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Vehicle routing for attended home delivery in city logistics

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Abstract

Cost-efficient and sustainable delivery of e-commerce products results in enormous challenges for city logistics service providers. We focus on the last mile of delivery in terms of reliable and efficient vehicle routing approaches. In recent years, telematics based traffic data collection has built the ground for time-dependent vehicle routing, which supports the fulfillment of customer promises as well as economic and sustainable delivery concepts. This becomes extremely important in Attended Home Delivery applications, requiring the presence of the customer during delivery. Based on Floating Car Data and Data Mining methods, we provide time-dependent travel time data sets and discuss the integration of time-dependent travel times in time-dependent vehicle routing models. A case study offers insights into effort and benefits of sophisticated travel time collection, data aggregation and time-dependent vehicle routing.

Keywords: Time-dependent vehicle routing; Attended Home Delivery; time-dependent travel times; last mile delivery

1. Introduction

In recent years, the ongoing success of online retail has promoted business models comprising direct delivery to consumers' homes. More and more e-commerce businesses compete against each other regarding price and service quality. Even fresh groceries can be ordered online on websites such as peapod.com. Digital outlets of brick-and-mortar shops complement their distribution channels by online shops. Forrester Forecast predicts that the share of online retail will continue to grow steadily [1].

From a consumer's point of view, online retail is associated with a number of benefits such as greater product choice, the ability to obtain goods not sold locally, better price comparison, etc. From a logistics

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point of view, however, the solution for delivery is very demanding. Efficient and reliable logistics are a key factor for the economic success of online shops, and shipping costs are one of the biggest concerns for online customers [2]. Especially the "not-at-home problem" has to be treated, which results from the delivery of goods requiring the presence of the customer. This leads to complex planning problems within the last leg in supply chains, i.e., the last mile to the consumer.

The last mile is currently regarded as one of the most expensive, least efficient and most polluting sections of the entire supply chain [3]. Increasing customer requirements exacerbate flexibility of delivery. In urban areas, traffic infrastructure is often used to capacity, resulting in traffic jams. City logistics service providers compete against other road user for the scarce traffic space, which cannot be extended unlimitedly. Defiance of varying infrastructure utilization may lead to lower service quality, higher pollution and higher realization costs of delivery [4][5].

Efficient and sustainable delivery solutions in urban areas are concluded by city logistics concepts. City logistics aims at the fast and reliable transportation of goods in terms of efficient and environmentally acceptable delivery tours. The complexity of planning operations in city logistics environments requires sophisticated planning systems setting up on quantitative optimization models. Common optimization models are based on static representations of the city road network. Network loads in urban areas, however, are highly fluctuant with respect to different network links and times of the day. For the most part, a single travel time value per network link, as provided by today's digital roadmaps, only insufficiently represents congestion in city traffic. Whereas static vehicle routing is well studied, the consideration of time dependency in vehicle routing models is still a field of potential research due to substantial efforts in data processing and complexity of time-dependent routing algorithms [6]. The provision and the integration of time-dependent travel time data sets into enhanced vehicle routing methods are rarely focused.

In this paper, we aim at the provision of time-dependent travel time data sets that can be incorporated in time-dependent vehicle routing models. We refer to recent technology in terms of telematics based travel time collection and advanced data processing in terms of Data Mining. Huge amounts of Floating Car Data (FCD), also known as probe vehicle data, provide time-dependent travel times representing typical traffic states. Data Mining methods allow for the consolidation of time-dependent travel times, focusing on time-dependent congestion in the evolution of city traffic. Planning of last mile delivery is made by time-dependent optimization. Here, travel time data sets are integrated into advanced vehicle routing models. Computational experiments based on huge amounts of FCD illustrate the effort for and the benefits of time-dependent vehicle routing with regard to costs and service quality of Attended Home Delivery applications.

