Abstract

In recent years logistic service providers face more and more dynamic challenges. Customers can request service at any point of time and at any location in the served region. This leads to highly dynamic and uncertain settings. For these settings traditional approaches may not be suitable, because they use a discrete set of possible customers as representatives. Thus, they may insufficiently model dynamic spatio-temporal stochastic customer requests. Hence, modeling customer locations as continuous random variables (e.g. in the Euclidean Plane) leads to a more realistic representation of customers.

In this paper, both the traditional and a new approach without representatives are compared by means of a Single Vehicle Pickup and Delivery Problem. The results of the new attempt indicate significantly increases in served requests and confirm the assumption, that more detailed planning can clearly improve the efficiency of routing and decision making.

Keywords: Parcel Services, Vehicle Routing, Representatives, Euclidean Plane

1 Introduction

In recent years the parcel service industry, especially the e-commerce sector, is booming. The service providers operate in a stochastic and dynamic environment [8]. Especially possible customer requests may occur during the day at any location in the served region. Accurate consideration and prediction of those requests are hereby essential for an efficient routing and decision making. For these purposes the providers can access both historical data and technical developments like global position systems, onboard communication and routing software [19]. Nevertheless Ghiani [9] observed, that “most delivery companies have not yet exploited these new technologies in their route design and execution.”

Although requesting customers are often spatio-temporal random variables, common scientific approaches map customers to a discrete set of nodes in a graph theoretical environment. Here, they are assigned to the closest node, serving as a representative. This mapping reduces the complexity of the problem and allows the application of efficient graph theoretical algorithms, but hereby distorts the data and may cause inefficient predictions and routing. This leads to a trade-off between the complexity of data and algorithm. On the one hand a reduction of data complexity allows the application of efficient algorithms, on the other hand accepting more detailed data may lead to better solutions. Hence we examine the effect of both the approach regarding representatives and the approach considering customer locations as (continuous) random variables for an exemplary routing problem. In this problem setting requesting customers appear during the day regarding to a random distribution in the Euclidean Plane (EP), i.e. the distance of two customers is Euclidean. We apply myopic algorithms without anticipation of future events.

This paper is organized as follows: At first an overview of the challenges of Vehicle Routing and the theoretical counterpart in the literature is given with focus on the customer representation. Based on an exemplary problem both the representative-based and the continuous approach in the EP are compared. In the first case the actual customers are mapped on representatives, in the second they are considered with their exact location. In section 5 experimental results for two different scenarios are displayed. The last section gives a conclusion and an outlook of further research.

2 Related Work

The work of Vehicle Routing Problems is vast, so we are focusing on problems regarding challenges of parcel services. Additionally approaches, which treat customer locations as random variables, are examined.

Tassiulas [21] stated, that “for several practical problems [...] the number of points requiring service is not fixed. [...] The locations [...] are not known in advance and have to be modeled as random quantities.” Bertsimas introduced the Dynamic Traveling Repairman Problem (DTRP) [4], the first problem, which is tackled in the EP:
A vehicle (e.g. a breakdown van) has to serve customers, which appear over time regarding a uniformly distribution in a certain region. The objective function is to minimize the average waiting time per customer while serving all requests. During the last twenty years a lot of contributions to the DTRP has been made, amongst others by Bertsimas himself [5], who introduced a partitioning policy, where the plane is divided in several sub regions, which are served successively. This partition policy was improved by Tassiulas [21]. Further research to the DTRP were made by Larson et al. [15], Itani et al. [12] and Pavone et al. [17], who added extensions of the original problem like different objective functions, the multi-vehicle case and different probability distributions for customer occurrence. Larson et al. also introduced a measure to illustrate the relation between customers on short notice and customers known in advance, the Degree of Dynamism (DOD) and sorted real-life applications from oil distribution to emergency services respective their DOD [15].

