Balancing Trailer Pool Network

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ABSTRACT

This study develops a data-driven model to optimize the locations and sizes of our client's trailer pools, enhancing fleet utilization and maximizing customer benefits. Efficient trailer allocation is critical in the transportation industry, as it reduces costs, improves service reliability, and ensures trailers are available where demand is highest. Poorly managed trailer pools lead to excess idle equipment in some areas while creating shortages in others, increasing operational inefficiencies. Addressing this challenge, we analyze telematics data, asset management records, storage locations, and market demand trends to assess trailer movements, utilization patterns, and freight activity across different regions. Our approach integrates quantitative modeling and geospatial analysis to determine the optimal placement and capacity of trailer pools. By leveraging predictive analytics and optimization modelling, we identify strategies to reduce underutilization, minimize repositioning costs, and improve network efficiency. The findings provide our client with actionable insights for data-driven decision-making, ultimately leading to more effective resource allocation, cost savings, and improved service levels for customers.

INTRODUCTION

The optimization of trailer fleet distribution has become an increasingly critical concern in supply chain logistics. Businesses must modify their distribution strategies in response to changes in the dynamics of global trade to stay resilient and competitive. One of the main challenges in the logistics industry is the effective distribution of trailers, which affects delivery times, transportation costs, and supply chain efficiency overall. Recent changes in the economy, trade, and geopolitics have made these issues worse, forcing businesses to improve their supply chain networks in order to guarantee cost-effectiveness and operational flexibility. Companies must also consider sustainability measures, reducing carbon footprints and optimizing fuel usage to align with evolving environmental regulations and customer expectations.

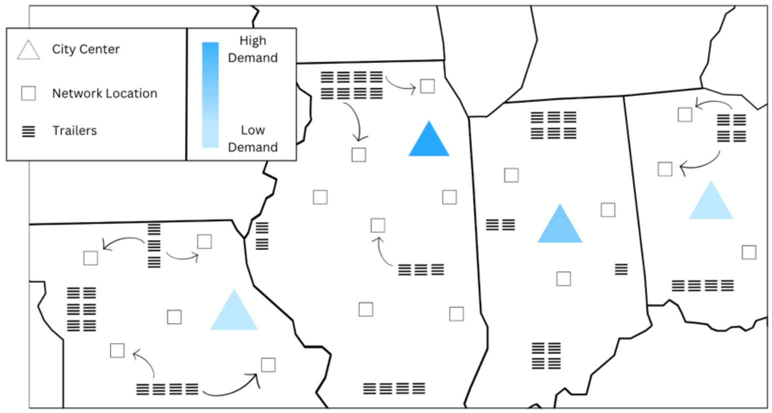

Figure 1: Trailer Allocation Based on Demand

Changes in the economy significantly shape supply chain tactics, obliging businesses to keep their distribution networks efficient and profitable regardless of economic trends. As highlighted by **BBC News (2025)**, recent tariff policies involving major economies (such as the United States, China, Canada, and Mexico) have increased costs and complicated logistics, underscoring the need for a strategic approach to trailer allocation. At the same time, shifting economic conditions affect fuel prices and labor availability, adding another layer of complexity to distribution planning.

Meanwhile, the field of supply chain management is undergoing major transformations. In the United States, numerous companies have significantly restructured their distribution networks due to disruptions linked to the COVID-19 pandemic, labor conflicts, and changing trade routes. **The Wall Street Journal (2025a)** reports that supply chain operations now require far more flexibility, as demonstrated by the growing reliance on East Coast and Southern ports rather than traditional West Coast import hubs. The significance of effective trailer distribution continues to rise, as businesses seek to reduce risk and enhance productivity. Simultaneously, advances in digitalization and artificial intelligence open the door for predictive insights and more sophisticated decision-making tools.

Geopolitical instability further complicates supply chain management by adding new uncertainties to logistics and transportation. Businesses have been forced to reevaluate their global sourcing and distribution frameworks due to disruptions in such vital trade corridors as the Panama and Suez Canals, as described by **The Wall Street Journal (2025b)**. Additionally, tensions in various markets and frequent regulatory changes continue to drive up freight expenses and put added pressure on network planning. These geopolitical dynamics place unique strains on U.S. manufacturers and retailers, which must implement more advanced logistics tactics to navigate uncertain global conditions. Companies must likewise account for cybersecurity threats, given how breaches in digital supply chain systems could significantly disrupt overall operations.

Given these challenges, this paper seeks to explore how data-driven optimization of trailer fleet distribution can help mitigate inefficiencies and enhance supply chain resilience. Specifically, we aim to address the following research questions:

- How can strategic trailer allocation improve fleet utilization and reduce operational inefficiencies?
- What external factors—such as economic trends, trade policies, and geopolitical risks—most significantly impact trailer pool optimization?

- How can predictive analytics and optimization models be employed to enhance trailer utilization in response to supply chain disruptions?

Our research will integrate supply chain analytics, optimization modeling, and industry case studies to develop a comprehensive framework for improving trailer allocation strategies. By leveraging real-world data and industry insights, we aim to provide actionable recommendations that will enable logistics providers to navigate evolving supply chain challenges effectively.

