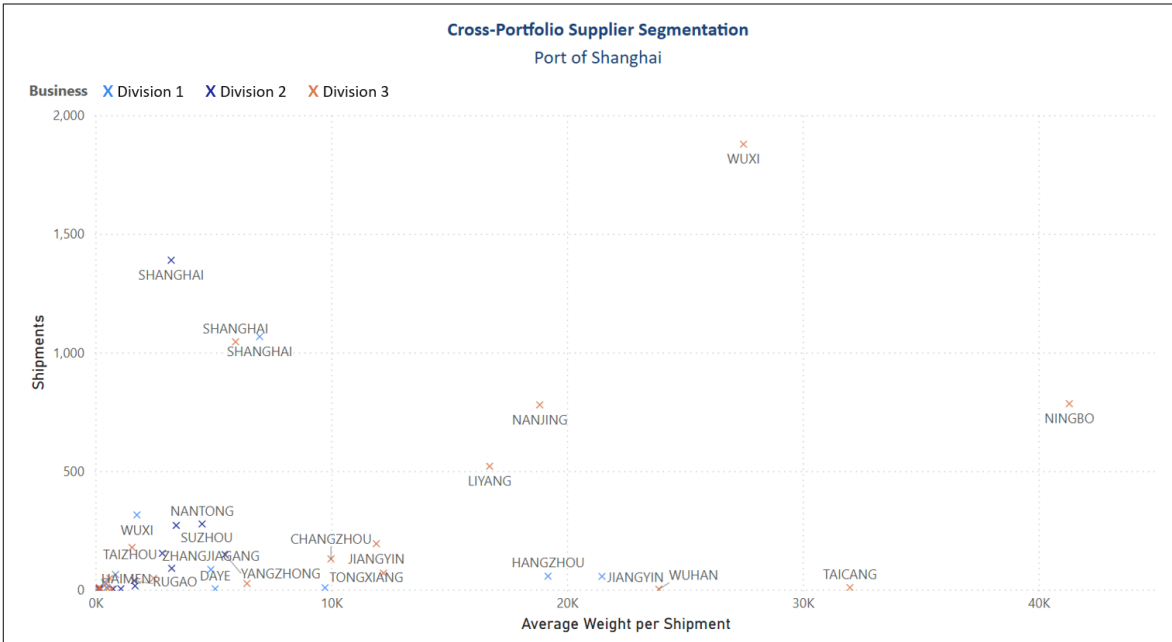
The segmentation chart for the Port of Shanghai (Figure 9) displays suppliers grouped by city across three business divisions: Division 1, Division 2, and Division 3. Shanghai itself stands out with multiple entries across all three segments, each recording over 1,000 shipments but with relatively low average shipment weights. This suggests high-frequency, small-load deliveries that enhance supply chain agility but may increase logistics costs per unit of weight.

In contrast, cities like Ningbo and Taicang, both linked to Division 3, appear in the bottom-right quadrant, indicating high average weights and low shipment frequency. This is typically an efficient logistics pattern, where fewer shipments with higher weight per load result in better truck utilization and lower transport cost per ton. These cities represent an existing strong consolidation strategy.

Similarly, suppliers tied to Division 3 tend to dominate the bottom-right area, not only in Shanghai but across other cities as well. This result may suggest that Division 3 suppliers are more likely to ship in bulk, possibly due to the nature of the components being heavier and more standardized. Meanwhile, Division 1 and Division 2 suppliers are more often positioned in the top-left quadrant (frequent, lighter shipments), possibly reflecting more customized or time-sensitive items.

Shanghai was selected for further analysis because of its strategic mix of high shipment activity across business segments and its geographic and infrastructural strength. While cities like Ningbo and Taicang may offer cost efficiency, Shanghai presents broader impact potential and cross-business leverage.

