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Assesment of the potential of cargo bikes and electrification for last-mile parcel delivery by means of simulation of urban freight flows

Carlos Llorca* and Rolf Moeckel

Abstract

Background: The paper presents a simulation model for freight. In the paper, this model is applied to understand the impacts of electric vans and cargo bikes for the last-mile delivery of parcels. Cargo bikes are electrically assisted vehicles that distribute parcels from micro depots located close to the final customers by means of short tours. The parcels are sent from the major distribution center to micro depots in vans (called feeders).

Materials and methods: An agent-based model is used for the purpose of the paper. The model is based on the disaggregation of commodity flows to represent trucks (for all commodities) and individual shipments (for parcel deliveries). The model represents microscopically every freight vehicle in the study area.

Results: The simulation of various scenarios with different shares of cargo bikes and electric vans assesses the impacts of electrification and cargo bikes. The use of cargo bikes to deliver parcels allows to reduce the number of motorized vehicles, although the presence of large parcels requires that at least half of deliveries by vans are still required. The shift to cargo bikes represents a slight increase in the total operating time to deliver the parcel demand. With low shares of cargo bikes, the total distance traveled increases, since the reduction of van tours cannot compensate the additional feeder trips from distribution centers to micro depots. The cargo bikes also do not reduce the number of vehicles for the served area, but modify the composition of vehicle types. Low noise, smaller, low emission vehicles increase, while delivery vans are reduced.

Conclusion: Both cargo bikes and electric vans are able to reduce CO2 emissions, even after accounting for the emissions related to electricity production.

Keywords: Last mile delivery, Urban logistic, Electric vehicle, Cargo bike, Freight model

1 Introduction

Both passenger and freight transport contribute to congestion of the transport system, road emissions, noise, and safety issues, among others. A major components of urban freight traffic is parcel deliveries. The increase of online shopping in recent years contributed to a rapid increase of the number of parcels delivered. As a consequence, the number of delivery vehicles and the impact on the transport system increased rapidly.

Various solutions have been proposed to make the delivery of parcels more efficient and environmentally friendly, including electric delivery vehicles, drones, autonomous robots or cargo bikes. The use of cargo bikes for last-mile deliveries has been introduced in some cities already, but scientific studies of actual implementations are still in an early stage. This paper models freight flows, while paying particular attention to the distribution of parcels. The goal of this research is to understand

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the effects of a partial substitution of vans with combustion engines by electric vans or cargo bikes.

1.1 Freight models

Compared to person travel demand modeling, freight modeling is substantially less developed. Limitations in data availability, heterogeneity of freight transport options and lack of interest to intervene with freight flows are important reasons why freight modeling is less common than person travel modeling.

Most freight vehicles do not travel in simple trips from A to B and back to A, but in tours that connect many stops. Holguín-Veras et al. [20] provided an overview of the state-of-practice of urban tour-based truck models (models that represent explicitly deliveries of freight units by vehicles). Noteworthy are also the operational tour-based models for Calgary, Alberta [22], Portland, Oregon [12], Guatemala City [19], Rome [40] and Phoenix, Arizona [26]. Such models have been found to be behaviorally richer and allow for the explicit representation of distribution centers, warehouses and intermodal facilities, which are used by more than half of all trucks [13]. However, truck surveys are commonly required for tour-based models, and stochastic variations between runs may pose an additional burden for such models [12]. Tavasszy et al. [45] developed the SMILE freight model that explicitly accounts for production, warehousing and transportation of goods. Chow et al. [9] developed a sophisticated framework for freight modeling in California, but readily admitted that this framework has data requirements that will be difficult to fulfill due to privacy issues.

Sometimes, urban tour-based models are combined with regional freight flow models, which may simplify the routes of vehicles compared to tour-based models. The most common example for regional freight models is the Commodity Flow Model. Such a model tries to represent the economic motivation behind a freight flow, which is exchanging goods between producers and consumers. Leontief [29] developed the framework in which economic interactions are captured in Input/Output matrices. Annual tons of commodity flows are converted into truck trips using daily truckload equivalents from truck intercept surveys.