The remainder of this paper proceeds as follows. Section 2 presents a literature review, synthesizing key research on trailer pool management and supply chain optimization to situate our study within the broader logistics context. Section 3 provides an overview of the proprietary and publicly sourced datasets employed, outlining how freight demand indices, network locations, and telematics records form the backbone of our analysis. Section 4 describes our three-stage methodology, detailing how we estimate demand, select network locations, and develop a relocation plan. Section 5 then introduces the optimization models that operationalize these stages, focusing on the mathematical formulations and constraints used to determine optimal trailer allocations. Section 6 highlights the results of our approach, including a profitability analysis and a discussion of operational efficiency gains. Finally, Section 7 concludes by summarizing the implications for trailer distribution, offering recommendations for future research, and identifying potential avenues for model enhancements.

LITERATURE REVIEW

Optimizing trailer fleet distribution remains a key challenge in logistics as it requires robust methodologies to balance demand fluctuations, operational efficiency, and cost reduction. This literature review synthesizes recent research contributions that guide our methodology, providing insights into demand forecasting, fleet optimization, geospatial allocation, and fleet planning.

Fleet planning: Effectively managing fleet is a critical component of transportation logistics as it impacts cost efficiency, service quality, and operational sustainability. Baykasoğlu et al. (2019) provides a comprehensive review of fleet planning problems in both single and multimodal transportation systems. Key challenges were found such as fleet size optimization, vehicle routing, capacity utilization, and demand uncertainty. The study highlights the application of operations research (OR) techniques, including linear programming and heuristic approaches, as well as computational intelligence (CI) methods like machine learning for predictive modeling. Despite these advancements, the authors emphasize gaps in integrating real-time telematics data, sustainability considerations, and multi-objective optimization frameworks. Their work aligns with recent research advocating for AI-driven fleet management and multimodal optimization to improve efficiency in dynamic logistics environments. By addressing these limitations, emerging studies continue to explore hybrid OR-AI approaches, real-time data analytics, and autonomous fleet operations to enhance decision-making in fleet management. This review serves as a foundational guide for understanding the history of fleet optimization strategies and the future direction of intelligent transportation systems.

An interesting study on 'Generalized Trapezoidal Intuitionistic Fuzzy Numbers (GTrIFN) and centroid-based decision-making' by Indira and Ravi (2021), which applies to a real world trailer allocation challenge for fluctuating freight demand due to the uncertainty in transportation costs and demand. The study is based upon fuzzy transportation scenarios using a centroid of centroids method, which improves decision-making under uncertainty. The proposed method 'Direct Optimization Without Initial Basic Feasible Solution

(IBFS)' is to find the optimal location directly by by-passing the traditional way trial and error method used in the transportation industry. By utilizing the centroid of centroid methods, we can incorporate a ranking methodology and assign the trailers depending on the demand, proximity and priority method. The IBFS helps us align to our goal of efficient trailer distribution by minimizing computational complexity. By integrating these insights, we can make better decisions on the optimization of the trailer fleet allocation.

A study by Carroll et al.(2024) on a 'Drop Trailer Forecasting in Volatile Networks' is on a critical aspect that of demand forecasting for optimal trailer placement which is one of the important aspect of the problem statement we are working on that is estimating demand using the OTVI details for the trailer allocation. The study states that the accurate demand forecasting is important for the optimizing trailer allocation, as it can further lead to the cost reduction which is an important aspect in any industry. The paper states that it is required to optimize trailer assets for strategically place the resources where they are most needed which we have incorporated in our research as the centroid approach allocation of the trailers. The study utilizes XGBoost as a predictive modelling tool for taking the advantage over the traditional time-series method to improve the fleet utilization. The research also discussed on the network imbalances, seasonal variations, demand fluctuations which validates our structured methodology that prioritizes trailer placement based on demand and proximity. Their study states the importance of integrating predictive analytics into the operational decision making, the potential of machine learning for demand forecasting is better than the traditional methods which states that we utilize predictive analytics for improved fleet management. The study concludes that by effectively forecasting trailer demand, significant improvements in operational efficiency, cost reductions, and service-level enhancements can be achieved, reinforcing our approach to trailer allocation optimization.

A research by Daaud and Mellouli on 'Network design and planning with resource pooling' which is a relatively new concept of logistic pooling of transportation and logistics optimization which is very important to practice. It is inspired from a real case of logistics service providers in western of France in the field of food distribution according to a Location-Allocation Problem (LAP) with a single-echelon network. The existing principles for managing logistics flows, such as, just-in-time, specialization and relocation of products units, increase the transport demand and decrease the load size resulting in an efficiency transport reduction. The study introduces LAP, a strategic framework to determine the optimal logictics for the placements with minimal operational costs which is aligning with our trailer fleet distribution. By using the demand profiling, in the research the raw demand is replaced with the structured shipment forecasts which supports our data driven methodology for trailer allocation. Their findings, especially the Mixed Integer Linear Programming (MILP) which is mathematical optimization model significantly show that there is reduce in logistics costs by consolidating storage, transportation and routing decisions. These insights also validate our approach of using optimization models to strategically allocate trailers, minimize repositioning costs, and enhance fleet utilization. Additionally, the logistic pooling also provides the sustainability, because it reduces CO_2 emissions and decreases fuel usage, which makes us consider environmental efficiency while operating fleet markets. align with our consideration of environmental efficiency in fleet operations. The computational results from the study confirm that resource consolidation and optimized allocation strategies improve service levels while reducing unnecessary fleet movements, which directly supports our goal of efficient trailer distribution by structured planning.

