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Evaluation of Alternative Paths for Reliable Routing in City Logistics

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Abstract

Due to varying traffic volumes and limited traffic infrastructure in urban areas, travel times are uncertain and differ during the day. In this environment, city logistics service providers (CLSP) have to fulfill deliveries in a cost-efficient and reliable manner. To ensure cost-efficient routing while satisfying promised delivery dates, information on the expected travel times between customers needs to be considered appropriately.
Typically, vehicle routing is based on information from shortest paths between customers, to determine the cost-minimal sequence of customer visits. This information is usually precomputed using shortest path algorithms. Most approaches merely consider a single (shortest) path, based on a single cost value (e.g., distance or average travel time). To incorporate information on travel time variation, it might be of value to consider alternative paths and more sophisticated travel time models such as Interval Travel Times (ITT).
In this work, we investigate the incorporation of alternative paths into city logistics vehicle routing. For this purpose, we compare our approach to classical shortest path approaches within a vehicle routing problem. Our approach considers a set of alternative paths and incorporates ITT. Experiments are conducted within an exemplary city logistics setting. Computational results show that the consideration of alternative paths allows to select better paths with regard to a trade-off between efficiency and reliability when travel times are varying.

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Keywords: reliability; travel time information; shortest path; alternative path; routing; city logistics;

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1. Introduction

Today, customers expect fast and reliable services, e.g., delivery at promised delivery times. Due to varying traffic volumes and limited traffic infrastructure in urban areas, travel times are generally uncertain and differ during the day, though. In this environment, city logistics service providers (CLSP) aim to fulfill deliveries in a cost-efficient and reliable way. To ensure cost-efficient routing while satisfying promised delivery dates, information on the variation of travel times between customers must be integrated in the planning of delivery tours.

Currently available telematics technologies offer opportunities to derive different types of travel time information from empirical real world data, e.g. Floating Car Data (FCD). When determining travel times from real-world data, this data is provided by means of a detailed digital roadmap which models the road network on a street level. Shortest path algorithms need to be applied to aggregate this information to a customer-to-customer edge level in order to make it accessible for vehicle routing algorithms. For the remainder of this paper, we refer to street level representation as “digital roadmap” and to the customer-to-customer edge level as “customer graph”.

Most approaches merely consider a single (shortest) path, based on a single cost value (e.g., distance or average travel time). These approaches do not allow to exploit available information on travel time variation as information is lost in the simple aggregation process. In order to consider travel time variation in the vehicle routing optimization we consider two major components: (1) a travel time information model that is suitable for providing information on travel time variations, and (2) the computation and evaluation of alternative paths that represent a customer graph with as little loss of information as possible.

The prevailing approach in vehicle routing is to consider *deterministic travel time information models*. Deterministic travel times represent a rough estimation of expected travel times, by aggregating all travel time observations to a single value, e.g., the average. Thus, only very limit information on the evolution and variation of real-world travel times is provided (Eglese et al., 2006). By considering time-dependency, a gain in accuracy is possible (Ehmke, 2014). However, deterministic models do not explicitly model the variation of travel times.

To provide a continuous representation of travel variation, *stochastic travel time information models* could be used. In form of probability distributions, information such as the mean value and the variance of travel times can be extracted. However, when selecting and aggregating of representative travel time distribution several problems arise (Gómez et al., 2015). Further, it remains controversial if any appropriate distribution exists that both representatively models the true nature of urban travel and is manageable for practical application at the same time.

Therefore, we consider the *quasi-stochastic information models*, e.g., Interval Travel Times (ITT). ITT are able to capture the variation of travel time while avoiding the overhead of stochastic information models. Further, no assumption on the distribution of travel times are required as well as the aggregation can be achieved with low effort. Thus, ITT is a more practical and suitable representation of travel time variation. (Groß et al., 2016)

In this work, we investigate the incorporation of information on travel time variation into city logistics vehicle routing. A step by step process is proposed, which describes the derivation of ITT, the aggregation of a digital road map to a customer graph and the final vehicle routing optimization. Within this process, we investigate approaches to derive alternative paths. Then we evaluate alternative paths in combination with ITT.