2. Attended Home Delivery

In recent years, business models comprising home delivery services have staged a comeback. From an e-commerce point of view, home deliveries are the "logistics element of the fulfillment process within consumer e-commerce transactions, other remote purchases from mail order, direct selling and television shopping companies and deliveries from retail outlets" [7]. Online retail requires the cost-efficient and customer-oriented design of home deliveries. Most deliveries are of parcels and small packages, large items and food. Deliveries may be made to the consumer's home, to reception/delivery boxes, collection points, locker banks or alternative places defined by the consumer [3]. The functionality of home delivery is crucial for online shopping business models and a key factor to their economic success. A comprehensive overview on solutions for last mile delivery is given by Allen *et al.* [7].

For home deliveries, the crucial question is whether the addressee has to be present at the time of delivery. In Attended Home Delivery, customers must be present for delivery due to security reasons, goods being perishable, goods being physically large or because a service is performed [8]. Food deliveries, for example, usually take place on a pre-arranged day and within a given time window as corresponding products may deteriorate over time. Thus, consumers expect a choice of narrow, reliable time slots, which may lead to high costs of delivery [9]. Punakivi and Saranen, for example, found that transportation costs of Attended Home Deliveries based on 1-hour time slots are 2.7 times larger than unattended deliveries [10]. Examples for order processes in Attended Home Delivery can be discovered at e-grocers like Peapod (www.peapod.com) and Albert.nl (www.albert.nl). Peapod is one of the largest internet grocers in the U.S., whereas Albert.nl operates in the Netherlands [11].

The realization of last mile delivery is undertaken by city logistics service providers. They should consider time-dependent information on congestion in order to determine more reliable itineraries, alleviating unnecessary delays and emissions resulting from traffic jams. In recent years, however, only a few authors have come up with approaches for planning systems providing and utilizing such information:

- For city logistics applications, Fleischmann *et al.* design a traffic information system [6]. Flow and speed data are collected in a field test with stationary measurement facilities and specially equipped vehicles in the metropolitan area of Berlin, Germany. The data is then aggregated and utilized in savings and insertion heuristics. Here, the data collection methods used have surpassed by progress in technology.
- Eglese *et al.* refer to FCD for time-dependent routing in a supra-regional road network in the UK [4]. The FCD originate from a communication network consisting of trucks and coaches. Data is transmitted via text messages and stored as a "road timetable" in a central database. In city logistics, text messages are not appropriate for data collection.
- Van Woensel *et al.* consider queuing theory to provide time-dependent travel time estimates [12]. They refer to a tabu search approach to solve the time-dependent capacitated vehicle routing problem. Donati *et al.* implement an ant colony heuristic [13]. Both publications are more focused on large area networks.
- Taniguchi *et al.* incorporate varying travel times by investigation of a probabilistic vehicle routing model for city logistics [14]. Travel time distributions are derived from a dynamic traffic simulation model. They apply their framework within a small test network consisting of 25 nodes and 40 links. Computational experiments show that the consideration of time-varying travel times leads to a lower risk of delay and a reduction of CO_2 emissions.
- Ehmke *et al.* analyze huge amounts of FCD for the determination of traffic quality as well as typical traffic states in urban areas [15]. They introduce a "data chain" in order to describe the process of empirical traffic data collection and data analysis. Due to complex routing data sets, they cluster routing data while keeping a certain level of reliability in order to support planning of shortest routes.
- Maden *et al.* present a case study with regard to the distribution of goods by an electrical goods wholesaler [5]. They introduce a tabu search heuristic aiming at the minimization of time-dependent travel times. The algorithm is used to schedule a fleet of vehicles operating in the South West of the United Kingdom. The results of the corresponding case study show savings in CO_2 emissions of about 7% compared to planning methods based on constant speeds.

In the following, we refer to telematics based data collection in terms of FCD. First, the most important parts of the data collection and data analysis process are sketched. The approach by Ehmke *et al.* is extended by utilizing time-dependent travel time data sets in time-dependent vehicle routing models. Benefits of time-dependent travel times are revealed within a city logistics case study.

3. Provision of time-dependent travel times

Reliable vehicle routing in urban areas requires the consideration of information about typical traffic states. Information about recurring congestion in city traffic can be provided by time-dependent travel times. In contrast to average travel times or distances, time-dependent travel times allow for the anticipation of typical phenomena in urban traffic and hence result in more reliable delivery tours. Thus, consumer promises can be realized faster and more efficiently.