Gołąbek et al. (2021) present an optimization framework for logistics and supply chain distribution, focusing on key factors such as transport costs, inventory levels, and customer demand fluctuations. Their study employs linear programming and the traveling salesman problem (TSP) to minimize transport costs, distance traveled, and delivery time-critical components of efficient logistics management. A notable contribution is their real-time optimization algorithm implemented in R, which enables adaptive distribution planning and dynamic fleet management. This aligns with our business problem, which seeks to optimize trailer allocation based on demand patterns, telematics data, and asset utilization.

Similar to Gołąbek et al.'s focus on computational optimization for logistics, the client aims to apply data-driven modeling to enhance trailer distribution efficiency. By integrating intelligent routing and adaptive optimization models, this study reinforces the importance of AI-driven decision-making in trailer pool management, supporting our end objective of creating a cost-efficient and responsive fleet distribution network.

Paper Title	Fleet Sizing	Trailer Allocation	Demand Forecasting	Optimization Method	Gradient Boosted Trees	Mixed Integer Programming
A Review of Fleet Planning Problems in Single and Multimodal Transportation Systems	☑	☑	☑	☑	☐	☐
An Unknown Transit Technique for Solving Generalized Trapezoidal Intuitionistic Fuzzy Transportation Problems Using Centroid of Centroids	☐	☑	☐	☑	☐	☐
Drop Trailer Forecasting in Volatile Networks	☐	☑	☑	☐	☑	☐
Network Design and Planning with Resource Pooling	☐	☐	☐	☑	☐	☑
Optimization of Logistics and Distribution of the Supply Chain, Taking into Account Transport Costs, Inventory, and Customer Demand	☐	☐	☑	☐	☐	☑

Figure 2: Reference papers for the respective model used.

DATA

As part of this study, we utilized proprietary data provided by the client. This data is not publicly available and has been categorized into three key components:

• **Freight Market Demand Index:** This is a measure of the number of requests shippers make for trucking capacity. This is a key indicator of demand for trucking services, and which help in predicting market shifts.

• **Network Locations:** This dataset includes the parking locations of trailers across various cities and states within the United States, providing insights into the geographical distribution of assets.

• **Asset Locations:** Derived from a telematics provider, this dataset contains detailed asset information, including Vehicle Identification Numbers (VINs) and encoded geolocation data, which track trailer movements.

In addition to proprietary data, we also incorporated publicly available data through Google Maps APIs to identify the city center for each city, ensuring accurate geospatial analysis and location-based insights.

Table 1: Data used in study

Variable	Type	Description
asset_vin	String	Unique identifier (VIN) of the asset (vehicle/trailer)
position	String	Encoded location of the asset in WKB format
location	String	Full address of the asset's current location
asset_motion_status	Categorical	Status of the asset (e.g., Stopped, Moving)

organization_anon	Integer	Anonymized identifier for the owning organization
telematic_provider	Categorical	The name of the service provider for data collection
reported_time	Timestamp	Time when data was reported
created_time	Timestamp	Time when data was logged in the system
Street Address	String	Physical location of the network site
City	String	City of the network location
State	String	State where the asset is located
Zip	Integer	Zip code of the location

METHODOLOGY

The aim of this study is to solve a logistical problem to create an optimization model for fleet allocation and relocation across the network utilizing the freight market demand, network location data, and real-time trailer telematics data.

