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Assessing the Potential Benefits of Taxi-sharing in Urban Areas using Graph Theory Algorithms: A Case Study of Downtown Vancouver

April 19, 2023

Abstract

Taxi services are an integral component of urban transportation and a significant contributor to traffic congestion and air pollution, resulting in significant adverse health outcomes. Sharing taxi rides could reduce taxi services' negative impacts on urban areas. The present study employs the notion of shareability to assess the aggregate benefits of trip-sharing while also taking into account the passengers' satisfaction. This research applies graph theory algorithms to determine the optimal pairs of requests that satisfy two optimization criteria: maximizing the number of shared trips and minimizing the total time required to facilitate all trips. This framework is applied to the actual street network of downtown Vancouver with random demands. The results indicate that sharing services can significantly improve urban transportation systems by reducing passenger travel time by up to 37% and decreasing traffic congestion by up to 45%. Experiments on randomly generated instances suggest that the proposed method can be used to tackle small to medium-sized instances.

Keywords

Ride-sharing, dial-a-ride problem, graph theory, intelligent transportation systems, sustainable transportation

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1. Introduction

For cities all around the globe, the issue of traffic congestion and the air pollution it causes is an urgent and prominent concern that comes with substantial financial and human implications. The economic ramifications of congestion in the United States are significant, with an estimated annual cost of approximately $121 billion, equivalent to 1% of the country's GDP. This reflects the 5.5 billion hours lost to traffic delays and the additional 2.9 billion gallons of fuel consumed (Schrank et al., 2012). Nonetheless, the aforementioned statistics fail to incorporate the adverse externalities associated with vehicular discharges, such as greenhouse gas emissions and particulate matter (Pant & Harrison, 2013), unpredictability in travel time (Carrion & Levinson, 2012), and increased probability of accidents. (Hennessy & Wiesenthal, 1999). In addition, the World Health Organization estimates that outdoor air pollution, most of which may be ascribed to vehicle traffic (Caiazzo et al., 2013), is responsible for more than a million fatalities annually. (World Health Organization, 2011). The consequences of vehicular congestion and pollution are far-reaching; road traffic deaths and financial losses from missed business chances are other negative impacts.

The utilization of digital information and communication technologies has the potential to enhance urban intelligence, specifically in vehicular traffic management (Batty, 2013; Santi et al., 2014). This new mode of urban mobility has gained significant popularity in recent times. The emergence of mobility-on-demand (MoD) systems, spearheaded by companies such as Uber, Lyft, and Via, can be attributed to the widespread use of smartphones and the reduction in cellular communication costs. These systems offer users a dependable means of transportation customized to their specific needs, thereby enhancing mobility for those incapable of operating a personal automobile. This, in turn, mitigates the waiting times and anxiety associated with travel. (Alonso-

Mora et al., 2017). Therefore, these intelligent transportation systems have the potential to effectively replace public transportation with individual mobility or taxi-like on-demand services (Dowling & Simpson, 2013).

Despite the potential advantages, stakeholders such as municipal authorities and city residents might show reluctance towards investing in a shared taxi service until a thorough assessment of its benefits has been conducted. The shared taxi service is based on the concept of ride-sharing or carpooling, which was initially introduced in the 1970s as a strategy to mitigate road traffic in response to the oil crisis. (Handke & Jonuschat, 2012). During this period, the economic incentives held greater significance than the psychological obstacles that often hinder the effectiveness of carpooling initiatives, including surrendering individualized transportation and embracing unfamiliar individuals as fellow commuters. (Santi et al., 2014). Thus, Ride-sharing was implemented as a means for individuals with similar itineraries and schedules to economize on transportation costs, including fuel, tolls, and parking fees. (Stiglic et al., 2016).

Several researches have indicated that the additional time requirements and loss of privacy are the two main factors deterring potential carpoolers (Dueker et al., 1977; Teal,1987). Therefore, the objective of this study is to evaluate the effectiveness of the ride-sharing model in reducing traffic congestion and maintaining passenger satisfaction using Metro Vancouver as a real case study. To accomplish this, we employ the shareability network concept, developed by (Santi et al., 2014), to model a dial-a-ride problem in a straightforward static manner and apply traditional graph theory methods to solve the taxi trip-sharing problem. Dial-a-ride services can operate in either a static or dynamic mode. The former involves pre-known requests, whereas the latter involves requests received gradually throughout the day, with vehicle routes being dynamically adjusted to meet demand. Purely dynamic problems are infrequent in practise, as a significant proportion of requests are typically predetermined. Therefore, the present study centres on the static version of the issue (Cordeau, 2006).

The remainder of this paper is organized as follows. The next section briefly reviews relevant work on the dial-a-ride problem and closely related issues. Section 3 describes the case study. Section 4 defines our methodology to deal with this problem. Computational experiments are reported in 5, and the conclusion follows in 6.

2. Literature review

In this section, the most important and relevant references are examined in the field of ride-sharing with respect to several criteria, such as problem characteristics, objective function, solution approach, and sample size.

