On Fairness Aspects of Customer Acceptance Mechanisms in Dynamic Vehicle Routing

Ninja Soeffker  
Technische Universität Braunschweig, n.soeffker@tu-braunschweig.de  
Marlin W. Ulmer  
Technische Universität Braunschweig, m.ulmer@tu-braunschweig.de  
Dirk C. Mattfeld  
Technische Universität Braunschweig, d.mattfeld@tu-braunschweig.de

In many service applications, customers can request service dynamically during the service time horizon and may be served the same day. For the service provider, these requests are stochastic and due to working hour limitations, usually not all customer requests can be accepted for same-day service. Decisions are made about service acceptances and routing. The objective is to maximize the expected number of accepted customers. Solution approaches can be classified as being either selective regarding the customer acceptance or as being non-selective. Non-selective approaches accept every feasible request, while selective approaches may decline same-day service although an acceptance would be feasible. This may save time for further acceptances later and may enable more overall acceptances. In this paper, we present an experimental setup to analyze the impact of the customer acceptance mechanism on the objective function and the “unfairness” within the service area. We show that selective customer acceptance mechanisms improve the objective value at the cost of a higher unfairness compared to non-selective customer acceptance mechanisms.

Keywords: dynamic vehicle routing, approximate dynamic programming, customer acceptances

1 Introduction

In many logistical service applications, resources like drivers’ working hours are limited. That is, service vehicles need to return to the depot before a deadline. As a result, service providers decide about the acceptance of customer requests to maximize their overall revenue. In many cases, these requests are uncertain and occur dynamically while the vehicles are already on the road. These problems are called dynamic vehicle routing problems with stochastic requests (for an overview, see Psaraftis et al. (2016)). Decisions are made about the acceptance of customers and their integration in the current routing plan. Early work on dynamic vehicle routing problems focus on determining efficient routing plans accepting all feasible requests, therefore being non-selective (see Gendreau et al. (1999), Bent / van Hentenryck (2004), Ichoua et al. (2006), Thomas (2007)). Recently, anticipatory algorithms are developed to explicitly select customers based on potential future customer requests. Amongst others, selective approaches are provided by van Hemert / La Poutre (2004), Campbell / Savelsbergh (2005), Angelelli et al. (2009), Cleophas / Ehmke (2014), Voccia et al. (2015), Ulmer et al. (2017), and Klapp et al. (2016).

These selective algorithms may tend to privilege “convenient” customers typically located centrally in the service area and close to the depot. This may lead to a systematic discrimination
of customers located in rural areas. If customers experience a high chance of their requests being rejected, they are more likely to be unsatisfied with the service and may even stop requesting service. From the service provider perspective, this bears the risk of negative reputation as well as revenue loss and thus should be avoided.

This research quantifies how the acceptance mechanism impacts the customer service for customers in different parts of the service area. To this end, an anticipatory selective approach is compared to a myopic non-selective approach. We show that the improvement in the number of overall served requests comes at the price of higher unfairness with respect to the chances of being served within the service area.

This paper starts with a description of the specific problem to be discussed in Section 2 along with the according modeling as a Markov decision process. The two solution approaches to be compared are presented in Section 3, the computational study follows in Section 4. The conclusion and future research are then briefly stated in Section 5.

2 Dynamic Vehicle Routing Problem with Stochastic Requests

The problem considered here is a basic dynamic vehicle routing problem with stochastic requests (Thomas (2007)). The vehicle starts its tour at a depot and ends its tour there as well. Due to working time regulations, there is a time deadline for the arrival at the depot. This deadline induces a time horizon for services. Customers in the service area request service throughout the horizon and the request will be accepted or rejected. Requests already given at the start of the tour must be served. The other requests are unknown in advance and follow a known spatial and temporal probability distribution. The travel times between customer locations are deterministic. We model the resulting stochastic and dynamic problem as a Markov Decision Process (MDP).

