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Integrating parking delay uncertainty in urban delivery tour planning

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ABSTRACT

Securing curb space near a delivery location is a major source of uncertainty for urban commercial vehicle drivers. While tour planning tools increasingly account for time-dependent traffic conditions, they typically ignore parking delays, even though evidence shows they vary systematically across locations and times of day. This paper empirically examines how expected parking delays affect urban delivery tour planning. Using GPS data from real-world delivery operations, we estimate time- and location-specific parking delays and incorporate them into a Time-Dependent Traveling Salesman Problem with Time Windows. We compare conventional parking-blind planning, which considers only travel times, with parking-aware planning, which additionally accounts for expected parking delays. The results show that parking-blind planning substantially underestimates tour duration and overestimates schedule feasibility. When realistic parking conditions are considered, parking delays accounted for about 33% of total delivery tour duration and generate substantial increases in lateness and time-window violations. Parking-aware planning reduces tour duration by 3.4% on average (17.4 min), with some instances obtaining total tour duration reductions of more than 10%, by trading slightly longer driving times for lower parking delays, while reducing time spent in parking delays by 11% on average. More importantly, it substantially improves service reliability, reducing average lateness and greatly decreasing the frequency of time-window violations. These improvements are achieved primarily through small adjustments in stop sequencing and service timing that shift deliveries toward periods with lower expected parking delays.

1. Introduction

Parking availability is a major source of uncertainty for urban commercial vehicle drivers. Each pickup or delivery requires not only navigating congested streets but also identifying and securing available curb space for parking, loading and unloading, and accessing the desired handover locations (Dalla Chiara et al., 2021). This uncertainty reduces delivery efficiency and can increase cruising, congestion, and emissions, thereby affecting the sustainability of urban freight systems.

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Moreover, urban street and curb congestion are expected to intensify in the coming years as urban populations continue to grow, increasing the demand for urban deliveries (United Nations, 2019). At the same time, curb space is increasingly being reallocated from parking to bicycle and pedestrian infrastructure (Conway et al., 2017), while the number of delivery vehicles competing for limited curb space continues to rise (World Economic Forum, 2020). Therefore, a better understanding of how parking availability affects delivery efficiency is essential for developing strategies to reduce parking uncertainty and improve urban freight operations.

Recent investments in information technology now support both delivery tour planning before drivers are dispatched and on-tour decision-making, helping drivers navigate increasingly complex urban street networks (Wang and Sarkis, 2021). A key enabler is the widespread use of mobile devices, which provide continuous traffic data (Siuhi and Mwakalonge, 2016). These data can predict time-dependent travel times and adjust routes as conditions change (Chen et al., 2025), allowing delivery drivers to avoid congestion, complete routes more efficiently, and reduce workload. While optimization tools now account for time-dependent traffic delays, they often treat parking as always available or, at best, assign a single, fixed (time-invariant) cost. Yet parking availability also fluctuates by hour and place, with curb scarcity peaking at busy times of day (Jaller et al., 2013; Kalahasthi et al., 2022; Ramirez-Rios et al., 2023). Ignoring this may lead to scheduling drivers to arrive at delivery locations when parking is hardest to find, resulting in unplanned delays that erode the efficiency of otherwise optimized delivery tours.

However, introducing parking considerations into delivery tour planning is not straightforward. When curb space is scarce, drivers adapt in different ways: waiting for a space to free up (idling and queueing), spending additional time cruising for parking, parking further away from the desired destination and walking longer distances, rerouting the vehicle to complete other stops first, or stopping in unauthorized locations (Allen et al., 2018; Amaya et al., 2023; Chen et al., 2017; Dalla Chiara et al., 2021; Schmid et al., 2018; Wenneman et al., 2015; Dalla Chiara and Goodchild, 2025). We refer to the time costs associated with these behaviors as *parking delays*, defined as delays caused by finding, waiting for, or accessing a usable parking location near the desired delivery destination. Previous studies show that such delays can account for a substantial share of delivery operations, vary by location and time of day, and raise operating costs (Figliozzi and Tipagornwong, 2017; Dalla Chiara and Goodchild, 2020; Ramirez-Rios et al., 2023). The consequences of uncertain parking availability extend beyond individual drivers. Curb space constraints, particularly during peak periods, contribute to double parking, cruising for parking, traffic congestion, safety risks, and local emissions. Conversely, dedicated loading zones and effective curb management policies are increasingly recognized as mechanisms for improving the efficiency and reliability of urban deliveries and the urban transportation system as a whole (Burns et al., 2024; Fransoo et al., 2022; Girón-Valderrama et al., 2019; Mora-Quiñones et al., 2024; Tao and Qian, 2024).

This study addresses the following research question: How does accounting for time- and location-dependent parking delays affect delivery tour planning and overall tour performance? More specifically, can incorporating parking delays into delivery tour planning improve urban delivery efficiency?

To address this question, we use data from the real-world operations of a beverage distribution fleet operating in Seattle, WA, to estimate when and where parking delays are likely to occur. These delay profiles are subsequently incorporated into a Time-Dependent Traveling Salesman Problem with Time Windows (TD-TSP-TW). We then compare two tour-planning approaches:

- *parking-blind tour planning*, which incorporates time-dependent travel times into the optimization model but ignores parking delays;
- *parking-aware tour planning*, which incorporates expected parking delays together with time-dependent travel times, thereby explicitly accounting for parking uncertainty during tour planning.

Comparing the performance of tours generated under parking-blind and parking-aware planning estimates the operational impact of accounting for parking delays during delivery tour planning.

The contribution of this work is empirical: we demonstrate how expected parking delays can alter the planning and evaluation of urban delivery tours. First, we show that parking-blind planning provides an overly optimistic assessment of tour duration and time-window feasibility. Second, we show that parking-aware planning improves overall tour performance by reducing parking delays and time-window violations, with only a modest increase in travel time. Third, we explain how parking-aware planning achieves these improvements by guiding delivery drivers to customer locations during low-peak times of parking congestion. In principle, these improvements come from re-sequencing and re-timing stops, adjusting depot departure time, inserting or avoiding waiting, or making smaller local changes in the tour. Finally, we test the impact of time window constraints on delivery tour performance and simulate the impact of relaxing these constraints in both a parking-aware and parking-blind tour planning scenario.

The results are relevant to both public- and private-sector actors. In recent years, cities and technology companies have invested in smart curb management systems that monitor, digitize, and manage curb use. Some initiatives, such as dynamic pricing for metered parking, primarily target passenger parking demand (San Francisco Municipal Transportation Agency, 2014). Others are directly relevant to urban freight, including sensors deployed at commercial vehicle load zones in Seattle (Dalla Chiara et al., 2022), automated curb monitoring and enforcement pilots in Chicago (City of Chicago, 2024), and federally funded initiatives to digitize and manage curb space in cities such as Portland, Minneapolis, and Los Angeles (U.S. Department of Transportation, 2025). The growing deployment of smart curb technologies has also stimulated the emergence of technology firms offering software and data solutions for curb management (Diehl et al., 2021). Our results provide empirical evidence of how such information can support delivery tour planning. At the urban planning level, the findings can inform targeted curb management strategies, including time- and location-specific allocation, pricing, reservation systems, and loading-zone management policies that reduce parking delays and improve the predictability of curb access, thereby enhancing the efficiency and sustainability of urban freight operations.

The remainder of the paper is organized as follows. Section 2 reviews the literature on commercial vehicle parking delays, routing models that explicitly consider parking, and time-dependent tour planning. Section 3 describes the methodological approach developed, including the data inputs used, parking-delay estimation procedures, the TD-TSP-TW formulation used to compare parking-blind and parking-aware planning, the tour simulation approach, and the development of tour performance metrics. Section 4 presents the results, including the effects of parking delays on tour feasibility, tour duration, time-window violations, lateness, and the mechanisms through which parking-aware planning improves tour performance. Finally, Section 5 discusses the implications for urban freight planning, curb management, and future research.

2. Relevant literature

2.1. Empirical evidence on commercial vehicle parking and related delays

Following prior empirical studies of commercial vehicle driver behavior (Amaya et al., 2023; Dalla Chiara et al., 2021; Dalla Chiara and Goodchild, 2025), we distinguish three time components relevant to this study. First, travel time refers to driving between stops. Second, parking delay refers to the expected pre-service time needed to find, wait for, access, or otherwise secure a usable stopping or parking location near the destination. Third, dwell time refers to the time spent at the customer's location after parking. We use this decomposition to define the scope of parking delay. Parking delay includes cruising (i.e., moving while scanning the area for a place to stop or park), queuing (i.e., stationary while waiting for a place to become available), and curb-access dwell (i.e., maneuvering into and securing the vehicle in a stopping or parking location). It excludes driving, service time at the customer, and departing. This definition does not assume that vehicles always find a legal parking space. Rather, it captures the time cost associated with observed parking and curb-access behavior. The remainder of this subsection synthesizes what is known empirically about the magnitude, variability, determinants, and outcomes of parking delay.

The notion of cruising for parking originates in passenger transport and urban economics, where it describes drivers circling to find a vacant spot (Shoup, 2006). Its application to urban freight transportation is comparatively recent. Two studies use GPS-based inference to quantify parking activity. The first estimates cruising for parking by comparing observed trip times with predicted driving times (Dalla Chiara and Goodchild, 2020), while the second analyzes GPS traces to separate driving from non-driving activities across different urban contexts (Mjøsund and Hovi, 2022). Using data from a large parcel delivery company in Seattle, Dalla Chiara and Goodchild (2020) estimate an average of 2.3 min of parking delay per stop, which, across a typical tour, amounts to about 1 h and 10 min per workday, or 28% of total tour time. Across seven Norwegian cities, Mjøsund and Hovi (2022) report that, during the inner-city segment of a tour, the median vehicle spends 57 min in the area, with 22 min driving and 35 min for curb-access dwell, service dwell, and departure (61%), with notable variation between vehicle type and location.

Extending the evidence from GPS traces to driver behavior, ridealongs in Seattle show drivers spend about 80% of operating time parked (versus about 20% driving) and rarely use the travel lane (less than 5% of stops), adapting instead via behaviors such as invisible queuing—waiting in the vehicle, sometimes in unauthorized curb space, for a preferred spot to open (Dalla Chiara et al., 2021). A stated-preference study among U.S. delivery drivers shows that search effort, walking distance, and parking cost shape parking choices, and that when legal spaces are lacking, drivers use any available spot or double-park to stay on schedule (Amaya et al., 2023).