2.1. Problem characteristic

As previously noted, there are two main categories into which the ride-sharing issue may be broken down: static and dynamic. The following is a comparison between a static DARP versus a dynamic one. A DARP is considered static if the decision maker can access all necessary information before operations begin. Even if available data changes over time, we assume that the decision-maker creates a comprehensive strategy for a fixed number of users throughout the planning horizon before operations begin. This strategy is either a routing policy or a collection of specific routes and schedules that cannot be altered after the fact. However, the issue is considered dynamic if the decision-maker is permitted to make adjustments to the plan as operations progress in response to (i) the unexpected emergence of new users, (ii) updated information about current users, or (iii) unanticipated disruptions such delays and vehicle failures. (Ho et al., 2018).

The evaluated papers mainly belong to the dynamic class. Wong et al. (2014), one of the publications tackling the dynamic nature of the ride-sharing issue, looked into how fluctuating demand affects the effectiveness of DRT operations. They noticed new user requests as the action that would cause a re-planning. The aim was to figure out whether and how the new request would be granted. In addition, Santos and Xavier (2015) extended the ride-sharing issue to include price considerations by introducing a new set of restrictions allowing riders to select their maximum trip fee. Jung et al. (2016), Stiglic et al. (2018), Mahmoudi & Zhou (2017), and others could be cited as more publications that fit within this category. (2016). Notably, Hosni et al. (2014) is the only study which devised a mixed integer programming that dealt with both the static and the dynamic aspects of the shared taxi system.

2.2. Objective function

The majority of objectives associated with shared mobility issues concentrated on improving the operational aspects of the ride-sharing problem. Operational goals typically involve optimizing system-wide operating costs, including but not limited to reducing total routing costs (e.g., Masmoudi et al. 2017; Braekers and Kovacs 2016; Wong et al. 2014; Huang et al. 2013; Alonso-Mora et al. 2017; Mahmoudi& Zhou 2016); minimizing vehicle miles and transportation time (e.g., Masson et al. 2014). For instance, Stiglic et al. (2018) studied the advantages of combining ride-sharing with public transportation to attract more passengers, particularly from the suburbs, and discovered that the two modes of transportation might work well together. Although ride-sharing may attract customers from less densely populated regions to the public transportation system, the public transportation system itself helps ride-sharing serve more customers and decrease drivers' detours. Furthermore, Vazifeh et al., 2018 tackled the issue of determining the minimum number of cars required to service all journeys without delays.

2.3. Solution methods and sample size

Realistic taxi-sharing systems have practical limitation that must be understood. Theoretically speaking, the ride-sharing problem is a generalization of the vehicle routing problem and the dynamic pickup and delivery problem, both of which involve meeting spatially and temporally dispersed demand that must be met within prespecified time windows (Braekers et al., 2016; Stenger et al., 2013; Pillac et al., 2013). The necessity to compute answers quickly enough to provide consumers with an experience of real-time booking and service is a crucial obstacle when attempting to solve this problem (Alonso-Mora et al., 2017). As a result, even the simplest forms of this issue are NP-hard (Gu et al., 2018), and the difficulty of addressing them increases in dynamic contexts. This has led to the development of accurate and heuristic methods for finding a solution.

In general, exact algorithms for ride-sharing problems are developed mainly based on branch-and-bound (B&B) and lagrangian concepts. These algorithms can be classified as branch-and-cut (B&C) (e.g., Braekers and Kovacs (2016), Liu et al. (2014), Cordeau (2006)), Lagrangian decomposition approach (Hosni et al. (2014)), and lagrangian relaxation algorithm (Mahmoudi& Zhou (2016)). Mahmoudi& Zhou (2016), for instance, employed dynamic programming with a Lagrangian relaxation strategy to solve a medium-scale single-vehicle routing problem, including pickup and delivery services and time windows.

Moreover, Cordeau (2006) employed a branch-and-cut technique to deal with the complexity of the multi-vehicle routing problem. However, the long computation time restricts the model's applicability to small issue cases, such as the 32 requests and four cars. Consequently, prior taxi-sharing research has concentrated chiefly on relatively limited routing issues, such as those within airport perimeters (Clare & Richards, 2011). In addition, the research studied by Agatz et al. (2011)

using a modest dataset from the Atlanta metropolitan area found that sophisticated optimization methodologies may improve participant-matching rates and system-wide travel cost reductions in dynamic ride-sharing systems.

Furthermore, Santi et al. (2014) provided a graph theory framework to systematically explain the trade-offs between the collective advantages of sharing and the inconvenience of individual passengers. Using their methodology on a massive dataset of taxi rides in New York City, they discovered that trip length might be reduced by as much as 40% with just a little increase in passenger discomfort. While Santi et al.'s 2014 work only addressed the issue of matching passengers to vehicles, Alonso-Mora et al.'s 2017 study explored the challenge of using a fleet of vehicles with varied passenger capacities and solved both the matching and the repositioning problems. They began with a greedy assignment, but their method gradually converged to the optimal possible assignment using constrained optimization.

