How to Improve Urban Delivery Routes' Efficiency Considering Cruising for Parking Delays

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Abstract

This paper explores the value of information on parking availability in urban environments for commercial vehicle deliveries. The research investigated how historic cruising and parking delay data can be leveraged to improve the routes of carriers in urban environments to increase cost efficiency. To do so, the research developed a methodology consisting of a travel time prediction model and a routing model to account for parking delay estimates. The method was applied both to a real-world case study to show its immediate application potential and to a synthetic data set to identify environments and route characteristics that would most benefit from considering this information. Results from the real-world data set showed a mean total drive time savings of 1.5 percent. The synthetic data set showed a potential mean total drive time savings of 21.6 percent, with routes with fewer stops, a homogeneous spatial distribution, and a higher cruising time standard deviation showing the largest savings potential at up to 62.3 percent. The results demonstrated that higher visibility of curb activity for commercial vehicles can reduce time per vehicle spent in urban environments, which can decrease the impact on congestion and space use in cities.

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Keywords: vehicle routing, parking efficiency, urban freight, logistics efficiency, parking cruising

1 INTRODUCTION

Parking availability is a source of uncertainty for urban commercial vehicle drivers. To fulfill urban pick-ups and deliveries, drivers not only have to navigate the urban road network through peak-hour traffic but also search for available parking locations upon reaching their delivery destinations. Urban road and parking congestion will further deteriorate as 60 percent of the world population will reside in urban centers by 2030 (World Economic Forum, 2020) and demand for home delivery services will increase as retail e-commerce sales will increase. From 2010 to 2016 alone, congestion in Los Angeles rose by 36 percent, in New York by 30 percent, and in Beijing by 9 percent (Hannon *et al.*, 2019). Retail e-commerce sales are expected to grow by 50 percent from 2021 to 2025, from 4.9 to 7.4 trillion U.S. dollars (Chevalier, 2022).

To help commercial drivers navigate the complex urban environment, carriers have invested in information technology and tools to provide drivers with optimized route plans. While traffic patterns and time-dependent traffic density are sometimes taken into consideration in route planning, to date, information on parking availability has not been part of these decision-making tools. To date, parking availability is still largely assessed by the driver in real-time upon arrival, which can cause significant delays if no parking is available. The phenomenon of cruising for parking, the time a vehicle driver spends searching for parking, is well-known in passenger vehicle studies (Shoup, 2006), but it was first analyzed for commercial vehicles by Dalla Chiara & Goodchild (2020). The authors estimated that a parcel delivery driver in Seattle, Washington, spends on average more than one hour per day cruising for parking. Moreover, Dalla Chiara *et al.* (2021) found that delivery drivers' parking behaviors are far more complex than simply cruise for parking and include the driver re-routing the vehicle to a different destination, waiting for availability of parking spots, covering longer distances by foot and parking in unauthorized locations.

These parking behaviors, triggered by a lack of available curb parking space and a lack of information, not only represent a costs for the carriers themselves that have to spend additional time to perform their jobs, but also cause social and environmental externalities, including safety concerns and air and noise pollution.

In recent years, cities and corporations have started investing in smart parking information systems that are able to provide parking availability information in real time, as well as provide a source of historical data to better understand drivers' parking behaviors. The city of San Francisco has deployed parking sensors in 7,000 metered curb parking (San Francisco Municipal Transportation Agency, 2011), while the city of Seattle installed 300 curb proximity sensors within a 10-block study area in commercial vehicle load zones and passenger load zones (Dalla Chiara & Goodchild, 2022). We therefore expect an increase in curb data availability in the near future in major urban centers, and therefore an increased need for understanding how this data can be used to reduce commercial vehicle externalities.

This paper explores the following research question:

What value does information on curb parking availability provide to urban delivery drivers and can it increase the cost efficiency of delivery routes?

Once a smart parking information system is available, curb parking availability information can be used in different ways. One way consists of providing drivers with curb parking availability through a mobile app in real time, such that the drivers can better choose their parking destinations. This was explored by Dalla Chiara *et al.* (2022). Another option is to consider parking availability information at the route planning level. By using historical data on cruising delays caused by a lack of curb availability, carriers can better route commercial vehicles, avoiding areas that have historically experienced higher cruising for parking delays during certain times of the day.

The research presented in this paper took the latter approach and combined cruising for parking time predictions obtained from real-world delivery data with vehicle routing through a time-dependent traveling salesman problem with time windows (TD-TSP-TW).

To demonstrate the utility of the presented methodology, two applications are presented. First, a real-world case study was conducted. Second, an experimental simulation using synthetic data was performed to identify the conditions under which in-route planning provides the largest efficiencies.

Following this introduction, a review of the relevant literature is presented, and the main contributions of the current work are highlighted. Then, the methodology is described, followed by the results from the real-world case study and the synthetic route study. The paper concludes with a discussion and conclusions.

2 PREVIOUS WORK

2.1 Vehicle Driver Behaviors and Commercial Challenges in Urban Area Parking

With curb-space and adequate infrastructure, especially those that cater to commercial vehicles, being already scarce in urban spaces, challenges for urban freight movement are expected to be amplified in the coming years. While drivers with experience and familiarity with the delivery region are often able to reduce drive times between destinations by better navigating traffic, the search for parking remains a constant regardless of experience. Dalla Chiara *et al.* (2021), through ridealongs with various logistic carriers in Seattle, determined three main criteria for how commercial vehicle drivers approach parking:

1. Guarantee safety for the driver and other road and curb users.
2. Minimize conflicts with other drivers and curb users.
3. Cooperate with other commercial drivers over parking space management.

They found that these decisions and considerations often meant that even when adequately large commercial vehicle parking zones were available close to a destination, a driver might forgo them if the spot required performing risky maneuvers or if it was better suited for larger trucks (Dalla Chiara *et al.*, 2021). Alternative parking methods with easier ways to exit, such as parking at the end of a block, were preferred, even if they were unauthorized. Other studies on commercial vehicle driver behavior have mainly relied on driver survey data, driver diaries, and GPS tracking (Allen *et al.* (2012)). However, these can be limiting when assessing how and why drivers approach challenges.

In the past, it was often assumed that, when faced with a lack of parking, drivers would simply stop on the travel lane. This would leave cruising for parking times as a negligible source of delays that could be ignored by routing models. Because of the privatized nature of commercial vehicle movement data, it can be difficult to study the validity of this claim. Instead, scientific papers have focused on citation records to perform empirical studies on the parking decisions faced by commercial vehicles (Wenneman *et al.* (2015), Kawamura *et al.* (2014)). Using citations to provide estimates for parking distributions, studies showed that most parking citations were not caused by travel lane violations. These were found to represent only 1.3 percent (Kawamura *et al.* (2014)) to 2.4 percent (Wenneman *et al.* (2015)) of violations. These findings were consistent with the theory that commercial drivers avoid conflicts with other curb users when possible, and especially avoid blocking road traffic. A study by Dalla Chiara *et al.* (2021) on commercial vehicle ride-alongs further confirmed this, reporting that only 4.5 percent of parking events occurred in the travel lane while the majority of parking events (53.4 percent) took place within authorized parking zones at the curb. Similarly, Girón-Valderrama *et al.* (2019) used parking data collected from commercial vehicles in Seattle and observed that 56 percent of parking events occurred at authorized curb zones and only 2.2 percent of parking events occurred in the travel lane. With an estimated 73.4 percent of parking events (Dalla Chiara *et al.* (2021)) occurring at the curb and only a small percentage double parking in the travel lane, commercial vehicles arriving at a destination often must compete with other curb users and therefore cruise or queue to find available parking.

2.2 Cruising for Parking

Cruising is a "disguised source of congestion" generated when curb parking is unavailable, causing a vehicle to continue circling until an appropriate curb vacancy appears (Shoup (2006)). This adds congestion to urban areas as well as increases route time for carriers – which are often time sensitive. While an abundance of studies have focused on cruising by passenger vehicles, few have explored this phenomenon for commercial vehicles. Holguín-Veras *et al.* (2016) used driver surveys from trucks in the New York City area to poll average search time for parking and found an average of 24 minutes from 16 responses. Unfortunately, the small sample size made it difficult to draw conclusions. The lack of empirical data has instead led to studies analyzing cruising from commercial vehicle parking simulations (Aiura & Taniguchi (2005), Figliozzi & Tipagornwong (2017)). However, these studies have often focused more on finding significant parameters for reducing costs rather than on generating accurate parameter estimates for variables such as cruising time.