A complementary body of empirical research shows that parking delays and non-compliant stopping arise where demand for parking and curb supply are misaligned in space and time. Field observations in Seattle document heterogeneous use of curb types and low shares of travel lane stopping (Girón-Valderrama et al., 2019), with parked time depending as much on site and operation features (e.g., dock design, internal handling) as on curb regulations (Kim et al., 2021). Large administrative datasets in New York City map when and where delivery vehicle parking violations cluster and indicate that non-compliant stops abound, but tend to be relatively short (Chen et al., 2017; Schmid et al., 2018; Zou et al., 2016). Parking violation records in Chicago, New York, and Toronto similarly show that most non-compliance occurs at the curb (not in the travel lane) and suggest some firms treat fines as a cost of doing business when legal parking space is scarce (Jaller et al., 2013; Kawamura et al., 2014; Wenneman et al., 2015). Finally, New York evidence on double-parking highlights behavioral and context contrasts between commercial and passenger vehicles, reinforcing that time-dependent curb scarcity—not just driver preferences—shapes observed non-compliance (Kim and Wang, 2022).

2.2. Optimization models considering parking

A few modeling studies have responded to these empirical insights by either embedding parking choices in tour planning before dispatch or developing tools to support drivers in making real-time adaptations in response to scarce curb space on tour. Most relevant to the current study is an optimization model proposed by Reed et al. (2024). In the context of last-mile e-commerce deliveries, they recast tour planning as a park-and-walk model, in which vehicle parking is an explicit decision. The objective is to minimize total tour completion time, which is the sum of driving, parking delay, and dwell time, with deterministic, location-dependent search and park times. They show that parking at every customer is optimal only below certain parking-delay thresholds, and their computational benchmarks show that explicitly accounting for parking can change visit sequences and improve completion times compared to standard optimization. Trott et al. (2021) adopt a similar approach, where drivers either park once in a designated commercial loading zone and walk to nearby customers or second-row park at the curb. Their combined simulation–optimization framework highlights how the assumed parking radius alters tour outcomes and reduces second-row activity, again under deterministic parking space availability.

On-tour decision support models shift the locus of choice to the driver. They represent the state of the curb and the tour as it unfolds, and help the driver choose among cruising, queuing, walking farther, or resequencing nearby stops. For example, Zhang and Thompson (2019) use an agent-based park-and-walk simulator with finite loading-zone capacity and time limits, where a courier re-optimizes between driving and walking under different information regimes (none, real-time occupancy, time-averaged) and a reservation-style upper bound. Other on-tour support models use micro-simulation to represent curb capacity and rules. Lopez et al. (2019) restrict trucks to freight loading zones with vacancy-driven search, varying zone density and policy levers (e.g., fines, spatial allocation) and linking outcomes to a cost function. Zhao et al. (2025) extend this to multiple curb uses with heterogeneous users and operator controls, allowing toggles for illegal behaviors and space management. Related policy evaluation embeds a parking-choice model in traffic simulation to study dedicated freight streets and time limits (Nourinejad et al., 2014). Learning-based approaches formulate the problem as a sequential decision-making process under uncertainty in which drivers choose among actions such as re-sequencing nearby stops or walking farther when a loading zone is unavailable (Muriel et al., 2024).

When optimization models treat parking activities, including cruising, queuing, and curb-access dwell, as design elements, visit sequences and tour quality can change (Reed et al., 2024). Complementary instruments providing curb occupancy information and reservation mechanisms can reduce cruising and reallocate time toward service (Zhang and Thompson, 2019; Mor et al., 2020), with field evidence confirming reduced cruising and fewer parking violations when drivers receive curb availability information (Dalla Chiara et al., 2022).

Recent curb-management studies complement these operational models by evaluating policies that change when and how delivery vehicles can access limited curb space. Burns et al. (2024) model a day-ahead reservation system for co-located curb spaces and show that such systems can reduce double parking and related congestion, but that the effect depends on arrival-time flexibility and uncertainty. Burns et al. (2025) extend this logic to dynamic reservation systems, showing that such systems perform best when parking requests are made sufficiently in advance and vehicle arrivals are flexible and reliable. Amaya and Reed (2025) take a demand-oriented policy perspective and show that commercial vehicle loading-zone rules can be improved by matching parking-session lengths, reservations, and pricing to observed delivery demand and driver choice. Together, these studies show that curb-management policies can shape the conditions that give rise to parking delay. They focus, however, on the design and operation of curb access itself, rather than on how expected parking delays can be embedded into urban delivery tour planning.

2.3. *Time-dependent tour planning*

Time-dependent tour planning arose once it became clear that distance is a poor proxy for travel time in congested street networks (Dabia et al., 2013; Fleischmann et al., 2004; Hill and Benton, 1992; Ichoua et al., 2003; Malandraki and Daskin, 1992). The basic Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP) formulations assume link travel times are fixed, which contradicts observed peaks and troughs in traffic and customer access hours. Time-dependent variants let travel time depend on when a street is entered and often include time windows to reflect delivery or service constraints (Malandraki and Daskin, 1992; Ichoua et al., 2003). Conceptually, the TSP is a sequencing problem for one tour, whereas the VRP couples sequencing with customer-to-tour assignment and additional constraints (e.g., capacity, driver shifts, heterogeneous fleets).

The Time-Dependent Traveling Salesman Problem with Time Windows (TD-TSP-TW) can be formulated on (partially) time-expanded networks and has been proven to be NP-hard (Savelsbergh, 1985). It is therefore challenging for model-independent commercial solvers. Recent work has produced generalized exact algorithms. The current state of the art includes (Vu et al., 2020), who propose a solution based on the Dynamic Discretization Discovery (DDD) framework on partially time-expanded networks that optimizes both makespan and duration, Lera-Romero et al. (2022), who develop a labeling-based dynamic programming approach with partial dominance that outperforms prior exact methods and addresses both objectives, and Lera-Romero et al. (2020), who implement a branch-price-and-cut algorithm for the related multi-vehicle time-dependent VRP with time windows, advancing pricing/labeling components widely used in time-dependent routing. Although head-to-head comparisons under identical conditions are limited, these exact methods perform strongly on standard benchmarks. Nonetheless, they can be computationally intensive as instance size grows or as time windows are relaxed, so scalability remains a practical challenge.

Metaheuristics offer a way to reduce computation time by accepting high-quality solutions without guaranteeing optimality. For TSP variants, these include local-search methods such as simulated annealing and tabu search, population-based methods such as genetic algorithms, and swarm- or learning-based methods such as ant colony optimization and neural networks. Schneider (2002), Ohlmann and Thomas (2007), and Qian and Eglese (2014) showcase applications of local-search techniques to generalizations of the TSP. Martinez et al. (2011) and Beltrão et al. (2021) apply the Biased Random Key Genetic Algorithm (BRKGA) to variants of the TSP, and related random-key approaches have been used for other routing problems (Krutein and Goodchild, 2022). Cheng and Mao (2007) and Verbeeck et al. (2014) describe ant colony optimization for generalizations of the TSP. Neural networks have also been applied to solve the TD-TSP-TW. For example, Chen et al. (2025) develop a deep reinforcement-learning policy for a dynamic, time-dependent, and stochastic TSP. These methods can reduce cost and runtime relative to baseline metaheuristics such as simulated annealing. However, many supervised learning approaches require a large number of instances solved to optimality to train reliable models.

2.4. *Research gap and contribution*

In summary, empirical studies have shown that parking delays arise under conditions of scarce curb space, are operationally significant, and vary systematically across locations and times of day. At the same time, optimization and simulation studies have demonstrated that parking choices, park-and-walk strategies, curb capacity, and reservation systems can influence urban delivery operations (Reed et al., 2024; Trott et al., 2021; Zhang and Thompson, 2019; Burns et al., 2024; Amaya and Reed, 2025; Burns et al.,

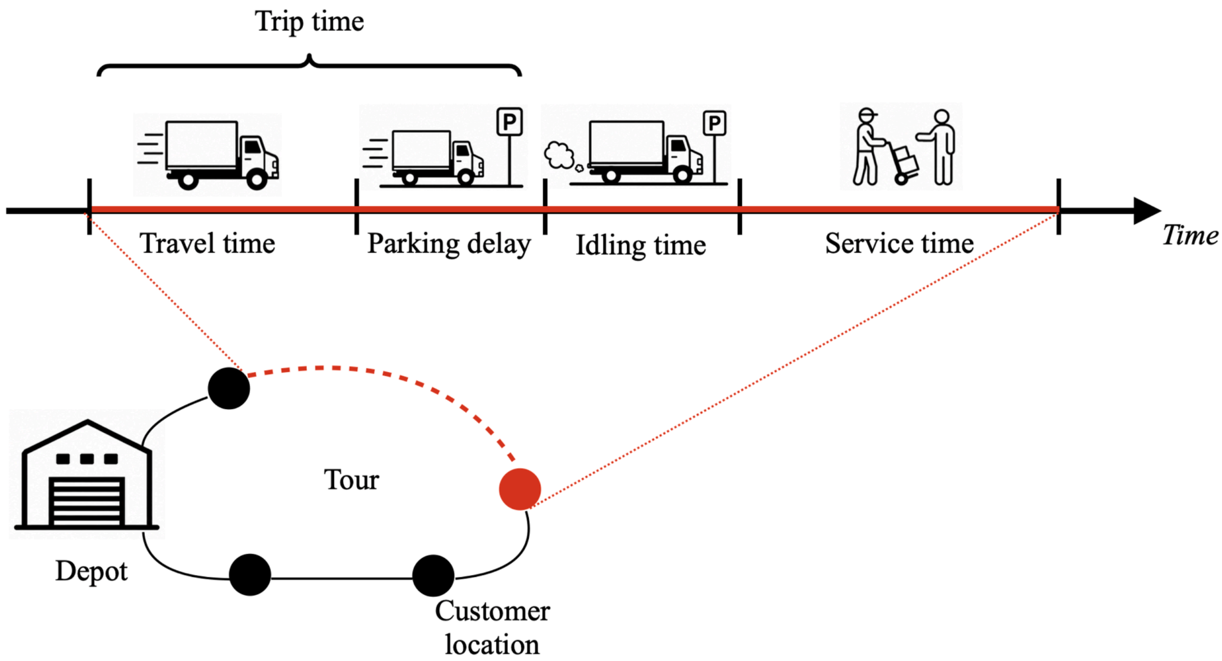

Fig. 1. Representation of a delivery tour and time distribution of a leg of the tour.

2025). However, existing studies have not examined how empirically estimated, time- and location-dependent parking delays affect the planning and evaluation of real delivery tours with customer time windows.

This study addresses this gap by estimating expected parking delays from operational GPS data and incorporating them into a Time-Dependent Traveling Salesman Problem with Time Windows (TD-TSP-TW). The contribution of this work is empirical rather than algorithmic. Rather than proposing a new optimization method, we compare a planning framework that relies exclusively on time-dependent travel times with one that additionally incorporates expected parking delays. This comparison allows us to quantify the effects of parking delays on tour duration, time-window violations, lateness, and tour feasibility, while also examining the mechanisms through which these effects arise. By linking empirical evidence on commercial vehicle parking delays with time-dependent tour planning, this study demonstrates how parking-delay information can be integrated into urban delivery planning and evaluates its operational value in a real-world setting.

