

DATA ALLOCATION AND APPLICATION FOR TIME-DEPENDENT DELIVERY IN URBAN AREAS

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ABSTRACT

In this paper, we discuss the planning and the realization of last-mile delivery in urban areas. Two main prerequisites are identified in order to increase service quality in attended home delivery. First, empirical traffic data has to be collected and analyzed, and second, this raw data has to be converted into time-dependent data sets for route planning. Thus, an optimization framework is designed, integrating telematics based data collection by Floating Car Data (FCD), data allocation by Data Mining and the modelling of the time-dependent road network typology. The data sets provided are utilized in time-dependent vehicle routing heuristics, considering customer time slots. We compare the data sets regarding usefulness for time-dependent delivery in terms of a real data example in city logistics. The resulting itineraries are expected to meet the customers' requirements regarding reliability and service quality of deliveries, keeping logistics service costs at a minimum.

Keywords: Time-Dependent, Traveling Salesman Problem, Attended Home Delivery, Floating Car Data, Vehicle Routing, City Logistics, Information System

1 INTRODUCTION

More and more e-commerce businesses compete against each other regarding price and service quality. Fast and reliable delivery of goods is a crucial part of service quality. E-commerce businesses have to ensure an efficient and effective "last-mile" delivery in order to meet customers' requirements while keeping delivery costs low (Agatz et al. (2008a)). Thus, planning and realization of customer-oriented delivery is a challenging task. Especially e-commerce businesses comprising attended home delivery are confronted with complex tactical and operational planning problems, since customers must be present when their order is delivered. On the one hand, customers expect a choice of narrow delivery time slots. On the other hand, time slots confirmed have to be realised on time within cost-efficient delivery tours.

In this paper, we focus the planning and the realization of last-mile delivery in urban areas. We refer to the field of city logistics, which comprises concepts for fast and reliable transportation of goods in terms of efficient and environmentally acceptable pickup and delivery tours. Logistics service providers have to consider service quality within their logistics planning processes, e.g., shorter delivery time, higher schedule reliability and delivery flexibility (Windt and Hülsmann (2007)). In urban areas, logistics service providers compete against other road users for the scarce traffic space. Here, traffic infrastructure is often used to capacity, resulting in traffic jams. This leads to lower service quality and higher costs for logistics service providers (Eglese et al. (2006)).

There are two main prerequisites for the incorporation of service quality into planning processes: the availability of adequate planning data and the integration of this data into advanced planning methods. Planning data can be extracted from historical traffic data. Recently, such data is available from telematics based data sources in large extents. Since realistic travel times are one of the most crucial factors for the quality of route planning, raw telematics based traffic data must be converted into time-dependent planning data. Average travel times provide information for time-dependent delivery in terms of vehicle routing problems.

Common vehicle routing approaches are based on static networks, i.e. on static distance or travel time matrices. However, network loads in urban areas are highly fluctuant with respect to different network links and times of the day. Hence, city logistics routing cannot rely on static travel times. For the most part, a single travel time value per link, as provided by today's digital roadmaps, only insufficiently represents the traffic situation. Thus, time-dependent travel times must be integrated into time-dependent vehicle routing algorithms in order to anticipate typical traffic states. Whereas common vehicle routing is well studied, time-dependent vehicle routing is still a field of potential research due to the substantial efforts in data processing and the resulting complexity in routing algorithms (Fleischmann et al. (2004)). The provision and the integration of time-dependent routing data into advanced planning methods are rarely focused.

In the remainder of this paper, we give an overview of attended home delivery including an application example as well as recent approaches regarding time slot management and time-dependent delivery (Section 2). Subsequently, telematics based data collection and data processing are sketched (Section 3). The resulting planning data sets are used for the modelling of time-dependent networks, which is a prerequisite for time-dependent vehicle routing algorithms (Section 4). Then, a city logistics application is discussed in order to illustrate data application by computational experiments (Section 5). Finally, the paper is concluded (Section 6).

2 ATTENDED HOME DELIVERY

In recent years, business models comprising attended home delivery services have staged a comeback. 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 (Agatz et al. (2008a)). Thus, customers expect a choice of narrow, reliable delivery time slots, which is usually leading to high delivery costs (Campbell and Savelsbergh (2005)). E.g. transportation costs of attended home delivery based on 1-hour time slots are

2.7 times greater than costs evoked by unattended delivery (Punakivi and Saranen (2001)). During the order process of typical e-commerce businesses, customers can usually choose between several delivery time slots of different length and shipment fees (cf. Figure 1).

