A Guided Insertion Mechanism for Solving the Dynamic Large-Scale Dial-a-Ride Problem

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ABSTRACT

We study a prospective transportation system where vehicles provide dial-a-ride services to fulfill a very large scale of passenger requests (around 300,000). The system operates dynamically, with newly submitted requests needing immediate processing. A crucial aspect of this system’s viability in real-time situations is therefore the implementation of an efficient routing algorithm that can deliver high-quality solutions. We address a dynamic large-scale dial-a-ride problem through a best-fit greedy insertion algorithm. Furthermore, large-scale requests are assumed to be dominated by daily commuting needs and thus should be similar and repetitive from one day to another. Therefore, there might exist recurring and similar patterns in vehicle trajectories if similar requests can be served in the same manner. We introduce a Guided Insertion Mechanism that relies on a representative reference resolution and guides the insertion of dynamic requests while maintaining high-quality solutions.

1 INTRODUCTION

In recent years, we have witnessed the emergence of novel transportation systems, offering efficient and sustainable alternatives to traditional modes of transportation. Among these, vehicle-sharing and ride-sharing systems are two predominant categories. In vehicle-sharing systems, vehicles positioned at stations are left for access by users. Related problems can be about the design of the systems, such as where to position the stations and how to relocalize vehicles [8]. Ride-sharing services allow users to share common journeys in the same vehicle. The most common problems are about the effective routing and scheduling of vehicles that take advantage of the mutualization of different services [1, 7]. Both systems promote reduced congestion and emissions while maximizing vehicular utilization. Dial-A-Ride (DAR) system can be regarded as a hybrid of the above two categories, where vehicles are owned by operators and provide demand-responsive transportation services to fulfill.

In this paper, we consider a prospective transportation system where a mid-capacity vehicle fleet offers Dial-A-Ride (DAR) services to a very large volume of passengers (around 300, 000 per day), catering to the transportation needs of a vast user base. The system operates in a dynamic context, where user requests are submitted and processed on-the-fly. Therefore, to ensure the viability of the system, we need to implement a routing algorithm that is both efficient and capable of delivering high-quality solutions. For that, we address a dynamic large-scale dial-a-ride problem. Due to the large-scale aspect, it is difficult to solve the problem through exact methods (e.g., branch and bound, branch and cut, etc.) or local search approaches (e.g., Large Neighborhood Search, Build and Destroy, etc). We rely on the classic greedy insertion heuristic for its simplicity and effectiveness. Furthermore, we consider that large-scale requests should be dominated by daily commute needs which exhibit recurring characteristics. Therefore, daily requests should be globally similar and repetitive. Under this assumption, we should be able to recreate similar travel patterns in vehicle trajectories. Based on this idea, as our main contribution to this work, we propose a Guided Insertion Mechanism (GIM) which utilizes the travel patterns constructed from a representative reference resolution to efficiently insert dynamic requests while maintaining the high quality of the routing solution.

The remainder of this paper is organized as follows: In Section 2 we introduce some related works in the literature. Section 3 formally defines our problem and introduces some important notation. Section 4 introduces the notion of insertion of a request. In Section 5, the solution scheme is outlined. Then, in Section 6, we detail the GIM. Experimental results are presented and discussed in Section 7 and we conclude in Section 8.

2 RELATED WORKS

On-demand DAR transportation systems provide personalized and efficient transportation services to customers. These systems utilize digital platforms and shared mobility concepts, offering convenient, flexible, and cost-effective travel choices. As the need for efficient urban transportation increases, there is a rising prevalence of studies focusing on large-scale systems. Studies are actively studying.
various system characteristics, encompassing the management of congestion issues resulting from the substantial vehicle fleet size [13], addressing recharging challenges in scenarios involving electric vehicles [2], and exploring the potential advantages of introducing ride-sharing into these systems [6]. In customer-facing systems like these, the rapid processing of user demands during dynamic scenarios is crucial. Hence, expediting the routing and scheduling process holds vital significance. The authors in [16] study a large-scale taxi system that serves at least 330,000 requests per day. To provide instant feedback in response to dynamic requests, they introduce a filtering algorithm *dual-side taxi searching* that rapidly retrieves some interesting (nearest) vehicles to be candidates to service the given request. Similarly, in [14], the authors propose a filtering system that not only provides candidate vehicles but corresponding candidate insertion positions within the routes as well.