3. Methodology

3.1. Problem description and terminology

We study a real-world case in which a delivery carrier plans a tour–an ordered set of delivery customers–for a fixed delivery manifest–an unordered set of customer orders–to be assigned to a delivery driver over a work shift. Each customer is associated with a specific delivery task, a customer location for delivery, and a time window within which the delivery should take place. The carrier's objective is to provide the driver with the optimal tour plan so that all customers are served within the work shift, in the shortest time, and while respecting customer time windows. The driver then performs the tour, and the carrier can observe realized tour performance metrics, such as tour duration, defined as the total time the driver takes to serve all customer locations and return to the depot.

To complete a planned tour, a delivery driver sequentially performs the following activities (see Fig. 1).

- *Trip time* is the total time a driver spends traveling, parking, and reaching the customer location.
- *Travel time* consists of the time a driver spends driving between customer locations or between the depot and the first/last customer location.
- *Parking delay* consists of the time a driver spends identifying and maneuvering into a parking location near the delivery destination, and walking the last 50 feet to reach the customer location.
- *Idling time* is the time a delivery driver spends waiting at the customer location for the time window to open to start servicing the customer.
- *Service time* is the time a driver spends at the customer location to perform the delivery task.

We treat service time as fixed and known in advance, while travel time, parking delays (and therefore total trip time), and idling time are uncertain. These uncertainties depend on the traffic congestion encountered while traveling, the parking conditions at arrival

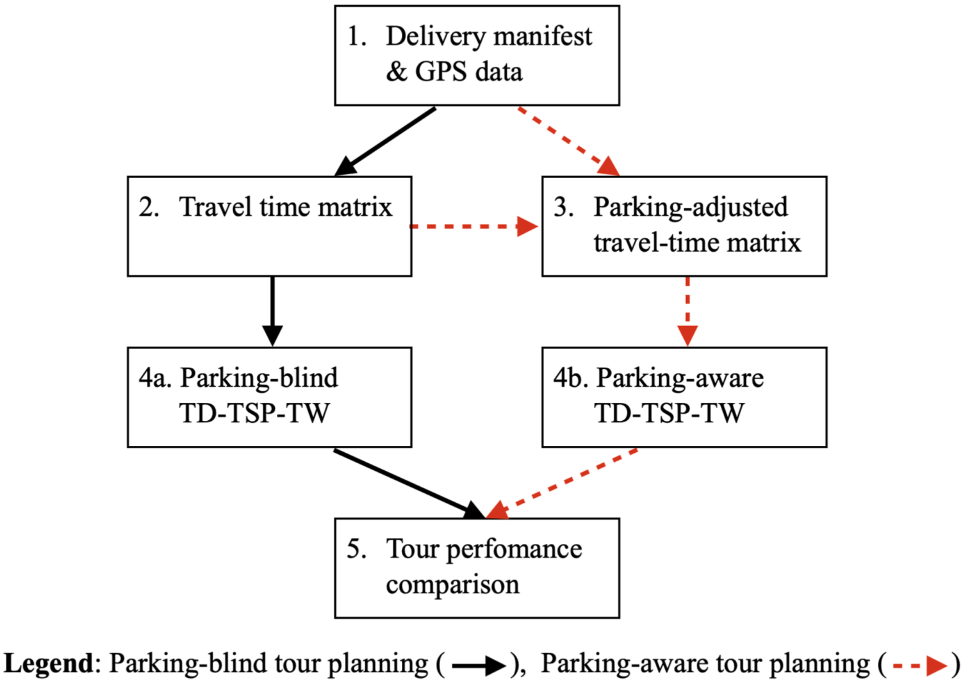

Fig. 2. Five-step methodology to compare parking-blind and parking-aware tour planning.

near a customer destination, and other contextual factors such as available road and parking infrastructure. In the rest of the section, we describe a parking-blind (considering only travel times, not parking delays) and a parking-aware (also considering parking delays) approach to optimally plan a delivery tour given a delivery manifest and obtain the resulting tour performance metrics.

3.2. Overview of methodology

The proposed methodology can be summarized in five key steps, described below and in Fig. 2.

Step 1: (Section 3.3) Assemble real-world input data from a beverage delivery company operating in Seattle, WA, including delivery manifests with customer locations and respective time windows, and realized tour plans, including GPS from the delivery vehicles, recording trip and service times.

Step 2: (Section 3.4) Construct the *travel-time matrix* for each origin–destination pair needed to optimize the observed delivery manifests.

Step 3: (Section 3.5) Construct the *parking-adjusted travel-time matrix* by estimating and adding expected parking delays to the travel-time matrix obtained in Step 2.

Step 4: (Section 3.6) Solve the tour planning optimization problem using a Time-Dependent Traveling Salesman Problem with Time Windows (TD-TSP-TW) to obtain a tour. For each manifest, the TD-TSP-TW is solved twice: in **Step 4a** using the *travel-time matrix* to obtain a parking-blind tour plan, and in **Step 4b** using the *parking-adjusted travel-time matrix* to obtain a parking-aware tour plan.

Step 5: (Section 3.7) Compare the performance of both tour plans under the *parking-adjusted travel-time matrix*, computing differences in tour duration, time-window violations, and lateness, to quantify how parking-delay information changes tour performance.

3.3. Data inputs: Delivery manifests and GPS data

We obtained data on real-world delivery operations of a beverage distributor operating in downtown Seattle, WA. Deliveries were made directly to customer locations, consisting of business establishments, in the form of cans, bottles, and kegs.

Two types of data sources were obtained: delivery manifests and GPS trip data.

First, a set of 472 delivery manifests, each consisting of a set of delivery customers that were assigned to a delivery driver for a given workday shift. The manifests contain a median of 13 customers, ranging from 10 to 22 customers per manifest, with the 25th and 75th percentiles being 12 and 16 customers, respectively. Each row in the manifest data contains a unique customer identifier, delivery address, customer location geo-coordinates, and a delivery time window. Table 1 shows a simplified example of a manifest with four customers.

Table 1
Simplified example of a delivery manifest with four customer locations.

Customer ID	Latitude	Longitude	Address	TW starts	TW ends	Delivery ID
1	47.6915181	−122.3398132	417 Gilman Ave W	04:00:00	08:00:00	10056
2	47.65056824	−122.349617	32 20th Ave W	04:00:00	20:00:00	21055
3	47.64965607	−122.3642654	200 15th Ave W	09:00:00	11:00:00	78454
4	47.6200206	−122.3606796	1307 S Hill St	12:00:00	15:00:00	98965

Table 2
Example of GPS data obtained from a realized delivery tour.

Trip start time	Trip end time	From customer ID	To customer ID	Stop end time	Service time	Delivery ID
06:25:44	06:32:16	4	1	07:08:02	36 min	10056
07:08:02	08:15:16	1	3	08:37:45	22 min	78454
08:37:45	08:40:55	3	2	09:06:22	26 min	21055

Table 3
Summary statistics for GPS data.

Statistic	Value
Number of trips	2442
Mean trip time (minutes)	11.5
Median trip time (minutes)	9.5
Std. dev. of trip time (minutes)	9.3
Mean service time (minutes)	38.0
Median service time (minutes)	27.7
Std. dev. of service time (minutes)	39.0
Mean trip distance (km)	2.8
Median trip distance (km)	1.6
Std. dev. of trip distance (km)	4.7

In addition to the delivery manifests, a separate dataset of realized tours was recorded. Data from in-vehicle sensors and GPS tracking devices were obtained. Throughout each tour, the timestamp and geo-location of specific events were recorded, including the departure time from a given location (trip start time), the arrival time at the next customer destination (trip end time), unique customer IDs of the start and end of a trip, and the start and end times of the time spent at the customer location. From such data, the respective trip times and service times were computed. Note that the observed trip time includes the time the driver took from door to door, including travel time and parking delays. Table 2 illustrates the GPS trip records for a realized tour that connects the four customers listed in Table 1.

An initial dataset of 9774 trips was obtained; however, only a subset of those were able to be matched with the respective delivery manifests. Only GPS trips with the same delivery ID that were performed on the same day as the respective delivery manifests were kept. The resulting subset of GPS-recorded trips consisted of 2442 observations. Table 3 summarizes the main descriptive statistics of this sample data. On average, a trip lasted 11.5 min with a standard deviation of 9.3 min. The distance covered was relatively short, with a mean trip distance of 2.8 km and a standard deviation of 4.7 km. Service times averaged 38 min, with a large standard deviation of 39 min.

3.4. Travel times without parking delays

Travel times are generated as the baseline input to the parking-blind planning model. For each origin–destination pair and departure hour needed to optimize the observed manifests, we queried the Compute Route Matrix method of the Google Maps Routes API (Google, Inc., 2026), using "traffic aware" routing preference and a fixed reference date to obtain predicted driving times under typical traffic conditions. Several studies have used Google Maps APIs as a reliable source of time-dependent travel-time predictions (Gruber and Narayanan, 2019; Rothfeld et al., 2019; Wang and Xu, 2011).

We issued API queries for a Tuesday with no proximate public holiday, as most delivery manifests in the dataset were operated on Tuesdays. To reduce API queries, we clustered customer locations by proximity, grouping any two addresses within 100 m to a single location. The resulting travel-time matrix covers 11990 directed origin–destination pairs across 171 clustered locations, queried at 13 departure hours from 4 AM to 4 PM, for a total of 155870 travel-time observations.

These travel times capture driving time under traffic conditions but do not include parking delay, because the Google Maps Routes API does not account for parking infrastructure or curb availability. In Section 3.5, we use observed GPS trip times together with these predicted travel times to estimate expected parking-adjusted travel times.

3.5. Estimating parking-adjusted travel times

We construct the parking-adjusted travel-time matrix by combining observed GPS trip times with travel-time predictions from the Google Maps Routes API.

Following Dalla Chiara and Goodchild (2020), we estimate the expected parking-adjusted travel time using historical GPS trip data by specifying a log-normal regression model with observed trip times obtained from GPS data as the dependent variable, the respective travel times obtained from the Google Maps Routes API as the main independent variable, and contextual factors as the other independent variables. We use a regression model because GPS data provide observed trip times but do not directly separate travel time from parking delays. We therefore use the Google Maps Routes API-estimated travel time as the baseline and model observed trip times as a function of this baseline and two sets of regressors affecting parking delays: curb allocation at destination and arrival time. Curb allocation is expected to affect parking delays: the more curb space is allocated to commercial vehicles, the more likely the driver is to find parking. The arrival time at the destination is expected to affect parking delays, as certain times of day may be associated with lower parking availability. The fitted value from the regression model therefore represents expected parking-adjusted travel time. The difference between this fitted value and the corresponding travel time can be interpreted as an estimate of the expected parking delay.