FIGURE 9. SUPPLIER SEGMENTATION - PORT OF SHANGHAI

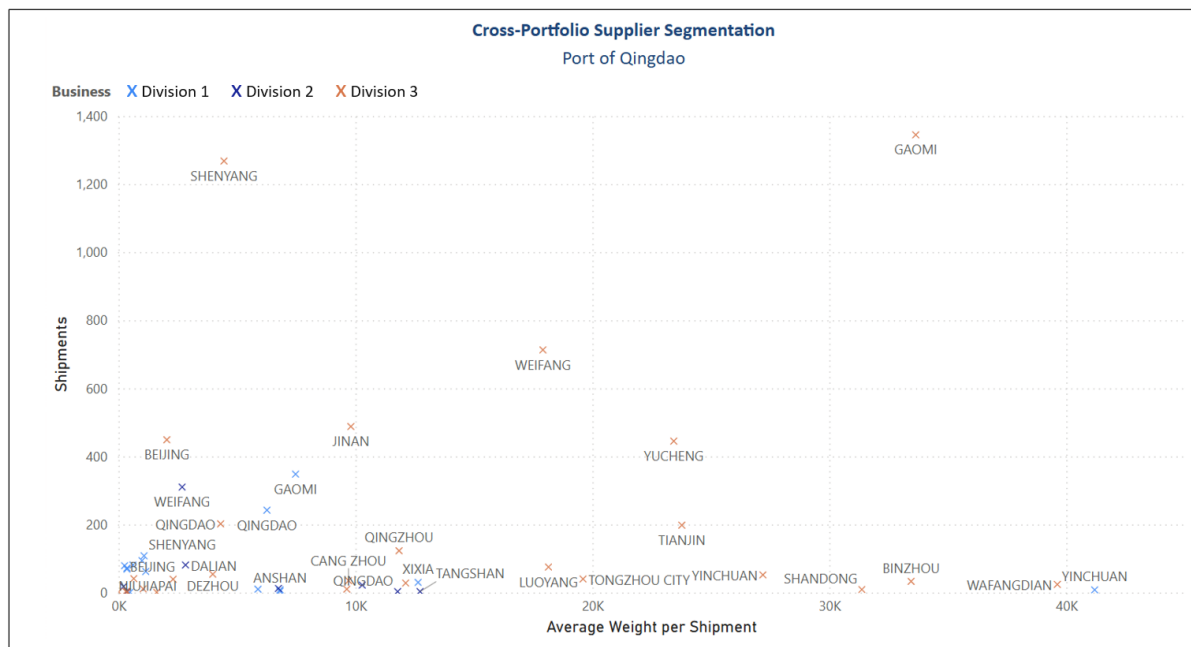


The supplier segmentation for the Port of Qingdao (Figure 10) highlights a wide distribution of suppliers across cities, with many clustered in the lower-left quadrant (low shipments and low average weight), indicating smaller-scale or less frequent suppliers. However, Shenyang stands out prominently in Division 3, with over 1,200 shipments but a low average weight per shipment. This pattern suggests a high-frequency supply flow likely designed to support tight production schedules or reduce inventory holding.

Bottom-right quadrant performers include cities like Yinchuan, Wafangdian, and Binzhou, all of which ship heavy loads in fewer batches, an efficient shipping pattern. These cities, as in the Shanghai chart, are primarily tied to Division 3, again reflecting a trend where Division 3 suppliers tend to consolidate shipments into fewer, heavier loads, possibly due to standardized parts or project-based logistics.

The selection of Shenyang for further analysis is based on its distinct pattern within Division 3. While most Division 3 suppliers lean toward fewer, heavier shipments, Shenyang stands out with exceptionally high frequency and low average weight, suggesting a different logistics approach. This makes it a unique case worth exploring further, especially to understand whether its supply pattern reflects operational necessity or an opportunity for consolidation.

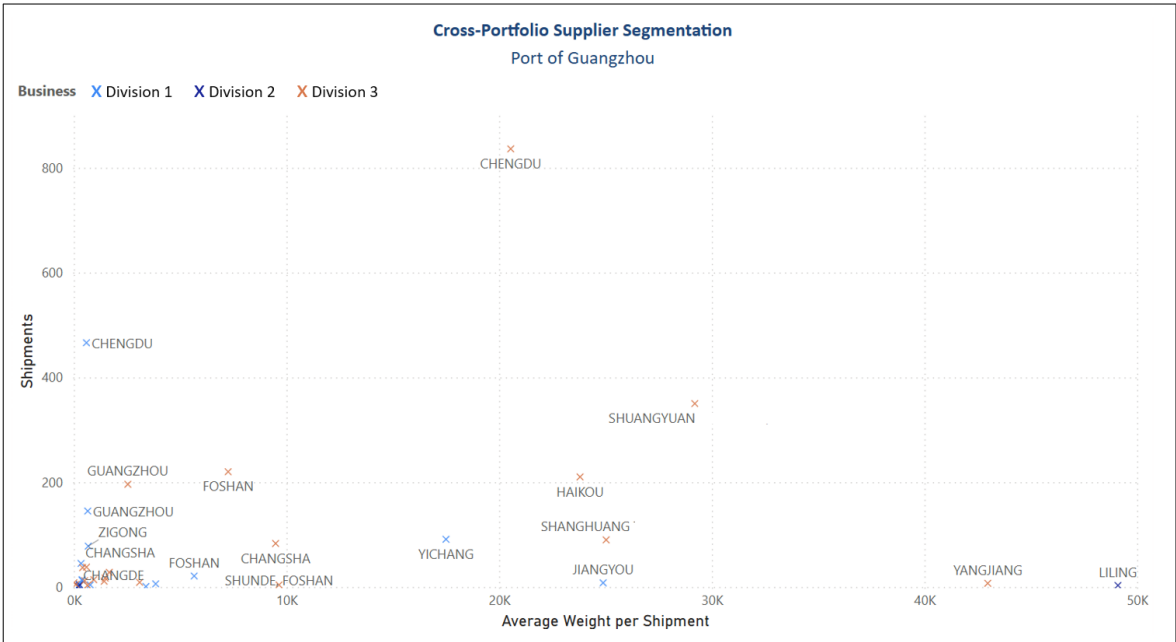
FIGURE 10. SUPPLIER SEGMENTATION - PORT OF QINGDAO



In the Port of Guangzhou (Figure 11), the distribution of supplier cities is more dispersed, with fewer extremely high shipment counts. Chengdu stands out as a key supplier city that appears in both Division 1 and Division 3 segments, with shipment counts of around 800 and 450, respectively. In both cases, the average shipment weights remain relatively low, suggesting frequent, small-batch deliveries. Moreover, the significant presence of Chengdu across multiple business divisions adds to its strategic value, offering a potential opportunity to streamline logistics across product lines.

The Port of Guangzhou has several cities positioned in the bottom-right quadrant, signaling an optimized shipment schedule. Cities like Yichang, Haikou, Jiangyou, Yangjiang, Liling, and Shanghuang exhibit high average weights per shipment (20K–50K) and very low shipment frequency. These suppliers are probably maximizing truck utilization, reducing freight costs, and simplifying transport planning. Most are associated with Division 1 or Division 3 segments.

FIGURE 11. SUPPLIER SEGMENTATION - PORT OF GUANGZHOU



The summary statistics presented in Table 6 reveal notable differences in supplier distribution, shipment volume, and shipment weight across the prioritized cities. Shanghai, for example, handles the highest number of suppliers (90) and shipments (3,501), but with a lower average shipment weight (5.17 thousand KG), indicating a fragmented supply pattern with smaller shipment sizes. In contrast, Chengdu operates with only 4 suppliers and 1,303 shipments while recording the highest average weight per

shipment (13.39 thousand KG), suggesting a more consolidated and efficient shipping model. Shenyang falls in between, with moderate shipment volumes and average weights.

