Modeling and analyzing the effects of differentiated urban freight measures – a case study of the food retailing industry

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Abstract

This paper examines the effects of differentiated urban transport policies in a real world scenario of food retailers in the city of Berlin. A microscopic model is constructed which maps several tactical and operational logistics decisions. It is an optimization problem for individual firms which is solved heuristically considering time-of-day dependent transport costs. The impacts of urban freight transport policies that differentiate between area, time-of-day and vehicle type are discussed and evaluated by the variations of distribution costs and environmental indicators. The model shows that policy measures restricted to a certain area and vehicle-types, can have significant impact on the whole area under examination.

1 Introduction

Urban commercial transport is steadily growing. And with its growth, its burdens in terms of congestion, noise, traffic vibrations, pollution and GHG emission become more and more visible. Urban transport policy has developed measures to influence, control and regulate urban freight transport [Munuzuri et al., 2005]. The European White Paper of Transport 2011 [EU, 2011] proposes a set of measures to achieve its ambitious goals to make the European Transport Area more competitive and resource efficient. For urban transport, it proposes user charges according to user's and polluter's pay principles, delivery time windows and vehicle type dependent access restrictions. A comparable strategic plan for Germany's cities [BMVBS, 2011] proposes environmental zones for areas that are particularly worth protecting. In these zones accesses of vehicles are strongly regulated. Most striking, there is a trend towards more and more differentiated urban transport policies differentiating between area, time of day, users and vehicle types. By this way, congestion problems and noise reduction goals can be addressed very precisely. This tendency is supported by new information and control technologies.

There is growing number of models to support transport policy by analyzing these measures in advance. A couple of models map urban commercial vehicle flows as a whole. With the exception of one or two hybrid models mapping shipments to tours (e.g. Wisetjindawat et al. [2007]), all urban commodity transport models focus on constructing tours and activity chains (e.g. Hunt and Stefan [2007] and Johan W. Joubert and Axhausen [2010]). They are well defined to support classical transport planning. Once it comes to the assessment of such differentiated measures, however, their sensitivity is still limited. One reason is that these models focus on individual vehicle movements rather than logistics behavior yielding to these movements.

City logistics models address logistics behavior and seek to optimize "the logistics and transport activities by private companies in urban areas while considering the traffic environment, traffic congestion and energy consumption within the framework of a free market economy" [Taniguchi et al., 2001]. To consider traffic congestion and environment, models with high spatial and temporal resolution are required. Such models are still scarce.

This paper develops a behavioral model to analyze differentiated urban freight policies with high spatial and temporal resolution. It is based on a model in which carriers make tactical and operational decisions to minimize their total costs. Carrier's behavior is modeled as follows: a vehicle routing algorithm determines fleet-size, vehicle types, vehicle departure times at depots and routes, and a time-dependent least cost path algorithm determines the paths through a physical network. The model is applied to a real world scenario of heterogenous food retailers in the city of Berlin. Here, we first derive the relevant firms and their urban logistics network in terms distribution centers and shops. The commodity demand is derived for a typical day in terms of shipments of different commodity groups. These shipments are transported with heterogenous vehicles inducing different fixed and variable costs. Transport costs emerge in a physical network that is loaded with a passenger transport scenario and thus exhibits typical peak-hour profiles to capture varying transport times throughout a day. Based on this setup we asses the impact of a vehicle-type dependent cordon and distance toll in Berlin's environmental zone, a prohibition for heavy vehicles and time-dependent noise protection schemes by comparative static analysis, i.e. the variation of carrier costs and environmental indicators.

The developed model is in line with current developments in city-logistics considering optimization models as "basic tool for understanding goods distribution in urban areas" [Taniguchi et al., 2012]. But also recent developments in multi agent transport modeling suggest focusing on individual actors and modeling their behavior with models from operations research such as Liedtke [2009] and Davidsson et al. [2008].

Our first contribution is to develop a behavioral carrier model of tactical and operational nature such that differentiated policies can be implemented in a network model. Based on this freight agents can pick up these measures and can consider them in their decision making. With regard to the applied algorithms, our approach is based on well known models from literature. However, we extend it by various elements such as departure time choice and time-dependent transport costs. As far as we know, we are the first that apply the used algorithm principle to solve this complex behavioral model.

Our second contribution is to apply this model to a real world population of heterogenous freight agents with focus on evaluating urban freight transport policies. We illustrate their effects on the basis of an important subset of the urban freight transport system and show that this model can be used as decision support system to help decision makers understanding the impacts of their developed measures.

The paper is organized as follows: After these introductory remarks, the second section introduces the carrier model. Then, we present the algorithms to solve this model in the third section. In the fourth section, we present the real world case by successively describing the setup, the policies to be evaluated and the results. We finalize our paper with a conclusion.

2 Introducing the Model

Urban freight transport concerns many stakeholders, i.e. shippers, customers or receivers, freight carriers, administrators and residents (see Taniguchi et al. [2012]). Modeling decisions of all actors on various decisions levels is rather complex and - depending on the application - not appropriate. Thus most models simplify and isolate relevant actors and decisions and thus focus on a particular subset.

We focus on the decisions of freight carriers and administrators, and assume others actors to be constant. Decisions of administrators are included exogenously by means of policy scenarios. Freight carrier decisions are endogenous.

These decisions have different time horizons. They can be strategic, tactical and operational. Even strategic decisions (e.g. location choice and network design decisions) become more and more important, we focus on tactical and operational decisions.

As already stated in the introduction, the overall model is closely related to city logistics models. The problem statement of a single carrier in turn is closely related to vehicle routing problems (see for example Laporte [2009] to get an overview). The solution algorithms are based on well known algorithms from the extensive literature of vehicle routing algorithms and graph theory.

