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Future Urban Mobility with MaaS

# Evaluating the Environmental Benefits of Personalized Travel Incentives in Dynamic Carpooling

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## ABSTRACT

In a dynamic carpooling system, drivers and riders with their own intended travel plans are matched on short notice. The performance of such a system largely depends on the carpool participants' travel flexibility (the extent to which a detour is tolerated or the willingness to accept a slightly different drop-off location). To increase travel flexibility, an incentive scheme can be introduced for carpool participants to opt for. For instance, a driver specifies how much she/he expects to be compensated (e.g., $5) if the earliest departure time is shifted to be earlier than the originally scheduled time by a certain amount (e.g., 10 minutes). Similarly, an interested passenger reports the expected incentive to willingly accept a different destination (such as a nearby transit stop or coffee shop) deviating from the request. In this dynamic carpool matching problem with incentives, the following decisions are jointly optimized from the perspective of a carpool matching coordinator: 1) incentive allocations to drivers and riders, 2) assignments of riders to drivers, and 3) vehicle routes of drivers. A case study based on data from Washington, D.C. is conducted to evaluate the potential of the personalized incentives offered to carpool participants in mitigating the environmental impact of transportation (quantified by the reduction of vehicle miles traveled). Two notable findings are reported. First, one dollar of incentive could reduce vehicle miles travelled by 2.88 in one benchmark case. Second, driver incentives are shown to be much more effective than rider incentives under reasonable cost assumptions.

## 1. Introduction

Numerous advances in information and communication technologies (such as mobile apps) have revitalized the practice of carpooling (Shen et al., 2021). Many commuter assistance programs in the United States (U.S.) now offer dynamic carpooling services to facilitate the matching of interested drivers and riders. For instance, King County Metro launched app-based dynamic carpooling services in Seattle, Washington, U.S. (Shen et al., 2021). The Commuter Connections Program in the Washington, District of Columbia (D.C.) area developed an app *CarpoolNow* to enable commuters in the capital region to be matched with other commuters with similar travel plans in a real-time manner (Commuter Connections, 2020). Carpooling is known to have great potential to reduce vehicle trips, improve vehicle occupancy, and mitigate the negative externalities of transportation (Chan and Shaheen, 2012), due to its defining feature: carpool drivers (who are not professional drivers) have their own predetermined travel plans to execute regardless of whether carpool riders are matched with them. They are matched with other carpool riders because of their similar travel plans. Generally, carpool drivers do not expect any net financial gains (positive profits) while their costs are shared by their matched riders. In contrast, Uber and Lyft drivers are profit-driven and generally do not share travel plans with their riders. Even though riders involved in ridesplitting (such as UberPool and Lyft Line) may travel toward a similar direction (Shaheen and Cohen, 2019), they do not have similar travel plans with their drivers. Because carpool drivers have their own travel schedules to follow, the performance of dynamic carpooling (measured by the saved vehicle miles, for instance)

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largely depends on the travel schedule flexibility (the extent to which detour is tolerated) of carpool participants (Masoud and Jayakrishnan, 2017; Sun et al., 2020a).

To fully exploit the potential of dynamic carpooling in promoting transportation sustainability, one promising way is to introduce an incentive scheme for carpool participants (drivers and riders) to opt for to lift some tight constraints on travel plans. For instance, a driver who opts for this incentive program specifies how much she/he expects to be compensated (e.g., $5) if the earliest departure time at the origin is shifted to be earlier than the originally scheduled time by a certain amount (e.g., 10 minutes). In addition, incentives can be offered to riders to influence their travel choices, such as the drop-off location choice. Although a rider has the most preferred destination, a few alternative destinations may become acceptable upon receiving certain incentives. Stiglic et al. (2015) has demonstrated the benefits of introducing such "meeting points" to reduce the number of rider pickups. In a dynamic setting, all those driver offers and rider requests along with incentive options are received by the carpool matching coordinator continuously over time. Given all predetermined travel plans provided by drivers and riders, as well as the extra flexibility in drivers' and riders' travel plans enabled by incentives, the matching coordinator makes the following decisions: allocating incentives, matching riders with drivers, and routing vehicles, as illustrated in Fig. 1. In this study, the matching coordinator is a government entity that is interested in maximizing a system-wide performance measure, subject to an exogenous incentive budget.

When incentives are absent, the dynamic carpool matching problem can be efficiently solved, thanks to various exact and approximation solution algorithms that have been recently developed (Mourad et al., 2019). Although fixed incentives have been widely adopted to encourage mode shifts to carpool, the effectiveness of personalized incentives in achieving transportation sustainability objectives is unexplored. The consideration of personalized incentives in carpooling is nontrivial because of the behavioral implications: drivers might game the platform by misrepresenting their required compensations to modify their travel plans. A naïve approach is to allocate incentives to those who require lower compensations than others until the budget constraint is met. However, the impacts of adding the same extra flexibility to various drivers' schedules are largely different. The marginal benefits brought by the extra flexibility depend on a few factors, such as the current driver-rider ratio in a travel direction. Moreover, incentive decisions are correlated because the benefit of influencing a driver's travel behaviors depends on whether some other interrelated drivers receive incentives and change their travel plans. Thus, the optimization method should ensure that incentives are allocated only to "efficient" drivers whose travel behavioral changes can directly benefit the system-level objective, for a given incentive budget limit. Similarly, the design of rider incentives to induce riders to accept alternative drop-off locations is equally complex.

Motivated by the above important research gaps, this paper intends to tackle the incentive design problem in dynamic carpooling and present an integrated optimization model that jointly considers personalized incentive allocation, rider-driver assignment, and vehicle routing. This study also expects to evaluate the potential of proposed travel incentives in reducing vehicle miles traveled through large-scale numerical experiments based on empirical data.

To achieve the study objectives, we first presented an integer program incorporating driver and rider incentives for a static carpool matching problem, which was an extension of the carpool matching model developed by Sun et al. (2020a). Then, a rolling horizon solution approach was adopted for the dynamic setting. As no real-world carpool demand data were available, the taxi trip data in Washington, D.C. were adapted to generate a range of test scenarios with varying incentive budget limits. Research results from the extensive numerical studies confirmed the high effectiveness of customized travel incentives for drivers. For instance, it was found that one dollar of incentive resulted in a reduction of 2.88 vehicle miles traveled in one case.

The rest of this paper is structured as follows. Section 2 briefly reviews the carpool matching optimization literature and scans various existing travel incentive schemes in shared mobility systems. Section 3 formulates the integrated optimization problem and presents a rolling horizon solution framework. Section 4 describes the data preparations for the empirical study and Section 5 analyzes the research findings. Section 6 ends this paper by highlighting major findings and summarizing future research directions.