TABLE 6. SUMMARY STATISTICS SUPPLIER SEGMENTATION

City	Number of divisions	Number of suppliers	Total shipments	Total weight shipped (in thousand KG)	Average weight shipped (in thousand Kg)
Shanghai	3	90	3,501	18,108	5.17
Shenyang	3	8	1,388	17,452	4.21
Chengdu	3	4	1,303	5,842	13.39

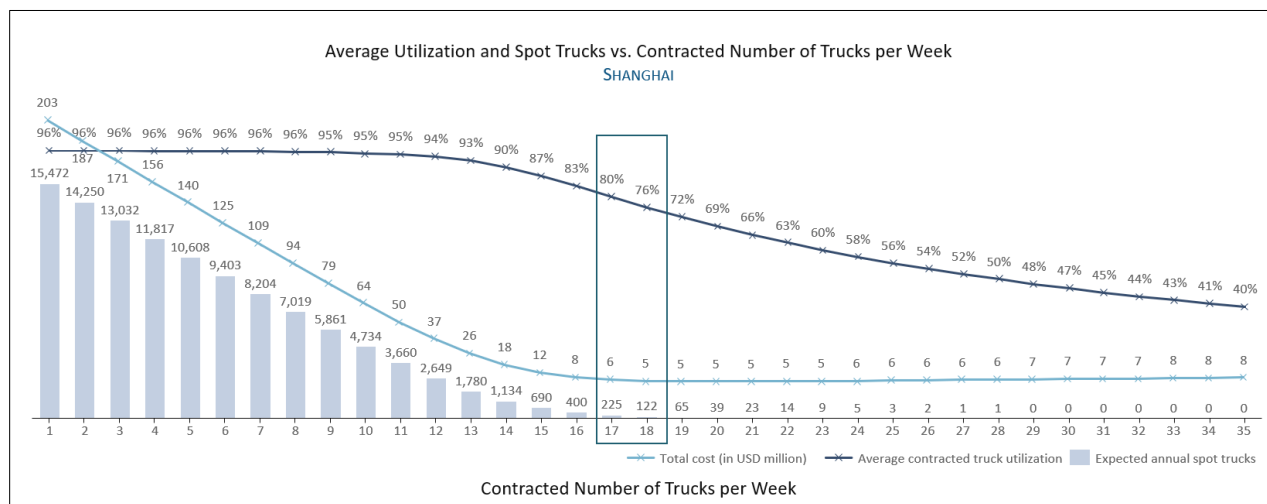
These variations underscore the complexity of the company's current supply network, where a one-size-fits-all logistics strategy would be ineffective. The dispersion in shipment sizes and supplier density highlights the need for region-specific approaches that account for logistical constraints, cost efficiency, and service level requirements. By adopting a segmented and tailored optimization strategy, the company can prioritize high-performing suppliers while identifying areas where additional efficiencies can be gained. This approach ensures that supply chain performance is maximized while controlling operational costs across diverse regions.

4.3 Pick-up Frequency Rationalization

In this section, we present the results of the supplier pick-up frequency rationalization for the three prioritized cities: Shanghai, Shenyang, and Chengdu.

The results for the average utilization per contracted truck vs. the hired weekly number of trucks, together with the expected number of spot trucks, can be found in Figure 12. This graph demonstrates that as the number of contracted trucks per week increases, both the average utilization and the number of contracted spot trucks decrease. The average contract rate considered for Shanghai is USD 0.17/kg and the average spot rate is USD 0.50/kg, as referenced by the partner company. This difference in rates creates a tradeoff between the contract rate and the spot rate that is considered for defining the best solution.

FIGURE 12. PICK-UP FREQUENCY RATIONALIZATION - SHANGHAI

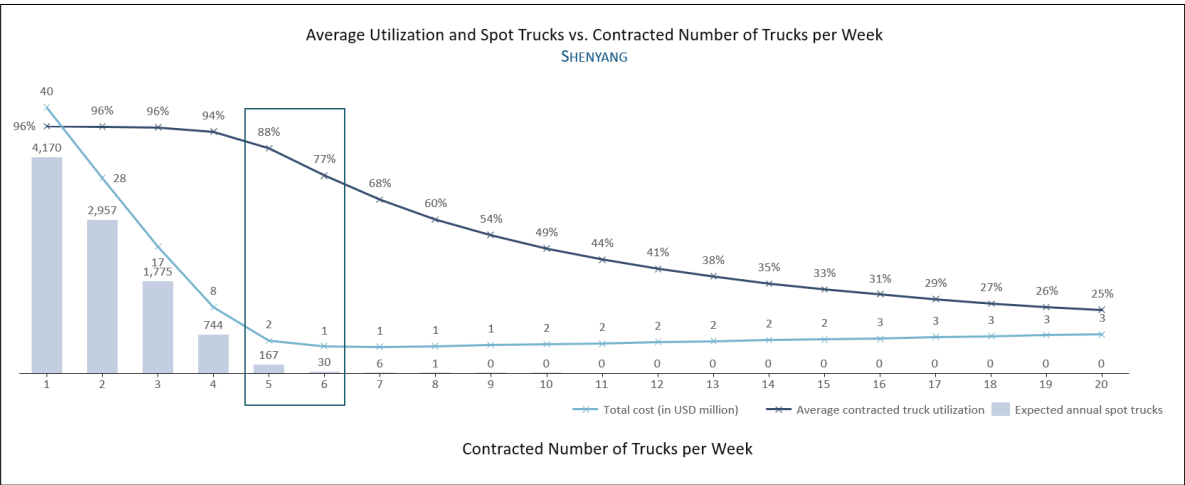


Moreover, the distribution of each data point also changes. As the number of contracted trucks increases, average truck utilization becomes more volatile, showing greater dispersion in results and, consequently, higher uncertainty. The opposite trend is observed for the annual spot trucks hired, as the number of contracted trucks increases and the reliance on spot trucks decreases, volatility and uncertainty also diminish. For a detailed visualization of this behavior, please refer to the Appendix.

