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Evaluating Carpool Potential for Home-to-Work SOV Commuters Using a Scalable and Practical Simulation Framework

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16. Abstract
Given that morning peak period vehicle occupancy rates are generally 1.1 to 1.2 persons per vehicle in urban areas, transportation planners have long argued that effective carpooling strategies could significantly reduce traffic congestion and the carbon footprint of commuters. Community-based carpooling, which is designed to match drivers and passengers that reside within subregions and that are traveling to similar destination zones, can be exploited once technology, communication, demographic, and economic barriers are overcome. While community-based carpool has the potential to provide sustainability benefits, integration into transportation plans and models is not prevalent, due to the lack of appropriate analytical tools. CarpoolSim is a new scalable analytical framework designed evaluate the potential performance and impact of intelligent carpooling system (ICS) for regional networks. Designed to be directly integrated into the travel demand modeling process, CarpoolSim uses a two-stage approach: 1) a filtering step with a set of comprehensive filtering conditions, to eliminate unreasonable carpool matches, given spatiotemporal constraints; and 2) an optimization step, to match as many carpools as possible (and eliminate any remaining assignment conflicts). Experiments using trip-level outputs from the Atlanta Regional Commission's activity-based travel demand model (ABM) show that, under conservative carpool matching constraints, about 24.1% of candidate single occupancy home-to-work commute trips to major employment centers along the I-85 corridor in Atlanta, GA could be carpooled by direct carpool. More than 19.2% of the same candidate commute trips could be carpooled via park-and-ride. Sensitivity analyses were applied. Among all of the control parameters, the minimum ratio between shared trip and individual trips travel time has the greatest impact on results. Although only 26,029 trips are selected for carpool matching (less than 0.5% of total daily trips originating near I-85), the experiments show that the potential for intelligent carpooling systems to manage commute trips to major employment center is reasonable, considering the spatiotemporal travel constraints of these travelers.

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Evaluating Carpool Potential for Home-to-Work SOV Commuters Using a Scalable and Practical Simulation Framework

A National Center for Sustainable Transportation Article

January 2024

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1. Introduction and Background

Despite the economic benefits that urban automobile-based travel has brought to society, numerous studies have highlighted its potential negative impacts on sustainable development. These include increased congestion (Walters, 1961), elevated carbon footprints (Fan et al., 2018), the promotion of urban sprawl (Wassmer, 2008), and the consumption of valuable urban land (McCahill and Garrick, 2012). This issue is especially pronounced in the United States, where morning peak period commute occupancy rates in urban areas hover around 1.1 to 1.2 persons per vehicle (FHWA, 2017). Over recent decades, carpooling has emerged as a promising form of shared mobility, offering an effective means to increase vehicle occupancy and counteract these challenges (Santos, 2018). Transportation planners believe that carpooling strategies can significantly reduce both traffic congestion and the carbon footprint of transportation systems (Meyer, 1999). By decreasing vehicle demand in job-centric urban districts, carpooling can also potentially free up parking spaces, allowing for alternative land uses and improving accessibility for lower-income households (Shaheen et al., 2017). Furthermore, by alleviating regional and local congestion during peak hours, carpooling can reduce the risk of system-level collapse and enhance network resilience (Fan et al., 2023).

Recognizing the myriad benefits of carpooling, transportation and planning agencies around the world have rolled out diverse incentives, particularly through infrastructure enhancements (Guensler, 1998). Agencies have introduced dedicated lanes, ramps, and roads to allow carpoolers to circumvent congestion and expedite travel. Examples include High-Occupancy Vehicle (HOV) lanes (Dachis, 2011), High-Occupancy Toll (HOT) lanes (Guensler et al., 2016; Konishi and Mun, 2010; Kall et al., 2009), and express carpool lanes (Guensler, et al., 2022; Small et al., 2006).

To facilitate carpooling pick-up and drop-off, designated stations and specific zones in densely populated urban areas have been established (Glasbeek, 1975). Additionally, carpoolers often benefit from preferred parking spots (Cools et al., 2013) or receive discounts or exemptions from parking fees (Olsson and Miller, 1978). Financial incentives further bolster carpooling, with measures such as reduced or waived congestion pricing (Yang and Huang, 1999), emission-based pricing discounts (Zong et al., 2021), and employer-based financial incentives (Canning et al., 2010). Integration with other modes of transport, like public transit (Minnett, 2013), also plays a pivotal role in promoting carpooling. As these initiatives gain traction, there's an escalating analytical demand to gauge the efficacy of these investments, both at the program level (in terms of incentive type selection) and the project level (focusing on site selection and specific implementation requirements).

Scholars have tackled this issue from two distinct perspectives. The first genre of study addresses the problem from the demand side, striving to comprehend influential factors on an individual's decision to carpool. These factors encompass household and neighborhood characteristics (Shin, 2017), job types (Vanoutrive et al., 2012), travel behaviors (Saxena and Gupta, 2023), and psychological elements (Julagasigorn et al., 2021). Researchers in this domain typically employ methods such as aggregate-level regression analysis (Benita, 2020), surveys or questionnaires (Lowe and Piantanakulchai, 2023), and stated choice methods (Le Goff et al., 2022). While these approaches have significantly advanced our understanding of travelers' behavior and trade-offs in mode choice (Zhou et al., 2022), their direct application in evaluating planning initiatives is often constrained by resultant models' lack of precision and quantifiability. Conversely, the second genre of study delves into the problem from the supply side, exploring the feasibility of carpooling in various contexts. This includes system-wide matching (Bakkal et al., 2017; Xia et al., 2015), self-organization (Kalczynski and Miklas-Kalczynska, 2018; Kleiner et al., 2011b; Nourinejad and Roorda, 2016a), and services provided by transportation network companies like Uber and Lyft (Agatz et al., 2012, 2011). This line of research has established a foundation for a repertoire of routing and matching algorithms, facilitating precise case-specific analyses. However, the predictive power of these studies regarding a network's carpooling performance is often hampered by the lack of model flexibility and practicality. To support project prioritization and evaluation in urban transportation planning, a carpool modeling scheme that is both scalable and practical is needed.

This study introduces a simulation framework tailored to facilitate transportation and planning agencies in addressing pivotal questions concerning carpool incentivization: Where are the carpooling hotspots within the planning area? Which infrastructure components demand prioritization? How might different planning scenarios impact the carpool matching rate? What are the factors that hinder users from carpooling in the current infrastructure system? In response to these questions, CarpoolSim is a carpool simulation framework crafted to meet several essential requirements for carpool planning analyses. The system provides precision (by offering detailed spatial and temporal data for each trip segment, enabling nuanced site comparisons and time-specific project prioritization), flexibility (by integrating diverse mediating parameters to depict varied carpool scenarios and ensuring compatibility with multiple incentivizing options), practicality (by designing parameters and matching schemes that reflect traveler behavior), and scalability (by incorporating optimization strategies suitable for large transportation system networks). Notably, CarpoolSim's output aligns seamlessly with standard travel demand modeling practice. To illustrate its capabilities, we delve into a case study based on the findings of a regional-scale activity-based travel demand model.

In the section of this paper that follow: **Section 2** discusses the latest updates in the research of related carpooling/ridesharing systems in terms of filtering conditions, optimizing algorithms, and partitioning methods; **Section 3** formulates the specific problem and methodologies used to solve the problem, wherein different components/modules of the proposed CarpoolSim are introduced; and **Section 4** tests the proposed method using the output of an activity-based travel demand. To assess model results, system performance is presented for the individual commuter, by different role (driver vs passenger), by spatial distribution, etc. A sensitivity analysis of CarpoolSim configuration parameters used to screen potential trip pairs is also presented to identify influential parameters on carpool match results. Lastly, **Section 5** summarizes the insights derived from the case study and the potential uses and strengths of the CarpoolSim analysis framework.

2. Literature Review

Certain conditions must be met for travelers (drivers and passengers) before they are likely to opt into carpooling as their commute mode. The most common shared condition in modeling is a pick-up and drop-off time window that both the driver and rider's start/end time must satisfy (Agatz et al., 2011; Peng and Du, 2022). Another condition defining the feasibility of carpooling is spatial proximity (Bakkal et al., 2017; Nourinejad and Roorda, 2016a). While sociodemographic factors do not appear as mainstream factors in current carpool matching processes, numerous studies underscore their influence. Factors such as gender (Molina et al., 2020), income (Shaheen et al., 2017), age, and education (Guensler et al., 2019) have been shown to potentially impact carpooling activity.

With respect to vehicle operation, carpools can also be categorized based upon passenger pick-up time constraints. While some models require that passengers be picked up at the beginning of the journey (Agatz et al., 2011), others allow a carpool to happen at any point along the driver's journey. The goal of carpooling is another consideration in several studies. For example, some studies try to minimize individual travel time, allowing a carpool match as long as a time-saving exists for any user (Agatz et al., 2011); however, a more commonly used approach is to minimize the total system-level travel time. Some studies seek to optimize a specific metric related to travel. For example, Bakkal et al. (Guo and Xu, 2022) sought to minimize wait time and detour time rather than total travel time, while Berlingerio et al. (Berlingerio et al., 2017) designed a measure of "enjoyability" as the goal for carpooling.

To optimize carpool matching, researchers have employed a wide variety of approaches. Those targeting system-wide performance optimization have leveraged methods, ranging from heuristic approaches (Xia et al., 2015) and greedy algorithms (Agatz et al., 2011; Nourinejad and Roorda, 2016a) to mixed integer mathematical programming (Peng and Du, 2022), pick-up and delivery problems (Agatz et al., 2012), insertion algorithms, and Tabu search algorithms (Kalczynski and Miklas-Kalczynska, 2018). Previous researchers have found that the system-wide utility will be higher when assuming each individual is rational and chooses to optimize his/her performance. For example, some studies use an auction-based mechanism for carpool matching, where riders "bid" on rides based on their utility (Kleiner et al., 2011b; Nourinejad and Roorda, 2016a). Kalczynski and Miklas-Kalczynska (2018) employ a similar algorithm called a "decentralized approach." More recent studies have started to combine system-wide optimization and individual utility. For example, Guo and Xu (2022) have applied a deep reinforcement learning approach to combine historical data with current carpool demand to achieve a trade-off between overall quality of service and individual utility optimization.

Faced with the goal of implementing carpool matching at the metropolitan region scale, and the complexity of the variety of algorithms that can be implemented, carpool matching often demands significant time and computational resources. To improve matching efficiency, researchers have devised various spatial partitioning schemes to reduce the need to test carpool pairs that are obviously inefficient based upon spatial and temporal distance separations between driver and passenger. One broad category is user-based partitioning, where users are partitioned into different carpooling communities. Some studies have performed user-based partitioning based on demographic characteristics (Peng and Du, 2022). Others have used more complicated methods, such as agent-based modeling (Nourinejad and Roorda, 2016a) and cluster analysis (Li et al., 2019). Another type of partitioning is performed using a bipartite graph, partitioning groups based on carpool potential (Tafreshian and Masoud, 2020). Table 1 summarizes some recent studies evaluating the potentials of the carpooling/ridesharing system. In summary, while these studies have either pioneered new carpool matching algorithms or explored implications in an idealized (Nie and Li, 2022) or limited (Kuwahara et al., 2022) context, there remains a gap in demonstrating the scalability and practicality of a holistic analysis framework.

In this paper, CarpoolSim, is proposed as a framework to seamlessly integrate data, algorithms, and spatiotemporal control factors to yield actionable insights. The CarpoolSim framework seeks to bridge this gap between the large quantity of trips and the complexity of the carpool problem. The proposed framework employs a set of filters to identify feasible carpool candidates, uses a scalable system based on the bipartite algorithm with heuristics for carpool matching, and integrates a rolling horizon algorithm and geo-fencing strategy to enhance model efficiency and scalability.

Table 1. A selective summary of recent studies on evaluating the performance and potentials of carpooling/ridesharing systems.