Experiments are conducted within an exemplary city logistics setting. Different path models are considered within the vehicle routing optimization. The vehicle routing tours are then evaluated to investigate the additional value of incorporating alternative paths and a more complex travel time model.

2. Considering Travel Time Variation in City Logistics Vehicle Routing

In this chapter, we discuss how to use information on travel time variation in city logistics routing. The proposed steps are depicted in Figure 1. The large blue box represents the task to be fulfilled in this step. The inner small box describes the methods required to fulfill the corresponding task. The large arrow indicates the information model that results as an output of the step. The dotted box comprises the current step of the process while at the bottom of the box the information that should be gained is displayed.

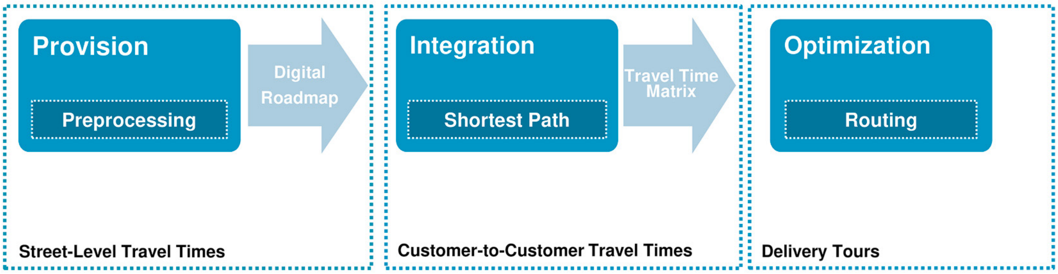

Fig. 1. Consideration of information on travel time variation in city logistics routing

The first step is concerned with the **provision** of travel times using preprocessing techniques. Besides plausibility checks and the removal of outliers a major task is the decision on an appropriate travel time information model to transform or aggregate the set of travel time observations. After the first step an enhanced digital map of the road network is available containing travel time information in the form of the chosen model for every street segment.

City logistics routing is commonly based on routing algorithms that require an abstract representation of customers, depots, and their relationships. Therefore, the second step achieves the **integration** of the travel information model into a representation that is feasible for the routing algorithm. As described in the previous section, this is usually done by using shortest path algorithms to derive customer-to-customer travel times represented by a distance or travel time matrix. However, suitable shortest path algorithms should be chosen or adapted to avoid a loss of information.

The third step deals with the **optimization** of delivery tours within a vehicle routing problem. Here the travel time information from the prior steps is utilized. Like the second step the solution methods utilized have to be chosen according to the travel time information provided.

In the following, we instantiate the three aforementioned stages according to our approach.

2.1. Provision: Determination of Interval Travel Times

To provide information on the variation of travel times we choose the so far less studied Interval Travel Times (ITT). ITT are able to represent the minimum and maximum expected travel times for a street segment as well as the respective variation by the gap between minimum and maximum travel time.

For the determination of ITT an arbitrary road network can be considered. For every street segment, related travel time observations have to be available. As parameters for the derivation of ITT lower and upper bounds must be chosen, e.g., the 5% and 95% quantiles of the travel times available for every street segment. Focusing on quantiles allows to exclude extreme cases of travel times, which do not represent the typical traffic behavior related to the street segment.

In real-world applications travel time observations could be gathered based on GPS technology implemented in the vehicles of the delivery fleet. Further, the quantiles can be adjusted to the preferences of the fleet dispatcher.

2.2. Integration: Alternative Paths for Vehicle Routing

The aggregation of the digital roadmap to the customer graph is usually done by shortest path algorithms such as Dijkstra's algorithm (Dijkstra, 1959). Additionally, several speed-up techniques exist to allow fast computation for large road networks (Bast et al., 2016).

When calculating customer-to-customer routes for delivery purposes, most approaches merely consider a single (shortest) path based on a single cost value (e.g., distance or average travel time). Thus, disregarding the variation of travel times (e.g., due to congestion). To incorporate information on travel time variation, it might be of value to consider alternative paths.