## 2. Literature Review

### 2.1 Evolution of Carpool Matching

As reviewed by Chan and Shaheen (2012), carpooling has

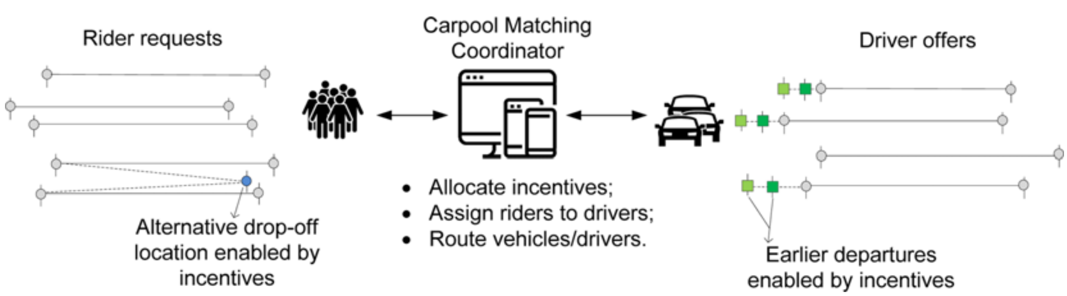


**Fig. 1.** Major Parties and Decisions in Carpool Matching Involving Incentives

experienced several phases of development in North America since World War II. In the 1940s, riders and drivers were matched through a bulletin board due to the unavailability of other technologies. In the 1970s, large employers started to identify potential carpool matches based on travel data collected from their employees. Telephone-based matching emerged in some U.S. cities in the 1990s, which were later enhanced by emails and web pages. At present, due to the widespread use of smartphones, most of the modern carpool matching platforms are built on the mobile internet, thus providing the most efficient way for drivers, riders, and the matching platform to exchange carpool-related information.

As early carpool matching was conducted manually, only regular trips, such as those home-to-work travels, could be registered and matched. Consequently, family members, friends, or co-workers with similar itineraries formed a carpool, which required long-term commitment. With the advent of the internet, significantly improved carpool matching became available, which further incorporated other non-commuting recurring trips as well as occasional trips. Dailey et al. (1999) described such an internet-based carpool matching platform, called Seattle Smart Traveler (SST). They found that the web-based platform could accommodate more carpool travelers than earlier matching platforms. Due to improved data support, the matching underlying SST was more systematic, which examined four trip attributes: departure time period, arrival time period, departure region, and arrival region. Two trips were considered matchable only when an overlap was identified between two trips for each of the four trip attributes. While this pairwise comparison of trip characteristics was simple to implement, it missed a few important elements in carpool matching. For instance, scheduling feasibility after carpool matching was not guaranteed; one-to-many matching (i.e., a single driver to be assigned multiple riders) was unavailable; vehicle routing was absent. At present, the dynamic carpooling service presents several new improvements, because mobile apps allow drivers to announce their driver offers and riders to request a ride, both shortly before their intended departures. Those driver offers and rider requests received by the matching platform will be matched and announced in near real-time. Quite a few practical constraints are considered in matching, such as vehicle capacity limits and time window constraints. Therefore, much more sophisticated carpool matching algorithms have recently been developed to meet the need for real-time decision-making, which are briefly reviewed next.

In the dynamic carpool matching literature, carpool matching is usually formulated and solved as a variant of the pickup and delivery problem with time windows (PDPTW), which is one of the most studied combinatorial optimization problems in operations research (Baldacci et al., 2011). Due to the intricacy of solving the dynamic carpool matching problem efficiently, approximation solution algorithms are usually developed in the literature (Cheikh-Graiet et al., 2020). For instance, Xia et al. (2015) formulated an integer program for carpool matching and employed widely used metaheuristics (namely simulated annealing and tabu search) to solve the optimization problem. Sun et al. (2020a) designed a graph-based method to generate rider-driver assignments and vehicle routing plans for drivers. To solve the matching optimization problem, they developed a column generation-based heuristic, in addition to an exact solution algorithm. Their numerical analyses indicated that the exact solution algorithm can solve large-scale problem instances involving around 600 drivers and 1,800 riders quickly; the column generation-based heuristic can find near-optimal solutions for even larger instances. The highly efficient solution algorithms were thus used to solve carpool matching problems in real-time. For more comprehensive and in-depth reviews of the carpool matching models and algorithms, see Mourad et al. (2019) and Tafreshian et al. (2020).

## 2.2 Travel Incentives in Shared Mobility

Monetary incentives are widely used in transportation demand management to trigger desirable travel behavioral changes (Sun and Zhang, 2018; Zhu et al., 2020). For instance, a fixed incentive of $2 was offered to each carpool participant between late 2018 and early 2019 by King County Metro in the Seattle area of Washington (Shen et al., 2021), although those fixed incentives were argued to be less effective as personalized incentives by Xiong et al. (2020). In a few shared mobility systems, such as bike sharing and car sharing, various travel incentivization schemes have been explored and a few example studies are reviewed as follows.

Pfrommer et al. (2014) studied the bike redistribution problem which was central in a bike sharing system. Since a user picking up a bike at one location could virtually return it to any other location, some bike locations may become overfilled over time while other locations do not have enough bikes available. To address this imbalance issue, expensive vehicle redistribution operations were needed. To reduce the redistribution cost, Pfrommer et al. (2014) optimized the incentives offered to bike users who were willing to revise their trip destinations. They conducted a case study of the bike sharing system in London to evaluate the effectiveness of the optimized incentives. Singla et al. (2015) studied a similar incentive design problem in bike sharing, while they explicitly considered the possibility that bikers may misrepresent their private information about incentives. In this case, a sophisticated incentive-compatible mechanism (Sun et al., 2020b) must be designed to ensure truthful reporting of private information.

Fanti et al. (2019) focused on the incentive design problem in one-way car sharing. In the proposed incentive scheme, users would get free travels or rewards if they participated in the vehicle relocation activities. They designed two integer programs to minimize the vehicle relocation cost with incentives being incorporated. Similarly, Wang et al. (2019) studied how to offer users rewards in order to relocate vehicles to those locations with a short supply of vehicles.

Song et al. (2021) assumed that subsidies could be offered to carpool participants based on travel distance and explored the effect of such subsidies in reducing traffic congestion through simulation-based studies. Similarly, Masoud and Tafreshian (2021) considered a subsidization scheme based on participants' value of time (VOT). Those fixed incentives have various

