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A disaggregate model of passenger-freight matching in crowdshipping services

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ABSTRACT

Crowdshipping (CS) is an emerging form of freight transport that is expected to reduce the externalities of urban freight transport. The supply of CS services originates from people with an intention to travel, who can choose to engage in a parcel delivery service as incidental carrier. The popular expectation is that this consolidation of freight and passenger trips could save freight trips and thus alleviate urban transport congestion and environmental pollution. A key challenge in the prediction of CS service volumes and impacts, however, is to match existing service demand and supply. This has not yet been addressed in the literature with models that give an empirically realistic representation of individual decision-making. We approach this problem using a disaggregate activity-based models for urban passenger transport and freight transport. Allocation of parcels to travellers is done based on a simulated random utility discrete choice model. We present a first case study for the city of The Hague, The Netherlands, to illustrate empirically the model. Our findings suggest that CS could result in increased CO_2 emissions and total vehicle distances travelled.

1. Introduction

Urban freight transport (UFT) as the last segment of supply chains is pivotal to provide access for consumers to everyday goods (Devari et al., 2017). The pandemic of COVID-19 has contributed to the already increasing e-commerce, from an increase of 20 % between 2017 and 2018 to an increase of 35 % from 2019 to 2020 (ACM, 2018, 2020). Delivery services are growing strongly, implying more frequent use of smaller commercial vehicles for local distribution out of huge logistics hubs. Modern cities are asked to facilitate retailers in making increasingly speedy, on time, secure, and sustainable deliveries to consumers. At the same time, UFT still results in major externalities including traffic congestion and polluting emissions. Therefore, it is necessary to develop smart, reliable and sustainable solutions. Urban transportation is one of the top concerns of European Commission, included in The European Green Deal (European Commission, 2021). In response to the Paris Agreement, the EU has set the ambition to be the first climate-neutral continent by 2050. This will be achieved with a two-step approach designed to reduce CO_2 emissions by 55 % by no later than 2030. The Commission in July 2021 set the "Fit-for-55" package, paving the road for zero emissions freight transport, including urban freight and passenger transport (European Commission, 2021).

Combined operation of passenger and freight systems using passenger transport capacity for freight could help to reduce

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externalities of UFT. The idea of integrating freight and passenger transport is not new, since first academic discussions date back to more than a decade ago. Innovative freight delivery solutions that function on a sharing economy concept such as Uber are expected to help in improving the potential social and environmental impact of UFT concerning emissions, noise, and safety. Innovative freight delivery services are being developed that provide "for-hire delivery services for monetary compensation using an online application or platform (such as a website or smartphone app) to connect couriers using their personal vehicles, bicycles, or scooters with freight (e.g. packages, food)" (Shaheen et al., 2015, pp. 17) and aim to improve last-mile logistics. These services capitalize the supply that can be offered by travellers in the form of crowdshipping (CS). Although CS could be able to offer important benefits such as improved lead times, reduced emissions by shared transport and more flexibility (Rougès & Montreuil, 2014), also concerns have been raised over reduced security and safety of parcels, and overall reliability. In addition, while CS could reduce the load on the freight system by utilizing passenger transport spare capacity, the pressure on passenger transport systems may increase, and the net outcome for traffic networks is uncertain.

Only recently, efforts have begun to explore impacts with large scale transport models (Alho et al., 2021). One of the biggest challenges identified here is to match the supply and the demand for this service, since the first is created by passenger transport while the latter is generated by freight transport. Our literature review reveals a very limited amount of attention so far in developing models that simulate both the supply and demand for CS services. We address this gap by joining passenger and freight behavioural transport demand models. The paper proposes an innovative Agent Based Model (ABM) that simulates the demand for CS, estimates the supply of CS services from the pool of commuters, and matches supply with the demand of the services. We assume that the CS platform limits itself to communication between demand and supply and does not optimize allocation across shippers and carriers. We develop the model using a disaggregate choice model that is applied for individual travellers. A set of CS strategies that include pricing and mode restriction are implemented to calculate the impact of CS in congestion and emissions in the city of The Hague, the Netherlands.

The key contributions of the study are threefold: Firstly, we implement a decentralised parcel to traveller allocation that is consistent with microeconomic theory and random utility maximisation assumptions. Secondly, we simulate the remuneration of CS considering the detour as working hours. Finally, we simulate the impacts of CS in congestion and CO2 emissions with data of The Hague.

The remainder of the paper is structured as follows. We introduce the state of the literature on the subject of modelling CS in Section 2. Section 3 describes the methodological framework that we used to model the combined systems. In Section 4, the effect of the CS on a city delivery services is analysed and Section 5 discusses the results. Finally, Section 6 concludes the paper.

2. Literature review

There are various definitions for CS in terms of by whom, to whom and how the service is provided (Ermagun & Stathopoulos, 2021; Gatta et al., 2018; Karakikes & Nathanail, 2022; Marcucci et al., 2017; Rechavi & Toch, 2020). Crowdshippers can be commuters who in their trips take along a parcel or van drivers from courier companies in their spare time. Senders can be either individuals or companies. Transport is possible to be realized either by own means or by public transport. In all definitions though, users can access the services via a smartphone app, publish shipment information (i.e. pick-up\delivery locations, package size) and then an algorithm matches shipments with transporters. Every citizen with a smartphone and a private vehicle or in some cases, a bike or travelling by public transport is able to become a transporter.

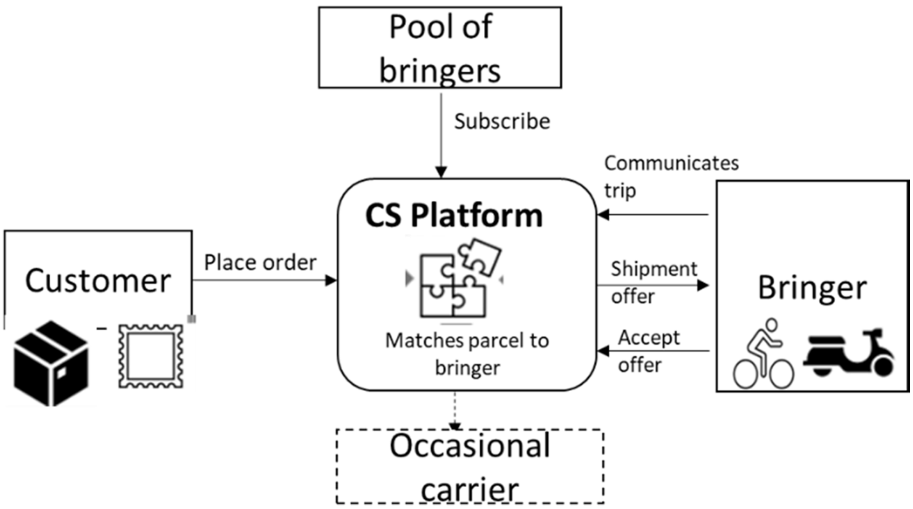

Fig. 1. Crowdshipping actors and their interactions.

2.1. Crowdshipping process and impacts

CS companies operate under a variety of business models (Shaheen et al., 2015). Some companies use only motorized vehicles (cars, motorbikes) while others only bikes (DelivCo, 2020; UberEats, 2020). A variety of products can be transported ranging from food and groceries (DelivCo, 2020; Roadie, 2020; UberEats, 2020), to library books (Paloheimo et al., 2016). CS operates with various ranges from long haul, where companies focus on packages between cities (Nimber, 2020), to city-range last-mile deliveries. The majority of companies offering CS services are start-ups and still face various issues such as experimental business models, under-capitalization, high failure rates and many mergers (Mckinnon, 2016). However, larger players have already started entering the market such as Amazon introducing AmazonFlex in 2016. AmazonFlex is a CS service aiming to improve the cost efficiency of last-mile deliveries (Amazon Flex, 2020).

The aforementioned platforms focus into different market segments, either B2B or B2C deliveries, and they handle different types of parcels and packages. Fig. 1 summarizes the actors engaged in crowdshipping services and their interactions in decision-making.

This innovative economy sharing UFT method can offer numerous advantages. First of all, the utilization of passenger transport capacity can potentially reduce the number of urban freight vehicle trips leading to a reduced congestion (Mckinnon, 2016). CS can provide receivers with more time flexibility as delivery times can be customized via the platform (Punel & Stathopoulos, 2017). On the environmental side, the utilization of trips already made by commuters does not add the extra emissions of the freight vehicles (Buldeo Rai et al., 2017; Paloheimo et al., 2016). Especially if CS is performed with an environmentally clean mode, emissions can be decreased (Buldeo Rai et al., 2018; Rougès & Montreuil, 2014). Research done by Arslan et al. (2019) proves the potential of CS to reduce costs both for customers and bringers, especially when they have to deal with the challenging scheduling task of same-day deliveries. Studies that apply crowdshipping at mobility-on-demand services show that crowdshipping can reduce by 2 % the vehicle kilometres (vkms) for both passenger and freight transport (Alho et al., 2021).