The model of our freight carriers can be described as follows: Carriers do all the transportation tasks in this model. A transportation task is a service to a customer to pickup or deliver goods and to transport them to a particular destination. A service at a customer determines type and quantity of goods to be carried. Additionally, it contains the respective location as well as service time windows and service times. All services and its assignments to carriers are exogenous to the model, i.e. shipment size and frequency decisions are not modeled explicitly, and they are assumed to be stable. Since the Carrier is designed to model a transport operator, its capabilities and resources include the locations of its depots and information about its vehicle stock. Carriers are assigned a stable endowment of depots. The number of vehicles is modeled endogenously. However, the set of vehicle types a carrier can employ is part of the initial endowment, and is assumed to be stable either. A vehicle type contains information about type-specific costs and physical characteristics such as capacity and engine information.

Carriers choose

- the number of vehicles of each type,
- the depot from which a customer is delivered,
- the sequence of customers on a vehicle route,
- the departure time of vehicles at their depots and
- the network path between customers and depots

to minimize the following objective function:

$$\min \left[C_F + C_V\right] \tag{1}$$

where C_F represents the total amount of fixed costs induced by the set of employed vehicles and C_V represents the variable costs. The variable costs are:

$$C_V = C^{transp} + C^{act} \tag{2}$$

where C^{transp} includes all costs that emerge from covering the distance from one location to another, e.g. fuel, driver costs or user charges. The activity costs C^{act} emerge from the service activity such as an pickup or delivery at the service location, e.g. waiting times, service times or penalties for missed time windows.

An action plan of a Carrier that minimizes equation 1 thus contains a set of vehicles, each equipped with the schedule of a tour starting and ending in one of the carrier's depots. The schedule contains the departure time from the depot and planned pick-up, delivery or arrival times at service locations as well as a network route, which is the actual path through the physical network. Thus this plan contains planned vehicle movements in time and in space.

To make the description more concise, the carrier model can be described as follows:

- carriers are cost minimizer,
- transport services and its respective customers, and thus all transportation tasks are known beforehand,
- each carrier has a number of depots that are known beforehand either,
- transportation services can be constrained by time windows and induce service times,
- each carrier operates a vehicle fleet consisting of vehicle types that are known beforehand,
- each vehicle type can exhibit different characteristics such as different capacities and costs,
- each vehicle can only be assigned to one vehicle route,
- vehicles start and end at one of the Carrier's depots,
- transport times and costs between customers and depots are dependent on departure time, vehicle type and on the physical transport network, e.g. congestion and implemented policy measures.

Due to the complexity of the model, optimal behavior cannot be derived analytically. To make it even worse, it cannot even be guaranteed that a solution to equation 1 is optimal. For problems with a certain size, derived solutions only approximate optimal solutions.

3 Solving the model

Carrier behavior is derived by solving the model heuristically with by means of two basic algorithms: a vehicle routing algorithm (VRA) and a time-dependent least-cost path algorithm (LCPA). The VRA determines fleet size, vehicle types, depots, routes and depot departure times. The LCPA provides the transport costs and times necessary for vehicles to get from one location to another. The following sections give a concise description of the solution algorithms. A detailed description about the various elements would go beyond this paper (see Schröder [2013] for more details).

3.1 Vehicle routing algorithm

The VRA is a heuristic approach based on the work of various authors being introduced in the following sections. Its basic idea has been developed by Schrimpf et al. [2000] who formulated the *ruin-and-recreate* principle. The *ruin-and-recreate* approach is a large neighborhood search that combines elements of simulated annealing and threshold-accepting algorithms [Schrimpf et al., 2000, pg. 142]. Starting with an initial solution, it disintegrates parts of the solution leading to (i) a set of customers who are not served by a vehicle anymore and to (ii) a partial solution containing all other customers. Thus, this step is called *ruin* step. Based on the partial solution (ii) all customers from (i) are reintegrated again, which is therefore referred to as *recreation*. This yields to a new solution. If the new solution has a certain quality, it is accepted as new best solution, whereupon a new *ruin-and-recreate* iteration starts. These steps are repeated over and over again until a final solution is reached.

We choose this approach for a number of reasons:

- it is best suited for complex problems that have many constraints and a discontinue solution space [Schrimpf et al., 2000, pg. 142],
- it is extendable to a number of problem types,
- it provides competitive results to these types,
- it can be computed concurrently in an intuitive way,
- basic search strategies (or local moves) can be easily varied to small and large moves according to the complexity of the problem,
- the number of search strategies can be kept low and
- it is appealing simple in structure and thus comparably easy to implement and understand.

The following sections briefly introduce the manifestations of the algorithm's basic elements: ruin strategies, recreation strategies as well as the applied acceptance function.

3.1.1 Ruin strategies

The strategies implemented here are: random and radial ruin which are adopted from Schrimpf et al. [2000], and fleet ruin which is based on Gendreau et al. [1999].

Random ruin: The random ruin strategy ruins a feasible solution of the vehicle routing problem randomly, i.e. a number of customers are identified according to a random number generator, and are removed from the solution. Here, this ruin strategy is selected with a probability of 0.3. If it is selected 30 percent of all customers are removed.

Radial ruin: The radial ruin strategy ruins a given solution more systematically. One customer node is randomly selected as target customer. This customer and its neighboring customers are then removed from the solution. The neighborhood is defined as customers that are closest to the target customer in terms of whatever distance measure is used, e.g. Euclidean distance. Here, this Euclidean distance is used, and it is selected with a probability of 0.5. The removed neighborhood has a size of 15 percent of all customers.

Fleet ruin: The fleet ruin strategy is based on a fleet change procedure developed by Gendreau et al. [1999]. They introduce it as strong diversification strategy. It selects a route r that has at least two customers. All customers of r are removed from the solution. Additionally, one of these customers is selected randomly, and its neighborhood is removed either (according to radial ruin) which might overlap with the customers in r. To avoid being just a slightly modified radial ruin and foster a fleet change, two new routes r', r'' are introduced to the partial solution, each with one initial customer (from the set of customer that were originally in r) and the cheapest possible vehicle. Here, this strategy is selected with a probability of 0.2 and the removed neighborhood consist of 15 percent of all customers.