For the problem considered, a decision point $k$ occurs upon the arrival of the vehicle at a customer. A state $S_k$ in decision point $k$ contains information about the point in time, the location of the vehicle, the planned tour through the locations of the accepted, but not yet served customers, and information about all requests that occurred since the last decision point. In a decision point, an action $x$ consists of an acceptance or rejection decision for every new request as well as an update of the tour. The chosen action leads to a reward $R_k(S_k, x)$ and a deterministic post-decision state $S_k^x$. A post-decision state (PDS) contains the same information as a state except for changes in the tour and no requests that have not been decided upon. A stochastic transition then leads to the next decision point $k + 1$ along with the next state $S_{k+1}$. This transition consists of the vehicle driving to the next customer and the possible occurrences of new stochastic requests. A solution for a MDP is a decision policy $\pi$, that is, a rule to choose an action for every combination of a state and possible actions.

The objective is to maximize the expected number of accepted customer requests.

3 Solution Methodologies and Tuning

In this section, two solution approaches are defined to solve the problem described above. The approaches can be distinguished in the decisions about the customer acceptances: One is a representative of the non-selective customer acceptance mechanisms, the other is a representative
for the selective mechanisms. For the routing of the accepted customer requests, both approaches apply a cheapest insertion heuristic.

3.1 Non-Selective Mechanism

The first approach is a representative for the non-selective customer acceptance mechanisms. It accepts as many customers in every decision point as possible. This means that requests will be accepted unless they cannot be included into the current tour. The decision policy therefore only considers the immediate contribution to the objective function and finds a policy \( \pi^* \) that solves the following Equation (1):

\[
X_k^\pi(S_k) = \arg \max_{x \in \mathcal{X}(S_k)} \{ R_k(S_k, x) \}
\] (1)

If several possible acceptance decisions provide the same immediate reward, an acceptance decision will be chosen such that the shortest tour is achieved.

3.2 Selective Mechanism

The second approach from Ulmer et al. (2017) uses a selective mechanism and applies Approximate Value Iteration (AVI, Powell (2011)), a method of Approximate Dynamic Programming (ADP). ADP attempts to find a policy \( \pi^* \) that approximately solves Bellman’s Equation (Eq. (2)), in each decision step (Bellman (1957)).

\[
X_k^\pi(S_k) = \arg \max_{x \in \mathcal{X}(S_k)} \left\{ R_k(S_k, x) + V(S_k^{'}) \right\}
\] (2)

The second part, \( V(S_k^{'}) \), represents the expected future rewards that will follow after the PDS \( S_k^{'}, \) also called value of the post-decision state. In contrast to the non-selective approach, not only the immediate contributions to the objective function are considered, but also the expected future ones that follow the potential PDS. Methods of ADP use simulation to approximate the expected future rewards as they typically cannot be computed exactly. \( V \) is then replaced by an approximation \( \hat{V} \).

For AVI, values for every post-decision state are initialized and stored. The stored values from the previous simulation iteration \( \hat{V}_{n-1}(S_k^{'}) \) are used for the simulation iteration \( n \). After the real observation becomes known, the stored values are updated as a running average and provide the approximation for the next simulation run.

To reduce the size of the post-decision state space, aggregation according to Ulmer et al. (2015) is used. That is, the aggregated features to represent a PDS in such a problem are the point in time as well as the time that remains between the end of the currently planned tour and the end of the time horizon, also called “slack”.

The post-decision states are then expressed by a two-dimensional vector containing time and slack. For an efficient approximation process, the state space is additionally partitioned with a dynamic lookup-table (DLT, Ulmer et al. (2017)) that starts with large intervals and provides the possibility to split entries. The threshold parameter for splitting is 1.5.
The selective approach employs an approximation phase of 1 million simulation runs to approximate the values. Both this approach as well as the non-selective solution approach use 1,000 runs for the evaluation in which the decision policy is applied.

4 Computational Study

In this section, the instances as well as the measures to evaluate the results are provided.

4.1 Instances and Measures

The instances hold the following properties. The number of expected total requests for one day is 30, 40, or 60. The degree of dynamism (Larsen et al. (2002)) is 75%, that is, 75% of the expected customers are dynamic requests. The service area size is 15km x 15km, 20km x 20km, or 30km x 30km, the depot is located in the center of the service area. The service vehicle drives at a constant speed of 25 km/h. The dynamic requests follow a uniform temporal distribution over the time horizon of 360 minutes. All requests follow a uniform spatial distribution over the service area to analyze how customers in different parts of the service area are treated differently.