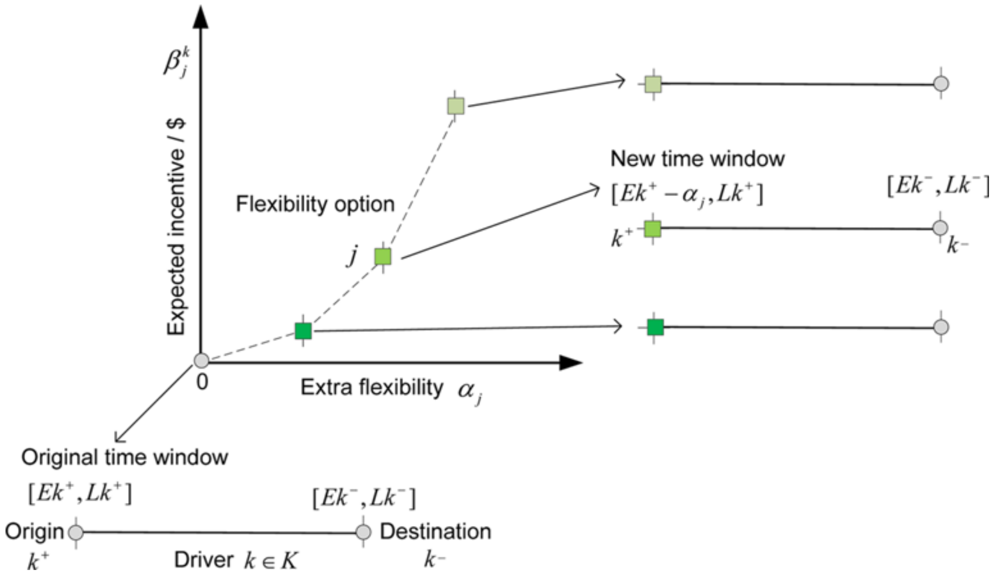


**Fig. 2.** A Driver Offer Associated with Multiple Flexibility Options

deficiencies. The travel distance-based subsidization does not capture the varying individual responses to the same incentive; applying the same incentive to two trips of equal distance likely yields different returns. Under the VOT-based subsidization scheme, a participant gets the same incentive regardless of the time period of travel. In fact, a driver with a certain travel plan in the morning period might be highly "desirable" and is thus being offered significant incentives; however, in a different period, this driver with the same plan may not get any incentives at all, due to the dynamics of driver-rider balance. For instance, in the morning two other riders have almost identical travel plans with the driver, justifying significant incentives for the driver, while in the other period, there are no such riders, meaning no incentives are needed. Therefore, customized incentives to individuals and periods should be considered to replace static and fixed incentives.

### 2.3 Summary

The carpool matching literature has been well developed, with recent studies devoted to dynamic carpooling. Various travel incentives have been adopted in bike sharing and one-way car sharing. In contrast, no personalized incentives have been considered in carpooling, static or dynamic. Therefore, none of the existing studies have jointly optimized the allocation of personalized incentives to carpool participants and carpool matching. Consequently, little is known of how personalized carpool incentives could translate into environmental benefits. This paper will thus fill those important research gaps.

## 3. Method

### 3.1 Static Carpool Matching Problem

A static carpool matching problem involves a set of drivers $K$ and a disjoint set of riders $R$. As illustrated in Fig. 2, each driver $k \in K$ has a departure time window $[Ek^+, Lk^+]$ associated with the origin $k^+$, where $Ek^+$ and $Lk^+$ represent the earliest and latest departure times, respectively. The arrival time window $[Ek^-, Lk^-]$ associated with the destination $k^-$ can be inferred from the departure time window $[Ek^+, Lk^+]$ since the direct travel time from $k^+$ to $k^-$ is known. All drivers who opt for the incentive program must specify how much incentive, denoted as $\beta_j^k$, is expected if the predetermined earliest departure is shifted earlier by $\alpha_j$. In other words, in option $j \in J$, the new departure time window of driver $k$ becomes $[Ek^+ - \alpha_j, Lk^+]$ upon receiving an incentive of $\beta_j^k$. For drivers who are not enrolled in this incentive program, $\alpha_j$ can be set to be zero while $\beta_j^k$ can be set as a very large constant. Each driver has a capacity limit, which restricts the maximum number of riders to be matched with driver $k$ to be $\eta_k$.

A rider $r \in R$ has a departure time window $[Er^+, Lr^+]$ at origin $r^+$ and an arrival time window $[Er^-, Lr^-]$ at destination $r^-$. Riders can only be picked up or delivered within the associated time windows; otherwise, time window constraints are violated. Instead of shifting the earliest departure time, riders are willing to accept alternative drop-off locations, such as a transit stop or coffee shop close to the requested drop-off location, when appropriate incentives are offered. As illustrated in Fig. 3, an interested rider can specify how much incentive is needed for an alternative destination $r_j^-$ to become acceptable. Note that each alternative destination is associated with its own time window $[Er^-, Lr^-]$.

Given the predetermined travel plans submitted by drivers and riders, as well as the extra flexibility in a driver's time schedule and a rider's drop-off location that can be activated by incentives, the carpool matching coordinator makes the following decisions: 1) allocating incentives to carpool participants to stimulate the desired behavioral changes, 2) assigning riders to drivers, and 3) routing drivers (or vehicles), subject to various constraints (such as driver capacity and incentive budget limit).

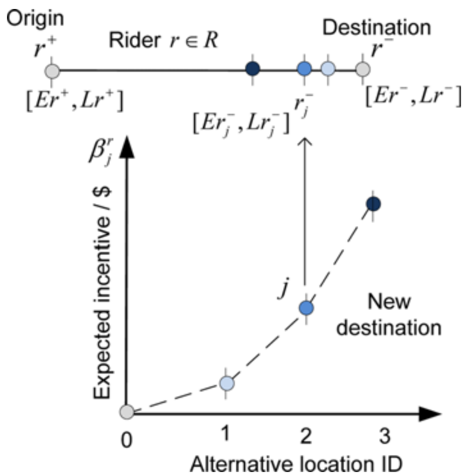

Fig. 3. Rider Request and Flexibility Options

The above optimization decisions are clearly interrelated, which can be explained by taking the case of driver incentives as an example. The incentive allocated to a driver directly impacts the driver's travel schedule flexibility, which further determines what riders can be assigned to this driver and how this driver should be routed; the effect of adding extra flexibility to a driver's travel schedule can only be evaluated through rider assignments and vehicle routing, which largely determines whether the required incentive for the corresponding extra flexibility is justified. The optimization objective of the carpool matching coordinator is to maximize the total travel cost savings (measured by reductions of vehicle miles traveled) due to carpooling, because the matching coordinator is a government entity in this study.

When a single rider is assigned to a driver, the resulting vehicle route is straightforward to find. When a driver is assigned multiple riders, there may exist multiple potential ways to pick up and drop off riders. Time window constraints should be checked for each involved participant to ensure the feasibility of a vehicle route. As carpool participants usually have highly diverse travel schedules, not all the drivers and riders can be matched. Unmatched drivers or riders travel alone from their origins to destinations. For instance, an unmatched rider $r$ may take a taxi with a known cost of $o_r$. For each route, the travel cost saving due to carpooling is defined as the difference between the cost without carpooling (corresponding to the case where all drivers drive alone, and riders are served by other services) and the cost with carpooling. Clearly, the travel cost saving can be positive only when a driver is matched with one or multiple riders; the cost saving is zero when drivers or riders are not matched. Note that cost here is not necessarily monetary. In this study, by travel cost, we mean the vehicle miles traveled of a trip.