Within the context of DAR transportation systems, we naturally rely on the Dial-A-Ride Problem (DARP) to formulate the problem. Designing a fleet of vehicles’ routes and schedules to accommodate a set of passenger requests—typically defined by a pickup location, a drop-off location, pickup and/or drop-off time windows, and a maximum ride time—is the basis of DARP. Objectives like maximizing customer service quality or reducing vehicle operating costs guide decisions [10]. DARP is NP-hard as it admits the Vehicle Routing Problem (VRP) as a special case. Very few studies seek to solve the problem on this graph. For example, [3] proposes a two-phase scheduling heuristic that aggregates services happening at the same location at the same time. Typically, a key point *K* contains: \( N \), the location of the service; \( q_K \), the load of \( v \) before departing from \( n_K \); \( R^v_K \), the list of requests scheduled to get onboard at \( K \); \( R^v_K \), the list of requests scheduled to get off at \( K \); \( \{ 0 \} \), the arrival time window at \( n_K \); and \( \{ 0 \} \), the departure time window from \( n_K \). Let \( ( K^v, \Theta^v ) \) denote the corresponding candidate positions within the routes as well.

In this section, we define our Large-Scale Dial-A-Ride Problem (LSDARP). We consider a transit network \( G = ( N, A ) \), where \( N \) contains all the intersections, and \( A \) contains all the arcs in the network. We only consider one depot, denoted by \( n_0 \in N \) in \( G \). The travel time of an arc \( ( i, j ) \in A \), \( i, j \in N^2 \), is denoted by \( t(i, j) \). By extension, we use \( t(u, v) \) to denote the shortest travel time from any node \( u \) to any node \( v \) in the network.

A request \( r \in R \) is submitted at time \( t^r_\text{sub} \) with the following information: a pickup service requirement \( O^r \), a drop-off service requirement \( D^r \) and the number of involved passengers \( q^r \). The pickup service \( O^r \) includes an origin \( o^r \in N \) and a pickup time window \( [ t^r_\text{sub}, t^r_\text{arr} ] \). And the drop-off service \( D^r \) includes a destination \( d^r \in N \) and a maximum ride time \( r^r \). We note that service times are not considered, and all requests are supposed to be feasible and non-preemptive, which means that each request must be fulfilled exactly once by exactly one vehicle.

Passengers are serviced by a fleet \( V \) of vehicles of capacity \( Q \). A route \( \theta^v \in \Theta \) followed by a vehicle \( v \) is a list of key points \( K \) that aggregates services happening at the same location at the same time. Typically, a key point \( K \) contains: \( N \), the location of the service; \( q_K \), the load of \( v \) before departing from \( n_K \); \( R^v_K \), the list of requests scheduled to get onboard at \( K \); \( R^v_K \), the list of requests scheduled to get off at \( K \); \( \{ 0 \} \), the arrival time window at \( n_K \); and \( \{ 0 \} \), the departure time window from \( n_K \). Let \( ( K^v, \Theta^v ) \) denote the key point where \( O^r \) (resp. \( D^r \)) is inserted.

When providing services, \( v \) follows the earliest arrival time \( e^r_K \) and earliest departure time \( d^r_K \). Vehicle routes must start, end at the depot \( n_0 \), and have a load that never exceeds vehicle capacity. And for every request \( r \) assigned to the vehicle, \( O^r \) precedes \( D^r \), and the schedule must not violate the pickup time window and the maximum ride time constraints.

We consider a lexicographic objective function. We assume that the number of vehicles is unlimited, so minimizing the fleet size is the primary objective. The total drive time of vehicles is considered the second criterion.