Due to the NP-hardness nature of the problem and the fact that exact methods can only solve small to medium-sized instances to optimality using a significant amount of computing time, many studies have focused on developing efficient and effective heuristic techniques (e.g., Vazifeh et al. (2018), Ma et al. (2013)). Various heuristics were used in the reviewed studies, such as Construction insertion heuristics (Wong et al., 2014), simulated annealing (Jung et al., 2016), variable neighbourhood search (Stenger et al., 2013), large neighbourhood search (Masson et al., 2014), genetic algorithms (Masmoudi et al., 2017), and hybrid algorithms (Santos and Xavier, 2015). Table 1 summarizes the papers on various aspects, including sample sizes, that have been addressed by either exact or heuristic approaches.

The research by Ma et al. (2013) is an essential first step towards real-world taxi ride-sharing systems, since the authors demonstrate the design of a dynamic ride-sharing system that includes a taxi dispatching method and fare management. For computational reasons, Ma et al. (2013) based their trip-sharing on a heuristic approach unique to the taxi-dispatching technique. Vazifeh et al., 2018 tackled the issue of determining the minimum number of cars required to service all trips without delays. For best computing efficiency and almost ideal real-time implementation, a network-based approach was presented using a "vehicle-sharing network." The methods were evaluated using a dataset of 150 million taxi rides in New York City, with the near-optimal option allowing for a 30% decrease in fleet size compared to existing taxi operations. Finally, Huang et al. (2013) introduced a kinetic tree technique to match trip requests to servers in a road network, enabling real-time ride-sharing. Experiments on a large taxi dataset demonstrate that this technique outperforms conventional approaches like a branch and bound and mixed-integer programming.

3. Problem Description

Metro Vancouver is a metropolitan area in the southern part of British Columbia, Canada. It comprises 21 municipalities, covers 2,882 square kilometres, and is home to over 2.5 million people, making it the most populous metropolitan area in Western Canada and the third-largest in the nation. The transportation system in Metro Vancouver is a crucial component of the region's growth and development. The system consists of diverse modes of transportation, including buses, ferries, sky trains, cycling, etc. These modes of transportation guarantee the efficient movement of products and people throughout the region (Wikipedia).

According to Statistics Canada in 2016, private vehicles were the dominant commuting mode in the region, with approximately 60% of commuters driving to work (see

Figure 1). For the 649,810 car commuters who work and reside in Metro Vancouver, the average commuting time was 26 minutes, with a median travelling distance of 23 minutes. These statistics highlight the significant role of private vehicles in traffic congestion in Vancouver and the need for a more sustainable transportation system (Statistics Canada, 2017).

Among the 21 municipalities that makeup Metro Vancouver, downtown Vancouver was chosen as this study's focus area. According to newly released data from Statistics Canada (Statistics Canada, 2017), downtown Vancouver has a population density of 18,837 residents per square kilometre, making it the most densely populated city centre among all primary downtowns areas in Canada's census metropolitan areas (CMAs).

To the best of our knowledge, no prior studies have evaluated the effectiveness of a ride-sharing program in reducing traffic in Vancouver. Therefore, this study aims to apply graph theory to solve the taxi-sharing problem in a provably efficient manner. To analyze and quantify the benefits of this programme, we employ a dataset consisting of 380 nodes and 1,250 edges in downtown Vancouver, with randomly generated requests in different instance sizes.

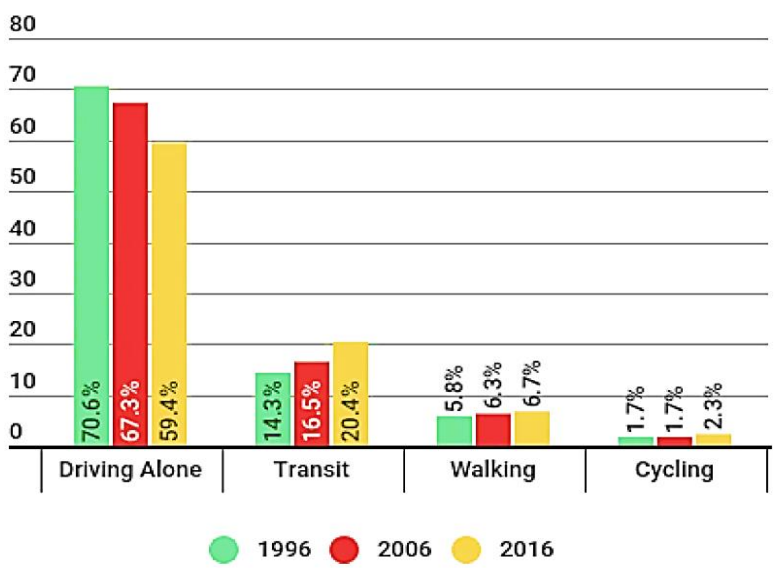

Figure 1. The distribution of commuting methods in metro Vancouver from 1996-2016