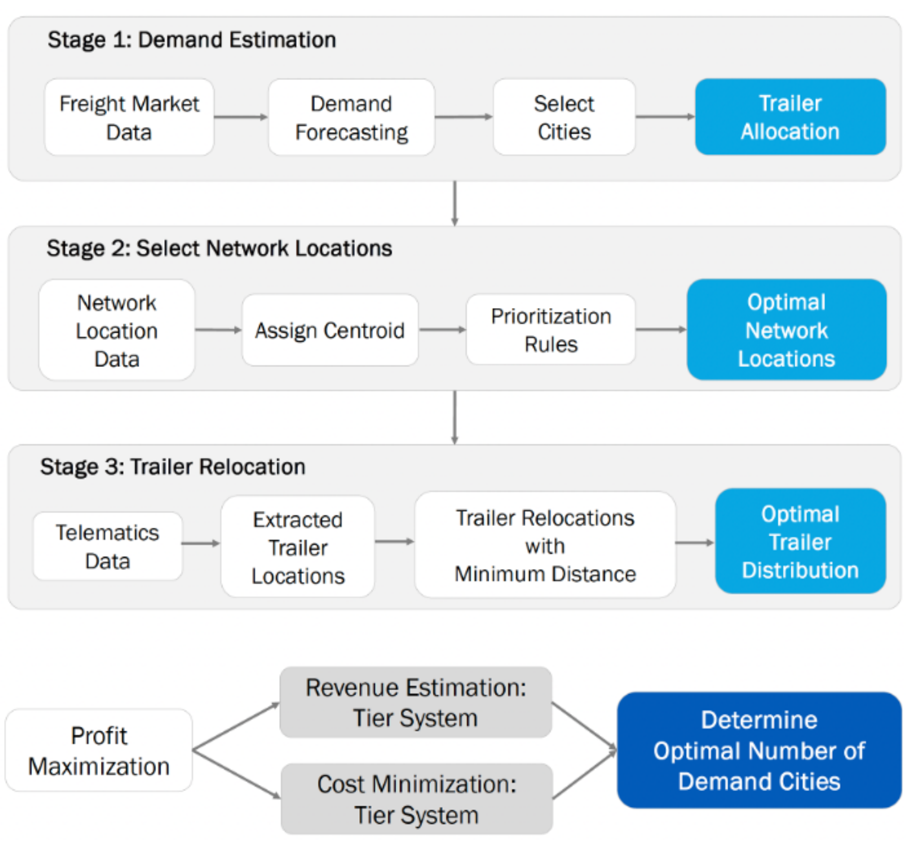

Figure 3: Methodology Overview

Stage 1: Demand Estimation:
The process begins with demand estimation by calculating a weighted average of recent freight market data values for each city, giving higher importance to the most recent days. This approach captures short-term market trends more effectively than a simple average. The result is a final demand score for each city. These scores are then aggregated across all cities to determine the total market demand. Each city's share of the total demand is calculated as a percentage, which is then used to allocate trailers proportionally to cities based on relative demand. This approach makes it a better trailer allocation strategy, ensuring the distribution is aligned with the market needs.

Stage 2: Optimal Network Allocations:
In this stage, the network locations are identified to strategically assign the trailers based on the proximity to the demand centers and also that are operationally feasible.
A centroid is identified for each city, which is typically the central commercial district or a nearby area of importance. These centroids represent the high-demand zones and serve as the reference point for trailer deployment, which ensures trailer availability near peak demand while improving service feasibility and minimizing deadhead miles. Below is the prioritization logic that is used to select network locations based on proximity and availability.

- First, the dealer locations within 25 miles of the city centroid are given the highest priority.
- If dealer capacity is unavailable or exceeded, the own locations within that range are considered.
- If demand still exceeds, then the next closest locations are chosen based on distance alone ignoring the type of the network location.

Each location is constrained to a maximum of **25 trailers**, which prevents overloading at one location and promotes balanced distribution.
This step ensures that trailer allocations are made efficiently, supporting revenue maximization and cost control. It also enables a scalable system that adapts to varying demand intensities across geographies. The selected locations are used in the next stage to guide actual trailer relocation decisions

Stage 3: Trailer Relocation
Once the network locations are identified, in this stage, the trailers are relocated utilizing the last known telematics data. A WKB hex format trailer position is decoded to pull out the exact longitude and latitude coordinates of the trailers, which are then used to relocate the trailers to the assigned network locations. The straight line (Euclidean) distance between each trailer location and a network location is calculated. This solves the optimization problem to find the lowest total relocation cost and identify the best way to move the trailers by minimizing the miles traveled. The model ensures the constraint is taken into consideration to assign each trailer to exactly one location, and the total capacity of the network location is considered. With this model, there is also an option to limit the number of miles a trailer is moved to relocate to the network location. This process is conducted using Python and Google's OR-Tools library, to create a relocation plan that is both practical and cost-effective.

Financial Evaluation:
To identify the best scale of deployment, the process is iterated across different numbers of the demand cities. A tier-based revenue and cost system is applied where the cities are categorized into tiers with revenue and parking assumptions. Key financial metrics like estimated revenue, parking costs, and transportation costs are used to compute monthly profit. This enables the selection of the number of cities to identify the maximum profit, providing both operational efficiency and strategic insight.

The detailed information about the model and results are shared in the next sections.

MODEL(s)

As specified above, we are dealing with a complex logistics problem in which we are applying an optimization model. The underlying allocation logic and optimization model depend heavily on rules specific to our client's business, which we will outline in this section.

To ensure an effective and structured approach to trailer allocation, we implemented the trailer distribution into three key phases: **1. Estimating Demand, 2. Assigning a Centroid and Selecting Network Locations,** and **3. Trailer Relocation.**

This methodology provides a systematic approach to allocating trailers efficiently across key freight metros, ensuring that demand is met while minimizing inefficiencies in resource placement.