Despites the positive impacts a possibility of rebound effect exists. The term rebound effect refers to the possible increase in the number of passenger vkms in order to satisfy the freight demand (Paloheimo et al., 2016) and can lead to an increase in the number of vehicles that can even be dedicated only to crowdshipping reversing the benefits of CS (Gatta et al., 2019). Depending on the mode used, CS could have a negative or a positive effect in congestion and GHG emissions (Buldeo Rai et al., 2017).

In addition, courier companies are always improving their operational efficiency by consolidating parcels and optimizing routes, while CS is much more inefficient since it relies in the available passenger capacity and delivers only one parcel at a time (Buldeo Rai et al., 2021). Consequently, the parcel delivered by the traditional delivery companies would require fewer trips to deliver the parcels compared to the crowdshipping service. However, the combination of CS with microhubs can significantly improve efficiency and reduce vkms of parcel vans in urban areas (Ballare & Lin, 2020).

2.2. Crowdshipping modelling

Literature on CS modelling has only developed recently. Broadly, we can distinguish between two separate streams of work, focused on the supply and the demand sides of the CS market. On the *supply side,* we identify the Willingness to Work (WTW) of a consumer as a bringer in a CS service. Studies in the literature reported sociodemographic factors to have a significant influence in the WTW as a crowd-shipper. Some of the most influential factors identified are age, gender, ethnicity, income, education, and number of people in the household. Compensation and maximum deviation time are identified as the most important factors for both acting as a bringer and accepting a trip (Buldeo Rai et al., 2021). Le and Ukkusuri (2019) analysed the WTW as a crowd-shipper by building a logit model that took into consideration variables such as age, employment, salary, people in the household and ethnicity. Their finding suggested that users earning below the average national income are more likely to act as crowd-shippers. This was also the case for users who were more than 30 years old. Other variables that were found significant on this study were gender, social media usage and mortgage. They calculate that in the USA bringers are getting paid between $10 and 12$ per hour (Le & Ukkusuri, 2019; Le et al. 2019). Marcucci et al. (2017) conducted an experiment with students in Rome and found that students are willing to be bringers for 5–10 euros per delivery with the maximum detour distance of 2.4 km. Punel et al. (2018) developed a two-part supply model defined by both the probability of bidding for a delivery and the bid count on a CS company in the US. Their results showed that an increase in the delivery distance decreased the chances of receiving a bid. This is not surprising as users are less likely to divert for longer times during their daily commute.

In the Netherlands, commuters that use cars have a WTW for 19.6 euros per hour and cyclists for 24 euros per hour (Wicaksono et al., 2021). In their study Neudoerfer et al. (2021) estimated a WTW for 10 euros per hour based also on parcel dimensions and travel detour distance. They also calculated that bringers are willing to make up to 2kms detour. Other parameters such as the size of the parcel (Punel et al., 2018) and trip purpose with people travelling for leisure purposes being more likely to act as occasional drivers (Miller et al., 2017). Regarding the socioeconomic characteristics Galkin et al., (2021) looked into the potential age of bringers in Bratislava, Slovakia. They showed that as the age increases WTW decreases.

On the *demand side* studies looked the willingness to use the crowd-shipping service (demand side) (Gatta et al., 2020; Punel & Stathopoulos, 2017), or both (Le Pira et al., 2017). Findings in Punel et al. (2018) revealed that users are not predominantly motivated by saving money but tend to be driven by environmental concerns. Their findings also suggested that past experiences with innovative logistic services allow users to overcome privacy and trust issues. According to findings in Gatta et al. (2020), a possible way of stimulating people to use CS is by giving them the option to plan the delivery date and its time schedule, as users in their dataset were more prone to use crowd-shipping services when given these options. The demand for CS is also affected by the socio-economic characteristics of the users as well as the built environment of the CS area. Ermagun et al. (2020) showed that larger shipment size (versus strict deadlines) leads to increasing the likelihood of bids being placed, while having the opposite effect when it comes to the delivery phase. Additional factors affecting the demand are how user -friendly is the CS platform (Frehe et al., 2017), the level of service (reliability, undamaged parcels, customization of the service) and the environmental friendly aspect of CS (Buldeo Rai et al., 2021).

In terms of crowdshipping simulation, Chen & Chankov (2018) presented an agent-based modelling and simulation approach to evaluate the performance of crowdshipping as a last-mile delivery service. Their approach included a number of scenarios where they employed different maximum detour times and numbers of available agents to assess the impact on total parcel deliveries. A similar study by Karakikes & Nathanail (2022) evaluated the impacts of crowdshipping through different demand scenarios employing a city scale urban freight traffic microsimulation model. They simulated the adoption of crowdshipping by public transport users willing to serve as agents, based on a real case study example.

Simoni et al. (2020) adopted a simulation-based approach to determine the environmental effects of crowdshipping in Italy. They employed a hybrid dynamic traffic simulation that used macroscopic features (triggering of congestion, traffic signal interaction), in combination with microscopic components of delivery operations (tracking of delivery vehicles, parking behaviour). They evaluated the effects on traffic emissions and determined that the mode of transport (private, public); along with the length of detour and daily traffic variations are crucial for the impact on the environment.

Alho et al. (2021) employed SimMobility, an agent-based simulation platform, to evaluate the impact of delivering parcels using Mobility-on-demand (MOD) services. Their results indicated the potential of MOD services to fulfil a considerable amount of parcel deliveries and decrease freight vehicle traffic but with an increase of passenger traffic.

In Dötterl et al. (2020) an agent-based simulator that emulated the decision making of the crowdshipping agents to accept a delivery task was presented if their deterministic utility is greater than zero. In their simulator, it was possible to monitor the delivery operations and depending on the status of the delivery, the system could attempt to transfer the parcel to a more promising courier nearby.

In the literature, many algorithms exist that match crowdshippers with packages. These models include different business strategies (Zhang, et al., 2017) and are sensitive to customer related factors such as penalties for late deliveries (Kafle et al., 2017). Li et al. (2014) matched parcels with taxis and calculated the benefits for the taxi drivers. Researchers have successfully solved the matching problem by connecting ride offers with ride requests in real –time, real-time recommendation algorithms for crowdsourcing systems (Safran & Che, 2017; Schreieck et al., 2016). Optimization models have also been used to match crowdshipping supply and demand (Boysen et al., 2022).

Arslan et al. (2019) investigated crowdshipping from the delivery routing optimisation perspectives. This study showed that by optimising the unused capacity of a vehicle, taking a small detour to deliver a parcel and paid with small compensation would bring more economic benefits compared to traditional delivery. This study found that crowdshipping would be most beneficial when used in addition to the traditional dedicated delivery service. Moreover, Arslan et al. (2019) argued based on their study that crowdshipping done by the in-store customer to deliver the parcel to the online customer along their route is the most suitable form of crowdshipping. Wang et al. (2016) studied the crowdshipping model in a network of pick-up points and modelled them as an assignment optimisation problem, to be solved using min-cost problem (minimising the total compensation fee paid to occasional couriers) and found that the crowdshipping is a potential method that could be implemented for handling real-time delivery request in the large scale. It should be noted that here vkms for each parcel during the first mile have not been taken under consideration. To understand full impacts, crowdshipping should be followed from origin to final destination, while usually calculations are done from the depot/hub to the final customer and pickup segments (from the sender to the drop-off point and then the depot/hub) are not taken under consideration. Table 1 summarises the simulation models from the literature.

The experience with modelling CS services so far shows the variety of design assumptions in the CS services, e.g. the pick-up points, compensation schemes, collaboration with senders such as stores or parcel carriers. Therefore, a comprehensive view is needed of parcel demands and service supply from the side of passenger transport. In this context, agent based models provide potentially comprehensive behaviour-based simulations, that provide the level of disaggregation needed to analyse the complexity of the problem. This applies both to passenger transport, as well as for the freight side of the problem.

Table 1
Simulation models summary.

