Improving Commercial Vehicle Routing Through the Consideration of Cruising for Parking

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1 INTRODUCTION

Parking availability is a source of uncertainty for urban commercial vehicle drivers. To fulfill pick-up and delivery activities, drivers have to not only navigate the urban road network in compliance with traffic rules, interacting with other road users, but also select appropriate parking locations. Over the last decades, carriers invested in technology and tools to provide drivers with optimized route plans. While traffic patterns and time-dependent traffic density are sometimes part of these considerations, to date, information on parking availability has not been part of these decision-making tools. The availability is still largely assessed by the driver in real-time upon arrival, which can cause significant delays in the routing process if no parking is available and drivers have to reroute, wait for availability and/or have to cover longer distances by foot. In addition, the lack of visibility can cause public and traffic safety concerns and inefficient use of urban space, if drivers choose to park in unauthorized spots due to a lack of alternative options (Dalla Chiara & Goodchild, 2020).

In recent years, cities and corporations have started investing into parking information systems to collect data on historic driver behavior and bring digital visibility of parking to drivers and planners. An important finding identified with these tools is the occurrence of cruising, which describes the decision of a driver to queue, reroute, or circle the area to find better parking Dalla Chiara & Goodchild (2020). Using historic data, cruising behavior can be predicted, considering the built environment in the area. While this insight raises different research questions for drivers and for planners, one research question relevant to planners derived from this development is: If information on historic cruising for parking delays is available to drivers and planners, how can this information be used to improve the routes of carriers in urban environments and increase the cost efficiency of delivery routes? To address this question, this research combines parking cruising estimates from real-world delivery data with vehicle routing through a time-dependent traveling salesman problem with time-windows (TD-TSP-TW) to show the effect of considering historic cruising delays in vehicle routing, against not using this information.

2 METHODOLOGY

2.1 Data Acquisition

The used methodology consists of five steps. First, a set of historic route data was obtained. This data was obtained from a beverage company that operates and delivers to a large set of customers in the Seattle metropolitan area on a regular basis. The data consists of two years worth of data with about 50 drivers, 2,000 customers and 60,000 deliveries, and has two components:

- Ordered manifest data for every planned route (incl. delivery addresses, delivery coordinates, time windows, planned dwell times, driver names, load sizes)
- GPS traces for every fulfilled route (incl. delivery addresses, delivery coordinates, experienced travel times from engine on to engine off in between stops, dwell times)

Furthermore, a time dependent travel time matrix for all delivery addresses in the data set was generated from travel time forecasting data from the Google Travel Distance API (Google, 2021).

2.2 Cruising Time Prediction

Using the GPS trace data, a cruising for parking time prediction model based on Dalla Chiara & Goodchild (2020) was developed to estimate the "true" travel time that reflects 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 the day and the curb space parking allocation in a 100m perimeter of the delivery addresses were included as additional predictors. The selected modeling method is a log-normal regression. The model structure is described in Equation (1), where c represents the corrected travel time from address a to address b, u represents the travel time as per travel time matrix, n represents the total length of available curb space of curb type i within 100m around delivery address b, and h represents the arrival hour at time t.

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

The model was used to create an alternative travel time matrix that considers the parking delay experienced at the curb. The adjusted R^2-value is 0.4005, the MSE is 0.416 min.

2.3 Routing Simulation

2.3.1 Model and Solution Method

To assess the impact of considering parking seeking on vehicle routing, a simulation study was conducted. To consider both the effect of historic cruising data and account for data variation at different times of the day, 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), is the goal to isolate the effect of the consideration of parking delays on a route and to make the routes comparable between base case and improved case, which would be more difficult with a VRP due to the higher degree of freedom. An important assumption made is that drivers choose one stop per delivery address. Therefore, if multiple delivery addresses in the inputs were in close proximity (less than 50m), they were combined into a single stop, and the expected dwell times were added up. Furthermore, it was assumed that upon finishing the delivery at an address, drivers immediately depart to go to the next stop, as real-world drivers would not wait for a better departure time, even if the model would allow this. Hence, this approach represents an alternative to the work presented by Martinez-Sykora *et al.* (2020), who consider the walking time in between parking spot and delivery address separately, and Reed *et al.* (2021), who further consider the cruising time as an explicit cost component in the objective, but do not consider the time-dependency of the cruising estimates. The cruising delays in their model were mostly compensated by a decision trade-off between walking and driving for deliveries.

Since the TD-TSP-TW requires time expansion and is therefore highly complex, the model was solved using a meta-heuristic instead of a commercial solver, which has not been attempted before. The chosen method is 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 feasible region of the TD-TSP-TW. The decoder follows a similar logic as the example case introduced by Bean (1994), where the order of deliveries is determined by the random key values provided by the genetic algorithm. Figure 1 visualizes how every position in the chromosome, which 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. Considering 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.