To determine a set of alternative paths *k-Shortest-Path* (KSP) (Yen, 1971) can be considered. The parameter k specifies the number of alternative paths to be computed. Using a sufficiently high number of k delivers paths that significantly differ from the initial path. Another approach comes from the field of multi-criteria optimization (Martins, 1984). By considering multiple edge costs like distance and travel time *Pareto-optimal paths* can be obtained. A path is called Pareto-optimal if there is no other path which is better with respect to both cost functions. *Penalty algorithms* (Chen et al., 2007) provide alternative paths by iteratively calculating shortest paths while increasing certain edge weights with each iteration.

To find efficient and reliable paths, alternative paths can be derived by choosing any of the stated shortest path algorithms and a corresponding travel time information model that captures travel time variation. However, implementing few of the aforementioned algorithms would not be straightforward; using Pareto-optimal paths would require additional decisions on the choice from the set of paths derived. Penalty algorithms would require some sophisticated penalty mechanism to find efficient and reliable paths. To avoid these additional processing stages, we use a KSP-based approach.

To evaluate the obtained set of alternative we consider ITT. This approach captures both efficiency and reliability, while avoiding additional overhead as explained before.

2.2.1. Integration: Robust Shortest Path with Interval Travel Times

To combine ITT with the KSP approach, we adapt the robust shortest path problem with interval data which has been studied in literature by (Karasan et al., 2001) and (Montemanni and Gambardella, 2004).

To formally describe the digital roadmap with ITT, we consider a graph $G = (V, E)$ to be a directed graph where V is a vertex set of locations $\{v_0, \dots, v_n\}$. E is the set of edges $\{(i, j) \mid i, j \in V, i \neq j\}$ representing street segments that are connecting different locations. For each edge e_{ij}, an interval travel time $[l_{ij}, u_{ij}]$ exists whereby $l_{ij} \leq u_{ij}$ applies. The value l_{ij} describes the minimum expected travel time, and u_{ij} represents the maximum expected travel time for the traversal of the corresponding edge.

The realization of edge travel times is represented by a scenario $r \in S$. For a scenario r, a travel time is chosen by $c_{ij}^r \in [l_{ij}, u_{ij}]$ for every edge. The objective is to find an efficient and reliable path. This objective can be achieved by applying the *robust deviation criterion* from the domain of robust optimization in combination with a *minmax strategy*. The found path minimizes the path travel time in the worst-case scenario while the corresponding alternative paths at best their best-case travel times do not deviate by a large value. In other words, (1) the absolute travel time u_{ij} minimized (2) in balance with the corresponding time variation $u_{ij} - l_{ij}$ is considered. Therefore, information provided by the ITT model is utilized to derive shortest paths between customers that are both (1) efficient and (2) reliable.

The *minmax regret approach* further allows us to reduce the complexity of the shortest path problem. (Karasan et al., 2001) show that the number of scenarios can be reduced to a finite number scenarios, which is the set of possible paths in the graph. We represent this subset of scenarios with the set R. To form a scenario $r \in R$, an arbitrary path in the Graph G is chosen. We call such a path "candidate path" $cand^r$. Based on the edges used by $cand^r$, the travel times of all edges in the scenario r are determined such that: All edges $e \in cand^r$ are weighted with their maximum travel time value ($c_{ij}^r = l_{ij}$), and all edges $e \notin cand^r$ are weighted with their minimum travel time value ($c_{ij}^r = u_{ij}$).