In the following, we rely on the source of FCD to develop and instantiate time-dependent travel time data sets. The FCD originate from a vehicular wireless communication network consisting of a fleet of vehicles equipped with a GPS device. From each vehicle, raw traffic data in terms of vehicle identification code, current position in the network and time of measurement is collected. An FCD record provides the travel time of a single vehicle being part of the current traffic flow. Given a fleet of taxis operating in a certain metropolitan area ("Taxi-FCD"), it is possible to collect huge amounts of speed data for most of the links of the traffic network considered. The resulting speed data is used for the description, the analysis and the visualization of average travel times. For the processing of the raw speed data, a general overview on Taxi-FCD and applications see [16] and [17]. In the context of travel time determination, FCD is supposed to enrich or substitute traditional sensor or census based traffic data [18][19].

In recent years, Taxi-FCD has become a popular data collection method, leading to the availability of huge amounts of empirical traffic data. We process historical FCD by means of a structured Data Mining process [15]. Here, incorrect or questionable travel time data is filtered, for example, in case of GPS shadowing effects or a link being only partly covered by a route. Empirical traffic data is amended by infrastructure data, i.e., a common digital roadmap. Single measurements are aggregated for planning and analysis purposes in terms of arithmetic means or medians (first level of aggregation). We refer to an aggregation in 24x7 time buckets, i.e., an average speed for each hour in each day of the week is derived. This voluminous data set is referred to as "FH data" (Floating Car Hourly averages).

FH data represents a data set which is so huge that more sophisticated consolidation is required. In particular, travel time variation is the most important attribute with regard to more reliable vehicle routing. Thus, a cluster analysis approach is applied in order to provide typical daily curves of speed variation, representing a more compact time-dependent travel time data set (second level of aggregation). Links are clustered into homogeneous groups according to their relative variation of daily speeds. To this end, the 24 FH values of a link per weekday are normalized by their mean travel time, representing the deviation from each link's average travel time. According to their daily speed variation, links are then clustered by the k-means algorithm [20].

An example result of clustering by k-means with $k = 6$ is given in Fig. 1, depicting typical city traffic patterns such as decreasing speeds during morning and evening rush hours at several levels of intensity. Each cluster represents a group of links in terms of 24 speed reduction factors (per weekday). Each link is associated with its groups' vector of 24 speed reduction factors, which are used for weighting link specific average speeds. This travel time data set is referred to as "FW data" (FCD Weighted Average).

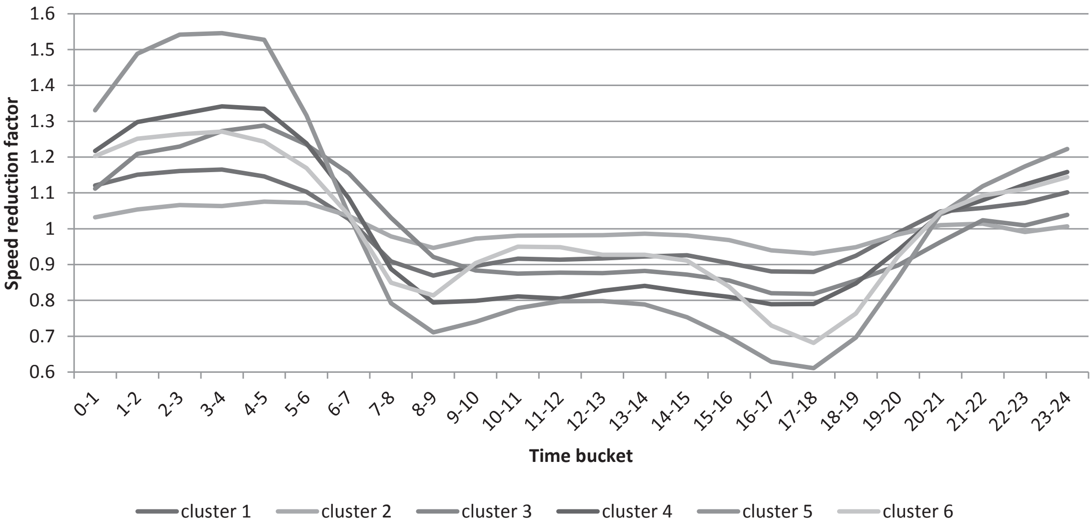

Fig. 1. Speed reduction factors for a typical working day (k = 6)

