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## Integrating Urban Last-Mile Package Deliveries into an Agent-Based Travel Demand Model

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### Abstract

With the expected increase of e-commerce activity, we can expect the share of delivery vehicles in cities to rise as well. On the one hand, this puts great pressure on cities and surrounding areas as emissions rise and space becomes scarce. On the other hand, people are adjusting their travel behaviour such that the increase in e-commerce affects not only last-mile delivery but also private passenger traffic. This paper presents an integrated approach of modelling last-mile deliveries using an agent-based travel demand model. It is intended to account for reciprocal effects between online shopping behaviour and last-mile deliveries. The package orders are generated by agents in the study area and distributed among the package centres. For each package centre, the tour for each delivery agent is created. The presented model allows for the simultaneous simulation of private trips and last-mile deliveries and thus realistic delivery conditions: the model can detect e.g. if an agent or another household member is at home to receive their order. We have applied the model to the city of Karlsruhe, Germany, and describe first results of that simulation. Application of the model allows for a detailed analysis e.g. of delivery success rates both in terms of time and space. The presented modelling framework provides insight into effects of last-mile deliveries on a transportation system and can be availed to analyse policy measures or alternative delivery strategies.

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## 1. Introduction

Urban goods movements have increased rapidly in recent years especially due to the rising popularity of e-commerce. In 2019, the revenue of courier, express, and parcel (CEP) services in Germany amounted to €21,300 mio., twice as much as it was in 2000 [8]. With this increase, we can expect the share of delivery vehicles in cities to rise as well. This puts great pressure on cities and surrounding areas as emissions rise and space becomes scarce. Because the last leg of the delivery chain is so costly, there have been many studies on how the last-mile issue can be diminished. Electric vehicles, for example, can replace conventionally powered delivery vehicles rather easily as usability remains the same. They can compensate emissions and have been put into practice already. However, they are still not an encompassing solution to the problems of last-mile delivery [13] and further solutions have to be investigated. One of such are parcel lockers which are used to drop off and pick up packages. They can be used by both the delivery service and the customer. When the number of lockers and their locations are optimised they have the potential to especially reduce the number of failed deliveries [7]. In an effort to ban large delivery vehicles from cities altogether, (case) studies have also investigated the effect and efficiency of cargo-bicycles [6, 9].

Policy makers and CEP service providers are interested in understanding the effects of different last-mile delivery solutions and how they influence travel behaviour of the customer. Demand models and simulations are an established tool in assessing policy changes and effects on the transport system. However, existing models of urban freight movements have been limited to the delivery vehicles and in some cases their effect on the transport system. To assess effects of different delivery solutions not only on the transportation system but also on the customers' travel behaviour, we have integrated last-mile deliveries into the agent-based travel demand modelling framework *mobiTopp*.

Research on freight modelling has been quite extensive and with increased computational power, agent-based models are used more and more due to their analytical advantage over aggregate models. Agent-based models allow for consideration of different stakeholders in one model. One such model is the MASS-GT model presented by de Bok and Tavasszy and de Bok et al. [3, 4] respectively. The authors avail the agent-based approach to differentiate between producers, receivers/consumers, shippers, carriers, own account carriers and, third party logistics which allows them to use the model as an assessment tool for logistics policy strategies. Joubert et al. [11] used the existing agent-based simulation framework MATSim to simulate both commercial and private vehicles. Due to the underlying data, the model does not differentiate between different trip purposes and thus delivery vehicles are not explicitly modelled. However, the authors' approach highlights the importance of modelling both private and commercial vehicles in the same model. This also holds true for the work of Schröder and Liedtke [19]. They designed a sandbox MATSim model in which both passenger and freight agents were regarded. The authors showed that policy measures aimed at freight transport may also have an effect on the utility of private transport. Another agent-based approach was presented by Alho et al. and Sakai et al. [1, 18] respectively. The authors used the modelling framework SimMobility and integrated urban freight movements. SimMobility Freight allows for analysis of operational efficiency. In a case study, Sakai et al. present the effects of nighttime and off-peak deliveries.