For the evaluation and interpretation of the results, we define a set of measures. One measure refers to the objective value, that is, the average rate of acceptances per run. The second one describes how “unfair” the two approaches treat dynamic customers. With the term unfairness, the differences in the rejection probabilities for customers in different parts of the service area are described. In order to answer this question, the service area is partitioned in subsegments. The unfairness is defined in Equation (3) as the coefficient of variation (CV) of the rejections between the subsegments of the service area. \( \mu \) is the mean number of rejections per subsegment, \( \sigma \) is the standard deviation of the rejections over the subsegments.

\[
CV = \frac{\sigma}{\mu} \quad (3)
\]

The third measure compares the chances of a request to be accepted within one of the subsegments of the service area for the two approaches. This describes in which parts of the service area which approach is more advantageous for customers.

4.2 Results

The first measure for comparison is the average rate of acceptances per run. The selective approach outperforms the non-selective approach for all instance sizes tested in terms of the percentages of confirmed dynamic requests in the 1,000 evaluation runs. On average over all instances, the non-selective approach accepts 63.1% of the dynamic requests, the selective one accepts 65.8% on average which is an improvement of 4.3% compared to the non-selective acceptance rate. As expected, this means that, in general, the chance for dynamic requests to be accepted is on average higher if the selective approach is applied. The higher number of services per day with the selective approach therefore leads to a higher revenue compared to the non-selective approach.
The second measure refers to the CV of the rejections per subsegment of the service area. In all tested instance sizes, the CV is larger for the selective approach. On average over all instances, the non-selective approach leads to a coefficient of variation of 0.1724, while the selective approach reaches a CV of 0.3168, this is 83.7% more than the non-selective approach. This higher CV can be interpreted as a higher unfairness between the subsegments of the service area. The detailed results of average acceptance rate and CVs for the instances are provided in the Appendix.

The third aspect refers to the chances of a request to be accepted within a subsegment of the service area. Figure 1 shows the acceptance rates for the dynamic requests for the 100 subsegments of a service area of 20km x 20km and 60 expected customers. On the left, the acceptance rate during the evaluation runs is shown for the non-selective approach, the middle figure shows the acceptance rate for the selective approach.

**Figure 1: Acceptance Rates of Non-Selective and Selective and Differences per Subsegment of Service Area, 60 Expected Customers, 20km x 20km**

In general, the requests in the outer areas of the service area have a smaller chance of being served because at some point in the time horizon, it is not possible anymore to include them into the current tour. Instead, more customers in the center of the service area, where the depot is located, are served as they may be on the way to the depot and can be inserted late in the tour. This behavior is very distinct for the selective approach where even more customers are accepted in the center. This strong difference between the subsegments also reflects in the higher CV for the selective solutions.

To show the comparison between both approaches, the two figures are combined. For this purpose, the difference between the percentages of accepted requests is determined for all subsegments. The result is a map that describes whether the chances for a request to be accepted are higher with the non-selective approach or with the selective approach. The right subfigure of Figure 1 shows the difference in the acceptance rates for the aforementioned instance setting. Positive numbers (bright colors) indicate that the chances for a request to be accepted are higher with the selective than with the non-selective approach, negative numbers indicate that requests were more often accepted in these areas with a non-selective approach.

In the center of the service area, the chance of a request to be accepted is higher with the selective than with non-selective approach. In the corners of the service area, less requests are accepted with the selective than with the non-selective approach. With ADP, those requests are
rejected more often as they cause detours and limit the possibilities for future requests to be accepted. The number of subsegments with a negative value is 39 (out of 100) for this instance, the mean difference is -0.052. The number of subsegments with a positive value is 60, their mean difference is 0.108.

In summary, it can be seen that the areas where the selective approach accepts more customer requests are larger and their mean improvement is higher than the mean deterioration in the other parts, which is the reason for the higher number of overall accepted requests.

