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POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

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

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Mémoire présenté en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

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Ce mémoire intitulé :

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présenté par **Marjan PADIDAR**

en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

a été dûment accepté par le jury d'examen constitué de :

Martin TRÉPANIER, président

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DEDICATION

To all the brave women in Iran, who are risking their lives every day and night to fight for their freedom. To my husband and my parents who with love and effort have accompanied me in this process, without hesitating at any moment of seeing my dreams come true, which are also their dream.

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RÉSUMÉ

Le marché du fret joue un rôle important dans les économies nationales, régionales et mondiales, ce qui affecte tous les autres secteurs économiques. Ce marché est complexe et dynamique et doit s'adapter aux conditions et tendances politiques, sociales et économiques en évolution rapide. Des plateformes de partage des ressources de fret ont été récemment introduites dans ce marché pour coordonner les ententes entre les clients et les fournisseurs de ressources de transport utilisant l’Internet et les différentes plateformes Web. Le recours à ces plateformes vise à améliorer l'efficacité de l'industrie du transport du fret en réduisant les coûts logistiques et les effets environnementaux négatifs et en offrant plus de transparence aux différents intervenants. Ces plateformes permettent de collecter un grand volume de données en temps réel et d’appliquer des modèles d'optimisation et d'intelligence artificielle pour l'analyse des données et la prise de décision.

La littérature sur les plates-formes de fret intelligentes peut être classée en trois thèmes essentiels : (1) les avantages environnementaux de ces plates-formes, (2) décisions d’allocation de ressources (3) décisions de fixation de prix

Notre recherche a révélé plusieurs lacunes dans la littérature que nous proposons de combler. Un domaine de recherche récent consiste à évaluer les avantages environnementaux des plateformes intelligentes de partage de fret. Ce sujet n'a pas encore été étudié à l'aide d'une étude de cas au Canada. Pour combler cette lacune, nous fournissons une évaluation de la durabilité basée sur des scénarios pour les flux de marchandises au Québec en 2021, basée sur la base de données du Cadre d'analyse du fret canadien.

Nous constatons également une lacune dans la littérature concernant d’allocation de ressources et de fixation intégrées dans les plateformes de partage de fret. La littérature n'aborde pas les problèmes d’allocation de ressources multi-acteurs et de fixation de prix à grande échelle. Pour tenter de combler l'écart, nous développons une approche hybride pour aider ces plates-formes à optimiser conjointement les décisions d’allocation de ressources et de fixation intégrées à grande échelle. L'approche proposée comprend sept étapes. La première étape concerne la collecte de données sur l'offre et la demande. À l'étape 2, une méthode d'analyse des données en deux étapes est proposée pour réduire la complexité de la prise de décision. Tout d'abord, en utilisant l'analyse des correspondances multiples (MCA), les positions des coordonnées spatiales des variables catégorielles sont déterminées. Ensuite, un algorithme K-means est utilisé pour regrouper les transporteurs et les expéditeurs en fonction de leurs emplacements géographiques. Les étapes 3 et 4 incluent les moteurs d'optimisation de décisions d’allocation de ressources et de fixation de prix. Ces moteurs d'optimisation aident à déterminer les prix, les itinéraires de livraison et les correspondances de la plateforme dans des espaces d'optimisation prédéterminés. La fourniture de commentaires aux clients est envisagée à l'étape 5. L'étape 6 consiste à évaluer la satisfaction des clients. Enfin, l'étape 7 est liée à la finalisation des décisions.

Les résultats de cette recherche incluent : (1) le potentiel des plateformes de fret intelligentes pour réduire les émissions de gaz à effet de serre du fret, et (2) la recommandation d'une tarification personnalisée tout en s'adressant aux acteurs existants du marché du fret dans les décisions d'appariement

ABSTRACT

The freight market plays an important role in national, regional, and global economies, which affects all other economic sectors. This market is complex and dynamic and needs to adapt to rapidly changing political, social, and economic conditions and trends. Freight resource-sharing platforms have been recently introduced in this 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. They collect a vast amount of real-time data and then apply optimization models and artificial intelligence for data analysis and decision-making.

The literature on smart freight platforms can be classified into three essential themes: (1) the environmental benefits of these platforms, (2) freight matching, and (3) pricing.

Our research has revealed several gaps in the literature. First, A recent field of research involves assessing the environmental advantages of smart freight-sharing platforms. This topic has not yet been studied using a case study in Canada. To address this gap, we provide a scenario-based assessment for commodity flows in Quebec in 2021 based on the Canadian Freight Analysis Framework database.

The second gap is joint matching and pricing in freight-sharing platforms. The literature does not address large-scale joint multi-actor matching and pricing problems. In an attempt to address the gap, we develop a hybrid approach to help these platforms jointly optimize matching and pricing decisions on large-scale. 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. First, using the multiple correspondence analysis (MCA), spatial coordinate positions of categorical variables are determined. Then, a K-means algorithm is used to cluster carriers and shippers considering their geographical locations. Steps 3 and 4 include matching and pricing optimization engines. These optimization engines help to determine the platform's prices, delivery routes, and matches within predetermined optimization spaces. Providing customers with feedback is considered in step 5. Step 6 involves assessing customer satisfaction. Finally, step 7 is related to finalizing the decisions.

The outcomes of this research include: (1) the potential of smart freight platforms in reducing freight greenhouse gas emissions, and (2) recommendations for customized pricing while also addressing the existing freight market actors in matching decisions.

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LIST OF SYMBOLS AND ABBREVIATIONS

ANN	Artificial Neural Network
AOA	Anticipatory Optimization Approach
CAFA	Canadian Freight Analysis Framework (CAFAF)
CP	Cyber Physical
DQNs	Deep Q Networks
GA	Genetic Algorithm
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GPS	Global Positioning System
ICT	Information and Communications Technology
ILP	Integer Linear Programming
LSVRP	Large-Scale Vehicle Routing Problems
MCA	Multiple Correspondence Analysis
MCMF	Minimum Cost Maximum Flow
MDP	Markov Decision Process
MILP	Mixed-Integer Linear Programming
ML	Machine Learning
MSP	Multistage Stochastic Programming
NLP	Non-linear Programming
PCA	Principal Component Analysis
RFID	Radio-Frequency Identification
RH	Receding Horizon

RL	Reinforcement Learning
SARSA	State-Action-Reward-State-Action
SR	Starting fare and extra charge Rate
ST	Step Toll
SVM	Support Vector Machine
VRP	Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time Window
WCSS	Within-Cluster Sum-of-Squares

CHAPTER 1 INTRODUCTION

1.1 Context

The Freight transportation and distribution of goods affect the performance of almost all other economic sectors and need to adapt to rapidly changing political, social, and economic conditions and trends. In Canada, road transportation is the main mode to move food products and manufactured goods. “Ontario and Québec have the busiest road border crossings in Canada, especially in the Ontario region where manufactured goods will cross and re-cross the border with the U.S”. Reports represented that trucking transportation accounted for more than 30% of the sector's share of GDP in Canada [1]. Road transportation (including personal transportation and freight transportation) also causes the most transport emissions. Trucks are the main source of freight transportation emissions in Canada, accounting for 87% of all freight emissions. By 2030, it has been estimated that they would become the main source of transportation emissions [2].

The freight market is complex and dynamic, and it encounters several challenges such as ineffective operations, coordination problems, and a lack of shipment visibility. Traditional freight companies particularly suffer from information asymmetry issues, which results in low freight efficiency and high logistics cost [3]. The increasing complexity of transportation chains triggered the emergence of new business models of freight transportation [4]. New opportunities have been identified to grow new business models in a global virtual environment. Thanks to the development of the Internet and information technology freight resource-sharing platforms have been developed to coordinate arrangements between customers and transport resource providers [5]. By offering visibility and integration across multiple actors, smart freight platforms could manage the transport process regardless of which carriers or shippers are involved [4]. These platforms could provide intelligent freight matching, accurate price matching, safe and optimized routes for trucks, and multiple destination deliveries [3]. They could also help to achieve more efficient, safe, secure, and sustainable transportation using new technologies such as Information and Communications Technology (ICT), Cyber-Physical (CP) technologies, radio-frequency identification (RFID), etc. [6].

The literature on smart freight platforms can be classified into three essential themes: (1) the environmental benefits of these platforms, (2) freight matching, and (3) pricing.

Studies on freight transportation have mostly focused on how new technologies have affected the reduction of greenhouse gas (GHG) emissions. The combination of GPS and vehicle sensors, according to earlier studies, could improve transportation efficiency while reducing costs [7]. In the case of truck platooning, cruise control systems may also result in reduced fuel use [8]. Additionally, it has been demonstrated in the literature that 1% adoption of Cyber-Physical technologies in the freight sector would be equivalent to GHG emissions savings from 46,930 passenger vehicles for one year [6]. [9] showed how smart freight platforms could reduce CO_2 emissions in road freight by reconstructing the demand and supply with integration technology. Evaluating the environmental benefits of freight-sharing platforms has not received much attention in the literature, despite the fact that they are crucial to the sustainability of cities and urban planning and could reduce emissions by maximising truck capacity utilisation, reducing traffic, and sharing potential. In this research, we try to address this gap by using a scenario-based analysis and a case study to demonstrate how smart freight platforms with various technologies could improve the sustainability of freight transportation.

The determination of prices and matches are the key decisions of the freight-sharing platforms. These decisions have a significant impact on the platform's profit and satisfaction of both sides of the market [10]. The prior literature on matching shippers (demand) with carriers (supply) considered the perspectives of just one [11–14] or, at most, two of the available actors in this market [15],[16]. The goal of the pricing problem in two-sided markets with an intermediary platform is to maximize the platform's profit [17],[18]. 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 [19], [20]. Recently, the importance of joint pricing and matching problem has been shown for ride-sharing platforms [21], [22]. This problem has been studied in the context of freight sharing with an emphasis on the perspective of carriers and a distance-based pricing policy [23]. In practice, freight sharing platforms need to consider more constraints in their decisions like time constraints and see the problem from the standpoints of all the actors in the market. Moreover, the complexity of large-scale joint pricing and matching decisions dealing with numerous transportation requests in a short period of time cannot be effectively addressed with existing models and need further research. To the best of our knowledge, there does not exist a study in the smart freight transportation field that investigates joint freight matching and pricing on a large scale while simultaneously taking into account the perspectives of various active participants in the freight market. This study tries aims to fill this gap using optimization and data analysis techniques.

1.2 Research objectives

This project aims to investigate how smart freight-sharing platforms can improve efficiency and sustainability in the freight market and create value to supply chain networks by optimizing matching and pricing decisions. The first objective of this study is to appraise the environmental benefits of smart freight platforms via a scenario-based approach. These scenarios aim to evaluate the total CO_2 saving resulting from the application of different technologies and features (such as connectivity technologies, optimization of routing, and sharing shipments) in smart transport platforms. The second objective of this study is to integrate multi-objective freight matching with a static pricing policy.

1.3 Research Contributions

This study proposes the following contributions via two articles corresponding to the research objectives:

Article 1: (Published in the proceedings of the Future Technologies Conference)

- The contribution of this paper is to evaluate the environmental benefits of a smart freight platform using the Canadian Freight Analysis Framework (CAFAF) database

Article 2: (Submitted to Journal of Transportation Planning and Technology)

- The main contribution of this paper is to integrate the freight matching problem with a distance-based pricing policy while addressing the perspectives of the available actors in the freight market for cargo matching.

- The development of a methodological framework using data analysis capabilities and optimization techniques to optimize decision-making in smart freight platforms is another contribution of this research.

Different elements of the two papers are given in Figure 1.1.

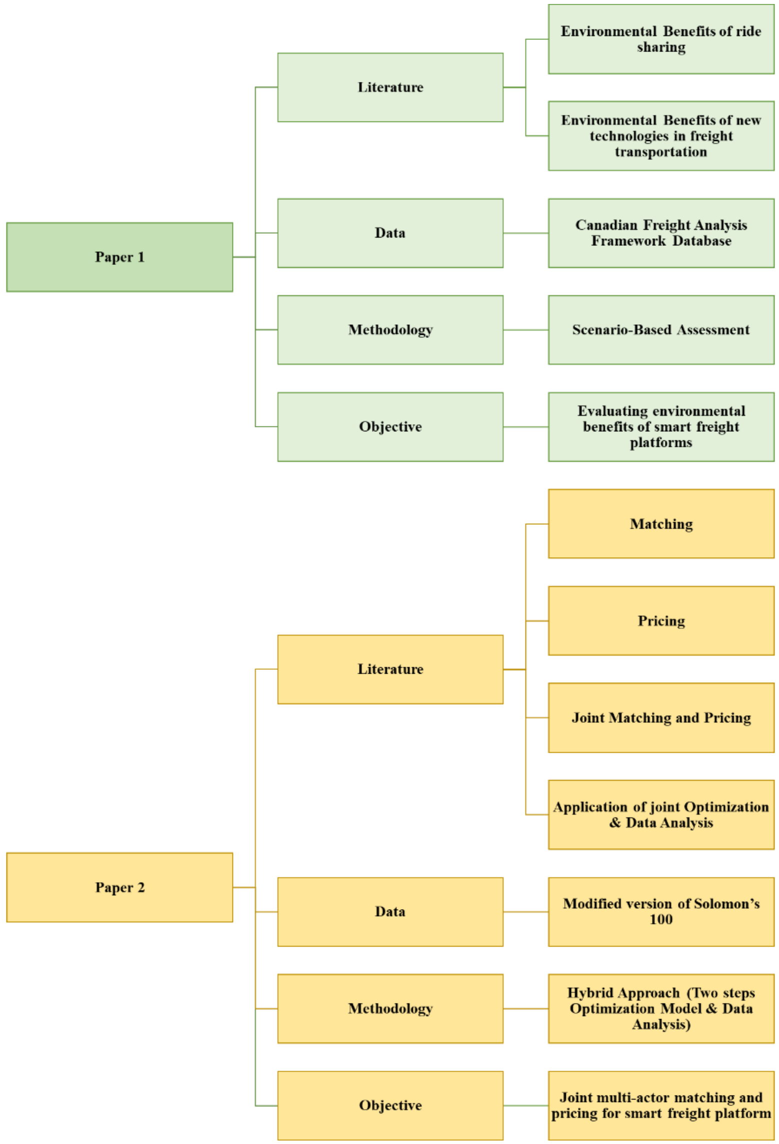

Figure 1-1. Elements of research papers

CHAPTER 2 LITERATURE REVIEW

First, we introduce ride-sharing and freight-sharing platforms in this section. Second, the study on environmental impact assessment, matching, pricing, and joint and matching problem for both platforms is reviewed. Finally, various techniques of multi-objective optimization and learning algorithms have been introduced, which could help in clarifying the methodology of this research. The literature review is presented with the structure given in Fig 2.1.

