Online vehicle routing and scheduling with continuous vehicle tracking

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Abstract

This paper proposes an extension to an online vehicle routing problem described in [3], with dynamic travel time perturbations (due to accidents, traffic jam, etc.) and dynamic customer requests. We show that the tracking of vehicles using GPS devices allows the dispatch office to take better decisions more quickly. In particular, a vehicle can now be diverted from its current destination as soon as a perturbation occurs. Computational results show the relevance of the new model and measure the improvement over previous models reported in the literature.

1 Introduction

Dynamic vehicle routing, where a part of the information about the customers to be visited is not known in advance, is attracting a growing attention from transportation companies (see, for example, [1, 6]). An interesting survey on this topic can be found in [4], where the problem is first discussed, applications are reviewed, and solution methods are presented. In particular, tabu search led to impressive results on different dynamic vehicle routing problems [4]. Nowadays, new possibilities offered by localization devices such as global positioning systems (GPS) can be exploited to improve vehicle routing management.

In [5], the authors are interested in a vehicle routing problem with time windows and dynamic travel times. The travel times include three different components: long-term forecasts, such as those based on long-term trends (time-dependency), short-term forecasts, where the travel time on a link is modified with a random uniform value to account for any new information available when a vehicle is ready to depart from its current location, and dynamic perturbations, which represent any unforeseen events that might occur while traveling on a link (e.g., accident causing sudden congestion). A modification to a planned route is only possible when the vehicle is at a customer location. That is, a planned route cannot be reconsidered while a vehicle is traveling on a link. An extension of this model is proposed in [3], where the position of each vehicle can be obtained when a vehicle reaches some lateness tolerance limit or when a new customer request occurs. Based on this information, the planned route of each vehicle is reconsidered, including the possibility of diversion (i.e., redirecting a vehicle en route to its current destination). The results show that the setting of an appropriate lateness tolerance limit can provide substantial improvements.

Here, we propose a further extension by assuming that the position of each vehicle is known at all time, thanks to accurate GPS devices. This assumption allows the system to detect much earlier perturbations to the travel times and to react appropriately.

2 Problem formulation

The description of our problem is based on [3]. A set of customers (some known in advance, some revealed dynamically) must be visited by a fleet of identical vehicles, represented by set K, where each vehicle travels a single route starting from and ending at a central depot. Customers who are known in advance can be used to create a set of initial planned routes. Then, as the other customers appear dynamically over time, they are integrated into the current solution.

Formally, let us consider a complete undirected graph $G = (V, E)$ with a set of vertices $V = \{0, 1, 2, \ldots, n\}$, where vertex 0 is the depot and the other vertices are customers. A travel time is associated with every edge $(i, j) \in E$. Furthermore, each customer vertex is characterized by a time window for service $[e_i, l_i]$. A vehicle arriving before e_i must wait, while a lateness penalty is incurred when a vehicle arrives after l_i. Also, each vehicle must return to the depot before an upper bound l_0, otherwise another penalty is incurred.

We note by $t_{i_p^k}$ the arrival time of vehicle k at customer i_p^k in position p in its planned route, $p = 1, ..., m_k - 1$, and by t_0^k the return time of vehicle k at the depot. The objective function takes into account (1) the travel time, (2) the sum of lateness at customer locations and (3) the lateness at the depot. It can be written as $f(S) = \sum_{k \in K} f(S^k)$, where $f(S^k)$ is equal to:

$$\sum_{p=1}^{m_k} t_{i_{p-1}^k, i_p^k} + \sum_{p\text{-}1}^{m_k\text{-}1} \max\{0, t_{i_{p-1}^k} - l_{i_{p-1}^k}\} + \max\{0, t_0^k - l_0\}$$

with $S^k = \{i_0^k, i_1^k, \ldots, i_{m_k}^k\}$ the route of vehicle k, $i_0^k = i_{m_k}^k = 0$ and $S = \bigcup_{k \in K} S^k$ the set of all routes (solution).

With regard to the time-dependent component of the travel time (long-term forecast), we do as in [2] and split the operations day in three time periods for the morning, lunch time and afternoon. With each period is associated a coefficient which multiplies the average travel time (namely, 1.25 for the morning, 0.5 for the lunch time, and 1.25 for the afternoon). To guarantee that a vehicle leaving earlier from some customer location also arrives earlier at destination, which is known as the FIFO property, the travel times are adjusted when a boundary between two time periods is crossed. The travel times also suffer dynamic perturbations due, for example, to unexpected congestion. A dynamic perturbation is thus added to the time-dependent travel time. Its value is generated with a normal probability law with mean 0 and different standard deviations σ. Negative perturbations are reset to 0 to represent the absence of any delay.

3 Models

Three different models are presented in this section. The paper is concerned about the third model, which is an extension of the two previous ones.