4 INSERTION OF A REQUEST

Given a triplet of insertion parameters \( ( \theta^v, K^v, K^d ) \), we introduce the procedure \( \text{INSERTION}(r, \theta^v, K^v, K^d) \) that inserts \( r \) into the route \( \theta^v \) at positions \( K^v \) and \( K^d \)

We first insert the pickup service \( O^r \). If \( n^r = n^{o_r} \), we aggregate \( O^r \) to \( K^v \) and \( K^v(O^r) = K^v \); otherwise, a new key point \( K^v(O^r) \) supporting \( O^r \) will be inserted between \( K^v \) and \( \text{succ}(K^v) \). In both cases, the load \( g_{K^v(O^r)} \), in inbound request list \( R^v_{K^v(O^r)} \), and the pickup and drop-off time windows on \( K(O^r) \) should be updated while considering the constraints about the vehicle and requests mentioned previously. Same rules applied for the insertion of the drop-off service \( D^r \) at \( K^d \). We note that when updating the arrival time windows of \( K(D^r) \), we need to take into account the maximum ride time \( r^r \) of \( r \).

3 PROBLEM STATEMENT

In this section, we define our Large-Scale Dial-A-Ride Problem (LSDARP).

We consider a transit network \( G = ( N, A ) \), where \( N \) contains all the intersections, and \( A \) contains all the arcs in the network. We only consider one depot, denoted by \( n_0 \in N \) in \( G \). The travel time of an arc \( ( i, j ) \in A \), \( i, j \in N^2 \), is denoted by \( t(i, j) \). By extension, we use \( t(u, v) \) to denote the shortest travel time from any node \( u \) to any node \( v \) in the network.
Once $O'$ and $D'$ are inserted, we increase the load of key points between $K(O')$ and $K(D')$ by $q'$ while ensuring that the new loads never exceed the vehicle capacity $Q$. We should also update the time windows of the key points along $θ'$ and checking that these time windows are never empty. For that, we implement a classic constraint propagation procedure ([17]) considering the above time constraints. The procedure has a complexity of $O(|θ'|^2)$, where $O(|θ'|^2)$ is the number of key points in $θ'$.

5 ALGORITHM FRAMEWORK

We define a set of decision epochs $E = \{E_0, E_1, \ldots, E_t, \ldots, E_{|E|-1}\}$. Each decision epoch lasts $I_e$ (for example, $I_e = 10$ min) time units. The starting time of $E_i$ is $t_{E_i} = i \times I_e$. For each decision epoch $E_i \in E$,

1. during the time slot $[t_{E_i}, t_{E_i} + r]$, where $r$ defines the maximum decision duration, the system makes the routing decisions for requests submitted during the previous epoch $E_{i-1}$, denoted by $R_{E_i}$.
2. at time $t = t_{E_i} + r$, the system updates the vehicles’ schedules, and informs unserved passengers whose requests have already been inserted about the updated information about their pickup (the vehicle’s passage time).
3. following the update, vehicles start implementing the new routes until reaching $t = t_{E_{i+1}} + r$.

Regarding the very large size of the problem and the need to make decisions on-the-fly, we address the problem to be solved for each decision epoch $E$ based on the classic best-fit insertion heuristic. During epoch $E$, requests $R_E$ are inserted one by one following a specific order, and for each request $r$, we try to insert it according to the best-fitted insertion parameters that minimize the insertion cost measured by the detour to service $r$. Depending on the implementation, searching for insertion parameters among the whole search space $Θ$ would generally require a computational effort of $O(|θ|^2)$. In addition, testing the insertion feasibility and the INSERTION process are also computationally expensive, as mentioned in Section 4. Due to the large-scale effect, the search space would contain thousands of vehicles along with hundreds of thousands of insertion positions to explore, which can be too large to fit the dynamic need. For that, we introduce a guided insertion mechanism upstream of the best-fit insertion that rapidly and wisely selects well-fitted insertion parameters and tries several valuable insertions.

Then, given a request $r \in R$ and the current route collection $Θ = \{θ^o, o \in \mathcal{O}\}$:

- We first invoke the Guided Insertion Mechanism (GIM) which uses knowledge learned from representative historical instances and solutions to guide the insertion of $r$. If a feasible insertion is found, we keep it.
- If GIM fails, we invoke a best-fit insertion heuristic over the entire search space $Θ$, and try to insert $r$ into the best-fitted vehicle route at the insertion positions (i.e., key points) that minimize the insertion cost.
- Finally, if both of the above steps fail, we activate a new vehicle $o$ to serve $r$ and add $θ^o$ to the current route set $Θ$.