Author & Year	Problem	Proposed Matching Strategy	Partitioning/ Clustering Method	Optimization Approach	Network Representation & Trip demands	Results & Findings
Guo & Xu (2022)	RS	Use Deep reinforcement learning to maximizing total Q-values measuring benefits; two modules are designed: vehicle routing module and request assignment module	N.A.	Bipartite graph matching problem solved by Kuhn-Munkres (KM) algorithm	New York region (12km×12km or 24km× 24km region); New York Taxi Data (40-80 vehicles)	Proposed reinforcement learning approach is the best among 4 tested methods
Peng & Du (2022)	RS	Semi-centralized ride-matching strategy combined with Integer Programming method.	User-based partitioning on demographics	Mixed Integer Programming	Hardee network (44 nodes, 134 links); 100 trip requests	Partitioning trips can save computation time significantly
Tafreshian & Masoud (2020)	CP	Divide the graph of matching between vehicles and travelers into different subgraphs to lessen the computational burden.	Graph partitioning	Integer Programming	New York Taxi Data set; 248 pre-defined "stations" as start/end points with over 22,000 trips	Run a sensitivity analysis on different parameters with respect to matching qualities
Li et al. (2020)	RS	Cluster-first-route-second approach;	Greedy heuristics or k-means algorithm	Mixed Integer Programming	4 benchmark network instances are used. The largest one has 101 nodes of vehicles and passengers	Proposed method achieved 12.8% increase for objective function with speed similar to greedy algorithm
Li et al. (2019)	RS	Cluster-based algorithm to cluster passengers for ridesharing in fewer vehicles (each vehicle has occupancy greater than 1)	User-based partitioning with cluster analysis	Integer Programming	A 20 × 20 grid network; Random requests ranging from 500 to 4000 are tested.	Proposed method saved about 12-48 vehicles compared to the insertion algorithm

Author & Year	Problem	Proposed Matching Strategy	Partitioning/ Clustering Method	Optimization Approach	Network Representation & Trip demands	Results & Findings
Kalczynski & Miklas-Kalczynska (2018)	CP	Decentralized approach assuming participant prefer to choose the match with more savings	N.A.	Integer Programming solved by Insertion algorithm and Tabu search algorithm	Local road network in Orange County, California; A real "pre-K to 8" school bus study case. 281 children from 195 families.	The proposed heuristics mimics the planning steps for carpool organization by also incorporating non-carpooled vehicle costs.
Nourinejad & Roorda (2016)	RS	A fast algorithm designed based on auction-based mechanism;	User-based partitioning with agent-based model	Greedy Algorithm	Network of 24 nodes, 76 transportation links and 1.96 million travelers simulated.	The algorithm is flexible to solve single/multiple drivers to be matched with single/multiple passengers
Xia et al. (2015)	CP	Use heuristics approach to speed up the time solving the algorithm.	N.A.	Simulated Annealing Heuristic Approach solving Integer Programming	Road network of Guangzhou, China is used. Cases of 4-50 commuters are evaluated.	Brute force searching is nearly as effective as Linear Programming when commuter size is less than 4.
Agatz et al. (2012)	CP/RS	A review paper on carpooling, ridesharing and logistics problem.	N.A.	N.A.	N.A.	N.A.
Agatz et al. (2011)	RS	Solve large scale problem using rolling horizon strategy.	N.A.	Greedy Algorithm; Bipartite algorithm	2008 Travel Demand Data in Atlanta, Georgia.	Increase participation rate can significantly increase success rate
Kleiner et al. (2011)	RS	Auction-based mechanism; Proposed a platform for flexible choices between riders and drivers	N.A.	Hungarian algorithm; auction-based solver	Freiburg, Germany. About 50 passengers and drivers.	The performance of the auction-based system is close to that of the optimal solution

Notes for abbreviation and acronyms: RS: ridesharing; CP: carpooling

3. Methodology

This study introduces CarpoolSim, a simulation framework estimating carpool potential, within the context of a series of user-defined spatiotemporal constraints. CarpoolSim comprises three analytical modules: a filtering module, an optimization module, and a simulation module. The **filtering module** utilizes comprehensive conditions to eliminate infeasible carpool suggestions, offers flexible parameter configurations to adjust carpooling conditions, and can adapt to various planning scenarios. The **optimization module** is crafted to resolve the driver-passenger role conflict while maximizing the number of carpool matches. Meanwhile, the **simulation module** deploys a rolling horizon strategy and geo-fencing strategy, aiming to enhance the efficiency of the algorithm without compromising the level of detail necessary for practical applications.

The methodology section is structured as follows: Section 3.1 describes the basic carpooling scenarios studied in the paper. Section 3.2 establishes the foundation for formulating carpool travel plans using networks and matrices. Sections 3.3 and Section 3.4 delve into the filtering scheme, detailing various parameters and their sequence in the filtering pipeline. While Section 3.3 is centered on direct carpooling, Section 3.4 lays the groundwork for filters used in park-and-ride carpools. Sections 3.4 and Section 3.5 explained the optimization and simulation modules, respectively. Finally, Section 3.6 offers a comprehensive summary of all parameters in the CarpoolSim discussed in the preceding sub-sections.

3.1 Two carpool modes and four carpool schemes between any pair of travelers

This research delineates a framework that combines two carpooling modalities: direct carpool and park-and-ride carpool. In this context, Figure 1 illustrates four potential carpool travel plans between two travelers. The red and blue dots represent the origins and destinations of the carpool driver and passenger, respectively, with the red lines indicating the driver's path and the thick translucent green highlight marking the shared carpool segment. Figure 1 (a)-(b) shows two different possible carpools for a direct carpool match (where each carpooler is either a driver or a passenger, and the driver will pick up the passenger at the passenger’s trip origin). Another practical way of carpooling is to let two passengers meet at a midpoint before they begin the shared portion of their trip. These meet-and-carpool trips are referred to as park-and-ride (PNR) carpool mode. Similar to the direct carpool mode, Figure 1 (c)-(d) depicts two possible PNR carpool plans for the same pair of travelers. The black square represents the midpoint for the meeting, the blue dashed line and solid red lone show the paths for the carpoolers to access that meeting place (as driver or passenger), and the green highlighted line shows the shared carpool path. The direct carpool and PNR carpool patterns look similar, except that carpool passengers needs to drive themselves to the meeting point before being picked up by the drivers. Given the four schemes for the carpool trips between two travelers, it is time to formulate the computational equations evaluating feasibilities and qualities of any specific carpool traveling plan.

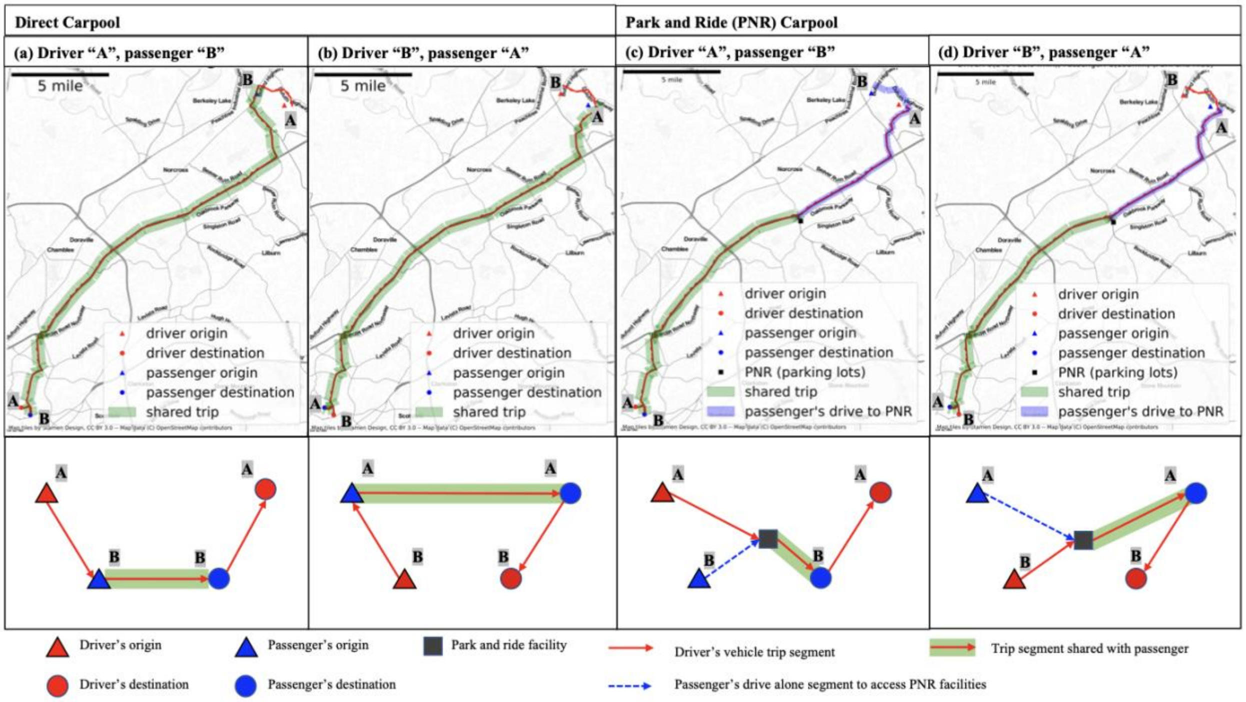

Figure 1. Four possible carpool traveling plans between the same pair of travelers.

It is important to note that carpool trips, in terms of their execution and sharing dynamics, can become much more complicated than those aforementioned cases. For example, a carpool trip can accommodate more than 2 travelers. Transitioning from 2-person to 3-person carpools has proven challenging, as matching with multiple individuals becomes less feasible when considering all three commuters' strict time constraints. Consequently, this study narrows its focus to the impacts of direct carpool and PNR carpool for 2-person carpools only, which are much more feasible for commuters to form.

3.2 Formulating carpool travel plans: from shareability network to matrix notations

To enumerate all possible carpool vehicles' travel plans among a group of travelers, it is important to record the information in a more compact way. To the best knowledge of the authors, the three primary ways of describing carpool plans among a group of candidates are by: shareability network, bipartite graph, and feasibility matrix. Figure 2 demonstrates the logical connections and relationships among the three different networks using a toy example with only five potential carpool candidates. In Figure 2 (a), all five travelers (each denoted as a node indexed from 1 to 5) originate as SOV (drive-alone) travelers. Each person can join and form a carpool trip either as a driver or a passenger. Figure 2 (b) uses directional links pointing from the passenger node to the driver node to denote all feasible carpool assignments. In this study, diagrams like Figure 2 (b) are referred to as the shareability network, where each node denotes a traveler, and each link represents a feasible carpool plan. Figure 2 (c) further splits each node in Figure 2 (a)/(b) into two disjoint sets by their specific roles (i.e., passenger or driver) in carpool trips. Moreover, the directional links in Figure 2 (b) are converted to undirected links to denote all five potential carpool assignments.

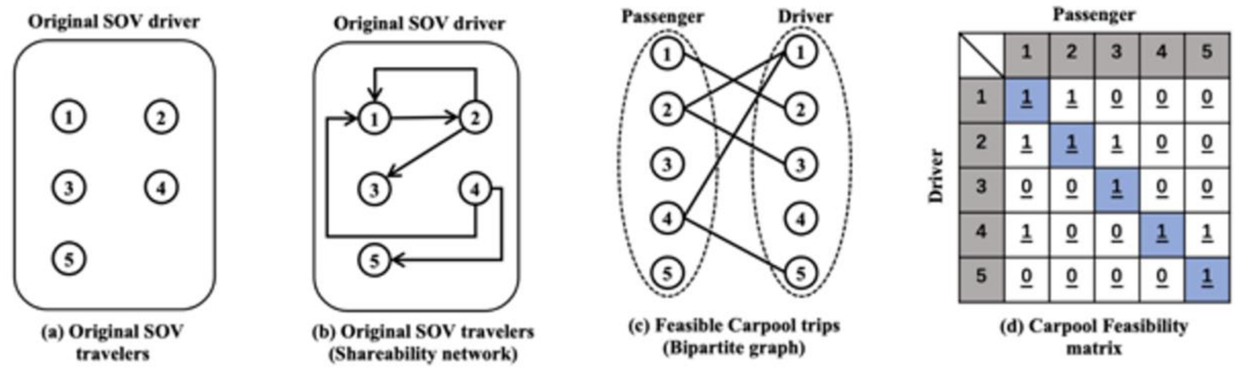

Figure 2. Three different notations for feasible carpool relationships: The shareability network notation, the bipartite graph, and the feasibility matrix.

Furthermore, the information in Figure 2 (b)/(c) (shareability network or bipartite graph) can also be represented by a feasibility matrix as shown in Figure 2 (d). In Figure 2 (d), the first index row and first index column (with grey background) denotes the index of the driver and passenger IDs, respectively. Within this feasibility matrix denoted as F, the entry corresponds to the i th row and j th column denote the carpool between i th driver and the j th passenger. Thus, $F(i,j) = 1$ denotes the case where driver i and passenger j can be assigned to a carpool. The diagonal entries (with blue background) are always 1 to denote that all travelers can always choose to drive alone if not assigned to a carpool.

In essence, given n potential carpool travelers within a group, there are $P(n, 2) = n \times (n-1)$ possible carpool trip configurations. Accounting for those who might opt to drive alone, the total possible travel plans amount to $n \times (n-1) + n = n \times n$ for n travelers. Consequently, a feasibility matrix of $n \times n$ dimensions can encapsulate the feasibility data among n travelers. Beyond the feasibility matrix, other information (e.g., travel time, distance, etc.) can be stored in matrices with the same shape. Note that if both carpool schemes (i.e., direct carpool and PNR carpool) are considered at the same time, two feasibility matrices are necessary to store the information.

3.3 Filtering module for the direct carpool mode

After explaining the carpool representation as network and matrices, to ascertain valid carpool trips, we need to implement a mechanism to efficiently filter out unsuitable/low-quality carpooling matches considering spatiotemporal constraints. There are three types of filtering constraints: (1) the Euclidean distance filter; (2) the temporal separation filter; and (3) the path distance filter. By default, all filtering conditions discussed in this section pertain to the direct carpool mode. The PNR mode, while conceptually similar, will be elaborated upon in Section 3.4.