4. Time-dependent vehicle routing

The computation of time-dependent delivery tours requires the consideration of time-dependent travel times in enhanced optimization models. In the following, we introduce the Time-Dependent Vehicle Routing Problem (TDVRP) as the corresponding optimization model, which is capable of processing time-varying travel times. The TDVRP demands for time-dependent distance matrices denoting time-varying durations between customer locations in the course of the day. Based on FH and FW travel time data sets, we describe the extension of a common digital roadmap to a time-dependent topology that efficiently provides the desired time-dependent information.

4.1. Time-dependent topologies

TDVRP solution sets up on time-dependent distance matrices representing time-varying itineraries and durations between customer locations. In contrast to static VRP solution, time-dependent optimization requires the representation of time-varying costs for each edge. Time-dependent distance matrices result from shortest path computation based on a time-dependent topology of the road network. In the following, a time-dependent topology is designed, which is instantiated by FH and FW travel times. The efficiency of TDVRP solution is strongly related to the structure of the underlying topology, i.e., efforts required and solution quality depend on simplicity and accuracy of the time-dependent topology.

In the literature, discrete as well as continuous approaches for the modeling of time-dependent travel times exist [21]. We focus on a discrete approach that features piecewise linear travel time functions. Efficient computation of time-dependent shortest paths requires a network topology ensuring “First In, First Out” (FIFO) behavior. In FIFO consistent networks, vehicles are not able to “pass” each other, i.e., vehicles arrive in the order they commence an edge (“non-passing condition” [22][23]). FIFO networks support time-dependent shortest path computation in terms of a trivially-modified variant of any label setting or label correcting shortest path algorithm like Dijkstra’s algorithm [24]. This is due to the following properties, leading to a reduced complexity of the time-dependent topology [21]: In FIFO networks,

- waiting at nodes delays arrival.
- one always finds shortest paths which are acyclic.
- one always finds shortest paths whose sub paths are also shortest paths.

FH and FW travel time data sets lead to piecewise-linear travel time functions, possibly ignoring the FIFO condition. The FIFO condition may be violated if an interval of a rather long travel time is followed by an interval of a rather short travel time. Thus, the travel time function "jumps" between the two intervals, and passing may occur. Fleischmann *et al.* solve this problem by a smoothed travel time function that transforms non-FIFO travel time functions into FIFO consistent travel time functions [6]. Here, the jump between two intervals is linearized.

In Figure 2, the derivation of travel times τ_{li} from average speeds v_{li} is illustrated for an example link l. $v_l(t)$ depicts a speed function resulting from FH or FW data, whereas $\tau_l(t)$ depicts the corresponding travel time function. Function values depend on the starting time t. The travel time function $\tau_l(t)$ features several jumps at z_i. At z_1, for example, the speed changes from a relatively low level to relatively high level, inducing a rather long or rather short travel time, respectively. This change is not FIFO valid; a vehicle starting shortly before z_1 would be passed by a vehicle starting shortly after z_1. Fleischmann *et al.* handle those jumps by linearizing the travel time function in the range $[z_i - \delta_{li}; z_i + \delta_{li}]$. δ_{li} determines the corresponding slope $-s_0$, which is not allowed to become larger than $s = 1$, assuring the FIFO condition. In case of increasing travel times, the slope can be chosen freely (here: $\delta_{li} = 1$).