As Sun et al. (2020a) have developed an efficient graph-theoretic approach for generating all possible vehicle routes for given drivers and riders, we adapt the vehicle generation approach by making multiple virtual copies of drivers and riders, each of which corresponds to one flexibility option associated with an incentive. For instance, if a rider accepts two additional destinations with various required incentives, in total three copies of the rider are made. Clearly, only one copy can be selected for a driver or rider. Once the flexibility option chosen by the matching coordinator is known, the incentive allocated to the involved carpool participant is clear. In this study, drivers have multiple earliest departure times; riders accept several alternative drop-off locations. Driver incentives are intended to increase temporal flexibility, while rider incentives are meant to enhance spatial flexibility. Given the above insights, we formulate the integrated carpool matching and incentive design problem, denoted as $\Pi$, as follows:

$$\max \sum_{s \in S} \rho_s z_s \ , \tag{1}$$

$$\text{s.t.} \ \sum_{s \in S} \varphi_{sr} z_s \le 1, \quad \forall r \in R \ , \tag{2}$$

$$\sum_{s \in S_k} z_s \le 1, \quad \forall k \in K \ , \tag{3}$$

$$\sum_{s \in S} \beta_s z_s \le \theta_m \ , \tag{4}$$

$$z_s \in \{0,1\}, \forall s \in S \ . \tag{5}$$

In the above binary integer program, $S$ represents the set of all vehicle routes. $z_s$ is the binary decision variable indicating whether route $s$ should be selected or not. $\rho_s$ is the cost saving of route $s$. Furthermore, $\varphi_{sr}$ is a parameter indicating whether rider $r$ is covered by route $s$ and $S_k$ is the set of routes of driver/vehicle $k$. $\beta_s$ is the total incentive requires for the involved driver and riders in route $s$ to make necessary behavioral changes such that route $s$ is feasible. The total incentive budget is $\theta_m$. This optimization problem aims to maximize the matching coordinator's total cost savings by selecting vehicle routes, subject to three constraints: a rider can be served only once (Eq. (2)); a single route can be selected for one driver (Eq. (3)); the incentive budget constraint is not violated (Eq. (4)). Eq. (5) is a feasibility constraint.

## 3.2 Rolling Horizon Optimization Framework for Dynamic Carpool Matching

In the static setting, all drivers and riders submit their carpool requests well in advance, which means the carpool matching problem is solved only once. In the dynamic case, carpool participants are not required to do so, as they likely submit their requests shortly before their intended travels. For driver $k$ and rider $r$, we denote their request submission times as $\lambda^k$ and $\lambda^r$, respectively. The matching coordinator must inform a carpool participant of the matching outcome by a prespecified due time. We use $\mu^k$ and $\mu^r$ to represent the due times of driver $k$ and rider $r$, respectively. Similar dynamic problem setups have been used in the literature, such as Masoud and Jayakrishnan (2017).

We next define a planning horizon [0, $T$], which is divided into $N$ epochs of equal length $T/N$. Epoch $n$ starts from $t_n$ and ends at $t_n = T/N$ or $t_{n+1}$. At $t_n$, we construct a static carpool matching problem $\Pi_n$ by considering all drivers and riders with a request submission time earlier than $t_n$ (i.e., $\lambda^k \le t_n$ and $\lambda^r \le t_n$) and with a due time later than $t_n + \Delta$ (i.e., $\mu \ge t_n + \Delta$ and $\mu^r \ge t_n + \Delta$), where $\Delta$ is a small constant. The constructed static problem $\Pi_n$ is solved at $t_n$, with optimization solutions available before $t_n + \Delta$. In other words, $\Delta$ represents the maximum available time to solve a static carpool matching problem in one epoch, which should be strictly smaller than $T/N$. At $t_n$, the optimization problem (1-5) is built and solved with an integer program solver, whose solutions are examined at $t_n + \Delta$ for dispatching decisions. For selected vehicle routes, they may be dispatched immediately or delayed on purpose. If a route is still feasible at the next dispatching time (i.e., $t_{n+1} + \Delta$) and each participant involved in this route has a due time later than the next dispatching time, it will be postponed for dispatching. Postponing some vehicle routes to the next dispatching point has been shown by Sun et al. (2020a) to be more advantageous than dispatching all vehicle routes immediately after solving problem $\Pi_n$. Those postponed vehicle routes along with their involved drivers and riders are intended to be re-evaluated and considered in the next epoch. Under the postponement policy, a driver or rider may be involved in the carpool matching over a few consecutive epochs before finally getting dispatched, which leads to the correlations of optimization problems in successive epochs. A related postponement policy is also used in Cook and Lodree (2017). Therefore, the way how drivers and riders dynamically enter, get matched or unmatched, and leave the carpool matching system is defined.

## 4. Data

### 4.1 Travel Plan Data

Although carpool matching has been studied by quite a few researchers, none of them have used real-world demand data. For instance, both Xia et al. (2015) and Cheikh-Graiet et al. (2020) have used simulated data to test their developed optimization algorithms. While randomly generated carpool matching instances may be sufficient to test the efficiency of proposed matching algorithms, a clear shortcoming of using simulated demand data is that empirical insights are very unlikely to be obtained. For instance, in most simulations, rider origins and destinations are uniformly sampled over a region, without considering any traffic flow patterns in the real world, such as heavy flows from a northwestern suburban area to downtown from 7 am to 9 am. Results from such randomly generated instances may thus underestimate the potential benefits of carpooling, because the travel plans of commuters in a certain corridor are highly correlated rather than independent. Although real-world carpool demand data are desirable, they are unlikely to be publicly available due to privacy reasons. In this study, we generate realistic dynamic carpool matching instances based on the open taxi trip data in Washington, D.C. and seek to derive practically valuable findings.

The latest taxi trip data made available by the District of Columbia through its open data platform (https://opendata.dc.gov/) were from June 2019. We selected one day (the first Monday of June 2019 or June 3, 2019) for analysis. Although each trip record consisted of many fields, only a few relevant ones to this study were kept, namely trip origin (in the form of latitude and longitude), destination, and start time. A trip record was dropped if one of the required fields had a missing value. Note that the exact times were unavailable, because all times were truncated to the whole hour (e.g., 9:31 am to 9:00 am). Fig. 4 shows how the 19,679 trips were distributed over time. Note that taxi travels may not exhibit morning and afternoon peaks, because the primary travel purpose of taxi trips is typically business or leisure travel, not commuting. Fig. 5 shows the spatial distribution of trip origins along with locations of metro stations within the city limits of Washington, D.C.

As the exact trip start time was unavailable due to truncation, a uniformly distributed random integer between 0 and 59 was drawn to be the missing minute. Given the trip origin and destination, the distance between them was estimated as the