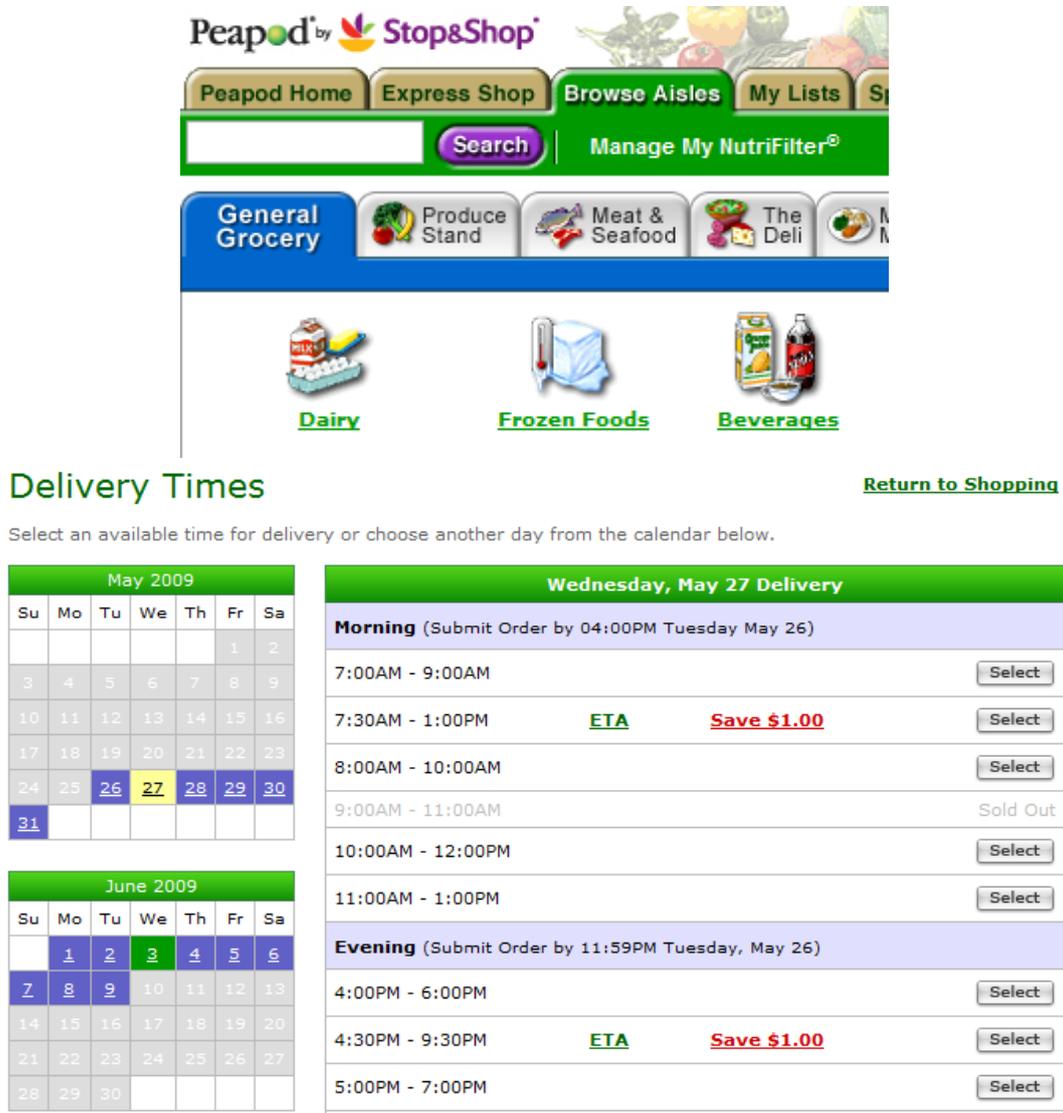


Figure 1 – Time slot selection (www.peapod.com)

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. and offers fresh groceries among others. In Figure 1, a screenshot from the Peapod website is shown, where a customer concludes the order process by choosing a time slot from a day specific time slot list. The single time slots overlap and differ in length, shipment fee and availability. E.g. the rather long morning time slot between 7:30 AM and 1:00 PM is offered with a discount of \$1, whereas the 9:00 till 11:00 AM time slot is “sold out” at the moment. Further details regarding the Peapod application example are analyzed by Agatz et al. (2008a). Details regarding Albert.nl can be found in Agatz et al. (2008b).

The design of an attended home delivery order process depends on two factors. On the one hand, customer requirements (e.g. customer demand) must be considered in the tactical

design of time slots. Agatz et al. (2008a) discuss the tactical development of time slot schedule design. Here, decisions comprise the length of time slots, time slot overlaps, the number of time slots offered and delivery charges. In this context, they address the Time Slot Schedule Design Problem, which assigns specific time slots to areas defined by zip codes, given a set of service requirements.