These models all utilise the advantages of agent-based models to analyse effects of freight policy and relationships between different stakeholders, however, they do not take the relationship between online shopping and travel behaviour into account. This connection, however, has been widely covered in previous research. Mokhtarian [17] for example investigated the impacts of B2C<sup>1</sup> e-commerce on transportation and found that e-commerce can both reduce and increase personal travel depending on the individual circumstances. Weltevreden and Rotem-Mindali presented the effects of B2C and C2C<sup>2</sup> e-commerce in the Netherlands. The authors showed that B2C e-commerce reduces personal travel while C2C e-commerce has the opposite effect. While there is an extensive body of research on this relationship (for a comprehensive literature review, see Bönisch et al. [5]), it has yet to be regarded in travel demand models. With this study, we aim to close this gap by incorporating the online shopping behaviour and subsequent travel behaviour into the agent-based travel demand modelling framework *mobiTopp*. We translate the orders into packages whose deliveries are simulated simultaneously with all other trips in the travel demand model.

This paper presents the modelling framework developed to account for last-mile package delivery in an agent-based travel demand model. After presenting *mobiTopp*, we detail the package delivery module *logiTopp* and the data used

<sup>1</sup> business to customer

<sup>2</sup> customer to customer

for the choice models. We go on to describe the results of the simulation, which we discuss in the subsequent section. We conclude this paper by addressing main outcomes of our work and implications for future work.

## 2. Modelling Framework

### 2.1. *mobiTopp*

We used the agent-based travel demand modelling framework *mobiTopp* [14, 15] to integrate last-mile package deliveries. As illustrated on the left-hand side of Figure 1, *mobiTopp* is made up of two parts: the long-term and the short-term module. In the long-term module, a synthetic population is generated consisting of individual people in the model area and their corresponding households. The generated people are the agents in the model and they each have the following characteristics attributed to them: age, gender, work status, place of work/education, drivers license, commuter tickets, and memberships to mobility services (e.g. carsharing, bikesharing, etc.). The attributes differentiated for each household are the number of household members, the number of cars, the location of the household, and its net income. Based on the personal and respective household characteristics, each agent is assigned an activity schedule for the simulation period which can be set to up to a week [10]. In *mobiTopp*, we differentiate six main activities: work, education, shopping, leisure, service, and home. These can be further refined to allow for a more differentiated model. Within the long-term module, each activity is assigned a preliminary start time and duration.

These activities are then simulated in the short-term module of the modelling framework. Within this module, a destination and a mode is chosen for the next activity. This process is repeated each time an activity is finished. As the activity schedules created in the long-term module work with estimated travel times between activities, they need to be updated according to the actual travel times which is also part of the simulation process. The simulation runs simultaneously for all agents which allows for a realistic interaction between agents in *mobiTopp*.

### 2.2. *logiTopp*

We have used the interaction between agents and the high level of detail regarding their characteristics to integrate package orders and last-mile package deliveries in an urban area. The model extension *logiTopp* uses information from *mobiTopp*'s long-term module to generate package orders in the study area. The points of integration are illustrated in figure 1. Like *mobiTopp*, *logiTopp* is implemented in Java and available as an open source project on GitHub [12].

We estimate the package orders using a multinomial logit model in which the number of packages ordered by each agent is the dependent variable and the attributes and characteristics from the long-term module, i.e. person and household attributes and activity patterns serve as the independent variables. We have defined the utility of agent  $i$  ordering  $n$  packages as:

$$V_{n,i}^{order} = \theta_n^{order} + \beta_{age}^{order} X_{age,i} + \beta_{gender}^{order} X_{gender,i} + \beta_{job}^{order} X_{job,i} \quad (1)$$

where  $\theta$  is the alternative specific constant,  $X$  is the respective attribute of agent  $i$  and  $\beta$  are the model parameters.

After the number of package orders per agent is determined, a respective place of delivery is chosen. We differentiate the alternatives home, work and parcel locker. The utility function of agent  $i$  choosing delivery location  $m$  is currently defined using the same information as in the order choice model:

$$V_{m,i}^{loc} = \theta_m^{loc} + \beta_{age}^{loc} X_{age,i} + \beta_{gender}^{loc} X_{gender,i} + \beta_{job}^{loc} X_{job,i} \quad (2)$$

We used Monte Carlo simulations to determine the number of packages and their locations respectively based on their utilities. We recognise that the choice models are still rudimentary and are currently used as a technical prototype. Both choice models will be improved upon in future work to account for more factors influencing online shopping behaviour for example household characteristics and income. The package orders are simulated for the entire simulation period.