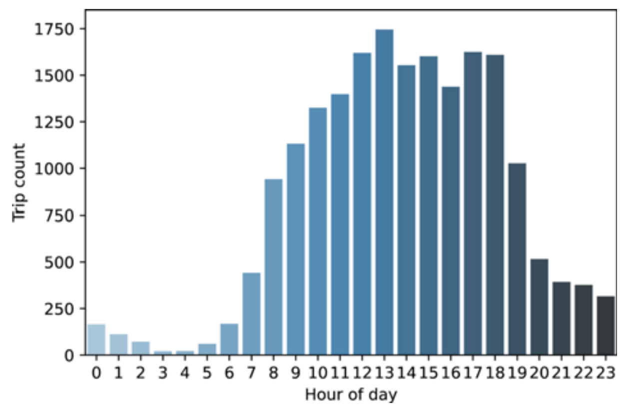


**Fig. 4.** Temporal Distribution of Travels

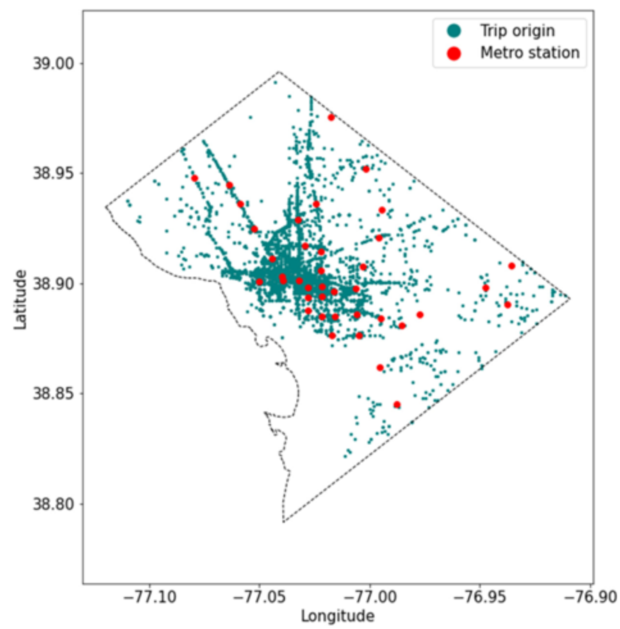


**Fig. 5.** Distribution of Trip Origins

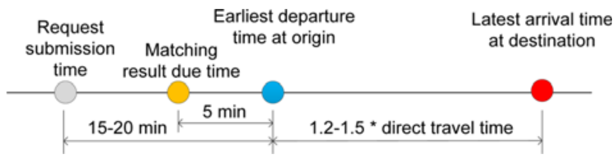


**Fig. 6** Time Points in a Carpool Request

great-circle distance multiplied by 1.2. We assume that an unmatched rider will be served by some third-party service (such as taxi) through the Guaranteed Ride Home (GRH) program, which results in 20% more vehicle miles than peer drivers. The extra 20% is added to account for the deadheading mileage of taxi. The direct travel time was estimated by assuming a constant travel speed of 35 miles per hour. The latest arrival time at the destination was estimated as the earliest departure time plus the direct travel time multiplied by the so-called TTB (Travel Time Budget) factor (Masoud and Jayakrishnan, 2017; Sun et al., 2020a), which was widely used to measure the travel schedule flexibility. In this study, the range for the TTB factor was 1.2 to 1.5. As shown in Fig. 6, the order submission time was 15 to 20 minutes (uniformly distributed) before the earliest departure time; the matching notification due time was 5 minutes earlier than the earliest departure time. All the 19,679 trips were converted to carpool requests, among which 25% were randomly selected to be driver offers. Each driver was assumed to willingly take a maximum of three riders. The rest of trips were assumed rider requests.

### 4.2 Driver Incentive Data

All rivers were enrolled in the incentive program, and there were three options to extend the travel schedule flexibility. The earliest departure time can be shifted earlier by 5, 10, or 15 minutes. As it was increasingly difficult to shift the earliest departure time, the required incentives for those three flexibility options were specified as $a_k$, $2.2a_k$, and $4a_k$, respectively. $a_k$ was the driver-specific incentive needed to enable driver $k$ to shift the earliest departure time by the initial five minutes, which was uniformly distributed on a range $[a_{\min}, a_{\max}]$. The baseline values of $a_{\min}$ and $a_{\max}$ were \$1.5 and \$2.5, respectively. In other words, on average a driver in the benchmark case expected \$2 to shift the earliest departure time by 5 minutes, while she/he expected much more (i.e., \$8) to shift the departure by 15 minutes.

### 4.3 Rider Incentive Data

As D.C. is covered relatively well by rail transit, especially in its downtown area, riders were assumed to accept nearby metro stations as alternative drop-off locations, when appropriate incentives are provided. For each carpool rider, the nearest metro was identified. If the distance between this identified metro station and the requested drop-off location was over 0.8 miles, this rider would not accept this alternative drop-off location due to the excess walking involved. If the distance was below 0.8 miles, the rider would accept the alternative drop-off location, and the required incentive would be computed as the involved walking distance multiplied by $b_r$, where $b_r$ measures the cost of walking per mile as perceived by rider $r$. For each alternative drop-off location, the latest arrival time is adjusted by considering a constant walking speed of 3 miles per hour.

## 5. Results and Discussions

Python 3.9 was used for necessary data manipulation described in Section 4. The static optimization model defined in Section 3.1 was solved by CPLEX v20.1 on a personal computer (Intel Core i7-8700 CPU 3.20 GHz, 32 GB RAM). An afternoon planning horizon from 2:30 pm to 6:00 pm was selected, because of the relatively steady and strong demand in this period, as illustrated in Fig. 4. A total of 4,649 carpool participants were involved in the following analyses. The carpool matching coordinator, a government entity as assumed earlier, seeks to maximize the vehicle mile savings, because vehicle miles traveled is a widely adopted metric of transportation-related emissions, energy consumption, and other negative externalities (Fang and Volker, 2017).

### 5.1 Effectiveness of Driver Incentives

We first consider driver incentives only. One problem instance is generated as the benchmark, where the incentive budget limit is \$25 per 2-minute epoch. Fig. 7 shows the numbers of submitted carpool requests (or called arrivals) and dispatched carpool participants (or called departures) in each epoch. The departure curve lags behind the arrival curve for about five epochs, which means a carpool participant spends approximately ten minutes in the matching process, from request submission to matching outcome announcement. Fig. 8 shows the optimization objective (i.e., total vehicle miles saved) in each epoch. On average, carpool matching in each epoch yields approximately 25 vehicle miles to be saved. Fig. 9 shows how allocated incentives are claimed in each epoch. Although the budget constraint, Eq. (4), is binding in almost all the epochs, the total incentives claimed by carpool incentives are less than the incentive budget limit. This is because a significant portion of the participants selected for incentives are postponed to later epochs.

Although on average around 60 carpool participants (drivers and riders combined) arrive and leave per epoch, as shown in Fig. 7, the number of carpool participants in each static matching problem is above 400. This is because carpool participants remain in the matching pool for approximately five epochs, as indicated earlier. For such problem sizes, it takes no more than two minutes to construct and solve a static matching problem in an epoch, as illustrated in Fig. 10. One-third of the total computation is spent on solving the integer program, while the rest is used to generate possible routes. Given the solution time needed per epoch, the value of the maximum allowable solution time $\Delta$ can be set to be 1.5 minutes. Since each epoch has two minutes, all static matching problems are solved, and matching results become available well within $\Delta$, thus satisfying the requirement of real-time decision-making.