With exception of the DTRP-case most of the dynamic VRP- and TSP-models are still using a discrete set of customers despite the fact that the assigned real life applications deal with unknown customer location. Especially in dynamic Pick Up and Delivery- (PDP), Traveling Salesman- (TSP) and Vehicle Routing problems (VRP) only few work model requesting customers as (continuous) random variables ([2], [20]), e.g. Jailliet ([14], [13]), who transferred the TSP to the Real Line. Ichoua et al. introduced the idea of representatives to cover sub regions for a VRP with Time Windows in the Euclidean Plane in 2006 [11], which allow anticipated planning. Branke and al. introduced 2005 a problem, where one additional customer appears in the Euclidean Plane. The objective was to find a routing policy with a high probability to serve this new customer regarding a given time limit [7].

3 A Single Vehicle PDP

We focus on an exemplary problem to show the difference in planning and decision making between a representative approach and the equivalent in the Euclidean Plane. Hereby, we are following Branke [7].

3.1 Problem Definition

A parcel service provider has to deliver and collect parcels during the day. For every region a single vehicle is used, which starts at a depot and has to return at the end of the day. There are no service times. Cause of the size of the parcels it is a less-than-truckload case, i.e. there are no loading space capacities and pickups and deliveries can be combined. Some pickup-request are known in advance, some occur during the day. If a pickup-request occurs, the driver has to decide immediately, if he can serve the customer or if he has to postpone the request to the next day. Objective is to serve as many requests as possible and return to the depot in time. As we can see this is an adaption of the problem Branke et al. introduced 2005 [7]. In contrary to the original problem the number of late request customers in the real life situation is quite higher, the DOD is increased.

The same problem was tackled for the case with a discrete set of customers by Wagner [23], Thomas [22] and Meisel [16]. Wagner and Thomas however allow postponing the decision whether to accept or reject a customer until the end of the day, which is not feasible in the real world, because it leads to a high dissatisfaction among the customers (and drivers). Meisel defined, that decisions are final. Related problems were described by Bent et al., Ichoua et al. and Ausiello et al. Bent et al. [3] discussed the possibility to reject customers, too. In their case the objective function was to minimize travel distances. Ausiello et al. [1] assigned every customer, which was not served, an individual penalty and tried to minimize the overall fine. All of those researches however consider less than 250, most of them less than 100 different customer locations, which is not applicable in a real world scenario.

3.2 Markov Decision Process

The problem can be formulated as a Markov Decision Process [18]:

In the beginning a set of costumers is given. The vehicle has to visit those customers. Possible actions are waiting or driving to the next customer. The next decision point occurs, when the vehicle arrives at a customer. Until this point of time some new stochastical requests appear. For every request a decision has to be made, if it is rejected or confirmed and integrated in the tour. Afterwards the vehicle visits the next customer, waits or returns to the depot. Every decision has to consider the overall time-constraint. So there are two different kinds of decisions: It has to be decided which route to take and which customers to confirm.

![Figure 1: Markov Decision Process](image)

In this Markov Decision Process a state (cf. \(S(t_i)\) in figure 1) consists of the point of time, the location of the vehicle, the customers to visit and the new requests. A decision \(d\) contains the acceptance/rejection of the candidates and the next customer, which has to be visited respectively waiting at the actual position. The post decision state
S(t_1, d) is the determined state after the decision d. This post decision state only contains of the time, the position, the next action and the customers in the tour. A stochastic event s maps this post decision state to the next state s(t_1). In this case a number of new requests is added randomly.

4 Solution Approaches

In the following section we tackle the problem both in a new continuous approach and by finding appropriate representatives. The main focus in this study lies on the difference of those two methods. Hence, we chose plain and classic confirmation and routing heuristics for an easy and genuine comparison.

4.1 Confirmation and Routing Policy

At every decision point there are two decisions to make: Which customers shall be confirmed and which route is to choose. To check whether a customer can be accepted the time limit is essential. For this reason a route through the candidates and remaining customers has to be calculated. The Nearest Insertion heuristic (NI) chooses the customer, which can be inserted in a given route with the lowest costs. We use the NI for two reasons: First of all it allows sorting the new customers by potential, the cheapest to insert first. Second it conserves the main structure of the route. The confirmation policy is greedy, i.e. we insert every customer, which is feasible regarding the time limit.