A phenomenon similar to cruising is queueing – where a vehicle waits for parking or loading zones to become available rather than circling the block. These wait times often occur in off-street parking facilities when loading/unloading bays are occupied. Observations of off-street loading bays by Dalla Chiara & Cheah (2017) revealed an average waiting time of 7.7 minutes by commercial vehicles waiting to access the facilities. However, queueing is not limited to off-street parking. In particular, commercial vehicles have been witnessed temporarily using an unauthorized curb space while waiting for a nearby authorized curb space to become available (Dalla Chiara *et al.* (2021)). Queueing for curb parking is most similar to cruising, but to the best knowledge of the authors, estimates or extensive studies of such queueing behavior related to the curb do not yet exist.

More recently, to estimate cruising delays, Dalla Chiara & Goodchild (2020) used available GPS data from a parcel delivery carrier to gain estimates for cruising time by analyzing the differences between observed trip times and estimated travel times. From 2,477 observations, an average estimated cruising time of 5.8 minutes and a median of 2.3 minutes were found, with parking infrastructure at a destination being statistically correlated with a reduction in estimated cruising time. A study by Dalla Chiara *et al.* (2021), used the same methodology applied to ride-along data from carriers in Seattle, in which an observer actively marked parking actions and recorded GPS data. An estimated mean cruising time of 3.8 minutes and a median of 1.4 minutes were found for this sample. Overall, while the literature for commercial vehicle cruising is limited, empirical evidence suggests that vehicle routing often includes drivers cruising while seeking parking near a destination.

2.3 Vehicle Routing in Urban Areas

Initial studies into vehicle routing have often focused on the minimization of travel distance or travel time, all the while, assuming that parameters such as travel speeds between destinations were time-invariant (Gendreau *et al.* (2015)). Naturally, this assumption falls short in practical applications for congested road networks for which deviations in travel times can quickly alter optimal routes. In an attempt to more accurately model real-world conditions, more recent studies have accounted for sources of congestion and applied time-dependent cost functions for travel between destinations, giving rise to the study of Time-Dependent Vehicle Routing Problems (TD-VRP).

TD-VRP models seek to find the optimal set of routes for a fleet of vehicles that will minimize the overall total routing cost – all with time-dependent travel times. The travel functions used by these models fall into one of two classifications: *deterministic* or *stochastic*. One of the first approaches using deterministic travel times was by Hill & Benton (1992). Their proposed model used time-dependent constant speeds at each node, which could then be averaged to estimate travel times between destinations. However, initial studies tended to be too naive, allowing for vehicle passing. Passing occurs when a vehicle leaving at a later time and following the same path of another vehicle is able to arrive earlier to the destination – violating the *First-in-First-out* (FIFO) property. Through the use of continuous piecewise linear travel time functions, Fleischmann *et al.* (2004) and Ichoua *et al.* (2003) were able to create frameworks that satisfied this FIFO property. Applications of these models use a variety of granularity in speed levels. Often due to the available data, the number of speed levels can range from 15-minute intervals, as was the case fpr Maden *et al.* (2010), to as few as 2 to 5 minute speed levels (Franceschetti *et al.* (2013)). On the other hand, stochastic models represent the travel time between nodes as a random variable whose distribution depends on the departure time. One such example is work by Taş *et al.* (2014) on a variant of VRP with stochastic travel times and soft time windows that minimize an expected comprehensive cost. By applying metaheuristics such as Tabu search, they generated solutions for problem instances with up to 200 customers.

Besides time-dependent travel objective functions, researchers have begun considering fuel emissions and consumption within routing models. This class of green vehicle routing problems can no longer use simplified objective functions that strictly decrease travel time or distance, as they will not lead to minimized costs. Rather, multi-objective functions are created to account for the driver's time as well as fuel consumption or other costs. One such example is a study by Ehmke *et al.* (2018), which considered the impact of a comprehensive cost function including both driver and fuel costs in comparison to baseline objective functions that minimized only time, distance, or fuel. They showcased substantial improvements by utilizing a mixed cost function in comparison to strictly time or distance. They largely accredited this improvement to the mixed objective function's ability to account for both time dependencies in speed and vehicle load. For interested readers, reviews of vehicle emissions being considered within vehicle routing can be found by Demir *et al.* (2014) and Bektaş *et al.* (2016), while Gendreau *et al.* (2015) and Pillac *et al.* (2013) provide comprehensive overviews of models, classifications, and applications of the TD-VRP.

A class of problems similar to VRP is the Traveling Salesman Problem (TSP). Rather than considering a fleet of multiple vehicles, TSP seeks to minimize the cost of a single driver starting and ending at a depot. One of the first formulations was by Malandraki & Daskin (1992) which utilized several simple heuristics to solve problem instances. More recent work on variations of the problem has allowed for routes of up to 40 destinations to be solved for instances of TD-TSP-TW (Lera-Romero *et al.* (2020a)). While some studies have focused on optimizing exact and approximate solutions of the TSP, fewer studies have discussed applications of the TSP to urban vehicle routing. Corporations tend to optimize routes and customers for a fleet of vehicles, which works better with a VRP model. However, decreased problem complexity in comparison to VRP allows TSP to excel for parameter experimentation. Work by Dündar *et al.* (2022) applied a TSP to showcase the effects of including realistic road gradients in fuel consumption calculations.

In a similar vein, this paper aims to showcase the influence of parking costs within vehicle routing in urban environments. Dalla Chiara & Goodchild (2020) identified the existence of cruising for parking behaviors in urban delivery vehicle drivers. Therefore, delays resulting from cruising should be considered in vehicle routing models. Instead, parking and routing phenomena have been studied separately. Table 1 summarizes previously described vehicle routing papers and other related literature. The table identifies the criteria minimized by each study. These tended to be either a focus on time or distance minimization, emission consumption, or a mix of both within the objective function. Finally, the table shows whether time-dependent travel times, delivery time windows, and cruising costs for travel matrices were utilized. No studies have considered the influence of time-dependent parking delays in tandem and vehicle routing with time windows. This paper aims to showcase the benefits of including the hidden cost of cruising for parking to drivers and to provide insights into which types of routes benefit the most from increased parking visibility.

Table 1 – *Previous Vehicle Routing Studies*

Paper	Objective		Parking	Time Windows	Time Dependent Travel
	Time/Distance	Emission			
Maden *et al.* (2010)	✓	✓		✓	
Franceschetti *et al.* (2013)	✓	✓		✓	✓
Taş *et al.* (2014)	✓			✓	✓
Qian & Eglese (2014)		✓		✓	✓
Xiao & Konak (2016)		✓		✓	✓
Ehmke *et al.* (2018)	✓	✓			✓
Soysal *et al.* (2018)	✓	✓		✓	✓
Martinez-Sykora *et al.* (2020)	✓		✓		
Reed *et al.* (2021)	✓		✓		
Dündar *et al.* (2022)	✓	✓			
This Paper	✓		✓	✓	✓

3 CONTRIBUTIONS

Considering the research gaps identified above, the main contributions of this paper are the following.

1. This is the first study that has investigated the effects of delays caused by cruising for parking on routing for commercial vehicles and demonstrated the value of using historic data to inform routing decisions.

2. The study furthermore provided a methodology that can be used to approximate the time-dependent traveling salesman problem with time windows (TD-TSP-TW) for instances too large to be solved with a commercial solver such as the Multi-Parent Biased Random Key Genetic Algorithm (MP-BRKGA).

3. The study furthermore showed the characteristics of delivery manifests that benefit the most from the consideration of cruising for parking.

4 METHODOLOGY

4.1 Overview

Figure 1 provides a high-level illustration of the analysis steps taken to investigate the route time savings potential while considering cruising for parking delays. The process shows four major steps.