Author	Scope	Method	Matching method
Alho et al 2021	City level demand	Agent Base Model	Min detour
Arslan et al., 2019	Simulated setting	Optimization	Min cost
Boysen et al., 2022	Simulated setting	Linear programming	Max assignment of parcels
Chen & Chankov, 2018	Specific demand	Agent Base Model	Min detour
Dötterl et al., 2020	Specific demand	Agent Base Model	Closest with positive deterministic utility
Karakikes & Nathanail, 2022	Simulated setting	Simulation	Min cost
Li et al., 2014	Simulated setting	Optimization	Max profit
Safran & Che, 2017	Simulated setting	Heuristic	Max score
Schreieck et al., 2016	Passengers (not parcels)	Optimization	Min detour
Simoni et al., 2020	Specific demand	Simulation	Exogenous
Wang et al., 2016	Specific demand	Optimization	Min cost
Zhang, et al., 2017	Simulated setting	Linear programming	Max profit

Most of the simulation studies simulate in an hypothetical setting (i.e. not in a city based scenario) or use a subset of the demand and do not look at the entirety of the freight demand. To our understanding, the only other ABM that takes into consideration freight related aspects specifically is SimMobility that, as stated before, has a CS application. Their approach assumes a central agent that allocates the parcel to vehicles that are part of a Mobility on Demand platform and does not consider other mobility agents, such as regular travellers. The next sections present an approach that takes into consideration mobility patterns, together with behavioural aspects regarding the matching between travellers and parcels.

3. Modelling framework

In our modelling framework, the CS service is embedded in a broader parcel delivery context. This delivery context is characterized by large e-commerce retailers and couriers that deliver the parcels with their established distribution structures. The methodology is based on existing ABM models for urban freight and passenger demand, and extends a parcel market model with CS services, that matches supply of CS services from a pool of commuters with the demand for CS delivery. To achieve this we apply and develop further an already developed model MASS-GT (de Bok et al., 2020). MASS-GT is a multi-agent simulator for urban freight transport demand, and has separate modules dedicated for the demand and delivery simulation of micro-freight. In this study, we use the modules that are related to the parcel delivery system. The activity based transport model ALBATROSS simulates passenger trip diaries (T. Arentze et al., 2000; T. A. Arentze & Timmermans, 2004) and is used to identify potential bringers.

The framework consists of the following functional building blocks that are explained in this section:

- Freight (household) demand module (from MASS-GT)
- Household mobility demand (from ALBATROSS)
- Parcel market:
- Conventional parcel fulfilment (from MASS-GT)
- CS-fulfilment
- Parcel delivery scheduling (from MASS-GT)

All the decision making, both on the freight and passenger side, are visualised in Fig. 2. For the CS use, case the parcel market module is enhanced with a submodule for CS-fulfilment. We elaborate each building block sequentially below.

3.1. Freight demand

The parcel demand module, as developed in MASS-GT, determines the number of parcels to be delivered in each zone based on the number of households and jobs and B2C- and B2B-demand parameters deduced from aggregate statistics of the ACM (2018). Furthermore, each parcel is assigned to one of the six largest parcel couriers of the Netherlands based on their market share in terms of volume.

Next, for the CS use case we simulate a proportion of those parcels to be local-to-local (L2L). For this, we introduce a study area that can include different groupings of neighbouring municipalities so we are not limited by administrative divisions. This way we can generate L2L per urban agglomerations. For the parcels that are not L2L, an origin in the closest depot is adopted, as the parcel generator module dictates.

3.2. Parcel market: Crowdshipping fulfilment

The CS platform that we simulate in this paper is a platform that presents transparently and visibility to all the bringers with all the parcels. This means that the platform itself does not do any matching or parcel allocation, but this is done by the preferences of each shipper and bringer, similarly to what happens with Nimber.[1] This possess the challenge on how to prioritize pairs of parcel-bringers across all the population of trips and parcels. For this we assume that the decision is made rationally by the bringers, because senders are indifferent because of the same cost of delivery and do not have any a priori preference among bringers. We do the allocation by a utility based, best parcel to best trip method.

The first step in the crowdshipping allocation is to generate the pool of bringers, which we define as a set of travellers that are willing to carry parcels in their trips, from the whole of passenger trips. The trips are characterized by the origin, destination, mode, purpose and socioeconomic characteristics of the traveller from the ALBATROSS model. We first introduce a socioeconomic filter, where we allow only travellers younger than 55 years old and that have a household income average or low, similarly as suggested by Le & Ukkusuri (2019). From the trips that are left, we then select randomly a percentage of the trips, depending on the scenario to be simulated. When more data about possible bringers' profiles is available for the Netherlands, this number can be derived from the socioeconomic data and the characteristics of the trip.

For each parcel that has been simulated as considering CS as an alternative, the choice must be made whether to send it via a traditional courier or via CS. This is done via a binary choice logit estimated using data from Cebeci (2021) that results in the

[1] Nimber is a crowdshipping company that operates in Norway. https://www.nimber.com/.

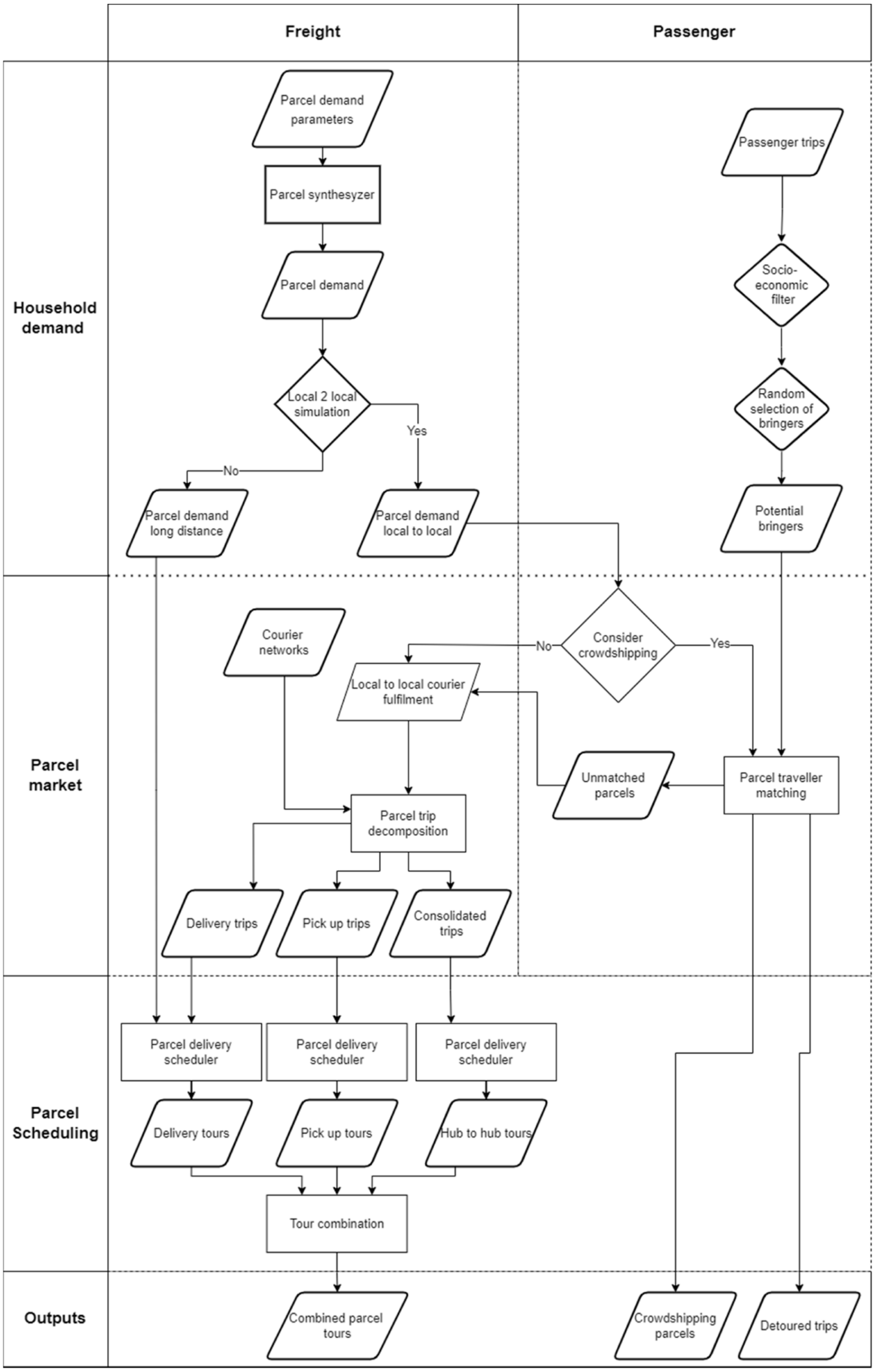

Fig. 2. Modelling framework.

probability of sending the parcel by crowdshipping. The probability that results from the choice model is transformed to a deterministic choice via the simulation of the error terms. Since at this stage we only have information about the parcel cost, the binary logit will be a simplified version with a utility function just with parcel cost (equation (1) and (2)).

$$U_{CS} = \beta_{cost} * Cost_{CS} + \varepsilon_{CS} \tag{1}$$

$$U_{trad} = \beta_{cost} * Cost\_Trad + \varepsilon_{trad} \tag{2}$$

In this simulations we used a β_{cost} of −3.292. This value was the result of fitting a binary logit to the data collected by Cebeci (2021), obtaining a t value of 15.3 and a rho2 of 0.12. The error terms are extreme value type I distributed and simulated for each parcel, according to the assumptions of logit models (Train, 2009). The cost of the parcel is fixed, but it could be based on the distance the parcel travels plus a commission by the CS platform.

