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# Integrating Neighbours into an Agent-Based Travel Demand Model to Analyse Success Rates of Parcel Deliveries

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## Abstract

The rapid growth of the e-commerce market leads us to expect a further increase in delivery vehicles in urban areas as well. This growth is expected to be accompanied by an increase in emissions while space becomes scarce. Meanwhile, people are adjusting their travel behaviour; therefore, the growing e-commerce market affects both last-mile delivery and private passenger traffic. Failed home deliveries are an important factor. They produce additional traffic by both "Courier, Express and Parcel" (CEP) service providers and private passengers in the form of repeated delivery attempts or trips to pick up parcels. In this paper we apply an integrated agent-based model of last-mile deliveries and private travel demand. This allows for analysis of interactions between delivery and private passenger traffic and the status of the recipients during delivery. Furthermore, we present a neighbourhood model to account for deliveries accepted by neighbours, which is crucial to reproduce realistic delivery success rates. We applied the presented model to the city of Karlsruhe, Germany, and simulated multiple delivery policy scenarios, which we compare to a static model without interactions between private and delivery agents. Our results show that the agent-based model produces more nuanced success rates with respect to different socio-demographic groups. Differentiating these groups is necessary when assessing measures that target specific groups and analysing effects of demographic changes. Also, we show the necessity of considering neighbours in such a model. This paper provides insight into the effects of e-commerce on a transport system and a framework to analyse policy measures or alternative delivery strategies.

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## 1. Introduction

The e-commerce sector has been showing rapid growth over the last 30 years. From 2017 to 2019 alone, the market revenue increased by about €500 billion and the e-commerce market is predicted to continue to grow even further [20]. At the same time, the number of parcel deliveries has experienced an equally rapid increase with about 21 billion

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parcel deliveries in 2019, twice as much as in 2014 and seven times higher than 30 years ago [22]. Nowadays, the business-to-customer (b2c) market makes up the largest share of e-commerce and shows a higher growth rate than business-to-business (b2b) and customer-to-customer (c2c) sales [20].

With this increase in parcel deliveries, the number of delivery vehicles can be expected to rise as well. The additional emissions and the required space put even more pressure on urban areas. Furthermore, the delivery time window, currently reaching from 7 am until 10 pm, almost completely exhausts the available time for parcel deliveries to private customers. In recent years, alternative delivery concepts like parcel-lockers or trunk deliveries have been established and have gained acceptance since, but home-delivery still remains the most common delivery method [5]. This raises the issue of failed deliveries which add to the existing emissions caused by delivery traffic as additional stops are needed and subsequent traffic is caused by pick-up of parcels by the customer [7, 1]. Policy makers and transport planners are interested in understanding how failed deliveries affect the transport system. To analyse policies and delivery scenarios, transport demand models that account for e-commerce activities provide a powerful tool. Such models also allow for analyses of failed deliveries that go beyond those based on historical data as e.g. presented by van Duin et al. [23].

In recent years, there have been multiple proposals of modelling frameworks that allow for the analysis of urban last-mile parcel deliveries and their impact on the transportation system. Most of these efforts have evolved around agent-based modelling approaches [10]. One such model is developed by Stinson et al. [21]. They propose an e-commerce supply and demand integration into the modelling framework POLARIS. This framework allows them to analyse the energy consumption of both private shopping trips and delivery tours. However, no further interactions between receivers and delivery agents are regarded and failed delivery attempts are not accounted for. Sakai et al. also propose a framework for modelling e-commerce [17] as an integration into the existing modelling framework SimMobility Freight [18]. While the authors consider different delivery options during the demand generation of parcels, they do not account for interactions between agents during the actual step of delivery and the model does not evaluate whether a parcel can be delivered or not. Llorca and Moeckel simulate urban parcel deliveries in MATSim to analyse the effects of electrification of the vehicle fleet and cargo bikes [12]. While the authors provide a thorough analysis of emissions in the different scenarios, they do not account for those caused by failed deliveries. Alves et al. propose an agent-based model of e-commerce delivery traffic to analyse urban freight policies by implementing several scenarios of delivery locker distribution in Belo Horizonte, Brazil [2]. While their model does account for failed deliveries, these are based on provided percentages and are not integrated based on a causal effect between receivers and delivering agents. A similar issue arises in the model proposed by Arnold et al. in which they analyse different delivery concepts such as cargo bikes and delivery points and their effects on operational costs [3]. They regard failed deliveries by adding stops to the tour for additional trips to the delivery points "from time to time". While both of the last approaches improve upon the quality of model results, they disregard the underlying causality of failed deliveries and do not model additional trips by customers to pick up their parcels. However, these additional trips by receivers actually account for the majority of emissions associated with failed deliveries [7].