5 Conclusion and Future Research

For a dynamic vehicle routing problem with stochastic requests and a given time horizon, customer requests can be accepted non-selectively or in a selective manner. While selective approaches may tend to increase the overall acceptance rates, the effects on the customer selection have, to the best of our knowledge, not been studied yet. We have compared the acceptance behavior of a selective approach with a non-selective acceptance approach. The application of the selective approach increases the number of accepted customer requests. This, however, happens at the cost of a higher unfairness, here measured by the coefficient of variation. The selective approach facilitates to reject customers that require to spend more time resources and therefore leads to parts of the service area with a lower service level. With a non-selective approach, the location and the resulting detour are not relevant as long as a customer can be feasibly inserted into the tour.

That is, for customers in the corners of the service area, the application of a non-selective approach is advantageous, for the customers in the center of the service area, the tested selective approach provides a higher chance of being served. It can be concluded that there is a tradeoff between higher acceptance rates and a higher fairness over the service area. For the service provider, this tradeoff is important as well, as it translates to a tradeoff between revenue and satisfied customers. As unsatisfied customers may lead to a loss in revenue on the long run, this factor should be incorporated in the choice of the customer acceptance mechanism.

In future research, the progress throughout the time horizon could be included. While this article discusses unfairness only based on spatial features, it is also possible to incorporate that the selective approach maintains the capability to feasibly insert requests into the tour longer than the non-selective approach. Also, the effect of pricing on the customer selection may be studied.

References


Appendix

In the Appendix, we provide the detailed results of the computational study. Table 1 shows the acceptance rates in % for different service area sizes and the different numbers of expected customers per day for both solution approaches. Table 2 shows the coefficient of variation for all instance settings.

Table 1: Acceptance Rates in % for Different Service Area Sizes and Different Numbers of Expected Customers per Day

<table>
<thead>
<tr>
<th></th>
<th>15x15</th>
<th>20x20</th>
<th>30x30</th>
</tr>
</thead>
<tbody>
<tr>
<td>30 Cust.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>non-selective</td>
<td>84.9</td>
<td>76.3</td>
<td>54.5</td>
</tr>
<tr>
<td>selective</td>
<td><strong>85.1</strong></td>
<td><strong>76.9</strong></td>
<td><strong>57.3</strong></td>
</tr>
<tr>
<td>40 Cust.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>non-selective</td>
<td>82.1</td>
<td>69.0</td>
<td>44.7</td>
</tr>
<tr>
<td>selective</td>
<td><strong>82.5</strong></td>
<td><strong>70.7</strong></td>
<td><strong>49.6</strong></td>
</tr>
<tr>
<td>60 Cust.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>non-selective</td>
<td>72.5</td>
<td>55.7</td>
<td>28.2</td>
</tr>
<tr>
<td>selective</td>
<td><strong>74.0</strong></td>
<td><strong>60.2</strong></td>
<td><strong>36.2</strong></td>
</tr>
</tbody>
</table>
Table 2: Coefficient of Variation for Different Service Area Sizes and Different Numbers of Expected Customers per Day

<table>
<thead>
<tr>
<th></th>
<th>15x15</th>
<th>20x20</th>
<th>30x30</th>
</tr>
</thead>
<tbody>
<tr>
<td>30 Cust.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>non-selective</td>
<td>0.307</td>
<td>0.233</td>
<td>0.174</td>
</tr>
<tr>
<td>selective</td>
<td>0.353</td>
<td>0.349</td>
<td>0.312</td>
</tr>
<tr>
<td>40 Cust.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>non-selective</td>
<td>0.238</td>
<td>0.144</td>
<td>0.125</td>
</tr>
<tr>
<td>selective</td>
<td>0.356</td>
<td>0.319</td>
<td>0.275</td>
</tr>
<tr>
<td>60 Cust.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>non-selective</td>
<td>0.16</td>
<td>0.107</td>
<td>0.064</td>
</tr>
<tr>
<td>selective</td>
<td>0.39</td>
<td>0.332</td>
<td>0.165</td>
</tr>
</tbody>
</table>