In general, given n customers in the set N of all customers and a fraction f of customers to be removed, the number of removed customers is $f \cdot n$. This yields to a partial solution $\bar{N}$ consisting of $(1 - f) \cdot n$ customers and a set of $\bar{\bar{N}}$ with $f \cdot n$ customers being not in the solution anymore. Latter are subsequently integrated into the partial solution again. The way this is done is part of the recreation step of the algorithm.

3.1.2 Recreation strategy

The basic idea of the implemented recreation strategy is adopted from Schrimpf et al. [2000] either. It is the simplest recreation strategy. The $f \cdot n$ customers are shuffled and subsequently inserted into the existing solution. Let k be the customer to be inserted next. For each route r in the existing solution, the best insertion position for k is determined such that insertion costs are minimal. This strategy is further called *BestInsertion*. To consider different vehicle locations, vehicle types and depot departure times, inserting k is not only evaluated against the existing route r (where r has a departure time and is operated by a certain vehicle) but also against a slightly modified route configuration as well. Existing routes are for example operated with another vehicle or they depart from depot earlier or later in time. The most intuitive way to insert k is to find the departure time, vehicle type and the position within the existing solution $\bar{S}$ where the additional costs imposed by inserting k are minimal, and to insert k at this position. These additional costs are:

$$\Delta C = C(\bar{S} \cup k) - C(\bar{S}) = \big[C_F(\bar{S} \cup k) + C_V(\bar{S} \cup k)\big] - \big[C_F(\bar{S}) + C_V(\bar{S})\big] \tag{3}$$
$$\Delta C = \Delta C_F + \Delta C_V \tag{4}$$

Equation 4 consists of additional fixed and variable costs.

Additional fixed costs are determined with an approach adopted from [Dell'Amico et al., 2007]. They choose a new vehicle type and assign the resulting additional fixed costs to customer k depending on the completeness of the solution as follows: If a significant share of customers still have to be inserted, vehicles with a low fixed costs per capacity ratio (which they call relative fixed costs) are preferred which usually prefers bigger vehicles. Thus total capacity is expanded. If almost all customers are already in the solution, vehicles with low absolute fixed costs are preferred which in turn prefers smaller vehicles. Thus total capacity is tighten and kept lean, respectively.

Additional marginal costs are evaluated on route level to cover the fact that the insertion of k does not only have local impact on its neighboring customers but also on previous and on subsequent customers, e.g. the employment of a new vehicle can induce a cordon toll on an earlier leg or the insertion of k might move subsequent legs into rush hours and thus increase total transport time of the whole route significantly.

After inserting customer k at its best position, practical time-windows are updated such as described in [Schrimpf et al., 2000].

3.1.3 Acceptance functions

We implemented a greedy approach. It accepts every new solution which is better than the current best solution. Due to the algorithm's inherent capability to build whole new neighborhood structures, it still generates reasonable good solutions. In our experiments even the greedy approach provides results which are in average not worse than 10 percent of the best-known solutions of classical benchmarking problems (see jsprit [2013]).

3.2 Least cost path algorithm

Travel times can vary significantly throughout the day, throughout the week and a year [Eglese et al., 2006]. They are thus dependent on vehicle's departure times. In urban areas, travel times are largely influenced by the rush hours of private traffic (e.g. from 7:00am-9:30am). To consider the variation in travel times during a day, the VRA is based on time-dependent (and vehicle-type dependent) transport times which results in time-dependent transport costs. These costs are usually computed in time-slices of constant average transport times. In this approach, time-dependent transport costs are computed with a modified time-dependent least-cost path algorithm (LCPA) based on the Dijkstra algorithm (see Lefebvre and Balmer [2007], Balmer et al. [2007]). To assure the FIFO (first in, first out) property the LCPA is modified such as proposed by Ichoua et al. [2003]. Here, the time slices have a width of 30 minutes. In our approach, time and cost of a transport relation are calculated on the fly and are cached for later use, i.e. it is calculated if it is required and then it is calculated only once. This yields to cached matrices that are dependent on the time slice as well as the vehicle and its type, respectively.

In essence, the LCPA is the mean to pickup congestion and implemented transport policies from the transport network and to propagate them to upstreaming logistics decisions of the carrier.

4 Case

4.1 Overview

The derived carrier model is applied to urban food distribution in Berlin. Berlin is the capital of Germany and - with 3.3 million inhabitants - the biggest city of Germany. The urban area of Berlin consists of 12 regions.

Food retailing in Germany comprise all retailers offering a range of goods with food as predominant share [MetroGroup, 2011]. Food retailers operate various logistics networks, from single- to n-tier networks. Most retailers operate at least one distribution centers to distribute their commodities to end-consumers (i.e. the shops).

This case study picks up the concept of distribution centers and models the "last mile" in food retailer's transport chains. That is shipments are transported from distribution centers typically located outside the urban area to shops located inside. Upstreaming logistics operations are assumed to be stable. The demand and supply data of food retailers used here have been mainly derived by Gabler et al. [2013]. Subsequent sections briefly describe this work and extends it by modeling heterogenous shops and by the way shipments are derived.

4.2 Food retailers and carriers

Firms in food retailing can be distinguished from each other by their business model, i.e. channel retailer, content retailer and lean discounter. The underlying business strategies are reflected in the size of their shops and in the range of offered products (see section 4.2.2).

Each retailer employs its own vehicle fleet, thus it is considered to be its own carrier. If it buys external vehicle capacities, it is assumed that retailers employ these capacities exclusively. Their distribution centers are assumed to be the depots of their vehicles.

Eleven retailers are modeled. These companies operate different brands, i.e. firms within the company with a unique business model. In total, twenty-one firms are modeled operating 17 distribution centers and 1040 shops in our examination area.

4.2.1 Distribution centres

For each retailer, we researched its distribution centers with corresponding locations (see figure 1). The data were partly collected from a commercial supplier (www.tradedimensions.de) and enriched with open data from retailer websites. As figure 1 shows, 17 distribution centers are located in a ring outside the city area.