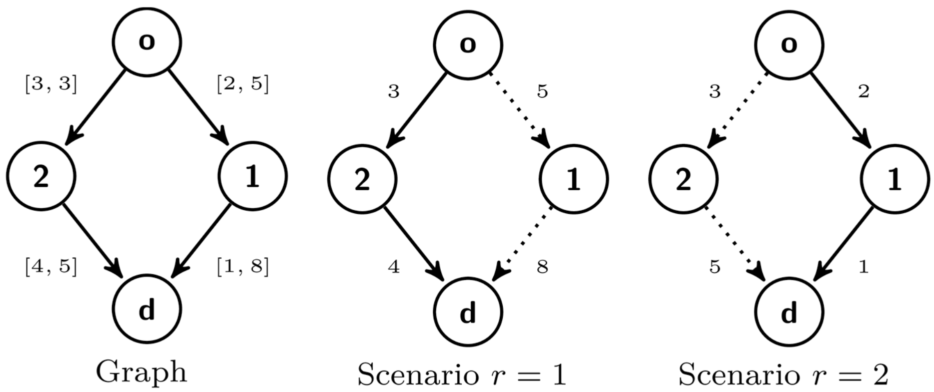

Fig. 2. Example graph and scenarios with candidate paths

In the following we describe within a small example how the maximum regret of a candidate path is derived. Illustrated in Figure 2 (left), the basic graph with its ITT is shown. For this graph two scenarios $r = 1, 2$ can be derived, which are displayed in the upper middle and upper right side of figure 2. The dotted lines correspond to the respective candidate path of the scenario. For the two scenario graphs the edges of the candidate path realize the maximum travel time, i.e., u_{ij} of the ITT. All other edges realize their lowest travel times, i.e., l_{ij} of the ITT.

Table 1 contains the scenario number as well as the corresponding travel time of the candidate tour and the travel time of the shortest path. In the last row, the maximum regret of the candidate tour is presented.

For scenario $r = 1$ the candidate path uses edge e_{o1} and e_{1d} according to the dotted lines, with a total path travel time of 13. The shortest path consists of edges e_{o2} and e_{2d} and yields a total travel time of 7. It is worth noticing that in a more complex case the shortest path could use some edges even if they are at their upper bound travel time if this is beneficial for the total path travel time. The maximum regret of the candidate path can now be determined by calculating the difference of the candidate paths travel times and the shortest path travel time in the scenario. We obtain a maximum regret of $13 - 7 = 6$.

For scenario $r = 2$ the maximum regret can be determined in the same way. Finally, the robust shortest path can be determined by choosing the minimum of the maximum regret values. For our example this is the maximum regret of 5 in scenario $r = 2$. Therefore, the candidate path of scenario $r = 2$ is chosen as the robust shortest path.

Table 1. Exemplary computation of minmax regret

Scenario r	1	2
Travel time of candidate path	13	8
Travel time of shortest path	7	3
Maximum regret of candidate path	6	**5**

To generate candidate paths within a full road network, we use the KSP approach proposed by (Yen, 1971). The choice of k also determines the number of candidate paths we have to evaluate. After calculating the maximum regret for the k candidate paths we choose the path that has the smallest maximum regret value.

2.3. Optimization: Vehicle Routing with Alternative Paths

We model the vehicle routing problem as a capacitated vehicle routing problem (Irnich et al., 2014). The objective is to find a delivery tour that minimizes the total tour duration.

For sake of simplicity, standard travel times are used in the vehicle routing optimization but based on the derived robust shortest path. As the travel time variation is explicitly considered within the robust shortest path the general effects should be recognizable. We are aware of the possibility to adapt to a robust vehicle routing problem, but due to space constraints we can't achieve a sufficient explanation of such an extension.

The corresponding customer graph can be described as follows. Let $G = (V, E)$ be a complete, undirected graph where V is a vertex set of locations $\{v_0, \dots, v_n\}$. Vertex v_o represents the depot, the vertices $v_1, \dots, v_n$ represent the customers to be visited by means of a delivery tour. E is the set of edges $\{(i, j) \mid i, j \in V, i \neq j\}$ connecting the customers. Each edge e_{ij} is associated with a travel time from customer i to customer j from a given travel time matrix $m \in M$where M is the set of available travel time matrices. The travel time matrices are derived from the corresponding costs of the shortest path and its travel time model. The capacity parameter k determines how many customers a single vehicle can serve. If the number of customers exceeds k an additional vehicle has to be deployed. The model does not include service times or demand variations.