We specify a log-normal regression with observed trip time as the dependent variable, the log of Google Maps API-based travel time as the main predictor, and two groups of covariates:

- **Curb allocation.** We measure curb allocation within 100 m of each destination. The mapped curb data layer was obtained from the City of Seattle Open Data Portal (City of Seattle Department of Transportation, 2025). Prior work shows that nearby curb supply influences parking behavior and parking delays (Chen et al., 2017). For each destination, we compute the length (in meters) of curb space by type. Commercial vehicle load zones (CVLZs) are portions of the curb reserved for commercial vehicle parking by vehicles holding an annual commercial vehicle parking permit. No-parking zones are portions of the curb where parking is prohibited (e.g., near intersections and driveways). Bus zones are curb areas reserved for buses, and paid parking zones are designated for passenger vehicle parking upon payment. Fig. 3 illustrates the curb-space classification used to compute these variables.
- **Arrival time.** We include hour-of-day indicators for the destination arrival time. Indicators equal 1 when arrival falls within the given hour; 04:00 is the reference. These variables capture time-of-day variation in curb demand and parking delay.

The regression specification is:

$$\log y_{ij}(t) \;=\; \beta_0 \;+\; \beta_1 \log \tau_{ij}(t) \;+\; \boldsymbol{\gamma}'\mathbf{f}j \;+\; \boldsymbol{\delta}'\mathbf{h}ij(t) \;+\; \epsilon, \tag{1}$$

where

$y_{ij}(t)$	denote the observed GPS trip time,
$\tau_{ij}(t)$	denote travel time for origin–destination pair (i, j) at departure time t, obtained from the Google Maps Routes API (Compute Route Matrix) (Google, Inc., 2026),
$\mathbf{f}j$	denote the vector of curb-space lengths by type within 100 m of destination j,
$\mathbf{h}ij(t)$	denote the vector of hour-of-day indicators for the inferred arrival hour,
$\boldsymbol{\gamma}$	is the vector of coefficients to be estimated on curb-space characteristics,
$\boldsymbol{\delta}$	is the vector of coefficients on time of the day effects,
$\epsilon_{ij}(t)$	is the error term.

The regression coefficients were estimated using a GPS sample of 2442 trips, with travel times estimated from the Google Maps Routes API. Table 4 reports the regression results. The adjusted R^2 equals 0.401, indicating a moderate fit. The Google Maps Routes API-based travel time is the strongest predictor with a positive coefficient. Two curb-allocation variables are statistically significant: more curb length allocated to Commercial Vehicle Loading Zone (CVLZ) is associated with lower parking-adjusted travel time, while greater bus-zone length is associated with higher parking-adjusted travel time. The model also includes arrival-time indicators that capture systematic time-of-day variation in parking delay. In particular, it is of interest to note that parking delays peak hours occur between 7–8 am and then at 12-2 pm. These results align with Dalla Chiara and Goodchild (2020), who show that allocating curb to CVLZ reduces parking delay by increasing the chance of parking at the destination.

The fitted regression coefficients were then used to predict, for each origin–destination pair, departure time, curb allocation at the delivery destination, and the expected parking-adjusted travel time. Because the model is estimated in log min, we convert the predictions back to min using the standard log-normal adjustment that accounts for the residual variance. These predictions populate the parking-adjusted travel-time matrix used in parking-aware planning and in the common evaluation of both planning approaches.

3.6. Time-dependent traveling salesman problem with time windows (TD-TSP-TW)

We adopt the TD-TSP-TW formulation of Vu et al. (2020) and solve it with a Multi-Parent Biased Random-Key Genetic Algorithm (Andrade et al., 2021).

3.6.1. Formulating the TD-TSP-TW

We model the tour planning problem as a TD-TSP-TW. We choose a TSP rather than a Vehicle Routing Problem (VRP) because the empirical unit of analysis is a delivery manifest, containing a fixed set of customers to be served by a given vehicle during a work

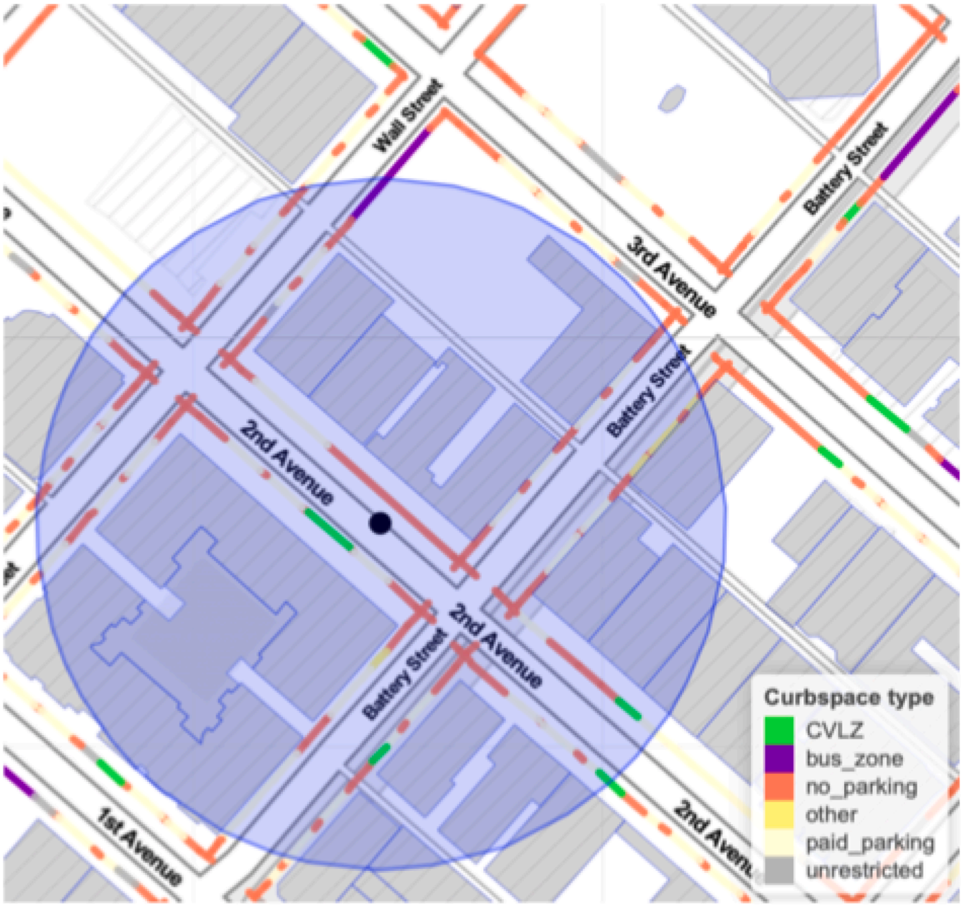

Fig. 3. Curb-space classification within 100 m of a delivery destination. Adapted from Dalla Chiara and Goodchild (2020).

Table 4
Regression estimation results for the trip times.

Variable	Estimate	Std. Error	Pr(> |t|)
(Intercept)	1.744	0.090	< 0.001***
Travel time (log)	0.464	0.012	< 0.001***
Curb allocation:			
CVLZ (m)	−0.0016	0.0004	< 0.001***
No-parking (m)	−0.00002	0.0001	0.752
Bus zone (m)	0.0005	0.0002	0.002**
Paid parking (m)	0.00005	0.00016	0.766
Arrival time (reference value 4 am):			
5 am	0.226	0.083	0.006**
6 am	0.387	0.080	< 0.001***
7 am	0.414	0.079	< 0.001***
8 am	0.393	0.080	< 0.001***
9 am	0.325	0.079	< 0.001***
10 am	0.299	0.080	< 0.001***
11 am	0.329	0.081	< 0.001***
12 pm	0.413	0.081	< 0.001***
1 pm	0.388	0.085	< 0.001***
2 pm	0.428	0.091	< 0.001***
3 pm	0.210	0.123	0.089.
4 pm	0.342	0.216	0.115

Model fit:
Residual Std. Error: 0.648 on 2424 df
Multiple R-squared: 0.405, Adjusted R-squared: 0.401
F-statistic: 96.93 on 17 and 2424 df, p < 0.001

Table 5
Notations for the TD-TSP-TW.

Sets	Set Description	Parameters	Parameter Description
$i \in N$	physical node set	t	time step
$(i,j) \in A \subseteq N \times N$	physical arc set from node i to j	$\tau_{ij}(t)$	travel time on arc (i,j) at time t
$(i,t) \in \mathcal{N}$	time-dependent node set	$[e_i, l_i]$	time window at node i
$((i,t),(j,t')) \in \mathcal{A}$	time-dependent travel arcs	$c_{ij}(t)$	time cost on arc (i,j) at time (t)
$((i,t),(i,t+1)) \in \mathcal{A}$	time-dependent waiting arcs		
Assumption	**Assumption Description**	**Variables**	**Variable Description**
$t \le t'$	arrival must be after departure	$x_{((i,t),(j,t'))}$	{**1**: if travel on $((i,t),(j,t'))$ selected, **0**: otherwise}
$t + \tau_{ij}(t) \le t' + \tau_{ij}(t')$	later departure cannot lead to earlier arrival		
$t \ge e_i$	at node i, departure cannot be before time window opening at i		
$t' = \max\{e_j, t + \tau_{ij}(t)\}$	at node j, arrival time cannot be before time window opening at j		
$t' \le l_j$	arrival time at node j cannot be after time window closing at j		

shift. Using a TSP keeps the manifest intact and allows a direct comparison between parking-blind and parking-aware tour planning for the same set of stops. A VRP formulation would add customer-assignment decisions outside the scope of this study and would make it harder to isolate the effect of accounting for parking delays.

Following the mathematical formulation of Vu et al. (2020), Table 5 summarizes the notation, and the complete TD-TSP-TW is reported below.

$$\min \sum_{((i,t),(j,t'))\in\mathcal{A}} c_{ij}(t)\, x_{((i,t),(j,t'))} \tag{2}$$

$$\text{s.t.} \sum_{((i,t),(j,t'))\in\mathcal{A}:\, i\neq j} x_{((i,t),(j,t'))} = 1, \qquad \forall j \in N \tag{3}$$

$$\sum_{((i,t),(j,t'))\in\mathcal{A}} x_{((i,t),(j,t'))} - \sum_{((j,\bar{t}),(i,t))\in\mathcal{A}} x_{((j,\bar{t}),(i,t))} = 0, \qquad \forall (i,t) \in N,\ i \neq 0 \tag{4}$$

$$x_{((i,t),(j,t'))} \in \{0,1\}, \qquad \forall ((i,t),(j,t')) \in \mathcal{A} \tag{5}$$

The objective (2) minimizes the total tour duration, where $c_{ij}(t)$ denotes the duration contribution of selecting arc (i,j) at time t. Constraint (3) enforces that each customer location is visited exactly once. Constraint (4) imposes flow conservation at every time-expanded node (excluding the depot start/end nodes), ensuring that the path is continuous. Constraint (5) defines binary arc-selection variables.