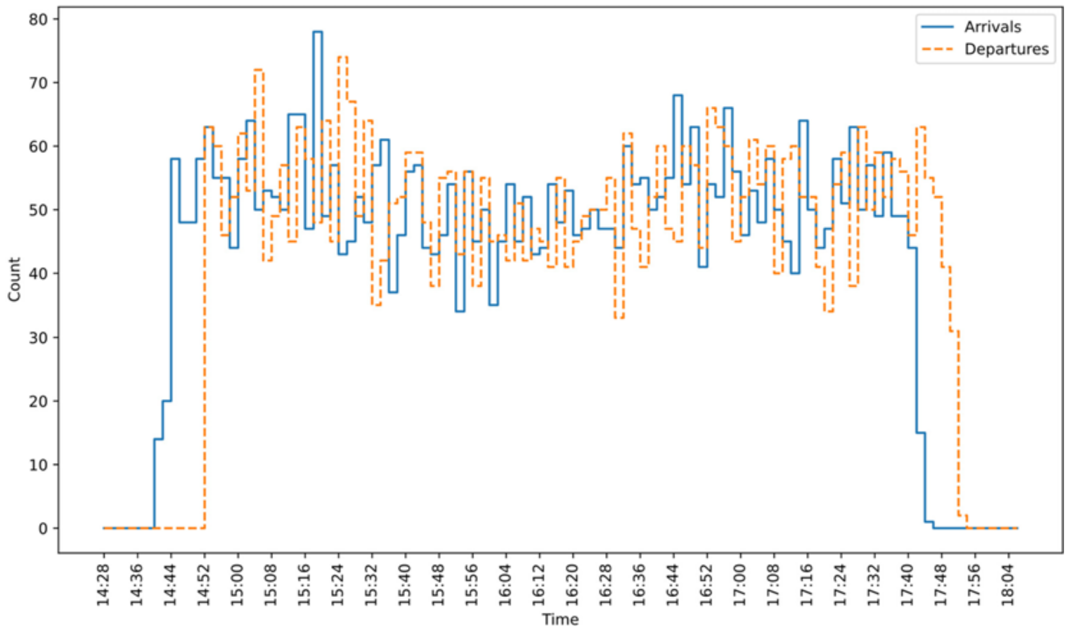


**Fig. 7.** Arrivals and Departures of Carpool Participants in Each Epoch over Time

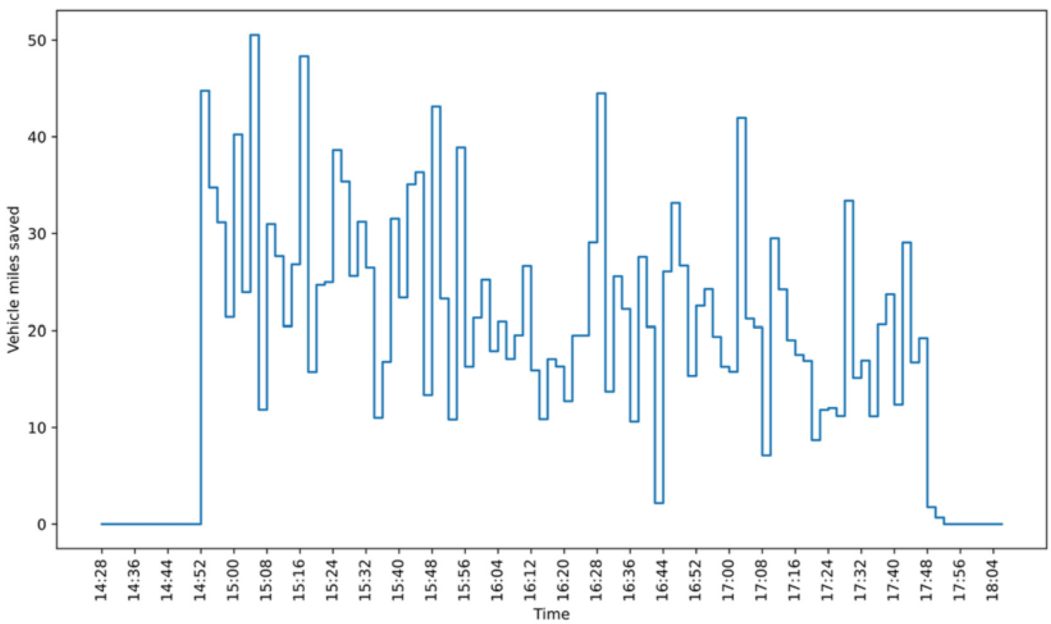


**Fig. 8.** Total Vehicle Mile Savings in Each Epoch over Time

In the benchmark case analyzed above, the incentive budget limit is \$25 per epoch. We now vary the incentive budget limit from \$0 to \$35 and show how the total vehicle mile savings change accordingly in Fig. 11. When no incentives are available, the vehicle mile savings are 1,129.8 (or 6.9%); when the incentive limit is \$5 per epoch, the resulting savings increase to 1,386.3 (or 8.5%). Therefore, allocating incentives to drivers to influence their schedules leads to significantly higher vehicle mile savings. When the budget limit is \$5 per epoch, the total incentives utilized over the planning horizon are \$89.1. Considering the increase in vehicle mile savings (256.5, which is the difference between 1,386.3 and 1,129.8), we conclude each dollar in incentives leads to 2.88 vehicle miles to be saved. Other numbers above the curve in Fig. 11 can be interpreted in the same way. When the incentive budget limit per epoch is \$35, the total vehicle mile savings are more than 100% higher than those without incentives. It should also be noted that the vehicle mile savings resulted from one dollar of incentive diminish as the incentive budget limit increases, which implies an upper bound on the budget limit. For instance, if one dollar of incentive is