4.2.2 Shops

The shops can be characterized by their size and business type. Based on MetroGroup [2011] and Hofer [2009]) the following four shop types can be differentiated ([area range in m^2], [article range in items]):

- discount store ([700 - 1,000],[800 - 2,000])
- supermarket ([100 - 1,000],[<12,000])
- hypermarket ([1,000 - 4,000],[15,000 - 40,000])
- department store ([5,000 - 10,000],[30,000 - 100,000])

1,039 shops were identified. The location of these shops were collected from openstreetmap.org (OSM) and validated against data published from individual retailers. In OSM, these shops were tagged with their brand name which allows a unique assignment to their business type. This yields to the geographical distribution of shops as depicted in figure 1. As expected, most of the shops are located within the center of the city area.
To cover heterogenous shops, each shop is assigned an area A_{shop} which is drawn from a uniform distribution U over the shop area interval listed above.

4.2.3 Commodity demand

This subsection derives the commodity demand of each shop on an average day. The products delivered to a shop are rather diverse and range from frozen pizza to Non-Food products like drugstore items. These heterogenous products require different transport conditions. To cover these requirements and, at the same time, to reduce complexity, products are aggregated to following groups:

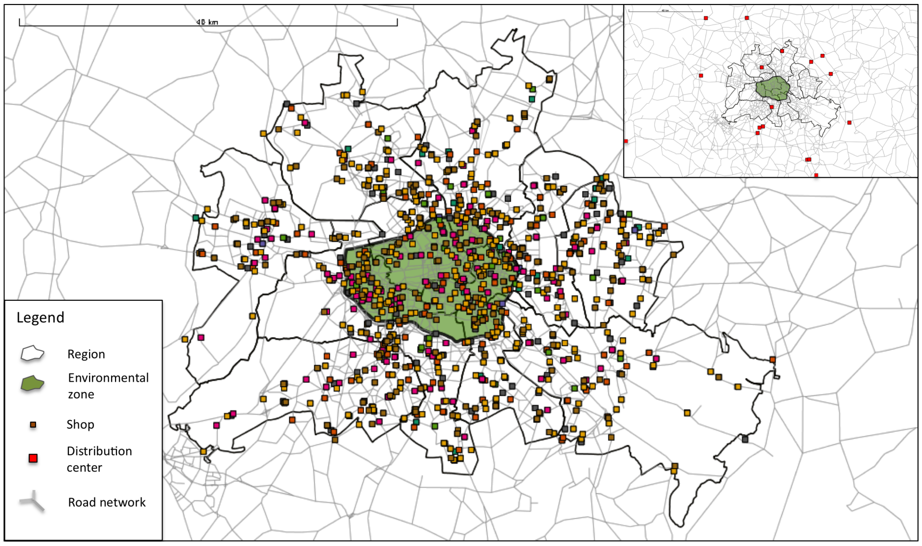

Figure 1: Berlin scenario

- **Fresh** products which include the commodity groups meat and sausages, fruit and vegetables as well as dairy products
- **Frozen** products including frozen food and ice-cream
- **Dry** products

Even this is a very rough distinction considering the variety of products in an average shop, these groups have favorable properties when it comes to logistics handling requirements. The most important one is that products within such a group can be transported with the same transport unit, because they require the same transport temperature.

The estimation of daily demand quantities is based on the yearly revenue R_i of a retailer i (from 2011). Revenues attributed to products transported via distribution centers lead $\widehat{R}_i$. Since a retailer can operate several business type and offer different products, $\widehat{R}_i$ can be further differentiated between business and product types (according to the GS1-classification[1]) yielding the turnover $\widehat{R}_{ijk}$ of retailer i in a shop belonging to business type j of product type k. Let P the set of modeled product types consisting of 41 types. The average daily demand are determined based on the following product type specific data (derived by Friedrich [2010]):

- average proportion of revenue pr_{jk} in a shop belonging to business type j and

[1] Global Standards One is an international organization providing Global Trade Item Numbers (GTIN), i.e. standard identification numbers for trade products.

- value density d_k (in EUR/kg).

The average daily quantity demands (in kg) for each product type k in a shop of retailer i operating business type j are thus:

$$D_{ijk} = \frac{\widehat{R}_{ij} \cdot pr_{jk}}{d_k \cdot 305}, \; \forall k \in P \tag{5}$$

which assumes 305 workdays per year.

To consider vehicle capacities and heterogenous weights and volumes of products, D_{ijk} is converted into transport units. The reference unit here is the europallet with an admissible weight w_{max} of 700 kg and a volume v_{max} of 2.5 m^3. D_{ijk} is either weight or volume critical. The average daily demand in transport units T_{ijk} (in europallets) is therefore:

$$T_{ijk} = \begin{cases} (D_{ijk} \cdot v_k)/v_{max}, & \text{if } v_k > v_{max}/w_{max}, \\ D_{ijk}/w_{max}, & \text{otherwise,} \end{cases} \tag{6}$$

where v_k is the specific volume (in m^3/kg) of the product type. Hereafter, the demanded transport units are aggregated according to G, the set of defined product groups (Fresh, Frozen and Dry) yielding to:

$$T_{ijg} = \sum_{k \in g} T_{ijk}, \; \forall g \in G \tag{7}$$

The average retailer specific demand intensity per product group is:

$$T_{ijg}^{int} = \frac{T_{ijg}}{A_j} \tag{8}$$

where A_j is the average shop area of business type j in square meters.

4.2.4 Shipments

How the derived quantity demands are actually delivered to the shops is part of the logistics strategy of the retailer. Some goods (whether because of their properties or their magnitude of demand) require frequent transports, e.g. every day. The rules approximating observed delivery patterns are based on the work of Gabler [2012].

For weekly patterns, the following rules are determined. Fresh products are delivered every day. Frozen and dry products are delivered every second or third day. Given a frequency of two times a week, we assume the following patterns: {Mon,Wed},{Tue,Thu} and {Wed,Sat}. With a uniform distribution over these patterns, the probability of a typical day is 1/3. For a frequency of three times a week, we assume {Mon,Wed,Fr} and {Tue,Thu,Sat} to be reasonable patterns yielding to a probability of 1/2 for a typical day.