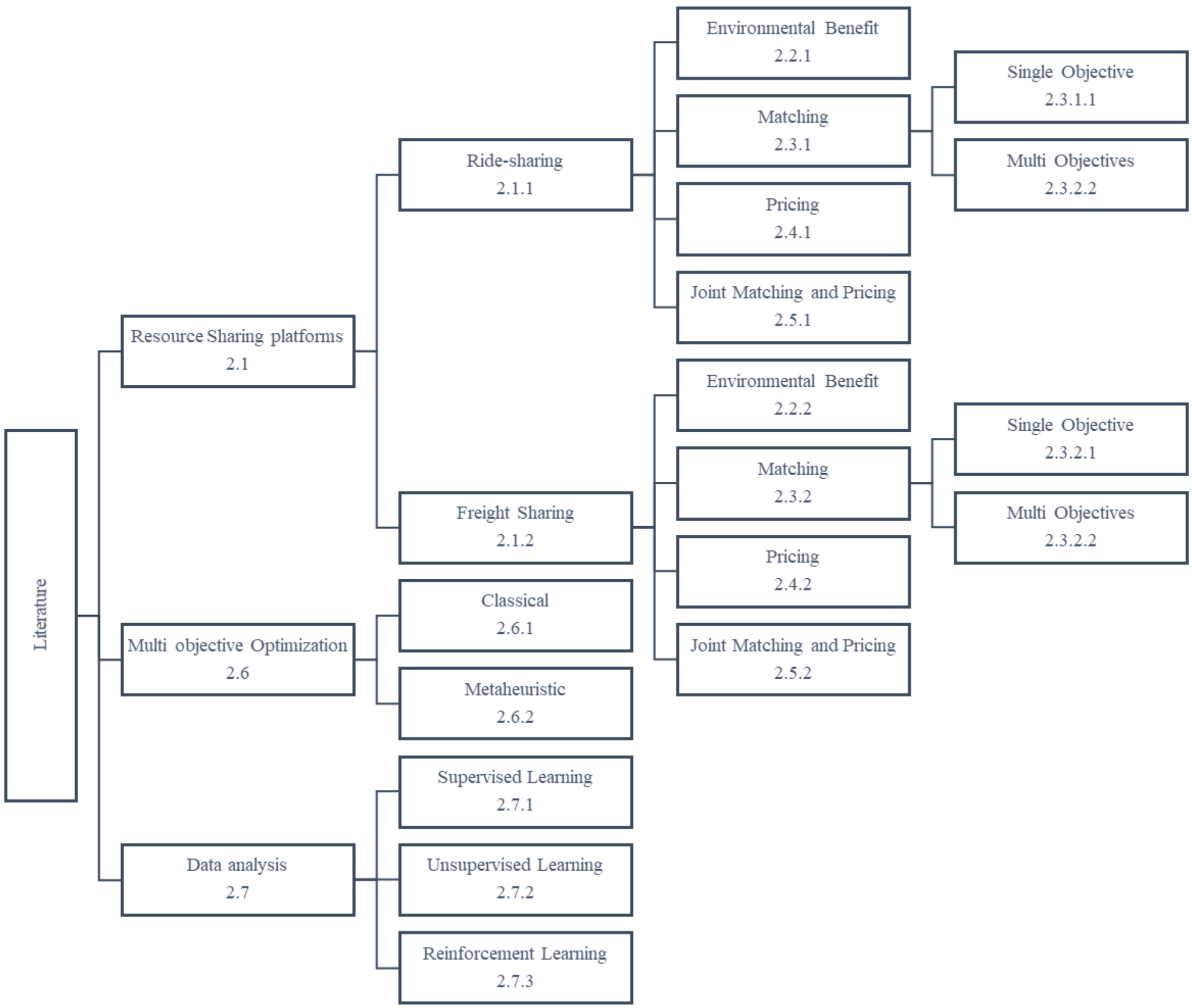

Figure 2-1. Structure of the literature review

2.1.1 Ride sharing platforms

The origin of ride-sharing can be traced back to World War II [24]. Ride sharing aims to promote sustainable transportation, reduce number of cars on the road, increase vehicle occupancy, and increase the number of people using public transportation. It is an innovative on-demand transport service facilitated by matching right drivers and passengers (supply and demand) through an intermediate platform [25]. Literature shows that the majority of the ride-sharing platforms operating in the EU (48%). Platforms located in the US and Asia made up 20% and 10% of all platforms, respectively, while 20% operate globally [26]. Uber and Lyft (USA), Ola (India), Grab (Southeast Asia), and Didi Chuxing (China) are some examples of ride-sharing platforms. Prior research on ride-sharing has mostly focused on ride-matching, pricing, and environmental benefits of ride-sharing [25].

2.1.2 Freight Sharing platforms

The business models of freight-sharing platforms and ride-sharing platforms are similar [27]. They use the Internet, cloud computing, and big data for connecting carriers and shippers and resolving issues like information asymmetry and low freight efficiency [3]. These platforms receive large sets of orders from large shippers and then re-distribute these orders among a set of other companies with actual transport capacity. These platforms provide one place for buying and selling transportation capacity through the internet. Both shippers and carriers have access to more business opportunities without requiring high advertising costs [28]. The determination of prices and matches are two key decisions of these platforms and have a significant impact on the platform’s profit and satisfaction of both sides of the freight market [10].

2.2 Assessment of environmental benefits

2.2.1 Environmental benefits of ride sharing platforms

Several studies have examined the environmental benefits of ride-sharing platforms in the literature. GPS data and data from mobile internet technologies have been used for these analyses. The census database and the logit model with the COPERT4 model were employed to show the environmental benefits of ride-sharing in Dublin [29]. A GPS log database and a multi-step approach have been applied to estimate emission reduction potential. The first stage is the motion detection mode to divide the moving and remaining segments. Then, a classification approach was used to segment traffic modes and vehicle types. A case study of the Tokyo area with over 1 million GPS travel records has been considered in this study. A learning-based approach was used to match feasibility, then two scenarios were considered to estimate the impacts of emission reductions. It has been concluded that, if half of the original public transit riders in their study case accept ride-sharing, CO_2 emission reduction by 84.52% would be achieved [30]. Taxi trajectory data in Shanghai and the COPERT 3 model were also applied to estimate the impacts of ride-sharing on traffic speed and emissions [31]. Similarly, trajectory data in Beijing, including vehicle ID, timestamp, GPS speed, and direction was used in another study. All shareable trips were identified based on time and distance constraints and resource availability. A matrix was developed to show the shareable journeys and extracted the travel economy to estimate the reduction in emissions [32]. Ride-sharing data and telephone surveys, along with life-cycle cost analysis were employed to show the environmental benefits of ride-sharing in Beijing [33]. The impact of several ride-sharing scenarios on travel conditions and CO_2 emissions in the Paris region were investigated. Effects of ride-sharing on the whole household decision process regarding transport and residential location were considered in this study. In addition to environmental benefits in the results, substantial rebound mechanisms were found [34].

2.2.2 Environmental benefits of freight sharing platforms

Studies related to freight transportation mostly addressed the impact of recent technologies on GHG emission reduction. New technologies such as the internet of things (IoT), cloud computing, and big data analysis tools provide opportunities to make logistic operations more intelligent and efficient [35]. RFID can collect and track different logistics data that can be used to optimize the transportation process [30]. GPS can be combined with RFID to monitor the transportation process [36]. Cloud computing can be applied to store, retrieve, and used the collected data by IoT technologies [37]. The massive data collected by IoT technologies need to be deeply learned to make further analysis and more intelligent decisions. These technologies bring many benefits to the freight sector, including real-time tracking and monitoring of transportation resources;

improving fleet management; optimizing vehicle configuration and routing; sharing traceability information [35]. A study demonstrated that how an Indian company gathered different logistics data including fuel, speed, acceleration, and coordinate data using vehicle sensors and GPS devices to improve transport efficiency and reduce costs [7]. According to [8] fuel consumption can be reduced by 7% in the context of truck platooning by using smart adaptive cruise control systems. The effect of smart GPS technologies on improving sustainability in the trucking industry of Tennessee has been also studied in the literature [6]. Integrating transport management and available technologies for freight tracking and vehicle monitoring are key factors to achieve more sustainable freight transportation [38].

A hierarchical conceptual framework has been developed to investigate how freight-sharing platforms could reduce CO_2 emissions using multiple data collection techniques including interviews, production observation, firsthand experience, and online-search summaries. This study focused on reconstructing the demand and supply with integration technology [9]. Although freight-sharing platforms play an essential role in the sustainability of cities and urban planning and could reduce emissions by maximizing truck capacity utilization, reducing traffic, and sharing potential, examining their environmental benefits has not received much attention in the literature.

2.2.3 Tools and Methods for Environmental Assessment

Tools and methods for evaluating the environmental impacts of shipping have been classified into three following categories: (1) procedural tools, (2) analytical tools, and (3) aggregated tools [39]. Examples of environmental assessment tools are presented in Table.

Table 2-1. Environmental Assessment Tools

Categories	Assessment tools	Objective	Reference
Procedural Tools	Environmental Impact Assessment	Identifying and evaluating the environmental impact of an action or activity in advance	[40]
	Multi-Criteria Decision Analysis	Exploring the balance between the pros and cons of different alternatives in terms of environmental impacts	[41]
	Risk Management	Making decisions for risk reduction initiatives by combining the results of the risk assessment with additional considerations	[42]
Analytical Tools	Life Cycle Assessment	Assessing environmental impacts connected with each step of a product or service's life	[43]
	Environmental Risk Assessment	Measuring the probability of a negative outcome from changes in environmental conditions	[44]
Aggregated Tools	Indicators, indices, Footprint	Providing a straightforward, understandable metric to monitor environmental condition	[39]

2.3 Matching in two-sided markets

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 for college admission and marriage problem (partner- partner) [45]. Matching problems are classified into three categories: 1) one-to-one matching 2) many-to-one matching, and 3) many-to-many matching [46],[47]. The one-to-one assignment can be modelled using a bi graph with two mutually exclusive sets of vertices and each member within a set can be matched to at most one member of the opposite set [48]. Many to one matching represents that at least one member of one set can be matched to multiple members of the opposing set, while in the other set, every member has exactly one match. Many-to-many matching allows at least one member within each of the two sets to be matched to more than one member in the other set [46]. This problem has been widely applied in different fields including display ads (keyword-advertiser) [49],[50] event arrangement (event-user) [51], personnel assignment (task-worker) [52], venture capital (investor-company) [53], job market (firm- worker) [54]. Therefore, various methods have been presented for dealing with a variety of practical two-sided matching problems such as mathematical programming, game theory, multi-criteria decision making, etc. [47]. In the following sections, a review of the research about two-sided matching in the context of urban and freight transportation is presented.

2.3.1 Ride Matching

Ride-sourcing companies, like Uber and Lyft, developed Internet-based platforms to realize on-demand transportation service and offer more efficiency on traffic management. They integrate passengers (demand) and drivers' (supply) mobility data in real-time to provide a convenient matching between them. The assignment of drivers to riders, known as the ride-matching problem [48]. Solving this problem is the key to any successful ride-sourcing platform because the quality of assignment can directly affect the utility of transportation capacity, level of customer satisfaction, and more [55]. Various objectives can be considered for this problem depending on different issues such as the type of company that is managing the system (public or private), and system acceptance level in the target community [56],[57]. Previous studies can be classified into two following categories with respect to their objective functions.

2.3.1.1 Single objective optimization models

Most of the studies focused on minimizing pick-up distance because it can be implemented easily. This objective tries to assign arriving passengers to their nearest available drivers with respect to the location of driver and passenger and surrounding traffic conditions [21]. Maximizing the overall number of passengers being served was considered a logical objective for a ride-sourcing system in its infancy [56]. Maximizing the platform's revenue was introduced as a popular objective function in practice. This objective has been investigated by giving priority to passengers with higher-order revenues in the matching decisions which can result in higher total profit for the platform. Maximizing the service quality was also proposed to improve the long-term reputation and service quality of the platform by giving priority to drivers with higher service quality [21]. Another study proposed the objective of maximizing the accumulated drivers' income. In this study, the assignment problem is formulated as a Partially Observable Markov Decision Process. Reinforcement learning techniques is also employed to find an optimal trade-off between the short-term and long-term rewards [55]. Reinforcement learning techniques has been also used to solve the matching problem from the perspective of the whole city instead of the drivers' point of view which means using fewer taxis to meet more demands. The crowd movement patterns in different regions using historical taxi trajectory data has been studied to balance the supply and demand in different areas of the city [58].