To the best of the authors' knowledge, there is currently no model that reflects the causality and effects of failed parcel deliveries. In this paper, we investigate failed deliveries through the interactions between last-mile delivery and private travel by considering the current location and activity of a recipient during the delivery in an agent-based travel demand model. We extended the agent-based travel demand model *mobiTopp* [13, 14] by the last-mile parcel delivery model called *logiTopp* [16].

We define delivery policies as a set of rules specifying whether a parcel can be delivered or not. In this paper, we analyse multiple policies, e.g. allowing other household members or neighbours as substitute recipients in case of the recipient's absence. We show that modelling neighbour deliveries is crucial for reproducing realistic delivery success rates. Furthermore, we propose an efficient distance-based neighbourhood model using Kd-trees for nearest neighbour search. To assess the benefits of modelling the causality and effects of failed delivery attempts, we compare our model to a static model without interactions.

In the following section we describe our model concept and the concrete implementation including a brief description of the modelling framework *mobiTopp*, the extension *logiTopp* and the neighbourhood model. Finally, we analyse and discuss the simulation results and conclude with a summary and an outlook for further research.

## 2. Methodology

We aim to model the causality and the effects of failed parcel deliveries. Therefore, we present an abstract concept stating the requirements for such a model as well as a concrete implementation of that concept.

### 2.1. Concept

There are various factors influencing whether parcels can be delivered successfully or not, the most prominent factor being the absence or presence of the recipient. Delivery agents usually deliver parcels only during a certain period of the day, e.g. from 7 am until 10 pm. Since most people tend to travel throughout the day to work, shop or pursue leisure activities, there is a chance of the recipient being absent. Hence, the employment status of the recipient, as well as their working hours, can influence the success rate of parcel deliveries. "Courier, Express and Parcel" service providers (CEPSP) usually allow other household members or neighbours to accept parcels for absent recipients. Therefore, the number of household members and neighbours, as well as their respective employment and working hours, can influence the success rate.

Secondly, the delivery policies of a CEPSP can influence the success rate. They specify the number of delivery attempts before a parcel is brought to a parcel-locker as well as who can accept a recipient's parcel in case of absence.

Lastly, parcels cannot be delivered if the end of the delivery time window (e.g. 10 pm) or the delivery agents working hours are exceeded. In that case, the rest of a planned tour has to be skipped. This can occur due to delays along the Tour. In this paper, we will focus on the socio-demographic factors and delivery policies, leaving out the influence of tour planning.

The demand of parcels to be delivered can be determined with respect to a person's socio-demographic attributes as well. Properties like age, gender, net household income and employment status can influence whether someone participates in e-commerce and therefore expects a parcel to be delivered or not. Hence, socio-demographic properties form a connection between parcel demand and someone's presence or absence at home. For example, a retiree is less likely to participate in e-commerce; however, they are more likely to be at home than a working person. Therefore parcel deliveries to retirees should have a high success rate.

To model these delivery interactions, both the delivery persons as well as the private recipients need to be modelled as individual agents. Delivery agents require a delivery schedule with delivery locations and times to meet the demand of parcels to be delivered. Recipient agents need an activity schedule to determine their whereabouts at a specific time, as well as information about their household and neighbours. Furthermore, socio-demographic attributes are required to determine their e-commerce participation. Therefore, we use a parcel demand and last-mile delivery model (called logiTopp), which is integrated into the agent-based travel demand model mobiTopp. logiTopp simulates private agents and delivery agents within the same model over a period of one week to capture interactions that do not occur in single-day simulations, like repeating delivery attempts or picking up parcels at a parcel-locker.

These activities and the intermediate trips are simulated in the short-term module. For each trip towards a new activity, a destination and a mode are chosen. The resulting travel times may differ from the estimated travel times used in the long-term module when planning an activity schedule. Hence, the activity schedule is updated before each trip to consider the actual travel times. These steps are repeated for each activity and are simulated for all agents simultaneously.