Table 1. A summary of reviewed papers

Author	Objective	Solution method		Sample size	Vehicle capacity	Characteristics	
		Heuristic	Exact			Static	Dynamic
Hosni et al. (2014)	Max. total Profit	✓	✓	16 requests, 2 taxis	✓	✓	✓
Ma et al. (2014)	Min. Travel Distance,	✓		20 million trips, 33000 taxis	✓	✓	
Jung et al. (2016)	Min. Travel Time, Min. total routing cost	✓		600 vehicles, 18000 requests	✓		✓
Braekers & Kovacs (2016)	Min. total routing cost	✓	✓	40 users 4 taxis 888 requests	✓	✓	
Liu et al. (2014)	Min. Travel Time		✓	2 vehicles, 22 requests	✓	✓	
Masson et al. (2014)	Min. Travel Distance	✓		193 requests, 13 vehicles	✓	✓	
Stiglic et al. (2018)	Min. Travel Distance, Max. Number of Participants		✓	1000	✓		✓
Masmoudi et al. (2017)	Min. total routing cost	✓		13 vehicles 144 requests	✓	✓	
Wong et al. (2014)	Min. total routing cost	✓		500 requests 20 vehicles			✓
Santos & Xavier (2015)	Max. Number of Participants,	✓		307 vehicles 750 requests	✓		✓

Author	Objective	Solution method		Sample size	Vehicle capacity	Characteristics	
		Heuristic	Exact			Static	Dynamic
	Min. total paid by all passengers						
Cordeau (2006)	Min. total routing cost		✓	32 requests	✓	✓	
Huang et al. (2013)	Min. total routing cost	✓	✓	432,327 requests 20,000 taxis	✓		✓
Vazifeh et al. (2018)	Min. Number of Used Vehicles	✓		150 million trips 13,586 taxi cabs	✓		✓
Santi et al. (2014)	Max. Number of shared trips Min. waiting time		✓	150 million trips 13,586 taxi cabs	✓	✓	
Alonso-Mora et al. (2017)	Min. total routing cost		✓	3,000 vehicles, 460,700 requests	✓		✓
Ma et al. (2013)	Max. Number of Participants Min. total routing cost	✓		307 vehicles, 750 requests	✓		✓
Mahmoudi & Zhou (2016)	Min. total routing cost		✓	15 vehicles, 60 requests	✓		✓
Agatz et al. (2011)	Min. total routing cost		✓		✓		✓

4. Methodology

The current methodology consists of three main stages of data preparation, processing, and analysis, which will be discussed in detail in the following. The methodology framework for this study is presented in Figure 2, which displays the various steps involved in the process.

4.1. Data preparation

Our analysis begins with a dataset comprising the street network of downtown Vancouver, along with randomly generated requests. The dataset contains the geographical coordinates of pickup and drop-off locations associated with the closest street intersection in the street map of Vancouver downtown for each trip.

The OSMnx package from the Python programming language was utilized to create the street network of downtown Vancouver. The OSMnx package is a robust tool that enables the retrieval, modelling, analysis, and visualization of street networks sourced from OpenStreetMap. Utilizing the OSMnx package provides access to real-world data, thereby augmenting the credibility of our analyses and outcomes (Boeing, 2017). The data retrieved from this package and used in this investigation include:

- The number of nodes and edges and their associated attributes, such as the street name, length, width, maximum speed and directionality.
- The length of individual edge

Subsequently, a series of requests are generated randomly, each with distinct pickup and drop-off coordinates. The distribution of these requests follows a poison distribution, with an arrival rate of one person per minute.

4.2. Data processing

The next phase of this research involves preparing the available dataset for the concluding analysis, which aims to determine the optimal pairing strategy. To accomplish this objective, it is necessary to identify the shortest route for each excursion. Given our intention to analyze the network under various time scenarios, considering the impact of rush-hour and non-rush-hour traffic congestion, the shortest route for each trip will vary. Consequently, Dijkstra's algorithm is employed to determine the shortest route between the pickup and drop-off points.

Dijkstra's algorithm is a path-finding algorithm that finds the shortest path between two nodes in a weighted graph. Starting from the source node, it calculates the distance to all nodes in the graph and adds them to a priority queue. It then selects the node with the smallest distance and relaxes its adjacent nodes, updating their distances if a shorter path is found. This process is repeated until the destination node is reached or all reachable nodes have been visited. The algorithm is guaranteed to find the shortest path if the graph weights are non-negative (Cormen et al., 1990).

4.3. Data analysis

In order to determine the optimal level of trip sharing, two metrics were devised: the shareability rate, denoting the maximum number of trips that can be shared, and match efficiency, which represents the percentage of overall travel time saved as a result of trip sharing. The corresponding formulas are as follows:

$$Match\ efficieny = 1 - \frac{shared\ travel\ time}{unshared\ travel\ time} \tag{1}$$

$$Shareability\ rate = \frac{total\ number\ of\ shared\ trips}{total\ trips} \tag{2}$$

The second measurement can be used as a proxy for the decline in total taxi trips since a single cab can accommodate two people on a shared trip. A decrease of 40% in the taxi fleet may be achieved, for instance, if 80% of trips are shared. Hence, it is sufficient to utilize a weighted maximum matching algorithm on the transportation network to determine the optimal solution based on the aforementioned criteria.