3.1 Model 1

In the first model [5], a central dispatch office knows the planned route of each vehicle. When a vehicle has finished serving a customer, it is informed by the central office of its next destination. It means that the drivers are not aware of their planned route, only the next customer to be served. It also means that the communication between the drivers and the dispatch office takes place only at customer locations. The initial routes are first computed with the static customer requests, which are known at the start of the day. The proposed heuristic inserts each customer in turn at the best possible position (i.e., with minimum increase of the objective value). A re-optimization procedure is then triggered, which is a local descent based on CROSS exchanges [8], where sequences of customers are moved from one route to another. Finally, a local descent is applied on each individual route, based on the relocation of each customer.

A lateness tolerance TL is included in the model, which is the maximum acceptable delay to a vehicle's planned arrival time at its current destination before some reassignment action is considered. For example, if we assume that s^k is the current destination of vehicle k and its planned arrival time is t_{s^k}, then $t_{s^k} + TL$ defines the tolerance time limit TTL^k of vehicle k. That is, if vehicle k has not reached customer s^k at time TTL^k, s^k is removed from its planned route and inserted somewhere in the planned route of another vehicle k' (note that vehicle k is not aware of this change and will continue toward s^k as communication between the dispatch office and vehicles only take place at customer locations). If it happens that vehicle k reaches s^k before vehicle k' and while k' is en route to s^k, then vehicle k serves s^k, but vehicle k' will only know when reaching s^k. A major drawback of this model thus occurs when two vehicles converge toward the same location.

3.2 Model 2

In [3], Model 1 was extended by adding diversion which allows any vehicle k to be redirected to another destination, while en route to its current destination, if it is beneficial to do so (with regard to the objective). It can serve two purposes: a pure diversion of vehicle k to serve a newly occurring customer request or the reassignment of its current destination to another vehicle k' when its tolerance time limit TTL^k is reached. In the latter case, vehicle k is diverted to the customer that immediately follows its current destination in the planned route. In these two situations, it is assumed that the dispatch office can obtain the current location of each vehicle to evaluate the benefits of a diversion. Figures 1 and 2 illustrate the pure diversion and reassignment actions. In Figure 1, a new customer request s occurs while vehicle k is located at position x between vertices i^k_{p-1} and i^k_p. In this case, vehicle k will serve s before i^k_p if it is beneficial to do so. In Figure 2, vehicle k has reached its tolerance time limit. Thus, its current destination $s = i^k_p$ is removed from its planned route to be reassigned to another vehicle k' and vehicle k is redirected to i^k_{p+1}. The results reported in [3] show that Model 2 significantly outperforms Model 1. Also, the best TL value was shown to be 0, which means that an appropriate action must be considered as soon as a perturbation is detected.

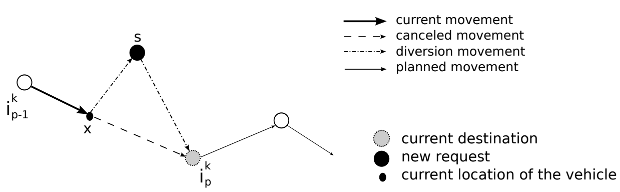

Figure 1: Pure diversion: vehicle k is diverted to the new customer location s

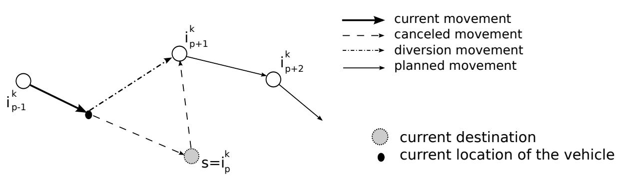

Figure 2: Reassignment: customer s is removed from the planned route of vehicle k

3.3 Model 3

Model 3 extends Model 2 by assuming that the position of each vehicle is known at all time, not only when the two types of situations described for Model 2 occurs. To this end, we first assume that the dynamic perturbation component of the travel time (or delay) is distributed uniformly along a link. Then, as soon as it is impossible for vehicle k to arrive at its current destination at time TTL^k, given its current location, a reassignment action is considered. For example, let us assume that vehicle k departs from i to j at time t, with a travel time $t_{ij} = 5$ and a dynamic perturbation $\Delta t_{ij} = 5$. That is, the vehicle is planned to arrive at j at time $t+5$, but will in fact arrive only at time $t + 10$. If $TL = 0$, then $TTL^k = t + 5$ and Model 2 will consider a reassignment at time $t + 5$ when it is observed that vehicle k has not yet reached j. On the other hand, by tracking the current position of each vehicle, Model 3 can detect the problem much earlier. For example, at time $t + 1$, vehicle k has still to cover $\frac{9}{10}$ of the distance, so that the planned arrival time at location j could be updated to $t + 1 + \frac{9}{10} \cdot 5 = t + 5.5$ (assuming no more perturbation on the remainder of the link) which already exceeds TTL^k.

4 Results

Tests were performed on a 3.4 GHz Intel Quad-core i7 with 8 GB DDR3 of RAM memory. The Euclidean 100-customer Solomon's benchmark instances [7] were used to compare models 2 and 3. In each instance, 50% of the customers are dynamic. Any dynamic customer request i occurs at time $e_i \cdot r$, where r is a random number between 0 and 1. In this work, the three classes of instances $R1$, $C1$ and $RC1$, with 12, 8 and 9 instances, respectively, are considered. In these classes, the customers are randomly generated (R), clustered (C) or both clustered and randomly generated (RC). Every instance is solved five times, using five different seeds, and the average values of the objective function over all runs and all instances are reported for each class. Note also that the computing times are not commented given that the optimization takes place within a fraction of a second.