Stage 1: Estimating Demand

Our methodology for estimating trailer demand in each metropolitan area proceeds in two connected steps: **(1)** Computing the Forecasted Freight Demand Index (FDI) for each city via a weighted geometric mean, and **(2)** Converting that final Freight Demand Index figure into a share of the overall market to determine how many trailers to allocate.

1. Weighted Geometric Mean of FDI:

Our methodology for estimating trailer demand in each metropolitan area proceeds in two connected steps. First, we derive each city's Freight Demand Index for multiple days, which we then aggregate using a weighted geometric mean. Let x_i represent the Freight Demand Index (FDI) for day i and let w_i be the assigned weight for that day. To account for multiplicative growth patterns and emphasize recent data more heavily, we employ the following weighted geometric mean:

$$\text{Forecasted FDI} = \exp\left(\sum_{i=1}^{n} \ln(x_i)\, w_i\right)$$

In this expression, the daily FDI values are logarithmically transformed and multiplied by their respective weights w_i . Assigning higher weights to more recent days ensures that current market conditions exert a stronger influence on the forecast. Summation over n days, followed by exponentiation, moderates outlier values while amplifying the effect of the most representative data points. After this step is completed for all cities, each city obtains a single, "forecasted" FDI figure reflecting its observed demand for the relevant time frame.

2. Percentage-Based Trailer Allocation

Once we have computed the final Freight Demand Index (FDI) for each city, we convert it into a share of total demand by percentage-based allocation. First, we sum the final FDI values across all k cities:

$$\text{Total FDI} = \sum_{c=1}^{k} \text{Final FDI}_c$$

For each city c, the fraction of total demand is then

$$\text{Percentage Demand}_c = \frac{\text{Final FDI}_c}{\text{Total FDI}} \times 100$$

This percentage indicates how much of the national (or system-wide) trailer pool should be placed in city. Suppose there are T trailers available. We allocate

$$\text{Number of Trailers in City } c = \left\lfloor \textit{Percentage Demand}_c \cdot \frac{T}{100} \right\rfloor$$

or a suitable rounding (e.g., standard rounding) to ensure that total allocated trailers sum to T.
As a concrete illustration, assume the final FDI for Milwaukee is 115.14, while the total FDI across all selected cities is 5757. Milwaukee's share of demand is:

$$\frac{115.14}{5757} \times 100 \approx 2\%$$

If the national fleet consists of 350 trailers, Milwaukee receives about 7 trailers. Even if the city's FDI was computed via the weighted geometric mean, the calculation remains the same once that final figure is known.

3. Tier Assignment

To translate Freight Demand Index values into financial considerations, each city is designated a tier based on its final FDI. This tier system creates a straightforward mapping between daily revenue, parking costs, and the derived FDI figure, giving decision-makers direct financial insights into trailer placement choices.

High-demand cities (FDI > 200) enter Tier 1, yielding higher daily revenue (80 USD) but also higher parking costs (7 USD). Medium-demand cities (100 < FDI ≤ 200) fall into Tier 2 (daily revenue = 50 USD, parking = 5 USD), and low-demand cities (FDI ≤ 100) default to Tier 3 (daily revenue = 30 USD, parking = 3 USD). By coupling demand-based FDI thresholds with operational costs and returns, businesses gain a clear perspective on where to deploy resources most profitably.

Stage 2: Optimal Network Allocations

Upon determining city-level demand in Stage 1, we next select network locations to accommodate the required trailers. Our approach distinguishes between dealer locations (existing corporate partners) and own locations (rented or flexible lots). The principal aim is to allocate trailers efficiently while aligning with the demand forecasts established previously.

A fundamental concept in this stage is the centroid: a single reference point within each city around which the allocation model concentrates available sites. We stress that choosing this centroid should reflect business-specific priorities—typically, an area with substantial client presence or high revenue potential. Although we use commercial districts as an illustrative example, the centroid could just as easily be an industrial hub, a major port, or any region the company deems critical for servicing clients and generating demand. This choice is left to the user's discretion, acknowledging that future or ongoing analyses might place the centroid somewhere more appropriate as business needs evolve.

Having established the centroid, we then prioritize sites within a 25-mile radius using a three-step selection rule:

1. Dealer Locations: Within the 25-mile zone, we first assign trailers to dealer sites. These have pre-existing arrangements, lower parking fees, and better operational infrastructure, making them more cost-effective and reliable.
2. Own Locations: If dealer locations either do not exist or become fully allocated, we shift remaining demand to own locations within the same 25-mile range. These sites may be less optimal in terms of cost or convenience but still provide an avenue to handle excess demand.
3. Extended Search: Once all demand within 25 miles is satisfied or no sites remain, the allocation process expands outward to more distant locations, ranking them by ascending distance from the centroid, without further distinguishing between dealer and own categories.

Additionally, we impose a capacity constraint—each site can hold a maximum of 25 trailers—thereby preventing over-concentration. This rule ensures realistic allocations while distributing trailers in a way that maintains logistical balance. By confining most trailers to within 25 miles of the centroid, the model minimizes transport times and supports high-demand areas in accordance with the city's overall Demand forecast.