The next step is to analyse the willingness of the bringers to carry each parcel. For this, we assume another binary logit for the decision of whether to take or not a parcel in the trip. For each parcel and bringer, we simulate the difference in utility, estimated through logit models, between having the normal trip and the trip collecting the parcel. The error term of both utility functions (take or not take a parcel) are also simulated with a Gumbel type I extreme value distribution. This allows us to have a simulated utility of the alternatives that can be compared across alternatives and individuals instead of probabilities. With this indicator, we can rank across the different parcels and travellers in a consistent way so we can identify the best bringer for each parcel. For this purpose we used the utility functions from de Jong et al. (2019) from a time of day and value of time study (equation (3) and (4)). Even though this model is not specific for the willingness to pick up parcels, it is a model that contains information on how Dutch passengers make their commuting decisions.

$$U_{pickup} = \beta_{TravelCost} * (Cost - Remuneration) + \beta_{TravelTime} * Time + \varepsilon_{pickup} \tag{3}$$

$$U_{currenttrip} = \beta_{TravelCost} * (Cost_{trip}) + \beta_{TravelTime} * Time_{trip} + \varepsilon_{trip} \tag{4}$$

The cost and time in equation (3) refer to the total travel time including the detours to pick up the parcel. The coefficients that were applied in the simulations were of $\beta_{TravelCost} = -0.039$ and $\beta_{TravelTime} = -0.0063$, both obtained from de Jong et al. (2019). The error terms are extreme value type I distributed and simulated for each parcel and trip.

The differences in utility between taking and not taking up a parcel are compared across all the combinations of parcel and bringers. The larger this difference, the more motivated a bringer will be to bid to take the parcel. Using this indicator, we allocate the most suitable parcel to the most suitable bringer taking into consideration the whole parcel supply and demand in the CS context. Currently we allocate one parcel to one trip. Fig. 3 illustrates the process to allocate travellers to parcels. The matching finishes when either: i) no more parcels to match or; ii) all difference in utilities is negative (indicating that nobody is willing to pick up a parcel).

We argue that through a CS platform the senders have a complete vision of all the travellers and would be able to identify the bringer that benefits the most. Even though the utility is not actually observed, the bringer would be able to signal via more flexibility

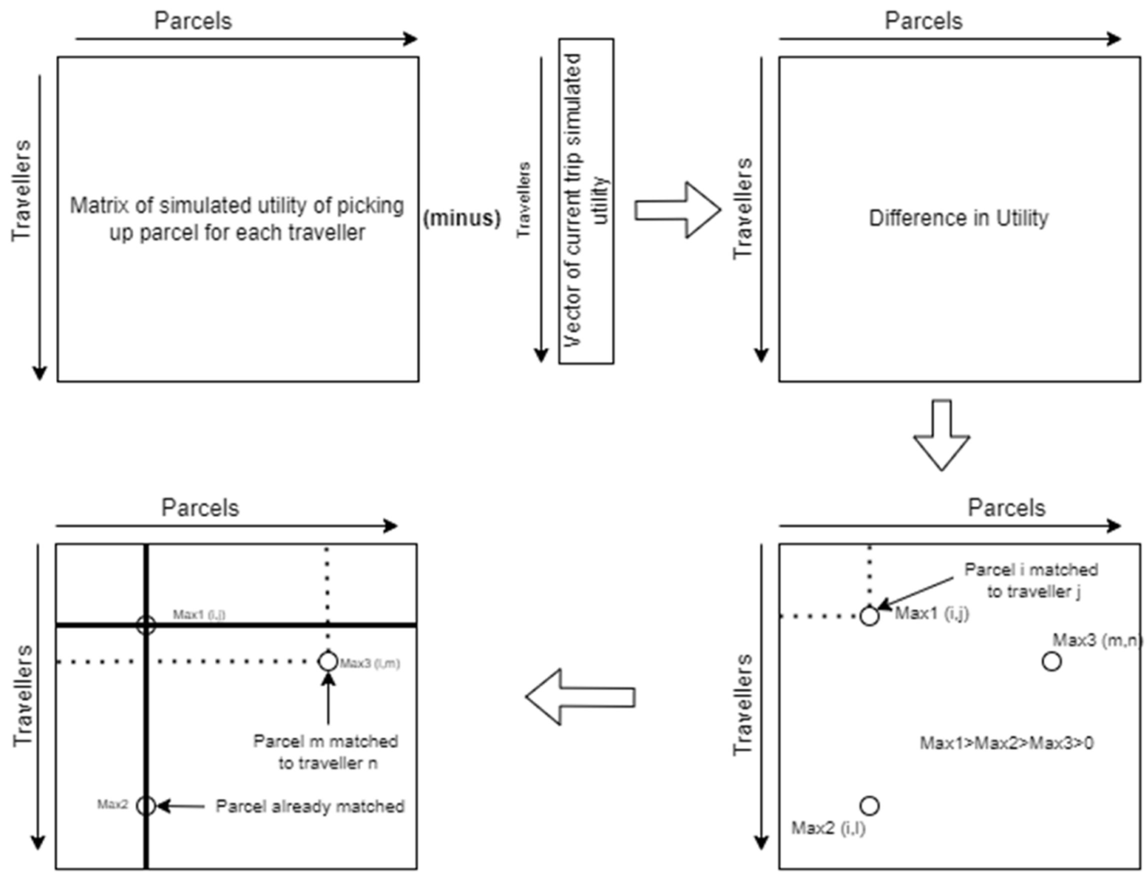

Fig. 3. Parcel allocation.

or even a discount. This differs from other optimizations approaches that assume a controller that allocates the parcel to the bringers according to relevant metrics, normally related to minimizing detour distances. Distance minimization matching usually involves a central agent that makes the decision for the individual carriers to allocate the parcels taking into consideration the whole of the system (parcels and bringers). Since the aim is to model a decentralized platform that reflects the behaviour of consumers and bringers, this assumption was not suitable. As a result of the maximum utility matching, it is likely that the detours (differences between normal travel distance and travel distance with pickup and delivery) estimated by our model are larger than a detour minimizing centralised service but are closer to a real-life decentralized setting, where the agents that accept or decline the offer are the bringers and not the platform.

The use of simulated utility functions across all the steps of the CS allocation module where a decision is made gives coherence to the framework and grounds it in the behavioural setting of the combined passenger-freight system. The utility functions are estimated to incorporate the behaviour of the different agents that participate in the CS process. By definition of the method (Ben-Akiva & Lerman, 1985), the results of these are probabilities, which then are simulated to obtain a discrete result. The way we simulate the error terms gives further alignment with the underlying assumptions done when estimating the models (random utility maximization assumptions), giving consistency across the whole model. In the literature, we have not encountered any ABM that includes these behavioural aspects and allocates the parcels in a decentralised (i.e. no central agent is responsible for the allocation) manner.

3.3. Parcel market: Conventional carriers

Once the demand by couriers is known (all the non-crowdshipped parcels), we can proceed to break it down to its different steps. This is relevant only for the L2L parcels, since the rest of the parcels would be delivered from outside the study area directly to the closest depot/hub. The L2L parcels have to be decomposed into: pick up, hub to hub (consolidated between depots or hubs) movement and delivery.

To do so, the each of the couriers' networks are simulated using NetworkX Python package (Hagberg et al., 2008). Each courier network consist of the depots/hub, which work as nodes, and are connected to each of the zones of the study area. As a simplifying assumption, we establish that the zones are only served by its closest depot/hub. Each network works in parallel from each other, unless specific nodes are established that allow the exchange of parcels among them.

Each of the parcels are allocated to the network using the Dijkstra minimum path algorithm. As a result, we breakdown the origin and destinations to a pick up trip, a consolidation trip (hub to hub) and a delivery trip.