3.3.1 Euclidean Distance Filters

The Euclidean distance filter is efficient in filtering out low-quality matches. Given the coordinates of each person, the traveling paths for each person can be simplified as one vector or a combination of consecutive vectors. In Figure 3, the coordinates of the driver's origin O_1 and destination D_1 are denoted as (x_1, y_1), (x_2, y_2), respectively. Thus, the vector $\overrightarrow{O_1 D_1}$ pointing from origin to destination can coarsely denote the trip's traveling direction and distance and helps compare similarities of trips among different travelers.

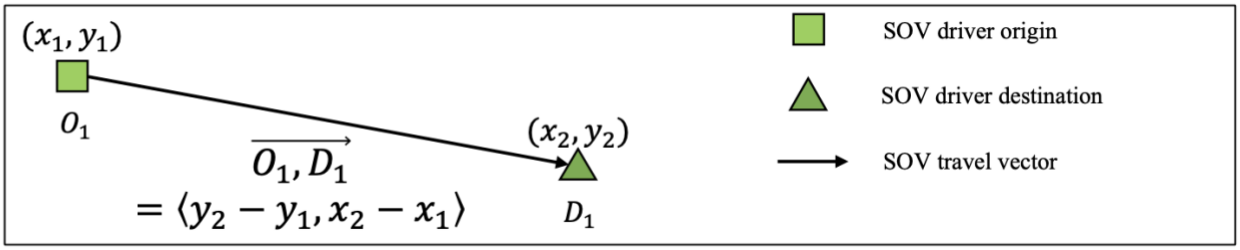

Figure 3. Use a vector to represent the SOV trip between the origin O_1 and the destination D_1.

Figure 4 illustrates the carpool travel plan between driver 1 and passenger 2 using three vectors: $\overrightarrow{O_1 O_2}$, $\overrightarrow{O_2 D_2}$, $\overrightarrow{D_2 D_1}$. These vectors represent the trip segments involved in a matched trip, where $\overrightarrow{O_1 O_2}$ denotes the driver's segment to the passenger's trip origin, $\overrightarrow{O_2 D_2}$ signifies the overlapping trip portion, and $\overrightarrow{D_2 D_1}$ indicates the driver's segment from the passenger's destination to the driver's own destination. Using these vectors, we formulate different filtering criteria as follows.

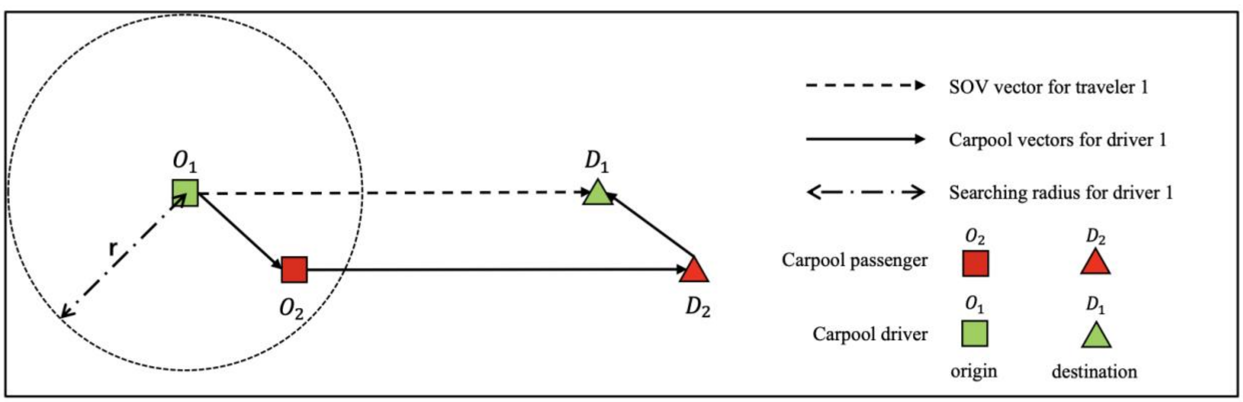

Figure 4. Use three vectors to represent a carpool trip as well as the driver's traveling path.

Criterion 1-1: The Euclidean distance between the driver's and passenger's origin coordinates are within an empirically determined threshold, r.

$$\left\|\overrightarrow{O_1 O_2}\right\| \leq r \tag{1}$$

where $\left\|\overrightarrow{O_1 O_2}\right\|$ denotes the L-2 distance (i.e., Euclidean length) of $\overrightarrow{O_1 O_2}$.

Criterion 1-2: The ratio in Euclidean distance between the driver's whole carpool segment and the shared trip segment should be capped by an empirically determined threshold μ_1:

$$\frac{\|\overrightarrow{O_1O_2}\|+\|\overrightarrow{O_2D_2}\|+\|\overrightarrow{D_2D_1}\|}{\|\overrightarrow{O_2D_2}\|} \leq \mu_1 \tag{2}$$

Criterion 1-1 and 1-2 effectively filter out many unsuitable carpool matches. However, to further refine the selection, we introduce an additional Euclidean filter. Figure 5 depicts a scenario where the carpool driver has to drive past their destination to drop off the passenger, subsequently driving in the reverse direction to reach their own destination. To account for such cases, we formulate Criterion 1-3. In this criterion, the numerator represents the length of the blue dashed line in Figure 5. If this length exceeds a certain proportion μ_2 of the driver's original distance, then the carpool match is not appropriate.

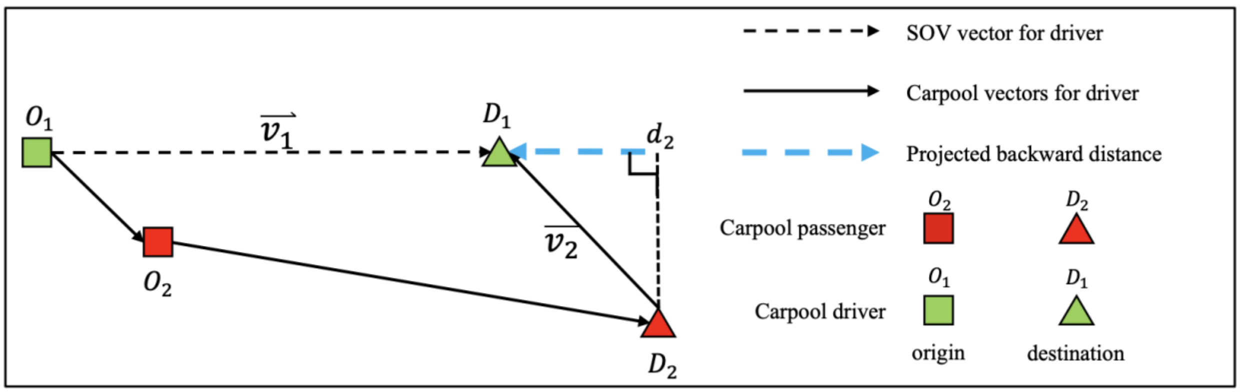

Figure 5. Use of a projected vector (in blue) to describe the "reverse travel" cost after dropping off the passenger.

Criterion 1-3: The ratio between the projected "reversal travel" distance and the shared distance should be smaller than an empirically determined threshold μ_2:

$$\frac{-\overrightarrow{v_1}\cdot\overrightarrow{v_2}}{\overrightarrow{v_1}\cdot\overrightarrow{v_1}} = \frac{-\|\overrightarrow{O_1D_1}\|\cdot\|\overrightarrow{D_2D_1}\|\cdot\cos\langle\overrightarrow{v_1},\overrightarrow{v_2}\rangle}{\|\overrightarrow{O_1D_1}\|\cdot\|\overrightarrow{O_1D_1}\|} = \frac{\overline{d_2D_1}}{\overline{O_1D_1}} \leq \mu_2 \tag{3}$$

3.3.2 Temporal Separation Filters

Temporal filters account for the time difference between two trips, adding an additional layer of complexity beyond mere distance, as factors like congestion can play a significant role in carpool viability. For this study, we introduce two temporal filtering criteria:

Criterion 2-1: The difference in departure times between two travelers should not exceed a predefined threshold:

$$\left|T_{O_1} - T_{O_2}\right| \leq \Delta_1 \tag{4}$$

Here, T_{O_1} and T_{O_2} represent the original departure times from O_1 and O_2 for the first and second carpool participants, respectively. The parameter Δ_1, a constant defined as the maximum allowable difference in departure time, is used to efficiently filter out candidate carpool matches that depart at very different times.

Criterion 2-2: The maximum waiting time for the carpool passengers at their origin (i.e., pick-up location) is capped by a threshold:

$$T_{O_2} \leq T_{O_1} + TT_{O_1O_2} \leq T_{O_2} + \Delta_2 \tag{5}$$

where $TT_{O_1O_2}$ denotes the travel time on road networks from O_1 to O_2 for the driver during the whole carpool trip. The driver's time of arrival at the passenger's pick-up point (origin) cannot be more than Δ_2 minutes after the passenger's original departure time. Because the driver has already rerouted to accept a longer distance for the carpool trip, it would be more reasonable if the extra waiting time cost is "paid" on the passenger's side. That is, by design, the passenger's departure time should be earlier than when the driver's arrival time at the passenger's origin.

3.3.3 Path Distance Filters

While the temporal previous filters efficiently eliminate low-quality carpool matches, they may not be sufficient. Hence, we propose supplemental path distance filters that employ actual travel path distances. These filters can be viewed as a more accurate version of the Euclidean distance filters using network distance. This category introduces three filters.

Criterion 3-1: The driver's total carpool travel time minus the driver's original SOV time is capped by a fixed amount:

$$\left(TT_{O_1O_2} + TT_{O_2D_2} + TT_{D_2D_1}\right) - TT_{O_1D_1} \leq \delta_1 \tag{6}$$

where δ_1 is the travel time cap of the extra traveling (reroute) time cost for carpool drivers. In this study, δ_1 is chosen to be either 10 or 15 minutes (any reasonable times can be specified).

Criterion 3-2: The ratio of post-carpool total travel time for the driver (shared travel time plus segments traveled by the driver alone) over the driver's original SOV travel time is capped by a ratio:

$$\frac{TT_{O_1O_2}+TT_{O_2D_2}+TT_{D_2D_1}}{TT_{O_1D_1}} \leq \gamma \tag{7}$$

where γ is the lower bound of the shared travel time for drivers. In practice, it is suggested that γ should be at most 1.5, and a value around 1.25 may be more appropriate to filter out lower-quality carpool matchings.

Criterion 3-3: The passenger's travel time takes a significant portion of the carpool driver's travel time:

$$\frac{TT_{O_2D_2}}{TT_{O_1O_2}+TT_{O_2D_2}+TT_{D_2D_1}} \geq \iota \tag{8}$$

where the Greek letter ι (iota) denotes the lower bound of the ratio between shared distance and the driver's total distance.

Considering the high computational demand required for these filters (searching shortest paths on networks), the path distance filters are executed as the last step of all filtering steps to minimize the total computational efforts.

3.3.4 Organizing the Filters for Improved Computational Efficiency

In practice, all the proposed filters are executed in matrix form to leverage vectorized computation. For efficiency, simpler filters are applied before the more complex ones. The computational sequence adopted in CarpoolSim for executing the criteria is:

"2-1"→ "1-1" → "1-2" → "1-3" → "2-2" → "3-1" → "3-2" → "3-3".

3.4 The filtering module for PNR carpool mode

As a reminder, the Park-and-Ride (PNR) mode involves two carpoolers meeting at a designated midpoint, such as a public parking lot, before initiating their shared journey. Given the limited number of parking lots specified in this study, the PNR matching mode can be conceptualized as a two-step process: 1) assessing whether a driver can bypass a midpoint without incurring too much reroute costs in time or distance; and 2) if the first condition is met, assessing whether two individuals can initiate a carpool from the identified midpoint.

Figure 6 illustrates the first filtering step. Adapted versions of Criteria 1-1 and 3-1 are employed to gauge accessibility to all PNR stations. This results in a feasibility matrix that maps from individuals to PNR stations, providing insights into travelers' accessibility to these stations (as depicted in the lower left of Figure 6).