As solution method, we propose a metaheuristic including the well-known savings algorithm (Clarke and Wright, 1964) and the tabu-based neighborhood search approach (Glover and Laguna, 1997). The initial solution is generated by melting pendulum tours with regard to the capacity. Then neighboring solutions are generated using a relocate operator based on destroy and repair strategies using a one-point-move. In particular, the current solution is destroyed by removing a customer from a particular tour. Then, the solution is repaired by inserting the customer back into another tour at the lowest cost. The new solution is accepted if it is feasible. The fitness of the new solutions is determined by the total duration of all tours. If a new solution has a lower total duration then the best known solution it becomes the new best solution.

As a criterion for efficiency and reliability we consider the case of self-imposed time windows (Jabali et al., 2013). A time-window for the arrival time of the delivery vehicle is set based on the planed arrival at each customer a time window range. If a vehicle arrives early, it has to wait for the time window to open. If a customer is served late, this counts as violation of the time window. However, time window compliance is not a hard constraint. Early arrivals are penalized by additional total tour duration due to waiting. Late arrivals are not penalized within the optimization but are evaluated later with regard to the reliability of the tours.

3. Case Study

To demonstrate the effect of including information on travel time variation by means of alternative paths we develop an exemplary city logistics instance. We then determine customer-to-customer shortest path based on ITT and two deterministic travel time models. The customer-to-customer shortest paths are utilized in the vehicle routing as travel time matrices. The resulting delivery tours are evaluated by simulation regarding their efficiency and reliability.

3.1. Instance

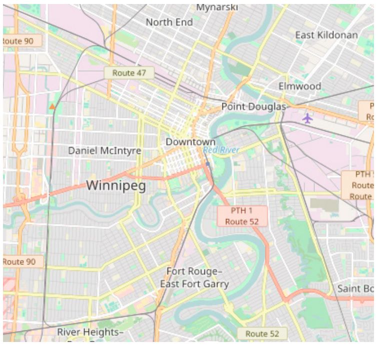

Fig. 3. Exemplary snapshot of the Winnipeg road network (OpenStreetMaps, 2017)

The exemplary instance is based on the road network of Winnipeg, Canada (INRO, 1999). As illustrated in Figure 3, Winnipeg has a mono-centric structure with a central core downtown and several adjacent districts. The traffic network includes several arterial roads as well as a dense structure of smaller roads. This allows us to consider several alternative paths between two specific origin and destination locations.

We derive 30 customer locations uniformly distributed over the city. The demand of all customers is considered equal (e.g., a parcel). The depot is located centrally near the center of the city, south of the downtown district. A single delivery vehicle can serve up to 15 respectively 30 customers. The self-imposed time window length is 10 minutes.

Due to the lack of suitable real-world data, we use a traffic assignment approach to derive link-based travel times. First we need to find the equilibrium flow pattern in the network, also known as traffic assignment (Sheffi, 1985). To this end, we need a demand matrix, representing the demand for travels for each origin and destination in the network. In our case study, we used four demand matrices: two represent the morning and the rush-hour afternoon demand and the other two represents the non-rush our demand. In addition we use information regarding the network itself: the capacity and the free flow travel time on each link. After performing the traffic assignment, we could retrieve both link-based traffic flows and link-based travel time data.

Based on the highest and lowest travel times we derive our ITT bounds. Additionally, we consider two deterministic travel time models. The worst-case travel times are derived by the upper bounds of the ITT. The average travel times are calculated by the center of the ITT.

We then obtain three travel time matrices according to the customer locations: (1) using the robust shortest path approach with ITT ("robust"), (2) using a regular Dijkstra's algorithm with worst-case travel times ("worst-case") and

(3) a regular Dijkstra's algorithm with average travel times ("standard"). The travel time matrices are then used by the vehicle routing approach (section 2.3) to derive suitable delivery tours.

All methods are implemented in JAVA and computations were conducted on a regular desktop machine with a 3.2 GHz i5-3470 and 8 GB RAM. The traffic assignment was implemented in MATLAB and run on a 3.2 GHz i5-3470 and 8 GB RAM (INRO, 1999).