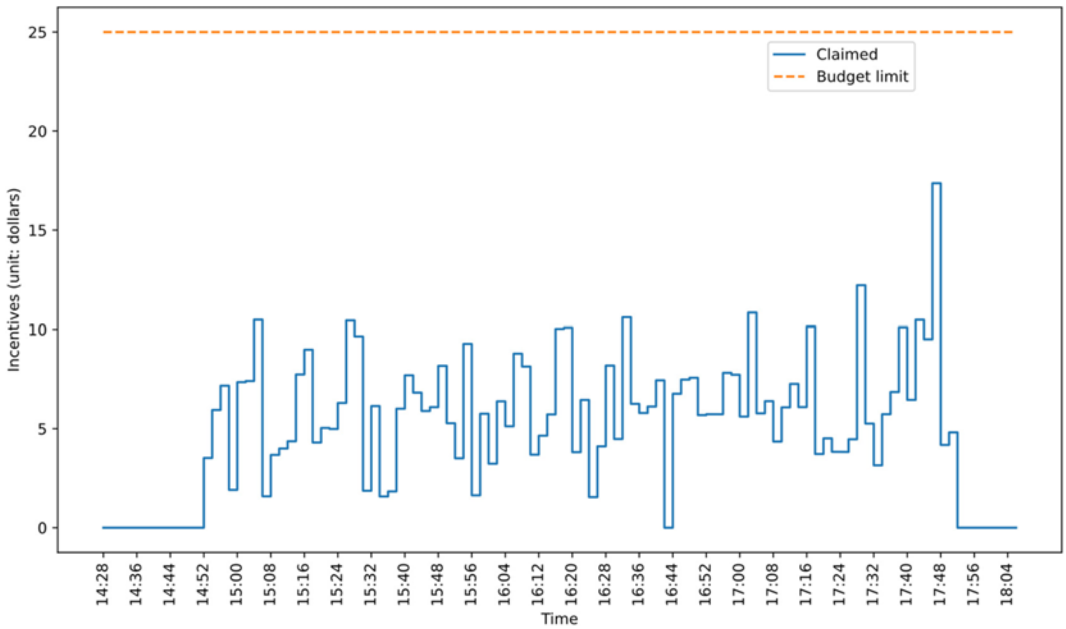


**Fig. 9.** Claimed Incentives in Each Epoch over Time

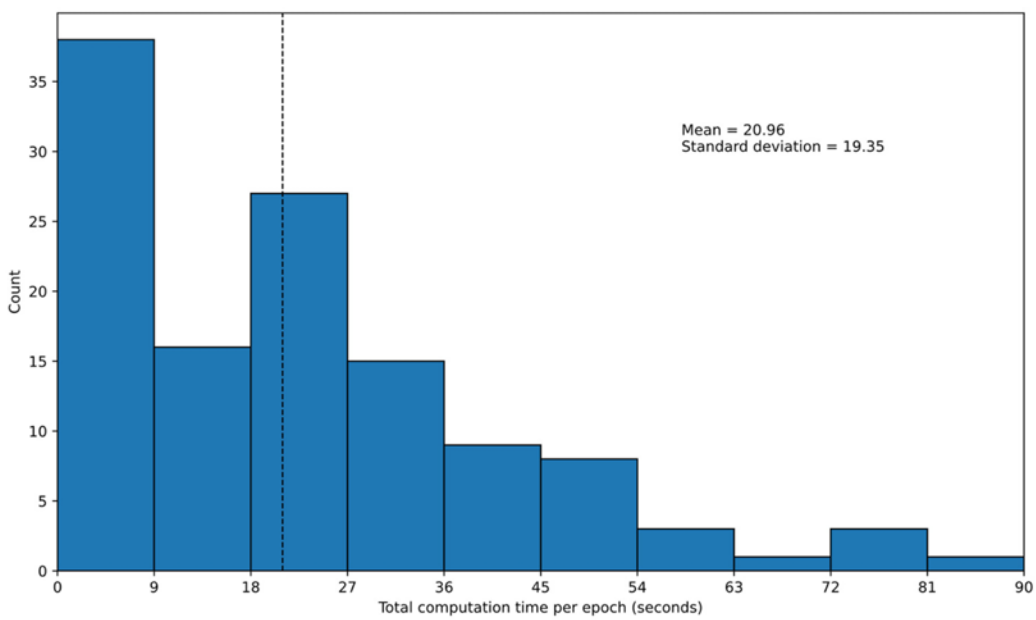


**Fig. 10.** Histogram of the Computation Time per Epoch

evaluated to be equivalent as 1.5 vehicle miles being saved to the coordinator, the incentive budget per epoch should be clearly below \$15.

In the benchmark case, the incentive needed by driver $k$ is uniformly distributed on range [1.5, 2.5], with an average value of \$2 per five minutes. We then explore the impact of the range for $a_k$ on the optimization objective in Fig. 12. As expected, as the expectation of $a_k$ increases from \$1 to \$4, the vehicle mile savings drop significantly, which is understandable. As more incentives are needed for an average driver to consider a more flexible travel schedule, the vehicle mile savings that can be achieved by incentives diminish, for the same incentive budget limit. Note that when the budget limit is zero, the vehicle mile savings are the same, regardless of the range for $a_k$. Similarly, as the expectation of $a_k$ increases from \$1 to \$4, the matching success rate (defined as the total number of matched participants divided by the total number of participants) drops, as shown in Fig. 13.

As some values in a problem instance are randomly sampled, we explore the variability of results for the same set of parameters used in generating instances. We adopt the same parameters that are used in the benchmark case while employing different random seeds. Fig. 14 shows that although variations in the results exist,

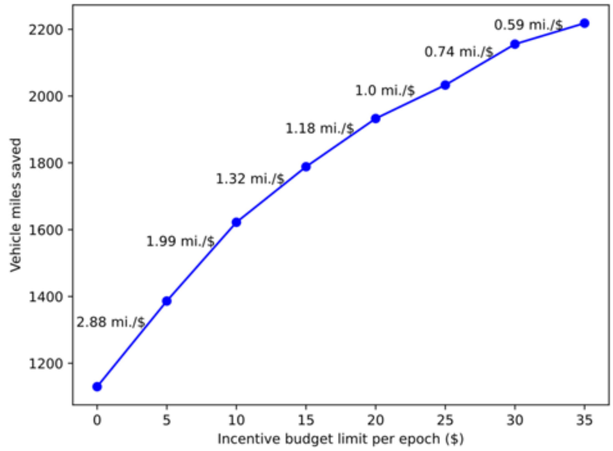


**Fig. 11.** Effect of Incentive Budget Limit

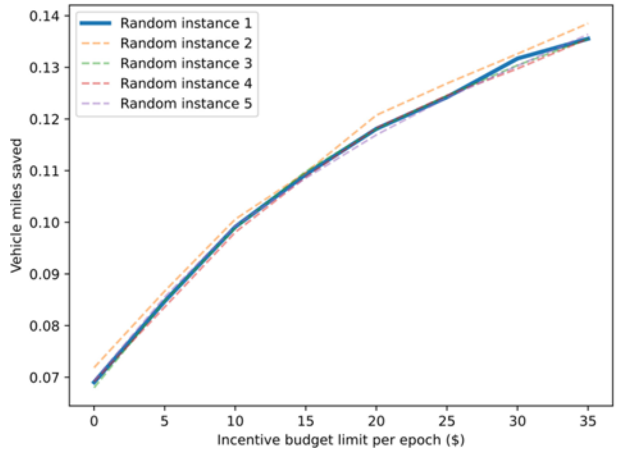


**Fig. 14.** Comparison of Results from Five Randomly Generated Instances

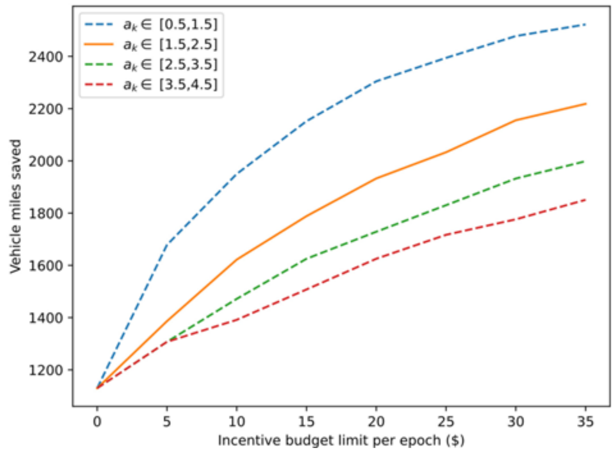


**Fig. 12.** Effect of the Incentives Requested by Drivers on Vehicle Miles Saved

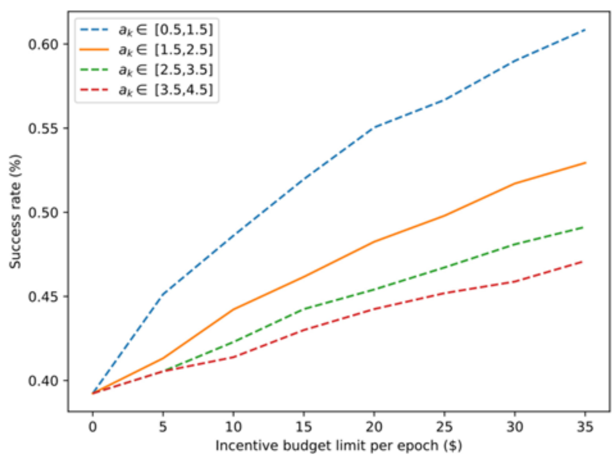


**Fig. 13.** Effect of the Incentives Requested by Drivers on Matching Success Rate

such variations tend to be small.