The set of $i = 1, \ldots, k$ trips, denoted as $T_i = (o_i, d_i)$, is defined such that o_i represents the trip's origin and d_i represents its destination. It is stated that a set of trips T_i can be considered shareable if a path exists that connects all the origin points (o_i) and destination points (d_i) in any order, while ensuring that each o_i precedes the corresponding d_i. However, it should be noted that this does not apply to cases where individual trips are combined without overlapping, such as $o_1 \rightarrow d_1 \rightarrow o_2 \rightarrow d_2$. The primary objective is to ensure that each customer is picked up and dropped off at their respective origin and destination locations. Imposing a bound of k on shareability implies that the k trips can be combined using a taxi of corresponding capacity (Santi et al., 2014).

For values of $k > 2$, the network takes on a hypergraph form where up to k nodes may be connected by a link simultaneously. The shareability parameter k has a major effect on the problem's tractability due to computational considerations. For $k = 2$, finding a solution is straightforward, for $k = 3$, it's heuristically feasible, but for $k \geq 4$, it's computationally impossible. This suggests there will be a limit on the number of trips shared via taxi-sharing services and other social-sharing technologies. However, research by Santi et al. (2014) indicates that the shareability rate of $k = 2$ is the best value for keeping customer satisfaction at an acceptable level. Additionally, they demonstrated that significant gains could be realized for New York City with the minimum possible number of trip combinations ($k = 2$). Consequently, we settled on the rate of sharing ($k = 2$) for the purposes of this research.

Matching M in G is a collection of pairwise nonadjacent edges in the graph $G = (V, E)$,. A weighted maximum matching is a matching where the total weight of all edges is the greatest possible. If the weights on the shareability network are interpreted as the travel time reduced by sharing, then the weighted maximum matching in this context minimizes the total time required to accommodate all trips. Due to the sparse nature of trip-sharing networks, weighted maximum matching with $k = 2$ can be performed in polynomial time $O(n^2 log\, n)$

(Galil,1998). Here, n is the number of nodes in the network. Although rapid approximations to the optimal solutions can be obtained for dimensions $k > 2$ (Chandra & Halldórsson, 2001), these solutions become computationally infeasible for $k > 3$.

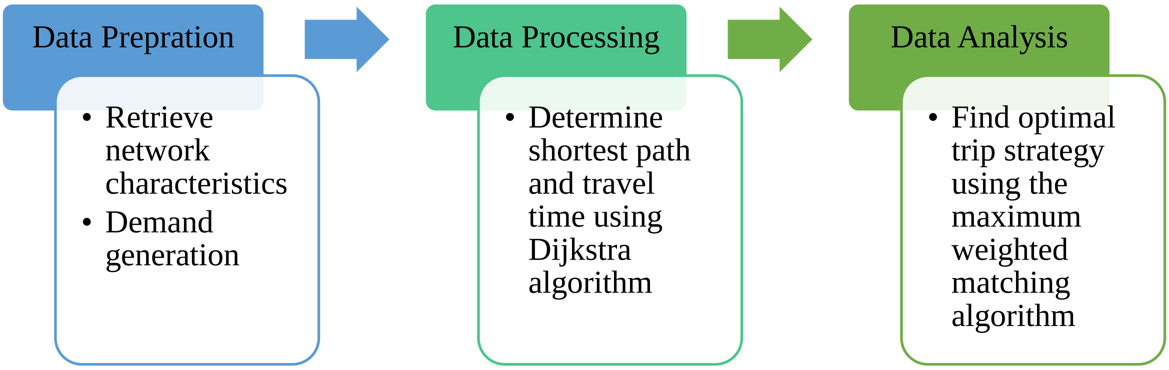

Figure 2. The methodology framework

5. Results

This section begins with an overview of the structure of the downtown Vancouver transit network. Figure 3 depicts a view of downtown Vancouver and its associated street network. The street network in Vancouver is characterized by a grid-like pattern of arterial roads that spans a significant portion of the urban landscape. The grid street network is a street layout that includes a pattern of intersecting streets arranged in a grid-like way. The streets typically run in two primary directions, namely north-south and east-west, creating a rectangular block sequence. In this network, intersections and dead-ends are represented as nodes, and the street segments connecting them are represented as edges. Grid street networks offer several advantages over other types of street networks. They are easy to navigate and provide efficient access to different parts of a city. However, they may be less efficient for car traffic than other networks, as they may not have as many direct routes to specific destinations.

According to the data extracted from the OSMnx, the street network in downtown Vancouver consists of 378 nodes and 1026 edges, with an average length of approximately 124 metres per edge. Table 2 contains supplementary statistics about the network.