Once the packages and their respective delivery location is determined, they are allocated to package distribution centres. We use the actual distribution centres located in the mode area with their location. There is only one CEP service provider that operates two distribution centres for our example region, all other service providers only operate

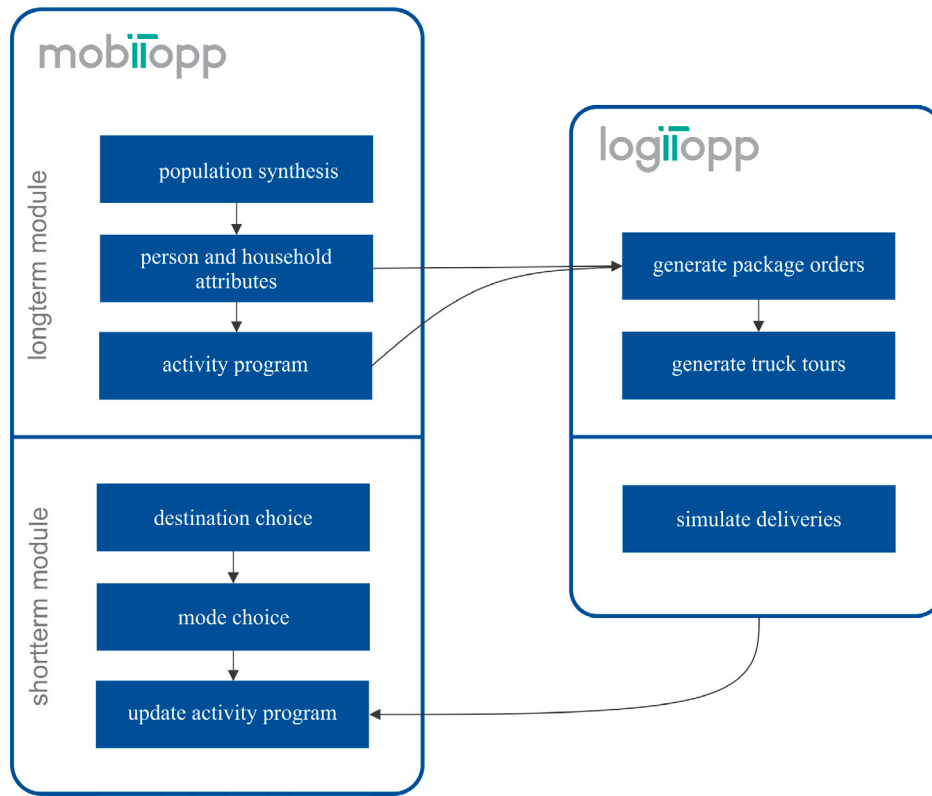


Fig. 1: Model framework of mobiTopp and principle of integration of logiTopp

one centre. Thus, the distribution among the centres is only determined by the size of the distribution centres and no other factors were considered.

After the packages are allocated to the distribution centres, the tours of the delivery trucks are formed. Finding the optimal sequence of deliveries for each vehicle is an application of the Vehicle Routing Problem (VRP). Because the VRP is NP-hard, solutions are often approximated using heuristics. One such heuristic is the *route first cluster second* approach [2]. In this approach, the first step is to build a giant tour where the constraint of vehicle capacity is relaxed and a route for all packages within one tour is determined. In the next step, the giant tour is partitioned such that conditions of vehicle capacities are met. Generating the giant tour can also be defined as the travelling salesman problem (TSP) which is also NP-hard. To form the giant tour for each distribution centre we used the Java library JGraphT [16] that approximates a solution to the TSP. To form the tour for each vehicle we partitioned the giant tour using two constraints: time and vehicle capacity. With an approximated time to deliver a package and time between stops, we constrained the maximum duration of the tour including the trip back to the distribution centre to 8 hours, i.e. one working day. Each delivery agent conducts one tour per day. As we have currently not implemented a model for shipment size, the vehicle capacity is normal distributed around a mean value of 160 packages with a variance of 16 packages. The min. and max. values of packages are 100 and 200, respectively. The delivery agents are regular mobiTopp agents who have had a distribution centre assigned as their workplace as part of mobiTopp's longterm module in the population synthesis. Their activity program is now updated such that the delivery activities are integrated.