On the other hand, the realization of last-mile delivery must be ensured in terms of efficient and reliable time slot schedule management, e.g. when to “close” a time slot due to capacity or routing restrictions. In this context, Campbell and Savelsbergh (2005) focus the interaction of “order promise” and order delivery. They introduce several insertion heuristics, which are used to determine whether a delivery request can be feasibly accommodated in any of the time slots, based on the set of already accepted customers and expected customers.

TIME-DEPENDENT DELIVERY

After ordering, logistics service providers have to realize orders in terms of reliable and efficient delivery tours. Here, a crucial component is the anticipation of the time slots' impacts on delivery routes. However, current literature mainly focuses the derivation of profitable time slots by demand estimation (revenue management).

In this paper, we enforce the allocation of reliable customer time slots from a routing perspective. A customer could set a time slot while ordering, which would only be accepted if it was feasible in terms of an efficient delivery tour. Alternatively, the logistics service provider could propose convenient narrow time slots, also based on feedback from time-dependent vehicle routing. Thus, a high service quality could be assured as early as in the ordering process, still maintaining realizability of delivery.

The prerequisite for reliable time-dependent delivery is the allocation and application of routing data in time-dependent vehicle routing approaches. Time-dependent information about typical traffic states support the determination of reliable itineraries. This allows for the derivation of reliable, narrow customer time slots. In recent years, a few authors have come up with approaches for information systems providing such routing data:

- For city logistics, Fleischmann et al. (2004) design a traffic information system. 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 route construction methods.
- Eglese et al. (2006) refer to Floating Car Data (FCD) for time-dependent routing in a supra-regional road network in the UK. The FCD originate from a communication network consisting of trucks and coaches. Data is transmitted via text messages (SMS) and stored as a “road timetable” in a central database.
- Van Woensel et al. (2008) consider queuing theory to provide time-dependent travel time estimates. They refer to a tabu search approach to solve the time-dependent capacitated vehicle routing problem. Donati (2008) focuses on ant colonies to solve time-dependent vehicle routing problems heuristically. Both publications are more focused on large area networks.
- Ehmke et al. (2009) analyze huge amounts of FCD for the determination of traffic quality as well as typical traffic states. They introduce a “data chain” in order to describe empirical traffic data collection and data analysis. Due to the complexity of

time-dependent routing data sets, they cluster routing data while keeping a certain level of reliability for the planning of shortest routes.

In the following, we refer to telematics based data collection in terms of FCD as a prerequisite for time-dependent vehicle routing in urban areas. We sketch the important parts of data collection and data analysis. The approach by Ehmke et al. (2009) is extended by utilizing time-dependent routing data sets for reliable time-dependent delivery. Thus, typical traffic states are considered in order to provide a more reliable time slot schedule management.

3 DATA ALLOCATION

The starting point for time-dependent delivery in urban areas is the collection of traffic data. Reliable decisions must be derived from this raw data. Therefore, empirical traffic data has to be transformed into time-dependent routing data sets. We sketch the phases of the corresponding data chain and focus the main steps in terms of raw data, first and second level aggregation and decision.

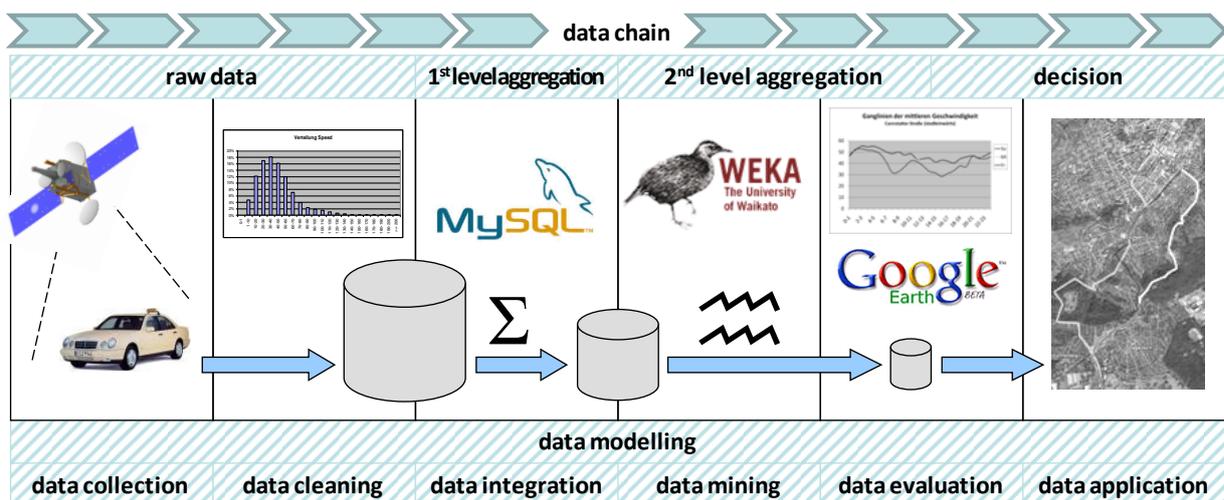


Figure 2 – Data allocation and application in the context of GPS based data collection and time-dependent vehicle routing in city logistics (Ehmke et al. (2009))