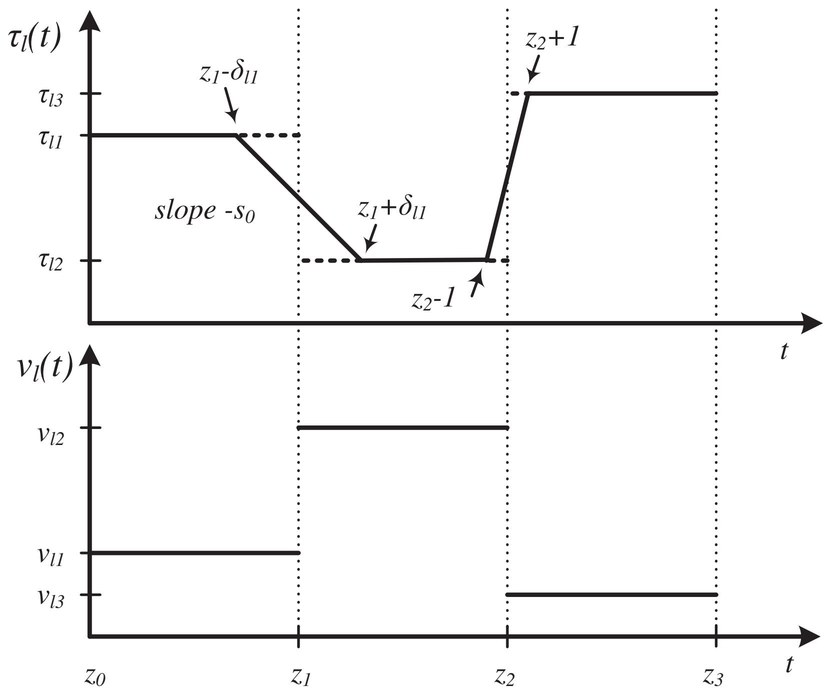

Fig. 2. Derivation of a FIFO consistent travel time function

FIFO consistent, time-dependent topologies allow for the efficient derivation of time-dependent distance matrices. However, TDVRP solution requires an individual shortest path for every possible departure time, leading to a potentially large number of required distance matrices. In order to limit the computational burden, we follow Maden *et al*. [5] and compute shortest paths for departures on every full quarter-hour only, resulting in 672 distance matrices for the entire week.

4.2. Time-Dependent Vehicle Routing

The TDVRP enhances the well-known Vehicle Routing Problem (VRP), which considers distances or travel times between customers to be a single constant. However, ignorance of time dependency might lead to a suboptimal solution with a different route structure and a different number of vehicles needed than would result from the time-dependent optimal solution [25]. The degree of infeasibility increases with the increase of the degree of time dependency. The static solutions, even if they might seem to be better, are usually infeasible, and even if the static solutions are feasible, they are often suboptimal [13]. Although the VRP is one of the most investigated optimization problems, literature on the TDVRP variant is still rather scarce. On the one hand, adequate travel time data has not been available in the past, which is recently changing due to ongoing advances in telematics. On the other hand, the TDVRP is harder to model and harder to solve than the VRP, because a time-dependent topology is required and because well-known principles of static problem solution do not hold [23].

The TDVRP can be defined as follows: Let $G = (V, E, C)$ be a complete, directed, evaluated graph consisting of vertices $V = \{0,1,\dots,n\}$ and edges $E = \{(i,j) | i,j \in V, i \neq j\}$. Vertex v_0 represents the depot, whereas remaining vertices represent customers. A time-dependent travel time matrix $C(t)$ represents the costs $c_{ij}(t)$ that arise when travelling from customer node v_i to customer v_j using the corresponding edge at time t. The entries of $C(t)$ denote time-dependent costs in terms of time-dependent travel times; once the time bucket during which a link is traversed is known, the travel time for this link is a known constant [25]. In sum, the TDVRP aims at the determination of the optimal tour plan where (1) every tour is starting at the depot at a given time T_0 and is terminating there at the end of the tour, (2) every customer is visited exactly once by one vehicle, (3) the number of tours as well as total travel time is minimized. A mathematical formulation of the TDVRP can be found in [26].

