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A Hybrid Modeling Approach to Joint Matching and Pricing in an Intelligent Freight Transportation Platform

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Abstract. The smart freight platforms aim to manage arrangements between carriers and shippers by leveraging information technology. The two most significant tasks performed by these platforms are matching carriers and shippers and setting prices. The purpose of this study is to develop a hybrid approach to help these platforms jointly optimize matching and pricing. The proposed approach consists of seven steps. The first step deals with demand and supply data collection. In step 2, a two-stage data analysis method is proposed to reduce the complexity of the decision-making. Steps 3 and 4 include matching and pricing optimization engines. The following steps are related to providing feedback for customers and finalizing the decisions. The performance of the framework was tested using a numerical example. Results demonstrate how this framework could provide customized pricing while considering the perspectives of different actors in the freight market when making matching decisions.

Keywords: smart freight platform, joint matching and pricing, clustering, multi-actor, vehicle routing, large-scale.

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1. Introduction

The freight market is complex and dynamic, and it faces numerous challenges such as ineffective operations, coordination problems, and a lack of shipment visibility (Padidar et al., 2021). Freight providers and cargo owners always look for gaining more market share and new transportation opportunities. The continuous entry of new carriers increases pressures in the market. From the perspective of shippers, working with multiple carriers can also cause some difficulties such as variation in the quality and the consistency of the services, price negotiations, and transparency issues. The increasing complexity of transportation chains triggered the emergence of new business models for freight transportation. These business models need to manage the transport process regardless of which carriers or shippers are involved by providing visibility and integration across multiple enterprises (Mukhopadhyay & Setaputra, 2006). Thanks to the development of the Internet and information technology, freight resource sharing platforms have been developed in a global virtual environment to coordinate arrangements between customers and transport resource providers (Bădică et al., 2020).

Freight-sharing platforms are similar to passenger transportation platforms (ride-sharing platforms such as Uber). They use the Internet, cloud computing, and big data for connecting carriers and shippers and resolving issues like information asymmetry and low freight efficiency (Wang et al., 2020). They act as intermediary company that aims to manage the capacities, allocation, and pricing of mobility services while maintaining high satisfaction (Cavalcante & Roorda, 2013; Min & Kang, 2021; Leungsubthawee et al., 2019). These platforms receive large sets of orders from large shippers and then re-distribute them among a set of carriers with actual transport capacity. These shipment requests can arrive in a relatively short time and decisions should be made quickly to avoid penalties (Min & Kang, 2021).

The determination of prices and matches are two key decisions of the resource-sharing platforms and need to be accomplished with respect to the immediate environmental changes. They have a significant impact on the platform's profit and the satisfaction of both sides of the freight market (shippers and carriers) (Fang et al., 2019). The prior literature on matching shippers (demand) with carriers (supply) considered the perspectives of just one (Leungsubthawee et al., 2019; Min & Kang, 2021; Guo et al., 2020a, 2020b) or, at most, two (Mu et al., 2016; Feng & Cheng, 2021) of the available actors in this market. The goal of the pricing problem in two-sided markets with an intermediary platform is to maximize the platform's profit (Liu et al., 2019; Dou et al., 2020). The earlier studies on pricing in the freight market mostly concentrated on the distance-based pricing method. This policy suggests a relationship between the price and the traveled distance (Gu et al., 2018; De Palma & Lindsey, 2011). In 2020, Özkan showed the importance of joint pricing and matching problem for ride-sharing platforms. Li et al. (2020) studied this problem in the context of freight sharing with an emphasis on the perspective of carriers and a distance-based pricing policy. Besides, various research areas, including market deployment plans (Kimiagari & Montreuil, 2018), Vehicle Routing (Huang & Hu, 2012; Costa et al., 2020), and ride-sharing (Li & Chung, 2020), focused on the importance of breaking down large-scale problems into smaller ones. The complexities of large-scale joint matching and pricing decisions for smart freight platforms coping with many shipment requests in a short period of time cannot be easily handled using available models and need to be investigated further.

To the best of our knowledge, there does not exist a study in the smart freight transportation field that combines data analysis capabilities and optimization techniques to handle large-scale joint multi-actor matching and pricing problems. This paper aims to fill this gap and provides a novel contribution to smart freight platforms for managing freight transportation services using optimization and data analysis techniques. More precisely, the contribution of this paper is summarized as follows:

(1) addressing standpoints of available actors in the freight market for cargo matching,
(2) integrating multi-actor freight matching problem with a distance-based pricing policy,
(3) developing a methodological framework using data analysis capabilities and optimization techniques to harness the computation complexity of the decision making in smart freight platforms.

The rest of the paper is organized as follows: In section 2, we provide a literature review on matching and pricing problems in freight sharing context. The problem and assumptions are described in section 3. Sections 4 provides an overview of the proposed methodological framework for joint matching and pricing including the data analysis, and optimization model. A numerical study is conducted and shown in Section 5. In section 6, we discuss some research implications. Section 7 provides conclusive remark and areas for further research.

2. Literature review

Related literature is divided into four parts. The first part is the matching problem in the freight transportation context. The second and the third parts are respectively related to the pricing problem and the application of joint matching and pricing problems. The last one is the application of joint optimization and data analysis approaches for solving large-scale problems.

2.1.Matching

The two-sided matching problem is essentially an assignment problem that is described by two sets of participants and their corresponding preference from the opposite set which was first introduced by Gale and Shapley (1962) for college admission and marriage problem (partner- partner). Matching problems are classified into three categories: 1) one-to-one matching 2) many-to-one matching, and 3) many-to-many matching (Gu et al., 2015; Zhao et al., 2020). These problems have been widely applied in different fields including display ads (keyword-advertiser) (Mehta, 2013; Kim & Moon, 2020) event arrangement (event-user) (Liang, 2019), personnel assignment (task-worker) (Liu & Xu, 2020), venture capital (investor-company) (SØresen, 2007), job market (firm- worker), ride-matching (drivers to riders) (Masoud & Jayakrishnan, 2017b), and cargo matching (shippers to carriers).

In the context of freight transportation, shippers are the entities that look for services to transport their goods such as freight forwards and ocean carriers. Carriers are the entities that provide transport services using trucks, trains, and barges (Guo et al., 2020a). In a freight resource-sharing platform, registered users can publish information about their available transportation capacity or cargo transport requirements, and the platform needs to find the best matches between their users (carriers and shippers) (Wang et al., 2020). Previous studies can be classified into two categories with respect to their objective functions including single-objective optimization models and multi-objectives optimization models.

2.1.1 Single objective optimization models

Leungsubthawee et al. (2019) focused on the collaboration of carriers to maximize the total number of matches. They proposed an integer linear optimization model considering different constraints including types of trucks and cargoes, cost of shipping and deliveries, time availability of each truck and cargo, and the loading and unloading times of the cargoes. The model was then solved using the branch and bound technique. In 2021, Min and Kang investigated the objective of maximizing the revenue of the platform with respect to practical operational characteristics, such as a territory-based approach and transferring. They formulated the problem as a Markov Decision Process (MDP) to represent an uncertain and sequential decision-making procedure and developed a reinforcement learning (RL) solution to solve the MDP model. Guo et al. (2020a) studied the cargo matching problem considering multiple modes of transportation and transshipment operations between different services. Minimizing the total cost including transport costs (transit costs, transfer costs, and storage costs), delay costs, and carbon tax of matching was considered as the objective function in this study. The matching problem was formulated as a mixed-integer linear programming model (MILP) considering time and capacity constraints. A preprocessing-based heuristic algorithm was proposed to reduce the computational complexity of the matching problem for real instances. The problem was then solved using the rolling horizon technique. These authors presented a stochastic version of their model in the other study. They used historical data for incorporating stochastic information regarding future shipment requests (origin, destination, volume, announced time, release time, and due time) to help the decision-maker to hold some barge and train capacity for more important shipment requests in the future. The problem is formulated using multistage stochastic programming with the objective of minimizing the expected total cost over the planning horizon which results in suboptimal decisions for current requests matching and optimal performance over the planning horizon. This study presented an RH approach using the sample average approximation method at each iteration called an anticipatory optimization approach

(AOA) to solve the matching problem (Guo et al., 2020b).