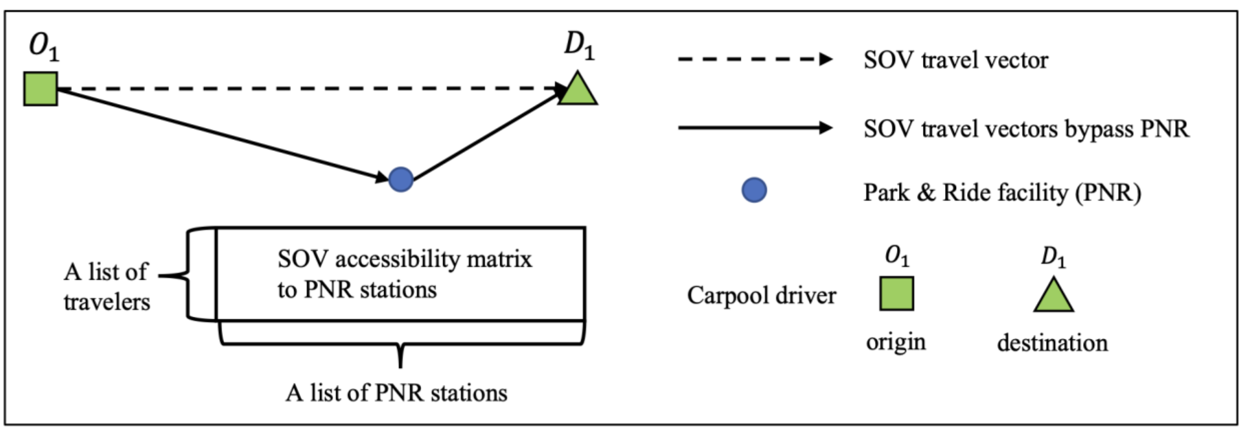

Figure 6. Use of projected vector to describe an SOV driver bypassing a PNR facility.

In evaluating the accessibility between travelers and PNR stations, the next step is to determine whether two individuals can carpool from each specific PNR station. This matrix can be initialized through matrix multiplication, as shown in the top left of Figure 7. Subsequently, all filters from Section 3.3 are reapplied, but with the assumption that both travelers commence from the PNR station and their trip requests align with their arrival times at these stations. It's worth noting that while this two-step filtering approach adopts slightly more lenient constraints compared to the direct carpool method, experimental results indicate that the quality of carpool matches remains on par with direct carpool outcomes.

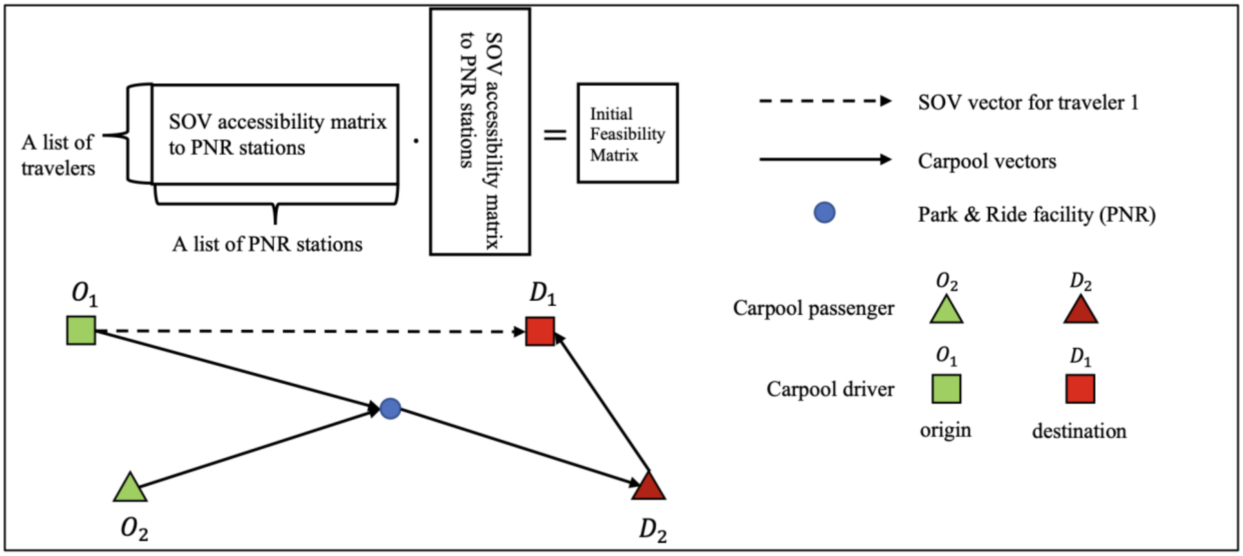

Figure 7. Evaluating PNR carpool from based on the accessibility matrix from travelers to PNR stations.

3.5 The Optimization Module

Upon completion of the filtering steps, we obtain a finalized version of the 0-1 feasibility matrix. In this matrix, entries with a value of 1 indicate feasible carpool trips. However, not every potential match can be realized due to two primary constraints: 1) **Time Conflict** - a driver can't carpool with multiple passengers simultaneously, and similarly, a passenger can't carpool with multiple drivers at the same time; and 2) **Role Conflict** - for each trip an individual can be a driver, or a passenger, but not both. To address these conflicts and maximize the number of carpool pairings, this study employs a two-step algorithm: 1) **Bipartite Algorithm** (as illustrated in **Figure 2 (c)**) - this algorithm is used to determine the maximum number of carpooling matches after resolving time conflicts; and 2) **Role Conflict Resolution** - this step addresses remaining role conflicts by eliminating the minimum number of carpool trips. The primary objective of this algorithm is to quickly identify a large number of feasible carpool trips. Unlike certain algorithms from other studies, such as auction-based algorithms (Kleiner et al., 2011a; Nourinejad and Roorda, 2016b), which prioritize certain matches over others, our approach treats all feasible carpool candidates equally during the optimization phase, given that they've already met the filtering criteria.

Figure 8 describes the carpool matching algorithm, building upon the example provided in Figure 2. Figure 8 (a)-(b) showcasing the transformation of the Bipartite problem into the Max-flow algorithm. In Figure 8 (b), the goal of the Max-flow problem is to determine the maximum flow from the source node (s) to the sink node (t), assuming each link has a capacity of one. The green lines in Figure 8 (a)-(b) represent a potential optimal solution for both the Max-flow and

Bipartite problems. This step effectively resolves all time conflicts. The results from Figure 8 (b) transition to Figure 8 (d), which represents a shareability network. Notably, travelers 2 and 4 are designated as drivers in one trip and passengers in another, indicating unresolved role conflicts. To address this, our role conflict resolution algorithm is straightforward: for each connected component in the network graph, links are numbered sequentially from 1 to k. Subsequently, links (or carpool matches) with even indices are removed. In essence, this two-step process combines the Bipartite algorithm with a heuristic rule to efficiently address both time and role conflicts.

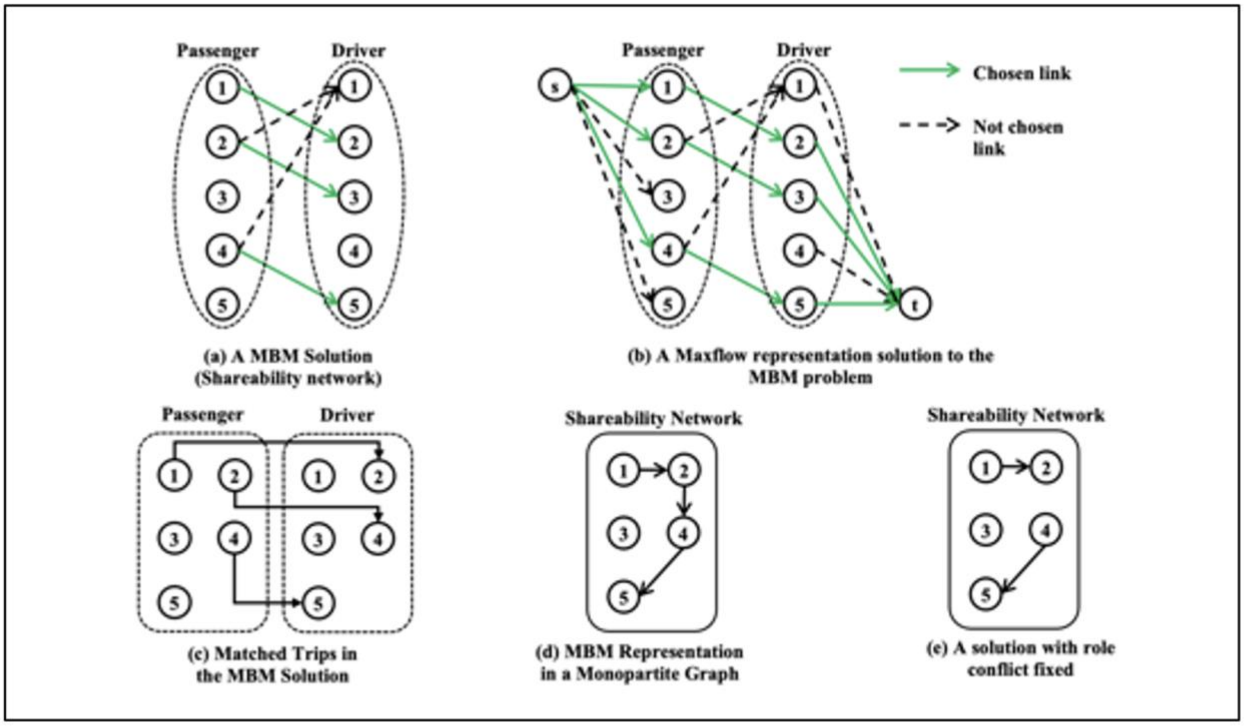

Figure 8. A small example of graph representations of solving the carpool matching problem.

3.6 The Simulation Framework

While the filtering and optimization modules effectively address the carpool matching problem, the computational efficiency can be further enhanced. Given that most travel demand is dispersed both spatially and temporally, the memory space required for analysis can grow quadratically $O(n^2)$ with the number of carpool candidates, n (considering $n \times n$ matrices are used). As such, it's more efficient to partition trips based on their spatiotemporal proximity.

In terms of temporal partitioning, the CarpoolSim operates in a simulation mode, focusing on trips in the immediate future. This is referred to as the rolling horizon strategy. As illustrated in Figure 9, if the current simulation time is t, trips departing between time t and time $t + t_0$ (represented by the green band) are potential carpool drivers. Meanwhile, trips departing between t and time $t + t_1$ (spanning both green and blue bands) can be carpool passengers. This design emulates a dynamic carpool system where users request carpools shortly before their departure. Consequently, the feasibility matrix is adjusted to a rectangular shape (since the number of passengers and drivers are different), as shown in the lower right of Figure 9 with $|S_d|$ and $|S_p|$ number of drivers and passengers, respectively).

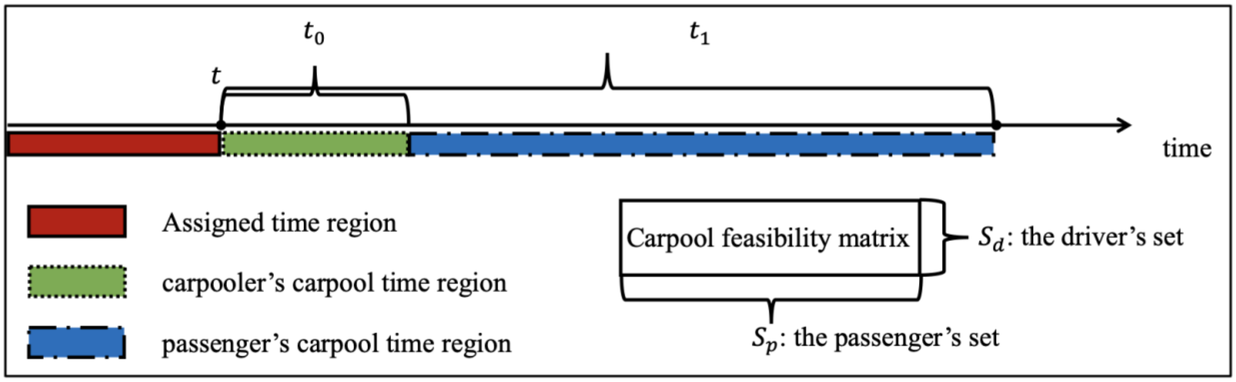

Figure 9. The relationship between time regions and carpool passenger/driver sets

Following the assignment at time t, the simulation clock advances by a small step of w minutes, as demonstrated in Figure 10. Before this update, several trip management steps are undertaken. Trips assigned to a carpool are removed from the candidate pool. Trips scheduled to depart before the current time t are also removed. Those without a carpool assignment default to their original SOV mode. As the time regions in Figure 10 shift right by w minutes, new carpool requests are added. By iterating through the simulation day, every carpool requester receives an assignment. They either join a carpool or retain their original SOV mode.