TDVRPs of practical size are usually solved by heuristics, which require the efficient evaluation of neighborhood moves. Here, a local neighborhood move involving deliveries near the origin of a route could have a significant effect on the timings later on. This makes it more difficult to determine the effect of a neighborhood move with respect to the goal of the optimization. The well-known Savings algorithm [27], for example, is in its pure form not suited for the determination of TDVRP solutions, although it is very successful in the case of static VRP solution. The Savings algorithm works with a precomputed list of savings that result from the “merger” of pendulum tours. This principle becomes questionable in time-dependent contexts, since the actual saving depends on the time of the day, which on the other hand determines the Savings value itself. More details on TDVRP heuristics can be found in [4], [6], [12], [23], [25], [28], [29] and [30].

In the following case study, we refer to a recent solution approach by Maden *et al*. [5]. They utilize a tabu search approach which improves an initial solution determined by a sequential insertion heuristic by Solomon [31] and a subsequent parallel insertion heuristic by Potvin and Rousseau [32].

5. City logistics case study

A case study for the urban area of Stuttgart, Germany, illustrates benefits and efforts of time-dependent travel times for vehicle routing. The case study is based on an optimization framework which is capable of utilizing FH and FW travel time data in a time-dependent vehicle routing heuristic. Computational experiments are conducted for a fictitious city logistics service provider that serves 50 randomly chosen consumers by several vehicles. The depot is located within a commercial area in the suburbs. Half of the consumers are located within the inner city or within outer boroughs, respectively. Consumer service time is 10 minutes; the maximum tour duration is fixed to 4 hours.

Tour plans are computed based on FW travel time data resulting from FCD which has been collected by the German Aerospace Centre (DLR) in the years 2003-2005. Raw data amount up to 230 million FCD and refer to an area of 35x35 km² and about 100 000 links, respectively. For computational experiments, we limit the area of investigation to the city of Stuttgart. Here, the most FCD measurements have been raised. Links within this area are featured by high standard deviations of speed measurements, implicating the necessity of time-dependent vehicle routing. Empirically collected FCD has been analysed and aggregated as described above. Aggregated speed data has been transformed into FW data sets, which are used for the determination of time-dependent distance matrices.

In Table 1, figures of computational effort for time-dependent routing applications are summarized. For a comparison of the travel time data sets from an algorithmic point of view, we point out the resulting input data per link for the relevant extract of the road network in the core city of Stuttgart. In case of static roadmap travel times, effort is rather low, but time-dependent optimization is not supported. Aggregation of empirical traffic data in terms of FCD leads to a voluminous FH data set, facilitating time-dependent planning by 168 travel time values per network link. FW data contrasts FH data in terms of a very compact time-dependent travel time data set, decreasing the required input data for optimization in volume of 96%.

Table 1. Comparison of the required volume of input data regarding different travel time data sets

Data set	roadmap travel times	FCD hourly averages (FH)	FCD weighted averages (FW)
Input data	n	$t \times d \times n$	$(n + (t \times k)) \times d$
Input data Stuttgart ($t = 24$, $d = 7$, $n = 6832$, $k = 6$)	6 832	1 147 776	48 832
Input data Stuttgart per link	1	168	7.1
Time-dependent routing	No	Yes	Yes

n = number of links, t = number of time buckets per day, d = number of days, k = number of clusters

In order to demonstrate the impact of time dependency, time-dependent vehicle routing is conducted in terms of 7x24 tour plans. In particular, the departure time at the depot is varied in 1-hour steps beginning with Monday, 00:00. Results are illustrated in Fig. 3. Individual days of the week are denoted by grey shadowing. Overall travel times are shown in terms of a black solid curve, depending on the specific departure time at the depot. The required number of vehicles for the delivery to all 50 consumers within a 4 hour time slot is denoted by a solid, grey line. Overall distances travelled are shown in terms of the dotted curve.

Depending on the departure time at the depot, temporal variations in overall travel times are clearly visible. Durations of tours vary between 159 minutes (departure Thursday, 1:00, 108 kilometres driven) and 283 minutes (departure Wednesday, 15:00, 143 kilometres driven). As far as deliveries can be completed during the night, i.e., in times of “free flow” traffic, overall travel times are relatively low (about 150-200 minutes), resulting in a requirement of 3 vehicles only. However, as soon as the execution of tours comes in touch with morning and afternoon rush hours, overall travel times increase a lot to up to 250 minutes, which is accompanied by increasing demand for transportation resources in terms of 4 vehicles. At weekends, temporal variations are not that distinct as during working days. Overall kilometres driven vary between 100 and 150 km, following the evolution of travel times.