2.1.2 *Multi-objectives optimization models*

Some studies focused on the cargo matching problem from several standpoints and proposed multi-objective models. Mu et al. (2016) considered two objectives for freight matching including maximizing the matching rate and minimizing the cost of transport with respect to capacity constraints. They converted these objectives to a single objective using the weighting technique and presented a quantum evolutionary algorithm to solve the problem. Another study also combined different objectives into a single merged objective. This paper proposed a two-phase truck-cargo matching model for the truck alliance and aimed to find a truck for each task in the set of tasks instead of searching for an optimal assignment for a single task. The objective function was to maximize demand-capacity fitness from the angles of cost, time, and reputation. The total cost was defined as the sum of task execution cost (dependent on the transport volume, transport distance, cargo type, and time requirement of the task), inter-task connection cost, and truck utilization cost. Total time is calculated based on task execution time and inter-task connection time. The problem was formulated as nonlinear programming and was solved using the Genetic Algorithm (Feng & Cheng, 2021). Peng et al. (2016) focused on maximizing the total surplus of carriers and shippers as the objective function. They investigated stable matches in the context of the dry bulk shipping market consisting of a large number of carriers and shippers with unique characteristics and preferences. This paper formulated the matching equilibrium between the shippers and carriers and introduced a game mechanism that concentrated on the disadvantaged side of the market and provided a condition of stable matching with changeable ordered lists of preferences.

Compared to ride-sharing, limited studies investigated the multi-objective matching in the context of freight transportation, and it was mostly studied from the perspective of the platform. There is a need to concern different standpoints of all available actors in the market including shippers, carriers, and the platform, and provide win-win solutions for the matching problem.

2.2.Pricing

Pricing decisions of two-sided markets with an intermediate platform are novel compared to traditional markets and play a determinative role in generating profit for intermediate platforms (Liu et al., 2019; Dou et al., 2020). There are many examples of two-sided markets with a platform in the literature. To name a few, electronic commerce websites such as Amazon, eBay which realize online trading between buyers and sellers, game consoles like Sony's PlayStation, and Microsoft's Xbox which lets players enjoy numerous games, sharing platforms like Uber and Didi that connect drivers and passengers (Dou et al., 2016). There are a series of publications that investigated the pricing problem in two-sided markets with platforms and these policies can be classified into the following categories. The most popular pricing policies in two-sided markets are presented in Table 1. The most appropriate pricing policy should be chosen considering the characteristics of the two-sided market.

Table 1. Pricing policies in two sided-markets

Pricing policy	**Definition**	**Benefits**	**Reference**
Transaction-based	Customers join the platform without any fee, and they need to pay a per-transaction for placing each order in the platform.	▪ Availability to more customers	(Kung & Zhong, 2017)
Membership-based	Customers pay a membership fee to join the platform and do not need to pay a fee for each transaction.	▪ Earliness in collecting money ▪ Maximizing the price sensitive order frequency	(Kung & Zhong, 2017)

Pricing policy	Definition	Benefits	Reference
Cross-subsidization	The platform needs to invest (subsidize) in one side of the market to increases utility and demand on the corresponding side and improve the utility on the other side.	▪ Attraction to more suppliers or demanders	(Fang et al., 2019; Liu et al., 2019; Kung & Zhong, 2017; Dou et al., 2016)
Differential	The platform proposes different prices for the same service considering different customer type, time of purchase, different service provider power or risk attitude, etc.	▪ Opportunity for platform to gain more profit	(Dou et al., 2020; Yu et al., 2019; Choi et al., 2020)
Dynamic	The platform sets prices by considering the demand-supply, competitor pricing, and other historical or current external factors of the market.	▪ Providing satisfaction to all stakeholders	(Saharan et al., 2020)

More specifically, distance-based pricing policy has been widely used in the freight transportation context. Teo et al. (2012) demonstrated how this pricing policy could assist carriers in choosing the quickest and consequently least expensive route to reach their destinations. They also proposed this policy for managing truck traffic within the Business to Consumer (B2C) e-commerce environment. Under this pricing policy, the price could fluctuate either linearly or nonlinearly as a function of the traveled distance (Gu et al., 2018; De Palma & Lindsey, 2011). Distance-based pricing policy could be both static and dynamic (Chang et al., 2018). Static distance-based pricing could be formulated as a fixed charge and a linear component proportionate to the traveled distance or as a staircase (step toll) structure. The first formulation has been criticized as too limiting in the literature while the second formulation the structure is the most common and easiest structure in the practice (Christensen et al., 2013; Li et al., 2020).

2.3.Joint matching and pricing

The joint pricing and matching problem is a novel research topic. In 2020, Özkan studied this problem in the context of ride-sharing. He showed that optimizing the pricing decisions under an assumed matching policy (such as matching with the closest driver) does not maximize the number of matchings in general and can result in subpar overall performance. Similarly, he showed that fixing the pricing decisions and optimizing only the matching decisions is not optimal in general. Indeed, both the pricing and matching decisions have a first-order effect on the system performance and need to be optimized jointly. Recently, Li et al. (2020) investigated this problem in the context of the freight market. They supposed that the matching problem aims to minimize the total travel cost of assignments with respect to the capacity constraint of the vehicles and the pricing problem focuses on determining the shortest vehicle route with minimum platform price. This problem was formulated using mixed-integer nonlinear programming for assigning orders to drivers and optimizing the platform's prices through routing and selection of pricing policies. Price was set using simple distance-based pricing policies: starting fare and extra charge rate (SR) strategy and the step toll (ST) strategy. A modified simulated annealing evolutionary algorithm was proposed to jointly resolve the matching and pricing process. In practice, freight-sharing platforms need to consider more constraints in their matching decisions like time windows and see the problem from the standpoints of all the actors in the market.

2.4.Application of joint optimization and data analysis approach to solving large-scale problems

Solving large-scale problems is considered particularly difficult in the literature due to their size. Various studies have suggested different strategies to reduce the search space to harness the complexity and solve these problems. A general way to solve complex large-scale problems is to first simplify them by breaking them down into sub-problems before solving them (Xiang & Yu, 2001). Kimiagari and Montreuil (2018) introduced hybrid modeling using the self-organizing clustering technique and Mixed-integer linear programming for developing a market deployment plan with a large number of potential markets. They showed how the clustering technique could tackle the scale and complexity of the problem by generating target market clusters. Huang and Hu (2012) partitioned customers into clusters using a database with geographical and experts experience data for providing a smart way to reduce the search space for Large-Scale Vehicle Routing Problems (LSVRP). Costa et al. (2020) proposed an adaptive clustering technique for LSVRP. This technique attempts to automatically prune the search space. Clusters are initially formed based on customer locations and evolve based on locations where better solutions are moving. They showed how the clustering technique could improve the search speed, without much loss of quality by limiting the search space. Li and Chung (2020) showed how the application of clustering approaches could resolve the very challenging computations of large-scale ride-sharing problems by decomposing them into small problems. They showed how k-means and greedy clustering algorithms could outperform non-clustering case outcomes in terms of computational tractability and solution quality.