DATA CHAIN

Varying traffic flows require time-dependent routing decisions in cities. GPS based traffic data may be the source for the derivation of such decisions. The corresponding data chain ranging from GPS based collection of raw traffic data to time-dependent routing decisions is shown in Figure 2. Efficient decisions are enforced by the transformation of raw data into first level aggregated data into second level aggregated data. In particular, the elements involved are as follows:

- Data collection: Taxi-FCD is a recent GPS based data collection method that provides raw traffic data in urban areas. Taxi-FCD results in a large data volume of city-wide traffic data, mainly based on the use of taxis as moving data sources.

- Data cleaning: Erroneous data records are removed. E.g. obviously unrealistic speed observations due to GPS shadowing effects are filtered. Data cleaning is the precondition for reasonable data mining.
- Data integration: The collected single Taxi-FCD records (empirical traffic data) are amended by a common digital roadmap (infrastructure data). The data is integrated into one database and aggregated for analysis purposes.
- Data mining: Aggregated Taxi-FCD is analyzed by means of cluster analysis. Cluster analysis is used for the memory efficient allocation of time-dependent travel time estimates.
- Data evaluation: The travel time estimates are subject to evaluation and presentation because routing algorithms require realistic travel time estimates. To this end, the travel time estimates are visualized in daily courses in order to be compared with typical traffic patterns. Furthermore, geographical information systems like Google Earth (Google Earth KML 2.0) are involved.
- Data application: The final step comprises the integration of time-dependent travel time estimates in time-dependent city logistics applications.

RAW TRAFFIC DATA

In order to derive travel time estimates for city logistics, city-wide data collection is necessary. To this end, conventional data collection methods like manual traffic census or counting traffic flows by induction loops are of limited use, because they require a tremendous amount of effort (Gühnemann et al. (2004)). Typically, no meaningful data samples are available for vast parts of the city road network.

Traffic data can be collected by using telematics systems in terms of FCD. Recently, GPS have been propagated and are widely used for routing purposes. The Taxi-FCD project run by the German Aerospace Center (DLR) implements the idea of using taxis as mobile data sources for the collection of FCD. Here, a fleet of taxis characterized by typically high mileage is the basis of the system. The taxis are already equipped with GPS based navigation systems used for taxi disposition, hence causing no further costs for data transmission. Taxis transmit their current positions approximately every minute via digital radio trunking.

A more detailed description of the data collection method can be found in Brockfeld et al. (2007). DLR has developed several map-matching and data handling algorithms. For the processing of the raw data, a general overview of Taxi-FCD and its applications see Lorkowski et al. (2004) and Lorkowski et al. (2005). More details of telematics based data collection and traffic data processing in general can be found in Ehmke et al. (2010).

PLANNING DATA (FIRST LEVEL AGGREGATION)

The raw Taxi-FCD records are filtered, integrated into a single database and then precalculated in terms of time-dependent aggregation. Here, raw traffic data evolve into planning data. The result is a mean FCD speed for each link and time interval, being the fundament for the derivation of time-dependent travel time estimates. Furthermore, the level of granularity in aggregation must be determined, i.e. the total number W of time intervals. Corresponding to common analysis methods from the area of traffic research (e.g. Pinkofsky (2006)), we refer to FCD by establishing 24 time intervals per day ($W = 24 \times 7$). The resulting

speed averages are referenced to as “FCD hourly average” (FH). FH is supposed to cover expected fluctuations in travel times during 24 hours of the day and 7 days of the week. FH based algorithms for vehicle routing must cope with a huge amount of travel time estimates. However, limited memory capacities, complex time-dependent vehicle routing algorithms and the desire for fast and reliable routing decisions require the reduction of the volume of input data without a significant decrease of reliability. The following cluster analysis approach responds to these requirements by providing weighted FCD averages in terms of second level aggregation.

CLUSTERED PLANNING DATA (SECOND LEVEL AGGREGATION)

In this section, the functionality of data mining as important component of the data chain is sketched. We perform a weekday dependent clustering of FH data for the efficient allocation of time-dependent travel time estimates. The resulting clusters are supposed to characterize included links with similar speed variations. Thus, the data input for vehicle routing algorithms can be reduced.

Normalized FH data is clustered by the *k*-means algorithm (MacQueen (1967)). The *k*-means algorithm is a partition-based clustering algorithm, requiring the number *k* of desired clusters and a distance function as input. The algorithm then iteratively minimizes the error sum of the data objects’ distances to the cluster centers. A detailed discussion of the cluster analysis can be found in Ehmke et al. (2009).