A recent review of freight modeling in the twentieth century [30] stressed the need for modeling commodity flows rather than just trucks. Research in Europe has been summarized by De Jong et al. [10], concluding that the ideal freight model should have two levels of resolution: a detailed high-resolution version shall be applied to very specific policy questions, while a fast and low-resolution version could answer simpler day-to-day policy questions.

1.2 Electrification and cargo bikes for city logistics

Traditionally, last-mile deliveries are carried out by vans, also called Light Commercial Vehicles (LCV). The use of electric vehicles has been proposed as a solution to the environmental impacts of urban logistics, by reducing noise and emissions. Giordano et al. Giordano et al. [15] assessed the life-cycle of battery electric and diesel vans for urban parcel delivery. They used average demand indicators and randomly generated trip lengths to evaluate the costs and externalities of both types of vehicles. The conclusions reported the need of incentives or taxation to accelerate the fleet conversion and reduce emissions. From the carriers' perspective, Quak et al. [42] compared diesel and electric delivery vans. They identified several limitations to the electrification, including the higher purchase costs and the lack of appropriate infrastructure. Martins-Turner et al. [32] performed agent-based simulations of electric and conventional delivery vehicles. They simulated an entire fleet that is converted from diesel to electric vehicles. The study simulated the delivery of food in Berlin (Germany). The results demonstrated a significant reduction of CO_2 emissions, even after accounting for the emissions caused by electricity production.

While most previous studies identify relevant reductions in emissions, the impacts on traffic congestion and on the operation of fleets do not change much. The routing of delivery vehicles remains similar, with the exception of the new constraint of limited vehicle ranges and recharge times [17, 47]. Regarding the limited range, Martins-Turner et al. [32] found in their simulations that 56% of vehicles could operate during 1 day without any recharging.

One particular type of electric vehicle (more precisely, an electrically assisted vehicle) is the cargo bike. The delivery of parcels using cargo bikes instead of diesel vans has been proposed to solve some of the current issues of urban logistics. Melo and Baptista [34] pointed out the limited use of cargo bikes for very specific deliveries, mostly smaller parcels. The combination of delivery vans and cargo bikes has been researched mostly in operations research [2]. The advantages of cargo bikes with respect of motorized delivery vehicles are: 1) they are smaller, so they can ride more easily on narrow streets and find parking locations faster and closer to the recipient, 2) they are electric assisted vehicles, and therefore, they do not produce noise nor direct emissions, 3) vehicles purchase costs and vehicle maintenance costs are lower, while labor costs are about the same ([28, 44]; Traject Mobility [31]). On the other hand, cargo bikes have significantly smaller capacity and their batteries limit their range. Driver fatigue could be an issue for cargo bikes [28], and the maximum speed is generally lower than for conventional vans [18, 34].

The distribution of goods by cargo bikes requires smaller distribution centers located in proximity to customer locations [27, 33]. These distribution centers are called micro depots that receive deliveries from large distribution centers by vans. Parcels are delivered out of these micro depots using cargo bikes.

Several studies analyzed the potential impacts of cargo bikes using freight models. Predominately, these studies solved vehicle routing problems [4, 27, 34, 38, 39, 49]. Such tour-based models optimize the design of the tours to deliver a given number of parcels subject to vehicle characteristics. Previous studies [3, 8, 49] suggest that cargo bikes have a capacities of 10–25 parcels (typically 5 to 15% of light trucks) and speeds of around 10–25 km/h. In the dense area of Seoul (South Korea), the use of cargo bikes with a substitution rate of about 3 bikes per truck could reduce costs by 14.1% (improving the service time thanks to reduced walking distances from the vehicle to the customer) and emissions of carbon pollutants by 10%. According to Zhang et al. [49], an almost complete substitution of vans by cargo bikes for commercial clients could reduce cost and emissions derived from parcel distribution by 28 and 22%, respectively. On the other hand, a study for Antwerp [4] found an increase in operational costs for providers that use cargo bikes, which could encourage providers to promote self-pick-ups that transfer part of the cost to their customers. A simulation for a small area in Munich [39] also identified significant reductions in distance traveled by motorized vehicles. Alternatively, some authors proposed analytical cost functions based on average delivery costs [44, 46]. They do not represent individual shipments and simplify variability of the demand, but they are faster in terms of optimizing fleet sizes or compositions. In any case, neither analytical nor simulation tools have not explained the impacts of cargo bikes in the whole supply chain.