4.2 Optimal Solutions

Because of the stochastic and dynamic nature of the problem an optimal solution only can be found after all information is revealed. Therefore we call this solution “ex post”. We also consider the optimal solution algorithm as “fair adversary” [6], i.e. the same solution can be found by a heuristic. This means for example, that a run to a customer only can be started, if the customer is already known at that point of time.

The ex post optimization problem is related to a TSP with Time Windows, except the objective function, which is to maximize the visited customers. Additionally not every customer has to be visited, which requires slight changes in the constraints. To solve the problem, we are using a adjusted branch and bound-algorithm, which allows to solve small instances of the NP-hard problem in reasonable time.

4.3 Test Scenarios

We examine two different scenarios (cf. Table 1), in each case for two probability distributions. The first scenario S_1 applies to a courier service vehicle, which has only a few requests in a short time period. Hence, S_1 contains a time limit of 120 minutes, an expected number of customers of 12, a DOD of 0.75 and a vehicle, which travels a region of the size 20km \times 20km with a uniform speed of 40km per hour. Scenario S_2 is applicable for a parcel service vehicle, which serves many customers during the day. Therefore S_2 has a time limit of 360 minutes, 100 expected customers and a DOD of 0.75. Hence, three of four customers appear dynamically. The vehicle travels with uniform speed of 50km per hour through a 40km \times 40km region. For both scenarios the depot is located in the middle of the region. We normalize each scenario into a coordinate system of 10.000 \times 10.000 points. Every distance of two points in this system is Euclidean, but rounded up to an integer value.

Table 1: Scenario Attributes

<table>
<thead>
<tr>
<th></th>
<th>time [min]</th>
<th>requests</th>
<th>region size</th>
<th>DOD</th>
</tr>
</thead>
<tbody>
<tr>
<td>S_1</td>
<td>120</td>
<td>12</td>
<td>20km \times 20km</td>
<td>0.75</td>
</tr>
<tr>
<td>S_2</td>
<td>360</td>
<td>100</td>
<td>40km \times 40km</td>
<td>0.75</td>
</tr>
</tbody>
</table>

S_1 allows a comparison to an optimal, ex post and fair solution, where each customer can only be approached after his appearance. For S_2 we calculate the violations of the time limit in the representative solutions.

We test each scenario regarding to two probability distributions. First the customers appear uniformly distributed (UD), second there are three intense zones (IZ) distributed in the plane. The requests in the IZ-case occur in regard to a normal
distribution within the zones. The number of requests per time is generated using a Poisson process. All requests appear in the first three fourth of the time horizon.

4.4 Generation of Representatives

To create a reasonable set of representatives, we generate 10,000 example points for both distributions and cluster those points with the $k$-medoid method [10]. This method generates $k$ clusters. At the beginning of the process, $k$ points (seeds) are chosen randomly and every point left is assigned to the seed, which is closest. In an update process, every seed is randomly exchanged with one of the remaining point, if the overall distance of the seeds to the assigned points is decreased hereby. For each clustering we choose 10 times randomly $k$ seeds and update these seeds 50 times per cluster. The remaining $k$ seeds are the representatives for the distribution. We vary the number of representatives from 20 to 200 for $S_1$ and from 20 to 400 in $S_2$ because of the higher distances.

In figure 3 an exemplary clustering with 200 representatives of the uniformly distribution is shown. As expected the representatives are also uniformly distributed. Figure 4 shows the clustering regarding the IZ distribution, where the representatives are grouped in three zones.

5 Experimental Results

We perform 100 different simulation runs for each scenario and distribution and compare the number of served customers regarding the number of representatives chosen. Additionally we compare the results for scenario $S_1$ with the optimal solutions. We count and calculate the times and average amount of lateness for scenario $S_2$ furthermore.

In both scenarios the EP-heuristic performs better. Especially in the courier service scenario $S_1$ detailed planning results in quite more efficient routing. But also in the parcel service scenario $S_2$ considering the customer requests as spatio-temporal random variables in the EP leads to better solutions and avoids lateness.