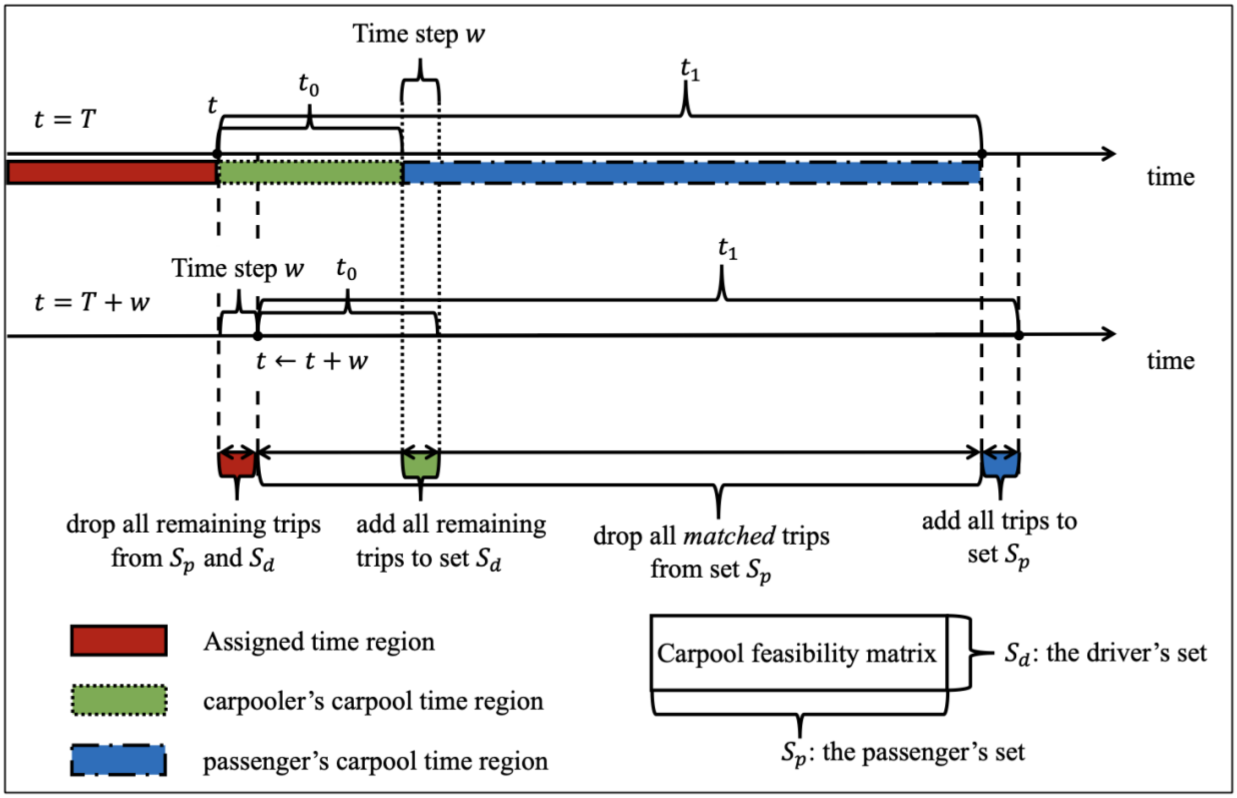

Figure 10. Updating the simulation module and data processing steps

Besides visually present the updating steps of the rolling horizon algorithm, a formal pseudocode detailing this simulation update process is provided in Figure 11. Executing this procedure ensures that each trip is assigned a unique index. As a result, assignment outcomes and trip details, including any designated carpool role and travel schedule, can be efficiently tracked using tabular data.

Procedure:

Input:

t: current simulating time
t_0: the number of minutes from t to be considered for available carpool drivers
t_1: the number of minutes from t to be considered for available carpool passengers
w: time interval for updating the simulation time. In this study, $w \leq t_0 \leq t_1$
s_P: the set of all travelers that could be assigned as carpool passengers (temporary)
s_D: the set of all travelers that could be assigned as carpool drivers (temporary)
s_A: the set of all travelers that already assigned as carpool trips (temporary)
S_N: the set of all travelers without assignment (i.e., trips haven't loaded in the future)
S_A: the set of all travelers with role assigned (i.e., trips have already scheduled from the past)

$t = 0$; $s_P = s_D = s_A = S_A = \phi$; $S_N =$ "all travelers" /*initialize time clock*/
$s_P, s_D, S_N =$ initializeSets(t, t_0, t_1, w);
For time index $i = 0$ to $\lfloor \frac{1440}{w} \rfloor${
  $s_M =$ matchAllCarpools(s_P, s_D); /*run optimization module, return matched trips*/
  $t \leftarrow t + w$; /*update simulation time clock*/
  $r_1 =$ getAllTripsBetweenTimeRange($t - w, t$); /*gather all outdated trips*/
  $s_D = s_D \cup$ loadFutureTripsBetweenTimeRange(t, $t + t_0$, S_N); /*load new driver trips*/
  $s_P = s_P \cup$ loadFutureTripsBetweenTimeRange(t, $t + t_1$, S_N); /*load new passenger trips*/
  $S_A = s_A \cup r_1 \cup s_M$; /*drop all assigned trips from set*/
  $s_D = s_D - s_A$; $s_P = s_P - s_A$; /*matched trips are dropped from S and recorded*/
  $s_A = \phi$; /*clear set for the next time step*/
}

Figure 11. Pseudocode for running the simulation program.

In addition to applying rolling horizon strategy to update in time, the geo-fencing strategy runs concurrently. To reach concurrence, one must group the computational tasks into groups by aggregating with distinct origins and destinations. To delineate the analysis zones, large distinct regional wedges are identified, surrounding major freeway commute corridors, and often demarcated by notable boundaries such as rivers. These distinct spatial wedges are large enough that most carpooling opportunities reside within wedges (see Figure 12).

3.7 The Control Parameters

All parameters discussed in Sections 3.1 through 3.4 are consolidated in Table 2 below. While most of these parameters serve to impose constraints on carpool matching, the last three specifically dictate the granularity of the simulation model's operational schemes.

Table 2. Default configuration parameters in the experiment (SOV mode and PNR mode)

Parameter name	**Definition/Interpretation**	**Default Settings**
Euclidean Distance Filters		
r	Euclidian distance from the driver's origin to the pick-up location of the passenger	5 miles
μ_1	The ratio between shared carpool distance and the carpool distance	1.5
μ_2	The ratio between the travel segment after the passenger is dropped off and the driver's original travel time	0.1
Path Travel Time Filters		
δ_1	Extra travel time for carpool modes for drivers compared to the SOV mode	15 minutes
γ	The minimum proportion of shared travel time over the driver's SOV time	1.3
ι (SOV mode)	The minimum proportion of shared travel time over the passenger's SOV time	0.85
ι (PNR mode)	The minimum proportion of shared travel time over the passenger's SOV time	0.5
Temporal Filters		
c_1	The maximum difference in the departure time	15 minutes
δ_2	The maximum waiting time for the carpool passengers (driver should never wait in a carpool)	10 minutes
Simulation program settings		
δ_t	The maximum number of minutes in the near future for passengers to send travel requests	10 minutes
ϵ_t	The maximum number of minutes into the near future for drivers to depart	2.5 minutes
w	The number of minutes to update the simulation clock each time	1 minute

4. Experiment

To gauge the efficacy and applicability of the CarpoolSim framework, we implemented it in the vicinity of the I-85 inbound highway corridor in Atlanta, Georgia. To prepare for experiment, Section 4.1 elaborates the data preprocessing steps. Section 4.2 initiates our assessment with an experiment based on default configuration parameters. To further understand the marginal impacts of these parameters, Section 4.3 conducts a sensitivity analysis using a one-variable-at-a-time (OVaaT) approach, where each carpool match constraint parameter was varied one at a time.

4.1 Data Processing

4.1.1 Study Area and Data

To experiment with carpool potential, the Atlanta Metropolitan Area ("Metro Atlanta"), the major urban cluster in Georgia, United States, is used as a study case. As of 2020, Metro Atlanta was home to over six million people and there is a heavy reliance on automobile transportation in Metro Atlanta (Crimmins and Preston, 1980; Henderson, 2002). For example, the observed average vehicle occupancy in the morning commute along the I-85 corridor is less than 1.3 persons per vehicle (Guensler et al., 2022); most vehicles on the road are single-occupancy vehicles (SOVs), where the driver is the only vehicle occupant. On the other hand, Metro Atlanta has established a relatively mature transit system with various options for riders, including fixed-route rail transit, bus service, and express bus service (ARC, 2021). Thus, it is important to measure the possibility of using existing parking lots (e.g., park-and-ride stations) for carpool activities. Moreover, a comparison between PNR carpool and direct carpool is also a meaningful study to evaluate the potential of carpool systems.

4.1.2 Identifying trips for the analysis: identify traveler of interests from the synthetic population

We have devised a systematic filtering procedure to identify potential carpool candidates. This procedure is delineated in Table 3, which encompasses details such as the total number of trips, the percentage retained from the preceding step, the cumulative retained percentage in both number and mileage, among other metrics.

Given our focus on the I-85 corridor, the initial step in curating candidate trips for carpool matching involved extracting a subset of regional trips emanating from this specific area, amounting to 4,984,177 trips (a little more than a quarter of total model-predicted daily automobile trips within the region). Out of these nearly five million trips, approximately 1.7 million have their starting point at homes, with 73,250 arriving at the employment hubs along I-285. Notably, 55.3% of these journeys are work-related, and 64.2% are undertaken by single-occupancy vehicles (SOVs). This narrows down the pool to 26,029 viable carpool trips for matching. In this study, roughly 0.522% of total regional trips (originating in proximity to I-85), or about 1.615% of the total daily regional trip mileage, are candidates for employment center carpooling. The cumulative sample size employed in this experiment stands at 26,029 trips, translating to a total distance of 553,805 miles per day of travel.

Table 3. The steps of identifying commuter of interest for the case study from the Atlanta's ARC ABM model results.

Trip Conditions	Number of Trips Retained	Percent of Trips Retained	Travel Distance Retained (miles)	Percent of Travel Distance Retained
Total Daily Trips	19,235,737		136,589,656	
Daily Departures along the I-85 Corridor	4,984,177	100.00%	34,290,538	100.0%
Corridor Departures from Home (34.22%)	1,705,854	34.22%	13,818,307	40.3%
Home to Employment Center Pairs (4.29%)	73,250	1.47%	1,478,443	4.31%
Center Arrivals that are Work Trips (55.32%)	40,519	0.813%	860,710	2.51%
Work Trip Arrivals by SOV Mode (64.24%)	26,029	0.522%	553,805	1.62%

Upon identifying the carpool population, we visualized the distribution of origin and destination pairs. Figure 12 (a) illustrates the spatial scope of the study and identifies the travelers of interest. The origins and destinations are geographically delineated by adjacent zones around the I-85 corridor and within the confines of I-285, a ring-shaped circulating highway encircling a vast central portion of Metro Atlanta. Four large regions (i.e., wedges) are identified within I-285. Two regions, plotted in orange and blue, are identified along I-85 and out of I-285. Figure 12 (b) offers a graphical representation of the origins and destinations of potential carpoolers within each Traffic Analysis Zone (TAZ) parcel. The areas shaded from white to red outside of I-285 represent the departure points of the 26,029 candidate travelers heading to work from their respective TAZs. Conversely, the areas transitioning from yellow to green within I-285 signify the destinations of these candidates, marking their arrival at employment hubs, as predefined by the Atlanta Regional Commission.

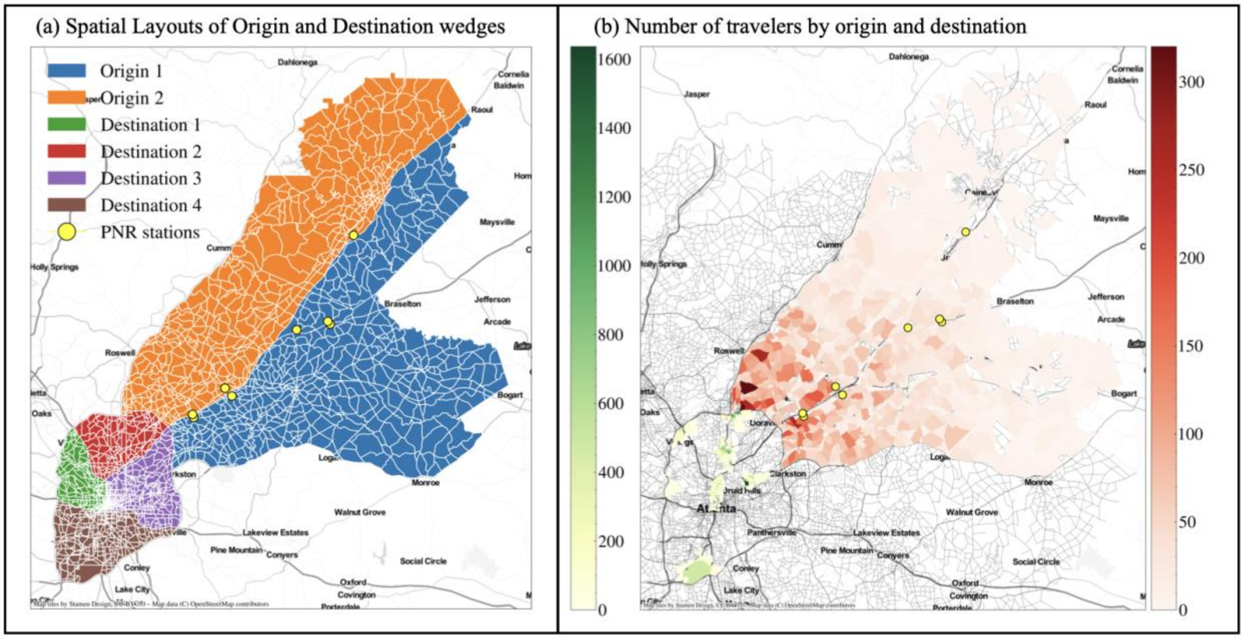

Figure 12. Distribution of trip demands by origins and destinations.