There are three input data sources: (*i*) historical real-world GPS traces from a carrier performing deliveries in Seattle, Washington, (*ii*) a time-dependent travel distance matrix that considers time-dependent traffic volumes (sourced from the Google Distance Matrix API Google (2021)), and (*iii*) the delivery manifest of interest, consisting of a list of delivery addresses where deliveries were made and the respective time windows.

Step (1) takes as input the original travel time matrix and outputs a second travel time matrix that incorporates delays caused by cruising for parking. The output from this model is a time-dependent travel time matrix with the same dimensions as the nominal matrix, but with travel time estimates updated by the expected "true" travel time, considering real-world data. We denote this matrix the "true" travel time matrix. This is accomplished by using the cruising time prediction model presented in Section 4.3.1, which takes the historical GPS data.

Step (2) uses a route optimizer to analyze the delivery manifest of interest. This is accomplished by using the TD-TSP-TW implementation presented in Section 4.3.2. The route optimizer runs twice. The first run uses the initial travel time matrix, and the outputs represent the base case, in which cruising delays are not considered during route optimization. The second route uses the true travel time matrix, in which cruising delays are considered during route optimization.

Comparing the two resulting routes directly would not lead to useful insights, as the travel times considered for both routes are different. In particular, the travel times considered for the base case do not include cruising delays. To make them comparable, step (3) uses the true travel time matrix to update the base case route, but it does not change the order of node visits. This update simulates the real-world experience of the driver when executing the base case route, as in the real world, a driver would experience cruising delays, even though they were not considered in the route optimization of the base case.

After this update, step (4)then directly compare the two routes generated and identifies drive and route time savings that can be generated by considering cruising times.

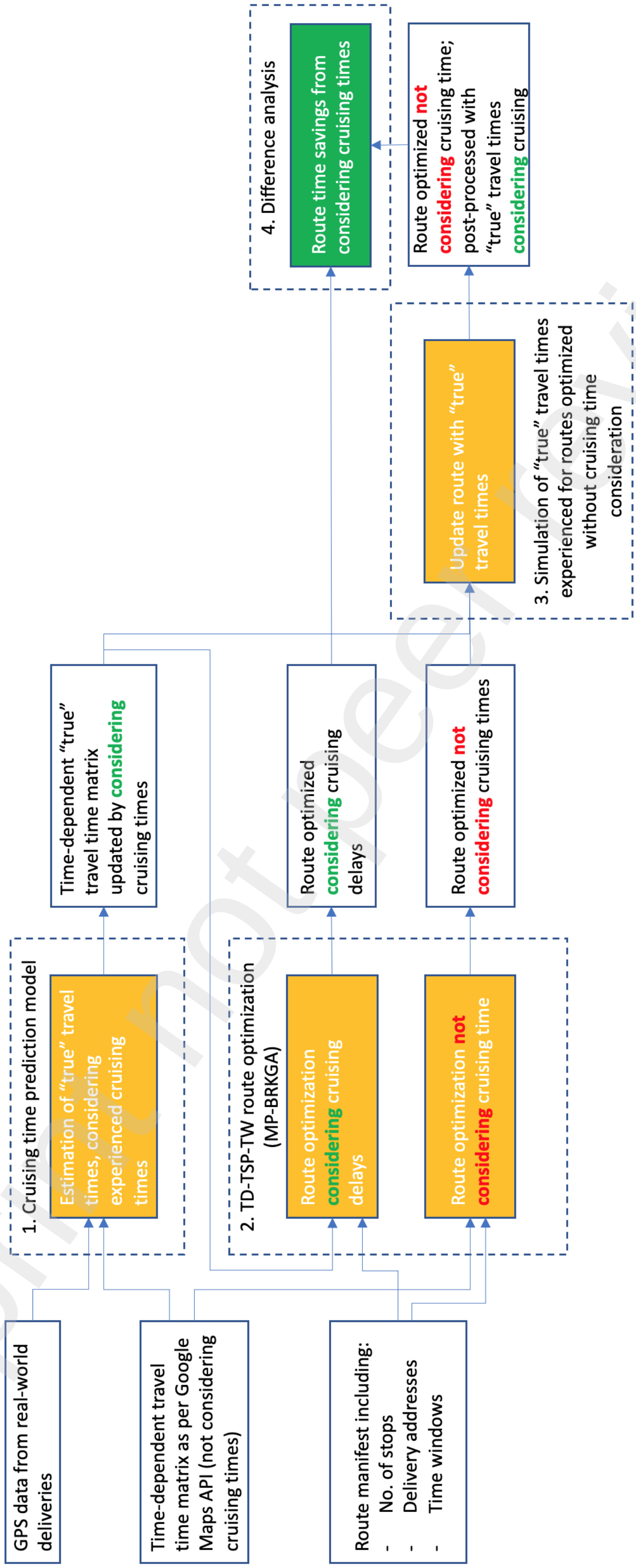

Figure 1 – *Overview of Analysis Steps to Identify Potential for Route Time Savings from Considering Cruising Delays in Vehicle Routing*

4.2 Data

4.2.1 Real-World Data (Case Study)

The real-world GPS data was obtained from a beverage company that delivers to a large set of customers in the Seattle metropolitan area on a regular basis. The data spanned over two years, 50 drivers, 2,000 customer locations and 60,000 deliveries, and they had two components:

- Manifest data, containing information about each planned route (including delivery addresses and coordinates, time windows, planned dwell times at the customers' locations, driver unique identifiers, and delivery volumes)

- GPS data, containing information about the realization of the routes as the drivers fulfilled them (including experienced travel times from engine on to engine off in between any two delivery addresses and realized delivery dwell times)

Table 2 presents summary statistics on the manifest data. Table 3 provides summary statistics for the GPS data.

Table 2 – *Summary Statistics for Real-World Manifest Data*

Statistic	**Value**
Number of routes	473
Mean number of stops per route	12.6
Std. dev. of stops per route	2.9
Min. number of stops per route	3
Max. number of stops per route	21
25th percentile number of stops per route	10
50th percentile number of stops per route	12
75th percentile number of stops per route	15

Table 3 – *Summary Statistics for GPS Data*

Statistic	**Value**
Number of trips	9774
Mean trip time (minutes)	11.5
Median trip time (minutes)	9.5
Std. dev. of trip time (minutes)	9.3
Mean dwell time (minutes)	38.0
Median dwell time (minutes)	27.7
Std. dev. of dwell time (minutes)	39.0
Mean trip distance (km)	2.8
Median trip distance (km)	1.6
Std. dev. of trip distance (km)	4.7

Using this data, it was possible to source a corresponding time-dependent travel distance matrix for each route manifest from the travel time forecasting data from the Google Travel Distance API (Google (2021)). Together, these data sets represented the base for the real-world case study.

4.2.2 Synthetic Data

In contrast to the real-world data described in Section 4.2.1, the objective behind using synthetic data was to exclude noise, and investigate the contribution of certain manifest characteristics on potential route time savings by considering cruising delays in truck routing. For that, synthetic data was generated that included different problem characteristics, with the objective of running a 2^k full factorial experiment (Montgomery (2013)) to identify the individual and confounded effects of the considered characteristics on route time savings potential. The main characteristics of interest were as follows:

1. The number of stops;
2. The size of the area in which the stops were located, expressed through the range from which the coordinates stop locations were sampled;
3. The distribution of stops, expressed through the standard deviation of the travel distance matrix;
4. The variance of cruising delays along the planning time horizon, expressed through the standard deviation of cruising delay estimates per node pair.

Table 4 shows the values considered for high and low levels in the simulation data set. Note that σ_{tt} was scaled by the size of the sampling area, since the standard deviation of the travel distance matrix was not scale-independent and thus needed the scaling parameter to be adjusted. Since there was no real-world equivalent of GPS traces to synthetic data, the cruising time prediction model was not relevant for this data set, as the cruising time was randomly sampled from a normal distribution and its variance was controlled by the values in Table 4. The values presented in Table 4 were chosen empirically based on typical route lengths in the real-world data, presented in Section 4.2.1, typical area sizes covered, and typical cruising time variances observed in between different time instances in the real-world data. The standard deviations of the travel time matrix were identified experimentally to obtain routes that either had homogeneous or heterogeneous spatial distributions.