When considering the total annual cost, we can observe a parabolic behavior where the cost decreases until a global minimum before increasing again. The optimal point for Shanghai is either 17 weekly contracted trucks, with an average utilization of 80%, and 225 annual spot trucks with an average utilization of 86%, or 18 weekly contracted trucks, with an average utilization of around 76%, and 122 annual spot trucks with an average utilization of 79%. The partner company must therefore decide on a balance between operational stability and utilization efficiency when determining the optimal number of trucks to contract.

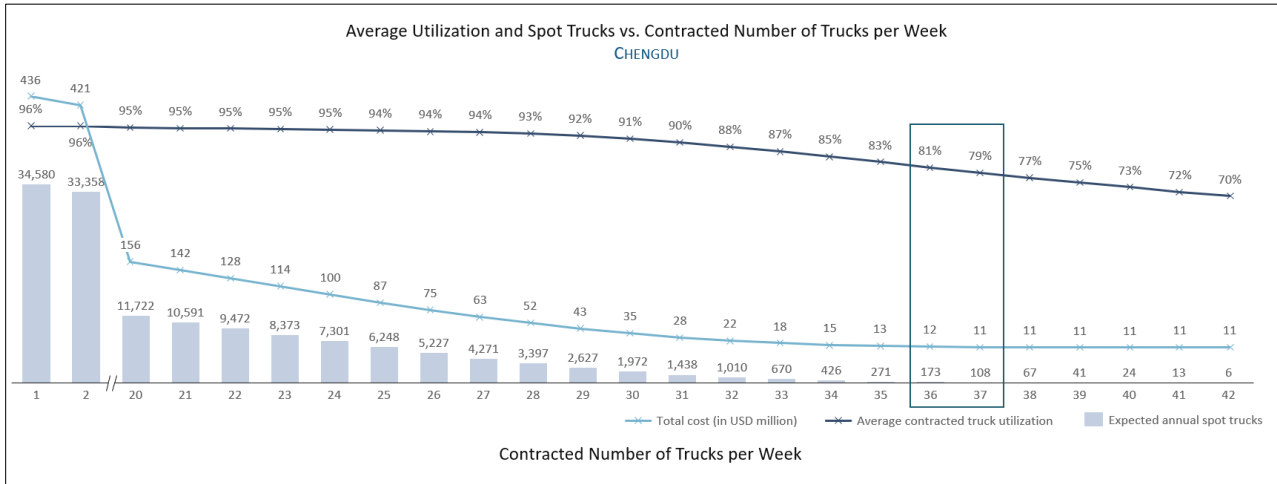
Similar patterns are observed for Shenyang (Figure 13). The tradeoff between average utilization and expected annual spot trucks remains the same; however, the required number of weekly trucks is significantly lower due to the available supply from Shenyang. The average contract rate considered for Shanghai is USD 0.12/kg and the average spot rate is USD 0.37/kg, as referenced by the partner company. An optimal balance between utilization and spot rates is achieved at 5 weekly contracted trucks, with an average utilization of 88%, and 167 annual spot trucks with an average utilization of 83%, or 6 weekly contracted trucks, with an average utilization of around 77%, and 30 annual spot trucks with an average utilization of 70%. The box plot distribution for Shenyang can also be found in the Appendix.

FIGURE 13. PICK-UP FREQUENCY RATIONALIZATION - SHENYANG



Finally, the same method was carried out for Chengdu (Figure 14). The average contract rate considered is USD 0.19/kg and the average spot rate is USD 0.48/kg, as referenced by the partner company. At lower contract levels, utilization remains high (96%), but spot truck demand is also high, exceeding 30,000 annually. As the number of contracted trucks increases, spot truck usage drops sharply, while utilization gradually declines. The decline in utilization becomes more pronounced beyond 28 trucks per week, falling below 85%. An optimal balance for Chengdu is found at either 36 weekly contracted trucks, with an average utilization of 81%, and 173 annual spot trucks with an average utilization of 84%, or 37 weekly contracted trucks, with an average utilization of around 79%, and 108 annual spot trucks with an average utilization of 72%. The box plot distribution for Chengdu is shown in the Appendix.

FIGURE 14. PICK-UP FREQUENCY RATIONALIZATION - CHENGDU



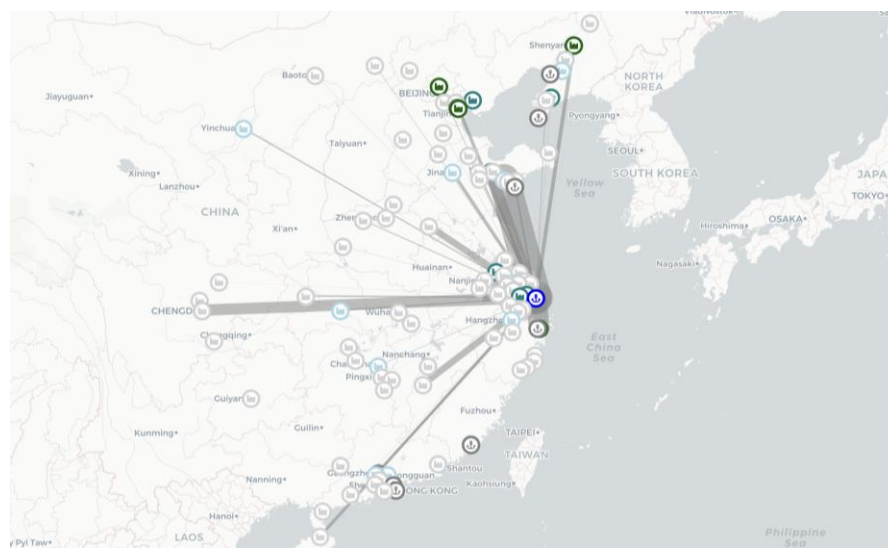
Overall, the analysis reveals a clear pattern: as the number of contracted trucks per week increases, reliance on spot trucks declines, while average truck utilization decreases. This pattern highlights a fundamental tradeoff for the partner company between cost efficiency and asset utilization. Additionally, the variability in results shifts depending on the metric. Higher truck contracts lead to greater fluctuation in utilization rates due to more uncertainty, while the opposite is true for spot truck use, which becomes more stable and predictable as dependency on them drops. These patterns provide critical insights for determining the optimal balance between flexibility and cost control.