The rules for daily patters are:

- Fresh products are delivered in a time-window of [4am - 9am] which is basically before opening hour,
- Frozen and Dry products are delivered evenly throughout the day, i.e. either in a time window of [9am - 2pm] or [2pm - 7pm] .

For each shop and product group, the daily demand of a typical day is sequentially determined by means of a Monte-Carlo simulation.

4.2.5 Carrier vehicles

Each distribution center is equipped with vehicle types. Four types of vehicles are considered (with their according admissible total weight, capacity, fixed costs per employment and distance-dependent costs):

- Light vehicles (7.5t, 10 pallets, 84 €/Empl., 0.00047 €/m)
- Medium vehicles (18t, 16 pallets, 107 €/Empl., 0.00061 €/m)
- Heavy vehicle (26t, 24 pallets, 130 €/Empl., 0.00077 €/m)
- Heavy vehicle (40t, 34 pallets, 140 €/Empl., 0.00086 €/m)

These types are typically employed in urban food distribution [Gabler et al., 2013]. Vehicle employment is dependent on business type and transported products. Light vehicles are employed to distribute Fresh and Frozen products and can be used by every business type. Medium vehicle are only employed to distribute Dry products for every business type. Heavy vehicles with 26t GVW can transport Fresh and Frozen products for every business type. Additionally, they are employed to distribute Dry products for supermarkets and discount stores. Heavy vehicles with a gross vehicle weight of 40t are used to carry Dry products for self-service department stores and hypermarkets which are usually equipped with extra delivery zones and ramps.

For the employment of these vehicle, we applied the time windows derived for daily delivery patters as work shifts. These are, [4am - 9am], [9am - 2pm] and [2pm - 7pm]. If we assume preparation times at depots, this approximates typical work shifts of seven hours length.

When it comes to the energy consumption of these vehicles, we assume that these vehicles are diesel-engined. Their specific consumptions are:

- Light - 20l/100km
- Medium - 25l/100km

- Heavy 26t - 30l/100km
- Heavy 40t - 35l/100km

We assume 2.68 kg CO2/liter diesel to calculate their average CO2 emissions.

4.2.6 Costs schemes

The total costs of carriers consist of fixed and variable costs. Latter can be further differentiated in transport and activity costs (see section 2). Transport costs in turn consist of time and distance-dependent costs as well as additional costs induced by a policy measure (e.g. user charges).

The cost parameters are derived by means of full cost accounting of a representative vehicle of each vehicle type. The main component of the fixed costs are depreciations on investment costs. Additionally, they include implicit interests, taxes and insurance charges as well as overhead costs. The distance-dependent part of the transportation costs includes a share of investment costs as well as for example fuels, lubricants, tire and maintenance costs, i.e. all cost components that are assumed to be proportional to the distance traveled. Fixed cost per employment as well as distance-dependent transport costs for each vehicle type are listed in section 4.2.5. Variable costs per operation hour are mainly driver costs such as wages and other driver related expenses which amount to 0.008 €/sec for all vehicle types. Thus, this part is proportional to the operation hours.

Activity costs emerge at service locations where transport activities occur, e.g. deliveries. These activities induce service and waiting times as well as penalties for missed time-windows. Since, missed time-windows are not allowed, their penalties converge infinity. When it comes to activity times, we assume that an average pallet takes 3 minutes[1] to be unloaded. Service and waiting times are then priced with the variable costs per operation hour (0.008 €/sec).

4.2.7 Loaded network

The network is generated from OSM and contains all roads of the urban area of Berlin and its catchment area which includes the locations of distribution centers (see figure 1). It is loaded with the equilibrium state of a passenger scenario with freight as background load (see Oliveros and Nagel [2011]). Thus it exhibits typical peak-hour profiles to capture varying transport times throughout a day. Link travel times are aggregated to time-slices of 30 minutes (see section 3.2).

4.3 Scenarios

As already stated we want to study the impact of policy measures that differentiate between area, time of day and vehicle type. The impacts are assessed by means of comparative analysis, i.e. we compare the outcome of a scenario

[1] This is an average value derived from expert interviews

with a reference case. All policies are implemented in the environmental zone which basically contains the inner city of Berlin (see figure 1). Five prominent measures are studied which are briefly described next.

Cordon toll

The cordon toll is an access charge. It falls due when a vehicle accesses the environmental zone. However, it is only charged for heavy vehicles, i.e. vehicles with 26t and 40t admissible vehicle weight. It amounts to 20 €. To implement this measure, we identified all access links to the environmental zone. If transport costs are requested to cover the distance from a location outside to a location inside the tolled area with a heavy vehicle, the charge is considered by the LCPA.

Distance toll

The distance toll is dependent on the distance travelled within the environmental zone. It is also charged for heavy vehicles only and amounts to 1 € per kilometer. To implement it, we identified all links within the environmental zone (incl. access links). If transport costs are requested to cover the distance from a location outside to a location inside the tolled area with a heavy vehicle, a link charge of all the links within the tolled zone is considered by the LCPA.

Prohibition

The prohibition policy prohibits heavy vehicles in the environmental zone. It is implemented as sufficient high cordon toll.

Noise protection

The noise protection measure is a time-limited measure. It prohibits the access of heavy vehicles to the environmental zone from [22pm-7am]. Light and medium vehicles have still no restrictions. It is implemented as sufficient high distance toll.

Due to random effects of the vehicle routing algorithm, we run the model five times for each scenario (with another seed for the random number generator) and averaged the results.

4.3.1 Results

Reference

In total, carriers travel 38,704 kilometers. The share of heavy vehicle kilometers amount to 30,871 kilometers (3,871 km by medium and 4,162 km by light vehicles). Total distance is covered by 531 vehicles which corresponds to the number of routes (heavy: 416, medium: 76, light: 39). The average number of stops per tour is 3.6. Based on the vehicle-specific fuel consumptions, this yields 30.37 tCO_2.

The analysis of departure times illustrate the effects of time-limited measures. Anticipating the noise protection policy, we limit the representation of our results on the departure times of heavy vehicles in the morning shift. In the reference case, they depart in average at 4am.