Table 1 – From the cluster analysis resulting discount factors (example with *k* = 4)

Cluster	0-1	1-2	...	3-4	...	8-9	...	16-17	...	22-23	23-24
1	0.71	0.76	...	0.79	...	0.25	...	0.23	...	0.59	0.65
2	0.64	0.65	...	0.63	...	0.52	...	0.53	...	0.64	0.64
3	0.43	0.46	...	0.55	...	0.30	...	0.27	...	0.38	0.41
4	0.78	0.76	...	0.77	...	0.48	...	0.45	...	0.71	0.75

Clustering of normalized FH data leads to a compact representation of time-dependent travel time estimates in terms of discount factors. The discount factors represent typical speed variations that are used for the derivation of time-dependent travel time estimates. The main idea is to look up a link’s discount factor and then weight a robust speed figure (e.g. average speed or maximum speed). Thus, the resulting data set is referenced as “Floating Car Data Weighted Averages” (FW).

An example result of clustering is given in Table 1. Each cluster represents a group of links. Each link is associated with its groups’ representative vector of 24 discount factors. Thus, time-of-the-day specific link speeds can be derived by using the time-of-the-day specific discount factor and weighting it by its link’s mean speed. This leads to enormous savings regarding input data for vehicle routing.

RELIABILITY OF PLANNING DATA SETS

The reliability of FH and FW data sets is evaluated by simulation experiments. Ehmke et al. (2009) plan routes with the routing data sets presented and then “realize” these routes by

simulation of the planned routes. Therefore, they recalculate the planned routes based on “true” travel times for specific days and time slots in order to incorporate varying travel times in route planning. They then compare planned itineraries to simulated itineraries in terms of robustness and reliability.

Concerning the actual realisation of the fastest itinerary, FH and FW data sets are superior in contrast to static route planning. FH data provokes reliable and robust routes, whereas FW data results in slightly worse routing decisions due to cluster analysis based aggregation. Nonetheless, FW data is much more efficient due to the tremendously reduced volume of input data for planning algorithms.

In the following, the planning data sets are applied to time-dependent optimization.

4 TIME-DEPENDENT OPTIMIZATION

In this section, the integration of time-dependent routing data sets into advanced planning methods is discussed. Therefore, we give a short overview of the modelling of time-dependent networks, which is a prerequisite for time-dependent vehicle routing, and build an optimization framework adapted to the requirements of attended home delivery. In this context, two simple heuristics for the calculation of efficient, time-dependent delivery tours are introduced.

MODELLING OF TIME-DEPENDENT NETWORKS

The determination of efficient delivery tours demands for an adequate representation of the typology of the road network, which is usually implemented by graphs that represent the relevant extract of the typology. In graphs, customers are represented by vertices, and vertices are connected by edges which represent shortest paths between customers in terms of distances or static travel time estimates. Each edge is associated with its static cost, duration or travel time that has been calculated by shortest path algorithms on the level of road network typology. Thus, shortest path calculation serves as “converter” between the road network typology and the problem specific model of delivery in city logistics.

In contrast to static networks, time-dependent networks consider varying travel time estimates for each edge due to a more realistic representation of the road network typology. Here, travel time is modelled as a function of departure time. Travel time functions are distinguished into integer and real valued functions, also known as discrete and continuous modelling (Dean (1999)).

In a discrete setting, time-dependent travel time estimates are usually approximated by piecewise-linear functions. Therefore, the time horizon considered is partitioned into an appropriate number W of time intervals. In the continuous case, travel time functions are estimated based on e.g. empirical traffic data.

Modelling time-dependent networks based on empirical traffic data does not guarantee “First In, First Out” (FIFO) behavior. In FIFO consistent networks, vehicles do not “pass” each other, i.e. vehicles arrive in the order they commence an edge (“non-passing condition”, Kaufman and Smith (1993), Ichoua et al. (2003)). FIFO networks allow for time-dependent shortest path calculation in terms of a trivially-modified variant of any label-setting or label-correcting static shortest path algorithm like Dijkstra’s algorithm (Dijkstra (1959)). This is due

to the following properties, leading to a reduced complexity of time-dependent vehicle routing (Dean (1999)):

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

More on basic concepts of time-dependent shortest paths can be found in a survey paper by Dean (1999). Pallottino and Scutella (1997) give an application driven overview on shortest path algorithms. A recent overview on algorithms for both the discrete and continuous case as well as a performance comparison is provided by Ding et al. (2008). Furthermore, Dell'Amico et al. (2008) introduce an approach for non-FIFO time-dependent networks.