2.3.1.2 Multi-objectives optimization models

Some studies focused on the ride-matching problem from different standpoints and proposed multi-objectives models for this problem. Different objectives can generate conflicting matching results and the matching result should provide a trade-off between these objectives [57].

Two objective functions including serve as many ride requests as possible and minimizing the repositioning cost of idle drivers has been addressed using minimum cost maximum flow (MCMF) formulation. This study focused on repositioning drivers to address future ride requests using a predictive control method. They proposed a receding horizon algorithm (RH) to optimize the objective function within a fraction of the interval between two consecutive times instead of solving the problem offline [59]. Another study focused on the importance of maximization platform's profit with respect to the preferences of drivers and riders and introduced stable matches in the context of ride-sharing. It has been assumed that the preferences of participants for different ride-share matches depend on the potential cost savings compared with driving alone. A model was proposed to minimize the expected total number of blocking pairs and maximize the expected total profit of the platform. The Rolling horizon approached was applied to solve the model in which plans are made using all known information within a planning horizon but decisions are not finalized until necessitated by a deadline [60]. A multi-objective optimization model was constructed in the literature to address the preference and psychological perception of drivers and riders and improve the sustainability of ride-sharing systems [47]. A bipartite graph model with two objectives (maximizing the total profit of the platform and minimizing the overall dissatisfaction about preferences among drivers and riders) has been also proposed in the literature [61]. Maximizing platform revenue and service quality as well as minimizing pick-up distance were investigated in the ride-sharing context. A matching policy called an adaptive matching policy has been presned to achieve a solution that has the smallest deviation to any pre-determined target in the ride-sourcing system [57].

2.3.2 Cargo Matching

Shippers are the entities that look for services to transport their shipments such as freight forwards and ocean carriers. Carriers are the entities that provide transport service services using trucks, trains, and barges [13]. In a freight resource sharing platform, registered users can publish information about their available transportation capacity or cargo transport requirements and the platform need to match services for shippers and carriers [3]. Like the ride-matching problem, various objectives have been considered for cargo matching in the literature and we classify them into two following categories.

2.3.2.1 Single objective optimization models

The collaboration of carriers has been focused to maximize the matching rate. This study 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 [11]. The objective of maximizing the revenue of the platform with respect to practical operational characteristics, such as territory-based approach and transferring has been investigated in another study. The problem was formulated as a Markov Decision Process (MDP) to represent uncertain and sequential decision-making procedure. Moreover, a reinforcement learning (RL) solution was applied to solve the MDP model [12].

The cargo matching problem has been also studied considering multiple modes of transportation and transshipment operations between different services. This research supposed that the freight platform could receive contractual and spot shipment requests from shippers and receives transport services from. 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. Authors of this study considered delay cost to represent service level and calculated the carbon tax using the activity-based approach to address the sustainability of the matching decisions. 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 including three steps: preprocessing of path generation with no specific considerations, preprocessing of feasible matches considering time constraints, and binary integer programming to generate optimal solutions at each epoch. The problem was then solved using the rolling horizon technique [13]. A stochastic version of this model was also provided. Historical data for incorporating stochastic information regarding future shipment requests (origin, destination, volume, announced time, release time, and due time) was applied to help the decision-maker to hold some barge and train capacity for more important shipment requests in the future. The problem was 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 [14].

2.3.2.2 Multi objectives optimization models

Two objectives for freight matching including maximizing matching rate and minimizing the cost of transport with respect to capacity constraint was studied in the literature. Two objectives have been converted to a single objective using the weighting technique and presented a quantum evolutionary algorithm to solve the problem [15]. Another study was 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 angels 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 (based on the drop and pull cost of the truck, and driving distance), and truck utilization cost. Total time 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 (GA) [16]. Maximizing the total surplus of carriers and shippers were also considered as the objective function in the literature. This study investigated stable matches in the context of the dry bulk shipping market consists 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 [62].

Compared to ride-sharing, limited studies investigated the multi-objective cargo 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.

2.4 Pricing in two-sided markets

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. [17, 18] Supply and demand are not always balanced in this market, where the demand for service exceeds or is less than the supply of capacity. It has been shown that there is a positive indirect network externality between two sides of the market which means two sides of the market are not independent and could affect the demand or benefit of each other. The operational strategy that the platform employs towards one side of the market has effects on the strategy towards the other side too [18, 63]. The price should be chosen for each side with respect to its impact on the other side's growth and willingness to pay [64]. The most challenging task of the platform is to optimally provide incentives for two sides to stay connected to the platform [63]. Indeed, the price must be high enough to cover the service provider's costs and, and low enough to remain attractive to the target customers. Finding such a balance is complicated which requires an accurate cost estimation and a clear insight into the market situation [65]. 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 [66]. There are a series of publications that investigated the pricing problem in two-sided markets, the most appropriate pricing policy should be chosen with respect to the characteristics of the two-sided market.

2.4.1 Pricing in ride-sharing platforms

Pricing has been widely studied in the context of ride-sharing as a two-sided market with an intermediate platform. This platform announces the price for service and both sides of the market react to this price. Ride-sharing platform keeps a fraction of the price paid by the customer as its commission and gives the rest of it to the service providers [67]. It needs to provide incentives for sharing to have enough supply, while also keeping prices low enough that customers are willing to pay for the service [10]. Due to the nature of this market, the platform can set a fixed price for each transaction independent of the state of the market or proposed different prices with respect to the current state of the market. Effective factors on the state of the market can change with time, weather conditions, and culture and need to be analyzed and prioritized periodically to achieve efficient pricing policies and solve problems like congestion control and peak load reduction. Dynamic pricing is the most popular pricing policy in the ride-sharing context which can be applied using three following techniques: mathematical analysis-based techniques, optimization-based techniques (dynamic programming and control theory-based techniques, computational modeling-based techniques, game theory-based techniques, mathematical optimization based-techniques), and queuing based techniques [68].

The queuing theory-based technique has been applied to set price for per transaction with respect to the state of the system. It has been also shown that dynamic pricing policy outperforms static pricing policy if both sides of markets react to the instantaneous price provided by the platform [67]. The control theory-based technique has been also used to propose the following dynamic pricing policies in the ride-sharing platform 1) unconstrained dynamic pricing 2) constrained dynamic pricing (varies the fare and wage but ensures that the latter is always lower than the former) for ride-sharing platform using. It has been demonstrated that the first strategy brings higher profit to the platform and provides a more stable rider waiting time compared to the other strategies [69]. Moreover, literature investigated the dynamic pricing in this context using the game theory-based technique. A model for the interaction of agents (drivers and riders) has been developed to play a game for obtaining the optimal solution. Results of this study revealed a strong alignment between profit and efficiency in practical settings and highlight the importance of subsidies to overcome supply shortages and reach the maximal potential revenue [10]. Other dynamic pricing strategies were proposed in the literature using the mathematical programming-based technique. To name a few, origin-based pricing, origin-and destination-based pricing, and cross-matching were introduced to address different amounts of demand among different areas and decrease the geospatial imbalances between supply and demand in the market [22], [70]. Spatiotemporal pricing was also presented to address the different amounts of demand with respect to both location and time [22].

2.4.2 Pricing in freight sharing platform

Freight transportation service procurement is accomplished using three mechanisms including catalogs, negotiation, and auction. Under the catalogs mechanism, carriers post their prices and shippers do not have any control over the posted price [71]. This mechanism has been studied under differential pricing policy in the air freight transport market. It has been assumed that carriers adopt the "low-before-high" (LBH) approach for pricing at each period to realize fairness within customers which means that the price at the later period is higher than or equals to the price at the former period [72]. The dynamic pricing under the catalogs mechanism has been also investigated. Two dynamic pricing policies were presented to minimize costs of the platform and keep individual carrier profits at the level of the collaborative setting. Using a real-world case study, they show that the dynamic pricing policy can balance the interests of the major parties involved in the case of platform-based collaboration [73].

The most popular mechanism in practice is negotiation wherein both carriers and shippers are involved in bargaining over the conditions of exchange. They can negotiate face-to-face or through e-mail, fax, telephone, or electronic marketplaces. Given the auction mechanism, one side of the market (usually shippers) post their requirements, and players on the other side of the market (most often the carriers) place bids. This mechanism is widely addressed by academia (more than 80% of the articles use this mechanism). Different bidding strategies have been presented for auction mechanisms which discussed three following questions who can bid, how to bid, and at what price. Few studies survey the application of this mechanism in practice which can be because of the complexity of implementing auction mechanisms in a freight market with the presence of a freight platform (market broker) and trust-building issues [71]. I has been also discussed in the literature that for all trucking auctions a final soft negotiation is required [74]. Research is trending toward new mechanisms managed by a third party based on trust and sharing responsibilities between all the actors to avoid loss of trust between shippers and carriers and their opportunism [71].

To accelerate the trading mechanisms in the freight market with the presence of a freight platform, new dynamic pricing policies need to be introduced. These policies should consider the preferences of the two sides of the market and cooperation between all the trading parties to achieve win-win solutions and answer changing circumstances coming from the environment.

2.5 Joint matching and pricing in transport

It has been proven that the platform's matching ability has a great effect on pricing decisions which depends on the technology, staff, etc. The platform can adjust the prices to regulate the supply-demand ratio (ratio of the number of participating service providers to the number of customers) [17]. In the following sections, we provide a review of the literature about joint matching and pricing optimization in ride-sharing and freight sharing platforms.

2.5.1 Joint matching and pricing in ride sharing platform

The joint pricing and matching problem is a novel research topic. Literature 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, it has been 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. This study proposed a fluid model for ride-sharing and partitioned the city into disjoint areas to capture the geospatial nature of the problem. It was assumed that customers are both price- and delay-sensitive which means if the prices increase, fewer customers arrive in the system and if the platform offers a ride with a longer pick-up time compared to the patience time of the customers, they would not accept the ride and leave the platform. Drivers decided when to work, where to work, and how long to work. This study did not address the time-homogeneity of customer demand and driver supply, therefore future research is required for jointly pricing and matching under time-dependency assumption [22].

2.5.2 Joint matching and pricing in freight sharing platform

The joint matching and pricing problem in the context of the freight market has been investigated in a study. This study 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. The 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 strategies. Price was set using simple distance-based pricing strategies: 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 [23].

To the best of our knowledge, this is the only study that investigates joint matching and pricing in the context of the freight market. In practice, freight sharing platforms need to consider more constraints in their matching decisions like time constraints and see the problem from the standpoints of all the actors in the market. To address the immediate changes coming from an uncertain environment, learning-based techniques need to be incorporated into the multi-objective cargo matching model to provide a trade-off between demand and supply in this market and improve the efficiency of freight transport.

2.6 Multi objective Optimization Techniques (In General)

Multi-objective optimization has been defined as an optimization problem with multiple objectives that need to be satisfied, simultaneously. The problem becomes challenging when the objectives have conflicting characteristics to each other. In comparison with single-objective optimization, multi-objective optimization does not have a single global solution and deals with a set of points that all fit a predetermined definition for an optimum that is called Pareto optimal solutions. Multi-objective optimization requires more computational effort, so different techniques have been developed in the literature including classical methods and metaheuristic methods [23], [75].

2.6.1 Classical methods

Classical methods aim to convert the multi-objective problem into a single objective problem. The weighted sum is the most common method for multi-objective optimization that allocate weight to each objective function and multiplies each function by its weights to optimize the weighted sum [23,75]. Although different methods have been presented for determining weights, many studies mentioned that prior selection of weights could not necessarily guarantee the acceptability of the final solution [76]. The ε-constraint method optimizes one objective function and considers the other objectives as model constraints. The Lexicographic method is another approach for multi-objective optimization that arranges the objective functions in order of importance [23,75]. The weighted min-max method or weighted Tchebycheff method aims to minimize the distance to an ideal utopia point in criterion space and is able to provide almost all the Pareto optimal points [77]. The LP-metrics method considers every objective function separately and formulates a single objective to minimize the normal difference between every objective function value and the optimum value of multi-objective [75]. Goal programming defines a specific goal for each objective function and aims to minimize the total deviation from the goals. Fuzzy goal programming is the extension of goal programming to incorporate uncertainty and imprecision into the formulation [75].

2.6.2 Metaheuristic methods

Metaheuristics are non-deterministic optimization methods that cannot guarantee to find optimal solutions while they try to gain near-optimal solutions with a reasonably low computational effort [78]. Different metaheuristic methods are developed to solve multi-objective problems like evolutionary algorithm, ant colony optimization, memetic algorithm, simulated annealing, tabu search, etc. Evolutionary algorithms follow the natural evolution with stochastic searching and optimization and are by far the most well-known metaheuristic techniques for solving multi-objective problems. These algorithms are well qualified to tackle a great variety of problems due to their ability to capture multiple Pareto optimal solutions in one experiment [77, 78]. Ant colony optimization applies the concept of ant colony natural wherein each ant will consider pheromone track for the next move [79]. In the memetic algorithm, an evolutionary algorithm and a local search are combined to address flexibility and efficiency in time usage for searching solutions [80].