Time windows and time dependence are handled implicitly through the arc set $\mathcal{A}$. We construct $\mathcal{A}$ under the FIFO assumption so that an arc $((i,t),(j,t'))$ exists only if $t' = \max\{e_j,\ t + \tau_{ij}(t)\}$ and $t' \le l_j$, where $\tau_{ij}(t)$ is the time-dependent input used in the planning run. In parking-blind planning, $\tau_{ij}(t)$ is the travel time. In parking-aware planning, $\tau_{ij}(t)$ is the parking-adjusted travel time.

The formulation above states the hard-window version of the TD-TSP-TW. For the empirical comparison, however, we use a soft-window implementation because many delivery manifests become infeasible once parking delay is included. This allows service outside the customer time window, but adds a penalty to the objective for each minute of time-window deviation. In the results, we do not include this penalty in the reported tour duration. Instead, we report time-window violations and lateness separately.

3.6.2. Solving the TD-TSP-TW

We solve the TD-TSP-TW using a Multi-Parent Biased Random-Key Genetic Algorithm (MP-BRKGA) (Andrade et al., 2021). MP-BRKGA solves the problem implicitly and requires a custom decoder function that translates between the $[0,1]$ space that the genetic algorithm uses to represent the solution and the solution space of the TD-TSP-TW. The decoder follows a logic similar to the regular Random Key Genetic Algorithm (RKGA) introduced by Bean (1994), in which the order of customer location visits is determined by the random key values provided by the genetic algorithm.

Fig. 4 depicts how every position in the chromosome is allocated to a customer location, with one additional position used to determine the depot departure time. Sorting the first n positions in the array by their random-key values provides the visit sequence. The final position determines when the tour starts within the depot departure-time window. The decoder then evaluates the resulting tour by calculating service timing, tour duration, and any soft time-window penalties. The algorithm is single-objective and returns one tour for each manifest and planning run. Because the method is heuristic, the resulting tour is a high-quality solution rather than a guaranteed optimum.

3.7. Tour performance evaluation

For each of the 472 manifests, we solve two tour planning methods: parking-blind planning, using the travel-time matrix from Section 3.4, and parking-aware planning, using the parking-adjusted travel-time matrix from Section 3.5. Each tour-planning method

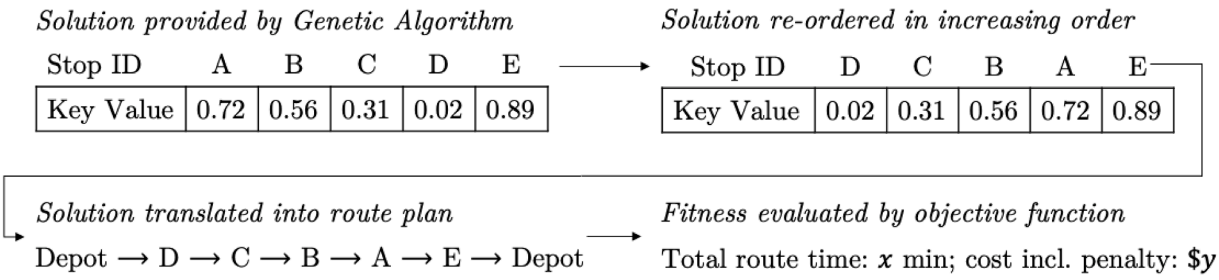

Fig. 4. Translation from random-key chromosome to TD-TSP-TW tour evaluation.

is evaluated over 10 random seeds, retaining the tour with the lowest objective value. Each obtained solution consists of an ordered sequence of customers.

We then simulate each tour plan to quantify its performance. A tour simulation retrieves the travel times for each origin-destination pair in the tour plan and the time of day when the trip occurs. In the results Section 4, different evaluation scenarios are presented using either the travel time matrix with no parking delays or the parking-adjusted travel time matrix estimated in Section 3.5. Upon arrival at a destination, the delivery driver starts service if the arrival time falls within the customer time window. However, if the driver arrives before the time window opens, the driver idles until it opens. If the arrival time is after the customer's time window, the driver still starts service immediately, and the lateness is recorded and included in the tour performance.

After simulating a tour, we compute performance metrics to assess the efficiency of the tour plan. We consider two sets of performance metrics: tour time performance and time window performance.

Tour time performance captures how much time is spent over the course of the tour on different activities. The following tour time performance metrics are computed.

- *Tour duration* is the total elapsed time between leaving and returning to the depot. Tour duration comprises four components: travel time, parking delay, idling time, and service time.
- *Travel time* is the time spent driving between locations under the true travel-time matrix.
- *Parking delay* is the additional time spent identifying a parking location, parking, and accessing the customer location.
- *Service time* is the time spent serving customers; we still track service time here for completeness, but it will not vary between tour planning methods because it is deterministic.

Time window performance captures how well the tour respects customer time windows. The following metrics evaluate a tour's time window performance.

- *Time-window violation* is the share of stops not served entirely within their window, which occurs in three cases: the driver arrives before the window opens, arrives after it closes, or arrives within the window but completes service after it closes.
- *Lateness* measures how late a driver's arrival is relative to the customer time window's closing time; arrivals before or within the window contribute zero lateness, including those times when service finishes after the window closes.

4. Results

4.1. Evaluating the impact of considering parking delays in tour planning

To understand the impact of considering parking delays in tour planning, we evaluate three scenarios, thereafter called scenarios A, B, and C, summarized in Table 6. Each scenario combines a tour planning method (parking-blind or parking-aware) with the "true" travel times against which the resulting tour is evaluated: either the travel time matrix with no parking delays, or the parking-adjusted travel time matrix. The optimizer first constructs a tour under its planning method, then tour performance metrics are simulated under the true travel times to recover its realized duration, arrival times, and time window violations.

The rest of the section considers the following evaluation scenarios.

- *Scenario A* represents a parking-blind tour plan simulated first with the travel time matrix with no parking delays. Here, parking delays enter neither planning nor simulation, so it serves as the idealized baseline scenario in which parking is non-existent, and we do not plan for it.
- *Scenario B* represents the parking-blind tour planning simulated using a parking-adjusted travel time matrix. This is the case when a state-of-the-art tour-planning method that does not consider parking delays is used in a world with parking delays.
- *Scenario C* represents a parking-aware tour planning simulated using the parking-adjusted travel time matrix. Here, the optimizer anticipates the same parking delays it is evaluated against and can shift departures and reorder stops accordingly. Scenario C is therefore the realized outcome of parking-aware planning.

Table 7 provides the results of the tour plan simulations under different evaluation scenarios described in Table 6, across the two sets of performance metrics described in Section 3.7: tour time and time window performance metrics. The rest of this section discusses each scenario and the comparisons between them.

Table 6
Experimental scenarios by planning method and travel time input.

		"True" travel times	
		Travel time matrix (no parking delays)	*Parking-adjusted travel time matrix*
Tour planning method	*Parking-blind*	Scenario A	Scenario B
	Parking-aware	—	Scenario C

Scenario A establishes the reference against which the cost of ignoring parking delays is measured. Averaged over the 464 considered tours, we obtained an average tour duration of 339.8 min, of which 81.5% is spent on service time (277 min), and the remaining 18.5% is spent driving between destinations (62.8 min). Parking delays are excluded because scenario A uses a travel time matrix with no parking delays. On time-window performance, the schedule the planner expects to achieve looks close to feasible. Average lateness is 1.9 min per tour, and only 7.3% of tours incur any lateness. Across all instances, on average, 10.0% of stops per tour fall outside their time window. These violations are predominantly structural rather than parking-related: 7.3% of deliveries were on time but completed after the customer's time window closure (late finish), 2.1% were early arrivals, and only 0.7% were late arrivals. Scenario A represents the optimized schedule that a parking-blind planner expects under the assumption of no parking delays.

Scenario B re-evaluates the same tours generated under a parking-blind approach, assuming the parking-adjusted travel-time matrix contains the true travel times. Total average tour travel time (62.81 min) and service time (277 min) are unchanged by construction, but average tour duration increases by about 52.5% due to accumulated parking delays. Parking delays now account for 34.4% of the total tour duration (178.47 min per tour on average). Time-window performance declines sharply: average lateness per tour increases by 90.6%, from 1.85 min to 169.54 min, and the share of tours incurring any lateness rises from 7.3% to 85.6%. Late arrivals increase from 0.7% to 24%, while early arrivals fall from 2.1% to 0.6% as parking delays push arrivals to later times. Scenario B reflects what a parking-blind operator actually experiences when parking delays occur (and we did not plan for them): roughly three hours of unanticipated parking delays accumulated over the tour, worsening both tour time performance and time window performance.

Scenario C is a parking-aware tour planning scenario, assuming the parking-adjusted travel time matrix contains the true travel times, so the optimizer accounts for parking delays when sequencing stops and timing departures. The average tour duration is 500.9 min: 55.3% is spent on service time (277 min, unchanged from previous scenarios as it is deterministic), 13% on driving between destinations (65.06 min), and the remaining 31.7% on parking delays (158.83 min). On time-window performance, average lateness is 7.57 min per tour, 11% of tours incur any lateness, and late arrivals account for 1.7% of stops.

We then compare scenarios B and C to quantify the impact of integrating parking delays in tour planning (parking-aware planning), assuming parking delays exist. Parking awareness reduces the average duration from 518.29 to 500.90 min, saving 17.39 min per tour and reducing total tour duration by 3.4% on average. This net saving results from a trade-off: parking-aware planning reduced time spent on parking delays by 11% (saving 19.6 min on average), at the cost of increasing travel time by 2.3 min on average. Therefore, the optimizer trades a small amount of additional driving to achieve lower parking delays. At the same time, time-window performance under parking-aware planning improves substantially: average lateness per route falls by 95.5% (162 min on average), the share of tours incurring any lateness falls from 85.56% to 11%, and late arrivals fall from 24% to 1.7% of customers served. Parking-awareness thus, while it delivers modest savings in tour duration, it provides a substantial reliability gain.

Fig. 5 shows the percentage change in tour performance over all the manifests when moving from a parking blind (scenario B) to a parking-aware (scenario C) tour planning, under the assumption that the true travel time matrix is the parking-adjusted one. This pattern holds across the full manifest distribution. Travel time is marginally higher under parking-aware planning (mean $+3.6\%$, range -22% to $+31\%$), while parking delay is lower by a comparatively larger margin (mean -11.0%, range -31% to $+10\%$). The net effect on tour duration is a consistent reduction (mean -3.4%, range -12% to $+6\%$), though the magnitude varies substantially across routes: for some manifests, parking-aware planning reduces tour duration by more than 10%, while for a small share of routes the difference is slightly positive.