To illustrate the impacts on the environmental zone, we calculate a set of indicators solely for this area. In total 3,712 km are traveled within the environmental zone (heavy: 3,038 km, medium: 305 km, light: 369 km). The number of vehicles accessing the zone at least one time amounts to 305 (254 of them are heavy vehicles). The average number of stops within the zone is 1.54 (according to the vehicles that have at least one access). If we compare this with the total average number of stops per route, it shows that a significant share of vehicles transit the zone without any stop. A closer look at this shows that 71 heavy vehicles just transit the zone.

To study the impacts on the modeled agents, we aggregate individual firms to business types and calculate cost indicators for discount stores, supermarkets, hypermarkets and department stores. The total costs amount to 129,462 € with 65,809 € fixed, 47,485 € transport and 16,168 € activity costs. A differentiation between business types yield to 53,695 € for discounters, 51,114 € for supermarkets, 11,536 € for hypermarkets and 13,118 € for department stores.

Cordon

If we introduce a cordon toll of 20 €, the total kilometers increase to 39,747 km (+2.7%). The distance covered by heavy vehicles increases slightly by 0.6 percent (31,075 km). Carriers employ 540 vehicles (+1.7%). The number of employed heavy vehicles decrease to 410. Due to the increase in kilometers, total CO_2 emissions increase as well to 31 tCO_2 (+2.1%). Departure times are not affected by this measure.

Total kilometers in the environmental zone amounts to 2,546 km which is a significant decrease by 31.4 percent. The distance covered by heavy vehicles decrease to 1,637 km which is 46.1 percent less. Note since the number of total heavy vehicle kilometers even increased slightly, the savings in the environmental zone are more than offset by kilometers travelled outside the environmental zone. The number of vehicles accessing the zone decrease to 201 (-34.1%) (heavy: 132 (-52%)). This significant decrease is not surprising since a cordon toll is essentially a tax on accesses. The average stops in the zone increase to 2.3 stops per vehicle accessing the zone. Only 6 heavy vehicles enter the zone without having any stop inside. That is, the increase in average stops is mainly attributed to a decrease in transit traffic.

The cost indicators show an increase of 3 percent to 133,486 which is mainly attributed to an increase in transport costs. The total amount of tolls adds up to 2,647 €. Activity costs does not change since they are induced by service times which are assumed to be constant. A differentiation between business types yields a cost increase by 3.5% for discounters, 3.4% for supermarkets, 1.4% for hypermarkets and 1.4% for self-service department stores. That is, discounters and supermarkets are more concerned by this measure since they operate the biggest share of shops inside the environmental zone.

Distance

The introduction of a distance toll of 1 € per kilometer yield to 39,241 (+1.4%) kilometers travelled. 31,102 km are traveled by heavy vehicles which is a slight increase of 0.7 percent. In total 534 vehicles are employed emitting 30.73 tCO2 (+1.2%). 414 of them are heavy vehicles.

The analysis of the environmental zone shows that the distance toll result in a significant decrease of kilometers travelled, i.e. 2,200 km which corresponds to a decrease of 40.7 percent. The number of heavy vehicle kilometers goes down to 1,332 which is 56.2 less than in the reference case. 262 vehicle access the zone, each with an average number of stops per tour of 1.8. 203 of them are heavy vehicles with 34 vehicles just transiting the zone.

The total costs increase by 1.5 percent to 131,407 € with 65,903 € fixed, 48,001 € transport costs and toll costs of 1,332 €.

Even one cannot exactly compare distance and cordon toll, the distance toll seems to be a more efficient measure to reduce the number of kilometers within the tolled area. In particular, if we compare the total cost increases and the number of kilometers travelled in the environmental zone in both scenarios. It suggests that if policy wants to reduce the kilometers travelled by heavy vehicles, it should charge kilometers instead of a proxy variable (e.g. accesses). However, this might induce side effects such as evasion effects on urban roads where freight vehicles are not desired at all.

Prohibition

The prohibition of heavy vehicles in the environmental zone yields to a significant increase in the total number of kilometers travelled amounting to 44,070 km (+13.9%). The distance covered by heavy vehicles is reduced by 15.7%. The employed total number of vehicles increase to 629 vehicles (heavy: 328, medium: 145, light: 126), i.e. the number of medium (light) vehicles increases by a factor of two (three). These vehicles emit in total 32.4 tCO2 (+6.7%). This is not as high as the increase in number of kilometers since medium and light vehicles consume less energy. The average number of stops is 3.07.

The analysis of the impacts on the environmental zone shows that 3,173 kilometers (-14.5%) are travelled (heavy: 349 km[1], medium: 1,025, light: 1,799 km). In total 270 vehicles access the zone (heavy: 42, medium: 88, light: 142). The majority of heavy vehicles is thus replaced by light vehicles. Note that even the prohibition is restricted to the environmental zone and even kilometers within the zone decrease by 14.5 percent compared to the reference case, the

[1] Note that even in the prohibition scenario, a few heavy vehicles operate in the environmental zone. This is attributed to the fact that a few shops demand shipments that can solely be transported by heavy vehicles. Thus they are inelastic to policy measures.

kilometers outside the zone increases dramatically. This is due to the fact that in our model light vehicles start at distribution centers as well which are located rather distant (according to the environmental zone).

The total costs in this scenario amount to 138,562 € which is 7 percent more than in the reference scenario. This is mainly induced by the change in vehicle fleet, i.e. total fixed costs increase to 71,041 €. The differentiation between business types yield 57,701 € (+7.5%) for discounters, 55,429 € (+8.4%) for supermarkets, 11,895 € (+3.1%) for hypermarkets and 13,480 € (+2.8%) for department stores. As already observed, discounter and supermarkets are much more concerned than the other business types.

Noise protection

The introduction of a temporal prohibition for heavy vehicles from 22pm to 7am yield to a total distance of 41,935 km (+8.3%). Heavy vehicles still cover 29,529 kilometers (-4.3%). In total, carriers employ 588 vehicles (heavy: 378, medium: 75, light: 135) emitting 31.72 tCO2.