5 MANAGERIAL INSIGHTS

Looking at the results, we can identify significant opportunities for consolidation across the supply chain. These changes can lead to stronger collaboration between business divisions and, ultimately, a meaningful reduction in logistics costs. The analysis points to the value of creating three consolidation hubs, strategically located to serve multiple divisions. Moreover, the pick-up frequency model introduces a more structured and reliable pickup process, allowing for consistent and predictable supply flows. By creating a regular schedule for pickups, variability in shipments would decrease, enabling better planning, reduced inventory buffers, and overall supply chain stability.

Our results show that opening one consolidation hub, specifically in Shanghai, can yield substantial incremental benefits. Based on this finding, we recommend launching a pilot consolidation hub close to Shanghai. This pilot could serve as proof of concept to test the viability of centralized consolidation under real-world operating conditions. By leveraging Shanghai's well-developed logistics infrastructure and its strategic position as one of China's leading freight hubs, the pilot can help assess whether this setup effectively reduces lead times, streamlines the deconsolidation process, and improves distribution efficiency. To minimize initial risk, we suggest outsourcing operations to a third-party logistics provider (3PL), allowing the company to focus on evaluating performance without committing to significant internal investment. Figure 15 illustrates how the network would behave if all shipments were consolidated in Shanghai.

FIGURE 15. ACTIVE HUB IN SHANGHAI



Legend: ● Active ports ● Inactive ports ● Used by all 3 business divisions ● Shared by 2 divisions ● Used by 1 division

In addition, if Shanghai is used as the main consolidation hub for all business divisions and handles shipments from all 93 suppliers, the total annual cargo volume would increase significantly. This increase, in turn, could lead to benefits from economies of scale and allow for smarter deconsolidation, helping optimize container space on outbound shipments. With more full containers leaving directly for the final destination, transportation costs would likely decrease. The number of inbound trucks per week would also increase, which could enable milk-run opportunities. For example, if a supplier located in Shanghai happens to be along the route from another supplier further inland, and there is still available space in the truck. On the other hand, this setup increases the average distance traveled, since not all suppliers are close to Shanghai and would need to reroute there rather than using a nearby hub. Table 7 shows the summary statistics with the results for a single consolidation hub located in Shanghai.

TABLE 7. SUMMARY STATISTICS SHANGHAI HUB

Consolidation Hub	Suppliers Served	Total Annual Cargo (in million KG)	Average Weekly Cargo (in million KG)	Average Distance from Supplier (in KM)	Average Weekly Inbound Trucks
Shanghai	93	281.91	5.42	512	209

Having a consolidation hub in Shanghai is similar to the current scenario, where most suppliers are shipping through Shanghai Port, which can result in unnecessary long-haul movements and congestion. A more efficient alternative would be to activate the three strategic ports across China. Utilizing these ports would reduce the distance traveled from supplier locations and increase flexibility in outbound shipping. Each port hub could also be managed by experienced 3PLs who would take charge of cargo deconsolidation and reconsolidation before shipments are sent abroad. This model would diversify logistical risk and potentially reduce bottlenecks associated with relying solely on Shanghai.

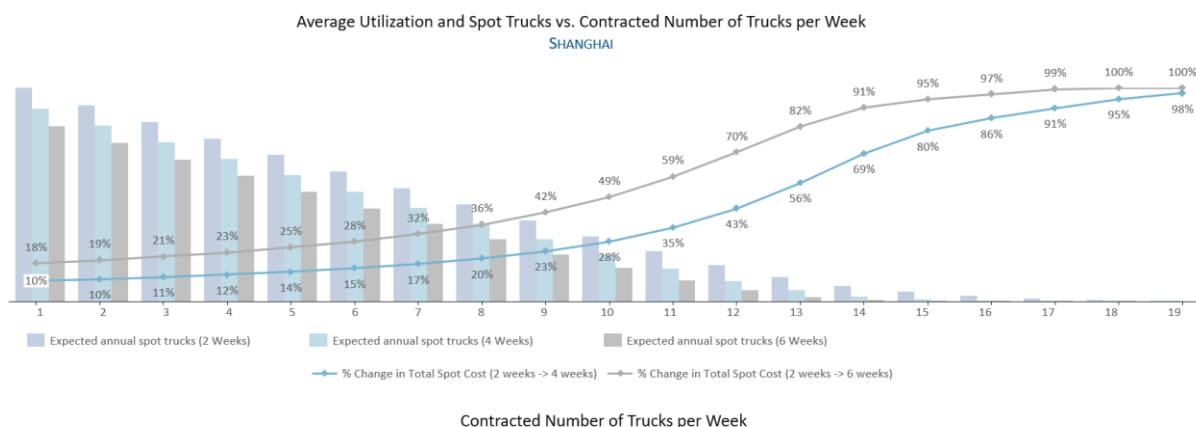
Insights from the segmentation analysis reveal that Division 3 has achieved a higher level of optimization in its supply chain operations compared to other business units. This division's performance provides a valuable benchmark for best practices in consolidation and logistics coordination. By examining the operational methods used by Division 3, the company can identify transferable strategies that, if applied across other divisions, may improve overall efficiency, reduce variability, and enhance coordination in inbound logistics.