Fig. 6 compares total tour duration for each manifest. Most points fall below the diagonal, indicating shorter tour durations under parking-aware planning. For 66 manifests, parking-aware tours have longer durations, but these cases mainly reflect a trade-off between tour duration and time window reliability: 64 of the 66 show parking-aware planning resulting in longer tour durations in exchange for lower lateness, and only 2 tours are worse on both dimensions. Whenever parking-blind planning has shorter tour durations, it is largely because it misses customer time windows. When parking-aware planning yields longer tour durations, an increase of about 8.8 min allows drivers to avoid about 178 min of lateness.

4.2. The impact of time window constraints on tour performance

So far, the tour evaluation used the observed customer time windows, as specified in the real-world delivery manifests. However, since time windows strongly constrain when each stop can be served, they may also determine how much impact parking-aware planning can have. We therefore simulate scenarios where time windows are widened by ±30, ±60, and ±120 min, as well as an unconstrained scenario in which any visit sequence and service timing is admissible (i.e., time windows are removed). Table 8 reports the mean total tour duration for parking-blind and parking-aware planning across these settings, with the baseline included for comparison.

Table 7

Tour performance across three evaluation scenarios and respective comparisons. Means are calculated over 464 tours (seven instances were excluded from the original 472 tours because the optimizer left customers unserved, and one because travel-time data was missing).

		Scenario evaluation			Scenario comparison	
		A	B	C	B–A	C–B
Scenario description	**"True" travel times** **Tour planning method**	No parking delays Parking-blind	Parking-adjusted Parking-blind	Parking-adjusted Parking-aware	Effect of parking delays	Effect of parking-aware planning
Tour time performance (minutes)	Tour duration	339.8	518.3	500.9	+178.5 (+52.5%)	−17.4 (−3.4%)
	Travel time	62.8	62.8	65.1	+0.0 (+0.0%)	+2.3 (+3.6%)
	Parking delay	0.00	178.5	158.8	+178.5 (n/a)	−19.6 (−11.0%)
	Service time	277.0	277.0	277.0	+0.0 (+0.0%)	+0.00 (+0.0%)
Time window performance	Average lateness (min/route)	1.9	169.5	7.6	+167.7 (+90.6%)	−162.0 (−95.5%)
	% of routes with lateness	7.3	85.6	11.0	+78.2 pp	−74.6 pp
	Time window violations per tour *of which:*	1.17 (10%)	3.54 (30.3%)	1.47 (12.6%)	+2.37 (+20.3 pp)	−2.07 (−17.7 pp)
	Late arrival	0.08 (0.7%)	2.80 (24%)	0.20 (1.7%)	+2.72 (+23.3 pp)	−2.59 (−22.3 pp)
	Early arrival	0.24 (2.1%)	0.06 (0.6%)	0.47 (4.0%)	−0.17 (−1.5 pp)	+0.40 (+3.4 pp)
	Late finish	0.85 (7.3%)	0.68 (5.8%)	0.80 (6.8%)	−0.17 (−1.5 pp)	+0.12 (+1.0 pp)

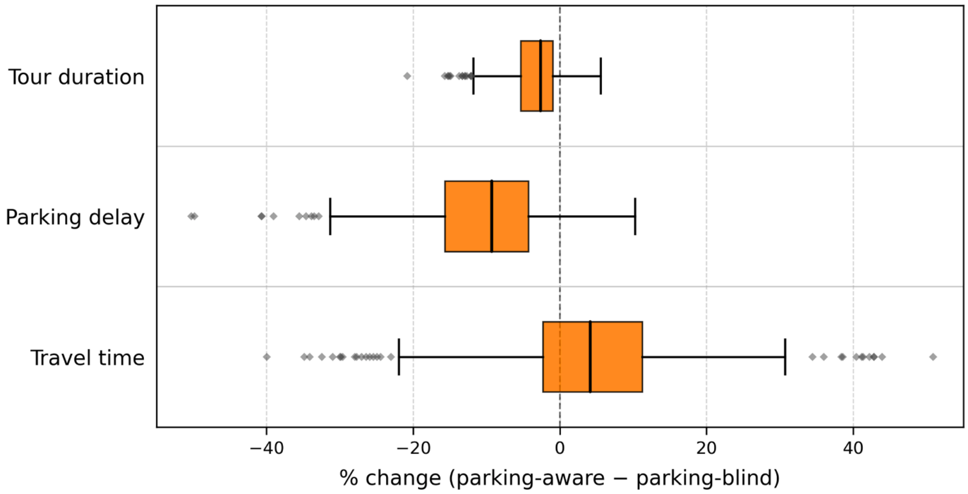

Fig. 5. Per-route percentage change in tour components when switching from parking-blind (in scenario B) to parking-aware routing (in scenario C) for all manifests. Negative values indicate a reduction relative to the parking-blind baseline (scenario B).

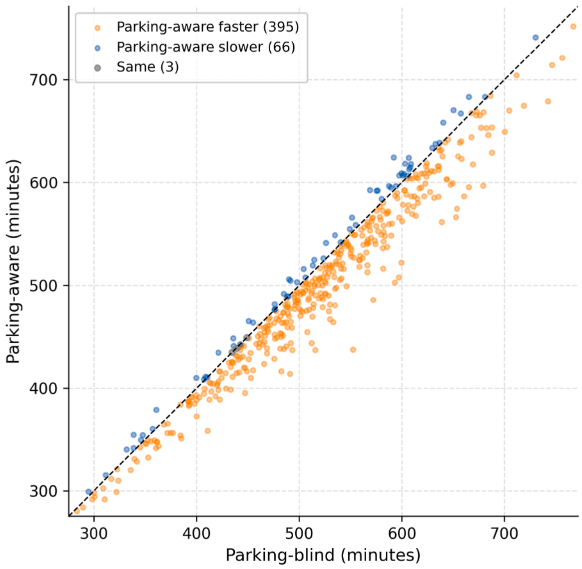

Fig. 6. Per-manifest total tour duration under parking-blind and parking-aware planning, both evaluated under parking-adjusted travel times.

Relative to the baseline saving of 17.4 min (3.4%), the duration savings from parking-aware planning grow as time windows widen, reaching 20.9 min (4.2%) at ±120, then fall to 15.5 min (3.3%) in the unconstrained setting. The saving is roughly unchanged at ±30 (17.4 min, 3.4%) and increases at ±60 (18.1 min, 3.6%). Across all settings, parking-aware planning reduces parking delay while accepting a small increase in travel time. The decline in the unconstrained setting occurs because removing time windows also gives parking-blind planning greater freedom to choose service timing, which can, incidentally, move some stops into lower-parking-delay periods under the common parking-adjusted evaluation.

The reliability pattern is even clearer. At baseline, the violation rate falls from 30.3% to 12.6%. As time windows widen, parking-blind planning becomes progressively easier to satisfy, with violation rates dropping from 25.0% at ±30 to 18.0% at ±60, 9.3% at ±120, and zero in the unconstrained setting. Parking-aware planning achieves near-complete feasibility much earlier: violations fall to 4.3% at ±30, 2.4% at ±60, 0.6% at ±120, and zero in the unconstrained setting. Lateness shows the same pattern. Parking-blind tours are late by 130.8, 93.1, and 43.9 min on average at ±30, ±60, and ±120, whereas parking-aware tours are almost on time in the same settings (1.6, 0.3, and 0.0 min).

Fig. 7 shows the underlying duration components across the time-window settings, confirming that the saving comes from reduced parking delay rather than travel time.

Table 8
Effect of parking on tour performance across time-window scenarios. Values report the parking-aware minus parking-blind difference, so negative entries indicate that ignoring parking inflates the metric. Averages are taken over $n = 464$ instances; for tour-duration and violation rows the percentage (or pp) figure in parentheses gives the corresponding relative change.

		TW scenario				
		Baseline	±30 min	±60 min	±120 min	Unconstr.
Tour time performance (minutes)	Tour duration	−17.4 (−3.4%)	−17.4 (−3.4%)	−18.1 (−3.6%)	−20.9 (−4.2%)	−15.5 (−3.3%)
	Travel time	+2.3 (+3.6%)	+4.2 (+7.2%)	+4.5 (+8.1%)	+4.8 (+9.1%)	+5.1 (+10.9%)
	Parking delay	−19.6 (−11.0%)	−21.6 (−12.3%)	−22.6 (−13.2%)	−25.6 (−15.4%)	−20.6 (−14.0%)
	Service time	—	—	—	—	—
Time window performance	Average lateness (min/route)	−162.0	−129.2	−92.8	−43.9	0
	% of routes with lateness	−74.6 pp	−80.4 pp	−69.0 pp	−47.8 pp	0 pp
	Time window violations *of which:*	−2.07 (−17.7 pp)	−2.41 (−20.7 pp)	−1.82 (−15.6 pp)	−1.01 (−8.7 pp)	0 (0.0 pp)
	Late arrival	−2.59 (−22.3 pp)	−2.14 (−18.4 pp)	−1.55 (−13.3 pp)	−0.79 (−6.8 pp)	0 (0.0 pp)
	Early arrival	+0.40 (+3.4 pp)	+0.06 (+0.5 pp)	+0.03 (+0.3 pp)	0 (0.0 pp)	0 (0.0 pp)
	Late finish	+0.12 (+1.0 pp)	−0.33 (−2.8 pp)	−0.30 (−2.5 pp)	−0.22 (−1.9 pp)	0 (0.0 pp)

Table 9
Overall visit-sequence similarity between parking-blind and parking-aware tours. Rank and positional metrics (ρ, τ, Hamming distance) require a unique position per physical location and are computed on the 405 tours without repeated clustered locations; Edge-Jaccard captures the 59 tours that revisit a clustered location non-adjacently and is reported for all 464 tours.

Metric	Median	IQR
Spearman ρ	0.725	[0.515, 0.867]
Kendall τ	0.600	[0.418, 0.745]
Hamming distance	0.714	[0.500, 0.867]
Edge-Jaccard	0.200	[0.091, 0.333]

4.3. Understanding the source of time savings

Parking-aware planning improves performance through two channels: (1) stop re-sequencing reorders stops so customers are reached at better times, at the cost of slightly increased travel time; (2) timing shifts change depot departure times to serve customers outside peak parking-delay hours.

To quantify how much the visit sequence changes between the two approaches, we use four complementary metrics:

- *Spearman's ρ* is the rank correlation between the positions of stops in the two tours, measuring how well the overall ordering of stops is preserved.
- *Kendall's τ* measures the agreement in the relative ordering of all pairs of stops, providing a stricter assessment of order preservation.
- *Hamming distance* is the fraction of stops that occupy a different position index in the two tours, measuring how many stops are displaced regardless of whether their relative order is preserved.
- *Edge–Jaccard* is the proportion of immediate predecessor–successor links (edges) shared by the two tours, capturing local adjacency rather than global ordering.