4.1.3 Enhancing accuracy: resampling and refining spatiotemporal data for CarpoolSim

After identifying the target population, it's essential to refine the trip data sourced from the ABM to ensure a more granular spatiotemporal resolution suitable for carpool analysis. To achieve this, each trip is allocated a refined longitude-latitude coordinate within its original and destination TAZ, effectively enhancing the spatial precision. Given that the ABM's output data clusters departure/arrival times in 30-minute intervals, we employed a spline curve fitting method to resample departure times down to a specific minute. The refined arrival time is then quantified by adding the shortest network travel time to the resampled departure time.

4.2 Experiment results for the default scenario

This section presents the experiment results from the default scenario. Section 4.2.1 introduces the overall carpooling potential, as illustrated by the upper bound condition allowed in the infrastructure setup. Section 4.2.2 discusses implications from the before/after analysis. Finally, Section 4.2.3 takes a closer look at the spatial representation and potential impacts of carpooling on traffic volume and congestion.

4.2.1 Overall carpool potential

To gauge the implications of smart carpooling in a specific scenario, we conducted a before-and-after analysis using the processed data. CarpoolSim model is executed by utilizing the default filter parameters in Table 2. These parameters ensure, for instance, that no driver spends over 15 extra minutes for passenger pick-up, no passenger waits beyond 10 minutes from their intended departure time, and the shared route encompasses at least 85% of the passenger's original SOV commute. The constraints for the default settings are neither too loose nor too strict to the authors perspective.

Applying the CarpoolSim framework, eligible SOV commute trips were paired through both direct carpool and PNR carpool. The results, using the default parameters from Table 2, revealed that approximately 24% of the potential single-occupancy home-to-work commutes to primary employment hubs along the I-85 corridor in Metro Atlanta could be facilitated through direct carpools. Furthermore, over 19% of these trips could be paired via the PNR carpool mode.

While the candidate home-to-work SOV trips heading to the primary employment centers along I-85 represent a mere 1.62% of the total daily travel mileages originating near I-85 (as per Table 3), the number is not small as many trips are not inbound trips towards those employment centers. Future studies will release the constraints towards employment centers to assess the potential of more widespread morning peak period carpool matching.

4.2.2 Implications from the before-and-after analysis

Upon implementing the CarpoolSim framework, we visualized the travel time variations before and after carpool matching. Figure 13 provides a comprehensive view of these variations. The histograms in Figure 13 (a)/(b) and Figure 13 (c)/(d) represent travel time distributions for the direct carpool mode and the park-and-ride (PNR) mode, respectively. Figure 13 (a)/(c) provide these distributions in terms of number of travelers, and Figure 13 (b)/(d) in terms of vehicle miles traveled (VMT). Each panel, from top to bottom, includes five histograms, showing the change in travel time distribution for all travelers, SOV trips, carpool drivers, carpool passengers, and all traveling vehicles, respectively. The white boxes in Figure 13 (a)/(c) show each type's share compared to the total population. In Figure 13 (b)/(d), the white boxes contain changes in VMT (area under the histograms) before/after considering the carpool.

In examining the subplots across various carpool roles, trips with durations under 10 minutes or exceeding 45 minutes have a limited match rate. This is attributed to the constraints set by the model. Short trips, in particular, face challenges in matching because rerouting costs surpassing the permissible limits set by the model's input parameters. On the other hand, longer journeys, which often originate from distant, exurban areas, encounter difficulties in finding suitable carpool matches. This is primarily because the potential shared segments of these routes frequently fall short of the requirement specified by the model's parameters.

As is introduced in the previous section, this experiment uses 26,029 SOV trips. By observing Figure 13 (a), most matched carpools have a travel time traveling time in range between 10 and 30 minutes. Moreover, the travel time distribution exhibits a heavily right skewed pattern, demonstrating a typical suburban travel profile.

In direct carpool mode, CarpoolSim estimates that up to 24.1% of SOV can participate in carpools. Given that these are two-person carpools, this translates to 12.0% acting as carpool drivers and another 12.0% as passengers. Consequently, the total number of vehicles in operation would be reduced to 88.0% compared to the scenario before carpooling was introduced. Before carpooling, both carpool passengers and drivers exhibit a similar travel time distribution, with the majority of trips ranging between 10 to 45 minutes, which is consistent with expectations (Figure 13 (a)).

In PNR mode, 19.2% of SOV riders can be accommodated in carpools, leading to a 9.6% decrease in the number of vehicles on the road. The travel time distributions for both carpool passengers and drivers in the PNR mode remain largely consistent, predominantly falling within the 10-45 minute range. However, a noticeable decline is observed in the shorter-travel-time zone, specifically between 14 and 18 minutes. This can be attributed to the PNR mode implementation of different filtering criteria than used in the direct carpool mode. Given that passengers in the PNR mode also need to make detours to the designated meet-up locations, the filtering criteria for short-distance segments of the trips become more restrictive (Figure 13 (c)).

The total VMT before carpooling is 551,841 miles. In the direct carpool mode, carpooling will not bring any changes in VMT for carpool passengers and SOV riders, but carpool drivers will typically experience an increase in travel distance, averaging 10.26% more driven mileage, due to rerouting to pick up and/or drop off passengers. Overall, on an individual basis, SOV riders, carpool passengers and drivers altogether will see an average of 1.39% increase in person-miles of travel (PMT). On a vehicle basis, since the two parties in a carpool share the VMT, the system will see a 12.1% reduction in total VMT (Figure 13 (b)). In the PNR mode, since both drivers and passengers need to reroute to park-and-ride location before starting carpool, an increased VMT is observed in both parties (4.4% for passengers and 9.2% for drivers). While solo drivers remain the same VMT as before, the individual-basis overall average increases by 1.63%. Similar to direct carpool, the system sees an overall reduction in total VMT by 7.31% (Figure 13 (d)). Detailed investigation of the impacts of such reduction is presented in a separate analysis in Section 4.2.3.

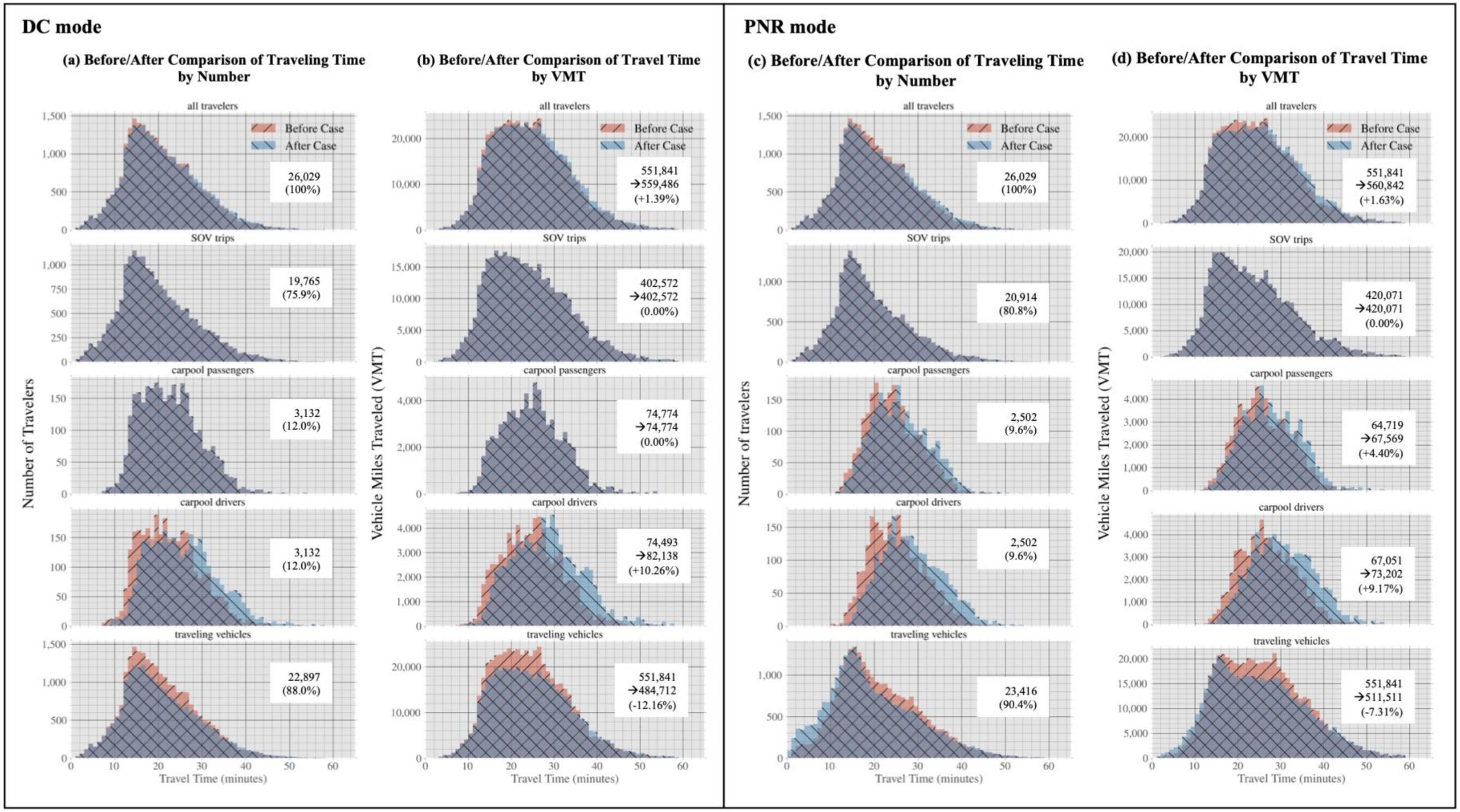

Figure 13. A before-after comparison of travel time by traveler's role.

To further understand the implications of carpooling on travel times, we introduced a graph to demonstrate the differences in travel times before and after the introduction of carpooling. This analysis was facilitated by examining histograms that depict these differences. Two distinct measures of travel time were considered: 1) **Extra Travel Time** – which refers to the additional time spent traveling due to carpooling. This analysis captures the time taken for detours, rerouting, or any other changes in the route that result from carpooling, and 2) **Extra Journey Time** – which encompasses the extra travel time and also factors in the waiting time for carpool partners. Essentially, this metric represents the total additional time from the moment a traveler is ready to depart to the moment they reach their destination.

In Figure 14, the distinctions between these two measures are visually represented. The red histograms depict the extra travel time, while the purple histograms illustrate the extra journey time. Similar to Figure 13, from the data in Figure 14 (a)/(c), we can infer the distribution of the number of travelers affected by these extra times. On the other hand, Figure 14 (b)/(d) provides insights into the VMT associated with these extra times.

In direct carpool mode, a key observation from the data is that the travel time for carpool passengers remains unchanged. This is because their route, from the pickup point to the destination, remains consistent regardless of carpooling. However, for drivers, the extra travel time is constrained to be less than 10 minutes, as dictated by the model parameters outlined in Table 3. Additionally, the waiting time for passengers, which contributes to the extra journey time, is also capped at 10 minutes according to the model's parameters. This means that any delay experienced by carpool passengers in their journey time is solely attributed to the time they spend waiting for their carpool driver.

In PNR mode, while the passengers extra journey time remain in a similar distribution as that of the direct carpool mode, a higher portion of it comes from the extra travel time. Drivers experience a slightly higher extra journey time in general, and a smaller portion of it comes from the extra travel time.