2.7 Learning algorithms in freight transportation

Machine learning is a branch of AI that teaches computers to learn from experience using computational methods without relying on a predetermined equation as a model. Machine learning overcomes traditional approaches and statistical modeling due to the following reasons: 1) It does not need any prior assumptions compared to traditional approaches 2) It can deal with complex operational environment wherein statistical models suffers from multi-collinearity 3) It needs less computational time compared to OR models that are computationally expensive in dynamic decision-making environments [81].

ML offers a promising avenue for freight transportation management with respect to its ability to harness the power of increasingly available data in the freight market. It has been mainly applied in the freight management context for predicting the following aspects: values such as fuel consumption, states like the condition of freight transportation assets, and actions like routing and assignment. ML techniques that have been applied for freight transportation management were classified in three main categories including supervised learning, unsupervised learning, and reinforcement learning [81]. The classification of these techniques is presented in Table 2.2.

2.7.1 Supervised learning

Supervised learning is defined as learning from examples. In supervised learning, two sets of data are considered, a training set and a test set. The training set lets the learner learn from a set of labeled examples, so it can identify the unlabeled examples in the test set with the highest possible accuracy [82]. The most popular supervised learning techniques are linear regression, k-nearest neighbors, artificial neural network (ANN), support vector machine, and decision tree [81].

2.7.2 Unsupervised learning

Unsupervised learning does not consider pre-knowledge of output labels and it allows the learner to discover hidden patterns in the data. Principal component analysis (PCA) and clustering are the two most widely used techniques in this category [70].

2.7.3 Reinforcement learning

Reinforcement learning (RL) is a learning tool that lets agents interact with the environment to learn how to behave in an environment without having any prior knowledge by learning. RL agent receives feedback from the environment regarding its actions, so it will learn by trial and error using feedback from its actions and experiences. RL agent can act by learning a transition probability between consequent steps which is called model-based RL. It can also act without learning any transition model which is called model-free RL [83]. Q-Learning, state-action-reward-state-action (SARSA), and deep Q networks (DQNs) have been mentioned as popular reinforcement learning techniques [81].

Table 2-2 Classification of learning algorithms in freight transportation management

Category	**Techniques**	**Definition**	**Reference**
Supervised learning	Regression	Defining the relationship between inputs and output using a linear function with a reasonable accuracy	[84]
	K-nearest neighbors	Predicting based on the majority label for classification and the average label for regression	[85]
	ANN	Extracting linear combinations of features and modeling output as a nonlinear function of the features	[86]
	SVM	Constructing linear boundaries in a transformed version of the feature space	[87]
	Decision Tree	Representing a classifier expressed as a recursive partition of the instance space	[88]
Unsupervised learning	PCA	Transforming several correlated variables into a smaller number of uncorrelated principal components	[89]
	Clustering	Partitioning a dataset into groups	[90]
Reinforcement learning	Q-Learning	Updating RL agent by maximizing Q-values over the action following a greedy approach (off-policy)	[91]
	SARSA	Updating RL agent according to the policy derived from the Q-function (on-policy)	[92]
	DQNs	Applying deep neural networks to learn the optimal policy or value functions in large scale problems	[83]

CHAPTER 3 RESEARCH APPROACH AND STRUCTURE OF THE THESIS

3.1 Research Methodology

In this study, we attempt to answer the question of how intelligent freight platforms may impact the effectiveness and sustainability of freight transportation. We used a research methodology with the following 5 phases:

1. Literature review: For two different articles coming from this research, we reviewed different concepts in the literature. For the first article, we reviewed studies about environmental benefits of ride sharing platforms as well as new technologies in freight transportation. For the second article, we reviewed studies about matching, pricing, joint matching and pricing, and application of joint optimization and data analysis techniques

2. Data collection: Different data sources have been provided for each article. For the first article, the Canadian Freight Analysis Framework data set provided by Statistics Canada has been used. This data Integrates data from several sources to create a comprehensive picture of freight flows across the country by geography, commodity, and mode of transport. For the second article, the modified version of Solomon's 100 customer (C101) Vehicle Routing Problem with Time Window (VRPTW) benchmark instances was applied. Solomon's 100 customers benchmark includes shippers along with their origin coordinates, demand, and time window intervals. Other features related to shippers and carriers were generated artificially considering simple assumptions.

3. Methodology: Different methodologies have been considered for each article. In the first paper, a scenario-based assessment has been applied to evaluate the environmental benefits of a smart freight platform. In the second paper, optimization and data analysis techniques have been combined to help smart freight platforms jointly optimize matching and pricing.

4. Validation: We had regular meetings with experts in ShipHaul Logistics Inc. to validate developed models and scenarios in this research project.

5. <u>Verification:</u> The efficiency of the developed models in this research project has been evaluated using different techniques. Caliński and Harabasz's index is used to validate the results of the clustering approach. A sensitivity analysis is carried out to assess the results of optimization models.

3.2 Thesis outline

Chapter 1 is the introduction which presents the research problem and highlights the significance of the solution to the research problem. Chapter 2 presents the state of the art in the relevant topic areas such as evaluation of environmental impacts, matching, and pricing in ride-sharing and freight-sharing context. The gap in the research literature is also highlighted. Chapter 3 outlines the methodology for developing the proposed solutions. Chapters 4, and 5 represent the contributions of this study. More specifically, Chapter 4 presents article 1 which addresses the environmental benefits of developing smart freight platforms using a scenario-based approach. Chapter 5 includes article 2 which proposes a hybrid modeling approach for joint matching and pricing in a smart freight platform. They are followed by the general discussion, conclusion and recommendations.

CHAPTER 4 ARTICLE 1: SMART FREIGHT TRANSPORTATION PLATFORM DEVELOPMENT AND IMPACTS ON CO_2 EMISSION IN QUEBEC

Published in the proceedings of the Future Technologies Conference

Padidar, M., Keivanpour, S., & BenAli, M. (2021, November, 4)

Abstract. *Freight transportation is introduced as one of the important contributors of greenhouse gas emission in Canada. In this paper, we have considered smart freight platforms with business models, similar to taxi calling applications, as a good opportunity to reduce greenhouse gas emission related to the freight sector. These platforms collect real-time data and employ decision support tools to provide efficient, reliable, and sustainable transportation services. We present three phases for developing a smart freight transportation platform considering different technologies and features. To analyze the environmental benefits of the proposed platform, we provided a scenario-based sustainability assessment for commodity flows in Quebec in 2021 based on the Canadian Freight Analysis Framework database. In our case study, the smart freight platform reduces CO_2 emissions by 24% in one year. Results demonstrate the potential role of such platforms in realizing 2050 GHG targets by guiding customers and suppliers towards the best logistics decisions to make.*

4.1 Introduction

Canada's greenhouse gas (GHG) emissions increased in 2018 [93]. Road transportation including personal transportation and freight transportation causes the most transport emissions. Trucks as the most important factor in freight transportation emissions contribute to 87% of Canada's freight emission. It has been predicted that they would turn into the largest source of transport emissions by 2030 [2], contrary to what is targeted. These statistics show that Canada not only failed to achieve 2050 GHG reduction goals (80% reductions from 2005 levels) in the freight sector, but it has witnessed an increase in freight emission [94]. Both government and stakeholders focus on reducing CO_2 as the largest contributor to total emissions through different policies and methods in freight transportation [2],[9].

The freight industry market is complex and dynamic and has many challenges, such as inefficient operations, coordination issues, lack of shipment visibility, market volatility, cargo thefts, road incidents, and quality assurance of sensitive products. The sustainability of the current freight systems is another challenge in the logistics and supply chain. A high ratio of empty trips causes more green gas emissions and higher logistic costs. Recently, the COVID-19 pandemic situation has brought disruption and new difficulties to the supply chain and freight industry in Canada and worldwide. Hence, the end-to-end visibility in the supply chain and logistics plays an essential role in facing these disruptions and uncertainties.

One of the most recent approaches is developing smart freight transportation platforms with business models similar to taxi calling applications [9]. Smart freight transportation platforms can offer intelligent freight matching, accurate price matching, safe and optimized routes for trucks and multiple destination deliveries, as well as efficient scheduling and dispatching [3]. Indeed, they act as an intermediary company that does not own the actual capacity to carry and aim to coordinate arrangements shippers and carriers thanks to the development of the Internet and information technology [3,5]. More specifically, these platforms provide one place for buying and selling transportation capacity through the internet. Both shippers and carriers have access to more business opportunities without requiring high advertising costs [28]. In these platforms, a vast amount of real-time data would be collected and then optimization models and AI would be applied for analyzing the data and using it in a decision-making dashboard to manage freight services in a robust, sustainable, and efficient way. The interaction of freight transportation platforms with other available actors in the freight market is provided in Figure 4-1. Shippers and carriers as main actors in the freight market exchange money and information through freight transportation platforms and these platforms propose good arrangements by collecting real-time data from road networks, weather conditions, the state of the market, etc.

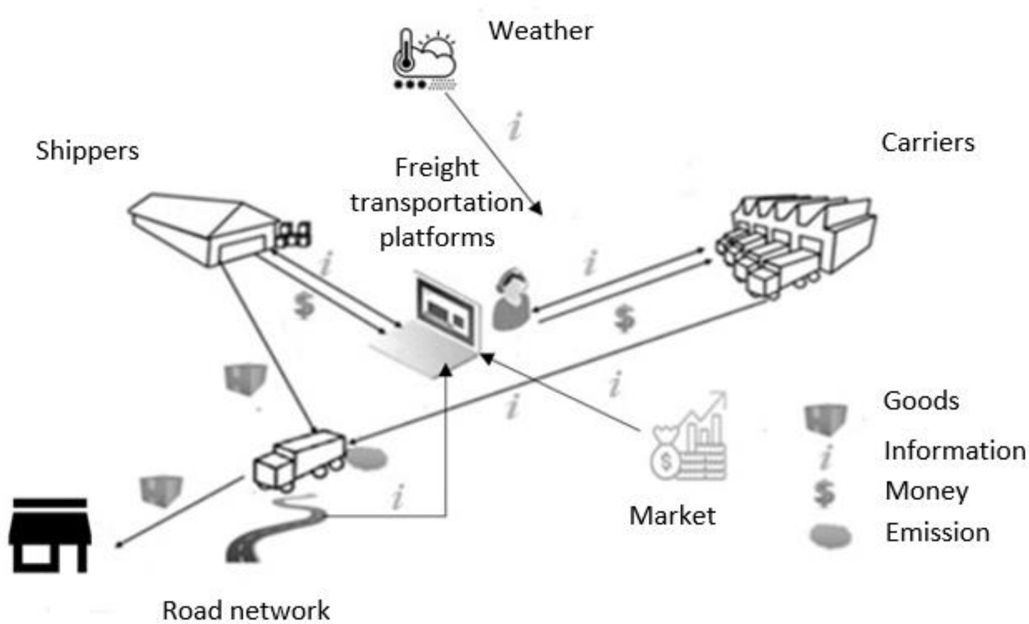

Figure 4-1. Freight transportation platforms interactions

To the best of our knowledge, the role of these kinds of platforms in achieving 2050 GHG goals for the freight sector has not been received much attention in the literature. To the best of our knowledge, this is the only study to evaluate the potential of the three-phase development of a smart freight transportation platform in reducing CO_2 emissions as well as realizing 2050 GHG goals. Main contributions of this research are:

- Proposing a three-phase development plan for a smart freight transportation platform with respect to different technologies in each phase,
- Applying of Canadian Freight Analysis Framework (CAFAF) database for commodity flows analysis
- Assessing potential environmental benefits coming from a smart freight transportation platform in Quebec in 2021.

The rest of the paper is organized as follows: In section 2, we provide a review of the potential of different presented approaches in the literature for emission reduction in the transportation sector. Section 3 outlines the three development phases of a smart freight transportation platform and the methodological approach for estimating truck traffic. Section 4 presents the results of the specific case study in Quebec. Section 5 concludes with some remarks and future research prospects.

4.2 Literature review

In 2018, the transportation sector accounted for approximately 30 percent of related greenhouse gas (GHG) emissions in Canada which includes transportation of both people and goods [93]. Most of the studies in the literature focused on reducing emissions from passenger transportation, while freight transportation has been addressed limitedly [95].

Many studies discussed the emission reduction of passenger vehicles [95]. The environmental benefits of ride-sharing, as a novel research area in passenger transportation, were analyzed through different case studies. A framework was proposed to survey the environmental benefits of taxi ride-sharing in Beijing. Sharable trips for a maximum of two riders were identified considering some conditions through GPS logs of taxis. Results of this study showed that the proposed platform can reduce fleet vehicle miles- traveled by 33% which leads to saving more than 77,000 gallons of gasoline per day and reduce CO_2 emission [32]. An analysis framework has been provided to assess the potential emission reduction by allowing people to provide mobility services and share trips with others. A case study of the Tokyo area with over 1 million GPS travel records was considered and a deep learning model was trained to find out this potential. It has been concluded that, if half of the original public transit riders in their study case accept ride-sharing, CO_2 emission reduction by 84.52% would be achieved [30]. The impact of several ride-sharing scenarios on travel conditions and CO_2 emissions in the Paris region have been investigated. Effects of ride-sharing on the whole household decision process regarding transport and residential location were considered in this study. In addition to environmental benefits in the results, substantial rebound mechanisms were found [34]. Due to the great similarity between transportation goods and people, it can be concluded that the application of trip sharing would provide many environmental benefits which have not received enough attention in the literature because of difficulties in having access to GPS Logs of trucks.