6 THE GUIDED INSERTION MECHANISM

In this section, we introduce the Guided Insertion Mechanism (GIM). Let us use $\text{LSDARP}(R)$ to denote the problem with an input instance $R$. Consider two similar request sets $R_1$ and $R_2$ in a way that for most of the requests in $R_1$, we can find a similar request in $R_2$. Then we believe that the optimal routing solution $θ_1$ to the problem $\text{LSDARP}(R_1)$ should be similar to $θ_2$, the optimal solution to the problem $\text{LSDARP}(R_2)$. Because if $r_1 \in R_1$ and $r_2 \in R_2$ are similar, they should be able to be inserted in a similar manner.

GIM is conceived based on the above idea. Thanks to the large-scale aspect and the fact that requests should be dominated by recurring daily commute requests, we assume that requests to be processed in the DAR systems are similar from one day to another. Therefore, the travel patterns of vehicles should also be similar from one day to another. Assuming that we have a representative reference set $R$ which captures the basic distribution (origin and destination and pickup times) of requests, then the static (i.e., offline) optimal solution $θ$ to the problem $\text{LSDARP}(R)$ should be able to guide any dynamic (i.e., online) resolution of any real problem $\text{LSDARP}(R)$, where $R$ is the set of real dynamic requests to be processed in the service period.

Extracting the daily mobility patterns of requests in an underlined system and solving the associated static problem to optimal are two independent problems. As mentioned previously, in this paper, we do not take care of either of the above-mentioned problems and assume that a representative reference set $R$ generated based on the daily request distribution is in our possession, along with its off-line (near) optimal solution $Θ$. We are interested in how the references $(R, Θ)$ can be informative and guide the insertion when solving a similar real dynamic problem $\text{LSDARP}(R)$.

6.1 Preprocessing: Obtain Vehicle Travel Patterns

For each reference route $θ \in Θ$, we compute a specific travel pattern $γ(θ) ∈ Π$ during the preprocessing phase. A travel pattern $γ(θ)$ is a simplified route defined as a list of pattern points, where each pattern point $P$ represents a cluster of key points in $θ$. The notion of key point cluster is defined as follows:

Definition 6.1 (key point cluster). Given a route $θ = \{K_0, K_1, \ldots, K_{|θ|} \}$ with $M$ key points, $\{K_i, K_{i+1}, \ldots, K_{i+m}\}$ is a key point cluster if and only if:

\[ t(K_{i+1} - K_{i+1} - 1) ≤ δ^K, \text{ for } 1 ≤ i ≤ m, \]
\[ t(K_{i+1} - 1) > δ^K, \text{ for } i > 0, \]

and

\[ t(K_{i+m}, K_{i+m+1}) > δ^K, \text{ for } i < M - 1 - m. \]

where $δ^K$ is the clustering threshold indicating the maximum travel time from a key point to its successor that are in the same cluster.

For example, in Figure 1 where three partial routes are shown, we see that $K_2$, $K_3$ and $K_4$ represent a key point cluster, so in the travel pattern $γ(θ)$, they are represented by a pattern point $P_2$.

The travel patterns are used in the guided insertion process. In GIM, each pattern guides the construction of at most one real route $θ \in Θ$. Specifically, if a real key point $K \in θ$ is created via GIM under the guidance of a pattern point $P \in γ$, then we call $K$ a child
6.2 Guided Insertion Process

Given a real request \( r \), GIM operates according to the following steps.

6.2.1 Step 1: Retrieve similar reference requests. We first identify from \( \mathcal{R} \) all the reference requests \( r' \) that are similar to \( r \). The similarity between requests is defined as follows:

Definition 6.2 (similarity between requests). Two requests \( r_1 \) and \( r_2 \) are similar if and only if

\[
|t(s_1, d_1) - t(s_2, d_2)| < \delta, \quad |l_c(r_1) - l_c(r_2)| < \delta',
\]

where \( \delta \) is a threshold indicating the maximum travel time between two locations, and the threshold \( \delta' \) indicates the maximum difference in the earliest pickup time between \( r_1 \) and \( r_2 \).