1.3 Research motivation

The lack of open or accessible data on parcel delivery demand under real-life conditions makes the analysis of potential shifts from diesel vans to electric vans or cargo bikes difficult. Previous research [28] identified the need to analyze potential impacts of using cargo bikes in city centers, and the potential demand distribution of cargo bike customers. Moreover, the existing research did not quantify the impacts of cargo bikes with respect to the entire supply chain including non-urban flows.

In the paper, we first develop a method to generate freight demand without using commercial or privately-owned data sources. The developed model is used to compare different shares of electrification and use of cargo bikes for the distribution of parcels in urban areas.

2 Methodology

The first part of this section describes the freight model and the second explains its application to the case study to the metropolitan area of Munich (Germany). The third section summarizes the calibration and validation of the model and the fourth proposes a set of scenarios.

2.1 Freight model

A freight model called FOCA (Freight Orchestrator for Commodity flows Allocation) was developed for this research. The model represents every long-distance freight flow (only flows by road vehicles are assigned to a network) starting at, ending at or crossing the study area. The model also represents urban freight distribution centers for a subset of the study area, namely the analysis area. Therefore, the model combines two levels of resolution and detail as proposed by De Jong et al. [10]. By combining a long-distance and an urban model we were able to understand the magnitude of policies and measures (e.g. electrification) for the entire distribution chain, and not only in the urban environment as if it was an isolated element.

The model is based on the disaggregation of commodity flows [35] into microscopic freight units (either trucks or parcels, depending on the level of analysis). The study area is divided into zones (larger zones, covering the entire study area), and the analysis area is further divided into micro zones (smaller zones, only in the analysis area).

2.1.1 Long-distance freight model

This module converts commodity flows into long-distance freight trips between zones of the study and assigns them to the network. Here, only the flows by truck are assigned, while flows by rail, air or water are merely reported. The steps are shown in Fig. 1. Although modeling long-distance trucks is not required to analyze urban last mile processes (which is the core of this paper), the total demand of parcels is obtained from the total volume of parcels sent or received to/from the analysis area via long-distance freight trips. Also, representing the entire commodity flow allows assessing the impact of cargo bikes on the entire delivery chain.

First, the annual flows (step 1 in Fig. 1) are converted to daily flows by dividing them by an annualization factor (2). The annualization factor is calculated by eq. 1 to distinguish weekdays from weekends. The temporal disaggregation is based on truck counts and are assumed not to vary among commodities.

$$f_{annualization,i} = 365 \cdot \frac{AADT_{trucks}}{ADT_{trucks,i}} \tag{1}$$

Where:

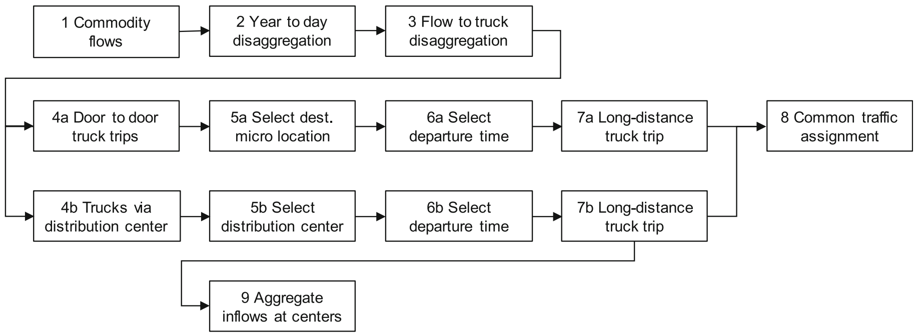


Fig. 1 Long-distance truck model

- $AADT_{trucks}$ is the average annual daily traffic count of trucks summed up across every traffic count station in the study area
- $ADT_{trucks,i}$ is the average daily traffic count of trucks summed up across every count station in the study area during day i

Next, the daily flows in tons that travel by truck are converted into long-distance trucks by average payload factors (for various distance bins, accounting for higher average loads for longer trips). In addition, empty trucks are generated based on average percentages of empty trucks by commodity (3).