The global ordering of stops is moderately preserved (median Spearman $\rho = 0.725$; median Kendall $\tau = 0.600$), whereas immediate adjacencies change substantially (median Edge-Jaccard = 0.200) and most stops shift position (median normalized Hamming distance = 0.71). Table 9 reports these metrics. This pattern indicates that parking-aware planning works mainly through local resequencing of neighboring stops, rather than complete route redesign. While this resequencing contributes to the overall improvement, it can also add cost, raising mean travel time by about 2 min.

The second source of savings is tour timing. Similar to traffic, the time-of-day effect on parking delay is double-peaked, with delays being highest around 07:00–08:00 and again around 12:00–14:00, with a lower-delay period between 09:00 and 11:00. Parking-aware planning exploits this pattern by shifting service toward lower-delay periods and away from the peaks, within the operational constraints given. In the case study presented in this paper, parking-aware tours depart from the depot 49 min earlier, on average, than parking-blind tours, and serve customers earlier within their time windows, reducing the mean gap between window opening and arrival from 197 to 135 min. The parking-blind planner, underestimating tour duration, generates tours that depart later because it does not account for the additional parking delays that would justify an earlier start. No depot-related constraints force this earlier start in the present analysis, as both parking-aware and parking-blind planning generate tours that depart after the depot opens at 04:30 am: parking-blind tours leave on average 95 min after opening time, while parking-aware tours leave about 46 min after opening time. Re-timing in the parking-aware planning is driven by customer time-window feasibility: once parking overhead is

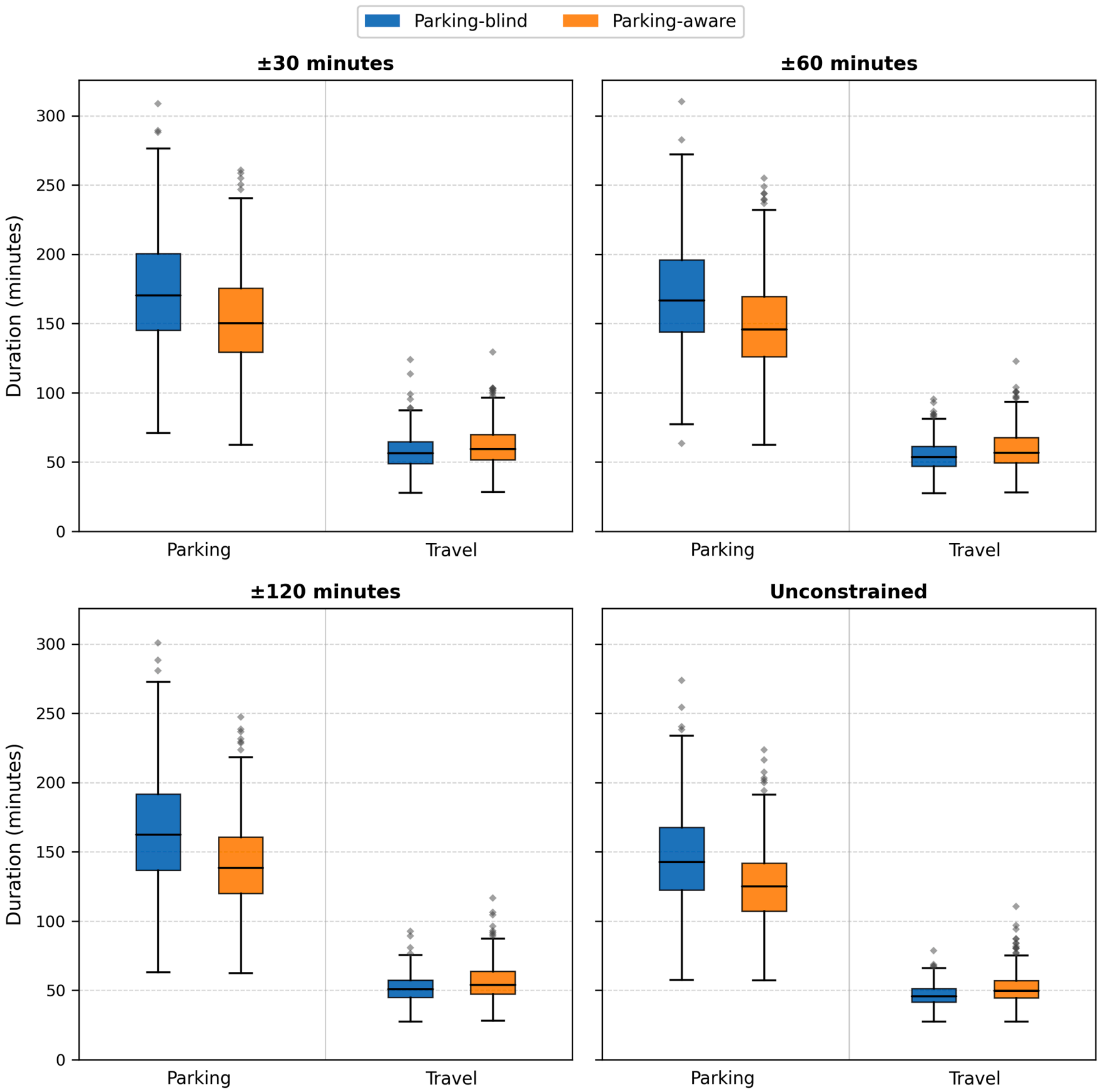

Fig. 7. Comparison of tour duration components under parking-blind and parking-aware planning across time-window expansion settings.

accounted for, late-day service becomes infeasible, with about 40% of stops in the 12:00–14:00 band arriving past their window close, so the parking-aware tour must begin earlier to serve the cluster of windows that open at 07:00 and close by late morning. These timing shifts move service into periods with lower expected parking delays while reducing time-window violations and lateness. Importantly, this does not mean that parking-aware tour planning always translates into serving customers as early as possible. Once the parking-delay distribution is known and integrated into planning, the optimal solution will exploit this additional knowledge to shift tour timing and re-sequence stops accordingly, which could also lead to late departures. However, stronger are the operational constraints, including customer time windows and depot opening/closing times or vehicle loading and range; these will limit the ability to exploit forecasted parking delays.

Fig. 8 illustrates an instance of a single tour before and after parking-aware planning (Scenarios B and C), where both stop re-sequencing and tour time shifts take place. In this example, parking-aware planning reduces tour duration by 47.8 min, a 9.7% reduction compared to parking-blind planning. Scenario C shows both re-sequencing and re-timing, as shown in the figures where stops are numbered by visit order.

4.4. Sensitivity analysis on penalty magnitude

The preceding results rely on a single penalty weight, which determines how strongly time-window violations are penalized relative to tour duration. To confirm that the results do not depend on this choice, we vary the penalty weight λ across 25, 50, 100,

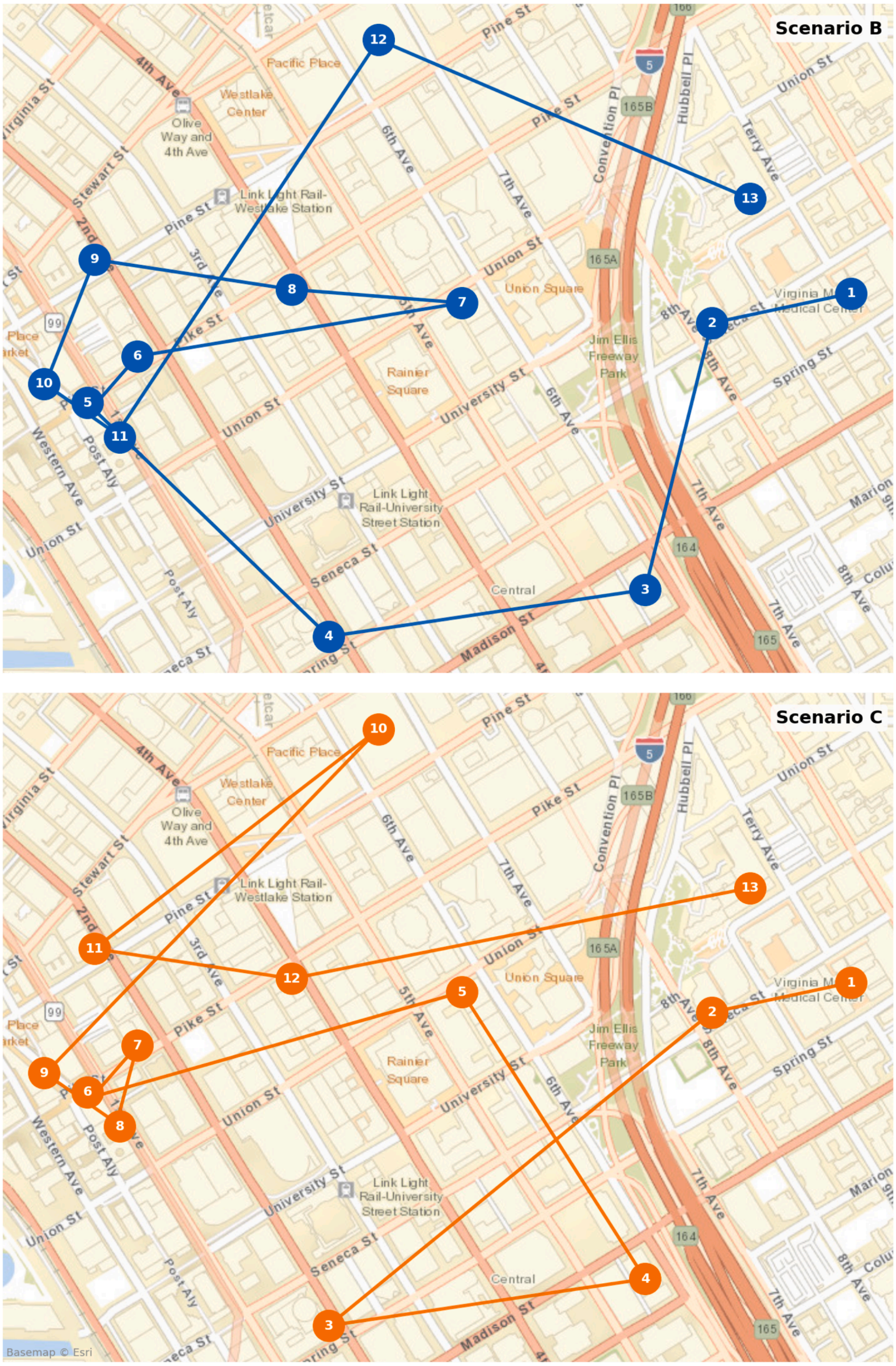

Fig. 8. Example tour under parking-blind (Scenario B, top) and parking-aware (Scenario C, bottom) planning. Maps show the visiting order for each route, stops numbered by visit sequence. This tour shows a larger-than-average improvement, chosen to make both the re-sequencing and re-timing mechanisms visible at once. The depot stop is excluded to ensure the figure remains readable; therefore, stop 1 corresponds to the first customer, not the starting point of the tour.