In the freight-sharing market dealing with a large number of shipment requests in a relatively short time like the ride-sharing market, the computation complexity of the decision-making problems needs to be harnessed. To the best of our knowledge, the joint matching and pricing by exploiting data analysis capabilities and optimization techniques has not received much attention in the freight market context despite its great effect on the key actors for maximizing the freight sharing platform's profit and satisfaction of both sides of this market. Table 2 represents the summary of the studies that investigated matching and joint matching and pricing in the context of freight transportation. The last row of the table clearly shows how our research could contribute to the current literature by addressing the standpoints of available actors in the freight market and integrating matching optimization with a distance-based pricing policy through data analysis capabilities and optimization techniques.

Table 2. Summary of the related research

Reference	Objective Function			Constraints				Optimization Model	Pricing Policy	Clustering	Solution Approach
	Carrier	Shipper	Platform	Capacity	Time	Distance	Quality				
(Leungsubthawee et al., 2019)	-	-	Maximize total number of matches	*	*			ILP	-	-	Branch & Bound
(Min & Kang, 2021)	-	-	Maximize platform's revenue			*		MDP	-	-	Q-learning
(Guo et al., 2020a)	Minimize total costs	-	-	*	*			MILP	-	-	Heuristic & RH
(Guo et al., 2020b)	Minimize expected total cost	-	-	*	*	*		MSP	-	-	AOA & RH
(Mu et al., 2016)	Minimize transport cost	-	Maximize matching rate	*				ILP	-	-	Evolutionary

Reference	**Objective Function**			**Constraints**				**Optimization Model**	**Pricing Policy**	**Clustering**	**Solution Approach**
	Carrier	**Shipper**	**Platform**	**Capacity**	**Time**	**Distance**	**Quality**				
(Feng & Cheng, 2021)	Minimize transport cost and time & Maximize service quality	-			*		*	NLP	-	-	Evolutionary
(Peng et al. ,2016)	Maximize utility	Maximize utility	-	*	*			MILP	-	-	Gale-Shapley
(Li et al., 2020)	Minimize transport cost			*				NLP	SR & ST	-	Heuristic
Present Paper	Minimize transport cost	Maximize service quality	Maximize total number of matches	*	*	*	*	MSLP	ST	*	Exact

3. Problem Description

The main actors in the freight market are shippers, carriers, freight-sharing platforms, and the government. In this study, we focus on the first three actors. Shippers are companies who buy transportation services. They are usually owners or providers of goods that need to be transported. Carriers are companies that sell transportation services. They are responsible for moving goods from the location of shippers to corresponding destinations using different types of trucks. Both shippers and carriers need to be registered to be able to use the platform and exchange information. Registered shippers with a shipment request need to enter information about their cargo transport requirements including origin and delivery points coordinates, the number of delivery points, weight (volume), time, price sensitivity, and other preferences. Registered carriers also need to enter information about their available transportation capacity including the capacity of trucks, location coordinates, time availability, cost sensitivity, and other preferences.

Platforms evaluate the transportation services of carriers with respect to the satisfaction of shippers and the performance of the carriers in terms of timely and quality delivery. Considering all this information, smart freight platforms need to take two key decisions. First, they should determine optimal matches between cargo transport requests and available transportation capacity with respect to their constraints and preferences. This problem is a two-sided matching (an assignment) and needs to be solved by addressing the standpoints of all available actors in the freight market. After the service confirmation between shippers and carriers, platforms need to decide on the price using different pricing policies. Platforms must first determine the delivery routes, which is a vehicle routing problem, in order to calculate the price of the platform (Li et al., 2020). To decrease the inherent complexity of platform decisions in dealing with a large number of shipment requests in a relatively short time, problems need to be broken down into small problems. Figure 1 represents the process of information exchange in the freight market.

4. Proposed methodological framework for freight platforms

In this section, we explain the methodological framework for joint cargo matching and pricing. We aim to provide a systematic approach for exploiting the benefits of data analysis capabilities and optimization techniques in decision-making for smart freight platforms. As presented in Figure 2, shippers and carriers post their information on smart freight platforms (Step 1). The platforms then apply a two-part data analysis method to segment customers and reduce the complexity of decision-making (Step 2). After data analysis, the platforms run the matching process to find matches within predetermined optimization spaces (Step 3). Then, the platform's prices and delivery routes are determined by the optimization engine of the platforms (Step 4). The platforms inform shippers and carriers about these decisions (Step 5). If carriers and shippers are satisfied with the results, these decisions will be finalized (Step 6). If not, they can change their preferences, and the decisions will be updated (Step 7).

Figure 1. Information exchange in the freight market

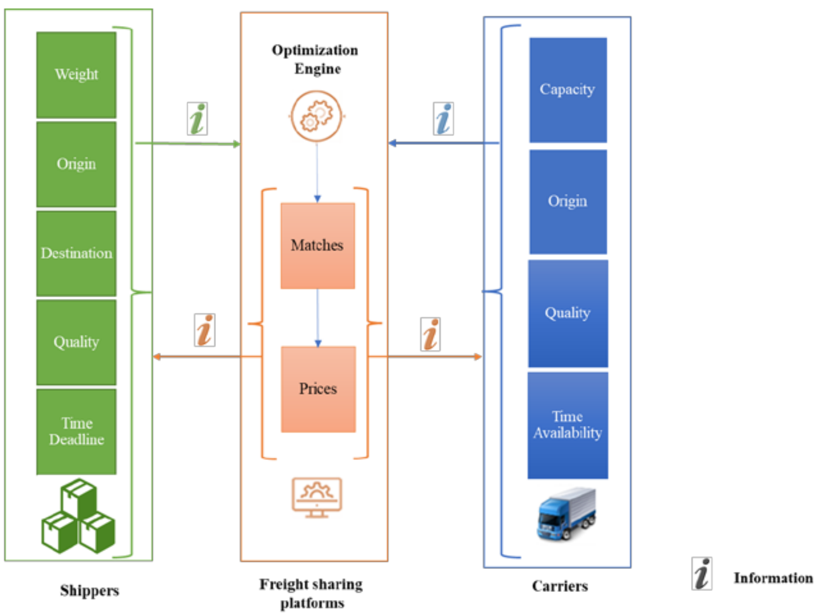
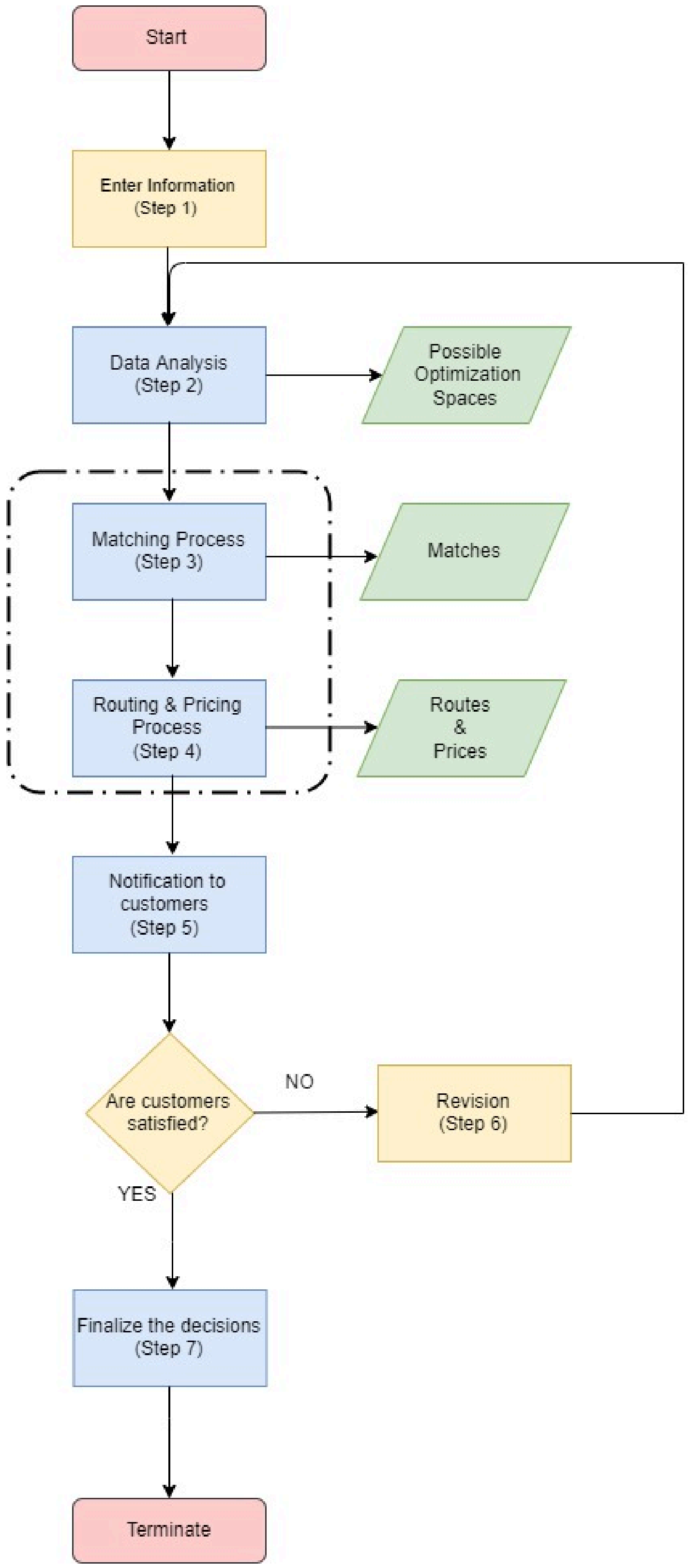