This measure changes the departures times of heavy vehicles operating the morning shift from 04:00am to 09:00am. Departure times are shifted from 04:00am to 04:58am in average which is actually less significant than expected. However, the model shows that customers outside the zone are delivered first before vehicles serve customers within the environmental zone.

The study of the impacts on the environmental zone shows that the total kilometers amount to 3,767 km which is slightly more than in the reference case. 1,917 km (-36.9%) are covered by heavy vehicles. These savings are offset by a significant increase in light vehicle kilometers (1,593 km). This has two reasons: First, they can access the zone early in the morning with low traffic. Second, the induce delivery time window turns some heavy vehicle routes being capacity-bounded in the reference scenario to routes that are time-bounded in this scenario. This in turn favors light vehicles. The number of accesses are 317 (171 of heavy type). 77 of them just transit the zone.

The analysis of the actor's total costs shows an increase by 4 percent to 134,884 € with fixed cost of 68,422 € (+3.9%) and transport costs of 50,217 € (+5.8%). The differentiation between business types yields to total costs of 56,294 (+4.8%) for discounters, 53,555 (+4.7%) for supermarkets, 11,784 (+2.1%) for hypermarkets and 13,173 (+0.4%) for department stores.

4.4 Summary and limitations of the results

There are few issues that are worth being mentioned and discussed again. First and foremost, a policy measure that is restricted to an area does not only have impacts on the operations within this area, but can have significant impacts on the whole area under investigation. For example, the cordon toll reduces the number of heavy vehicle kilometers within the environmental zone significantly. However, these savings are more than offset by an increase of kilometers outside the zone. This might be desired but might also raise questions of fairness according to residents living outside the zone.

Second, if policy wants to reduce the kilometers travelled by heavy vehicles, it should charge kilometers instead of proxy variables.

Third, prohibitions have the biggest impact on the operations of carriers. That is, it changes vehicle fleet by a significant increase in light vehicles. This might yield desired effects in the environmental zone, however it might yield undesired overall effects as well (e.g. a significant increase in CO2 emissions). This can be compensated for by supporting multi-tiered networks and their required technology where heavy vehicles transport commodities from distribution centers to transshipment points right at the entrance of the environmental zone. Here, commodities are transshipped to light vehicles which can operate customers in the environmental zone. The additional energy demand induced by light vehicles can be compensated for by the employment of electric freight vehicles.

Fourth, since carriers have a range of measures to adapt to changes in the transport system which is at least partially incorporated in the developed model, they are capable to keep total cost increases quite moderate even policies are invasive.

However, the results have to be interpreted with care. First, we made the strong assumption that we − as modelers − have complete information about the costs of carriers. Second, we assumed that carriers have complete information about the traffic system and about good solutions for their vehicle routing problem. These assumptions limit the application of our model and brings us to a third issue: validation of the results. We compared our results with data we were provided from the biggest food retailer in Germany. The comparison shows that the results in terms of number of stops and load per vehicle route are quite good. However, when it comes to the average distance and time per vehicle route, our values deviate significantly from what the empirical data suggest (we modeled shorter distances and transport times per vehicle route). We have not yet find a reasonable and systematic way to calibrate our model to the observed values. We find that the relaxation of the assumption of complete information is a good point to start from. Our idea is to relax this by means of incorporating bounded rationality. That is, first, carriers do not have complete information about the traffic system. This can be incorporated by equipping carriers with a perception of the traffic system, e.g. average travel times in the morning rather than in 30-minutes time-slices. Second, they even do not have complete information about good solutions for their vehicle routing problem[1]. This can be incorporated by making a more granular search and define neighborhoods to restrict the solution space. To evaluate the effects of bounded rationality, the behavioral model needs to be linked to a transport simulation. Latter has already been implemented and described in [Schröder et al., 2012].

[1] The retailer we interviewed plans its vehicle routes by means of expert knowledge rather than routing software.

5 Conclusion

Growing agglomerations, economic activities in large cities and thus limited space to build new infrastructure create the need to develop more and more target oriented and differentiated transport policy measures. Mapping their effects on different decisions of heterogeneous freight agents remains a big challenge.

In this paper we proposed a behavioral model to evaluate differentiated urban freight policies with high spatial and temporal resolution. It is based on an optimization model in which carriers make tactical and operational decisions to minimize their total costs. The model is applied to a real world scenario of heterogenous food retailers in the city of Berlin.

We have demonstrated that our modeled carriers can adapt to changes in the transport system by changing departure time, depot locations, customer sequences in routes, fleet compositions as well as actual paths through the physical network considering varying transport costs in the traffic system. In a number of scenarios, we illustrated and discussed the impacts of policy measures that differentiate between area, time of day and vehicle types. But we also discussed the limitations of our approach. Due to the high data requirements and the strong underlying assumptions of complete information, the application of this model is limited, especially when it comes to classical transport planning. However, we think it is a promising tool to support urban policy by analyzing the effects of their developed measures.

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References

M. Balmer, M. Rieser, K. Meister, N. Charypar, N. Lefebvre, K. Nagel, and K.W. Axhausen. Matsim-t: Architecture and simulation times. In A.L.C. Bazzan and F. Klügl, editors, *Multi-Agent Systems for Traffic and Transportation Engineering*, pages 57–78. Information Science Reference, Hershey, 2007.

BMVBS. *Weißbuch Innenstadt*. Bundesministerium für Verkehr, Bau und Stadtentwicklung, 2011.

Paul Davidsson, Johan Holmgren, Jan A. Persson, and Linda Ramstedt. Multi agent based simulation of transport chains. In *Proceedings of the 7th international joint conference on Autonomous agents and multiagent systems - Volume 2*, AAMAS '08, pages 1153–1160, Richland, SC, 2008. International Foundation for Autonomous Agents and Multiagent Systems. ISBN 978-0-9817381-1-6. URL http://dl.acm.org/citation.cfm?id=1402298.1402381.