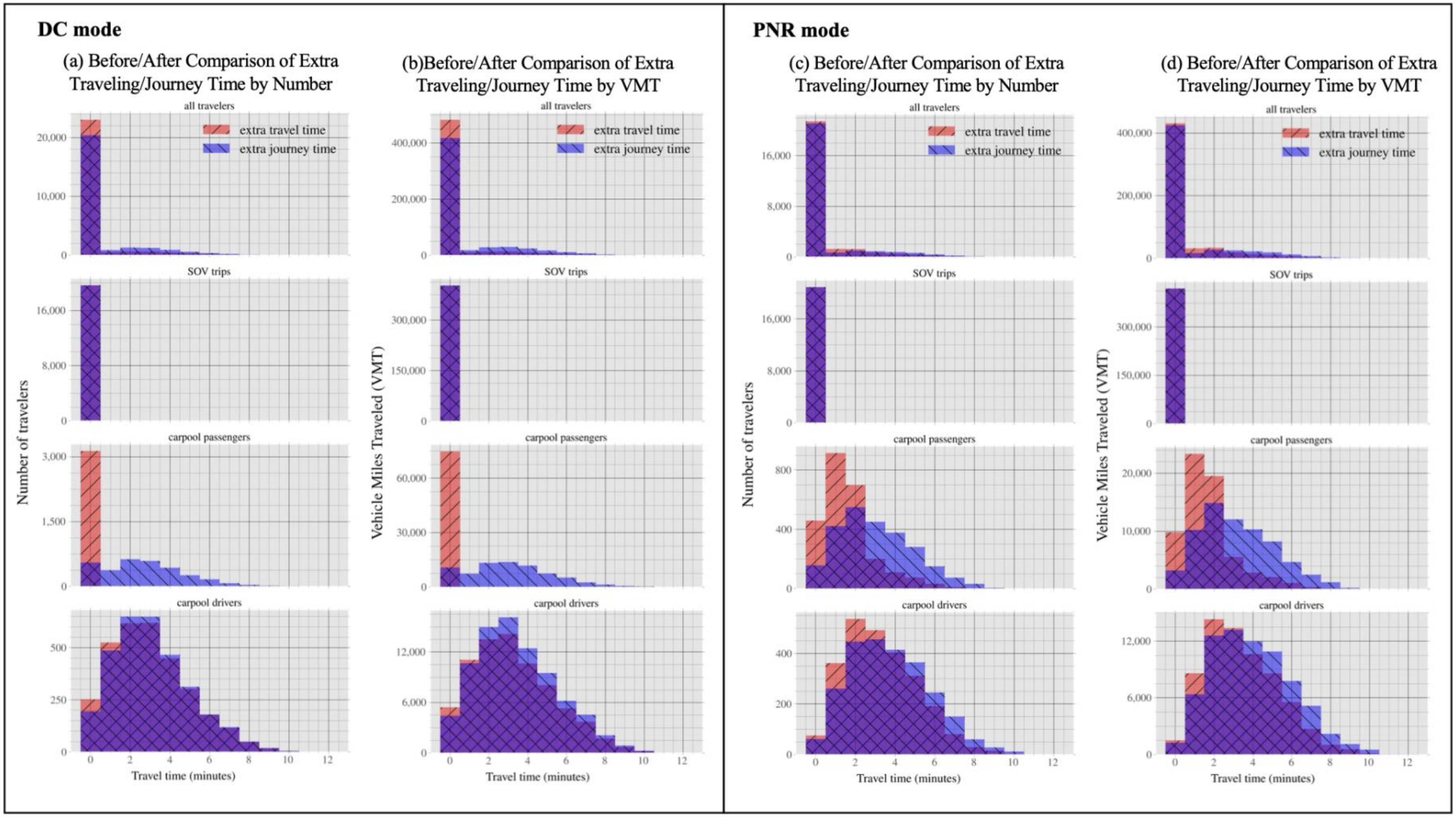

Figure 14. A before-after comparison of traveling time plotted by each group of travelers.

The scatterplot in Figure 15 shows the influence of the filtering criteria on the simulation outputs. Each scatterplot compares the baseline travel/journey time (x-axis) with the post-carpooling time (y-axis). Figure 15 (a)-(d) focuses on the direct carpool mode, while Figure 15 (e)-(h) examines the PNR mode. The plots differentiate between travel time (actual commuting duration, as shown in the first row) and journey time (commuting plus waiting time, as shown in the second mode). Several reference lines in the scatterplots represent some of the carpool quality constraints. Red lines (i.e., a 45-degree line) indicate the case where pre and post-carpooling durations are equal. Solid blue lines set a boundary where post-carpooling time shouldn't exceed 1.3 times the original. For the PNR mode, the dashed blue lines set this limit at 1.5 times. Green dotted lines mark the maximum reroute time of 10 minutes.

The before-after scatterplot is useful as a safeguard of the simulation results. In Figure 15 (b), the travel and journey times for carpool drivers are identical. This outcome aligns with the experimental setup where passengers are configured to wait for drivers and not otherwise. Most data points in the scatterplots adhere to the predefined boundaries, consistent with the model's input parameters. However, Figure 15 (g) displays a few outliers. These deviations arise from the recalculation of shortest travel paths using Dijkstra's algorithm, after initial results from CarpoolSim are implemented. It's worth noting that CarpoolSim employs a faster, albeit less accurate, query-based shortest-path search algorithm. Despite these outliers, the boundaries in Figure 15 effectively highlight the influence of the model control parameters, as detailed in Table 2.

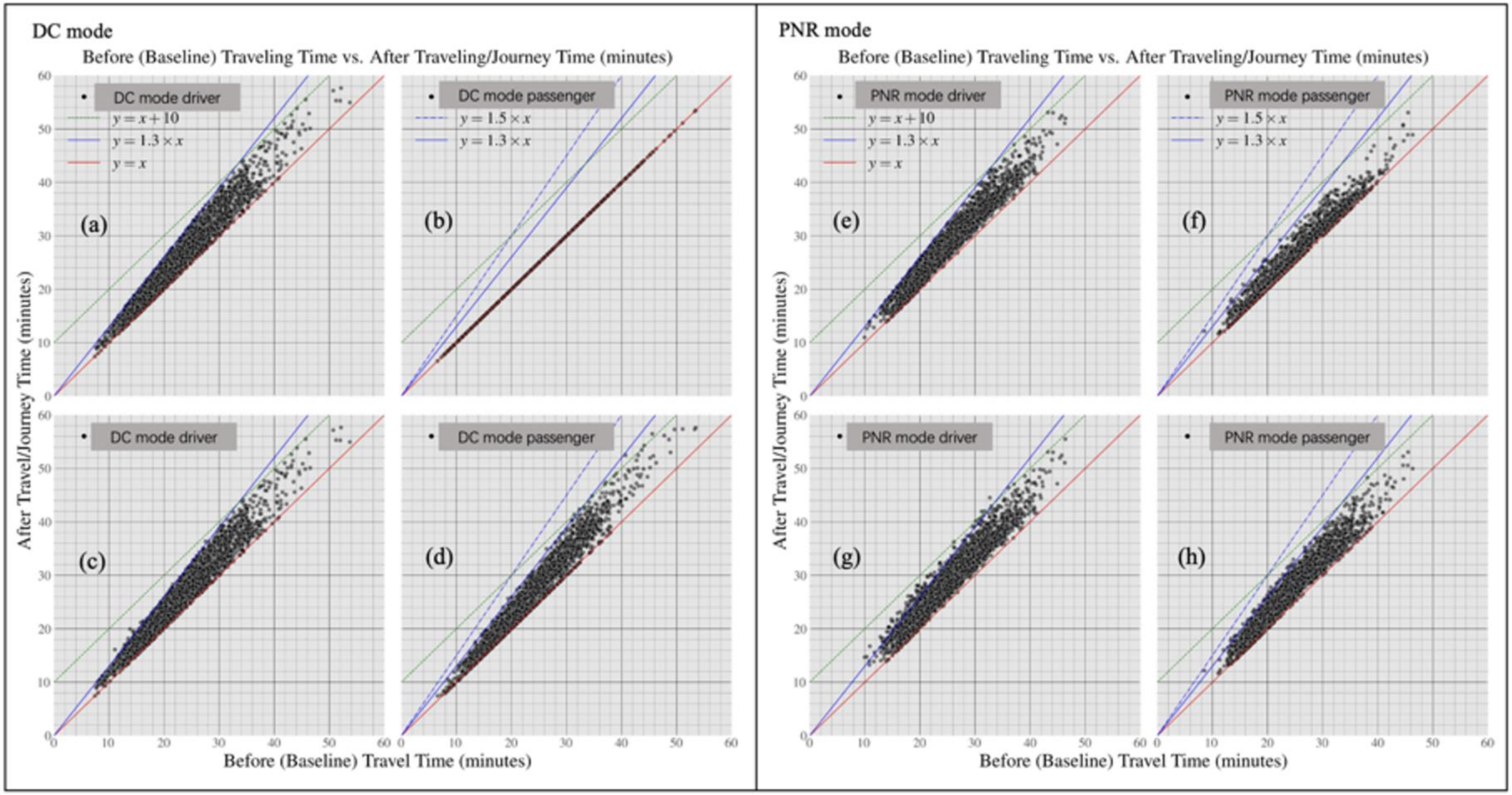

Figure 15. Journey time vs. Travel time for different carpool modes.

4.2.3 Spatial patterns

Analyzing spatial patterns that result from aggregating matched trips based on their origins or destinations can provide some valuable insights. In Figure 16 (a)-(b), the number of matched travelers by their origin is depicted. Specifically, Figure 16 (a) presents the percentage of matched trips grouped by Traffic Analysis Zone (TAZ). Note that trips either too proximate or distant from the destinations have a diminished match percentage. Despite the higher travel demands near I-285, as shown in Figure 12, the match rate is lower. This is attributed to the impedance cost of carpool formation, which makes matching short-distance trips challenging based on the model's filtering conditions.

Furthermore, assessing changes in traffic volumes on the network can highlight broader impacts. Figure 16 (f) illustrates the changes in traffic volume across the subregion being assessed. Notably, there is a significant reduction in traffic volumes along I-85 and its neighboring major arterials for both SOV and PNR modes. Figure 16 (f) provides a detailed breakdown of matched carpoolers allocated to each PNR station and the corresponding traffic volume changes in the vicinity of these stations. Some PNR stations experience an uptick in traffic as vehicles converge on these locations, while others see a reduction, especially if the SOV trips that previously passed these stations are now converted to PNR carpool trips.

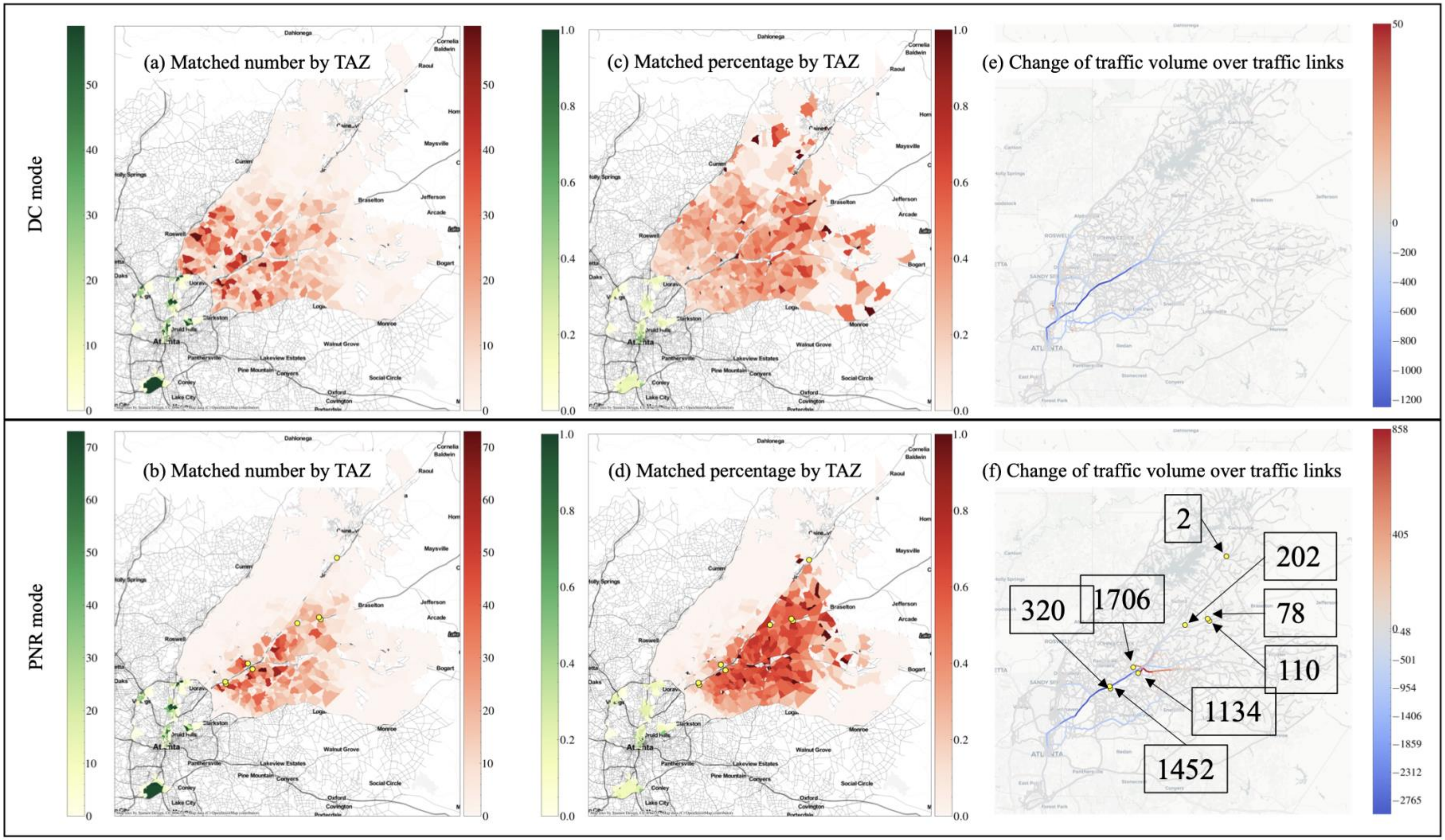

Figure 16. Spatial distribution of travel demand by TAZ and by network link.