Figure 2. Joint matching and pricing methodological framework



4.1.Data Analysis

In this study, we proposed two-part data analysis method. For the first part, the multiple correspondence analysis (MCA) is applied to find spatial coordinate positions of categorical variables. Greenacre (1984) introduced MCA as a multivariate version of correspondence analysis. Cross tables need to be created first from the categorical variables. The outcomes then can be graphically shown. It is also possible to determine relationships between variables in the row and column, as well as relationships between various levels of each variable (Costa et al., 2013).This data analysis technique could identify and depict underlying structures in a data set with categorical attributes by displaying row and column points in biplots (Greenacre & Blasius, 2006). Arimond and Elfessi (2001) showed how MCA could provide an attribute-positioning map data reduction tool and a preliminary spatial representation of multistate categorical data.

Second, a K-means algorithm is used to cluster carriers and shippers considering their geographical locations. The K-means clustering algorithm aims to minimize the sum of the distance of data points to centroids via k clusters. The squared error between the centroid of each cluster and the points is given in equation 1. The sum of the squared error over all K clusters is given in equation 2.

$$J(c_k) = \sum_{a_i \in c_k} \|a_i - \mu_k\|^2 \tag{1}$$

$$J(C) = \sum_{k=1}^{K} \sum_{a_i \in c_k} \|a_i - \mu_k\|^2 \tag{2}$$

where μ_k is the mean of the cluster c_k and $A = \{a_i\}, i = 1, .., n$ is the set of points. The K-means clustering algorithm was selected for this study since it is a more often used technique in the literature due to its simplicity and effectiveness (Jain, 2010). Apparicio et al. (2015) also mentioned that the K-Means algorithm requires continuous or dichotomous variables for classification. GPS coordinates can be considered as a continuous variable for which Euclidean distance measures can be also calculated.

Applying this two-part data analysis method brings us advantages from two aspects:

- addressing the challenge of mixed-type variables by reducing the dimensionality of the data set (Arimond & Elfessi, 2001),
- minimizing the complexity of the decision-making in the freight sharing market dealing with a large number of shipment requests in a relatively short time.

The framework focuses on the feasibility of matching decisions which means that, given the cost and price sensitivity of shippers and carriers, matching can be formed only if the truck is located at a specific predetermined distance from the shipper's origin.

4.2.Mathematical Formulation

In this study, we propose a cargo matching model to find the optimal matches between carriers and shippers, and at the same time find the optimal routes for delivery in multiple destinations providing the minimum platform price. The joint matching and pricing problem is formulated using a multistage linear programming model (MSLP). In the first stage, the freight-sharing platform assigns shipment requests from cargo owners to appropriate trucks in terms of capacity, time, quality, and cost sensitivity. This stage is formulated as a matching problem. In the second stage, the assigned trucks should deliver the cargo to different destinations considering the delivery route and pricing decisions of the platform. This stage is formulated as a routing problem. The assumptions made in the development of the model are as follows:

(1) All shipments have one single pickup point and multiple delivery points,

(2) Distances are exogenous (inputs for the model),

(3) Traffic is not considered in the model,

(4) The quality of the carrier's service is indicated by a quantitative index (service score). Freight platforms will use feedback from shippers, such as Amazon's customer reviews, to determine this score for each carrier.

(5) Shippers could set the minimum carrier service score they are willing to accept, such as the ability to only choose products with four star or more in Amazon.

(6) Carries could specify the maximum cost that they are willing to accept. For our simplicity, we consider this value as the average of fixed and variable costs of all carriers.

The mathematical notations are depicted in Tables 3, 4, 5, and 6. Then, the multistage linear programming model is explained.

Table 3. Set

Sets	Description
I	Set of cargos
J	Set of trucks
K_i	Set of destinations for cargo i except origin and end point,
K'_i	Set of destinations for cargo i
R	Set of stairs (price structure)
S	Subset of K_i

Table 4. Parameters

Parameters	Description	Units
q_i	Weight of the cargo *i*	Ton
b_j	Capacity of truck *j*	Ton
d_{ij}	Distance between the pick-up point of the origin of cargo *i* and the position of truck *j*	mile
$d'^{i}_{k,k'}$	Distance between the destination k, k' of cargo *i*	mile
$\tau_i^{cargo\_min}$	Earliest acceptable time for picking up cargo *i*	Time
$\tau_i^{cargo\_max}$	Latest acceptable time for picking up cargo *i*	Time
$\tau_j^{truck\_min}$	Earliest available time of truck *j*	Time
$\tau_j^{truck\_max}$	Latest available time of truck *j*	Time

Parameters	Description	Units
$\pi_i^{cargo\_min}$	Earliest acceptable day for picking up cargo *i*	Time
$\pi_i^{cargo\_max}$	Latest acceptable day for picking up cargo *i*	Time
$\pi_j^{truck\_min}$	Earliest available day of truck *j*	Time
$\pi_j^{truck\_max}$	Earliest available day of truck *j*	Time
α_j	Starting fare	$
${\beta_j}^r$	Extra charge rate of stair *r*	$
d_{max}^r	Critical distance of stair *r*	mile
p_j	Platform price offered to the truck j	$
c_j^{fix}	Fixed cost of truck j	$/mile
c_j^{var}	Variable cost of truck j	$/mile
s_j	Service score of truck *j*	Index
η_i^{acc}	Minimum acceptable service score for shipper with cargo *i*	Index

Table 5. Decision variables

Variables	Description
X_{ij}	1 if cargo i is matched with truck j; 0 otherwise
$\mathrm{X'}_{ijkk'}$	1 if arc (k, k') is done by truck j for cargo i; 0 otherwise

Table 6. Auxiliary variables

Variables	Description
Y_{ij}	1 if $\tau_i^{cargo\_min} \leq \tau_j^{truck\_min} \leq \tau_i^{cargo\_max}$ OR $\tau_i^{cargo\_min} \leq \tau_j^{truck\_max} \leq \tau_i^{cargo\_max}$; 0 otherwise
Z_{ij}	1 if $\pi_i^{cargo\_min} \leq \pi_j^{truck\_min} \leq \pi_i^{cargo\_max}$ OR $\pi_i^{cargo\_min} \leq \pi_j^{truck\_max} \leq \pi_i^{cargo\_max}$; 0 otherwise