For every truck that starts or ends in the analysis area, origin and destination micro-locations are assigned. Selected commodities, such as minerals, oil or machineries are distributed door-to-door (4a). A micro-zone within the trip end zone is selected by a weighted random choice (5a). The weight of each zone is calculated based on employment by industry and make/use coefficients [35]. Make/use coefficients describe how many goods of a given commodity are produced/consumed per employee of a given industry. This results in the delivery (or pick up) of goods that are produced or consumed by different industry types. Geographical x/y coordinates within the micro zone are sampled randomly.

Other commodities are shipped via distribution centers (4b). The long-distance truck trip ends at a distribution center (5b) that can handle the given commodity type near the shipment's final destination. Goods are reloaded on smaller trucks and sent to their final destination in the urban freight model.

A departure time is chosen for each long-distance truck (6a,b). A list of long-distance truck trips is

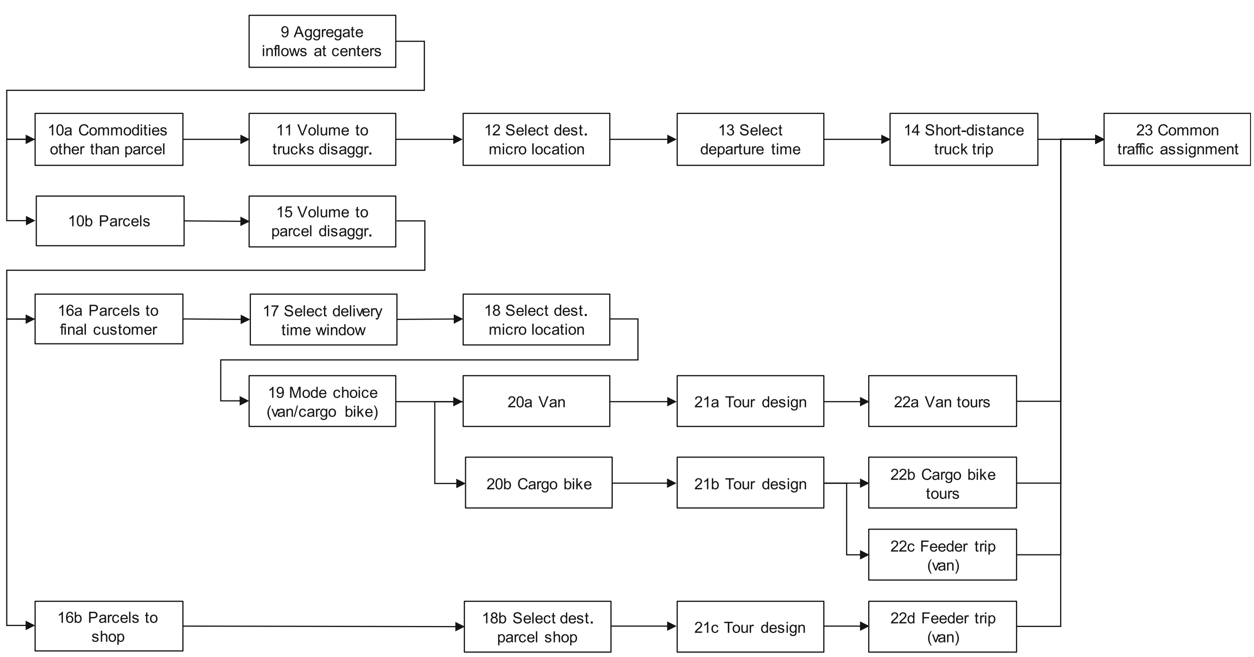


Fig. 2 Urban freight model

generated (7a,b) that serves as an input to the traffic assignment model described further below (8).