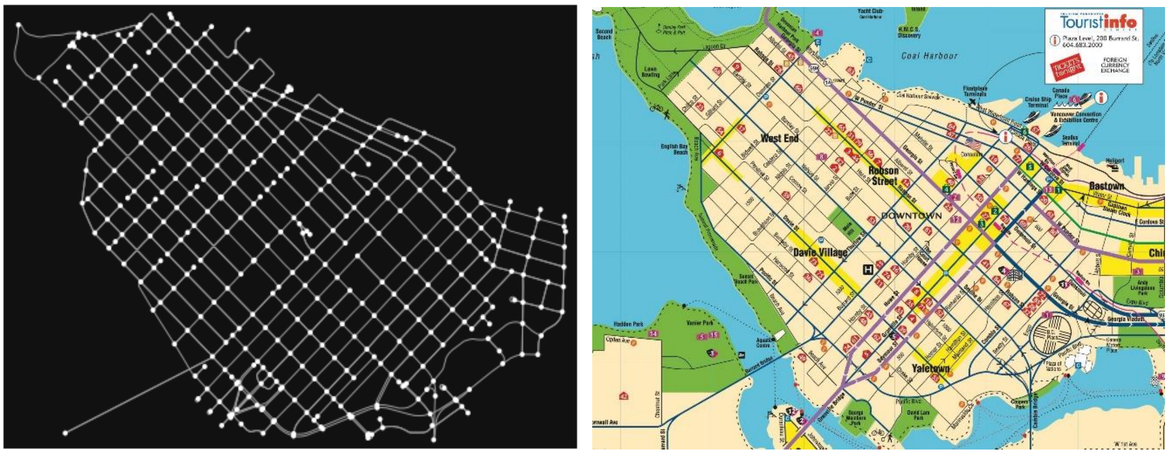

Figure 3. A view of Vancouver downtown and the corresponding street network

Table 2. Statistics of Vancouver Downtown Street Network

Statistics	Definition	Value
Edge_length_total	The total length of all edges, in meters	127210.2
Streets_per_node_avg	The average number of streets connected to each node	3.36
Streets_per_node_counts	The number of nodes that have 0, 1, 2, 3, 4, or 5 streets connected to them	{0: 0, 1: 29, 2: 13, 3: 133, 4: 198, 5: 5}
Intersection count	The number of intersections	349
Street_length_total	The total length of all streets, in meters	77333.15
Street_segment_count	The number of street segments	628
Circuity_avg	The average ratio of the shortest path distance between two points	1.02
Max_speed	maximum city road speed	50

Given the purpose of this study, which is to analyze the network under various traffic congestion circumstances, it is necessary to calculate the shortest path algorithm for each trip by determining the average speed during different time periods. There are two rush hours in the downtown area of Vancouver, namely the morning and evening rush hours. During the morning commute hour, which occurs between 7 am and 9 am, the average speed is approximately 25 kilometres per hour. According to TomTom, the evening commute hour occurs between 4 pm and 6 pm with an average speed of 22 km/h. In contrast, a typical rate during regular hours is approximately 35 km/h.

The model's performance was evaluated based on two optimization criteria, the results of which are presented in

Figure 4. The graph illustrates that the ride-sharing model performs better during peak hours regarding the percentage of travel time saved and the number of shared journeys. During non-rush hours, match efficiency and shareability rates were approximately 35% and 83%, respectively, whereas they reached approximately 37% and 90% during rush hours.

Since the sharing rate (k) was assigned to 2 in this study, the match efficiency value would lie between 0 and 0.5. The utmost value of 0.5 can only be achieved if all trips are shared, which is practically impossible. In the present research, a maximum match efficacy value of 37% was determined. In addition, the model shared up to 90% of the trips, demonstrating its potential to reduce traffic by up to 45%.

Moreover, it is noteworthy that average speed tends to decrease during rush hour due to traffic congestion, which increases the total travel time for all journeys. This trend is evident in the graph, where the transition from non-rush hour to rush hour corresponds with an upward trend in total travel time, which makes perfect sense.

Furthermore, a sensitivity analysis was conducted on the model to determine the effect of demand fluctuations on the model's efficacy, assuming a constant 35 km/h average speed. Figure 6 illustrates the findings of this analysis. As shown in the graph, an increase in demand positively affects the model's efficacy in terms of the percentage of travel time saved and shared trips. This is anticipated because an increase in requests creates more potential common routes, resulting in a larger number of joined trips and, consequently, a rise in match efficacy and shareability. Additionally, the cumulative travel time for all passengers within the network increases as demand increases.