Table 4 – *Data Set Characteristics Considered to Generate Synthetic Data*

Characteristic	**Low Value**	**High Value**
n = Number of delivery addresses	5	15
a = Size of address sampling area	$1km^2$	$4km^2$
σ_{tt} = standard deviation of travel time matrix	$0.35 * \sqrt{a}$	$1.5 * \sqrt{a}$
σ_{cd} = standard deviation of cruising time delays	0.5	2.0

To obtain a sufficiently diverse data set that would allow us to draw reliable conclusions, 25 instances were generated for each configuration, controlled by a random seed. Table 5 presents summary statistics on the synthetic data.

4.3 Modeling

4.3.1 Cruising Time Prediction Model

Using historical GPS data, a travel time prediction model based on Dalla Chiara & Goodchild (2020) was developed to estimate the "true" vehicle travel time that would reflect not only the time spent on the road driving to a certain destination but also the time spent searching for available parking. The time of day, the curb parking allocation near each delivery address, and the expected travel time (without considering parking delays) were included as predictors.

Table 5 – *Summary Statistics for Synthetic Manifest Data*

Statistic	**Value**
No. of routes	400
Mean no. of stops per route	10
Std. dev. of stops per route	5
Min. no of stops per route	5
Max. no of stops per route	15
25th percentile no. of stops per route	5
50th percentile no. of stops per route	10
75th percentile no. of stops per route	15

The selected method was a log-normal regression whose parameters are estimated by using real-world GPS data. The model observational unit consisted of individual route legs between any two delivery destinations. The model structure is described in Equation (1), where c represents the real travel time between any two delivery addresses obtained from GPS data, u represents the expected travel time as per a third-party sourced travel time matrix (Google, 2021), n represents the total length in meters of available curb space by different curb types i within a buffer of a diameter of 100 meters centered at a given delivery address, and h represents the rounded time t to the hour of arrival at a given delivery destination.

$$\log c = \beta_0 + \beta_1 \log u + \sum_{i \in I} \beta_i n_i + \sum_{t \in T} \beta_t h_t + \epsilon \tag{1}$$

Of particular relevance in this travel time estimation model is the incorporation of infrastructure information around the delivery address of interest located at the end of a route leg. This was based on the assumption that the total length of curb parking space available for commercial vehicles in the perimeter of the delivery address has a significant influence on cruising time, and with that, total travel time. Figure 2 illustrates the incorporated curb space for an example delivery address. The types of curb space that could be used for commercial vehicle parking are Commercial Vehicle Loading Zones (CVLZs) and unrestricted areas. Furthermore, the incorporation of different hours of the day allowed consideration of variability in curb space usage throughout the day, as experienced by drivers. The adjusted R^2-value of the model was 0.4005, the MSE was 0.416. With the help of this model, an alternative travel time matrix that considered the parking delay experienced at the curb was generated, which was denoted the "true" travel time matrix. This true travel time matrix then incorporated the information of cruising for parking, whereas the nominal travel time matrix did not.

4.3.2 Time-Dependent Traveling Salesman Problem with Time Windows

To consider both the effect of historic cruising data and account for data variation at different times of the day as represented in the true travel time matrix, the route generation was modeled through a time-dependent expansion of the Traveling Salesman Problem with Time Windows (TD-TSP-TW) (Albiach *et al.*, 2008). The reason for choosing a TSP instead of a Vehicle Routing Problem (VRP), which is a generalization of the TSP for multiple vehicles, was the goal to isolate the effects of considering cruising for parking delays on a route and to make the routes comparable between the base case and improved case. This would have been more difficult with a VRP because of the higher degrees of freedom and routes with potentially different delivery addresses and violations of vehicle capacities, on which data was not available for the analysis presented in this paper. Key notation for a formulation of the TD-TSP-TW by Hewitt *et al.* (2020) is introduced in Table 6, and the corresponding mathematical formulation can be found below.

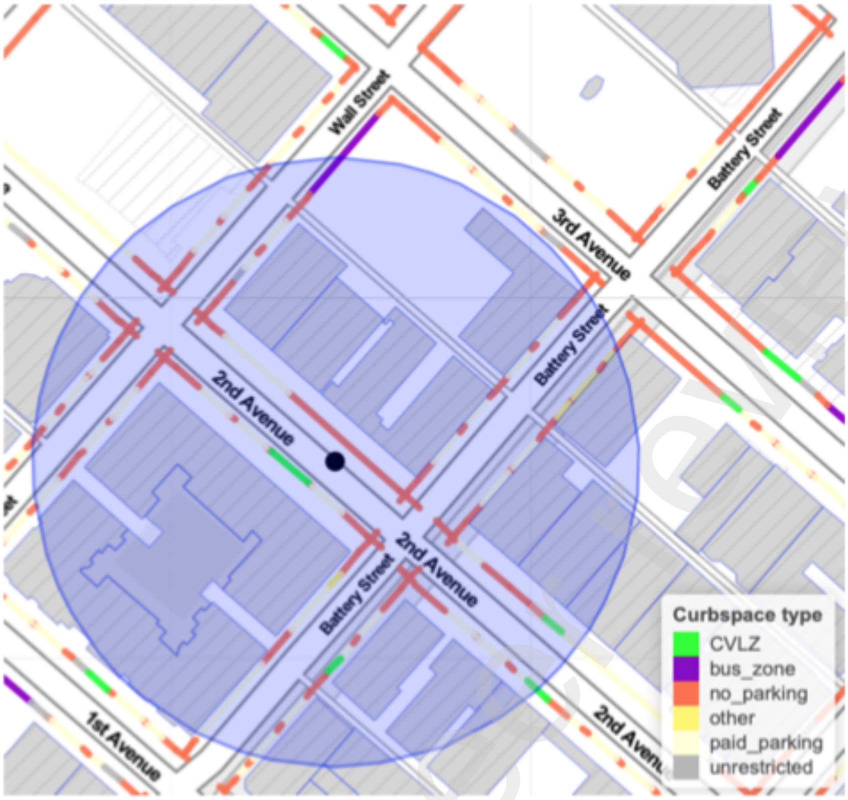

Figure 2 – *Curb parking allocations to different vehicle types contained in a 100-meter diameter buffer centered at a delivery destination were considered as predictors in the cruising time prediction model*

Table 6 – *Notation Key for 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	$c_{ij}(t)$	travel 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**
$t \leq t'$	arrival must be after departure	$x_{((i,t),(j,t'))}$	$\{\mathbf{1}$: if travel on $((i,t),(j,t'))$ selected, $\mathbf{0}$: otherwise$\}$
$t + \tau_{ij}(t) \leq t' + \tau_{ij}(t')$	later departure cannot lead to earlier arrival		
$t \geq e_i$	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		
$t' \leq l_j$	arrival time at node j cannot be after time window closing at j		

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

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

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

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

The model objective (2) minimized the make span of the entire route including the dwell times. The constraints (3) ensured that every node was visited, and constraints (4) ensured that a vehicle also departed a node it visited, except for the depot. Lastly, constraints (5) defined the decision variables as binary. The time window constraints were incorporated implicitly through the assumptions listed in Table 6 through the time-expanded network.

4.3.3 Additional Assumptions

To assess the impact of considering parking seeking on vehicle routing in a simulation study based on real-world data, additional assumptions were necessary to make the experiments realistic:

- If multiple addresses on a route were in close proximity (less than 50 m), they were aggregated to a single stop, and expected dwell times are added up, since a delivery driver would practically not relocate the vehicle for such a short distance; however, the time spent walking was not part of the model itself.
- Upon finishing delivery at an address, drivers immediately departed for the next stop.

Hence, the approach presented in this study represents an alternative to the work presented by Martinez-Sykora *et al.* (2020), who considered the walking time in between the parking spot and delivery address separately, and by Reed *et al.* (2021), who further considered cruising time as an explicit cost component in the objective but did not consider the time-dependency of the cruising estimates. The cruising delays in their model were mostly compensated for by a trade-off between walking and driving for deliveries.