3.2. Evaluation Results

We evaluate the vehicle routing solutions by simulation. Therefore, we sample travel times from the BURR Type-12 distribution (Susilawati et al., 2013) which should be a suitable approximation of urban travel times. We used our ITT bounds to analytically derive the parameters for the distribution for every edge. This was done by solving non-linear equations based on the percentile functions of the distribution. One realization of the network is computed by sampling each edge travel time once. One evaluation run represents a concrete realization of travel times. Every solution is evaluated by 500 simulations.

Table 2. Evaluation results for vehicle routing with different travel time matrices. Average over 500 simulations.

Number of vehicles	Travel time matrix	Avg. total travel time in minutes	σ_{TT} in minutes	Average number of violations	$\sigma_{violations}$
	Standard	174.3	4.8	11.7	10.8
1	Worst-case	186.6	3.6	5.3	9.5
	Robust	182.1	3.8	5.3	8.0
	Standard	253.0	4.7	3.2	5.1
2	Worst-case	263.7	4.8	2.1	6.2
	Robust	261.2	3.7	1.6	4.0

Table 3 illustrates the effects of using different shortest paths for the vehicle routing. The first column depicts the number of vehicles used. The second column represents the travel time matrix that was derived by the respective shortest path approach. The third column shows the average total travel of the delivery tours. We consider this as the criterion for the efficiency of the delivery tours. In the fifth column the average number of violations of the self-imposed time window is depicted. Column four and six contain the standard deviation of the total travel times and the time-window violations.

For the one vehicle case, using the standard travel time matrix the vehicle tours achieve a relatively low level of total travel time. In comparison, using the worst-case travel time matrix the duration of the vehicle tours is relatively high. The robust approach achieves a total travel time higher than standard but lower than the worst-case travel times approach. With regard to the violations of the time window the using the standard travel time matrix a high number of violations occurs. For the other two travel time matrices the number of violations is much lower and relatively similar.

Using more vehicles increases the total travel time of all tours and the same relations as with one vehicle can be observed. Due to the individual tours serving less customers the number of violations is reduced as lateness is less likely to build up to a critical point.

3.3. Discussion

From these results, the effect of considering of travel time variation is visible. For the standard travel time matrix, the lower level of total travel time is achieved by focusing on total travel time as objective. However, paths are taken that are affected by relatively high variation of travel times. This also leads to poor estimates for the planned arrival time, causing a large number of violations. Using the worst-case travel time matrix leads to a more pessimistic path choice, resulting in longer travel times. This pessimistic estimate also leads to a lower number of violations. However, even this pessimistic approach is not appropriate as travel time variability is not explicitly considered. Therefore, also these paths are prone to variations.

The robust travel time matrix succeeds in considering travel time variation properly. Paths can be chosen more efficiently as with the worst-case travel time matrix and more reliable as with the standard travel time matrix. The robust approach balances the travel time accordingly to the variation. Therefore, a trade-off between total travel time and a lower number violations can be achieved as paths are less prone to variations.

We are aware that the results are limited for our instance and have to be further validated by improved modelling and more realistic instances with higher travel time variability. However, we could observe the general effects of considering travel time variability by means of alternative paths. This also aligns with similar research results from a pure vehicle routing context (Groß et al., 2016).

4. Conclusion

Performing cost-efficient and reliable deliveries poses a major challenge to CLSP, due to the varying travel times in urban areas. In this work, we proposed a step by step process to consider travel time variation. A major component is the computation and evaluation of alternative paths. We identified the KSP as suitable approach to derive alternative paths. In combination with ITT we adapted to a robust shortest path approach. The derived paths were used to consider travel time variation within the vehicle routing optimization.

The influence of incorporating travel time variation within city logistics routing was examined by means of alternatives path in an exemplary city logistics setting. Here, providing alternative paths with ITT leads to a trade-off between cost-efficiency and reliability of vehicle tours.

Future research will consider a more realistic test network to better reflect city logistics properties incorporate more realistic travel time variations. Real world data should be considered to derive ITT and specify suitable parameters for the ITT bounds. Additionally, different alternative path approaches will be considered and compared to current approach. Further, we will consider the case of explicitly using ITT in the vehicle routing approach.

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