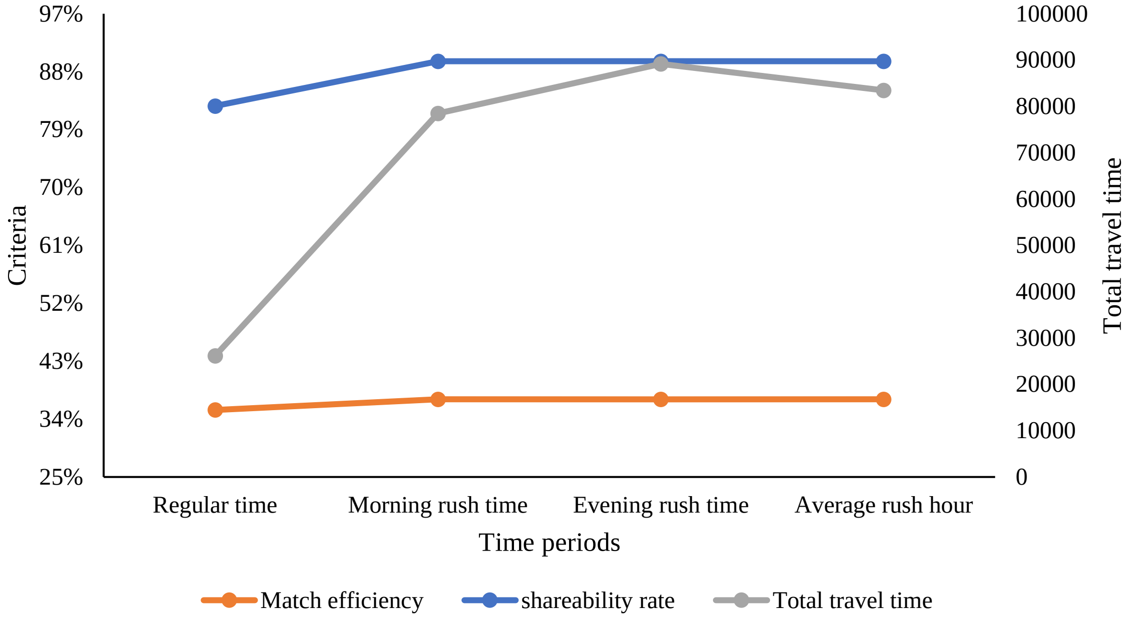

Figure 4. The efficiency of the ride-sharing model in regular times vs rush times

It should be noted, however, that the model's computation time increases exponentially as demand grows. This is because the model solves the ride-sharing problem by enumerating all possible solutions. In other words, the model performs well for small sizes, but it may no longer provide a reliable solution as it becomes more complex.

Finally, as an example for demonstrating the model's functionality, five requests were selected from the dataset, as depicted in Figure 5. It is possible to share request A with both B and C. Sharing of A and C results in a reduction of 48 seconds in travel time. On the contrary, when A is shared with B, there is an observable decrease in travel duration by roughly 3 minutes. The weighted maximum matching algorithm is designed to optimize the selection of edges by maximizing the cumulative weights of all selected edges. Thus, the full advantage of ride-sharing is achieved by matching trip requests A and B. The subsequent optimal pairing involves travel requests D and E, resulting in a reduction of travel time by 2 minutes.

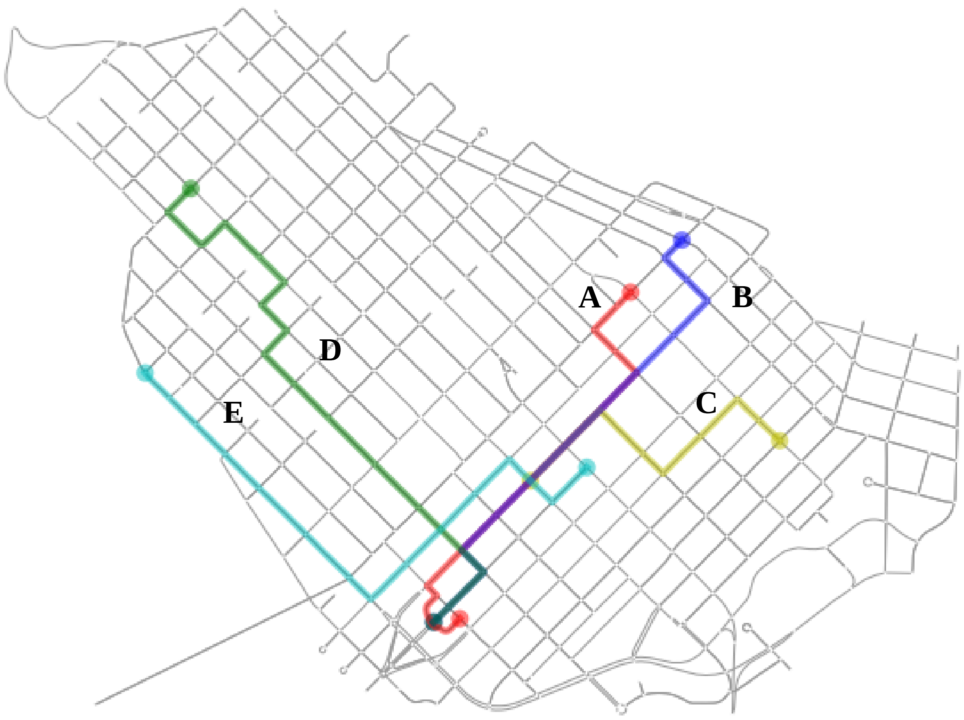

Figure 5. The Benefits of trip sharing in the Street network of Vancouver downtown