As a further step toward building an integrated supply chain, identifying three key suppliers, each located near one of the modeled cities, can provide a strong starting point for piloting cross-divisional

logistics. By collaborating with these suppliers to coordinate joint pickup schedules, the company can pilot a cross-divisional logistics approach. These pilot sites can provide critical insights into how well different divisions can align their inbound needs and cooperate logistically. If the trials prove successful, the approach can be scaled to more suppliers, forming the groundwork for a unified inbound logistics system.

At the same pilot supplier sites, the company can experiment with revised inventory buffer rules, particularly by extending the overstock window from the current standard to four or six weeks. This change allows for more flexible pickup scheduling and could lead to more efficient truckload utilization. The results from this sensitivity analysis would help determine the trade-offs between inventory holding costs and transportation efficiency, enabling data-driven decisions for long-term policy adjustments. Figure 16 shows how the number of trucks contracted per week in Shanghai affects the need for spot trucks, depending on how long inventory can be held at the supplier. Overall, as more trucks are contracted weekly, the reliance on spot trucking drops significantly. The flexibility to hold inventory for longer reduces the need for spot trucks, since pickups can be better scheduled and consolidated. The biggest improvements occur between 1 and 13 trucks per week, after which the benefits start to level off. By the time 14 trucks per week are contracted, the need for spot trucks becomes nearly zero, particularly when using the 6-week overstock rule. Moreover, we can further see this benefit in the expected percentage of total spot rates cost, which significantly increases as the number of hired trucks increases. The blue and grey lines in the figure demonstrate that increasing inventory held at the supplier from 2 weeks to 4 weeks can have significant cost-saving opportunities. This further suggests that either increasing the number of contracted trucks or allowing for a longer inventory holding window can lead to major efficiencies and cost savings.

FIGURE 16. SENSITIVITY ANALYSIS FOR INCREASING OVERSTOCK WINDOW



Finally, the company can leverage different truckload procurement strategies, particularly by comparing fully centralized, decentralized, and hybrid models. A hybrid approach, where core routes are managed centrally while localized decisions remain flexible, can offer a balance between control and adaptability. While centralization may yield better rates through volume bundling, it can also introduce rigidity. Decentralization allows responsiveness to local needs but may miss out on cost-saving synergies. Carefully weighing these pros and cons will help the company select the best procurement model to support the evolving logistics strategy.

6 CONCLUSION

In this capstone, we addressed inefficiencies resulting from fragmented inbound logistics management across business divisions. In collaboration with a partner company, we developed two complementary models to improve coordination and optimize consolidation opportunities. The first model used historical shipment data and applied a mixed-integer linear programming (MILP) formulation with the p-median approach to determine the optimal number and location of consolidation hubs. Our results showed that placing hubs in Shanghai, Qingdao, and Guangzhou reduced total transportation distance by nearly 50%, significantly improving efficiency.

The second model optimized pickup scheduling under demand uncertainty. We simulated weekly full truckload (FTL) operations for three high-priority cities, Shanghai, Shenyang, and Chengdu, and analyzed how different pickup frequencies affected truck utilization and reliance on spot trucking. We found a clear trade-off: increasing contracted weekly trucks improved reliability but reduced truckload utilization and flexibility, leading to more spot truck usage. The optimal balance occurred at 80% contracted truck utilization, corresponding to 17 weekly trucks in Shanghai, 5 in Shenyang, and 36 in Chengdu. These differences reflected variations in shipment volume and cargo weight across locations.

We also conducted a sensitivity analysis to explore the impact of extending inventory holding windows to four and six weeks. Allowing suppliers to hold inventory longer provided greater flexibility in scheduling, improved consolidation opportunities, and reduced the need for spot trucks. The results suggested that increasing the number of contracted trucks or lengthening the inventory window both contributed to significant cost savings and operational efficiency.

While this project provided valuable insights, it also had several limitations that can be explored in future studies. One key challenge was the lack of complete equipment data. Because we relied solely on the weight of goods, we could only estimate shipment quantities, which added complexity to routing and handling. Future iterations of the model should incorporate cargo volume (in cubic meters) to better reflect dimensional constraints. In addition to technical refinements, further work can be done to enhance the model's robustness. This includes applying deeper statistical analysis to strengthen confidence intervals and using iterative modeling techniques to test alternative assumptions and scenarios. Exploring more flexible contractual arrangements with suppliers could also expand consolidation opportunities.

Finally, a critical next step involves incorporating real-world cost data. Mapping actual real estate costs for consolidation hubs, transit routes, and transport pricing would make the model more realistic and actionable for strategic decision-making.

Overall, with this capstone, we demonstrated how a data-driven, cross-divisional approach to inbound logistics can reduce inefficiencies, enhance transportation planning, and support the development of a scalable and cost-effective supply chain. This work lays a strong foundation for future improvements, including dynamic routing, real-time supply chain data integration, and more flexible contractual arrangements with suppliers. Beyond the partner company, other firms facing similar inbound logistics challenges can apply these insights to unlock greater value from consolidation and coordination strategies.