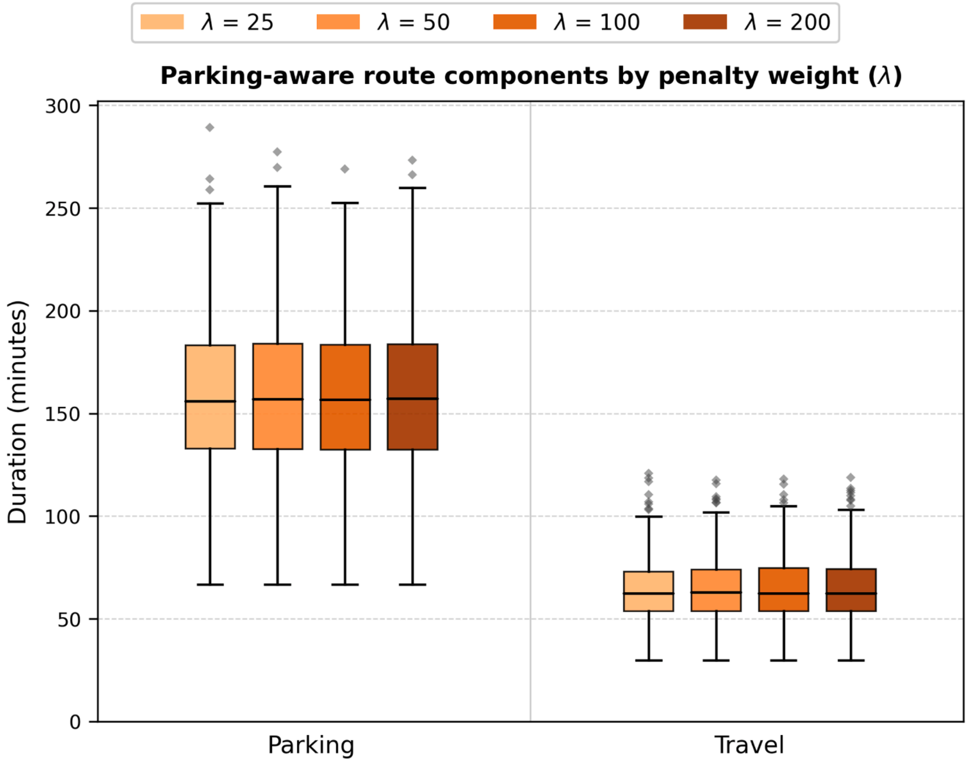

Fig. 9. Distribution of parking delay and travel time for parking-aware routes across different penalty weights ($\lambda = 25, 50, 100, 200$), averaged over n = 464.

and 200, with 100 being the baseline value used throughout the main analysis (N = 464 at each level). The results of this analysis are presented in Fig. 9. The parking-aware duration components are effectively unchanged: mean total duration stays within 0.9 min (500.1 to 500.9), and mean parking delay and travel time vary by less than one minute (parking delay 158.6 to 159.2; travel time 64.6 to 65.1). The duration saving over the parking-blind baseline is likewise stable, ranging from 17.1 to 17.9 min, with the parking-delay reduction holding near 19 min (19.0 to 19.6) across all levels. Lateness moves as expected: as the penalty rises, the share of parking-aware tours with a delay falls from 13.2% to 9.1%, and mean lateness among violating tours drops from 111.2 min to around 70 min. The penalty weight, therefore, sets the operating point on the duration–lateness trade-off without altering the parking-delay reduction.

5. Discussion and conclusions

5.1. Theoretical implications

This study contributes to the urban freight and routing literature by showing that parking delays are an important source of operational uncertainty largely absent from existing tour-planning approaches. Previous studies show that curb access matters for delivery operations and that parking choices and curb-management policies can affect tour performance (Reed et al., 2024; Trott et al., 2021; Zhang and Thompson, 2019; Burns et al., 2024; Amaya and Reed, 2025; Burns et al., 2025). At the same time, routing models have increasingly incorporated time-dependent travel times while generally treating parking as either deterministic or negligible. The present study connects these two streams of research by showing how empirically estimated parking delays can be incorporated into time-dependent tour planning.

The first implication of this study indicates that parking-blind planning systematically underestimates both tour duration and the difficulty of satisfying customer time windows. When parking delays are introduced during tour evaluation, tour duration increases substantially, and lateness rises considerably. These findings suggest that travel-time uncertainty alone does not fully capture urban delivery operations. Parking availability constitutes a distinct source of temporal uncertainty that affects tour feasibility and service reliability.

The second implication concerns how parking-aware planning improves delivery tour performance. Improvements come not from major changes in route structure, but from small adjustments to stop sequencing and arrival times that shift deliveries toward periods and locations with lower expected parking delays. Parking-aware tour planning, in essence, looks for small changes to customer sequencing, considering the existence not only of road traffic peak hours, but also parking peak hours when parking delays are at the highest (which were found from the real-world data to be double-peaked, with parking delays being highest around 7-8 am and again around 12-2 pm). This finding suggests that parking information influences delivery scheduling as much as routing decisions. In dense urban environments, the timing of customer visits may therefore become an important operational decision variable alongside travel-time minimization.

Finally, the results show that a major benefit of parking-aware planning is improved reliability: the observed reductions in lateness and time-window violations are significant. This distinction contributes to the growing literature emphasizing service reliability and schedule adherence as important dimensions of urban freight performance.

5.2. Managerial implications

Our study provides three actionable takeaways for fleet or delivery managers seeking to account for parking-related delays in urban delivery planning. First, carriers should be cautious when evaluating tours using travel times only. Parking-blind planning substantially underestimates tour duration and overstates time-window feasibility once expected parking delays are included. Even when the mean duration effect is moderate, the reliability effect can be large. In our empirical setting, parking-aware planning sharply reduces the share of tours with time-window violations and lowers lateness among violating tours.

Second, the operational value of parking information does not necessarily require a complete redesign of delivery tours. The main margin in our empirical setting is service timing. Parking-aware planning leaves visit sequences broadly similar, but adjusts departure and service times to avoid high-parking-delay periods.

Third, the results indicate that historical operational data can provide valuable information for tour planning. GPS records, historical delivery data, and curb information can be combined to estimate expected parking conditions and incorporated into existing route-planning systems. Because the observed improvements arise primarily from better scheduling decisions rather than major route changes, implementing parking-aware planning may require only limited modifications to existing optimization frameworks. This suggests a practical implementation path: carriers can leverage historical operational data to improve expected service timing within existing manifests, before investing in more complex real-time routing systems.

Finally, customer time windows are central to the value of parking-aware planning. Tight time windows can force service into high-parking-delay periods and limit the planner's ability to respond. Making these interactions visible can support more concrete discussions with customers about delivery windows, service-level expectations, and operational feasibility. In this sense, parking-delay information is useful not only for optimization but also for explaining when delivery commitments create avoidable lateness or inefficient service timing.

5.3. Societal implications

The obtained results also highlight several implications for transportation planners and urban policymakers seeking to improve the efficiency and reliability of the urban freight transportation system. Cities increasingly collect or digitize curb information, but its operational value depends on whether it translates into planning-relevant inputs. Our results show that time- and location-specific curb information can support commercial vehicle planning by helping carriers anticipate expected parking delays and shift service away from high-delay periods.

For policymakers, this suggests that curb-management interventions should focus not only on increasing curb supply but also on making curb access more predictable over time. Loading-zone allocation, time-of-day curb rules, pricing, reservations, and enforcement can reduce parking delay and its variability. Open, machine-readable curb maps and schedules can also lower the cost for carriers to incorporate curb information into planning systems. Such interventions make parking-aware planning more feasible and more effective.

The findings also point to the importance of coordination beyond curb infrastructure. When customer delivery windows coincide with periods of high curb pressure, even well-planned tours can become unreliable. Cities can use curb-delay information to support discussions with carriers, building managers, receivers, and shippers about more realistic delivery windows and service-level expectations. This complements regulatory and infrastructural measures with coordination mechanisms that improve the predictability of urban freight operations.

5.4. Limitations and future research directions

This study has several limitations that open avenues for future research. First, the empirical analysis is based on delivery operations from a single beverage distributor in Seattle. The setting is useful because it provides real manifests, GPS traces, and recurring customer locations, but results may differ in other sectors, cities, vehicle types, or delivery models. Future research could test whether similar timing-based mechanisms appear in other urban freight contexts.

Second, we infer parking delays rather than directly observing them. The GPS data provide trip time between consecutive stops, but do not directly separate travel time from parking delay. We therefore estimate expected parking-adjusted travel time and infer expected parking delay as the difference between the fitted parking-adjusted travel time and the corresponding travel time. Future research could combine GPS traces with direct curb-occupancy data, driver observations, or vehicle sensors to measure the components of parking delay more precisely.

Third, our approach uses expected parking delays as deterministic time-dependent inputs. This is appropriate for studying how historical curb-access information changes planning and evaluation, but it does not explicitly model day-to-day uncertainty. Future work could extend the approach to stochastic or robust tour planning, especially when real-time curb-availability information becomes more widely available.

Fourth, we keep delivery manifests fixed. This lets us isolate how parking-delay information changes planning for the same set of stops, but it excludes customer-to-tour assignment, fleet-level routing, and manifest construction. Future research could extend the analysis to settings in which manifests themselves are decision variables, for example, by examining whether different customer groupings or vehicle assignments create more opportunity to use time-dependent parking-delay information.

5.5. Concluding remarks

This study shows that expected parking delays affect both the planning and evaluation of urban delivery tours. Parking-blind planning gives an overly optimistic view of time-window feasibility and tour duration. Parking-aware planning reduces parking delay, time-window violations, and lateness, even when this requires a small increase in travel time. For carriers, this study shows how historical curb-access information can support better planning. For cities, digitized and time-dependent curb information can help make urban freight operations more predictable. Treating parking delay as a planning input therefore provides a practical bridge between delivery tour optimization and urban curb management.

CRediT authorship contribution statement

Giacomo Dalla Chiara: Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization; **Claudia Fasano:** Writing – review & editing, Validation, Software, Methodology, Formal analysis, Data curation; **Klaas Fiete Krutein:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation; **Paul Buijs:** Writing – original draft, Validation, Investigation, Formal analysis; **Todor Dimitrov:** Writing – original draft, Software, Methodology, Formal analysis, Data curation; **Sarah Dennis-Bauer:** Writing – original draft, Formal analysis; **Anne Goodchild:** Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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