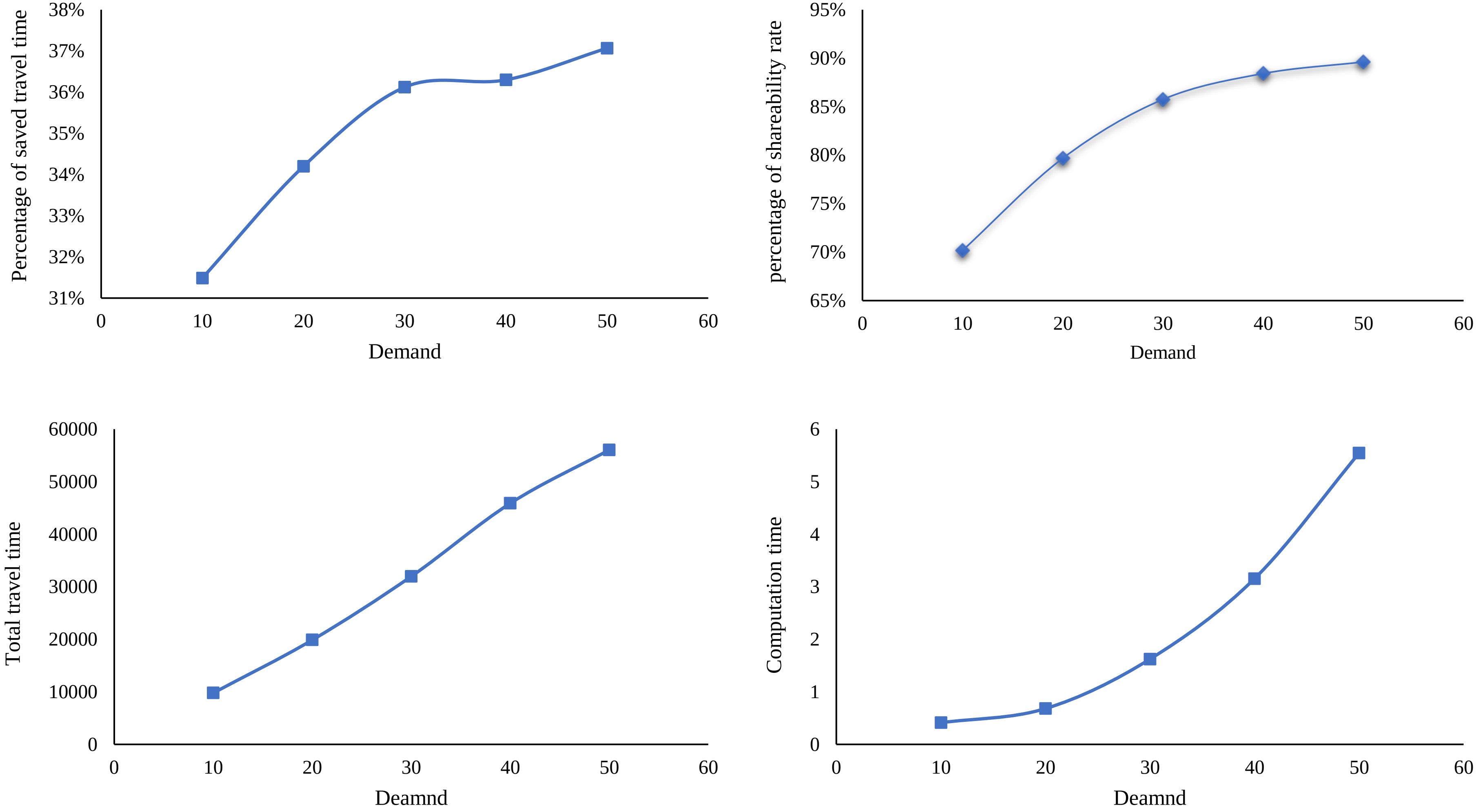

Figure 6. The results of the sensitivity analysis

6. Conclusion

This study aimed to assess how well ride-sharing in downtown Vancouver assists in reducing traffic congestion. To achieve this objective, the maximum matching algorithm from graph theory was utilized to determine the most efficient possible pairs of requests, optimizing for both a significant decrease in travel time and a maximum percentage of shared trips. The OSMnx package was used to apply the approach on the actual street network of the case study, and random requests were generated to test the model for a more accurate representation of the world.

The study revealed that Vancouver provides ample opportunities for trip sharing with minimal passenger discomfort without resorting to a computationally demanding sharing strategy that would require already-started trips to be rerouted on the fly. The identified opportunities are realistic and can be implemented in a new taxi system. The investigation showed that with a shareability rate of k=2, traffic congestion may be reduced by at least 40%. Moreover, customers' trip times were cut by at least 35% compared to when they travel alone, illustrating how ride-sharing services may greatly enhance urban transportation networks.

However, the current research has limitations that must be taken into account. From a computational standpoint, the employed algorithms exhibit exponential runtimes, indicating that this method is best adapted for small to medium-sized requests. The model cannot provide a valid solution for requests of a greater size. Future research should therefore concentrate on developing new methodologies that can eliminate this limitation and extend the model's applicability to large instances. In addition, it is suggested that the sharing analysis be expanded to other regions of Metro Vancouver to obtain a greater comprehension of the results' generalizability. Notably, the study presumed there was no delay between the time passengers requested a ride and the time the vehicle arrived, despite the fact that taxis require time to travel to the pickup location, especially during rush hours. Future research can consider a prespecified time window for pickup and delivery to accommodate the passenger's preferences in travel sharing, thereby enhancing the applicability of the model and the quality of service.

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