### 2.2. mobiTopp

mobiTopp [13, 14] is a travel demand modelling framework which consists of two modules: a long- and a short-term module. The long-term module generates a synthetic population of households and their individual agents. The agents are assigned socio-demographic attributes, including age, gender, work status, highest degree of education, income, place of work/education, drivers license, commuter ticket and membership to mobility service providers like bike-sharing or car-sharing. Similarly, households are assigned a number of household members, a number of cars, a home location and a net income. Each person references such a household context and thereby the other household members. Households and persons are drawn from a population pool provided by the German Mobility Panel [6], which is a national household travel survey, and weighted based on general population distributions. Additionally,

activity schedules are generated for each agent, including work, business, education, shopping, leisure, service and home activities. These activity schedules contain activities for the entire simulation period of one week [9].

### 2.3. logiTopp

The mobiTopp extension logiTopp [16] integrates a parcel demand model and the simulation of their last-mile delivery into mobiTopp and is available as an open-source project on GitHub [11]. logiTopp mostly extends the short-term module of mobiTopp. Before the activities and trips of all agents are being simulated, a parcel demand model is applied to all potential recipients (i.e. simulated persons) to determine the number of parcels to be delivered during the simulated period of one week. logiTopp distinguishes three delivery types: home deliveries, workplace deliveries and parcel-locker deliveries. When generating the parcel demand, each parcel is assigned a delivery type to determine its destination. Furthermore, a CEPSP, a distribution centre (DC) and the parcel's arrival date at the DC are selected.

The number of parcels, as well as the delivery type, are determined by means of discrete choice models. Both models take the properties of the recipient into account, including their age, gender, employment status and household income (comparable to [16]). This models the demand of parcels to be delivered. During the demand simulation, selected delivery agents are assigned tours consisting of delivery activities. The interaction between delivery agents and recipient agents takes place while executing a delivery activity. Since logiTopp simulates all agents simultaneously, the current activity and location of the recipient are known at the time of delivery.

### 2.4. Delivery Policies

logiTopp allows defining custom delivery policies for each CEPSP. This is useful since the maximum number of delivery attempts  $a_{max}$  varies among different CEPSP. Failed deliveries can produce up to  $a_{max}$  additional trips for a parcel. Once a parcel reaches the maximum number of delivery attempts, its destination is rescheduled to a parcel-locker. Upon depositing the parcel at the parcel-locker, the delivery agent informs the recipient about the delivered parcel. The recipient plans a pick-up activity before the next home activity and adds it to their schedule, which produces an additional trip for the recipient.

In addition to the maximum number of delivery attempts, the delivery policies also state whether a parcel can be delivered depending on the delivery type and the recipient's status. Deliveries at parcel-lockers are assumed to be always successful as we do not model their capacity. Workplace deliveries can only be received personally by the recipient; therefore, the recipient has to be at work at the time of delivery. Home deliveries, which are the focus of this paper, can be received by the recipient themselves, another household member or a neighbour. If the recipient of a parcel is not at home, the presence of other household members can be checked by using the recipient's household context, which references the other household members. If any other household member currently performs a home activity, they can receive the parcel instead. Analogously, the presence of neighbours is determined by their current activity. However, mobiTopp does not model neighborhood relations between households or persons.

### 2.5. Neighbourship Relations

Defining neighbourhood relations is difficult as common household surveys do not provide information about neighbours. Neighbourhoods are a social network of households rather than a cluster of closely spaced households. However, from the delivery agent's point of view, the social relationships are irrelevant as long as the walking distance and delivery time to a neighbour are within reasonable bounds. Therefore, we use a distance-based definition of neighbourhoodship as an approximation. Using household coordinates, we define the neighbours of a household  $h$  as the  $k$  nearest neighbours to  $h$  (by distance) within a maximum radius of  $r$  meters. This maximum radius defines the maximum distance a delivery agent will walk to deliver parcels to a neighbour.

When simulating a large population, retrieving a household's neighbours has to be efficient with respect to both computation time and required memory. The number of neighbour deliveries scales linearly with the size of the population; therefore, the time required to compute the neighbours has a linear influence on the duration of the demand simulation. After the population is generated by mobiTopp, the neighbours of each household could be precalculated. Finding a household's neighbours requires computing its distance to all other households and sorting them by proximity. As we have continuous distance values, sorting can be solved in  $O(n \log n)$  time. This would allow obtaining a

given household's neighbours in constant time  $O(1)$ . However, precalculating the neighbours of all households has a time complexity of  $O(n^2 \log n)$  in the number of households  $n$  and requires memory space of  $O(k \cdot n)$ . Moreover, this would precalculate neighbour relationships that are never used during the simulation since not all households receive parcels. Also, for those households that do receive parcels, the recipient or another household member could be at home, in which case the neighbourhood model is not needed. To avoid precalculating unnecessary neighbourhoods, the distance to all other households could be determined during the simulation. This, however, would take  $O(n \log n)$  time per neighbourhood query.