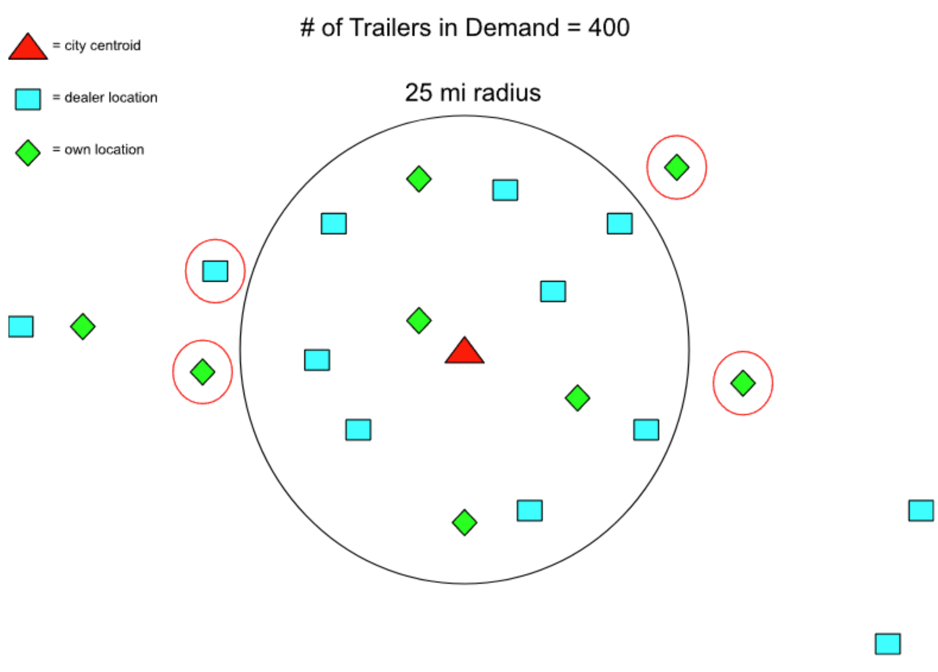

Figure 4: Network locations selection criteria

Figure 4 illustrates a hypothetical metropolitan area with 400 trailers in demand. The red triangle marks the city centroid, while beige squares represent dealer locations and gray diamonds indicate own sites. Each site within the 25-mile radius is considered for allocation, with dealers prioritized first. Sites beyond this circle receive trailers only if local demand remains unmet.

In sum, Stage 2 merges geographical concerns, business rules, and user-defined choices. The centroid ensures that trailers congregate near the most critical or revenue-rich zones yet remains fully modifiable by future users should market conditions, client sites, or strategic imperatives change. After the sites have been selected and filled, Stage 3 focuses on physically relocating assets, guided by telematics data, to finalize the placement of trailers in a manner that further reduces mileage and overall costs.

Stage 3: Trailer Relocation

After determining which network locations will receive trailers (Stage 2), the final step is to physically move trailers from their current positions to these chosen sites. To accomplish this in an efficient and cost-effective manner, we employ real-time telematics data and a mathematical optimization model leveraging Google's OR-Tools library. This step ensures each trailer's assignment is both feasible and optimal in terms of mileage.

1. Telematics Data and WKB Encoding

Each trailer's last known position is recorded in WKB (Well-Known Binary) hex format, which stores geospatial coordinates as binary data. In our preprocessing, we convert this WKB hex into a pair of longitude and latitude values for each trailer i By extracting these precise coordinates, we obtain an accurate real-world position—effectively enabling a direct calculation of the trailer's distance to potential network locations.

2. Distance Calculation

To compute the cost of relocating a trailer from its current location to a specific network site, we apply the Haversine distance formula. Let (λ_j, ϕ_i) be the longitude and latitude of trailer i, and let (λ_j, ϕ_i) be the longitude and latitude of network location j. The distance d_{ij} between these two points is given by

$$d_{ij} = 2r \ \arcsin\Big(\sqrt{\sin^2(\tfrac{\Delta\phi}{2}) + \cos(\phi_i)\cos(\phi_j)\sin^2(\tfrac{\Delta\lambda}{2})} \Big)$$

where r is Earth's approximate radius (e.g., 3959 miles), $\Delta\phi = \phi_j - \phi_i$, and $\Delta\lambda = \lambda_j - \lambda_i$. By accounting for the curvature of the Earth, the Haversine formula provides a more accurate estimate of the great-circle distance than a simple Euclidean calculation.

3. Relocation Optimization Model (Linear Program)

We model the relocation as a minimum-cost assignment problem using Google's OR-Tools library. Let $i \in (1, \dots, I)$ represent the set of trailers and $j \in (1, \dots, J)$ represent the set of allocated network locations. We define a binary decision variable xij such that

$$x_{ij} = \begin{cases} 1 & \text{if trailer } i \text{ is relocated to site } j, \\ 0 & \text{otherwise.} \end{cases}$$

Objective Function

$$\min \sum_{i=1}^{I} \sum_{j=1}^{J} d_{ij}\, x_{ij}$$

Where dij represents the haversine distance between trailer i and site j. By minimizing the total distance, the model identifies the **lowest overall relocation cost**.