First stage (Matching)

Objective function

$$Maximize \ \sum_{i \in I} \sum_{j \in J} X_{ij} \tag{3}$$

Constraints

$$\sum_{i \in I} X_{ij} \leq 1 \qquad \forall\, j \in \mathrm{J} \tag{4}$$

$$\sum_{j \in J} X_{ij} \leq 1 \qquad \forall\, i \in \mathrm{I} \tag{5}$$

$$X_{ij}\big(b_j - q_i\big) \geq 0 \qquad \forall\, i \in \mathrm{I}, j \in \mathrm{J} \tag{6}$$

$$X_{ij}\big(s_j - \eta_i^{acc}\big) \geq 0 \qquad \forall\, i \in \mathrm{I}, j \in \mathrm{J} \tag{7}$$

$$X_{ij} d_{ij}\big(c_j^{fix} + c_j^{var}\big) \leq \frac{\sum_{j \in J} c_j^{fix} + c_j^{var}}{|J|}\, d_{ij} \quad \forall\, i \in \mathrm{I}, j \in \mathrm{J} \tag{8}$$

$$X_{ij} \leq \frac{Y_{ij} + Z_{ij}}{2} \qquad \forall\, i \in \mathrm{I}, j \in \mathrm{J} \tag{9}$$

$$X_{ij} Y_{ij}, Z_{ij} \in \{0,1\} \qquad \forall\, i \in \mathrm{I},\ j \in \mathrm{J} \tag{10}$$

The objective function of the first stage (3) maximizes the total number of matchings. This objective is inspired by Masoud and Jayakrishnan (2017a) and is a logical objective for resource-sharing platforms in their infancy. Constraints (4) ensure that each truck could be matched with at most one cargo. Constraints (5) ensure that each cargo could be matched with at most one truck. Constraints (6) concern the capacity constraint of trucks. The threshold required quality of the cargo's shipper could be satisfied using constraints (7). Constraints (8) ensure that the carrier's total cost including fixed and variable travel costs of trucks should be less than or equal to less than or equal to the maximum acceptable cost of carriers. Constraints (9) guarantee the availability of trucks within the acceptable time interval of the cargo's shipper. Constraints (10) ensure that variables are binary.

Second stage (Routing and Pricing)

Objective function

$$Minimize \sum_{\boldsymbol{i}\in \boldsymbol{I}} \sum_{\boldsymbol{j}\in \boldsymbol{J}} \sum_{\boldsymbol{k},\boldsymbol{k'} \in \boldsymbol{K'}_{\boldsymbol{i}}, \boldsymbol{k}\neq \boldsymbol{k'}} d'^{i}_{kk'} X'_{ijkk'} \tag{11}$$

Constraints

$$\sum_{\boldsymbol{k},\boldsymbol{k'} \in \boldsymbol{K'}_{\boldsymbol{i}}, \boldsymbol{k}\neq \boldsymbol{k'}} X'_{ijkk'} = (|K'_i| - 1)X_{ij} \qquad \forall\, i \in I, j \in J \tag{12}$$

$$\sum_{\substack{k' \in K'_i \\ k' \neq s}} X'_{ijsk'} = X_{ij} \qquad \forall\, i \in I, j \in J \tag{13}$$

$$\sum_{\substack{k \in K'_i \\ k \neq e}} X'_{ijke} = X_{ij} \qquad \forall\, i \in I, j \in J \tag{14}$$

$$\sum_{\substack{k \in K_i \\ k \neq k'}} X'_{ijkk'} - \sum_{\substack{k \in K_i \\ k \neq k'}} X'_{ijk'k} = 0 \qquad \forall\, i \in I, j \in J, k' \in K_i \tag{15}$$

$$\sum_{\substack{k,k' \in K_i \\ k \neq k'}} X'_{ijkk'} \leq |S| - 1 \quad \forall\, i \in I, j \in J, and \;\; 2 \leq |S| \leq |K_i| - 1 \tag{16}$$

$$X'_{ijkk'} \in \{0,1\} \qquad \forall\, i \in I, j \in J, k, k' \in K'_i \tag{17}$$

The objective function of the second stage (11) minimizes the total traveled distance deliveries. Constraints (12) define the relationship between the first two decision variables and mean that a truck could travel between destinations of a cargo only if it is matched with that cargo. Constraints (13) and (14) ensure trucks start from an appointed pick-up point (origin) and end at the virtual end node respectively. The one-to-one connection between a vertex and the next vertex on the route is guaranteed by constraints (15). Constraints (16) assure that there is no sub-tour along the route. Constraints (17) guarantee that the decision variable is binary. Finally, we consider a stair-step structure for the platform's price. The relationship between the price and the route distance is depicted in equation (18).

$$p_j = \begin{cases} \alpha_j & 0 < \sum_{i\in I}\sum_{j\in J}\sum_{l,k\in K'_i, l\neq k} d'^{i}_{l,k} X'^{ij}_{kl} \le d^0_{max} \\ \alpha_j + \beta^1_j\left(\sum_{i\in I}\sum_{j\in J}\sum_{l,k\in K'_i, l\neq k} d'^{i}_{l,k} X'^{ij}_{kl} - d^0_{max}\right) & d^0_{max} < \sum_{i\in I}\sum_{j\in J}\sum_{l,k\in K'_i, l\neq k} d'^{i}_{l,k} X'^{ij}_{kl} \le d^1_{max} \\ \alpha_j + \sum_{r=1}^{R-1}\beta^r_j(d^{r+1}_{max} - d^r_{max}) + \beta^N_j\left(\sum_{i\in I}\sum_{j\in J}\sum_{l,k\in K'_i, l\neq k} d'^{i}_{l,k} X'^{ij}_{kl} - d^{r-1}_{max}\right) & d^{r-1}_{max} < \sum_{i\in I}\sum_{j\in J}\sum_{l,k\in K'_i, l\neq k} d'^{i}_{l,k} X'^{ij}_{kl} \le d^r_{max} \end{cases} \tag{18}$$

5. Numerical Example and discussion

The mathematical model, data analysis, data generation, and decision plan windows were implemented using Pulp v2.6, scikit-learn v1.0.2, prince v0.7.1, and PySimpleGUI v4.60.3 software packages and accessed using the python interface. All tests were carried out on a computer with an Intel® Core (TM) i5-10210U, CPU@ 1.60GHz processor, and 12 GB of RAM.

5.1.Data

The proposed methodological framework is tested using the modified version of Solomon's 100 customer (C101) Vehicle Routing Problem with Time Window (VRPTW) benchmark instances. More specifically, Solomon's 100 customers benchmark includes shippers along with their origin coordinates, demand, and time window intervals (Solomon, 1987). Time window intervals of C101 were converted to time stamps in our calculations. For instance, if a shipping request has 912 as the earliest time and 967 as the latest time, those times were considered as 3:12:00 PM and 4:07:00 PM of the same day, respectively. Due to the lack of available data sets containing the required features related to shippers, some simple assumptions were made to artificially generate additional attributes. For each cargo, three different destination points located within 100 km of the origin were assumed. Uniform distribution (1,10) was considered for the minimum acceptable service scores of shippers (1,10). Two types of trips (shorthaul and long haul), and three types of vehicles (Flatbed, Dryvan and Reefer) were considered. Trip and vehicle preference as well as price sensitivity were generated randomly. Three groups of shippers were considered to categorise the sensitivity of shippers to price: those who won't accept price increases and those who can afford increases of 5% and 10%.

Attributes for 50 freight service providers have also been generated artificially with respect to the features of cargo owners. Tables 7 and 8 clearly present the synthesized part and Solomon part of the dataset used in this study.