Finding the  $k$  nearest neighbours in a multidimensional (metric) space is a known problem in computer science. As a trade-off between required memory of the data structure and computation time of  $k$  nearest neighbours, spacial index trees have been developed, which recursively split a space into smaller sub-spaces. In our approach, we use a simple Kd-Tree data structure [4] which requires less time to precalculate ( $O(n \log n)$  [8]) and less memory space ( $O(n)$  [8]) than precalculating the neighbours of all households. The average query time for finding the single nearest neighbour using a Kd-tree is  $O(\log n)$  [8]. Our implementation uses the sliding-midpoint rule [15] for recursive space splitting. Table 1 shows the theoretical time complexities for preprocessing and queries of the three alternatives. Additionally, actual computation times measured with our implementation are given.

Table 1. Time and space complexity of nearest neighbour computation as well as measured preprocessing and query times for 30k, 60k and 100k households (queries with  $k = 10$  neighbours) for three approaches: brute force before runtime (a priori), using a Kd-tree and brute force at runtime.

	preprocessing	n=30k	n=60k	n=100k	query	n=30k	n=60k	n=100k	space
a priori	$O(n^2 \log n)$	0.87 h	3.8 h	11.2 h	$O(1)$	0.2 $\mu$ s	0.2 $\mu$ s	0.2 $\mu$ s	$O(k \cdot n)$
Kd-tree	$O(n \log n)$	0.39 s	1 s	2 s	$O(\log n)$	0.4 ms	1.4 ms	3.1 ms	$O(n)$
at runtime	-	-	-	-	$O(n \log n)$	102 ms	228 ms	416 ms	$O(n)$

### 3. Results and Discussion

We applied our model to the area of Karlsruhe, Germany. Karlsruhe is a city in the South-West of Germany with a population of just over 300,000 people. The area is serviced by six different CEPSP. Two of them perform only one delivery attempt, one performs two, and the rest perform three. We simulated four different policy scenarios as well as one scenario with a static success rate for comparison:

- **personal:** Parcels can only be received by the recipient themselves.
- **household:** Parcels can be received either by the recipient or another household member.
- **4 neighbours:** Parcels can be received by the recipient, household members or one of the four nearest neighbours within a maximum radius of 50 meters.
- **unlimited neighbours:** Parcels can be received by the recipient, household members or any arbitrarily distant neighbour. An less practical scenario to evaluate the potential of checking additional neighbours (See Figure 3).
- **delivery probability:** Parcels have fixed a 94% chance of being delivered (as observed by Statista [19]).

Each scenario was simulated threefold to account for stochastic variation caused by randomness in the model.

Comparing the success rates of first delivery attempts show that the chance of a successful delivery increases with the number of potential substitute recipients, as displayed in Figure 1. It also shows that the variation of the success rate decreases if more agents can accept a parcel instead of the recipient.

Inversely, the share of unplanned pick-up trips relative to the total number of pick-up trips decreases as the success rate increases (see Figure 2). Unplanned pick-up trips occur if a parcel could not be delivered to the recipients home or workplace and is instead deposited at a parcel-locker. Planned pick-up trips, on the other hand, are trips to pick up parcels that were destined to the parcel-locker by choice. In the static **delivery probability** scenario, 5% of the pick-up trips are unplanned, which is more than double the share of the dynamic scenarios that involve neighbours.

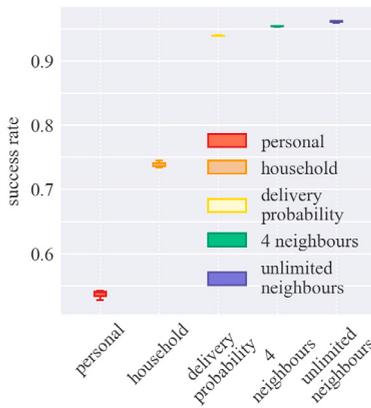


Fig. 1. Overall success rate of parcel deliveries in the five scenarios.