Studies related to freight transportation mostly addressed the impact of recent technologies in GHG emission reduction. New technologies such as the internet of things (IoT), cloud computing, and big data analysis tools provide opportunities to make logistic operations more intelligent and efficient [35]. RFID can collect and track different logistics data that can be used to optimize the transportation process [30]. Global Positioning System (GPS) can be combined with RFID to monitor the transportation process [36]. Cloud computing can be applied to store, retrieve, and used the collected data by IoT technologies [37]. The massive data collected by IoT technologies need to be deep learned to make further analysis and more intelligent decisions. These technologies bring many benefits to the freight sector, including real-time tracking and monitoring of transportation resources; improving the fleet management; optimizing vehicle configuration and routing; sharing traceability information [35]. For example, a company in India collects different logistics data including fuel, speed, acceleration, and coordinate data through vehicle sensors and GPS devices to improve transport efficiency and reduce costs [7]. Another study showed that fuel consumption can be reduced by 7% in the context of truck platooning via using smart adaptive cruise control systems [8]. Moreover, the effect of smart GPS technologies on improving sustainability in the trucking industry of Tennessee has been studied. Results of this study showed that the environmental benefits of 1% Cyber-Physical technologies penetration in the freight industry would be equivalent to GHG emissions savings from 46,930 passenger vehicles for one year [6].

Integrating transport management and available technologies for freight tracking and vehicle monitoring are key factors to achieve more sustainable freight transportation [38]. A management information system is required to combine IoT, cloud computing, and big data for planning, and coordinating facilities in smart freight. The joint use of these advanced Information and Communications Technology (ICTs) can contribute to make a smart collaborative logistics system. Promoting the collaborative advanced ICTs to develop a smart freight system is still a research gap. On the other hand, new market entrants need to build smart logistics based on new technologies to take market share [35]. In this study, we focus on the development of smart freight platforms and highlight the potential of such platforms in emission reduction.

4.3 Methodology

Effective factors in freight emission can be classified into five categories including vehicle-related, environment-related, traffic-related, driver-related, and operations-related factors [9]. Smart platforms can focus on different categories during each phase of development to combine several policies for freight emission reduction and increase the probability of reaching deep GHG targets. First, three phases for developing a smart freight platform are presented. In the following the methodology for converting commodity flows to truck trips is discussed to assess the environmental impacts of the proposed smart platform. Three phase development of the platform are given in Figure 4-2.

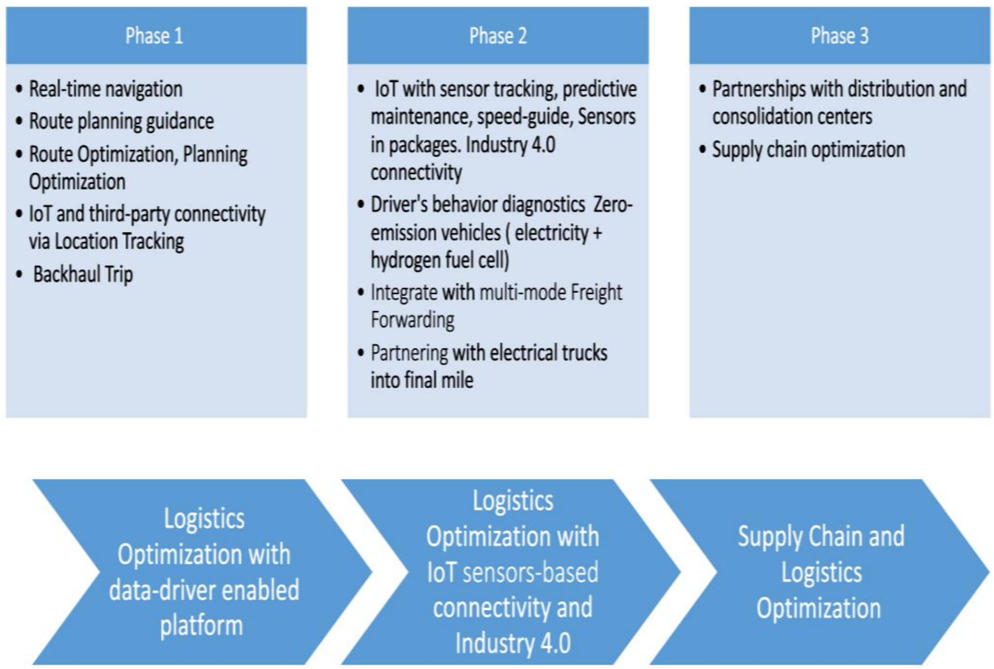

Figure 4-2. Three-phase development of the platform

4.3.1 First Phase

In the first phase of the platform development, we focus on operation-related factors that are effective in freight emission. An auto-match mechanism will be introduced to better matching the carriers and the shippers in Quebec. The proposed mechanism tries to improve the average vehicle loaded and decrease truck's empty trips as the most important operation-related factors in GHG. Our matching algorithm prevents trucks from under-utilization and returning empty trips. These two aspects strongly affect the most important factor of the fright emission: total vehicle-kilometers of trucks. After matching, for the carriers and the shippers based on their origin and destination and time window, real-time navigation and route planning guidance can be provided to reduce the energy consumption [9].

4.3.2 Second phase

In the second phase, more features to improve the efficiency and visibility of logistics services can be added. Real-time engine monitoring and trailer environmental monitoring capabilities can be considered to provide features such as predictive maintenance, driving guiding, and quality assurance of shipments.

Secondly, other logistics services and strategies will be added such as shared trucking services, trailer and container sharing, shipment consolidation, multiple legs shipments. Furthermore, matching, pricing, and partnerships strategies can be used to encourage the use of low-emission or zero-emission vehicles (ZEV), especially in urban areas as one of the strong factors in achieving GHG reduction goals [97–99]. Reports represent that the vast majority of trucks in Quebec runs on diesel or gasoline [99]. These two sources of energy accounting for the largest GHG emission in the freight sector [100]. ZEVs due to their high potential in GHG emission reduction, with 65% market share can reduce freight emission by 80% [97–99].

In this phase of the platform development, vehicle-related, traffic-related, and driver-related factors can be combined to more efficiently achieve GHG reduction.

For driver-related factors, the platform can collect and extract insight on the truck driver behavior to help trucking companies achieve more efficient driving behaviors since there is a relationship between driver behavior and emission and eco-friendly behavior can decrease the GHG emission by 10% [101].

For vehicle-related factors, intelligent functioning engine control of trucks can be used, since malfunctions of trucks increase the fuel consumption as well as CO_2 emission by 43% [102]. By installing this intelligent control tool, carriers can be informed about detected failures and required maintenance which can lead to more facilitated pave for reaching deep GHG targets.

For traffic-related factors, a speed-guided intelligent system can be applied to decrease the frequency of stops, the strength of acceleration, etc. which can manage traffic congestion and reduce energy consumption as well as GHG emission by 10% [103].

4.3.3 Third phase

In the 3rd phase, features of supply chain management can be added to the platform to help companies achieve better logistics efficiency through better supply chain management. At this stage, it is assumed that there is a large network of freight services providers and a network of logistics facilities services providers such as warehouse and consolidation center. Different logistics strategies need to be used such as sourcing, item demand prediction, and intelligent location storage of items. To assess the potential environmental benefits of the proposed platform we consider three features from all the presented features in three-phase development of the platform including routing optimization, connectivity, and backhaul minimization and truck operations optimization. First of all, we need to calculate the annual truck traffic based on the commodity flow.

4.3.4 Conversion of commodity flows to truck traffic

Conversion of commodity flows to truck traffic involves the following steps [6],[97] :

1. allocating commodity tonnage to the five truck types (table 4-1) using the allocation factors for the appropriate distance range
2. estimating the average payloads by five truck types and 9 body types (table 4-2)
3. converting assigned tonnage to equivalent loaded truck traffic values for each truck type with nine body styles using the truck equivalency factors for each commodity group
4. adjusting loaded truck traffic of truck types using the empty truck factors

We use the parameters presented in Table 4-3 to convert commodity volumes to the number of trucks.

Table 4-1 Truck Configurations

Truck Group	**Description**
1	Single Unit
2	Truck Plus Trailer
3	Tractor plus Semitrailer Combinations
4	Tractor plus Double Trailer Combinations
5	Tractor plus Triple Trailer Combinations

Table 4-2 Truck Body Types

Body Group	**Description**
1	Automobile
2	Livestock
3	Bulk
4	Flatbed
5	Tank
6	Dry Van
7	Reefer
8	Logging
9	Other

Table 4-3 Parameters

Symbol	Definition
i	Commodity Group {1, 2, ..., 5}
j	Truck Type {1, 2, ..., 5}
k	Truck Body type {1, 2, ..., 9}
$\mathbf{x_i}$	Tonnage of commodity i
$\mathbf{b_{ijk}}$	Fraction of commodity (i) moved by truck type (j) with body type (k)
$\mathbf{w_{ijk}}$	Mean payload of truck type (j) with body type (k) transporting commodity (i)
$\mathbf{TEF_{ijk}}$	Truck equivalency factor
$\mathbf{Y_j}$	Number of trucks type j

We use the following equation (Eq.1) to calculate the number of truck type j utilized to transfer $x_i b_{ijk}$ tons of commodity group i:

$$Y_j = \sum_{k=1}^{9} \frac{x_i b_{ijk}}{w_{ijk}} \tag{1}$$

The sum of all truck types for all commodity types represents the total number of trucks (annual loaded truck traffic) which amounts only accounts for loaded trucks (Eq.2).

$$Y = \sum_{i=1}^{5} \sum_{j=1}^{5} \sum_{K=1}^{9} \frac{x_i b_{ijk}}{w_{ijk}} \tag{2}$$

The truck equivalency factor is a function of truck type, body type, and commodity type which is defined as Eq.3 and used to convert the tonnage of the commodity into the number of trucks.

$$TEF_{ijk} = \frac{b_{ijk}}{w_{ijk}} \tag{3}$$

To have a better estimation of the total number of trucks (annual loaded and empty truck traffic), we use empty truck factors considering the truck and body type, since empty trucks can cause a reduction in the tonnage of commodity flow.

4.4 Case study

Quebec is selected as a target area due to its large network of roads (nearly 138, 500 km) and connection to the USA. Published report for Quebec represents that more than 50% trucks run with less than half of their capacity in this province. It has also been reported that around 36% of the trucks running empty [99].

The Canadian Freight Analysis Framework (CAFAF) database is utilized to predict the flow of five important commodity types (agricultural products, automobiles, and transportation equipment base metals and articles of base metals, coal, and food) from Montreal to Quebec City in 2021. As shown in Table4-4, the Commodity flows are then converted from tonnage to truck trips through the introduced methodology in section 4.3.4. The total predicted tonnage of the five important commodity types would be equal to 488,722 with 158.6 Mile average traveling distance which can lead to approximately 12,200 metric tons of CO_2 in 2021. The annual traffic of different trucks from Montreal to Quebec is provided in Table 4-5.

Table 4-4 Conversion commodity flows to truck numbers (2021)

Commodity group	Total Freight (Tons)	Total Trucks	Loaded Trucks	Empty Trucks	Distance (Mile)
Agricultural Products	48,905	3,256	2,153	1,103	707,241
Automobiles and other Transportation Equipment	9,404	760	542	218	139,083
Base metals and Articles of Base metals	127,382	23,761	16,127	7,634	4,712,807
Coal	18	0.88	0.52	0.36	93
Food	303,014	22,513	16,444	6,069	4,017,082
Total	488,722	50,291	35,266	15,025	9,576,305

Table 4-5 Annual truck traffic of different truck types (2021)

	Type 1	Type 2	Type 3	Type 4	Type 5
Numbers of trucks	20,200	7,182	18,304	4,605	0
Ratio	40.17%	14.28%	36.40%	9.16%	0%

We provided a scenario-based assessment to show the environmental benefits of developing smart freight platforms. The impacts of connectivity technologies, truck operations optimization and minimizing backhaul, and routing are assessed in different categories. Each category includes 10 different scenarios.

4.4.1 First category

First, we tried to evaluate the environmental benefits of using connectivity technologies in smart freight platforms. The estimated number of truck types, fuel usage for traveling each truck type [104], and saving factors from Cyber-Physical technologies are used to calculate the fuel-saving [105]. The energy-based approach is applied in this category to calculate the emitted CO_2.

In this category,10 different scenarios were considered. The connectivity (Cyber-Physical) technologies could reduce fuel consumption by a certain percentage in each scenario. A range from 0.5% to 5% is assumed for saving factors from these technologies since research has shown that they can reduce fuel consumption by 12% [6]. For example, the saving factor equals to 0.5% is applied to calculate the fuel-saving under first scenario of this category. Then, fuel-saving is multiplied by the CO_2 coefficient of diesel fuel (10.21 kg CO_2 per gallon) to calculate the CO_2 emission reduction [106].

4.4.2 Second category

For the second category, we tried to assess the environmental impacts of truck operations optimization and minimizing backhaul feature in small freight platforms. The activity-based approach is applied to calculate emitted CO_2 considering freight tonnage, traveled distance, and average CO_2 emission factors recommended by McKinnon for different percentages of truck payload and empty running trip. Based on the Quebec Report, 36% of trucks running empty and more than 50% of trucks run with less than half of their capacity, so with consider 10 different combinations (scenarios) of payload rise and empty trip reduction to show how can our platform impact on CO_2 emission through avoiding empty trip and underutilization (Table 4.6).