Table 7. First 10 lines of shippers' dataset

Solomon						New features (Synthetic)										
ID	Long origin	Lat origin	Weight	Earliest	Latest	Sensitive	Type Vehicle	Type Trip	Service Score	Long dest1	Lat dest1	Long dest2	Lat dest2	Long dest3	Lat dest3
C1	45	68	10	912	967	0%	FLATBED	SHORT	8	44.51	68.62	44.67	68.23	45.21	68.41
C2	45	70	30	825	870	0%	FLATBED	LONG	1	44.81	69.17	45.73	69.75	44.64	69.26
C3	42	66	10	65	146	10%	DRYVAN	SHORT	2	41.14	65.84	42.00	65.42	41.28	66.21
C4	42	68	10	727	782	10%	DRYVAN	LONG	5	42.57	67.75	41.64	67.31	41.79	68.24
C5	42	65	10	15	67	10%	DRYVAN	LONG	7	41.34	65.58	42.38	65.72	42.07	65.54
C6	40	69	20	621	702	0%	FLATBED	LONG	10	39.61	69.42	39.62	68.79	40.63	69.37
C7	40	66	20	170	225	0%	DRYVAN	SHORT	2	40.53	65.90	39.54	65.35	40.35	66.05
C8	38	68	20	255	324	0%	REEFER	SHORT	10	38.63	67.44	37.90	67.68	37.87	68.36
C9	38	70	10	534	605	0%	DRYVAN	LONG	6	37.33	69.45	38.60	69.45	37.68	69.52
C10	35	66	10	357	410	0%	FLATBED	SHORT	6	35.03	66.38	35.32	65.40	35.06	66.60

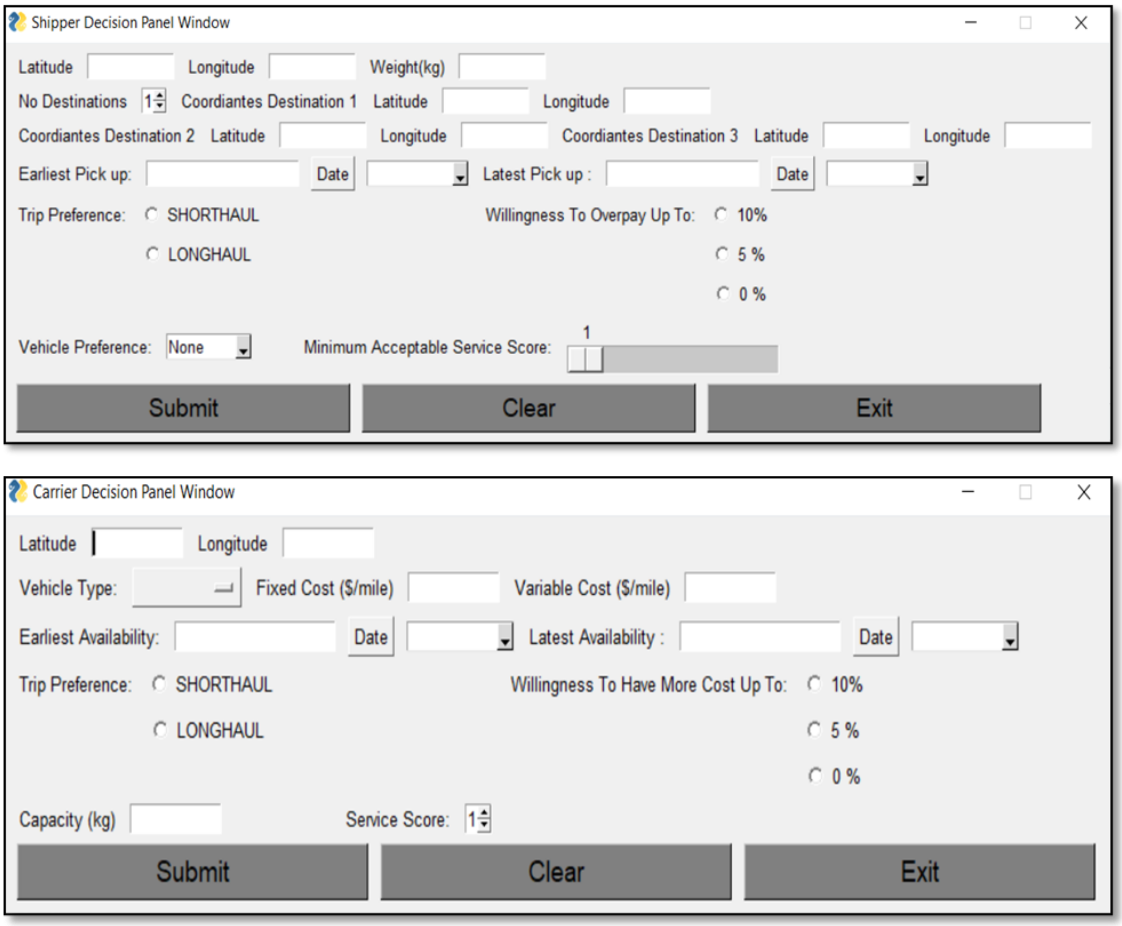
Table 8. 10 first line of carriers' dataset

Synthetic											
ID	Long	Lat	Earliest	Latest	Sensitive	Type Vehicle	Tripe Type	Service Score	Capacity	Fixed cost	Variable cost
T1	25	85	412	423	10%	FLATBED	SHORT	9	10	0.29	0.31
T2	22	85	408	551	0%	DRYVAN	SHORT	1	50	0.34	0.35
T3	20	85	923	1018	5%	REEFER	LONG	2	10	0.31	0.33
T4	15	75	26	546	5%	FLATBED	LONG	8	10	0.32	0.43
T5	10	35	40	953	10%	REEFER	SHORT	4	30	0.35	0.36
T6	8	40	545	651	0%	FLATBED	SHORT	8	50	0.35	0.29
T7	5	35	1036	1041	0%	REEFER	LONG	8	10	0.38	0.29
T8	2	40	365	547	10%	REEFER	LONG	5	50	0.31	0.38
T9	0	45	41	1097	10%	DRYVAN	LONG	1	50	0.34	0.3
T10	42	10	517	692	0%	REEFER	LONG	3	10	0.36	0.42

5.2.Entering information (Step 1)

Based on the first step of the methodological framework (see Figure 2) carriers and shippers need to enter their information into the freight-sharing platforms. An example of platforms' interfaces for shippers and carriers is given in Figure 3.

Figure 3. Freight Platform Interface (A) Shipper (B) Carrier



5.3. Results of the data analysis (Step 2)

To reduce the complexity of decision-making and segmenting the freight platform customers, two-part data analysis was applied to synthesized data sets including both categorical (vehicle type, trip preference, and price sensitivity) and numerical (origin coordinates) features. First, MCA was applied to reduce the dimensionality of the data set and illustrate its underlying structure. The MCA analysis for categorical attributes of the data set is plotted in Figure 4. The plot shows that the categories with the same attribute that are close to one another share more similarities than the categories with the same attribute that are far apart. As an example, the plot shows that customers who prefer the Flatbed vehicle type are far away from those who prefer Dryvan or Reefer. Customers who prefer the Dryvan vehicle are more interested in Shorthaul trips and are more price sensitive.

In the following, the K-means clustering algorithm was employed to cluster carriers and shippers considering their geographical location. The optimal number of clusters was determined with the assistance of the elbow method and Within-Cluster Sum-of-Squares (WCSS). WCSS evaluates the sum of the squared distance between each point and the centroid of each cluster (Cui, 2020). Results of the elbow method and k-means clustering are given in Figures 5 and 6 respectively. Figure 5 demonstrates how the WCSS value will start to drop as the number of clusters increases. The graph has an elbow and moves almost parallel to the X-axis when the number of clusters equals 3. The optimal number of clusters is displayed at the elbow point. In Figure 6, three clusters are shown in different colors, and the centroid and center of each cluster are represented by triangles. The location of shippers and carriers are shown using circles and stars, respectively.