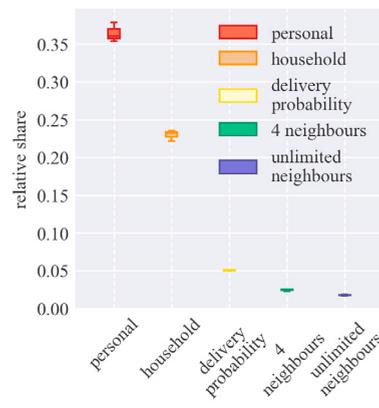


Fig. 2. Share of unplanned pick-up trips relative to the total number of pick-up trips.

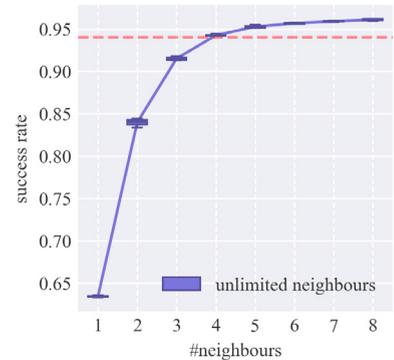


Fig. 3. Delivery success rate over the number of neighbours checked during a delivery attempt. The red line marks a success rate of 94% (4 neighbours). Checking more shows the potential to slightly increase the success rate.

In the following, we will compare the success rates of the four dynamic scenarios with respect to various socio-demographic attributes of the recipient.

Figure 4 shows the success rates for different age groups. Overall the success rate increases with the recipient's age except for the **household** scenario, in which recipients of age 0 – 24 have a higher success rate than recipients of age 24 – 64. The oldest age group of 65+ years has a noticeably higher success rate in all scenarios, the most significant difference being visible in the **personal** scenario. The average retirement age in Germany is 65 years. Since retirees tend to stay at home, they are more likely to be present at the time of delivery, resulting in a higher success rate.

Furthermore, we analysed the success rate with respect to the recipient's gender, as shown in Figure 5. Female recipients show a higher success rate in all scenarios; however, the difference reduces to about 1% when including neighbours.

Figure 6 shows the success rates for persons with and without mobility tools. Here, persons with mobility tools have at least one of the following: a bike, a driver's license or public transport season ticket. Persons without mobility tools have neither of them and show a higher success rate in all scenarios. Persons who travel a lot tend to have more mobility tools than persons staying at home which explains the increased success rate for immobile persons.

Similarly, in all scenarios, working persons show a lower success rate than unemployed persons (including pupils, students and retired persons), as portrayed in Figure 7. The average working hours are from 8 am to 4 pm resulting in long periods of absence during which parcels cannot be delivered at home.

Additionally to the person attributes, we evaluated household attributes, i.e. the number of persons or cars. As depicted in Figure 8 and 9, they both show a similar pattern. In the **personal** scenario, the success rate decreases with an increasing number of household members resp. cars. This trend is inverted in the **household** scenario. The increasing trend seems to hold true for the two neighbour scenarios, except for the values at the upper end of the scale where the success rate slightly decreases. This could be explained by the fact that households with five members or five cars rarely occur in the investigated area; hence these socio-demographic groups only have a small sample size.

Another influence on the success rate is the number of neighbours a delivery agent checks before aborting a delivery attempt. Figure 3 shows that 94% of the parcels can be delivered by checking up to 4 neighbours. Checking more neighbours has only little effect on the success rate. The **4 neighbours** scenario produces an overall success rate on the first delivery attempt of 95.35% on average with a standard deviation of less than 0.1%. This matches the average success rates of about 94% observed in a survey by Statista [19]. Moreover, the influence of the socio-demographic attributes in the **household** or **neighbor** scenarios as described above are in line with the findings of Duil et al. [23] which are based on historical data.