Table 4-6 Scenarios for logistic efficiency

Scenario	Payload (Tons)	% of empty trip
1	19	35
2	18	30
3	20	35
4	19	30
5	18	25
6	20	30
7	19	25
8	18	20
9	20	25
10	19	20

4.4.3 Third category

For the third category, we tried to appraise the environmental benefits of routing feature in smart freight platforms. Similar to the second category, the activity-based approach is applied to calculate the emitted CO_2 of shorter traveled distances obtained from the routing optimization. A range from 0.5% to 5% is assumed for shorter traveled distance (10 scenarios) , since research has shown that routing optimization can result in 7% distance saving [107]. For example, in the first scenario, it is assumed that the distance traveled is reduced by 0.5% due to the application of routing optimization. Then, CO_2 emission reduction is calculated.

Considering the considered scenarios, the potential CO_2 savings resulting from the application of two features of smart freight platforms are shown in Figures 4-3, 4-4, and 4-5.

Figure 4-3. CO_2 metric tons saving, the impacts of {less than truck operations optimization and minimizing backhaul} and {Energy saving as the results of Connectivity}

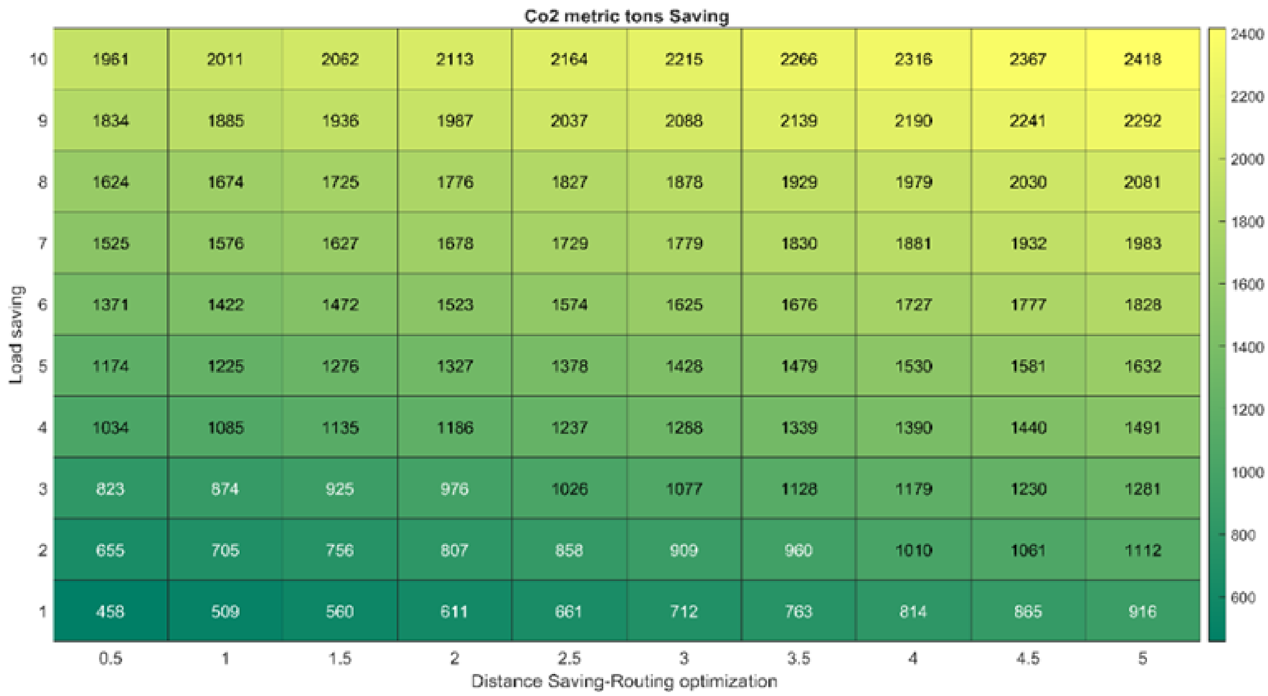

Figure 4-4.CO_2 metric tons saving, the impacts of {less than truck operations optimization and minimizing backhaul} and {distance saving as the results of routing optimization}

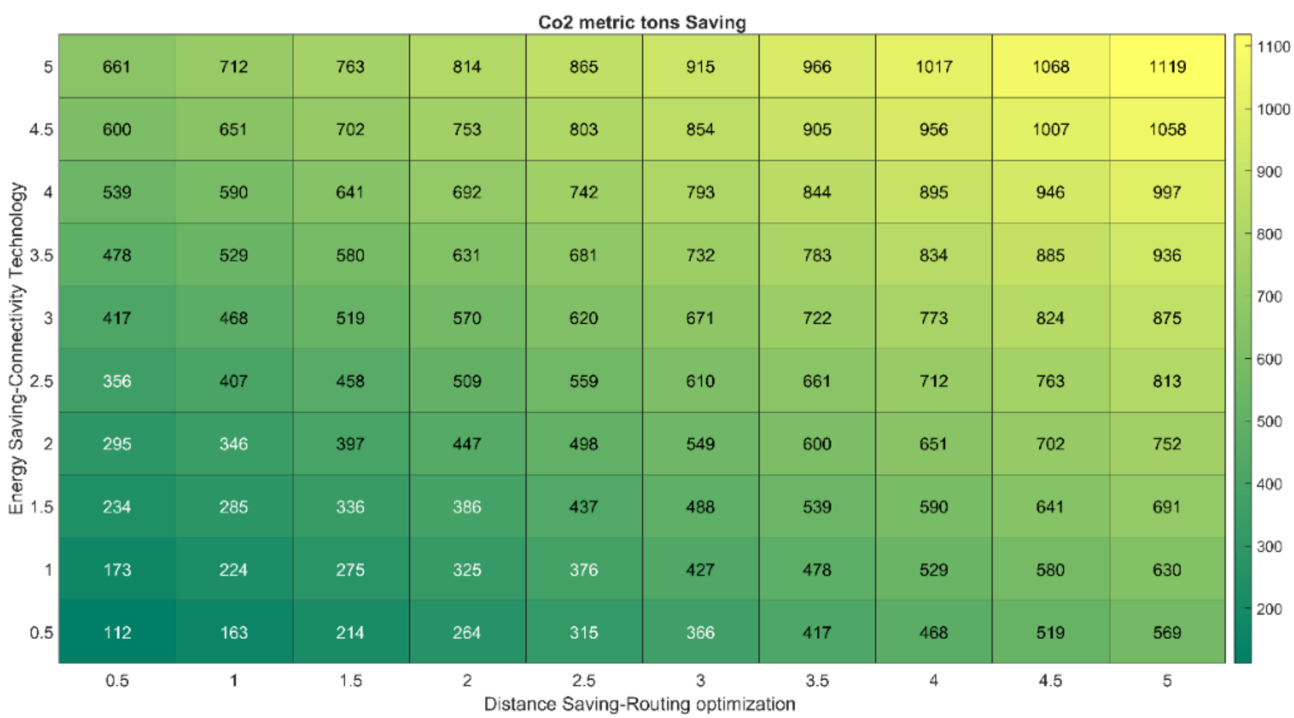

Figure 4-5. CO_2 metric tons saving, the impacts of {Energy saving as the results of Connectivity} and {distance saving as the results of routing optimization}

The total saving for three features of the platform based on the annual traffic of Montreal to Quebec for five major commodities (short-term forecasting based CAFAF data in 2021) in ten scenarios is presented in Table 4-7. It should be mentioned that we only considered three features of the platform in our assessment, so this platform has a higher potential for reducing CO_2 emission considering all features presented in Figure 4-2.

Table 4-7 Total CO_2 saving in ten scenarios based on three features based on the annual traffic of Montreal to Quebec for five commodities (one year estimation)

Scenarios / Features	1	2	3	4	5	6	7	8	9	10
Load Saving	407.21	603.80	772.30	982.93	1,123.35	1,319.94	1,474.40	1,572.69	1,783.32	1,909.70
Energy Saving	61.04	122.07	183.11	244.14	305.18	366.21	427.25	488.29	549.32	610.36
Routing	50.83	101.66	152.49	203.33	254.16	304.99	355.82	406.65	457.48	508.32
Total	519.08	827.54	1,107.91	1,430.40	1,682.69	1,991.14	2,257.47	2,467.63	2,790.13	3,028.37

4.5 Conclusion

Freight transportation has a considerable contribution to GHG emissions in Canada, so Government and stakeholders try to present different mitigation policies and methods to address freight GHG emissions. Although transport emissions cannot be completely eliminated in the short term, we have identified opportunities to help reduce GHG emissions. We proposed a three-phase development of a smart freight platform with a business model like a taxi calling application. In each phase, different technologies and features were considered for the intelligent freight platform.

We also evaluated the environmental impacts of the proposed platform through a scenario-based assessment. Results show that the total CO_2 saving for only three features of the platform based on the annual traffic of Montreal to Quebec for five major commodities in 2021 would be equal to 24%. It can be concluded that this platform has even a higher potential for reducing CO_2 emission considering all proposed features. Future research could be application of agent-based simulation for providing more realistic scenarios. GPS Logs of trucks could also be used to appraise the real environmental benefits of trip sharing through similar frameworks that have been applied in the context of ride sharing. Additional considerations to expand this study include the comparison of the proposed method with other similar methods.

CHAPTER 5 ARTICLE 2: 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 decisions in large-scale. 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.*

5.1 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 [108]. Freight providers and cargo owners always look for gaining more market share and seeking 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 [4]. 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 [5].

Freight-sharing platforms are similar to passenger transportation platforms (ride-sharing platforms such as Uber) [27]. They use the Internet, cloud computing, and big data for connecting carriers and shippers and resolving issues like information asymmetry and low freight efficiency [3]. They act as intermediary company that aims to manage the capacities, allocation, and pricing of mobility services while maintaining high satisfaction [11], [12], [27]. 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 [12].

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) [10]. The prior literature on matching shippers (demand) with carriers (supply) considered the perspectives of just one [11–14] or, at most, two of the available actors in this market [15],[16]. The goal of the pricing problem in two-sided markets with an intermediary platform is to maximize the platform's profit [17], [18]. 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 [19], [20]. Recently, the importance of joint pricing and matching problem has been showed for ride-sharing platforms [21]. This problem has been also studied in the context of freight sharing with an emphasis on the perspective of carriers and a distance-based pricing policy [23]. Besides, various research areas, including market deployment plans [109], Vehicle Routing [111],[112], and ride-sharing [112], 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.

5.2 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.

5.2.1 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 for college admission and marriage problem (partner- partner) [45]. Matching problems are classified into three categories: 1) one-to-one matching 2) many-to-one matching, and 3) many-to-many matching [46],[47]. These problems have been widely applied in different fields including display ads (keyword-advertiser) [49], [50] event arrangement (event-user) [51], personnel assignment (task-worker) [52], venture capital (investor-company) [53], job market (firm- worker) [54], ride-matching (drivers to riders) [48] 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 [13]. 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) [3]. Previous studies can be classified into two categories with respect to their objective functions including single-objective optimization models and multi-objectives optimization models.

5.2.1.1 Single objective optimization models

The collaboration of carriers has been considered to maximize the total number of matches. In this study, an integer linear optimization model has been presented 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 [11]. The objective of maximizing the revenue of the platform with respect to practical operational characteristics, such as a territory-based approach and transferring has been investigated in the literature. The problem was formulated as a Markov Decision Process (MDP) to represent an uncertain and sequential decision-making procedure. A reinforcement learning (RL) solution was also developed to solve the MDP model [12]. The cargo matching problem considering multiple modes of transportation and transshipment operations between different services has been also studied. 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 [13]. Stochastic version of this model has been also provided. Historical data for incorporating stochastic information regarding future shipment requests (origin, destination, volume, announced time, release time, and due time) was used to help the decision-maker to hold some barge and train capacity for more important shipment requests in the future. The problem was 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 [14].

5.2.1.2 Multi-objectives optimization models

Some studies focused on the cargo matching problem from several standpoints and proposed multi-objective models. Two objectives were investigated for freight matching including maximizing the matching rate and minimizing the cost of transport with respect to capacity constraints. Tese objectives were converted to a single objective using the weighting technique. A quantum evolutionary algorithm was also presented to solve the problem [15]. Another study 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 GA [16]. Maximizing the total surplus of carriers and shippers as the objective function has been also addressed in the literature. This study 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 [62].

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.

5.2.2 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 [17, 18]. 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 [66]. 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 5-1. The most appropriate pricing policy should be chosen considering the characteristics of the two-sided market.

Table 5-1 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	[63]
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	[63]
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	[10], [17], [52], [63], [66]
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	[18],[72],[114]
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	[68]

More specifically, distance-based pricing policy has been widely used in the freight transportation context. It has been demonstrated that 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 [114]. Under this pricing policy, the price could fluctuate either linearly or nonlinearly as a function of the travelled distance [19], [20]. Distance-based pricing policy could be both static and dynamic [115]. 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 [23], [116].

5.2.3 Joint matching and pricing

The joint pricing and matching problem is a novel research topic. This problem has been studied in the context of ride-sharing. It has been shown 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, it has been shown 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 [22]. Recently, this problem has been investigated in the context of the freight market. It has been 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 [23]. 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.