4.3 Understanding the impacts of quality control parameters: a sensitivity analysis.

Sensitivity analysis is a crucial tool for understanding the influence of various parameters on the carpool system's performance. This section begins by identifying the key control parameters. A series of experiments is then conducted, using a one-variable-at-a-time (OVaaT) sensitivity analysis approach, where all parameters are held constant except for one, which is varied to observe its impact. The matching percentage under different model input parameter assumptions are detailed in Table 4 for both direct carpool mode and PNR carpool mode.

Table 4. A set of sensitivity analysis for important model control parameters in CarpoolSim.

SOV mode	Sensitivity Analysis (Matched Percent)						
Share of carpooled segment	ι	0.7	0.75	0.8	0.85	0.9	0.95
		59.64%	53.45%	41.62%	24.17%	8.70%	1.46%
Extra driver's costs	γ	1.5	1.4	1.3	1.2	1.1	1.05
		25.35%	25.21%	24.17%	21.21%	14.24%	7.13%
	δ	15	10	7.5	5	2.5	1
		24.21%	24.17%	23.76%	21.98%	15.60%	6.62%
Temporal Parameter	Δ_1	10*	7.5	5	2.5	1	0
		24.17%	24.17%	24.17%	23.16%	19.70%	9.99%
	Δ_2	7.5*	5	3	2	1	0
		24.17%	24.05%	22.72%	20.50%	13.94%	0.76%
Simulation Parameter	δ_t	20	15	10	7.5	5	2.5
		24.17%	24.17%	24.17%	24.17%	24.17%	23.85%
	ϵ_t	10	7.5	5	2.5	1	0
		28.86%	28.20%	27.13%	24.17%	21.66%	N.A.
PNR mode	Sensitivity Analysis (Matched Percent)						
Share of carpooled segment	ι_{PNR}	0.2	0.3	0.4	0.5	0.6	0.7
		20.94%	20.93%	20.70%	19.31%	14.06%	7.52%
Extra driver's costs	γ	1.5	1.4	1.3	1.2	1.1	1.05
		28.72%	25.19%	19.31%	10.37%	2.15%	0.28%
	δ	15	10	7.5	5	2.5	1
		19.54%	19.31%	18.06%	12.02%	3.00%	0.19%
Temporal Parameter	Δ_1	10*	7.5	5	2.5	1	0
		19.31%	19.31%	19.31%	19.31%	17.79%	12.62%
	Δ_2	7.5*	5	3	2	1	0
		19.31%	19.31%	19.31%	19.28%	19.18%	0.29%
Simulation Parameter	δ_t	20	15	10	7.5	5	2.5
		19.31%	19.31%	19.31%	19.31%	19.31%	19.31%
	ϵ_t	10	7.5	5	2.5	1	0
		30.94%	28.30%	24.59%	19.31%	12.62%	N.A.

In Table 4, the parameter ι (iota) dictates the shared percentage of distance between carpoolers. A higher ι value indicates closely located origins/destinations for the carpoolers, implying a higher quality of carpool matches. As the value of ι rises from 0.8 to 0.9, there's a sharp decline in the matched percentage from 41.62% to 8.70%. The parameters γ and δ are associated with the additional costs borne by carpool drivers. While γ represents the maximum additional cost as a ratio, δ denotes the cost in absolute terms. The matching results are less sensitive to these extra cost parameters than to ι. Even with stringent constraints (δ=1 or γ=1.05), over 6% of trips can still be matched for carpooling.

Temporal filtering parameters are also evaluated. Δ_1 restricts the difference in departure times between travelers. When Δ_1 exceeds 2 minutes, its impact becomes negligible. Δ_2 sets the maximum waiting time for a passenger when being picked up by a driver. Reducing Δ_2 from 7.5 minutes to 2 minutes results in a modest decrease in the matched ratio from 24.1% to 20.5%.

Parameters governing the simulation process (i.e., δ_t, ϵ_t) are also assessed. These parameters dictate the time window within which drivers and passengers can form carpools. The sensitivity analysis reveals that reducing δ_t or ϵ_t has a minimal effect on the matching ratio. Even under stringent conditions, the benefits of matching current drivers with future passenger requests are limited.

The sensitivity analysis offers valuable insights into the CarpoolSim system's responsiveness to various parameters. Among them, ι, which determines the shared carpool segment's ratio, emerges as the most influential. Absent this constraint, drivers on long routes might pick up or drop off any short-distance passenger with a similar trajectory.

The same experiments were also conducted for the PNR mode, with results presented in Table 4’s lower section. In comparison to the direct carpool mode, the PNR mode is less sensitive to the constraining parameters. This is attributed to the limited number of selected parking lots for the PNR mode, which inherently restricts the number of potential matches. However, the potential for higher match rates exists if more PNR stations are introduced along adjacent corridors, such as SR 19 and SR 78 (Pelzer et al., 2015; Tafreshian and Masoud, 2020b).

5. Discussion

5.1. Carpooling Potential

Under the predefined filtering criteria, this analysis reveals that 24.1% of morning commute trips to employment centers along I-85 have the potential to form carpool trips via direct carpool mode, and 19.2% of these trips have the potential to form carpool trips via Park-and-Ride (PNR) mode, leading to a 12.2% and 7.3% reduction in VMT, respectively. This reduction in VMT will translate to a significant decrease in energy use and emissions, given the strong correlation between VMT and emissions on this corridor (Kall et al, 2009; Fan et al., 2022), promoting a more sustainable and environmentally-friendly transportation system.

The analysis reveals a marked reduction in traffic volumes on I-85 and adjacent arterials for both SOV and PNR modes. The forecast decline in traffic volume presents several advantages. Commuters, especially carpoolers using HOV/HOT lanes, will experience shorter travel durations. Furthermore, traffic volumes on the corridor should decrease, further enhancing travel times for all commuters and improving overall transportation system efficiency. Finally, the shared-cost aspect of carpooling (sharing fuel and parking costs) also helps make carpooling a more attractive commute choice for participants.

CarpoolSim currently employs a fixed-cost traffic network structure. That is, the simulator does not dynamically adjust link travel time costs as a function of changes in traffic volumes and congestion. This static approach does not capture the full range of potential benefits offered by Intelligent Carpool Systems (ICS), especially when considering the ripple effects of congestion reduction. As congestion decreases, travel times across the corridor will likely decrease, which may make carpooling a more favorable option for some trips that do not meet current filtering criteria, potentially increasing carpool mode share. On the other hand, as congestion declines, some users may have less incentive to carpool. This dynamic relationship requires further assessment for simulator integration.

While the PNR mode analysis shows promise, especially for those living close to the corridor and PNR stations, it also presents potential challenges. Increased use of PNR stations could lead to increased traffic volumes and congestion on local roads near these stations. Potential shifts in local traffic patterns underscores the importance of thorough planning and simulation before implementing PNR stations. Proactive measures should ensure that the introduction of these stations doesn't inadvertently lead to localized congestion, undermining the broader benefits of carpooling. By strategically placing additional PNR stations along other key corridors, it should be possible to optimize the carpool match rate, while ensuring that local arterial roads remain free-flowing and efficient.

5.2. Contribution of Current Research to Existing Literature

The present research offers several noteworthy contributions to the existing body of literature on transportation and carpooling systems. These contributions can be categorized into four main areas: flexibility, scalability, accuracy, and practicality:

Flexibility: One of the standout features of this research is the design of numerous filtering parameters, where each can be adjusted individually by the modeler. This design allows for a tailored approach to carpool matching, accommodating various scenarios and conditions. This flexibility enhances the adaptability of the model, building upon the foundations set by existing models in the field.

Scalability: A major challenge in transportation modeling is ensuring that the model can handle large datasets without compromising on speed or accuracy. This research introduces a spatiotemporal partitioning scheme that effectively addresses this challenge. Minimizing total model run time ensures that even extensive datasets can be feasibly processed. This scalability ensures that the model remains relevant and usable as data sets grow in size and complexity.

Accuracy: Model accuracy is crucial. This research has diligently focused on maintaining model accuracy throughout each linked model phase, by carrying the travel demand model input data trajectory data throughout the entire process. By carrying accurate estimates of the trip trajectories, calculations of change in traffic volumes at each stage provide detailed insights that can inform transportation planning and policy. Furthermore, changes energy consumption and emissions can be calculated using these trajectories (Xu et al, 2015; Zhao, 2021).

Practicality: Beyond the technical aspects, the research also stands out for its practical relevance. All parameters incorporated into the model have been chosen for their significance in representing real-world travel conditions. This ensures that the model's outputs are not just theoretically sound, but also practicable, making this a valuable tool for transportation planners, policymakers, and other stakeholders.

In summary, this research bridges several gaps in the existing literature, offering a model that is flexible, scalable, precise, and practical. Its contributions are poised to drive advancements in the field and inform future transportation strategies and decisions.

5.3. Limitation and Future Research

The CarpoolSim framework, while promising, has several limitations that need to be addressed. One of the primary limitations is the lack of consideration of individual psychological preferences. Constraints applied that are uniformly in the analysis might not capture differences in preferences of commuters across various demographic groups. Without comprehensive data capturing real-world carpooling behavior, modeling such heterogeneity remains a challenge. Furthermore, the current study predominantly focuses on morning home-to-work trips, leaving out the work-to-home segment. While it's posited that the return journey (work-to-home) might be simpler to match due to factors such as more flexible home arrival times and priority matching for carpool passengers, this assumption requires further verification. Another limitation is the rigidity of the travel plans in the model. Once set in motion, travelers cannot modify their plans, and there is currently no provision for on-the-fly matching, reflecting the reality that punctuality often takes precedence for most commuters. The optimization algorithm, based on a bipartite approach, might also have room for improvement, especially when compared to more sophisticated machine learning optimization solvers. Lastly, the reliance on a static travel network, which doesn't account for real-time traffic congestion dynamics, remains a current limitation. A dynamic model that considers congestion and other real-time factors could offer a more accurate representation, even if it's not an immediate priority.

Looking ahead, there are several aspects of enhancing and expanding the CarpoolSim framework. Given the similarities between the ARC ABM model and those used by other US urban planning agencies, there's potential for adapting CarpoolSim for different travel corridors and urban contexts. With the rise of autonomous vehicles, the CarpoolSim framework, with some modifications, could play a pivotal role in analyzing future carpool dynamics. Additionally, features like multi-passenger carpools and real-time assignments could be integrated to make the system more versatile. On the computational front, besides the algorithm itself, there's ample scope for optimization by optimizing the current code used to implement CarpoolSim (continuous code optimization is always needed to take advantage of new and improved computing systems).

6. Conclusions

In light of the rapid advancements in communication and computation technologies, carpool matching is emerging as a feasible solution to address transportation challenges and has garnered significant research interest. This study introduces CarpoolSim, a novel scalable analytical framework, designed to estimate the maximum potential of carpools under a set of realistic spatiotemporal constraints. The overarching goal is to pave the way for a future Intelligent Carpool System (ICS) that can be integrated in transportation planning decisions related to carpooling.

Distinct from many existing studies that primarily focus on optimizing algorithms, this research emphasizes the development of an efficient computational pipeline, leveraging established methodologies. CarpoolSim is structured around three core modules: 1) the filtering module, which refines potential carpool matches based on a range of criteria; 2) the optimization module, which ensures maximum feasible matches; and 3) the simulation module, which replicates the matching process in a dynamic environment. The framework's flexibility, scalability, precision, and practicality, as discussed earlier, underscore its potential to contribute significantly to the existing literature.

A case study centered on the Metro Atlanta I-85 corridor was conducted to evaluate the efficacy of ICS. Preliminary findings suggest that approximately 24.1% of the morning commute trips to employment centers along I-85 could be carpooled directly, while 19.2% could utilize a park-and-ride carpool system. While these figures might seem modest in the context of the entire regional travel demand, they hint at the promising potential of automated carpool matching systems in the long run. The benefits of ICS are twofold: it promotes sustainability by reducing individual commute costs and alleviates traffic congestion, benefiting the broader commuting community.

The sensitivity analysis further illuminated the influence of various model parameters on carpool formation. Notably, the proportion of shared travel time emerged as a critical factor, more so than the additional time costs for carpool drivers. As real-world data becomes available, and if it indicates a willingness among commuters to deviate from their shortest paths for carpooling, the potential for carpool formation could be even greater than the current estimates.

In terms of contributions to the existing literature, this research stands out in its flexibility, scalability, precision, and practicality. The model's adaptability, its capability to handle expansive datasets efficiently, its meticulous attention to precision, and its real-world relevance make it a significant addition to the field. In essence, this study not only provides insights into the potential of carpooling but also offers a robust and adaptable framework that can shape future transportation strategies and decisions.

While CarpoolSim presents a robust framework for analyzing carpool potentials, it also highlights the need for continuous refinement and validation against real-world data. As carpooling systems evolve and become more integrated into our transportation networks, research like this will play a pivotal role in shaping sustainable and efficient urban mobility solutions.

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