If \( r_1 \) and \( r_2 \) satisfy the above conditions, we use \( |l_c(r_1) - l_c(r_2)| \) to define their similarity measure. Let \( \mathcal{R}' \) denote the set of retrieved similar reference requests. The set \( \mathcal{R}' \) is sorted according to the descending order of their value of similarity measure with \( r \).

6.2.2 Step 2: Construct guide object set. Next, we construct a set of guide objects, denoted by \( GO' \). A guide object is a triplet \((y, P^o, \hat{P})\) used to guide the guided insertion of \( r \), where \( P^o \) and \( \hat{P} \) are two pattern points in the travel pattern \( y \). For example, as illustrated in Figure 1, a reference request \( r' \) inserted in \( \hat{y} \) at \( K(O') \) and \( K(D') \) corresponds to the guide object \((y(\hat{\theta}), P^o, \hat{P})\). Then, \( GO' \) is constructed by sequentially capturing and organizing the corresponding guide objects of all the reference requests \( r' \) in alignment with the order specified in \( \mathcal{R}' \). We note that it is possible that several reference requests may correspond to the same guide object. In \( GO' \), we only keep one occurrence of the same guide objects.

6.2.3 Step 3: Insert \( r \) according to the guide object. As mentioned before, the concept of guided insertion is that similar requests should be able to be inserted in the same manner. Given a target request \( r \) and the set \( GO' \), we try to insert \( r \) under the guidance of elements in \( GO' \).

Given \((y, P^o, \hat{P}) \in GO'\), we use \( \hat{P} \) to guide the insertion of \( O' \), and \( P^o \) to guide the insertion of \( D' \).

If \( y \) has not been related to any real route in \( \Theta \), then we activate a new vehicle \( v \) to service \( r \). Its route \( \hat{\theta} \) is initialized as two key points \( K_1 \), the initial depot, and \( K_2 \), the final depot. Next, two key points \( K(O') \) and \( K(D') \) supporting the pickup and drop-off services are inserted between \( K_1 \) and \( K_2 \). Then we relate \( \theta_0 \) to \( y \) by correctly setting the pointers \( l_c \) and \( r_c \) for all \( \hat{P} \in y \) (see Figure 2).

Figure 1: Illustration of the relationships between the reference route, the travel pattern, and the real route

Figure 2: Illustration of the creation of the new route via GIM

If \( y \) is already related to a real route \( \theta \in \Theta \), then we utilize \( P^o \) to construct a list of candidate insertion positions for the pickup service. Specifically, in case \( r_c \) is a null pointer (which means that \( P \) has no related child yet), the candidate list only contains the key point pointed by \( l_c \); otherwise, the list contains all the key points between the two key points pointed by \( l_c \) and \( r_c \). We obtain a candidate list for the drop-off services in the same way. Then, we proceed with a best-fit scheme while trying the insertion feasibility of \( r \) at the selected candidate key points for the pickup and drop-off services. This means that if at least one feasible insertion is found, we keep the candidates that minimize the insertion cost.

Finally, every time \( r \) is inserted in \( \hat{\theta} \) at \( K(O') \) and \( K(D') \) via GIM with the guide object \((y, P^o, \hat{P})\), we need to update the pointers \( l_c \) and \( r_c \) of pattern points \( P \) along \( y \).

We note that the goal of GIM when inserting \( r \) is to replicate the insertion mode of the most similar reference request. We know that the further forward positioned the guide object \( GO' \), the more similar the corresponding reference request is to \( r \). Therefore, we implement a first-fit scheme to explore \( GO' \). If \( r \) can be inserted under the guidance of \((y, P^o, \hat{P})\), we proceed with the insertion, stop the exploration of \( GO' \), and continue to insert the next request. Otherwise, we explore the next guide object in \( GO' \).

7 NUMERICAL EXPERIMENTS

We programmed the algorithms in C++ language and solved the problem on a 512 GB RAM machine with an AMD EPYC 7452 32-Core Processor.

7.1 Input Data

We take the transit network of the city of Clermont-Ferrand, France, and its peri-areas. The underlined area contains 13,839 nodes and 31,357 arcs. Among all nodes, 1,469 are selected to be valid pickup and drop-off locations.

The system we study in this paper is still prospective, so there are no available real-life request instances. The instances tested in this paper are self-generated and simulate the intended use cases of the system: providing services to all kinds of travel requests, which are in addition dominated by daily commute demands.