4.3.4 Solution Method

Since the TD-TSP-TW consists of a time-expanded network structure, is NP-hard Savelsbergh (1985), and is therefore highly complex, it is challenging for model-independent commercial solvers to solve the problem. In the past, analysts have attempted to solve the problem by using different structural and heuristic methods.

Algorithms focused on providing exact solutions to TD-TSP-TW have generally solved it under one of two objectives: *makespan* or *duration*. Under a makespan objective, the return time to the depot is minimized, while under a duration objective, the total route time is minimized. Recent work has produced generalized algorithms that focus on minimizing both the makespan and duration of the route. The current state-of-the-art algorithms include work by Vu *et al.* (2018), which proposed a solution based on the Dynamic Discretization Algorithm (DDD) framework, Lera-Romero *et al.* (2020b), which applied a variation of the Branch and Price algorithm, and Lera-Romero *et al.* (2020a), which utilized dynamic programming techniques to solve TD-TSP-TW instances. While a direct comparison of the three under identical conditions has not been performed, all three showcase the ability to minimize both objectives when the number of customers is less than 40. However, these techniques can be time consuming and often do not scale well as problem complexity increases. For example, with 40 customers on a route, Lera-Romero *et al.* (2020a) saw average run times of up to 35 minutes per instance under certain conditions. Especially as time windows are relaxed and the number of instances to be solved increases, the run times can quickly become so long that solving the problem is impractical with this method. Therefore, some papers have proposed meta-heuristics to accelerate solving at the relaxation of optimality. In general, meta-heuristics applied to TSP problems often fall under one of two classes: local search and learning algorithms. The local search class includes methods such as simulated annealing, tabu search, and genetic algorithms. Papers by Jiang *et al.* (2005), Schneider (2002), Ohlmann & Thomas (2007), and Qian & Eglese (2014) all have showcased applications of these techniques to generalizations of the TSP problem class. Specifically, Martinez *et al.* (2011), Beltrão *et al.* (2021), and Krutein *et al.* (2022) successfully applied the Biased Random Key Genetic Algorithm (BRKGA) to variants of the TSP and other routing problems Krutein & Goodchild (2022). The learning class includes methods such as neural networks and ant colony optimization. Examples of ant colony optimization for generalization of the TSP were described by Kanoh & Ochiai (2012), Cheng & Mao (2007), and Verbeeck *et al.* (2014). Neural networks have also been applied to solve TD-TSP-TW problems. Work by Wu *et al.* (2021) leveraged trained deep learning models by reformulating the problem into a Markov decision process. This method provided cost minimization and run time decreases in comparison to other baseline meta-heuristics such as simulated annealing. However, to use learning-type solution approaches, a very large amount of instances solved to optimality is required to train a learning-type model to produce reliable predictions; these were not available for this study.

Given the advantages and disadvantages of the model types described above, the TD-TSP-TW was solved by using the BRKGA instead of a commercial solver, which had not been attempted before. The chosen variant was the Multi-Parent Biased Random-Key Genetic Algorithm (MP-BRKGA) (Andrade *et al.*, 2021), which 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 that of the example case for the regular Random Key Genetic Algorithm (RKGA) introduced by Bean (1994), in which the order of deliveries is determined by the random key values provided by the genetic algorithm. Figure 3 visualizes how every position in the chromosome, whose length equals the number of delivery nodes n plus one additional position, is allocated to a specific delivery address. Sorting the first n positions in the array by the random key value in increasing order provides a route. The last position of the array indicates at what time in the depot departure time window the route starts. Given soft penalties in the objective function for time window violations at the delivery nodes, a solution can be evaluated quickly by the fitness function that minimizes the total route time. Depending on the number of iterations, the algorithm yields a near-optimal objective value. This solution approach has not been applied to the TD-TSP-TW before in related literature. Testing of the above algorithm has showed it to be effective in finding high quality routes.

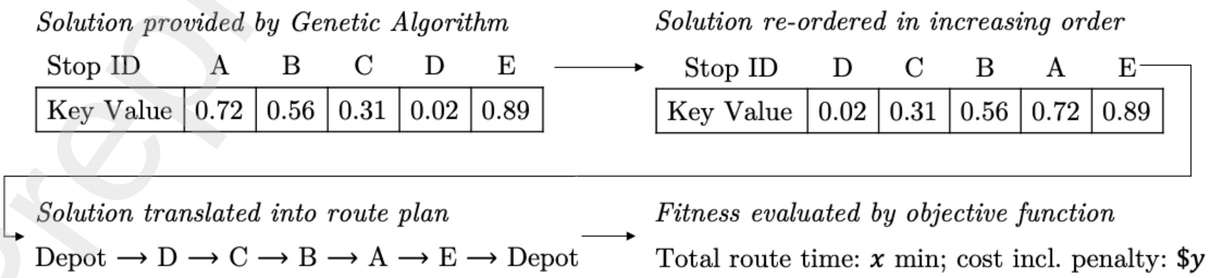

Figure 3 – *Translation from random key chromosome into fitness to TD-TSP-TW*

4.3.5 Simulation Methodology for Synthetic Data Set

As previously mentioned in Section 4.2.2, the methodology used to isolate and simulate the effects of considering cruising delays, is a 2^k full factorial design (Montgomery (2013)), followed by an ANOVA.

5 RESULTS

5.1 Real-World Case Study

The methodology presented above was evaluated with the introduced real-world data set, which resulted in a mean drive time savings of 1.5 percent (1.02 min per route). The distribution of results is visualized in Figure 4. The plot shows that considering cruising for parking does not always lead to drive time savings and that overall, a high amount of stochasticity is included in historic data on urban delivery routes.

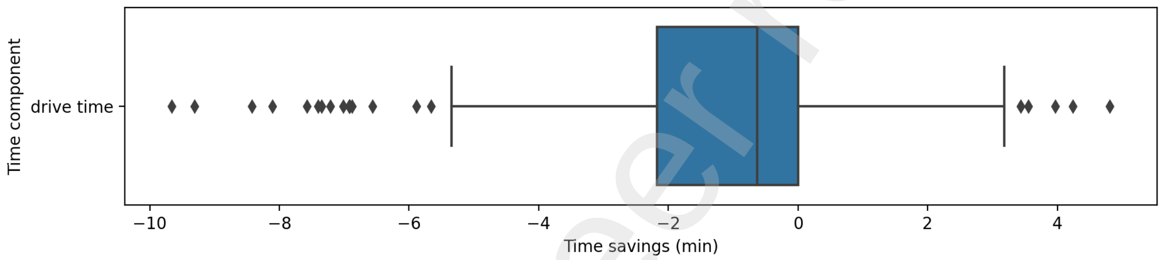

Figure 4 – *Drive Time Savings from Considering Cruising for Parking in Routing for Real-World Data*

Furthermore, the accuracy of the proposed method was found to be highly dependent on the prediction quality of the cruising time prediction model and the meta-heuristic solution to the TD-TSP-TW. It was furthermore discovered that routes with more concentrated shapes in spatial distribution of stops allowed for higher drive time savings, as differences in cruising time estimates throughout the planning time horizon could be exploited more effectively by the algorithm. Another factor that influenced the effectiveness of using historic data was the initial setup of the route manifest. Since the manifests used in this real-world data set were generated by a non-disclosed logic not known to the authors of this study, improvement potential may have interacted with this logic. For that reason, the results from the synthetic study presented in the following section provide a more isolated look at the effect of considering historic cruising delays on the TSP.

5.2 Synthetic Route Study

Figure 5 shows the results per difference in main effect from using the same methodology that was used with the real-world data, except for the cruising time prediction model (see Section 4.2.2).