5.2.4 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 [117]. A hybrid modeling using the self-organizing clustering technique and Mixed-integer linear programming has been introduced in the literature for developing a market deployment plan with a large number of potential markets. This study showed how the clustering technique could tackle the scale and complexity of the problem by generating target market clusters [109]. Another study 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) [110]. An adaptive clustering technique has been proposed 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 [112]. It has been also shown that how the application of clustering approaches could resolve the very challenging computations of large-scale ride-sharing problems by decomposing them into small problems. This study demonstrated how k-means and greedy clustering algorithms could outperform non-clustering case outcomes in terms of computational tractability and solution quality [113].

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 5-2 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 5-2. Summary of the related research

Reference	Objective Function			Constraints				Optimization Model	Pricing Policy	Clustering	Solution Approach
	Carrier	Shipper	Platform	Capacity	Time	Distance	Quality				
[11]	-	-	Maximize total number of matches	*	*			ILP	-	-	Branch & Bound
[12]	-	-	Maximize platform's revenue			*		MDP	-	-	Q-learning
[13]	Minimize total costs	-	-	*	*			MILP	-	-	Heuristic & RH
[14]	Minimize expected total cost	-	-	*	*	*		MSP	-	-	AOA & RH
[15]	Minimize transport cost	-	Maximize matching rate	*				ILP	-	-	Evolutionary

Table 5-2. Summary of the related research (Continued)

Reference	Objective Function			Constraints				Optimization Model	Pricing Policy	Clustering	Solution Approach
	Carrier	**Shipper**	**Platform**	**Capacity**	**Time**	**Distance**	**Quality**				
[16]	Minimize transport cost and time & Maximize service quality	-			*		*	NLP	-	-	Evolutionary
[62]	Maximize utility	Maximize utility	-	*	*			MILP	-	-	Gale-Shapley
[23]	Minimize transport cost			*				NLP	SR & ST	-	Heuristic
Present Paper	Minimize transport cost	Maximize service quality	Maximize total number of matches	*	*	*	*	MSLP	ST	*	Exact

5.3 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 [23]. 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 5-1 represents the process of information exchange in the freight market.

5.4 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 5-

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).

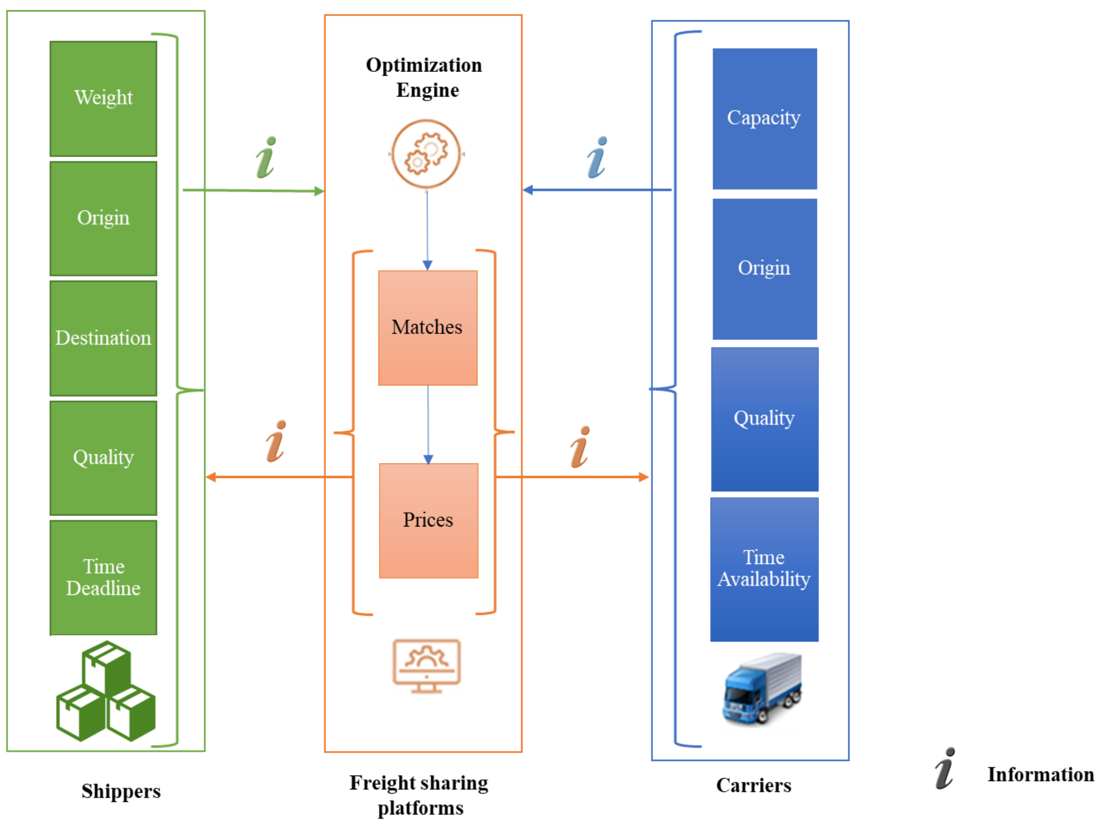

Figure 5-1. Information exchange in the freight market

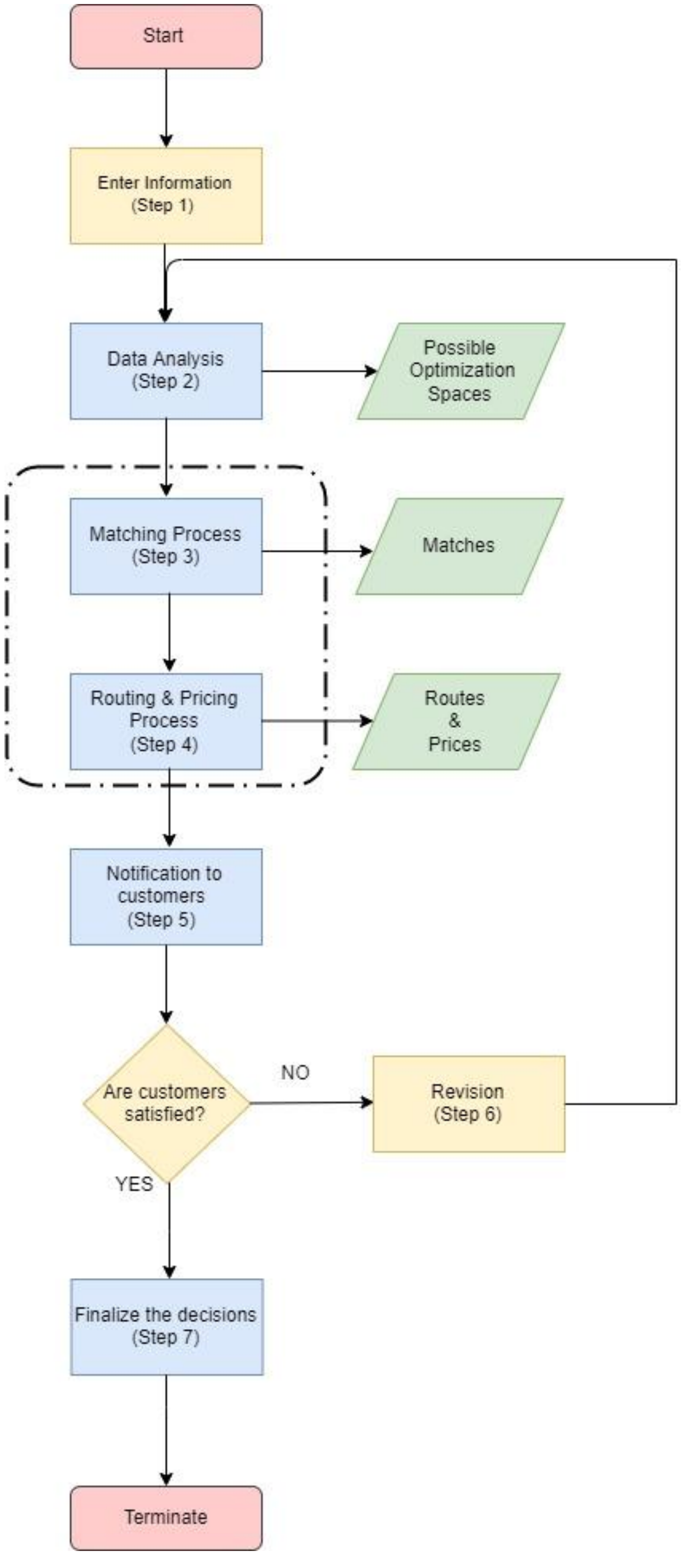

Figure 5-2. Joint matching and pricing methodological framework

5.4.1 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. MCA has been introduced as a multivariate version of correspondence analysis. This data analysis technique could identify and depict underlying structures in a data set with categorical attributes [118]. Literature showed how MCA could provide an attribute-positioning map data reduction tool and a preliminary spatial representation of multistate categorical data [119].

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 [120]. It has been 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 [121].

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 [121], [124],
- 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.

5.4.2 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 pay. 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 5-3, 5-4, 5-5, and 5-6. Then, the multistage linear programming model is explained.

Table 5-3. Set

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

Table 5-4. Decision variables

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

Table 5-5. 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

Table 5-6. 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
$\pi_i^{cargo\_min}$	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

Table 5-6 Parameters (Continued)

Parameters	**Description**	**Units**
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

First stage (Matching)

Objective function

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

Constraints

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

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

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

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

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

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

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

The objective function of the first stage (3) maximizes the total number of matchings. This objective is inspired from [56] 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 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

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

Constraints

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

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

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

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

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

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

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 staircase structure for the platform's price. The relationship between the price and the route distance is depicted in equation (18).

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

5.5 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.

5.5.1 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 [123]. 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). Trip and vehicle preference as well as price sensitivity were generated randomly. Attributes for 50 freight service providers have also been generated artificially with respect to the features of cargo owners. Tables 5-7 and 5-8 clearly present the synthesized part and Solomon part of the dataset used in this study.

Table 5-7. First 10 lines of shippers' dataset

Solomon						New features (Synthetic)										
ID	Long origin (Degree)	Lat origin (Degree)	Weight (Ton)	Earliest (Minute)	Latest (Minute)	Sensitive	Type Vehicle	Type Trip	Service Score (1 to 10)	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 5-8. First 10 lines of carriers' dataset

Synthetic											
ID	Long (Degree)	Lat (Degree)	Earliest (Minute)	Latest (Minute)	Sensitive	Type Vehicle	Trip Type	Service Score (1 to 10)	Capacity (Ton)	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

5.5.2 Entering information (Step 1)

Based on the first step of the methodological framework (see Figure 5-2) 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 5-3.

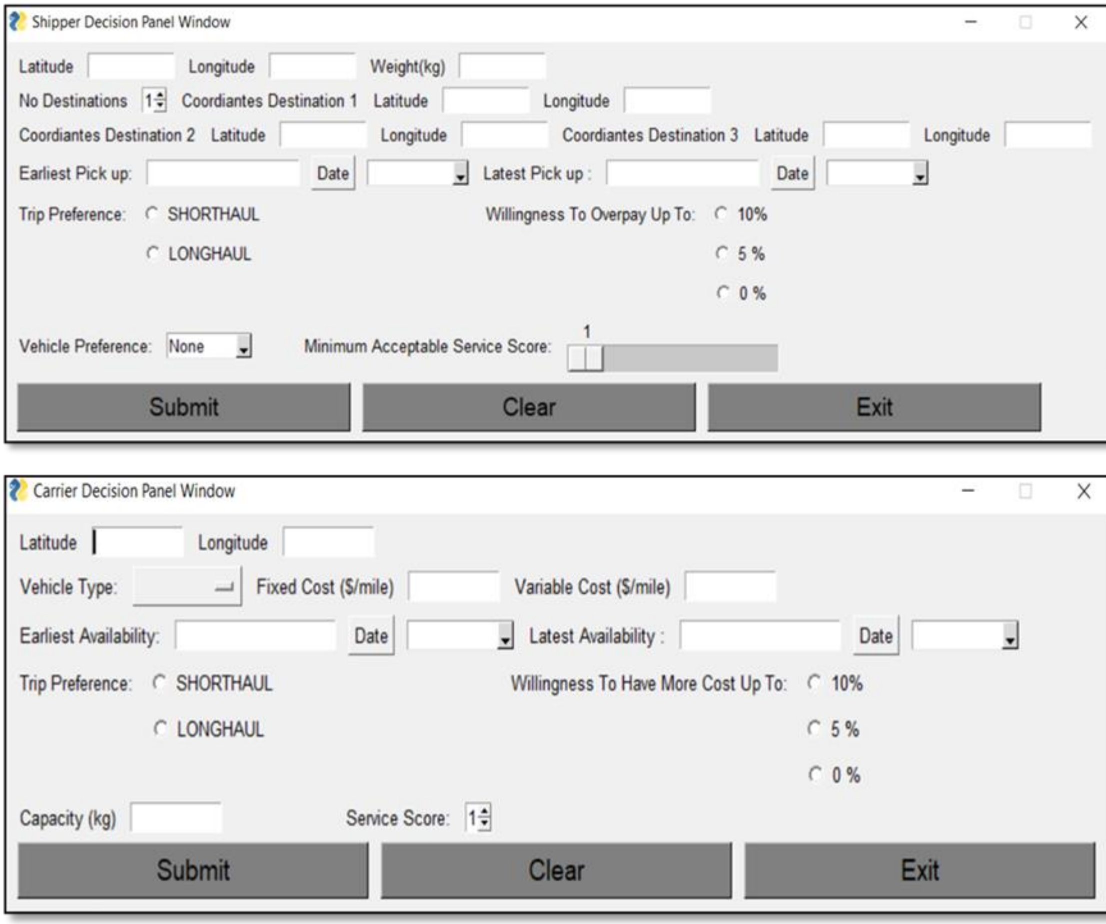

Figure 5-3. Freight Platform Interface (A) Shipper (B) Carrier

5.5.3 Results of the data analysis (Step 2)

To reduce the complexity of decision-making and segmenting the freight platform customers, two-past 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 5-4. 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 [124]. Results of the elbow method and k-means clustering are given in Figures 5-5 and 5-6 respectively. Figure 5-5 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 5-6, 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 was 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) [125]:

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

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.