Constraints

a. Single Assignment

$$\sum_{j=1}^{J} x_{ij} = 1 \quad \forall i.$$

Each trailer must be moved to exactly one location, preventing a split allocation of a single asset.

b. Location Capacity

$$\sum_{i=1}^{I} x_{ij} = \text{AllocatedTrailers}_j \quad \forall j$$

Each network site j must receive precisely the number of trailers ($AllocatedTrailers_j$) assigned to it during Stage 2, ensuring the capacity constraints are met and the plan remains consistent with earlier decisions.

c. Optional Constraint

$$\sum_{j=1}^{J} d_{ij}\, x_{ij} \le t \quad \forall i$$

This threshold t can limit the distance any single trailer may travel. Although including this constraint might force some trailers into less ideal solutions, it ensures no trailer is relocated an excessive or undesirable number of miles, reflecting additional business policies or driver-labor considerations.

Implementation with OR-Tools

We implement this model in Python, employing OR-Tools' specialized functions for integer linear programming. Telematics records, having been preprocessed to yield each trailer's latitude–longitude, are translated into an $I \times J$ cost matrix representing d_{ij}. We derive d_{ij} by applying the Haversine distance formula:

$$d_{ij} = 2r \ \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_j - \phi_i}{2}\right) \ + \ \cos(\phi_i)\ \cos(\phi_j)\ \sin^2\left(\frac{\lambda_j - \lambda_i}{2}\right)}\right)$$

Where (ϕ_i, λ_i) and (ϕ_j, λ_j) are the latitude and longitude (in radians) for trailer i and location j, respectively, and r is Earth's approximate radius (e.g., 3959 miles). This cost matrix is then fed into OR-Tools along with the linear program's objective function and constraints (single-assignment, capacity, etc.). OR-Tools solves the problem and produces a relocation plan specifying which trailer is assigned to which location, minimizing overall travel distance while respecting the required conditions.

4. Outcomes

This relocation strategy is both practical and cost-effective, as it ensures that (i) every location gets the number of trailers it requires, (ii) no asset is assigned to multiple sites, and (iii) total mileage (and thereby transportation cost) is minimized. Should operational policies demand it, managers may impose the optional constraint to further restrict maximum trailer movement. By integrating telematics data on asset positions with previously determined location capacities, Stage 3 delivers a final, real-world–ready plan for trailer redistribution.
With this Stage 3 complete, trailers are physically moved from their current positions to their assigned sites, thereby bringing the demand forecasts (Stage 1) and network allocations (Stage 2) into reality. This closed-loop approach—from data-driven site selection to final asset relocation—ensures that the entire logistics network is optimized at both the strategic level (where trailers should go) and the operational level (how they are best moved).

RESULTS

The profitability analysis across varying numbers of demand cities is displayed between revenue, costs, and trailer distribution. Profit is maximum when trailers are allocated across 4 cities, which provides an effective balance between capturing demand from Tier 1 freight metros associated with relocation and operational costs. After 4 cities, the profit begins to decline slightly due to lower returns from lower-tier markets and increasing transportation costs.

Revenue is high within the n = 1 to 5 range, due to high-volume freight cities. If n=1 the transportation costs are higher since the trailers have to travel longer distances, but as the number of cities increase, transportation costs gradually decrease due to a more distributed demand network that reduces average trailer travel distance.

Parking costs remained relatively stable across all scenarios from n = 1 to 15, suggesting that parking expenses were not significantly impacted by changes in city count or trailer dispersion.

Overall, the model demonstrated that focusing on a small set of strategically selected high-demand cities yielded the best financial outcome, validating the importance of targeted network planning in maximizing trailer profitability.

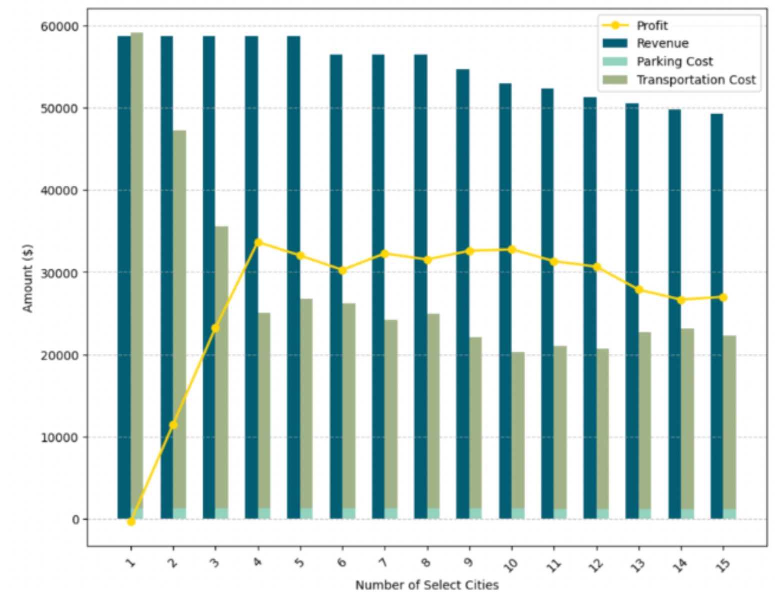

Figure 5: Profit trend across different cities (Amount($) and number of cities scaled)