As Table 5 shows, all treatments resulted in differences in drive time savings. The mean drive time savings per stop achieved was 3.12 minutes. The mean drive time savings per route was 26.4 minutes. Most significant savings were generated for manifests with fewer stops, a higher standard deviation of cruising time, and a homogeneous spatial distribution of the stops in the area. The corresponding ANOVA with significant interaction effects only, presented in Table 7, showed that the size of the area did not have a statistically significant influence on drive time savings. Furthermore, the standard deviation of the travel time matrix, and with

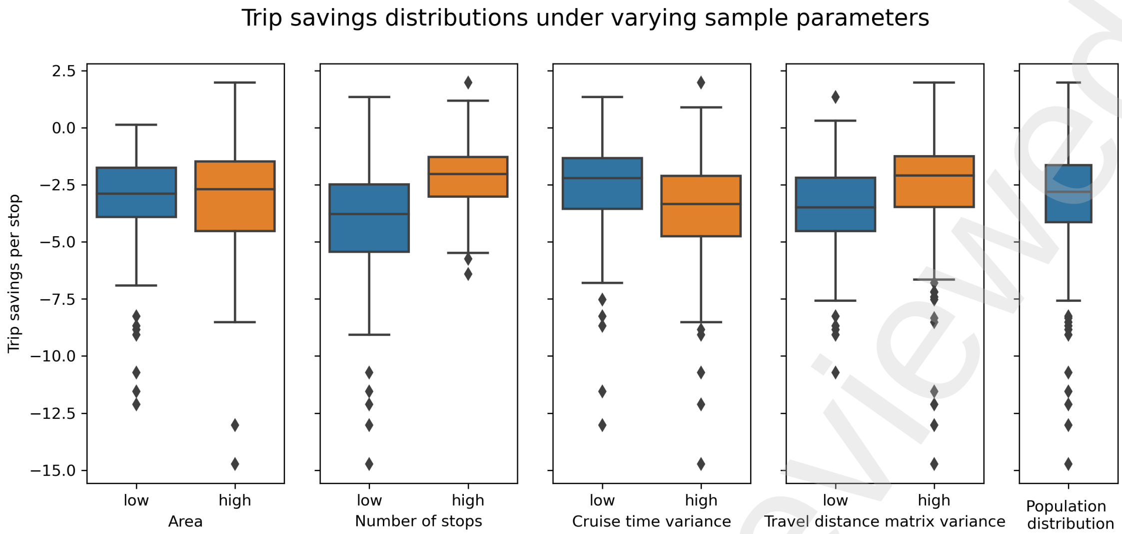

Figure 5 – *Drive Time Savings Per Stop From Considering Cruising for Parking in Routing for Synthetic Data*

that the distribution of stops, was almost statistically significant with a p-value close to 0.05. The other tested main effects were statistically significant. In addition, a statistically significant interaction effect between the number of stops in the delivery manifest and the shape of the route (standard deviation of travel time matrix) was observed. This implies that only the distribution of stops and the standard deviation of the cruising time have a clear effect on drive time savings when cruising delays are considered in vehicle routing. The effect of the distribution of stops affects the problem only implicitly through an interaction effect with the number of stops. Visual inspections of QQ-Plots confirmed that the normality assumption held, and parametric Kruskal tests confirmed the model properties.

Table 7 – *ANOVA Results for Synthetic Study*

	Sum of Squares	df	F-value	p-value
Intercept	4,364.374	1.0	853.244	1.248e-100
Area	25.282	1.0	4.943	2.677e-02
No. of stops	263.744	1.0	51.562	3.483e-12
SD cruising time	70.337	1.0	13.751	2.386e-04
SD travel time matrix	18.553	1.0	3.627	5.757e-02
No. of stops : SD travel time matrix	92.117	1.0	18.009	2.744e-05
Residual	2,015.325	394.0		

6 DISCUSSION

Intuitively, the relationships presented in Figure 5 are reasonable. With a larger standard deviation of cruising time, drivers will experience more extreme and longer parking times, meaning that accounting for these delays will generate more savings in comparison to routes that do not. Similarly, a high standard deviation for the travel distance matrix implies a heterogeneous distribution in stops. This leaves more room for route optimization when parking is not considered and, therefore, a lower average trip savings per stop. For example, in the extreme case in which all trips have identical travel times, the only difference between trip paths will be the cruising times at destinations. However, the relationship presented between the distributions of few and many stop manifests is the opposite of what might be expected. In theory, more stops would produce an increase in complexity in the form of more feasible routes, leaving room for error when cruising is not considered. Instead, the inverse relationship was observed: the average savings per stop of the manifests with few stops was larger than that of the manifests with many stops.

Analyzing total drive time savings helps to explain this phenomenon. Figure 6 shows the total drive time saving distributions of both manifests with few stops and many stops, under varying run time limits. Using a one-hour limit per route showed an average of 32 minutes of savings for manifests with 15 stops and 20 minutes of savings for those with 5 stops. Although the manifests with many stops posted a 60 percent larger total drive time savings when normalizing for the number of stops, this relationship was inverted. One possible reason is that the relationship between the number of stops and total drive time savings is not quite linear. Another possible reason is the difficulty of reaching optimal solutions. With increased stop counts also comes increased complexity. While applying a genetic algorithm like BRKGA can produce a viable solution immediately, reaching an optimal solution can often lead to very high run times for larger problems. With less problem complexity (as was the case with 5 stops), this is not an issue, as the optimal solution can be found quickly. However, with an increase in the number of stops, the sheer number of possible routes to consider leads to a much longer time to approximate the global minimum. With further run time, the approximations approach the minima. This can be seen with the average total drive time savings shifting to 32 minutes from 28 minutes when the run time limit per route increased from 24 minutes to 60 minutes. Similarly, with the increase in run time the number of routes with a gain in drive time decreased from 13 to 7.

Table 8 showcases a ranking of the manifests based on two normalized metrics: average drive time savings and trip savings per stop. Overall, the class of routes with the most significant savings was generated for manifests with fewer stops, a higher standard deviation of cruising time, and a homogeneous spatial distribution of the stops in the area. These manifests posted the largest savings, with an average trip savings per stop of 5.18 minutes and an average drive time savings of 39 percent. Once again, using average savings per stop, manifests with many stops performed worse than those with fewer stops. Using percentage of total drive time savings as an indicator produced a different ranking. While not as heavily weighted towards manifests with fewer stops, this metric tended to favor routes with shorter total drive time, as smaller savings yielded a larger percentage.

Overall the question remains: what key messages do the results obtained from the two case studies deliver for urban logistics? First and foremost, the results from both studies demonstrated that increased transparency regarding parking information and cruising delays has the potential to improve routing for urban delivery vehicles and to reduce their drive times. Even more so, the synthetic study demonstrated that if cruising delay data can be predicted from historic data with great accuracy, then the potential for route time savings increases significantly. The main demand for future developments in commercial vehicle infrastructure in urban environments is therefore for both the public and the private sectors to focus efforts on boosting transparency on parking visibility. This will have a positive impact on route generation and commercial vehicle operations and thus will measurably support the achievement of congestion and emissions reduction targets.

7 CONCLUSIONS

In summary, this paper provides multiple insights. First, the research showed that for real-world data, the proposed method is able to consider parking delays in vehicle routing that can result in mean drive time savings of 1.5 percent, despite uncertainty over the exact cruising time experienced in the collected data, as this had to be inferred through the cruising time prediction model. Second, the investigation based on synthetic data showed that when cruising delays can be clearly identified and separated from other drive time delays, drive time savings per stop may