The routing data sets presented lead to piecewise-linear travel time functions, ignoring the FIFO property. Thus, the travel time function jumps between two time intervals, and passing may occur if the travel time decreases. Fleischmann et al. (2004) solve this problem by a "smoothed" travel time function that transforms non-FIFO into FIFO networks. Here, the jump between two intervals is linearized.

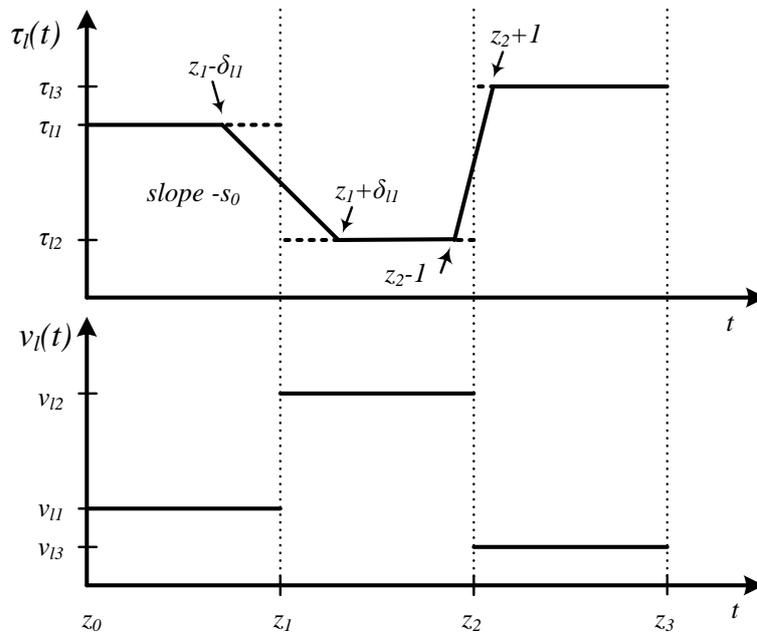


Figure 3 – Construction of the piecewise linear travel time function, including linearization at jumps z_1 and z_2 .

In Figure 3, the derivation of travel times τ_{ii} from average speeds v_{ii} is illustrated for an example link I. The travel time function $\tau_I(t)$ results from the FH or FW routing data set and features several jumps at z_i . E.g. at z_1 , the average speed changes from relative low to relative high speed, inducing a rather long or rather short travel time, respectively. This change is not FIFO consistent; a vehicle starting shortly before z_1 would be overtaken by a vehicle starting shortly after z_1 . Fleischmann et al. (2004) handle these jumps by linearizing the travel time function in the range $[z_i - \delta_{ii}; z_i + \delta_{ii}]$. δ_{ii} determines the corresponding slope $-s_0$, which is not allowed to become larger than $s = 1$, assuring the FIFO property. In the case of increasing travel times, the slope can be chosen freely (here: $\delta_{ii} = 1$).

For the FH and FW data sets presented, we implement a FIFO consistent, time-dependent road network typology. In the following case study, this leads to 16.8 million travel time

estimates (FH) and 100,672 travel time estimates (FW), respectively. In contrast, a common digital roadmap would result in 100,000 travel time estimates only (which corresponds to one travel time estimate per link). Furthermore, a time-dependent shortest path algorithm is implemented in order to provide time-dependent travel time matrices as input for time-dependent vehicle routing heuristics.

HEURISTICS FOR TIME-DEPENDENT VEHICLE ROUTING

Efficient and reliable delivery tours are provided by time-dependent vehicle routing algorithms, considering varying travel times. For the exemplary provision of time-dependent round trips, we discuss the Time-Dependent Traveling Salesman Problem (TDTSP). Two heuristics for the TDTSP are introduced, both based on the idea of finding the next nearest customer.

The TDTSP is defined as follows: find a tour of minimum time that starts from the depot at a given starting time, visits every customer exactly once, and then returns to the depot. The travel time between two customers or between a customer and the depot depends on the time of the day. The TDTSP is an extension of the well known traveling salesman problem, which considers the travel time between two points as constant (Schneider 2002). As a generalization of the TSP, the TDTSP belongs to the class of problems for which it seems unlikely that polynomial-time exact algorithms can be developed (Lenstra and Rinnooy Kan (1981)). Thus, the provision of optimal solutions in an acceptable time is only possible for small problem instances. For larger practical problem instances, heuristics are needed which provide near optimal results in relatively short calculation times.

An intuitive and simple heuristic is the Nearest Neighbor approach (NN). NN constructs a delivery tour beginning with a start vertex ("depot") and then calculating the current travel times to all vertices left ("customers"). The nearest vertex is then added to the tour, and the procedure is repeated until all customers have been inserted ("visited"). Due to its simplicity, NN can be easily adapted to time-dependent networks by using time-dependent shortest path calculation. We implement NN referring to time-dependent shortest path calculation on the level of time-dependent road network typology.