## 5.2 Effectiveness of Rider Incentives

Since driver incentives have been thoroughly studied in Section 5.1, we investigate rider incentives here. The incentive needed for rider $r$ to willingly walk for one mile from an alternative destination to the preferred drop-off location is defined in Section 4.3 as $b_r$. Two ranges for $b_r$ are considered, namely [3, 5], and [7, 9]. As mentioned in Section 4.3, we assume that when a rider is dropped off at an alternative destination (e.g., a transit station), the rider walks to the requested destination (e.g., workplace) while not violating the pre-specified time window at the destination. For instance, if the latest arrival time at the workplace is 9:30 am and it takes 10 minutes to walk from a transit stop to the workplace, the latest arrival time at the transit stop should be 9:20 am. The default walking speed is 3 miles per hour.

We consider a similar case to the benchmark case in Section 5.1 (e.g., assuming an incentive budget limit of $25 per epoch), while considering rider incentives only. It turns out no riders could feasibly accept alternative drop-off locations, which means nil of the incentives are allocated and zero improvements in the optimization objective due to rider incentives are observed. In other words, rider incentives are futile in this case.

The motivation for allocating incentives to riders is that requested drop-off locations could be “clustered”, so that a driver could drop off multiple riders at once at a common location that is not far from other individual destinations. That way, the number of drop-offs performed by drivers and vehicle miles dedicated to rider drop-offs decrease. However, the clear shortcoming of dropping riders prematurely is that riders must be dropped much earlier than the requested latest arrival time to save time for walking to the requested destination. This shrinkage in riders’ schedule flexibility has a major impact on the route feasibility, as shown in Fig. 15. Suppose that enough incentives have been provided so that each rider is willing to accept the alternative drop-off location. When the walking speed is extremely large (more than 100 miles/hour, which is clearly unrealistic), the adjusted arrival time window at the alternative destination is very close to the original one at the requested destination. As the walking speed decreases, the latest arrival at the alternative destination must be shifted earlier, which implies an increasing

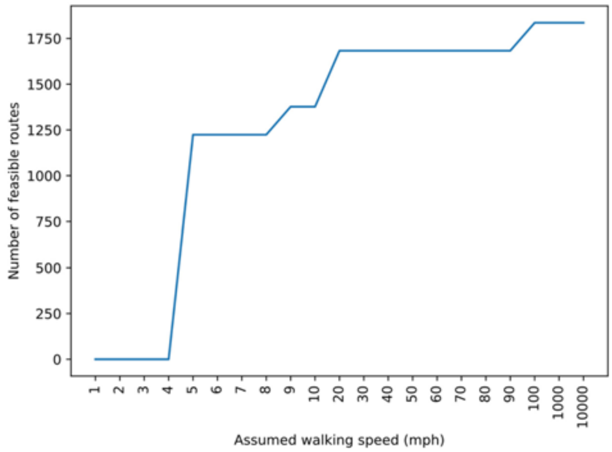


**Fig. 15.** Effect of Walking Speed on Route Feasibility

difficulty of finding a driver for matching. As the walking speed further drops to the normal range (such as 3 mph to 4 mph), significant walking is involved from the alternative destination and requested destination; the arrival time window at the alternative destination turns very narrow, which greatly reduces the rider's chance of being matched with other drivers. This explains why as the walking speed drops, the number of feasible vehicle routes drops rapidly. Since humans tend to walk 3 to 4 miles per hour, Fig. 15 shows riders cannot be feasibly matched with other drivers if riders must walk to their requested destinations.

Therefore, if the arrival time window at the requested destination cannot be violated even when a rider is dropped off at an alternative destination, the effectiveness of rider incentives in improving system-level vehicle mile savings is almost none under normal assumptions about walking speed, regardless of the magnitude of incentives requested by riders.

It is thus understandable that almost all the incentives would be allocated to drivers to incur their departure time changes in a scenario where both drivers and riders are eligible for incentives. The primary reason is that drivers' departure time changes enabled by incentives can yield much more vehicle mile savings than trip destination changes by riders.

## 6. Conclusions

In this study, we have evaluated the effectiveness of personalized travel incentives in reducing vehicle miles traveled in a dynamic carpooling system. We considered two incentive schemes: driver incentives to influence the departure time choices of drivers, and rider incentives to encourage the adoption of alternative drop-off locations by riders. As incentive allocations are closely related to other carpool matching decisions, an integrated optimization model adapted from Sun et al. (2020a) was introduced. A rolling horizon solution framework was then employed to address the dynamism of this optimization problem. Real-world taxi trip data in Washington, D.C. were enhanced to create a range of dynamic carpool instances. We derived the following findings after conducting the numerical studies:

1. The developed optimization framework can satisfy the need for real-time decision-making, which can thus be implemented in a real-world dynamic carpool system.
2. Personalized driver incentives can significantly improve the system-level objective (maximization of vehicle mile savings) of a dynamic carpool ing system. In one benchmark case, it is found that one dollar in incentive can increase the optimization objective by 2.88 miles, although the effect diminishes as the incentive budget limit increases.
3. Under practical assumptions about key parameters, the driver incentive scheme is shown to be significantly more effective than rider incentives.

The primary takeaway from this study is that incentives should be customized and offered to certain drivers, whose changes in their travel schedules are critical to the improvement in the optimization objective. The developed optimization framework in this study is thus useful in identifying such "critical" drivers and optimizing the incentive allocations, as well as other carpool matching decisions.

This paper presents the first known study to explore the effectiveness of personalized incentives in dynamic carpooling based on empirical data, which is the contribution of this paper to the literature. Nonetheless, this study should be improved in several ways, as follows:

1. Some real-world taxi trip data were used to approximate carpool demand in this study; a few other key parameters, such as the average incentive needed for a driver to shift the departure time by five minutes, were assumed. Carpool matching coordinators should use their own demand data and conduct further user surveys to conduct more relevant numerical analyses. This is because the performance of an incentive scheme clearly depends on the travel patterns (e.g., distributions of origins and destinations, and widths of travel time windows) and user preferences (e.g., incentives demanded per unit of time) in a carpool system.
2. In this current study, each driver had only three flexibility options, which was limited. In case a driver has many options, directly solving the static optimization problem defined in Section 3.1 can be time-consuming. Therefore, a column generation-based heuristic can be designed. To begin with, initial columns representing vehicle routes are generated, assuming zero incentives. After solving the linear programming relaxation of the restricted formulation including initial columns only, new columns (routes) which are resulting from applying incentives are added and only those columns with the potential to generate net benefits at the system-level are added to the matching optimization problem, whose solution triggers the next iteration. This iterative process terminates when no such columns can be found.
3. This study does not consider any uncertainty in the behavioral responses of carpool participants. In reality, even when appropriate incentives are offered as needed, participants may decline to revise their travel plans. In that case, matching results and incentive allocations must be reoptimized.

4. Although this study aims to maximize the total vehicle mile savings (proxy for the environmental benefits), the developed model can accommodate other optimization objectives with little modifications, such as minimizing the number of unmatched carpool participants and minimizing the total travel time.

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