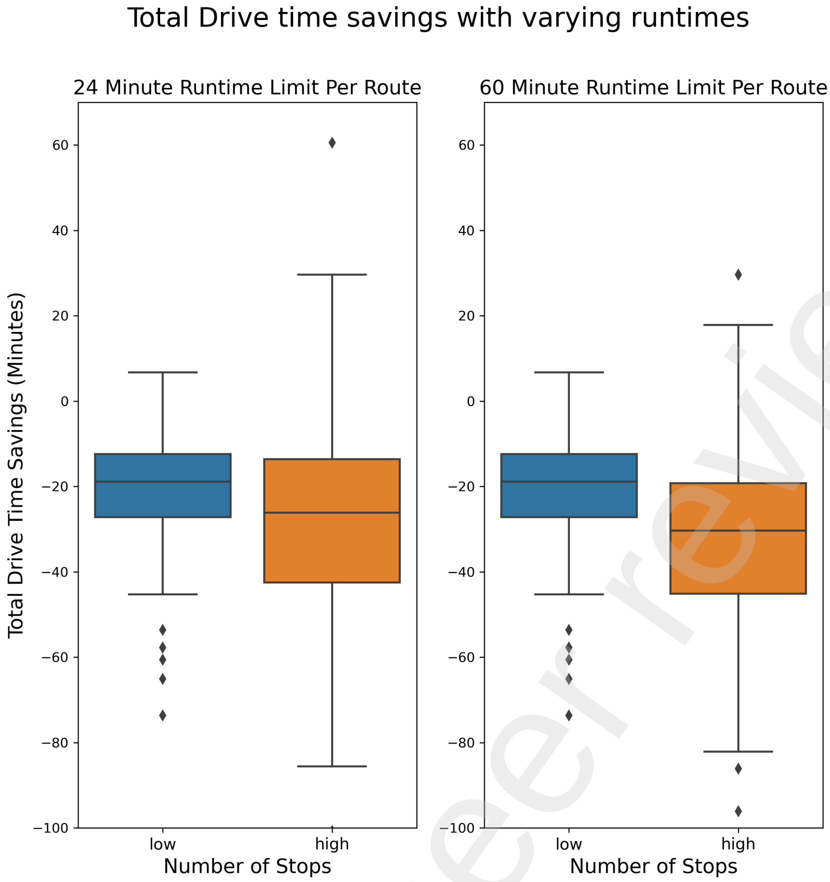

Figure 6 – *Comparison of Total Drive Time Savings for Few and Many Stop Manifests with Varying Run Time Lengths*

reach 21.6 percent on average. These results are astonishingly similar to the results obtained by Dalla Chiara *et al.* (2022) in a real-world test using a parking app with real-time data (18 percent). Third, the ANOVA conducted for the drive time savings demonstrated that route manifests with a lower number of stops, a higher standard deviation for the cruising time, and a lower standard deviation for the travel time matrix (through an interaction effect with a lower number of stops) result in the highest savings when cruising delays are considered, with up to 60 percent of route time savings for some routes. Carriers can take advantage of this information, since many deliveries occur in urban environments where the spatial distribution of stops is usually homogenous and the difference in potential cruising delays among different times of the day is relatively large because of congestion and similar delivery time windows for different carriers. Together, these results demonstrate the value of considering parking information in urban delivery and routing decisions. This confirms that more transparency regarding freight curb activity will ultimately benefit urban environments, as carriers will be able to save time and resources, and that will ease the impact on traffic and space use by commercial vehicles in urban areas. Both the public and the private sectors should therefore advocate for more technology that can collect data on curb activity and provide real-time visibility of curb availability.

Regarding future research, next steps should focus on both further improving algorithms and implementing technology. One area of future research is to improve the accuracy of data collection on urban deliveries through development of smart city infrastructure that allows cruising times to be collected externally instead of in the vehicle, which should provide an additional point of reference. Another area of future research is to improve the prediction of accurate travel times

Table 8 – *Savings for various manifest classes sorted by savings per stop. Values highlighted in red represent the largest savings.*

Manifest				Saving per Stop	Percent Total Drive Time Savings
Number of Stops	Shape	Travel Matrix Standard Deviation	Cruise Time Standard Deviation		
low	low	low	high	-5.35	-43.90%
low	high	low	high	-5.02	-33.75%
low	high	high	high	-4.84	-17.39%
low	low	high	high	-3.87	-21.33%
low	low	low	low	-3.83	-31.60%
low	high	low	low	-3.74	-24.25%
low	high	high	low	-3.13	-10.91%
high	low	low	high	-3.10	-32.70%
low	low	high	low	-2.91	-15.44%
high	high	low	high	-2.87	-24.32%
high	low	low	low	-2.42	-25.41%
high	high	low	low	-2.01	-17.25%
high	low	high	high	-1.94	-15.79%
high	high	high	high	-1.94	-11.50%
high	low	high	low	-1.59	-13.20%
high	high	high	low	-1.35	-8.08%
Population Average				-3.12	-21.68%

that include cruising time delays. Potential extensions in that direction may consider more traffic related variables and take advantage of more sophisticated methods from machine learning used for regression, such as random forests. Furthermore, revising the decoder for the MP-BRKGA algorithm presented in this paper to consider more variability in the solution generation could benefit the routing algorithm. From a technology perspective, future research may focus on monitoring not only curbs designated for commercial vehicles but also the remainder of the curb. This would allow researchers to do more real-world experiments that could further incorporate the interaction effects between different curb users, ultimately leading to better decisions.

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References

Aiura, Nobunori, & Taniguchi, Eiichi. 2005. Planning on-street loading-unloading spaces considering the behaviour of pickup-delivery vehicles. *Journal of the Eastern Asia Society for Transportation Studies*, **6**.

Albiach, José, Sanchis, José María, & Soler, David. 2008. An asymmetric TSP with time windows and with time-dependent travel times and costs: An exact solution through a graph transformation. *European Jounral of Operational Research*, **189**(3), 789–802.

Allen, Julian, Browne, Michael, & Cherrett, Tom. 2012. *Survey Techniques in Urban Freight Transport Studies.*

Andrade, Carlos E., Toso, Rodrigo F., Gonçalves, José F., & Resende, Mauricio G.C. 2021. The Multi-Parent Biased Random-Key Genetic Algorithm with Implicit Path-Relinking and its real-world applications. *European Journal of Operational Research*, **289**(1), 17–30.

Bean, James C. 1994. Genetic Algorithms and Random Keys for Sequencing and Optimization. *ORSA Journal on Computing*, **6**(2), 154–160.

Bektaş, Tolga, Demir, Emrah, & Laporte, Gilbert. 2016. Green Vehicle Routing. *Pages 243–265 of:* Psaraftis, H. (ed), *International Series in Operations Research and Management Science*. Springer.

Beltrão, Augusto Pizano Vieira, Ochi, Luiz Satoru, Brito, José André de Moura, Semaan, Gustavo Silva, Maculan, Nelson, & Fadel, Augusto César. 2021. A new approach for the traveling salesperson problem with hotel selection. *EURO Journal on Transportation and Logistics*, **10**(November).

Cheng, Chi Bin, & Mao, Chun Pin. 2007. A modified ant colony system for solving the travelling salesman problem with time windows. *Mathematical and Computer Modelling*, **46**.

Chevalier, Stephanie. 2022. Global retail e-commerce market size 2014-2025. *Statista*.

Dalla Chiara, Giacomo, & Cheah, Lynette. 2017. Data stories from urban loading bays. *European Transport Research Review*, **9**.

Dalla Chiara, Giacomo, & Goodchild, Anne. 2020. Do commercial vehicles cruise for parking? Empirical evidence from Seattle. *Transport Policy*, **97**.

Dalla Chiara, Giacomo, & Goodchild, Anne. 2022. Giving curb visibility to delivery drivers. *American Planning Association - Transportation Planning Division (Ed.), Intersections + Identities: 2022 State of Transportation Planning*, 134–143.

Dalla Chiara, Giacomo, Krutein, Klaas Fiete, Ranjbari, Andisheh, & Goodchild, Anne. 2021. Understanding urban commercial vehicle driver behaviors and decision making. *Transportation Research Record: Journal of the Transportation Research Board*, **2675**(9).

Dalla Chiara, Giacomo, Krutein, Klaas Fiete, Ranjbari, Andisheh, & Goodchild, Anne. 2022. Providing curb availability information to delivery drivers reduces cruising for parking. *Article under review.*

Demir, Emrah, Bektaş, Tolga, & Laporte, Gilbert. 2014. A review of recent research on green road freight transportation. *European Journal of Operational Research*, **237**.

Dündar, Hasan, Soysal, Mehmet, Ömürgönülşen, Mine, & Kanellopoulos, Argyris. 2022. A green dynamic TSP with detailed road gradient dependent fuel consumption estimation. *Computers and Industrial Engineering*, **168**.