The results are reported in Tables 1 to 3 for classes $R1$, $C1$, $RC1$ respectively, for various tolerance TL and σ values in Euclidean units (where σ is the variance of the dynamic perturbations to the travel times). Apart from the average objective value, there is also a pair of numbers between parentheses: the first one is the average number of times a reassignment action was considered and the second one is the percentage of times the reassignment action took place because it was beneficial. The results indicate that small TL values lead to better results, with the best value being $TL = 0$ in most cases. It means that an action should be considered as soon as a perturbation to the planned routes is detected. Table 4 then shows the improvement in percentage of Model 3 over Model 2. As we can see, Model 3 is clearly superior and provides larger improvements when the magnitude of the perturbations, as indicated by the σ value, increases.

Table 1: Results of Model 3 on class R1

TL	$\sigma = 1$	$\sigma = 4$	$\sigma = 16$	$\sigma = 32$
0	1715.64 (53.9,10.4%)	2212.62 (57.6,19.6%)	3935.67 (74.7,55.7%)	5246.38 (85.4,73.2%)
σ	1757.62 (16.2,7.5%)	2284.18 (16.5,20.0%)	5116.46 (16.9,45.5%)	9130.65 (15.4,56.1%)
2σ	1759.90 (2.1,4.8%)	2335.89 (2.1,20.3%)	5230.58 (1.8,33.3%)	9472.23 (1.4,40.7%)
3σ	1761.19 (0.1,0.0%)	2337.80 (0.1,0.0%)	5237.70 (0.1,50.0%)	9493.16 (0.1,50.0%)
1000σ	1761.19 (0.0,-)	2337.80 (0.0,-)	5234.47 (0.0,-)	9491.62 (0.0,-)

Table 2: Results of Model 3 on class C1

TL	$\sigma = 1$	$\sigma = 4$	$\sigma = 16$	$\sigma = 32$
0	2088.55 (52.2,7.0%)	2369.31 (52.6,9.3%)	3841.45 (55.9,18.3%)	5703.40 (60.4,28.9%)
σ	2074.06 (16.1,6.9%)	2396.31 (16.1,10.1%)	3839.04 (14.0,19.9%)	5656.81 (10.2,40.2%)
2σ	2101.42 (2.1,4.3%)	2415.90 (2.1,8.4%)	3920.15 (1.4,29.0%)	5946.18 (0.6,59.3%)
3σ	2103.16 (0.1,25.0%)	2423.74 (0.1,0.0%)	3955.09 (0.1,33.3%)	6000.31 (0.0,-)
1000σ	2103.33 (0.0,-)	2423.74 (0.0,-)	3958.24 (0.0,-)	6000.31 (0.0,-)

Table 3: Results of Model 3 on class RC1

TL	$\sigma = 1$	$\sigma = 4$	$\sigma = 16$	$\sigma = 32$
0	1882.10 (53.0,7.1%)	2351.59 (56.3,15.8%)	4212.73 (72.6,49.3%)	5605.93 (81.8,66.6%)
σ	1903.45 (15.7,5.4%)	2446.37 (16.0,12.3%)	5175.86 (15.5,36.2%)	8746.32 (13.7,49.8%)
2σ	1914.84 (2.0,5.0%)	2482.16 (1.9,13.0%)	5203.06 (1.8,31.9%)	8808.90 (1.3,44.0%)
3σ	1911.76 (0.1,0.0%)	2478.94 (0.1,0.0%)	5177.29 (0.1,33.3%)	8797.24 (0.1,0.0%)
1000σ	1911.76 (0.0,-)	2478.94 (0.0,-)	5182.56 (0.0,-)	8774.24 (0.0,-)

Table 4: Improvement of Model 3 over Model 2

		$\sigma = 1$	$\sigma = 4$	$\sigma = 16$	$\sigma = 32$
R1	Model 2	1752.31	2298.89	4402.67	6070.87
	Model 3	1715.64	2212.62	3935.67	5246.38
	% Imprv.	2.14%	3.90%	11.87%	15.72%
C1	Model 2	2098.69	2413.72	3945.31	6130.17
	Model 3	2074.06	2369.31	3839.04	5656.81
	% Imprv.	1.19%	1.87%	2.77%	8.37%
RC1	Model 2	1910.61	2419.64	4731.05	6545.70
	Model 3	1882.10	2351.59	4212.73	5605.93
	% Imprv.	1.52%	2.89%	12.30%	16.76%

5 Conclusion

This paper proposes an extension to a previous work in [3], where an online vehicle routing problem with dynamic perturbations to the travel times is addressed. The positive impact of vehicle position tracking devices on solution quality was demonstrated for this type of problem. Also, the results indicate that a reassignment action should be considered as soon as a perturbation to the current plan is detected.

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