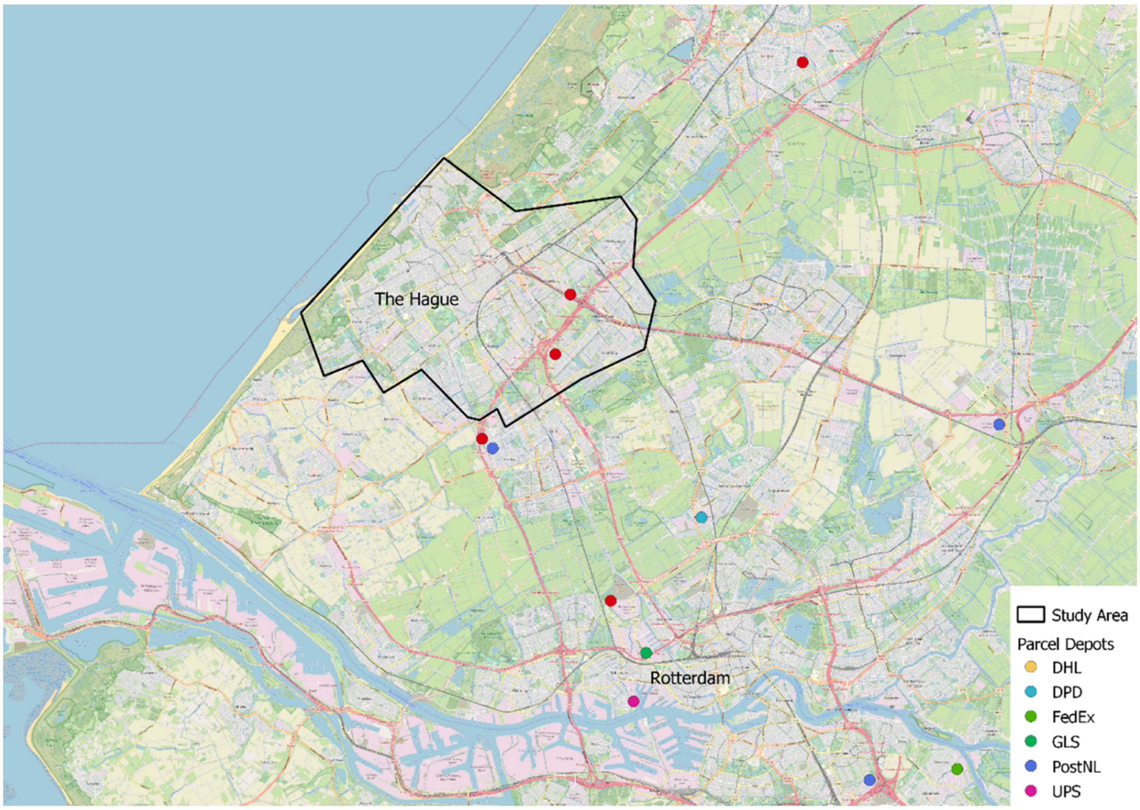

Fig. 4. The city of The Hague.

3.4. Parcel scheduling

The parcel scheduling module aims to generate the delivery tours by the courier companies. Parcels are scheduled for each courier company. The module has a two-phased set-up (Thoen, et al., 2020b). The first phase is to create clusters of parcels by bundling parcels that are geographically close together and taking into consideration truck sizes constraints. Each of these clusters will represent a tour. Second, the module takes the bundled parcels in each tour and generates the sequence of distribution obtaining a schedule of deliveries.

In this model, we will generate three different sets of parcel schedules: i) for delivery (last-mile) trips; ii) for pick-up tours of the L2L parcels and; iii) consolidated trips between hubs of the picked up parcels. The pick-up tours are then combined with the schedule of the delivery trips, so they are picked up after a delivery tour is done.

4. The Hague case study

4.1. Context

An application of the framework was done for the city of The Hague (Netherlands) under the framework of the LEAD project (LEAD, 2020). The LEAD project aims to develop digital twins to represent urban logistics and support decision making of the stakeholders in the urban freight system. In this work, MASS-GT is included in a broader generic urban freight digital twin architecture (Belfadel et al., 2021).

The city of The Hague is home of around 0.5 million people and expected to grow by 20 % until 2040. It is a dense urban area with a density of 6,500 people per square kilometre (Statistics Netherlands, 2021) and it is undergoing a process of further development and densification, especially in the city centre and surrounding areas. This will bring extra tensions to the already stressed urban delivery system, which is still adapting to the post-pandemic demand levels, due to the need of supplying the new and current inhabitants.

The Dutch parcel delivery market has 6 main service providers who together capture more than 80 % of the flows: PostNL, DHL, FedEx, DPD, UPS and GLS. For the final deliveries, Post NL has the largest share with approximately 50 % of the deliveries, followed by DHL with 23 %, DPD and UPS with 10 % (ACM, 2018). The area is served by several hubs of PostNL and DHL, while the other couriers serve the city with hubs positioned to deliver also to the neighbouring city of Rotterdam. The parcels will be simulated for the whole region of South Holland (also including Rotterdam), but crowdshipping would only be available in our study area of The Hague. Fig. 4 shows the study area, together with the main courier hubs.

4.2. Data

The data used in this simulation comes from a multiplicity of sources. The parcel demand parameters and courier market shares for the baseline model come from ACM (2019). The data obtained from here are the market shares of the couriers and annual parcel demand. The locations of parcel depots/hub were collected using OpenStreetMap and Google Maps. The percentage of L2L parcels of 4 % was obtained through interviews with local logistical parties.

The activity demand from ALBATROSS in the study area consists of 1.227.212 activities, where 889.288 corresponded to passenger trips (the other were activities like stay home). From those, 98 % had valid postcodes in the Netherlands, totalling 860.147 trips in the region. From those around 700.000 are done either by car or by bike/walking. Even though the ALBATROSS model does not distinguish between walking and cycling trips, we assume that these are done mainly by bike because, since the model only distinguishes movements between postcodes, the distances tend to be too large for walking commutes. It is worth noting that the trips do not limit to trips done entirely within the study area, but also consider trips coming to and going from the study area. A summary of the car and bike trips is shown in Table 2.

Table 2
Trip composition (in thousands).

Passenger trips by car and bike (in thousands)											
	Age < 35		Age 35-<55		Age 55-<65		Age 65-<75		Age 75+		Total trips
	Trips by Car	Trips by Bike	Trips by Car	Trips by Bike	Trips by Car	Trips by Bike	Trips by Car	Trips by Bike	Trips by Car	Trips by Bike	
High income	104	124	46	43	18	16	10	12	9	12	395
Medium Income	28	35	9	9	4	4	4	5	3	4	104
Low Income	10	20	9	13	4	5	8	11	7	17	103
Minimum Income	28	42	8	9	2	2	1	1	1	2	97
Total trips	170	220	72	74	29	27	23	30	20	35	699

4.3. Scenarios

We run 12 different simulation runs to analyse the effect of mode availability and CS price. The different scenarios include the combination of the different mode policies (car only, bike only and both modes) and different prices of the CS service (5, 6, 7 or 9 euro per parcel). The summary of the main assumptions for a selected subset of models is shown in Table 3 while the rest of the simulation results can be found in Annex I.

The reference parcel cost used was of 9.20 euros (PostNL, 2022). This is the value of a standard local parcel with track and trace and 500 euro insurance, which is the closest equivalent to what other CS services in Europe offer (Nimber, 2020). The express delivery, costing around 30 euros, could also be considered a service match, since CS delivers the same day it is picked up. However, this service is intended for fast deliveries across the Netherlands and unlikely to be adopted for L2L deliveries.

The platform commission was set to 15 %. This value is common across delivery platforms and it is the approximate value used by Nimber in Norway. The utility functions and other parameters from Table 2 were kept constant across the scenarios. The KPIs obtained are explained in Table 4.

5. Results

Table 5 presents the results of 5 the simulations: C6: car based CS with a remuneration of 6 euros; B6: bike based CS with a remuneration of 6 euros; A5-7: bike and car based CS with remuneration ranging from 5 to 7 euros.

The matching rate of CS is of 100 % in all simulations except for the bike-based ones. This is probably because of the relative large amount of trips considered. For example, in the simulation with a remuneration of 5 euros, CS had a demand of 1225 parcels and had approximately 20.000 trips available.

The simulations with all the modes available (A) threw a car market share around 55 %. The remuneration per hour is estimated based on (time) detours, which are lower for cars. This means that the car drivers get proportionally larger returns of being a CS, making them more willing to do so. Moreover, car detours tend to be longer, averaging around 10 km/parcel, while bike tours have an average detour distance of 9 km/parcel. Even though the detours were larger for cars than bikes, the detours represented a lower percentage of the total travelled distance than bikes, due to the typically larger commutes done by car. This is consistent with the intuition that active modes are more likely to travel smaller distances.

In all scenarios the parcel van delivery km are relatively comparable across scenarios. The detour km in total and the detour km by car offset any reductions with increases in the total km between 14 and 30 %, depending on the remuneration level. This has a correlation in the GHG emissions for parcel delivery, which can increase up to 16 %. Fig. 5 illustrates the increase in travelled kms and GHG.

From the results of the simulations, we can plot the CS demand and remuneration considering the CS remuneration. Fig. 6 shows the remuneration and CS demand for a bringer remuneration of 5, 6, 7 and 9 euros. It can be seen that the maximum platform revenue occurs when the remuneration to the bringers is of 6 euros per parcel (6.90 to customers). Assuming that the platform has control of the pricing and no intention of regulating the mode used by the bringer, we will detail the analysis for the scenario where all modes are available and the remuneration is of 6 euros (A6).