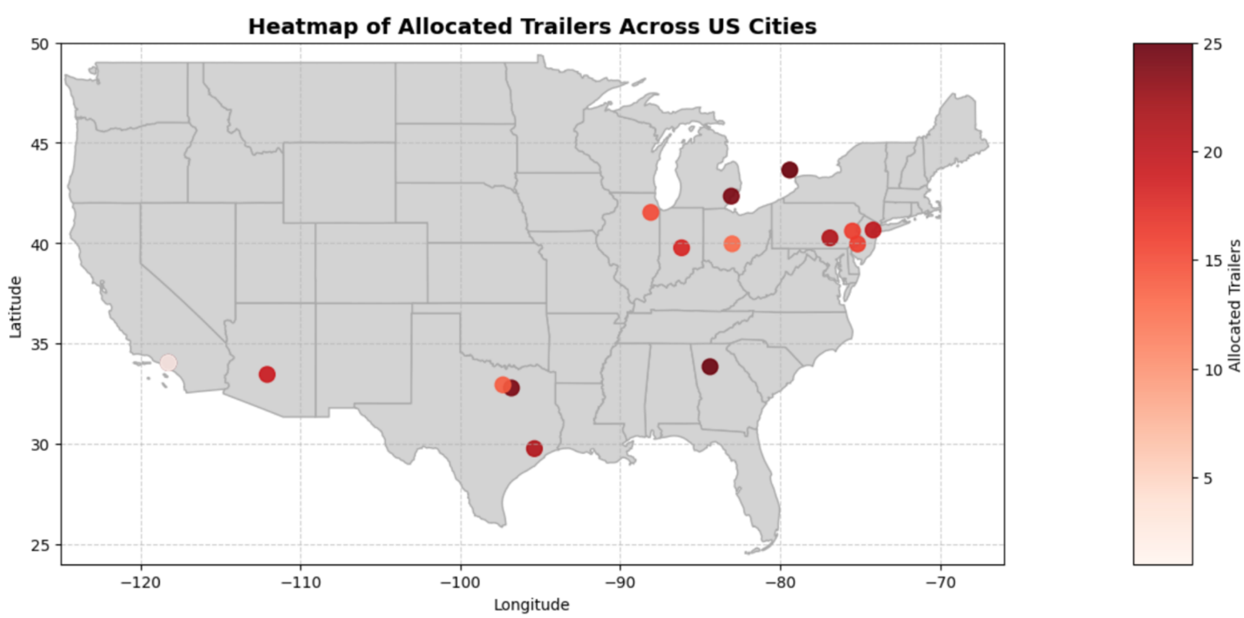

Figure 6: Heatmap of allocated trailers across US cities

The above figure presents a heatmap of trailer allocations across selected U.S. cities, where darker shades indicate higher trailer concentrations, with a maximum of 25 trailers per location. The visual highlights dense allocation clusters in the Midwest, Northeast, and Southern regions, these areas identified as high-demand freight corridors in the demand forecasting stage. This spatial distribution supports the model's profitability results, showing that focusing on a select group of Tier 1 cities not only aligns with forecasted demand but also contributes to operational efficiency by minimizing relocation distances and associated costs.

CONCLUSIONS

While trailer allocation may appear to be a small part of logistics, it plays a crucial role in today's fast-changing supply chain environment. With rising costs, shifting trade routes, and frequent disruptions, the ability to strategically position trailers has become essential to meeting freight demand efficiently and cost-effectively. This study examined how data-driven approaches to trailer allocation and relocation can support more agile and resilient logistics operations.

Our findings suggest that allocating trailers across four high-demand cities yields the highest profit by balancing market reach with relocation cost. This directly answers our first research question, strategic allocation enhances trailer utilization and reduces inefficiencies, especially when focused on a select set of high-volume freight markets. In addressing the second question, we observed that external factors such as fuel costs, labor availability, and regulatory shifts play a significant role in shaping optimal trailer strategies. While our model didn't simulate these inputs directly, it is designed to be adaptive, capable of integrating such variables in future iterations. Lastly, our approach answers the third question by demonstrating that predictive modeling and optimization tools can provide real-time decision support, enabling more agile responses to disruptions and fluctuating demand.

While the model offers strong business value, it assumes stable demand, fixed cost estimates, and no disruptions in the network simplifications that may limit real-world accuracy. Further research is recommended to enhance model robustness, such as incorporating time-series demand forecasting, route-level distance calculations, and transportation cost variability. Additionally, integrating external factors like weather patterns or seasonal freight cycles could further improve allocation precision. As with any operational optimization, this solution is a strong starting point, but continuous iteration will be key to maintaining competitive advantage in evolving freight markets.

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