After the tour formation step, the simulation is run and the delivery agents start to deliver the packages of their tour. For each package, the model checks the chosen delivery location. Depending on the delivery location different conditions have to be met for the delivery agent to be able to successfully deliver the package:

**Delivery location = work:** When a package was ordered to a place of work, the delivery agent can deliver the package if the agent who ordered the package is at work during the time of delivery. This approach allows for a

realistic delivery behaviour as most packages cannot be delivered to a place of work on Saturdays and delivery attempts would be unsuccessful.

**Delivery location = parcel locker:** If the delivery agent has to deliver packages to a parcel locker the delivery is always successful. At this state of the model, we assume that there is always enough space left for the packages on the current tour. The parcel lockers for each agent are currently based in their home zone.

**Delivery location = home:** A delivery to the home of an agent works similarly to the delivery to a place of work. The model checks if the agent who ordered the package or any other household member is currently at home. If that is the case the package is delivered successfully. The agent-based approach and simultaneous simulation of activities also allows for the model to check how many neighbours are at home at any given time during the simulation. Although the neighbourhood search is currently not implemented into logiTopp, this will be included in future versions of the model.

The strategy for packages that could not be delivered is currently the same for all delivery service providers: Whenever a delivery agent fails to deliver a package they take it back to the depot at the end of the tour and try again on their next tour, i.e. next day. This process is repeated three times. After the last delivery attempt, the delivery agent drops the package at a parcel locker. This delivery strategy and the analysis of different strategies require a multi-day simulation approach, which we are able to apply using mobiTopp. In the case that a package is delivered to a parcel locker after several failed delivery attempts, the agent who ordered the package is notified that their package is now in a parcel locker and ready for pick up. The activity program is then updated and the *pick-up* activity is inserted into the program. The tours are re-formed after each simulation day to account for packages that could not be delivered on the previous day and need to be considered in during the next tour.

### 3. Results and Discussion

We have chosen Karlsruhe, Germany, as a model area for the first application of logiTopp. Karlsruhe is a city in the South-West of Germany and populated with just over 300,000 people. The area is serviced by nine parcel delivery companies which are represented in the model with their geo-locations. mobiTopp's synthetic population of Karlsruhe and it's surrounding areas includes about 1.9 mio. agents in about 879k households. We limited orders to agents living in the city of Karlsruhe as the shorter runtime allows us to analyse initial results faster and because most policies regarding last-mile delivery target cities. Because of the rather long runtime for the simulation period of one week we have chosen to simulate 10% of the synthetic population. This allows us to efficiently analyse and calibrate results. As the calibration is ongoing we present results from the latest 10% run of the simulation. The modelling framework allows for a detailed analysis of deliveries.

Based on the 10%-population, logiTopp generates 20,165 packages that are distributed among the delivery centres. Packages can be delivered between Monday and Saturday from 8 a.m. to 8 p.m. Figure 3 shows on the left the number of orders placed over the simulation period of one week. As of now, the orders are distributed evenly over the week. The resulting distribution of deliveries is presented on the right side of figure 3. These include both successful and failed delivery attempts. The distribution is not as even as the distribution of orders as unsuccessful deliveries result in additional delivery attempts which increase towards the end of the week as the current version of logiTopp does not account for additional delivery attempts due to unsuccessful deliveries during the previous week. Comparing the number of orders to the number of deliveries, we can see that not all orders are currently delivered within the simulation period. This is because not enough delivery agents are generated during the population synthesis. We are currently mitigating this effect in the calibration process.

Although we have not yet finished calibrating the model, we can already see benefits from the integrated modelling approach. One such benefit is that we can analyse the the success rate of deliveries that depends on the receiving agents' locations. We have calculated the success rates of deliveries and visualised them both in terms of time and space (see figure 4). The success rate is defined as the number of successfully delivered packages over all deliveries. Figure 4a shows the delivery success rate for each hour of the day over the course of the simulation week. The plot shows that the success rates are lower in the morning and early afternoons of working days. This effect is reversed on Saturday due to receiving agents being at home in the morning able to receive packages and having more leisure