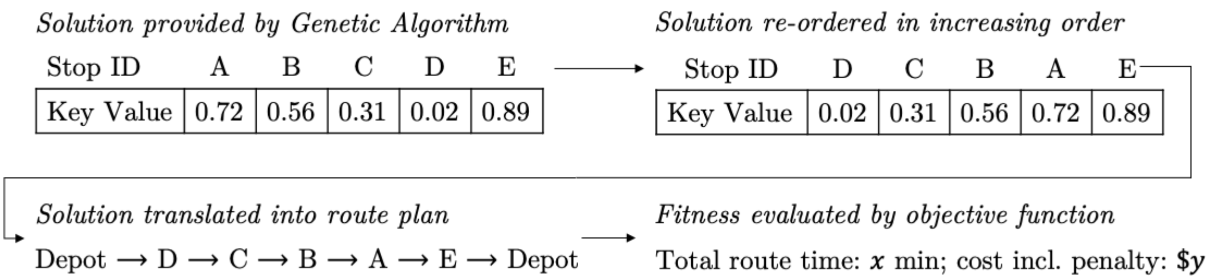

Figure 1 – *Translation from random key chromosome into fitness to TD-TSP-TW*

Depending on the number of iterations, the algorithm yields a near-optimal objective value. To the authors' knowledge, this solution approach has not been applied to the TD-TSP-TW before.

2.3.2 Simulation Set Up

To establish a base case, where cruising for parking is not considered in routing, a benchmark was created through optimizing routes with the TD-TSP-TW from step 2.3.1, using the original time-dependent travel distance matrix from Google Travel Distance Matrix API Google (2021). Since drivers still experience these delays in reality even if the data is not considered in the route generations step, the experienced route time is simulated through retroactively updating the generated route using the corrected travel time matrix from step 2.2. To evaluate the effect of using the travel time matrix corrected by cruising for parking delays, the experiments were repeated for the same routes, but this time using the corrected travel time matrix, where travel times include cruising for parking time delays, already in the route optimization phase.

3 PRELIMINARY RESULTS

The performance was evaluated and resulted in mean drive time savings of 1.5% (1.02 min per route). The distribution of results is visualized in Figure 2. The plot shows that considering cruising for parking does not always lead to drive time savings. The main reason is that the problem was solved using a meta-heuristic, which cannot guarantee solution optimality. However, the simulation study shows that in the majority of cases savings could be generated through considering the cruising delays in routing, in some cases with larger impacts.

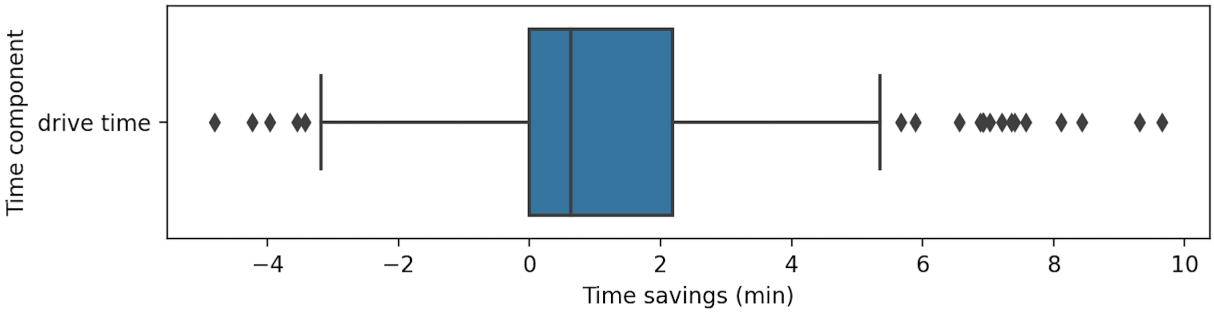

Figure 2 – *Savings From Considering Cruising for Parking in Routing*

4 DISCUSSION

An analysis of the detailed route plan results has shown that the largest savings occur when the addresses in the manifest are distributed in geographically uniform, clustered, or random shapes, which allows for many viable alternative routes, and when the cruising delays vary substantially between different time intervals. Most route manifests tested, however, follow a more linear geographic distribution and thus, reversing the route is often the only viable alternative that does not generate significantly longer routes. Therefore, the savings generated by considering cruising delays are small for the tested data set, as the resulting routes are often similar, or at best reversed. In addition, urban environments are exposed to many random events that are difficult to model, hence the high noise levels found in the simulation. Nevertheless, the analysis has provided evidence that time savings can be generated using historic data on cruising for parking in routing based on real-world data and that the significance of savings is dependent on a few factors in the input data. Future research will focus on generating synthetic routes to explore these effects further.

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