These evaluations show that a single static success rate like in the **delivery probability** scenario can over- or underestimate success rates for certain socio-demographic groups. However, when it comes to assessing different measures (like implementing additional parcel-lockers in a student district), it is important to differentiate these groups so the

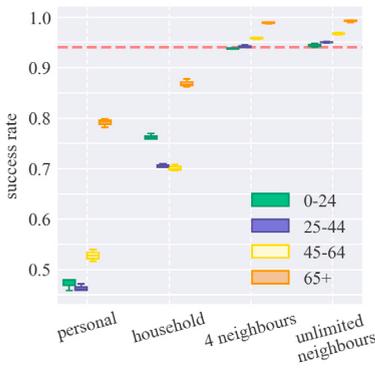


Fig. 4. a) age

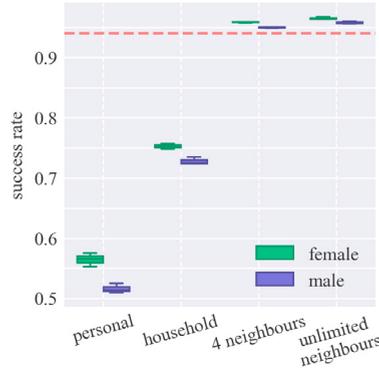


Fig. 5. b) sex

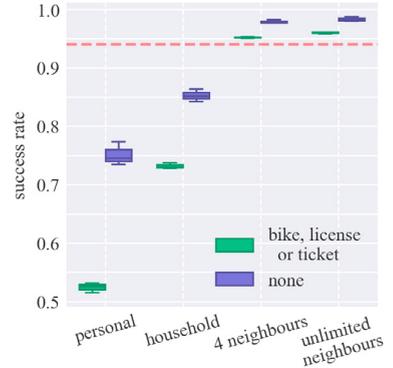


Fig. 6. c) mobility tools

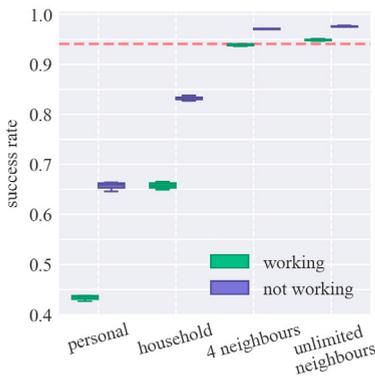


Fig. 7. d) employment status

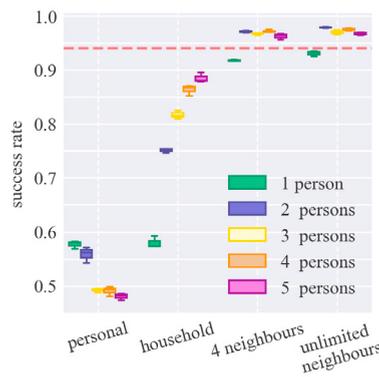


Fig. 8. e) household size

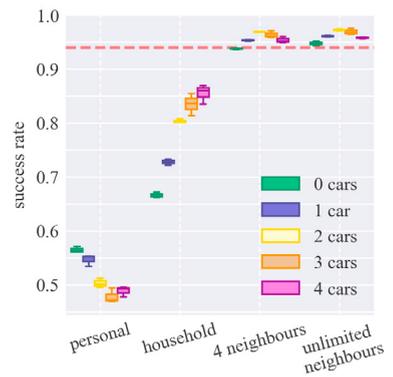


Fig. 9. f) number of cars

Fig. 10. \*

Fig. 4-9: Delivery success rates over different person attributes: a) age (4), b) sex (5), c) mobility tools (6), d) employment status (7), e) household size (8), f) number of cars (9). The dashed red line marks the expected success rate of 94%.

measures can be targeted to those groups where they show the most promising effects. Additionally, the comparison of the scenarios shows that it is necessary to model neighbour deliveries to reproduce the expected delivery success rate of 94%. Only considering personal deliveries merely produces an average success rate of 53.6%, which is increased to 73.8% when considering other household members.

#### 4. Conclusion

In this paper, we developed a concept for modelling interactions between delivery agents and recipient agents in an agent-based travel demand model. This model is integrated into the demand modelling framework *mobiTopp*. Furthermore, we modelled neighbourship relations between households through nearest neighbour search using *Kd-trees*. We showed that modelling the causality and effects of failed deliveries is useful when differentiating socio-demographic groups e.g. to develop targeted measures. Moreover, we showed that it is crucial to model neighbour deliveries to reproduce realistic delivery success rates. The presented approach and the related findings are of interest to policy makers and CEP service providers as the model provides the means to analyse how failed deliveries affect the transport system and to find areas with potential for improvement. The *logiTopp* model currently does not consider parcel sizes which could affect the success rate since small parcels can be left in the mailbox. Furthermore, the effects of the Covid-19 pandemic and the accompanying increase of home-office on both the e-commerce frequency and the delivery success rate present a compelling use case that can be analysed with the presented model.

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