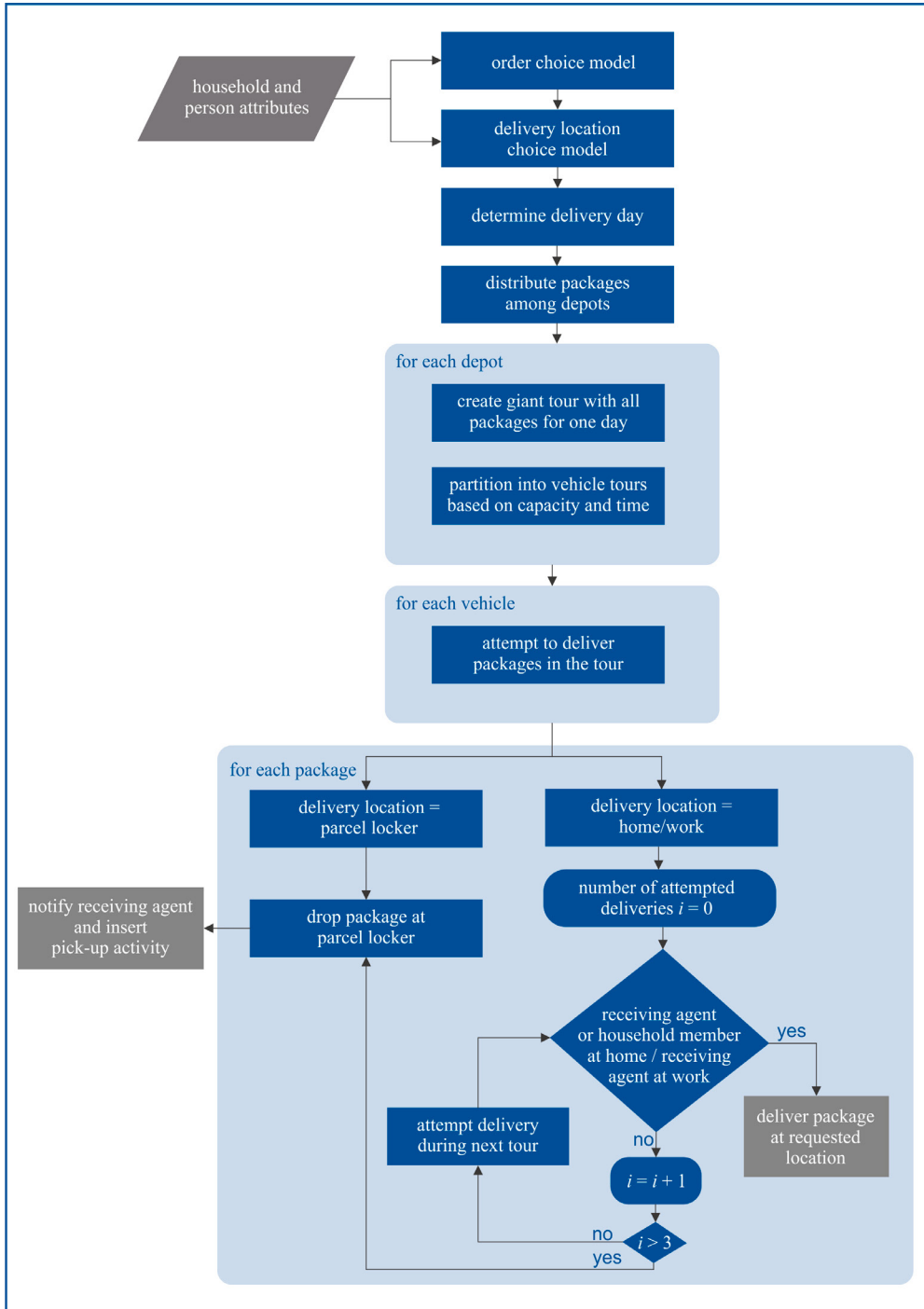


Fig. 2: Detailed flowchart of logiTopp

activities planned later in the day and thus cannot receive packages then. Figure 4b shows the delivery success rate in each traffic analysis zone (TAZ) of the model. The plot allows for a spatial analysis of delivery success rates and could help policy makers and delivery service providers identify possible locations for e.g. parcel lockers which help mitigate problems of failed deliveries.