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https://www.transportation.gov/sites/dot.gov/files/2022-03/EO%2014017%20-%20DOT%20Sectoral%20Supply%20Chain%20Assessment%20-%20Freight%20and%20Logistics_FINAL_508.pdf

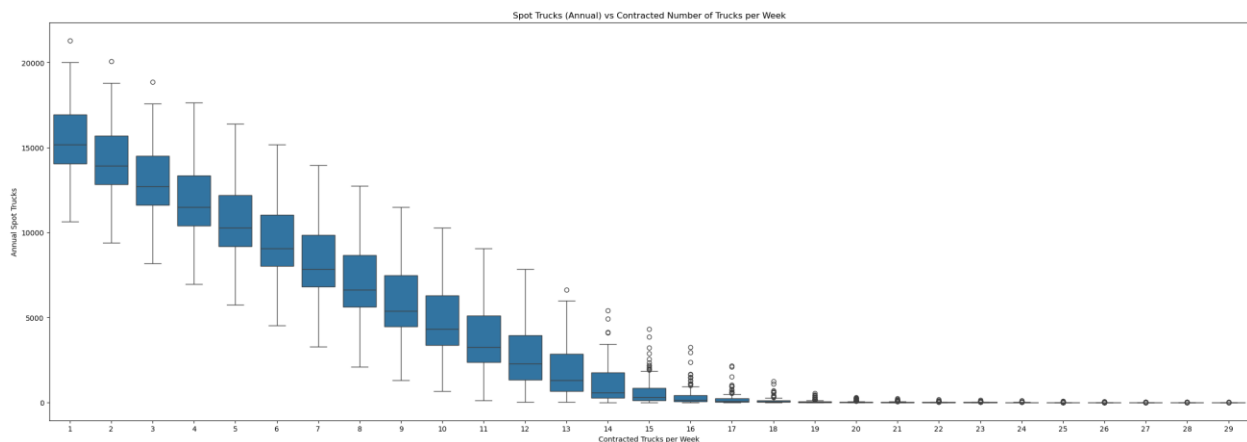
APPENDIX

This appendix contains supplementary materials that support the analysis and modeling presented in the main body of the capstone. These include visualizations of simulation outputs, additional statistical insights, and detailed box plot distributions related to truck utilization and spot truck usage. The figures and accompanying explanations provide deeper insight into the sensitivity of results and serve as a reference for key trade-offs identified in the proposed inbound logistics strategies.

Shanghai Analysis

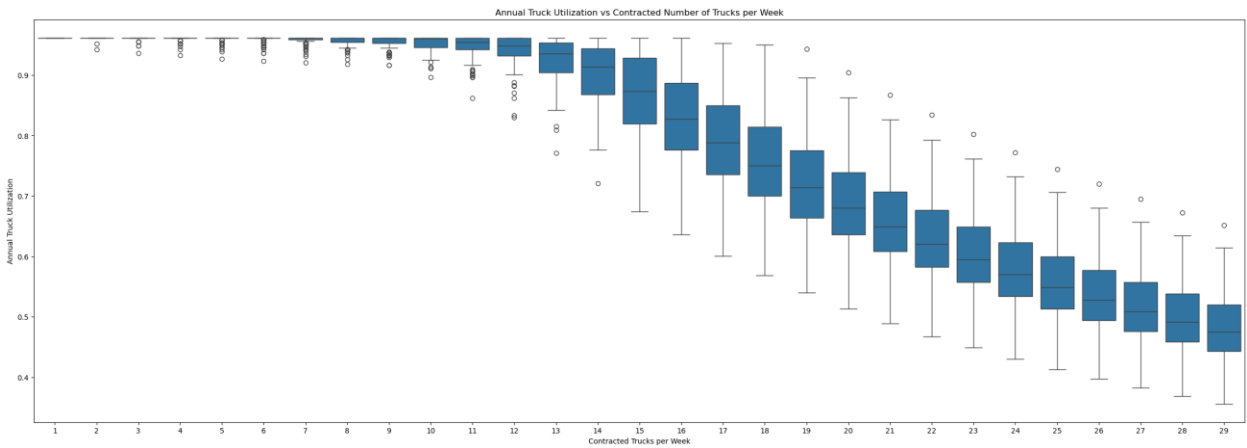
The boxplot in Figure A1 illustrates the dispersion of annual spot trucks vs. contracted trucks per week and shows that as the number of contracted trucks increases, the median number of annual spot trucks decreases significantly. Additionally, the variability of the data also narrows, indicating reduced uncertainty in spot truck usage. From around 16 contracted trucks per week onward, both the median and variability in spot truck demand approach zero, suggesting that increasing contracted capacity leads to more stable and predictable operations.

FIGURE A1. CONTRACTED TRUCKS VS. SPOT TRUCKS SHANGHAI



The boxplot in Figure A2 illustrates the relationship between the number of contracted trucks per week and the corresponding annual truck utilization. As the contracted trucks per week increases, average truck utilization decreases and becomes more variable. While contracting more trucks reduces reliance on spot capacity, it also results in less efficient use of each truck and more unpredictable utilization levels.

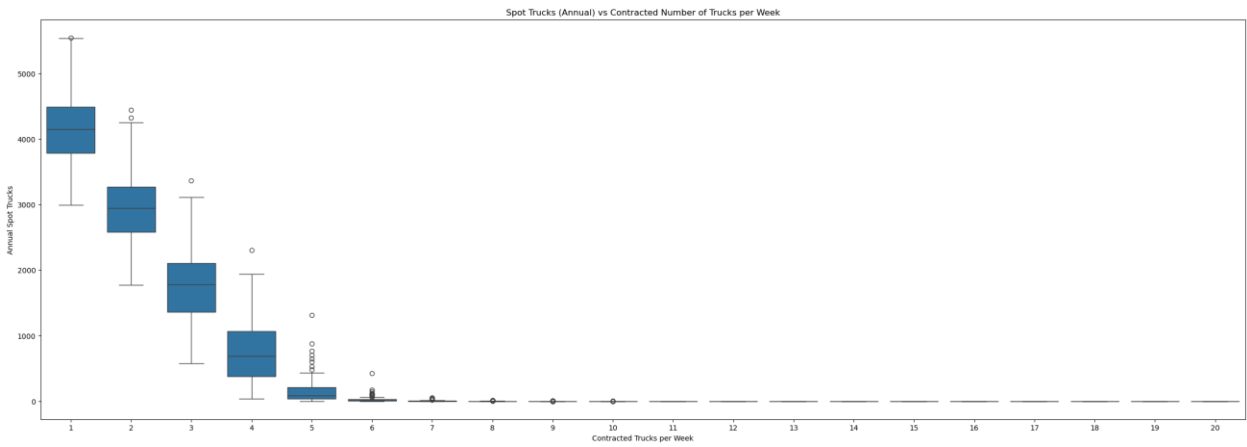
FIGURE A2. CONTRACTED TRUCKS VS. TRUCK UTILIZATION SHANGHAI



Shenyang Analysis

Figure A3 shows that spot truck demand in Shenyang drops off rapidly as contracted trucks increase. After just six contracted trucks per week, both the median and variability in annual spot truck usage approach zero. This early stabilization suggests that Shenyang’s operations can be made highly predictable with minimal contracted capacity due to more consistent shipment volumes, lower cargo weight shipped, and more consolidation opportunities.