Caliński and Harabasz's (1974) index is used to validate the results of the clustering approach. This index evaluates the ratio of between-cluster variance to within-cluster variance and can be calculated as follows (equation 19):

$$F = \frac{(BSS)/(K-1)}{(WSS)/(N-K)} \tag{19}$$

where, N is the total number of points, K is the number of clusters, BSS is the between-clusters sum of squares, and WSS is the within-cluster sum of squares. The within-cluster variance gauges how closely clusters fit together. The between-clusters variance calculates how far apart the clusters are from one another. Greater values of this index indicate dense and well-separated clusters. The F index is equal to 120.37 which indicates the acceptable quality of the clustering results.

Figure 4. MCA analysis of categorical attributes

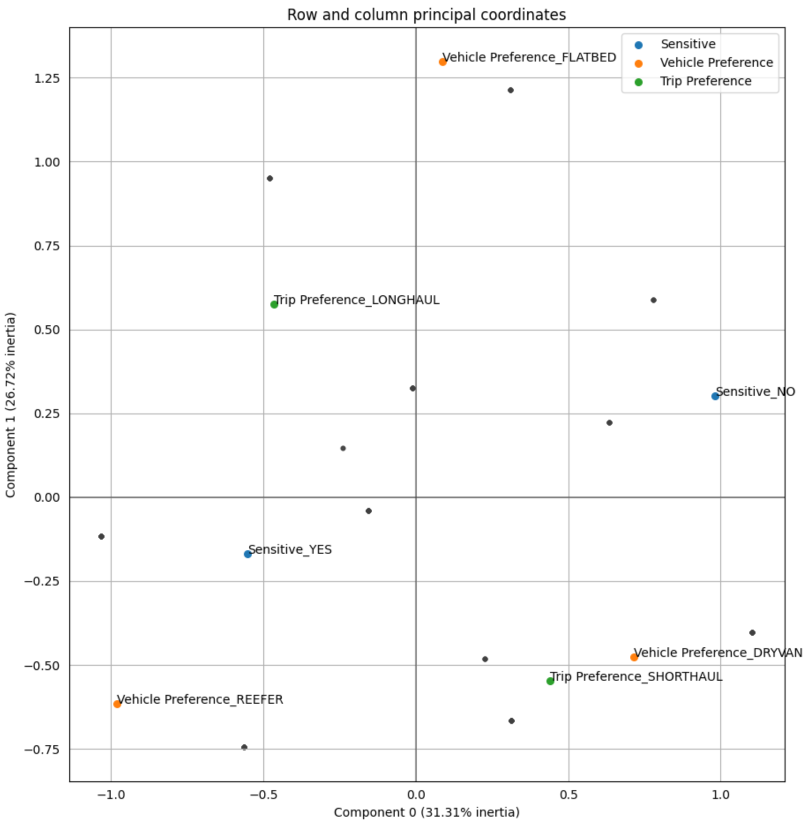


Figure 5. Results of the elbow method

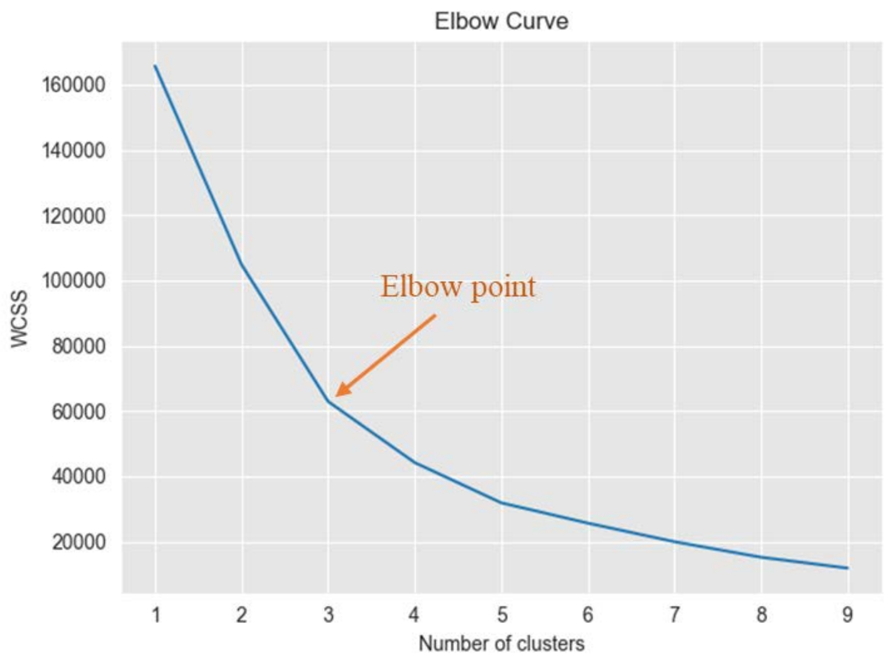
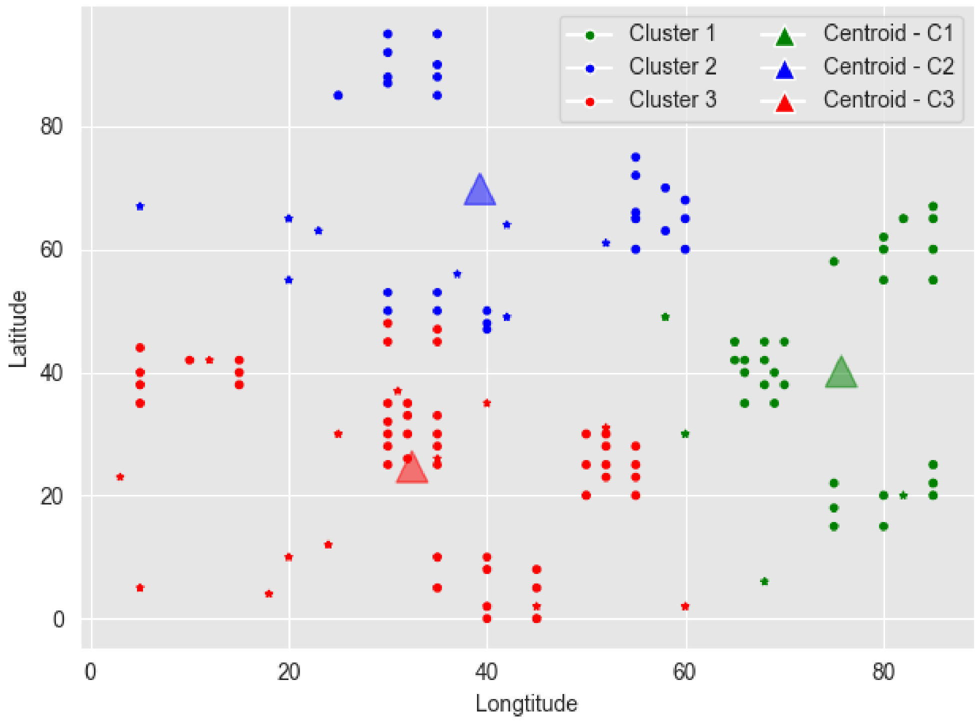