Mauro Dell'Amico, Michele Monaci, Corrado Pagani, and Daniele Vigo. Heuristic approaches for the fleet size and mix vehicle routing problem with time windows. *Transportation Science*, 41(4):516–526, November 2007.

Richard Eglese, Will Maden, and Alan Slater. A road timetable to aid vehicle routing and scheduling. *Computers and Operations Research*, 33(12):3508 – 3519, 2006. ISSN 0305-0548. doi: 10.1016/j.cor.2005.03.029. URL http://www.sciencedirect.com/science/article/pii/S0305054805001243. Part Special Issue: Recent Algorithmic Advances for Arc Routing Problems.

EU. *White paper 2011 - Roadmap to a Single European Transport Area - Towards a competitive and resource efficient transport system*. European Commission, 2011.

Hanno Friedrich. *Simulation of logistics in food retailing for freight transportation analysis*. PhD thesis, Karlsruher Institut für Technologie, 2010.

Manuel Gabler. Analyse und agentenbasierte modellierung des städtischen distributionsverkehrs im lebensmitteleinzelhandel. Master's thesis, Karlsruher Intitut für Technologie, KIT, 2012.

Manuel Gabler, Stefan Schröder, Hanno Friedrich, and Gernot Liedtke. Generierung der nachfragestrukturen für die mikroskopische simulation des städtischen distributionsverkehrs im lebensmittelhandel. In Uwe Clausen and Carina Thaller, editors, *Wirtschaftsverkehr 2013*. Springer Vieweg, 2013.

Michel Gendreau, Gilbert Laporte, Christophe Musaraganyi, and Éric D. Taillard. A tabu search heuristic for the heterogeneous fleet vehicle routing problem. *Computers and Operations Research*, 26(12):1153 – 1173, 1999. ISSN 0305-0548. doi: 10.1016/S0305-0548(98)00100-2. URL http://www.sciencedirect.com/science/article/pii/S0305054898001002.

F. G. Hofer. *Management der Filiallogistik im Lebensmitteleinzelhandel: Gestaltungsempfehlungen zur Vermeidung von Out-of-Stocks*. PhD thesis, Hochschule für Wirtschafts-,Rechts- und Sozialwissenschaften (HSG), Universität St. Gallen, 2009.

J.D. Hunt and K.J. Stefan. Tour-based microsimulation of urban commercial movements. *Transportation Research Part B: Methodological*, 41(9):981 – 1013, 2007. ISSN 0191-2615. doi: 10.1016/j.trb.2007.04.009. URL http://www.sciencedirect.com/science/article/pii/S0191261507000495. Behavioural insights into the Modelling of Freight Transportation and Distribution Systems.

Soumia Ichoua, Michel Gendreau, and Jean-Yves Potvin. Vehicle dispatching with time-dependent travel times. *European Journal of Operational Research*, 144(2):379 – 396, 2003. ISSN 0377-2217. doi: 10.1016/S0377-2217(02)00147-9. URL http://www.sciencedirect.com/science/article/pii/S0377221702001479.

Pieter J. Fourie Johan W. Joubert and Kay W. Axhausen. Large-scale agent-based combined traffic simulation of private cars and commercial vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, 2168: 24–32, 2010.

jsprit. open source vehicle routing, August 2013. URL https://github.com/jsprit/jsprit/wiki/Benchmarks.

Gilbert Laporte. Fifty years of vehicle routing. *Transportation Science*, 43:408–416, November 2009. ISSN 1526-5447. doi: 10.1287/trsc.1090.0301. URL http://dl.acm.org/citation.cfm?id=1656425.1656427.

N. Lefebvre and M. Balmer. Fast shortest path computation in time-dependent traffic networks. Technical report, IVT, ETH, 2007.

Gernot Liedtke. Principles of micro-behavior commodity transport modeling. *Transportation Research Part E: Logistics and Transportation Review*, 45(5):795 – 809, 2009. ISSN 1366-5545. doi: 10.1016/j.tre.2008.07.002. URL http://www.sciencedirect.com/science/article/pii/S1366554509000507.

MetroGroup. *Metro-Handelslexikon 2011/2012: Daten, Fakten und Adressen zum Handel in Deutschland, Europa und der Welt*. MetroGroup, 2011.

J. Munuzuri, J. Larraneta, L. Onieva, and P. Cortes. Solutions applicable by local administrations for urban logistics improvement. *Cities*, 22(1):15–28, 2005.

Manuel Moyo Oliveros and Kai Nagel. Automatic calibration of microscopic, activity-based demand for a public transit line. Technical report, Berlin Institute of Technology, 2011.

Gerhard Schrimpf, Johannes Schneider, Hermann Stamm-Wilbrandt, and Gunter Dueck. Record breaking optimization results using the ruin and recreate principle. *Journal of Computational Physics*, 159(2):139 – 171, 2000. ISSN 0021-9991. doi: 10.1006/jcph.1999.6413. URL http://www.sciencedirect.com/science/article/pii/S0021999199964136.

Stefan Schröder. Policy dependent vehicle routing: An approach for evaluating urban transport policy measures. Technical report, Karlsruhe Institut für Technologie, KIT, 2013.

Stefan Schröder, Michael Zilske, Gernot Liedtke, and Kai Nagel. Towards a multi-agent logistics and commercial transport model: The transport service provider's view. *Precedia- Social and Behavioral Science*, pages 649–663, 2012.

E. Taniguchi, R.G. Thompson, T. Yamada, and R. van Duin. *City Logistics - Network modelling and Intellgent Transport Systems*. Pergamon, January 2001.

Eiichi Taniguchi, Russell G. Thompson, and Tadashi Yamada. Emerging techniques for enhancing the practical application of city logistics models. *Procedia - Social and Behavioral Sciences*, 39(0):3 – 18, 2012. ISSN 1877-0428. URL http://www.sciencedirect.com/science/article/pii/S187704281200554X.

W. Wisetjindawat, K. Sano, and S. Matsumoto. Micro-simulation model for modeling freight agents interactions in urban freight movement. *86th Annual Meeting of the Transportation Research Board*, 2007.