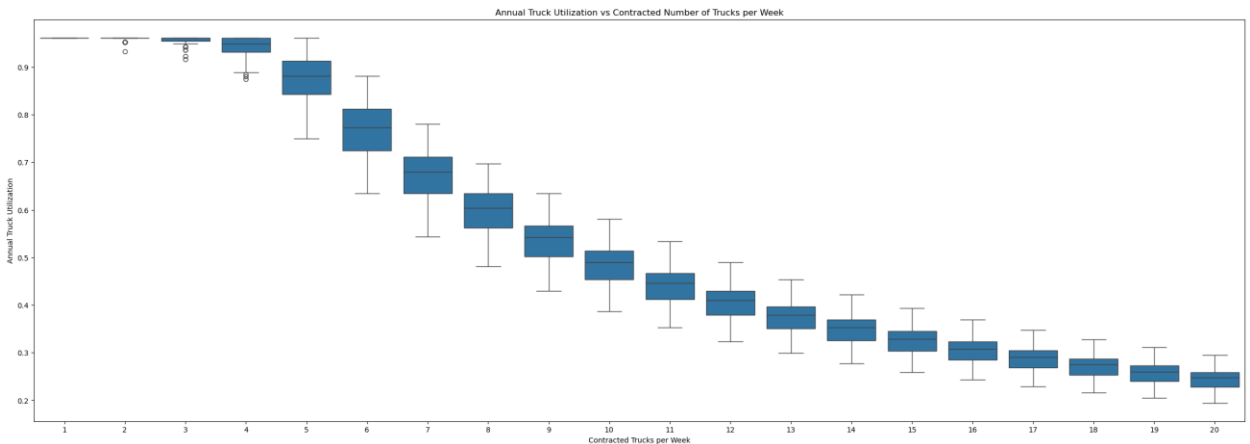
FIGURE A3. CONTRACTED TRUCKS VS. SPOT TRUCKS SHENYANG



Moreover, Figure A4 illustrates contracted trucks and their utilization. Truck utilization starts near maximum levels and decreases gradually as more trucks are contracted. The decline is smoother and less

variable than in Shanghai, indicating that Shenyang maintains relatively efficient and stable operations across a broader range of capacity levels.

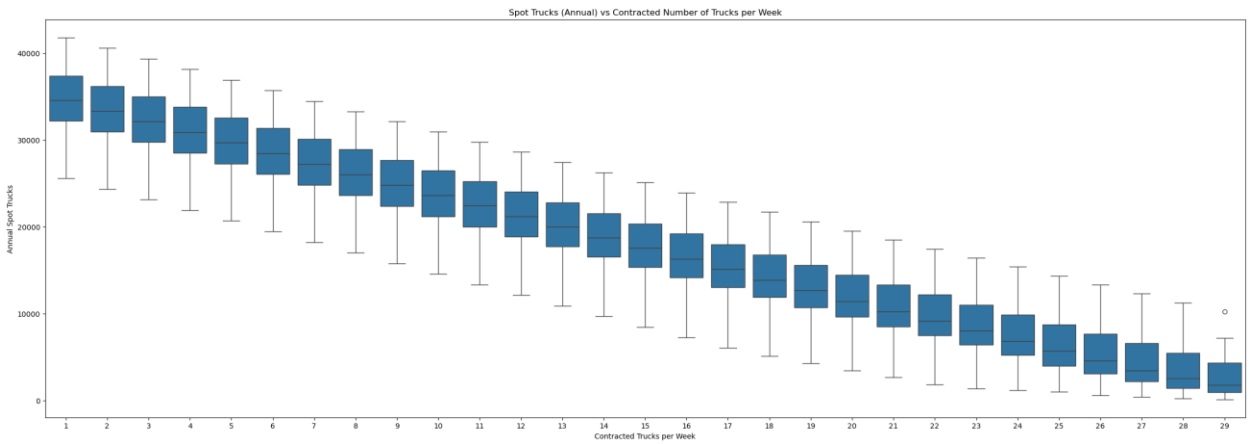
FIGURE A4. CONTRACTED TRUCKS VS. TRUCK UTILIZATION SHENYANG



Chengdu Analysis

In contrast, Figure A5 shows a slower, more gradual decline in spot truck demand in Chengdu. Even at higher levels of contracted capacity, spot truck usage continues to taper rather than flattening out completely. The widespread nature across all levels suggests greater demand variability or more fragmented pickup requirements, making full replacement of spot trucking more difficult. This is likely due to the characteristics of the products originating from Chengdu, which primarily consist of large, heavy equipment.

FIGURE A5. CONTRACTED TRUCKS VS. SPOT TRUCKS CHENGDU



Finally, truck utilization trends in Figure A6 reinforce this challenge. Utilization decreases sharply beyond 10 contracted trucks per week, with a noticeable rise in variability, especially past 20 trucks. This pattern suggests that while contracted capacity helps reduce spot usage, Chengdu experiences diminishing efficiency and predictability as it scales, highlighting the need for careful balancing in truck allocation.

FIGURE A6. CONTRACTED TRUCKS VS. TRUCK UTILIZATION CHENGDU