Figure 6. Result of the k-means clustering

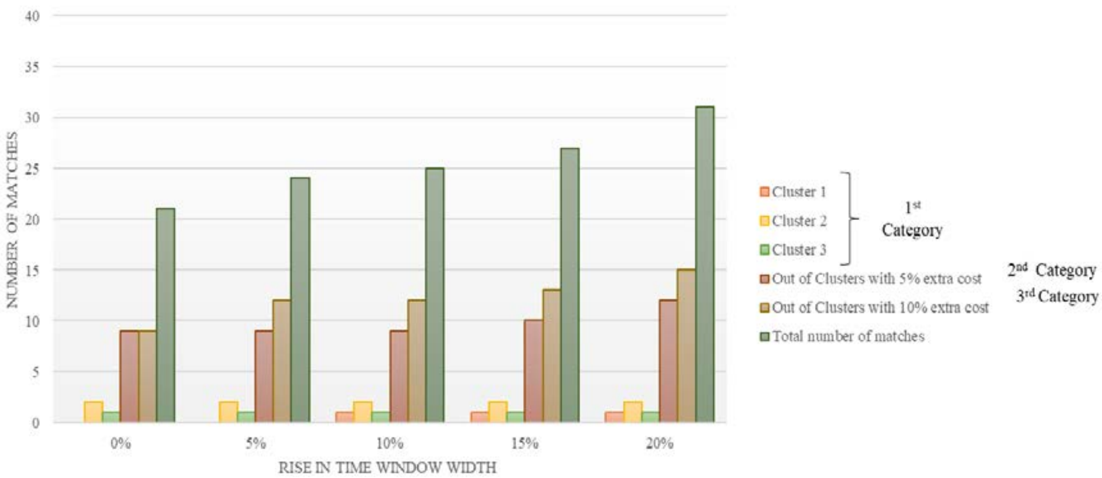


5.4.Results of the matching process (Step 3)

The obtained result for the matching process is 21 matches. 14% of the proposed matches are 100% compatible with the preference of shippers in terms of the type of trip and vehicle. 66% and 57% of the matches are different in terms of the type of trip and the type of vehicle which shows the potential of the proposed optimization model to identify possible solutions with minor deviations of preference. These percentage may result from the randomness of the data and the dataset's size. For larger datasets, higher compatibility percentages can be expected.

A sensitivity analysis is carried out to assess the sensitivities of the objective function to the input values. The number of matches given in rectangular bars with varying time window widths (Figure 7). These bars can be classified into three main categories. The first category represents the number of matches in three predetermined clusters including carriers and shippers that are sensitive to extra cost or price. The second category indicates the number of matches for carriers and shippers that are compatible with up to 5% extra cost or price. The last rectangular bar for each time window length displays the number of matches between carriers and shippers with an approval level of up to 10% for price and cost. The final category shows the total number of matches. A 14% to 48% higher matching rate is also seen in this figure as a result of raising the shippers' latest acceptable time from 5% to 25%. It can be concluded that the matching process is sensitive to changes in the acceptable time interval width of shippers. By relaxing the time constraint, the total matching increased to 36 matches.

Figure 7. Sensitivity analysis for time window width of shippers



5.5.Results of the routing and pricing process (Step 4)

The results for the routing and pricing process including the total traveled distance, sequence of deliveries, and the minimum platform price are given in Table 9. Price was determined using a staircase structure with 4 stairs respectively 40,80,100, and 150 miles. By minimizing the traveled distance using a VRP model, we could ensure that the minimum platform price was provided. Similar to the results of the matching process, results of the routing and pricing process are provided in three different categories. As can be seen in the first row of the first category, the carrier (T6) should deliver cargo (C45) to three different destinations. According to the results of the routing and pricing process, T6 should visit delivery locations 2,3, and 1 of C45 respectively, to obtain the minimum distance traveled. The total traveled distance of 71.89 miles is calculated for this delivery which requires the second step of the staircase pricing structure to determine the platform price. Although the second and third categories of the results showed higher prices for carriers and shippers compatible with up to 5% and 10% extra cost or price compared to the traveled distance, it can still be assured that the minimum surcharge is provided using a VRP model.

Table 9. Results of routing and pricing process

Category	Matches	1st Delivery	2nd Delivery	3rd Delivery	Traveled Distance (Miles)	Recommended Price ($)
1	C45-T6	2	3	1	71.89	347.03
	C49-T7	1	2	3	63.06	267.54
	C1-T23	2	3	1	59.37	234.34
2	C32-T17	2	3	1	94.2	505.2
	C43-T4	3	1	2	69.3	323.71
	C44-T46	3	1	2	69.63	326.73
	C47-T41	3	2	1	133.66	674.64
	C55-T32	2	1	3	132.98	671.95
	C17-T48	1	2	3	94.09	504.59
	C67-T42	2	3	1	130.54	662.19
	C80-T27	2	3	1	142.36	709.47
	C90-T43	3	1	2	76.43	387.94
3	C21-T5	3	2	1	132.9	671.63
	C50-T30	3	1	2	65.14	286.31
	C59-T11	3	2	1	144.25	717.03
	C3-T28	3	1	2	88.51	471.1
	C14-T16	1	2	3	91.74	490.44
	C16-T50	2	1	3	74.2	367.81
	C75-T25	1	2	3	117.36	609.47
	C93-T31	2	1	3	31.64	60
	C83-T14	2	3	1	71.73	345.61

5.6.Results of Steps 5,6, and 7

The platform would inform carriers and shippers regarding previous results (steps 3 and 4), and they could provide their feedback to finalize the process or revise their preferences and other features such as acceptable time widows and service scores.

5.7.Discussion

Testing the proposed methodological framework in this study, show how this framework could address the standpoints of different freight market actors in matching decisions and at the same time provide customized prices considering the customers' particular circumstances. By focusing on different standpoints, we could help freight-sharing platforms offer available actors in the freight market win-win solutions and prevent long-term market share loss. We also compared the results of this framework with and without step 2 (data analysis) to verify the role of this step in harnessing the computation complexity of the decision-making. These results showed that this step could improve the computation time significantly (from 65.17 sec to 22.28 sec) without much loss of quality. These results agree and align with other studies such as (Li & Chung, 2020).

6. Research implications

The proposed methodological framework offers the opportunity to integrate pillars of sustainability (including economic, and environmental pillars) into the core business activities of freight-sharing platforms. This could help manage freight transport operations more efficiently. Owners of freight-sharing platforms would benefit from more customers being served which can be translated into greater profits. From the standpoint of carriers, improving freight operations could result in cost minimization. From the shippers' perspective, greater efficiency could be defined as receiving more qualified services. Finally, from a societal standpoint, improving transport efficiency could translate into reduced environmental impacts and GHG emissions.

7. Conclusion and future research

Freight resource-sharing platforms have been recently introduced in the freight market to coordinate arrangements between customers and transport resource providers using the Internet and web-based platforms. These platforms aim to improve the efficiency of the freight industry by reducing logistics costs and environmental impacts and offering more transparency to both sides of the market. The most critical decisions that these platforms will have to make are matching and pricing. In this paper, we presented a methodological framework using data analysis and optimization techniques to help smart freight platforms jointly optimize matching and pricing decisions on large-scale. The multi-actor integrated matching and pricing model was formulated using a multistage linear programming model to address the standpoints of existing freight market actors including smart freight platforms, carriers, and shippers.

Using our proposed methodological framework, platform owners will be able to coordinate arrangements in the freight market in a more robust, sustainable, and efficient way. They can encourage more carriers and shippers to use their platforms and gain more market share by providing win-win solutions to both carriers and shippers. Our proposed methodological framework can also bring environmental benefits to the whole city by addressing sustainability aspects in routing decisions and its attempts to reduce traveled distances.

The most important limitation of this study is having access to data sources. Compared to the urban transportation context, databases related to freight transportation are very limited and we did not have access to them. The current study can be improved by considering stochastic parameters such as traffic conditions and dynamic distance-based pricing policy. Future research could be in two main directions. On one stream, the dynamic matching problem could be investigated to respond to emerging events using new and updated information. On the other hand, introducing new learning-based pricing policies could be studied to respond to market fluctuations and facilitate trading mechanisms.

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