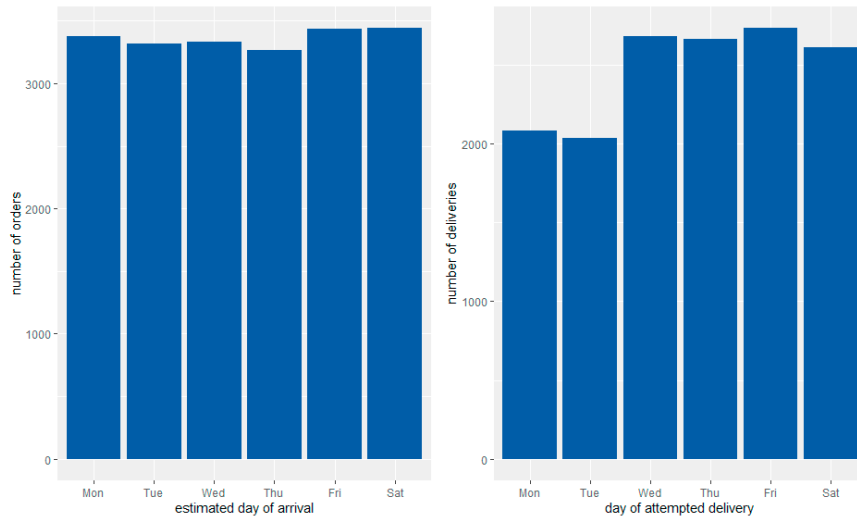


Fig. 3: Number of orders and deliveries over the simulation period of one week

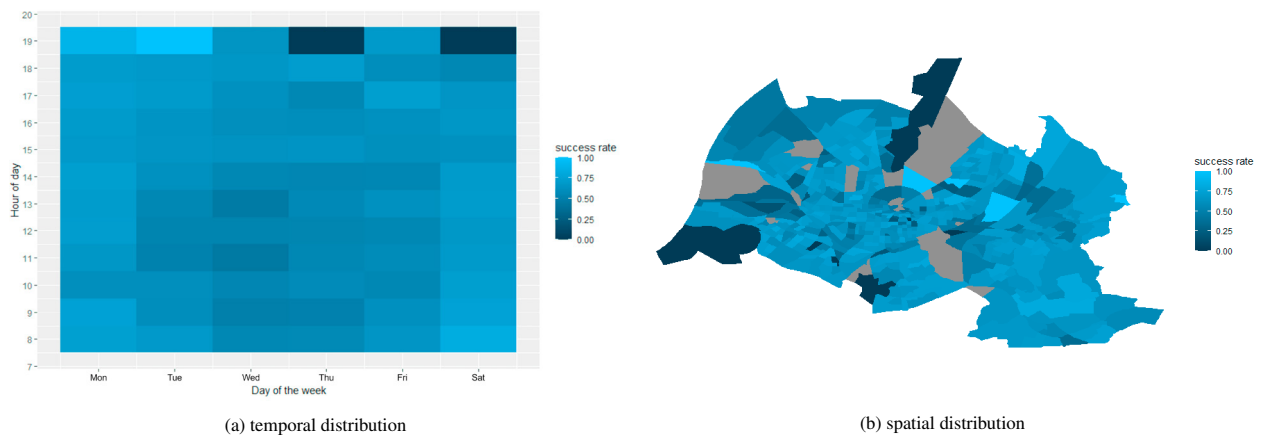


Fig. 4: Temporal and spatial distributions of delivery success rate

#### 4. Conclusion

This paper presents an integrated approach of modelling last-mile deliveries in an agent-based travel demand model. It is intended to account for reciprocal effects between online shopping behaviour and last-mile deliveries.

The framework allows for simultaneous simulation of private trips and last-mile deliveries and thus a realistic model of delivery conditions. Results show that the success rate of deliveries is temporally distributed as expected: it is low during working hours when no household members are at home to receive a package and high on Saturday when agents are more likely to receive a package. The spatial distribution of the success rates allows for an indication of where parcel lockers would be beneficial. However, these results are solely model based and would have to be checked against real world data. The model currently only includes one delivery strategy. As we include the real parcel distribution centres in the study area, we can take into account individual delivery strategies which we will implement in a future version of logiTopp. This will allow us to analyse delivery success rates on a more detailed level. The chosen approach allows us to analyse different scenarios such as last-mile deliveries by cargo bicycles and resulting changes in emissions on a high level of detail which will be the scope of future model applications.

The model currently uses rudimentary choice models to integrate online shopping behaviour. As we are currently designing a survey according to the needs of an agent-based model approach, these choice models will be improved upon in the next steps. This will also allow us to better compare our results to past studies on the relationship between online shopping and travel behaviour such as [5, 17, 20] have presented.

The presented approach and the related findings are of interest to policy makers and delivery service companies as the model allows for a comprehensive analysis on how last-mile delivery traffic affects the transportation system. Scenario-based analyses integrated into the model would furthermore allow for an analysis of how different policy measures and delivery strategies could mitigate current problems.

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