Regarding the stability of the results to different random draws, the scenarios that considered all modes were repeated 20 times. In all of the simulations, the remuneration that yielded the highest profit for the platform was 6 euros. The number of kilometres oscillated within 3 % for cars and under 1 % for vans, while from the average and the GHG estimated within 7 % from the average.

6. Discussion

To give context of the impact that crowdshipping has in the parcel fulfilment volumes, Fig. 7 shows how the L2L parcels are being

Table 3
Main scenario assumptions.

		C6: Car based; 6 eur/par	B6: Bike based; 6 euro/par	A5: All Modes; 5 euro/par	A7: All Modes; 6 euro/par	A9: All Modes; 7 euro/par
Scenario Specific	CS Remuneration	6 (eur/parcel)	6 (eur/parcel)	5 (eur/parcel)	6 (eur/parcel)	6 (eur/parcel)
	CS price for customers	6.9 (eur/parcel)	8.08 (eur/parcel)	5.75 (eur/parcel)	6.9 (eur/parcel)	8.08 (eur/parcel)
	Mode	Car	Bike	Car and Bike		
	Reference parcel	9.20 eur/parcel				
Common settings	Bringer Age	<55 years old				
	Bringer Income	minimum, low				
	Emission Factor Car	220 g/Co2 (Nijland & Meerkerk, 2017)				
	Emission Factor Van	303 g/Co2 (Thoen et al., 2020a)				
	Drop off time Car	5 min				
	Drop off time Bike	2 min				
	Car Speed	30 km/h				
	Bike Speed	12 km/h				

Table 4
KPI definition.

KPI	Description
Total Demand	Total demand for the city of The Hague
Local to Local	Local to Local demand for the city of The Hague
Crowdshipping Platform Revenue	Revenue of the platform excluding payments to bringers
Crowdshipping Parcels	Number of parcels shipped via CS
Crowdshipping Accept Rate	Percentage of parcels that were matched to a bringer
Crowdshipping Car Share	Percentage of CS parcels brought by car
Crowdshipping Bike/Walk Share	Percentage of CS parcels brought by bike
Crowdshipping Average Remuneration	Average hourly remuneration. The time used is the time of detour
Crowdshipping Hour Remuneration Car	Average hourly remuneration by car bringers
Crowdshipping Hour Remuneration Bike/Walk	Average hourly remuneration by bike bringers
Crowdshipping Extra Total Km	Total detour km by bringers
Crowdshipping Extra Km Car	Total detour km by bringers by car
Crowdshipping Extra Km Bike	Total detour km by bringers by bike
Crowdshipping average detour Car	Average detour made by car bringers
Crowdshipping average detour Bike	Average detour made by bike bringers
Crowdshipping Extra CO2	Extra CO2 emitted by the detours
Parcel Vans Km	Total vehicle km by van (L2L, interregional and international)
Parcel Vans CO2	CO2 emitted by van delivery
Scenario CO2	Total ton of CO2 emitted
Scenario Delivery Km (cars and vans)	Total km of cars and vans

Table 5
Results from selected simulations.

	Baseline	C6:Car based; 6eur/par	B6: Bike based; 6 euro/par	A5: All Modes; 5 euro/par	A6: All Modes; 6 euro/par	A7: All Modes; 7 euro/par
Total Demand	89.979					
Local to Local	3.559					
Crowdshipping Platform Revenue	–	816.62	748.3	796.09	823.86	748.65
Crowdshipping Parcels	–	789	781	923	796	620
Matching rate		100	92.6	100	100	100
Crowdshipping Car Share	–	100	–	57.96	54.4	55.48
Crowdshipping Bike/Walk Share	–	–	100	42.04	45.6	44.52
Crowdshipping Average Remuneration	–	6	6	5	6	7
Crowdshipping Hour Remuneration Car	–	17.34	–	14.46	16.67	19.53
Crowdshipping Hour Remuneration Bike/Walk	–	–	7.45	6.68	7.96	9.37
Crowdshipping Extra Total Km	–	8,192	6,989	9,035	7,962	6,173
Crowdshipping Extra Km Car	–	8,192	–	5,551	4,677	3,699
Crowdshipping Extra Km Bike	–	–	6,989	3,484	3,285	2,474
Crowdshipping average detour Car	–	10.38	–	10.38	10.80	10.75
Crowdshipping average detour Bike	–	–	8.95	8.98	9.05	8.96
Parcel Vans Km	26,486	26,464	26,458	26,428	26,435	26,459
Crowdshipping Extra CO2	–	1.31	–	0.89	0.75	0.59
Parcel Vans CO2	7.95	7.94	7.93	7.93	7.95	7.96
Scenario CO2	7.95	9.25	7.93	8.82	8.70	8.55
Scenario Delivery Km (cars and vans)	26,486	34,656	26,423	31,980	31,178	30,218

fulfilled according to the model for the run costing 6€ with all the modes available. It can be seen that around one third of the parcels choose CS and most of the parcels go by car, this mode getting an approximate market share of L2L parcels similar to DHL, the second largest player.

It is also important to notice that the CS, although it can have potential, it is part of a larger urban logistic system. The L2L parcels are a segment within the total parcel market, where the majority of the parcels come from other regions. This is the main reasons why the reductions achieved by CS are modest when compared to the van-km of the baseline, even when taking the first mile (collection from customer) into consideration. To take this into perspective, Fig. 8 puts the L2L and CS services shown in Fig. 7 in the same diagram, where it can be seen that the share of CS is smaller to that of the traditional couriers with smaller market shares.

Taking the perspective of the whole of the urban freight system, we can see the effect of CS at an urban level. It can be seen that CS has a small share of the total deliveries. Nevertheless, when we consider the emissions and the emission potential we can see the disproportion. CS delivers under 1 % of the parcels and contributes with 10 % of the GHG emissions. This is reflected in the average distance covered per parcel. Traditional couriers, with larger vans and centrally planned tours, travel 0.29 km/parcel while CS around

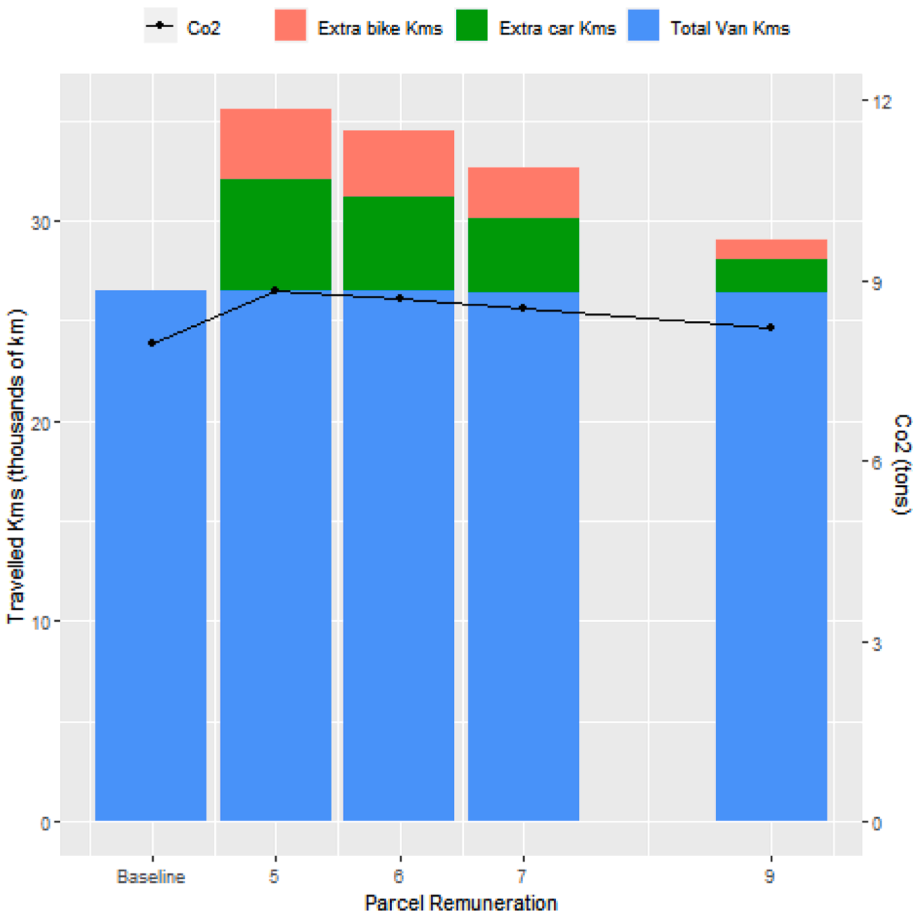

Fig. 5. GHG emissions and travelled km across scenarios.