In figure 5 the results normalized to the optimal solutions are shown. In the uniformly distributed setting of $S_1$ the optimal solution serves 10.0 customers in average, the greedy-heuristic in the EP 9.0. In contrary the solution using the representatives performs much worse. Even an increase of the number of representatives (shown on the x-axis) does not lead to significantly better results. Dependent on the number of representatives the heuristic reaches only 6.0 (60%) in the best case with 200 representatives, that is half of all requesting customers.
For the IZ distribution the results are similar. In this case the EP-heuristic exceeds the representative-heuristic by more than 2 customers per day, which is an increase of 25%. The optimal solutions serves 11.2 customers, the heuristic in the EP reaches 10.3 customers in average and the representative-heuristic up to 8.0 (70%) customers. All heuristics perform better than in the UD case. This is due to the design of the distributions. In the IZ-case, more customers accumulate in smaller regions; especially the route through the customers known in advance is in general quite shorter than in the UD-case.

Figure 6: $S_2$: Comparison of the representative-heuristic with the heuristic in the EP regarding the number of representatives

Those observations are also confirmed in the scenario $S_2$. In the UD-case the benchmark of the EP-heuristic is 55.9 visited customers in average, in the IZ-settings it is 74.0. In comparison to the representative-heuristic the ratio is in both cases the same (cf. figure 6). The more representatives are considered, the better the results get. But in all cases the EP-heuristic performs more than 5% better.

Table 2: Lateness regarding the number of representatives

<table>
<thead>
<tr>
<th>representatives</th>
<th>20</th>
<th>100</th>
<th>200</th>
<th>300</th>
<th>400</th>
</tr>
</thead>
<tbody>
<tr>
<td>violations UD</td>
<td>87%</td>
<td>77%</td>
<td>75%</td>
<td>74%</td>
<td>70%</td>
</tr>
<tr>
<td>violations IZ</td>
<td>82%</td>
<td>83%</td>
<td>82%</td>
<td>74%</td>
<td>74%</td>
</tr>
<tr>
<td>minutes UD</td>
<td>16.0</td>
<td>15.0</td>
<td>10.1</td>
<td>9.4</td>
<td>7.7</td>
</tr>
<tr>
<td>minutes IZ</td>
<td>16.3</td>
<td>14.4</td>
<td>12.8</td>
<td>11.6</td>
<td>10.5</td>
</tr>
</tbody>
</table>

As shown in Table 2, the percentage of solutions of the representative-heuristic with a late arrival is high. The time limit is violated in more than 70% of the test runs regardless the number of representatives. In many cases customers are confirmed because inserting their representative is valid, although inserting the actual customer is more expensive. This often results in a violation of the time limit. With more representatives and therefore more accurate planning the percentage of violations decreases slightly. The average violation is reduced increasing the number of representatives from about 16 down to 7.7 minutes in the UD and down to 10.5 in the IZ. If the number of representatives increases, generally the distances between actual customer and representative are shorter. Therefore, the amount in minutes of the violations decreases.

6 Further Research and Conclusion

As we can see, even in such simple cases and for basic heuristics the use of representatives leads to an evident loss of solution quality. The number of visited customers decreased by more than 5% in the parcel service scenario $S_2$ and even more in the courier service scenario $S_1$, in which the representative-based heuristic only reaches about 70% of the optimal solution. Considering the customers in the Euclidean Plane in $S_1$ leads to an increase of the objective value of 25%. Additionally we experience a huge quantity of late arrivals in case $S_2$ by applying the representative-heuristic. A consideration of the exact customers in contrast to representatives is therefore valid and promising, especially in cases with a short number of customers.

Hence, the trade-off between complexity of data and algorithm is evident. Thus, in further research the impact of more sophisticated (anticipatory) algorithms using historical data has to be examined. These algorithms are widely used in a graph theoretical environment, but have to be modified for an EP-setting. Because of the design as a Markov Decision Process an approach of approximate dynamic programming and anticipatory optimization might be promising. Because of the modeling of customers as random variables in the EP the challenge is to design a reasonable and efficient state space, which can assign similar states to similar decisions and avoids the curse of dimensionality.

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References