Ehmke, Jan Fabian, Campbell, Ann M., & Thomas, Barrett W. 2018. Optimizing for total costs in vehicle routing in urban areas. *Transportation Research Part E: Logistics and Transportation Review*, **116**.

Figliozzi, Miguel, & Tipagornwong, Chawalit. 2017. Impact of last mile parking availability on commercial vehicle costs and operations. *Supply Chain Forum*, **18**(2).

Fleischmann, Bernhard, Gietz, Martin, & Gnutzmann, Stefan. 2004. Time-varying travel times in vehicle routing. *Transportation Science*, **38**.

Franceschetti, Anna, Honhon, Dorothée, Woensel, Tom Van, Bektaş, Tolga, & Laporte, Gilbert. 2013. The time-dependent pollution-routing problem. *Transportation Research Part B: Methodological*, **56**.

Gendreau, Michel, Ghiani, Gianpaolo, & Guerriero, Emanuela. 2015. Time-dependent routing problems: A review. *Computers and Operations Research*, **64**.

Girón-Valderrama, Gabriela del Carmen, Machado-León, José Luis, & Goodchild, Anne. 2019. Commercial Vehicle Parking in Downtown Seattle: Insights on the Battle for the Curb. *Transportation Research Record: Journal of the Transportation Research Board*.

Google, Inc. 2021. *Google Distance Matrix API.*

Hannon, Eric, Knupfer, Stefan, Stern, Sebastian, Sumers, Ben, & Nijssen, Jan Tijs. 2019. An integrated perspective on the future of mobility, Part 3: Setting the direction toward seamless mobility. *McKinsey Quarterly*, **2019**(1).

Hewitt, Mike, Vu Duc, Minh, Boland, Natashia, & Savelsbergh, Martin. 2020. Solving Time Dependent Traveling Salesman with Time Windows Problem. *Unpublished Manuscript*.

Hill, Arthur V., & Benton, W. C. 1992. Modelling Intra-City Time-Dependent Travel Speeds for Vehicle Scheduling Problems. *The Journal of the Operational Research Society*, **43**.

Holguín-Veras, José, Amaya, Johanna, Encarnacion, Trilce, Kyle, S., & Wojtowicz, Jeffrey. 2016. *Impacts of Freight Parking Policies in Urban Areas: The Case of New York City.* Tech. rept. Rensselaer Polytechnic Institute.

Ichoua, Soumia, Gendreau, Michel, & Potvin, Jean Yves. 2003. Vehicle dispatching with time-dependent travel times. *European Journal of Operational Research*, **144**.

Jiang, Q., Sarker, R., & Abbass, H. 2005. Tracking moving targets and the non-stationary traveling salesman problem. *Complexity International*, **11**.

Kanoh, Hitoshi, & Ochiai, Junichi. 2012. Solving time-dependent traveling salesman problems using ant colony optimization based on predicted traffic. *Advances in Intelligent and Soft Computing*, **151 AISC**.

Kawamura, Kazuya, Sriraj, P. S., Surat, Havan R., & Menninger, Martin. 2014. Analysis of Factors that Affect the Frequency of Truck Parking Violations in Urban Areas. *Transportation Research Record: Journal of the Transportation Research Board*, **2411**(1).

Krutein, Klaas Fiete, & Goodchild, Anne. 2022. The Isolated Community Evacuation Problem with Mixed Integer Programming. *Transportation Research Part E: Logistics & Transportation Review*, **161**(102710).

Krutein, Klaas Fiete, Goodchild, Anne, & Boyle, Linda Ng. 2022. A Meta-Heuristic Solution Approach to Isolated Evacuation Problems. *Proceedings of the 2022 Winter Simulation Conference.*

Lera-Romero, Gonzalo, Miranda-Bront, Juan José, & Soulignac, Francisco J. 2020a. Dynamic programming for the time-dependent traveling salesman problem with time windows. *Technical report, Optimization Online.*

Lera-Romero, Gonzalo, Bront, Juan J. Miranda, & Soulignac, Francisco J. 2020b. Linear edge costs and labeling algorithms: The case of the time-dependent vehicle routing problem with time windows. *Networks*, **76**.

Maden, W., Eglese, R., & Black, D. 2010. Vehicle routing and scheduling with time-varying data: A case study. *Journal of the Operational Research Society*, **61**.

Malandraki, Chryssi, & Daskin, Mark S. 1992. Time dependent vehicle routing problems: Formulations, properties and heuristic algorithms. *Transportation Science*, **26**.

Martinez, C., Loiseau, I., Resende, M. G.C., & Rodriguez, S. 2011. BRKGA algorithm for the Capacitated Arc Routing Problem. *Electronic Notes in Theoretical Computer Science*, **281**, 69–83.

Martinez-Sykora, Antonio, McLeod, Fraser, Lamas-Fernandez, Carlos, Bektaş, Tolga, Cherrett, Tom, & Allen, Julian. 2020. Optimised solutions to the last-mile delivery problem in London using a combination of walking and driving. *Annals of Operations Research*, **295**(2), 645–693.

Montgomery, Douglas C. 2013. *Design and Analysis of Experiments.* 8 edn. John Wiley & Sons.

Ohlmann, Jeffrey W., & Thomas, Barrett W. 2007. A Compressed-Annealing Heuristic for the Traveling Salesman Problem with Time Windows. *INFORMS Journal on Computing*, **19**.

Pillac, Victor, Gendreau, Michel, Guéret, Christelle, & Medaglia, Andrés L. 2013. A review of dynamic vehicle routing problems. *European Journal of Operational Research*, **225**(2), 1–11.

Qian, Jiani, & Eglese, Richard. 2014. Finding least fuel emission paths in a network with time-varying speeds. *Networks*, **63**.

Reed, Sara, Campbell, Ann Melissa, & Thomas, Barrett W. 2021. Does Parking Matter? The Impact of Search Time for Parking on Last-Mile Delivery Optimization. *Unpublished Manuscript.*

San Francisco Municipal Transportation Agency. 2011. *SFpark: Putting Theory into Practice.* Tech. rept. San Francisco Municipal Transportation Agency.

Savelsbergh, M. W.P. 1985. Local search in routing problems with time windows. *Annals of Operations Research*, **4**.

Schneider, Johannes. 2002. The time-dependent traveling salesman problem. *Physica A: Statistical Mechanics and its Applications*, **314**, 151–155. Horizons in Complex Systems.

Shoup, Donald C. 2006. Cruising for parking. *Transport Policy*, **13**(6).

Soysal, Mehmet, Çimen, Mustafa, & Demir, Emrah. 2018. On the mathematical modeling of green one-to-one pickup and delivery problem with road segmentation. *Journal of Cleaner Production*, **174**.

Taş, Duygu, Dellaert, Nico, van Woensel, Tom, & de Kok, Ton. 2014. The time-dependent vehicle routing problem with soft time windows and stochastic travel times. *Transportation Research Part C: Emerging Technologies*, **48**.

Verbeeck, C., Sörensen, K., Aghezzaf, E. H., & Vansteenwegen, P. 2014. A fast solution method for the time-dependent orienteering problem. *European Journal of Operational Research*, **236**.

Vu, Duc Minh, Hewitt, Mike, Boland, Natashia, & Savelsbergh, Martin. 2018. Solving time dependent traveling salesman problems with time windows. *Optimization Online*, **6640**.

Wenneman, Adam, Habib, Khandker M.Nurul, & Roorda, Matthew J. 2015. Disaggregate analysis of relationships between commercial vehicle parking citations, parking supply, and parking demand. *Transportation Research Record: Journal of the Transportation Research Board*, **2478**.

World Economic Forum. 2020. The Future of the Last-Mile Ecosystem. *World Economic Forum.*

Wu, Guojin, Zhang, Zizhen, Liu, Hong, & Wang, Jiahai. 2021. Solving Time-Dependent Traveling Salesman Problem with Time Windows with Deep Reinforcement Learning. *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics.*

Xiao, Yiyong, & Konak, Abdullah. 2016. The heterogeneous green vehicle routing and scheduling problem with time-varying traffic congestion. *Transportation Research Part E: Logistics and Transportation Review*, **88**.

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