10.67 km/parcel. It is worth noticing that these km take into consideration the pick-up tours and consolidation trips of the L2L parcels.

These results contradict other works that suggest that CS has a positive impact concerning emissions and congestion (Buldeo Rai et al., 2017; Paloheimo et al., 2016), but it is not the first to suggest that there might be negative impacts from CS depending on the mode choice (e.g. Gatta et al. (2019); Simoni et al. (2020)). We believe that these differences are given by the modelling set up of the simulations. Our model considers the whole of the city logistics environment for the baseline comparison through an ABM, meaning that the parcels that are taken by couriers benefit from their economies of scale. Moreover, the matching is done through behavioural aspects of the traveller and not optimized centrally to reduce distances. This generates matches that are perhaps not optimal from the urban freight system perspective, but maximise the utility of the individual travellers. It is another case where the individual optima is different from the global optimum.

Regarding the efficiency of the courier delivery structures, they have efficient hub-spoke delivery structures and have been optimized to minimize cost and travelled km because the parcels are bundled in larger shipments. This means that taking one parcel away from these tours does not necessarily reduce the use of delivery van km in the streets.

However, if we assume that the CS deliveries are done with electric vehicles (that is only taking into consideration the van emissions) the reduction in Co2 emissions is<1 %, instead of the 9 % of increase simulated. This is a strong assumption to do, since the CS tend to be of lower income, where the penetration of electric vehicles is lower. Moreover, electrification trends are likely to be higher for the parcel delivery couriers since they will be affected by new legislation (European Commission, 2021). Nonetheless, electrification will not help when it comes to analyse congestion. Delivery vehicle km in the A6 scenario are 17 % more, from 26.400 km to 31.100 km. This is a key indicator for public authorities, since the increase in vehicle km also have a negative impact in quality of life.

Our results are in line with the work of Alho et al., (2021), albeit in a different assumptions regarding who is the bringer and how the matching is done. Alho et al model with the perspective of a mobility on demand management and allocate parcels to existing passenger trips or idle vehicles that are part of the service from a central controlled centre. Contrarily, we assume that we have a platform that displays the available parcels and who chooses which parcel to be picked up are regular travellers with the platform just as an intermediate, such as the system provided by Nimber (Nimber, 2020). This makes that the matching is done taking into consideration the senders' and bringers' perspectives, incentives and preferences.

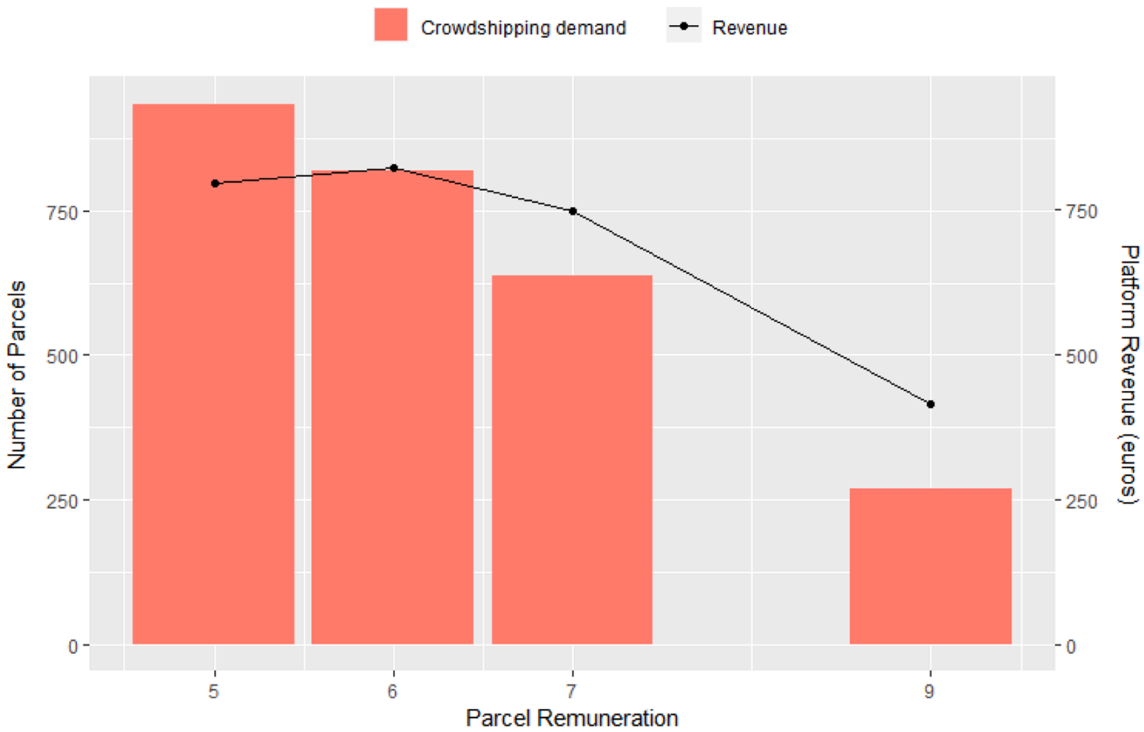

Fig. 6. Demand for crowdshipping.

Another relevant KPI to consider when implementing platforms that connect customers with providers is how much are the bringers earning. The simulations estimated a remuneration of around 9.05 €/hour for the bike CS, which in range of the minimum wage in the Netherlands of 9.96 €/hour.

However, this estimation is done purely on detour (i.e. the extra time that it takes to deliver a parcel). This means that if the bringer "works" full time for the platform, these results might no longer be valid because there is no existing trip to share capacity. Full time bringers are a large risk for cities, because it can also worsen the travelled km and emissions KPIs of CS.

All the utility functions used in this paper (sending the parcel via CS and accepting a parcel) come from SP data. This makes the results of these functions to be less suitable for forecasting compared to versions that contain RP data as well. For example, the difference in scale between the SP model and an RP + SP model would not mathematically affect the ranking of bringers, but it might affect the decision of being willing to become a bringer. Our framework allows for easy parametrization of these utility functions, so it is a limitation of the application rather than the modelling framework. However, this simulation model can provide insights on how the trade-offs between the variables happen, how it can affect the results, give an estimate of the magnitude of the effects and be a tool that the public administration can use to estimate the possible earnings of workers under this modality.

Another limitation of this study is that it does not include public transport as an option for crowdshipping (as discussed in Gatta et al. (2018). Moreover, we have not addressed in this framework the impact that the decision of picking up a parcel may have on the scheduling of passenger trips. It would be interesting for future works to include a feedback loop to a passenger model, such as Albatross or Matsim, to analyse further the effect of crowdshipping on passenger travel behaviour.

7. Conclusions

Modern logistics have received a considerate amount of attention from governments, business organizations and researchers from all over the world. The application of innovative freight services for improving the environmental sustainability of 'last mile' delivery has been motivated by the growing demand of e-commerce in modern cities. A potential disruptive logistic concept is crowdshipping. Researchers have already developed simulation-based studies to evaluate different environmental, economic, and operational aspects of CS. However, the simulations lacked to represent the full scale of the urban parcel delivery or the behavioural aspects.

The contributions of this paper are threefold. Firstly, a new model and use case has been developed taking into account many of the complexities that involve the CS problem within the MASS-GT framework. An agent-based simulation approach to compare and assess the effectiveness of different CS strategies. The simulation developed allows us to see the urban freight system as a whole and to explore the interactions between passengers and freight by allowing travellers to act as crowdshippers. The trips considered are by either car or bike.