The advantages of NN are its speed and simple adaptability to time-dependent networks. Unfortunately, NN usually results in rather inefficient delivery tours due to "expensive" customers being postponed to the end of a tour.

Malandraki and Dial (1996) improve the NN approach by proposing a restricted dynamic programming heuristic (NNDYN). Referring to the general idea of NN, they build tours by appending remaining vertices step by step. In contrast to NN, *all* partial tours are calculated in every step, but only the H most promising tours are retained for further investigation in the next step. Thus, exponential explosion of time and storage requirements can be avoided. If only the best partial tour is retained ($H = 1$), the approach corresponds to NN exactly. Malandraki and Dial state improvements of 13.8 % in their computational tests compared to the NN approach.

In contrast to the simple and fast calculation of NN, NNDYN demands for a huge number of time-dependent shortest path calculations, requiring to the precalculation of time-dependent travel time matrices. We implement NNDYN by providing a time-dependent travel time matrix for every quarter hour, resulting in 96 travel time matrices for one weekday. Furthermore, we

allow for the retaining of $H = 100,000$ partial tours in every calculation step, considering memory limits.

In the following case study, the routing data sets (FH, FW) and the time-dependent planning methods (NN, NNDYN) are integrated.

5 CASE STUDY

The applicability of time-dependent routing data sets in time-dependent delivery is demonstrated by computational experiments. We investigate a fictional scenario of a city logistics service provider in the area of Stuttgart, Germany. Therefore, a large amount of telematics based traffic data from this area is analyzed, which serves as input for the determination of the time-dependent routing data sets. We introduce the experimental setting first and present the computational results afterwards.

EXPERIMENTAL SETTING

The experimental setting is as follows: a city logistics service provider schedules itineraries in order to deliver to 20 customers, located all over the city of Stuttgart, Germany. Each customer expects a narrow, reliable time slot set by the city logistics provider. In order to demonstrate the influence of time dependency, the corresponding time-dependent traveling salesman problem is solved for 24 different depot starting times on a typical Monday (00:30 till 23:30). There is a customer service time of 10 minutes for every customer.

Computational experiments are executed on FCD collected in Stuttgart in the years 2003-2005, resulting in about 230 million empirical traffic data sets. This empirical traffic data is processed as described in the data chain (cf. Section 3), leading to two types of planning data sets: planning data from first level aggregation (FH) and clustered planning data from second level aggregation (FW). Preliminary experiments have shown that FH data sets lead to routes that are more reliable than FW data sets, but they require a tremendous amount of computational effort (cf. Ehmke et al., 2010). FH and FW data sets are used for the initialization of the time-dependent planning framework as described in Section 4. A time-dependent topology of the road network of Stuttgart as well as a time-dependent model of this road network is implemented. A common digital roadmap serves as the fundament for the modelling of the road network in terms of vertices and edges, whereas time-dependent edge costs are provided by FH and FW data sets.

Based on the given framework, the time-dependent traveling salesman problem is solved heuristically by NN and NNDYN. In the NN case, results are improved by a time-dependent 2-opt heuristic. NN works on the time-dependent, FIFO adapted topology of the road network, whereas NNDYN requires time-dependent, precalculated travel time matrices. Thus, we provide time-dependent shortest paths between all customers for every quarter-hour, resulting in 96 travel time matrices for one weekday.

EXPERIMENTAL RESULTS

In Figure 4, durations of the 24 round trips calculated are compared regarding the total time of delivery tours, including customer service times. As expected, tour durations vary in the course of the day. NN and NNDYN lead to relatively short round trips at night and in the

evening, whereas round trip durations increase throughout the day due to increasing traffic flows. E.g. a round trip starting at 3:30 AM is completed after 4:32 hours (NNDYN FH), whereas a round trip beginning during morning rush hour at 7:30 AM is finished after 4:50 hours (NNDYN FH).

Comparing the quality of NN and NNDYN algorithms, NNDYN is able to find shorter round trips than NN in all cases. Round trips build by NN were improved by 2-opt exchanges. Nonetheless, NNDYN outperforms NN calculated tours on an average level of 11.2% (including 2-opt improvements) and 15.6% (without 2-opt improvements) in terms of pure travel time.