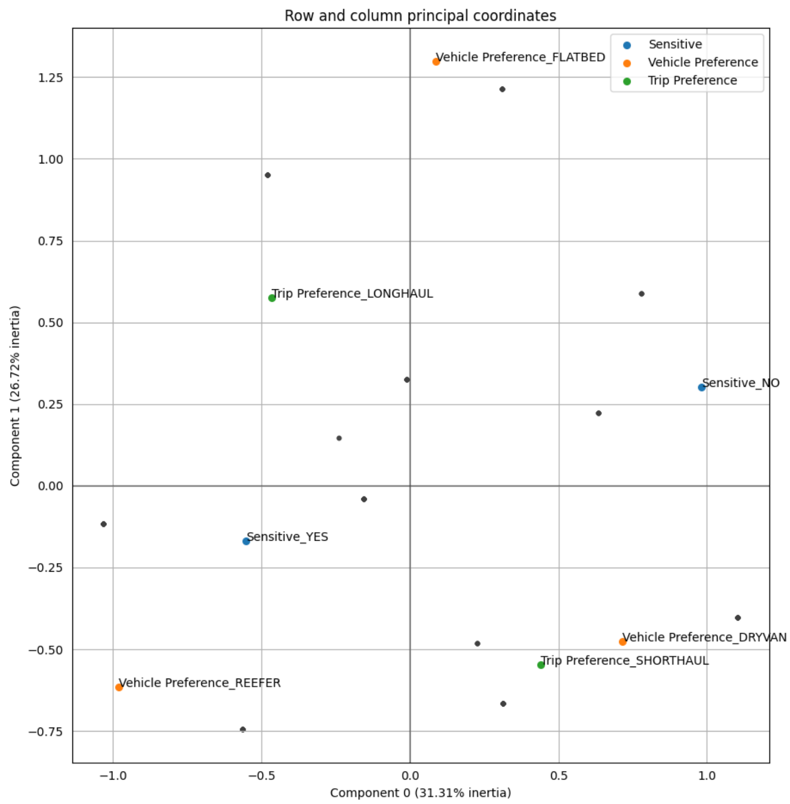

Figure 5-4. MCA analysis of categorical attributes

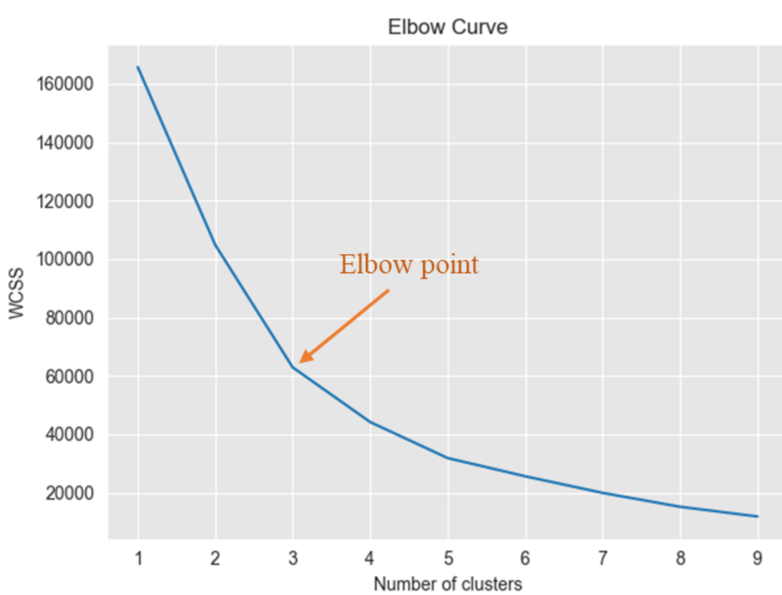

Figure 5-5. Results of the elbow method

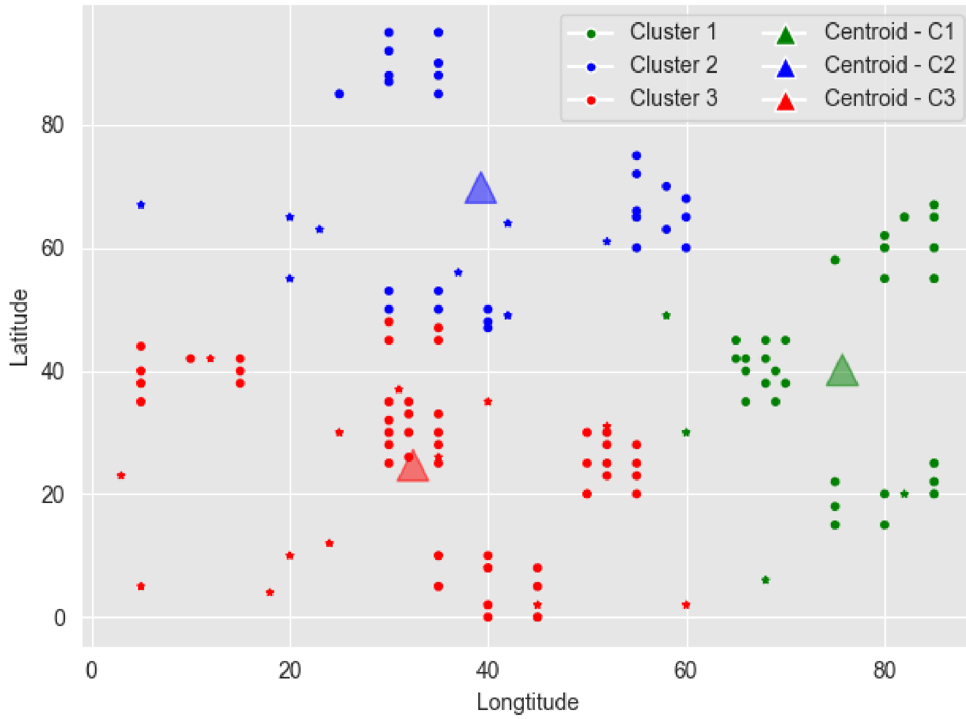

Figure 5-6. Result of the k-means clustering

5.5.4 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 5-7). 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.

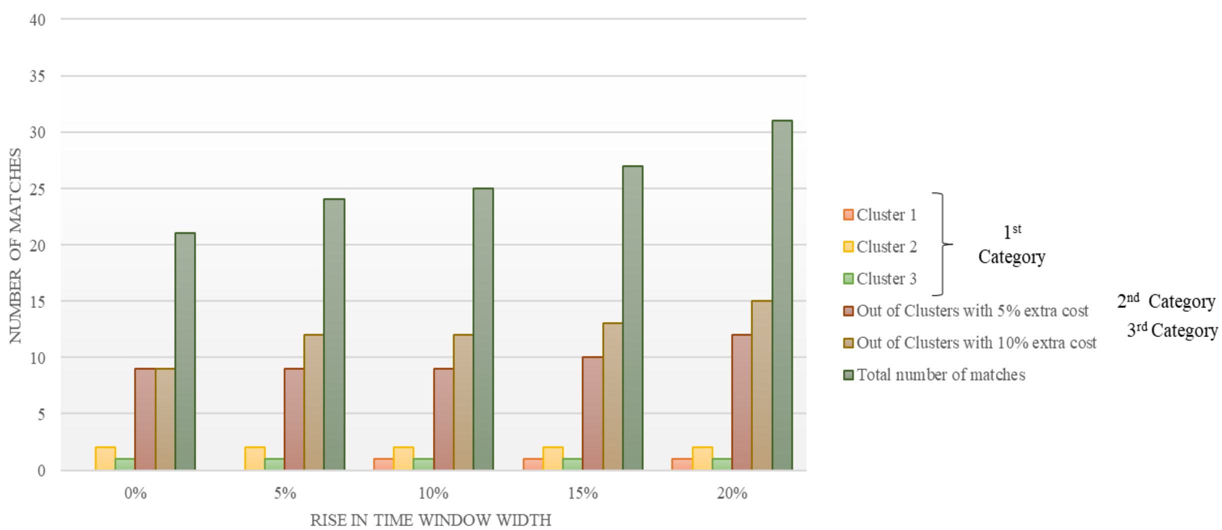

Figure 5-7. Sensitivity analysis for time window width of shippers

5.5.5 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 5-9. 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 5-9. 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

5.5.6 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.

5.5.7 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 [112].

5.6 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. As Maden et al. (2020) showed routing optimization can decrease traveled distance by 7%, and the suggested framework has the potential to reduce CO_2 emissions by 7% as well [107].

5.7 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 travelled 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.

CHAPTER 6 GENERAL DISCUSSION

6.1 Comments on the Methodology and Results

The methodology employed in this research is developed and presented as a set of different components (provided in Chapters 4 and 5) to assess how smart freight platforms affect the efficiency and sustainability of freight transportation. The performance of the suggested methodology has been assessed using synthesised data sets. However, real data sets are still needed for further research.

6.2 Limitations

The following limitations can be pointed out for this study:

- Compared to the urban transportation context, databases related to freight transportation are very limited and we do not have access to them.
- More realistic scenarios need to be considered for synthesized part of the dataset.
- All parameters are assumed to be deterministic and stochastic parameters like traffic conditions were not covered.
- An exact method is used to solve a multistage linear programming model. It is necessary to present and evaluate heuristic and metaheuristic algorithms.
- Trip sharing for shipment requests (consolidation) has not been covered in this study.
- The dynamic pricing policy has not been addressed in this study.
- The environmental impact of freight trip sharing cannot be studied due to the challenges in gaining access to GPS Logs of trucks.
- The Co_2 saving estimations are approximate and overlapping effect of different features have not been addressed in the calculations.

CHAPTER 7 CONCLUSION AND RECOMMENDATIONS

7.1 Findings

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 literature on smart freight platforms can be classified into three essential themes: (1) the environmental benefits of these platforms, (2) freight matching, and (3) pricing.

Despite the essential role of freight-sharing platforms in the sustainability of cities and urban planning, little research has been undertaken to investigate their environmental benefits. To address this gap, this project first proposes a three-phase development for a smart freight platform. In each phase, different technologies and features are considered. A scenario-based analysis is used to evaluate the proposed platform's environmental impacts. Results demonstrate the potential role of such platforms in GHG emission reduction by guiding customers and suppliers toward the best logistics decisions to make.

The most critical decisions that these platforms will have to make are matching and pricing. The literature lacks studies that investigate joint freight matching and pricing on a large scale while simultaneously taking into account the perspectives of various active participants in the freight market. This project proposes a methodological framework using data analysis and optimization techniques to help smart freight platforms jointly optimize matching and pricing decisions on a large-scale. The multi-actor integrated matching and pricing model is formulated using a multistage linear programming model to address the standpoints of existing freight market actors including smart freight platforms, carriers, and shippers. 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. In the second stage, the freight-sharing platform determines the sequence of deliveries for assigned trucks and prices. Using a VRP model, we ensure that the minimum platform price is provided. By focusing on different standpoints, freight-sharing platforms could offer available actors in the freight market win-win solutions and prevent long-term market share loss.

The results of the study represent how the proposed methodology could reduce the complexity of the decision-making and improve the computation time significantly using a two-stage data analysis method.

7.2 Research Implications

This research project has practical and academic implications. It could help managing freight transport operations more efficiently. Owners of freight-sharing platforms would benefit from more customers being served which can be translated into greater profits. They could coordinate arrangements in the freight market in a more robust, sustainable, and efficient way. 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.

This research project contributes to the literature from different aspects. The role of smart freight platforms in the sustainability of cities and urban planning has been highlighted. Multi-actor freight matching and pricing decisions can be optimized jointly on large-scale using data analysis capabilities and optimization techniques.

7.3 Future research

Trending toward new freight procurement mechanisms managed by a third party increases the importance of applying dynamic pricing policies to respond to market fluctuations and satisfy all trading parties. This mechanism needs to valorize real-time data to provide the best price recommendation according to the market circumstances. The recommended price can facilitate the trading mechanisms and provide a balance between supply and demand in the market. Future research could be introducing new learning-based pricing policies.

The need for customized medium-and long-haul freight is rising, necessitating the consideration of additional attributes in decision-making to fit real-world applications. These attributes come from the preferences of available actors in the market and aim to improve service quality. Assignment of known shipment requests, pricing, and first route decisions must be performed in a static environment without knowledge of incoming requests in the future. Then, utilizing real-time data, these decisions should be revised in a dynamic environment to react to emerging events. Customized matching and pricing in a dynamic setting to respond to modern supply chain needs for medium- and long-haul freight transportation services need to be studied in the future.

Freight trip sharing will offer numerous environmental advantages, which need to be further investigated by utilizing GPS logs of trucks and comparable frameworks that have been used in the context of ride-sharing.

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