We allocate the parcels and trips through a utility based best parcel to best trip method. The allocation algorithm provides a decentralised (i.e. no single agent allocates all parcels to bringers) matching process of supply and demand which is behaviourally

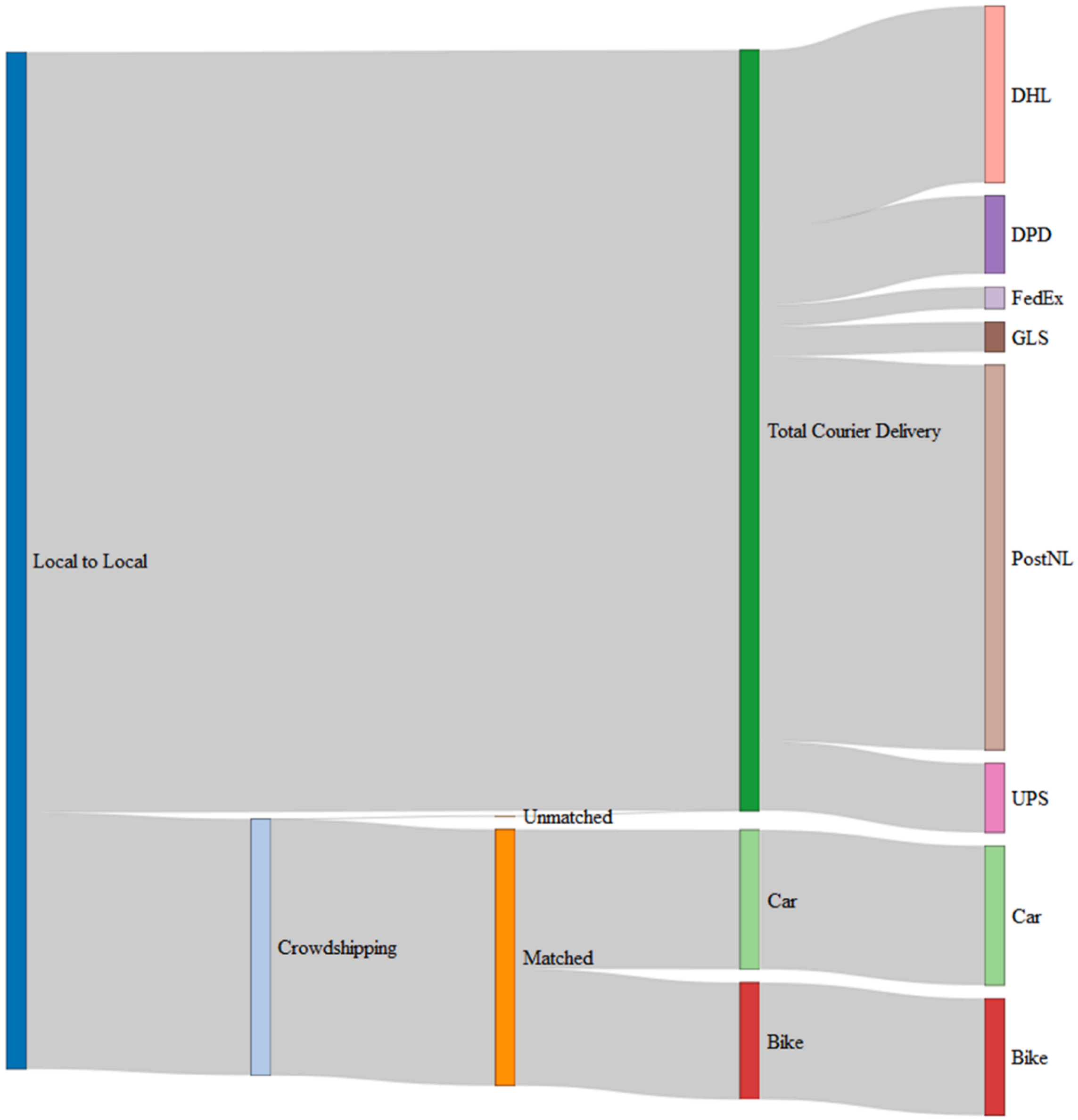

Fig. 7. Local to Local parcel fulfilment.

consistent, meaning that it is compatible with microeconomic theory and in line with the assumptions used to develop the choice models that compose it. The allocation is done in a way that allows the traveller who benefits the most to pick their preferred parcel, without having any constraints given by the order of the analysis. The decentralisation is given by the individual motivation of the agents that decide to carry a parcel and the lack of a centralised controller that allocates the parcels to trips. A feature that can be added in future developments is a negotiation feature that is present in some CS platforms.

The second contribution is the estimation of approximate remuneration values for bringers. The simulations provide an estimation of the remuneration that the bringers receive considering the time spent detouring to deliver the parcel, which is in line with the minimum wages of the Netherlands. However, the estimates are for existing trips, thus, not considering if any new trip is generated or if any person is working full time as a bringer. This problem can be considered in future applications of the model.

Our third contribution relates to the impact of CS. Model results showed that CS could offer a cheaper alternative for consumers, since the cost of the parcel that maximises the revenue of the platform is lower than the reference value. However, the results indicate that it has an overall negative impact in the city due to the high share of car trips. This makes that CS platforms can become a problem, such as the transport network companies like Uber are now in the passenger transport.

Simulations suggest that the introduction of CS for L2L deliveries increase the amount of vehicle km and CO2 emission, contrary to other studies. This is a result of the larger relative detours compared with the full truckload hub spoke deliveries of couriers, even when

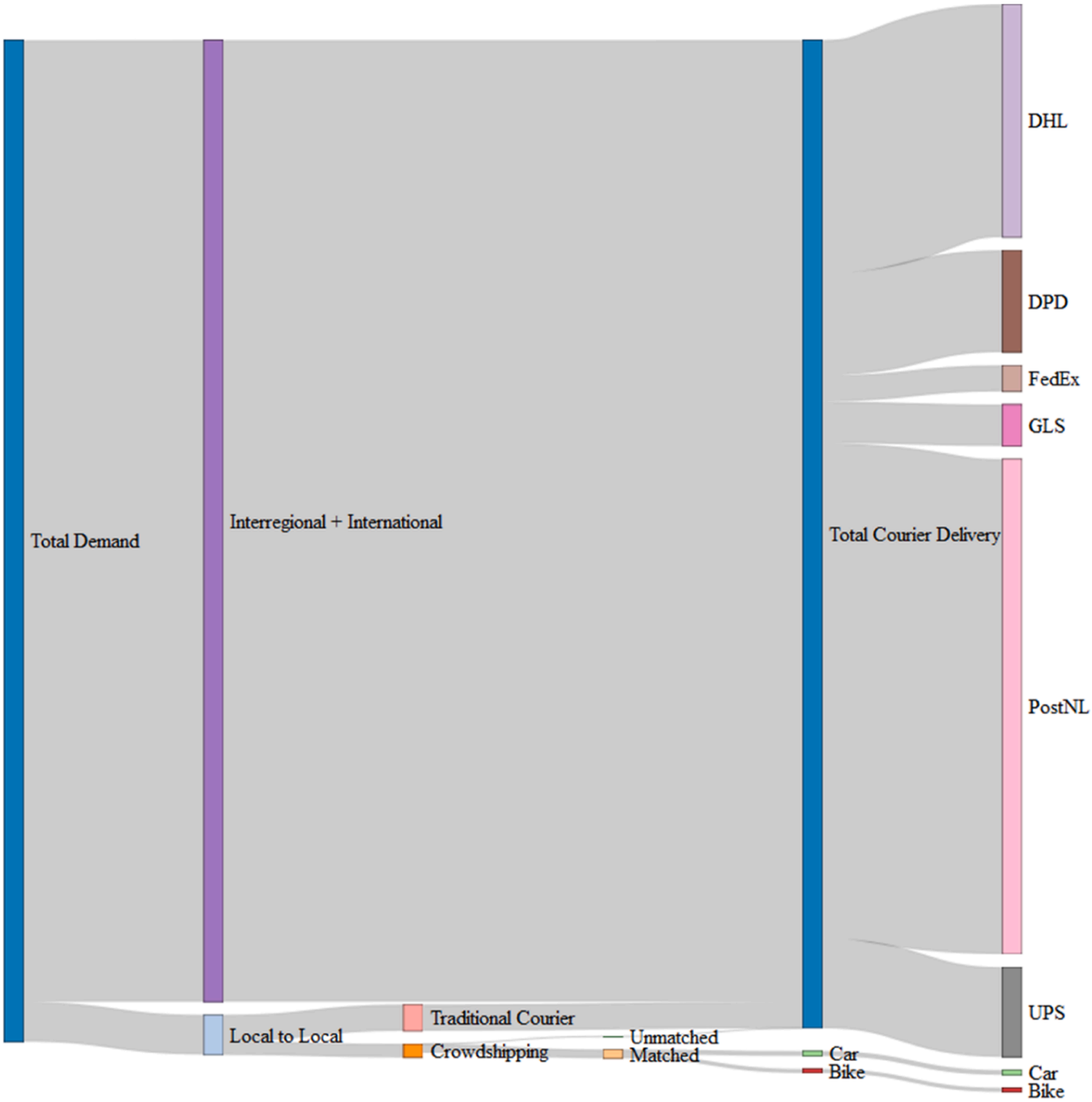

Fig. 8. City demand Parcel fulfilment.

taking into consideration the pickup km. However, CS may still have a valid use case that can bring benefits. The Hague is a dense city, where the hub-spoke structure of couriers is particularly efficient. In less dense areas and in inter-urban travel of low-density countries CS can have a successful business model that can provide benefits to the environment and traffic. This is supported by successful cases such as Nimber in Norway. This angle is worth investigating further.

For dense cities, it can be targeted as a bike delivery and avoid car modes. This can help making the case of taking some van-km off the streets while reducing the parcel delivery costs of consumers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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