The service period lasts \( T = 24 \) hours, from \( 00 : 00 \) to \( 24 : 00 \). We divide the entire period into five time slots: MS (Morning Slack, 00:00 ~ 06:00), MP (Morning Peak, 06:00 ~ 10:00), NH (Normal Hours, 10:00 ~ 15:00), EP (Evening Peak, 15:00 ~ 19:00) and ES (Evening Slack, 19:00 ~ 24:00). We assume requests to be processed
in one day generally obey the following basic distribution: During
MP, around 50% are typical that travel from a residential location
to a working location. Reversely, EP requests follow a symmetric
pattern, with half of the requests being typical that move from a
working position to a residential position. For the requests of MS,
NH and ES, their origin and destination are randomly distributed
over the network.

To guarantee the representative property of the reference request
set \( R \) used in GIM, we randomly construct it according to the above-
introduced basic distribution.

Real requests should globally obey the basic distribution and be
“similar” from one day to another while exhibiting some random
variations. To simulate such a phenomenon, real request instances
are decomposed into two parts: the “random” part and the “similar”
part. Requests in the “random” part are randomly generated using
the above-defined basic distribution. The “similar” part simulates
the stable and recurring pattern of daily requests. We rely on \( R \)
to generate the corresponding requests. Typically, when generating
a request \( r \) in this part, we randomly select a reference \( f \). Then \( f' \)
(resp. \( d' \)) is randomly selected among the nodes that are reachable
within 3 arcs from \( f' \) (resp. \( d' \)). And the earliest pickup time \( e_{f'} \) is
a random value selected between \( e_{f'} - 7.5 \) minutes and \( e_{f'} + 7.5 \)
minutes. In terms of the daily recurring pattern, we consider two
scenarios: (high): “similar” part accounts for 90% of the requests;
and (moderate): “similar” part accounts for 50% of the requests.

For each instance, we generate 300,000 requests. The time length
of the pickup window is set at 15 minutes for all requests. The
maximum ride time \( T' \) is twice the shortest travel time from \( f' \) to
\( d' \). The load for each request is 1. And as real requests are supposed
to be dynamic, we randomly set the submission time \( t_{sub} \) of \( r \)
between \( t \) and \( e_{f'} \). Requests are submitted on average one hour
before \( e_{f'} \). And in line with the no-rejection assumption, values of
\( t_{sub} \) also satisfy that when processing \( r \) at epoch \( E \), we can always
activate a vehicle \( e \) currently parking at the depot to serve \( r \).

7.2 Analyses of the Effectiveness of GIM

In this work, the static reference problem LSDARP(\( R \)) is solved
by a best-fit insertion heuristic. The resulting solution \( \Theta \) contains
routes of 1,621 vehicles. It is worth noting that there are other
approximation algorithms (Large Neighborhood Search, Adaptive
Large Neighborhood Search, etc.) capable of offering more optimal
solutions, but at the expense of significantly increasing the
processing time.

The length of each decision epoch \( \epsilon \) lasts \( L_\epsilon \) = 10 minutes, and for
the reason of comparing the efficiency of different approaches, the
maximum decision duration \( \tau \) is not explicitly fixed, and we count
the CPU time spent required for each decision epoch. The GIM
parameters \( \delta_k \) (key point cluster threshold), \( \delta_s \) and \( \delta_t \) (request
similarity thresholds) are fixed at 2 minutes, 2 minutes, and 15
minutes, respectively.

In order to test the performance of the GIM, we consider three
sets of baseline algorithms: BF (Best-Fit insertion heuristic), PFS
(Partial Filtering System), and FS (Filtering System). PFS and FS
are two approaches proposed in [14], in which a best-fit insertion
heuristic is implemented over the candidate vehicles and insertion
positions selected by a filtering system. Specifically, given a request
\( r \), in PFS, the search space contains all the filtered candidate vehicles
and insertion positions; while in FS, the search space is further
reduced to a subset of selected candidate vehicles along with their
candidate insertion positions. The FS implemented in this study
involves keeping the top 10% best vehicles from the candidate pool.
The number of selected vehicles is also bounded between 40 and
140. Then, we can integrate the GIM on the upstream side of these
three baseline algorithms. Accordingly, we propose three methods:
GIM-BF, GIM-PFS and GIM-FS.