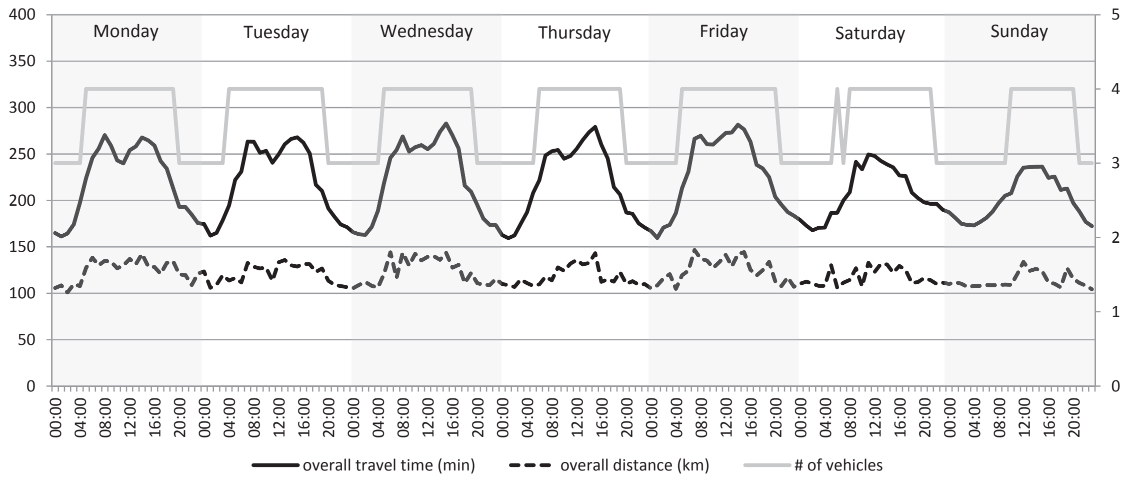

Fig. 3. Overall travel times, distances and number of vehicles required

As a benchmark, the solution of a static VRP based on an average speed per link and the same set of consumers would result in a travel time estimation of 197 minutes and 104 kilometres driven, leading to a constant requirement of 4 vehicles. This corresponds to an overestimation of travel times of 24% and an underestimation of 44% at the maximum, respectively. The static benchmark thus underlines the importance of time-dependent vehicle routing with regard to consumer satisfaction as well as to economic and environmental goals of city logistics concepts.

6. Conclusion

Cost-efficient as well as consumer-oriented delivery of e-commerce products results in enormous challenges for city logistics service providers. In this paper, prerequisites for the improvement of planning procedures have been discussed with regard to the fulfillment of consumer promises as well as economic meaningful delivery concepts. Telematics based data collection and sophisticated analysis of travel time data allow for the determination of compact travel time data sets, which represent typical phenomena of urban traffic flows. In particular, the focus has been on the modelling of time-dependent topologies based on FCD being available city-wide. An optimization framework has been presented, comprising time-dependent distance matrices and a state-of-the-art TDVRP heuristic. The framework has been used for the demonstration of advantages of time-dependent vehicle routing in terms of more reliable and cost-efficient delivery tours.

In the future, the optimization framework will be enhanced regarding predefined customer time windows (VRPTW). Here, the impact of the variation of time-dependent travel times on the reliability of customer time windows will be investigated. Furthermore, structural quality of resulting tour plans will be examined with regard to the reliability of chosen routes as well as to the adaptability of heuristics to time-varying input data.

Although time-dependent vehicle routing may lead to more reliable travel time anticipation, the impact on overall city traffic and overall emissions remains an open question. On the one hand, time-dependent travel times might reduce costs of city logistics providers due to decreasing overtimes and consumer dissatisfaction. On the other hand, increasing reliability of Attended Home Delivery might lead to a further increase of online retail share, reducing customers' trips to shopping centres. Thus, investigations on the overall impact on sustainable and environment-friendly delivery will have to be explored furthermore.

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