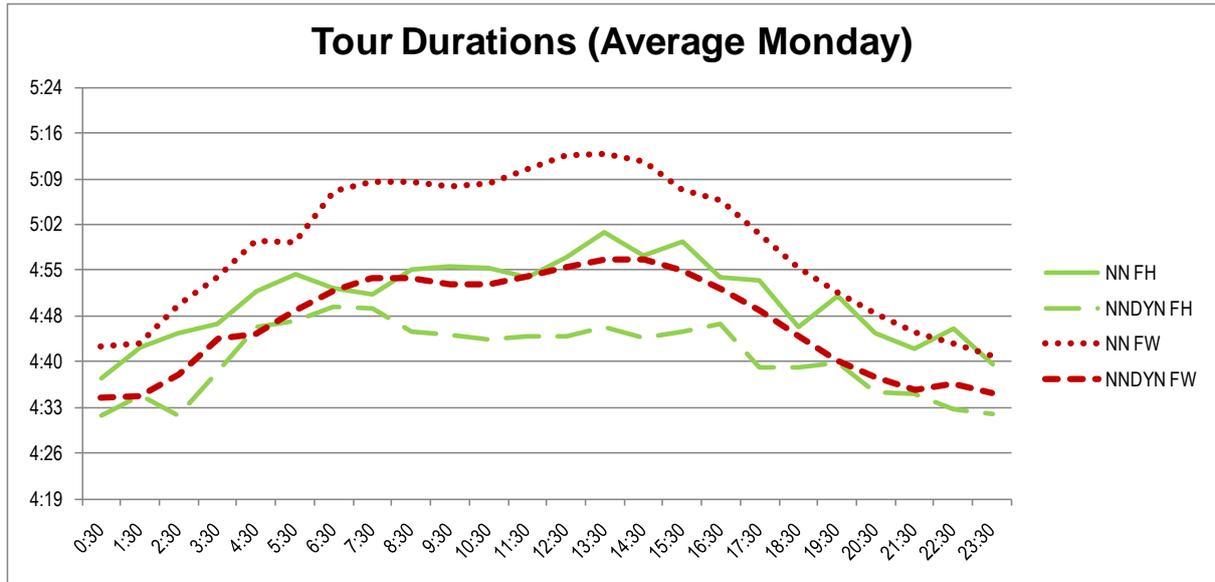


Figure 4 – Comparison of tour durations and Nearest Neighbor heuristics (duration / start time)

Regarding the applicability of planning data sets, FW data results in an overestimation of round trip travel times of about 7.8% due to the cluster analysis based grouping process. Still, FW based itineraries lead to similar results regarding the traffic flow characteristics of a typical Monday, keeping memory requirements low and increasing computational speed.

In Figure 5 and Figure 6, exemplary results of NNDYN are shown for starting times 13:30 and 19:30, respectively. The order of customers is determined by NNDYN and mapped to the road network topology by a time-dependent shortest path algorithm. The position and the delivery time of customers is displayed next to each pin, representing a single customer. The depot is denoted by pin “(0)” and pin “(21)”. Comparing Figure 5 and Figure 6, the order of the customer delivery and the expected time slots change due to evolving travel times, leading to the contrary direction of the itinerary and demonstrating the necessity of time-dependent planning approaches.

Altogether, computational experiments underline the benefits of sophisticated data allocation and application in order to provide more reliable and efficient delivery tours. Customers profit from narrow time slots that can be set based on feedback from time-dependent vehicle routing. The framework presented allows for an enhancement of common planning methods, implying sophisticated data allocation and a consistent, time-dependent topology.

6 CONCLUSION

This paper is about data allocation and data application for time-dependent delivery in urban areas. To increase service quality in attended home delivery, two prerequisites are identified: the availability of adequate planning data and the integration of this data into advanced planning methods. We focus the improvement of deliveries from a routing perspective, and build a framework consisting of enhanced data collection, data allocation and modelling of time-dependent typology.



Figure 5 – Result of NNDYN for starting time Monday, 13:30 (Picture source: Google Earth KML 2.0) (customers denoted by pins, position in itinerary in (), arrival times denoted by [Ⓢ])

In this context, planning data results from telematics based traffic data. We sum up the corresponding data chain that comprises the transformation of raw empirical traffic data into two types of planning data. Then, the modelling of time-dependent networks is described in detail. The time-dependent calculation of shortest paths is identified as important part of an efficient and realistic conversion of the road network typology into time-dependent planning models. Two heuristics based on the principle of Nearest Neighbour are discussed.



Figure 6 – Result of NNDYN for starting time Monday, 19:30 (Picture source: Google Earth KML 2.0)
(customers denoted by pins, position in itinerary in (), arrival times denoted by [⌚])

Finally, planning data sets and time-dependent planning methods are integrated in a fictional case study. Results and benefits of time-dependent delivery are demonstrated exemplarily. The NNDYN heuristic outperforms the common NN approach on a level of 11.2-15.6%. Further research should discuss more complex approaches in time-dependent route planning. The introduced framework is to be extended by a more sophisticated integration of time windows in planning methods. Thus, a closer feedback from vehicle routing in order processes of home attended delivery could be achieved.

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