Table 1 shows the results of the final fleet size, the total drive
time of vehicles, and passengers’ average in-vehicle time. The varia-
tions represented in percentage are calculated based on the baseline
approach BF. First, in terms of fleet size, we see that in both sce-
narios, all the approaches integrated with GIM outperform their
corresponding baseline approaches. In addition, GIM-BF and GIM-
PFS further reduce the fleet size established by BF by almost 6%.
Furthermore, thanks to the reduction in the number of used vehicles
and the fact that GIM helps better organize the routes by following
the pre-defined travel patterns, the total drive times of vehicles are
also improved. Meanwhile, passenger travel comfort remains the
same because better organized routes decrease detours and increase
the ride-sharing. All evidence indicates that, by learning from the
well-resolved reference solution, GIM has the potential to promote
vehicle utilization and alleviate emissions. Finally, we also notice
that GIM is not sensible to similarity scenarios high and moderate.
A possible reason is that, due to the large-scale aspect, we have a
great chance of finding a similar reference request, even though it
was not deliberately generated as such.

Let us now focus on the scenario high to analyze the CPU times
spent to process the requests during each decision epoch (see Fig-
ure 3). First of all, we observe two peaks in the processing time for
almost all approaches, corresponding to the high ratio of request
submissions during the two peak periods MP and EP. During most
of the epochs corresponding to the time slots MS, MP, NH and ES,
all approaches using GIM outperforms their baseline methods. This
advantage is especially pronounced during peak hours. During the
first few epochs (corresponding to MS), methods with GIM tend to
be less efficient. This is because GIM activates numerous vehicles
at the beginning of the process, resulting in a larger search space
compared to other baseline approaches.

![Figure 3: The execution time during each decision epoch](image-url)
solutions in terms of the fleet size, total drive time and passenger comfort. This highlights the potential of the utilization of GIM in solving the dynamic LSDARP.

8 CONCLUSION

We introduce a GIM upstream of the classic best-fit insertion heuristic. The experiment results show that by learning and imitating a reference static solution, GIM stands out in dynamic scenarios by encouraging the fleet to follow optimal vehicle travel patterns. Moreover, its integration with state-of-the-art accelerating algorithms such as the filtering system substantially reduces processing time without compromising solution quality. We firmly believe that with a more representative reference problem and a more optimal reference solution, GIM should emerge as a highly effective algorithm that is very suitable for addressing dynamic online problems. GIM is currently in its early stages as an emerging technology. Our upcoming focus aims to enhance its performance by maximizing the proportion of successful guided insertions within each epoch.

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REFERENCES


Table 1: Results with different approaches under different similarity scenarios with 300k requests

<table>
<thead>
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<th>scenario</th>
<th>approach</th>
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<td></td>
<td>FS</td>
<td>2,583 (+18.3%)</td>
<td>+22.7%</td>
<td>16.7</td>
</tr>
<tr>
<td></td>
<td>GIM-BF</td>
<td>2,061 (-5.6%)</td>
<td>-4.9%</td>
<td>16.9</td>
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<tr>
<td></td>
<td>GIM-PFS</td>
<td>2,053 (-6.0%)</td>
<td>-4.9%</td>
<td>16.9</td>
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<tr>
<td></td>
<td>GIM-FS</td>
<td>2,326 (+6.6%)</td>
<td>+15.8%</td>
<td>16.7</td>
</tr>
<tr>
<td>moderate</td>
<td>BF</td>
<td>2,191</td>
<td>25,641.0</td>
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<tr>
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<td>PFS</td>
<td>2,176 (-0.7%)</td>
<td>+0.1%</td>
<td>17.0</td>
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<tr>
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<td>FS</td>
<td>2,548 (+16.3%)</td>
<td>+23.0%</td>
<td>16.8</td>
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<tr>
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<td>2,063 (-5.8%)</td>
<td>-4.7%</td>
<td>17.0</td>
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<td>2,066 (-5.7%)</td>
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<tr>
<td></td>
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<td>2,347 (+7.1%)</td>
<td>+16.8%</td>
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