2.1.2 Urban freight model

The flows that are shipped through distribution centers are processed in the urban freight module, as defined in Fig. 2.

For each distribution center, the flows of the same commodity that arrive are summed up (step 9 in Fig. 2) and disaggregated into shipments on smaller trucks. Trips between distribution centers and customers depends on the commodity and are defined in two different ways:

1) All commodities that are not parcels (10a) are shipped from a distribution center by short-distance trucks to their final destination. The volumes processed at each distribution center are disaggregated into short-distance (and smaller) trucks (11) by an average payload factor for short-distance trips. Similar to long-distance trucks, a micro location (12) is chosen for the receiving trip end (based on employment and make/use coefficients), as well as a time of departure (13).
2) For post and parcels (10b), the volumes are disaggregated from tons into individual parcels (15). Parcel sizes are generated randomly, based on a given parcel weight distribution. The customer type (private customer, business customer or parcel shop/warehouse) is selected for each parcel.

For each parcel of the private and business customer groups (16a), a time window is assigned (17) and a geographical x/y coordinate is selected. Business customer locations are assigned (18) similarly to non-parcel commodities (using employment numbers and make/use coefficients). Private recipient locations are micro zones selected by population. A service time is added for each delivery by adding a fixed time plus a distance-dependent term (which depends on the distance between the parking location on the road network and the recipient). Delivery tours are organized to deliver those parcels (21a). We use the transport simulation model MATSim (Multi Agent Transport Simulator) [21] and its extension "freight" [50] to generate delivery tours. With this extension, we create carriers at each distribution center and generate delivery services for each one of the parcels. This extension creates and iteratively optimizes the tours to deliver every parcel to every private or business recipient.

The use of cargo bikes (20b) is designed as a deviation from the distribution by van. Cargo bikes are assumed to be electrically supported by require peddling by the rider, which reduces electricity consumption. To distribute parcels with cargo bikes, we define intermediate, subsidiary distribution centers (micro depots) that receive parcel shipments from a major distribution center. Goods are sent from a distribution center to the micro depots with vans (22c) before the parcel delivery time windows. After that, parcels are delivered to the final recipient by cargo bikes (22b).

Parcels delivered to or picked-up at parcels shops or warehouses are distributed by van (16b).

2.1.3 Traffic assignment

The trips of long-distance trucks, short-distance trucks and parcel delivery vehicles are jointly assigned with MATSim (step 8 in Fig. 1 and 23 in Fig. 2). Moreover, the trips made by private cars generated by the passenger travel demand model MITO [36] are loaded and jointly assigned with trucks. The output of MATSim includes individual route choices of freight and passenger vehicles in the study area.

2.2 Case study: a distribution center in Munich (Germany)

This model is applied to the study area of Germany to test the impacts of cargo bikes for the last-mile delivery in several districts in central Munich. The analysis area is defined as the city of Munich (Fig. 3). The analysis is focused on one distribution center located to serve the districts of Altstadt, Maxvorstadt and Ludwigvorstadt.

The following data sources are used to apply the model:

- Commodity flows estimated by the German Federal Ministry of Transport and Digital Infrastructure (Verflechtungsprognose 2030) [6] for the base year 2010.
- Truck load factors and empty truck shares by the German Office for Motorized Transportation [24].
- Employment and population of Munich in form of a synthetic population for the analysis area [37].
- Make/use coefficients for Germany published by the European Commission [14].
- Location of distribution centers of the major parcel delivery companies from openstreetmaps.org.
- Road network from openstreetmaps.org.

In absence of observed data, the following assumptions for further model parameters were done. These assumptions were discussed with eight stakeholders of the German parcel industry and confirmed as reasonable:

- Share of individual customers (business or private) and parcel shop delivery/pick up services: parcels that are received by customers are split into 40% private customers (home), 40% business customers (companies) and 20% parcel shops. Outgoing parcels

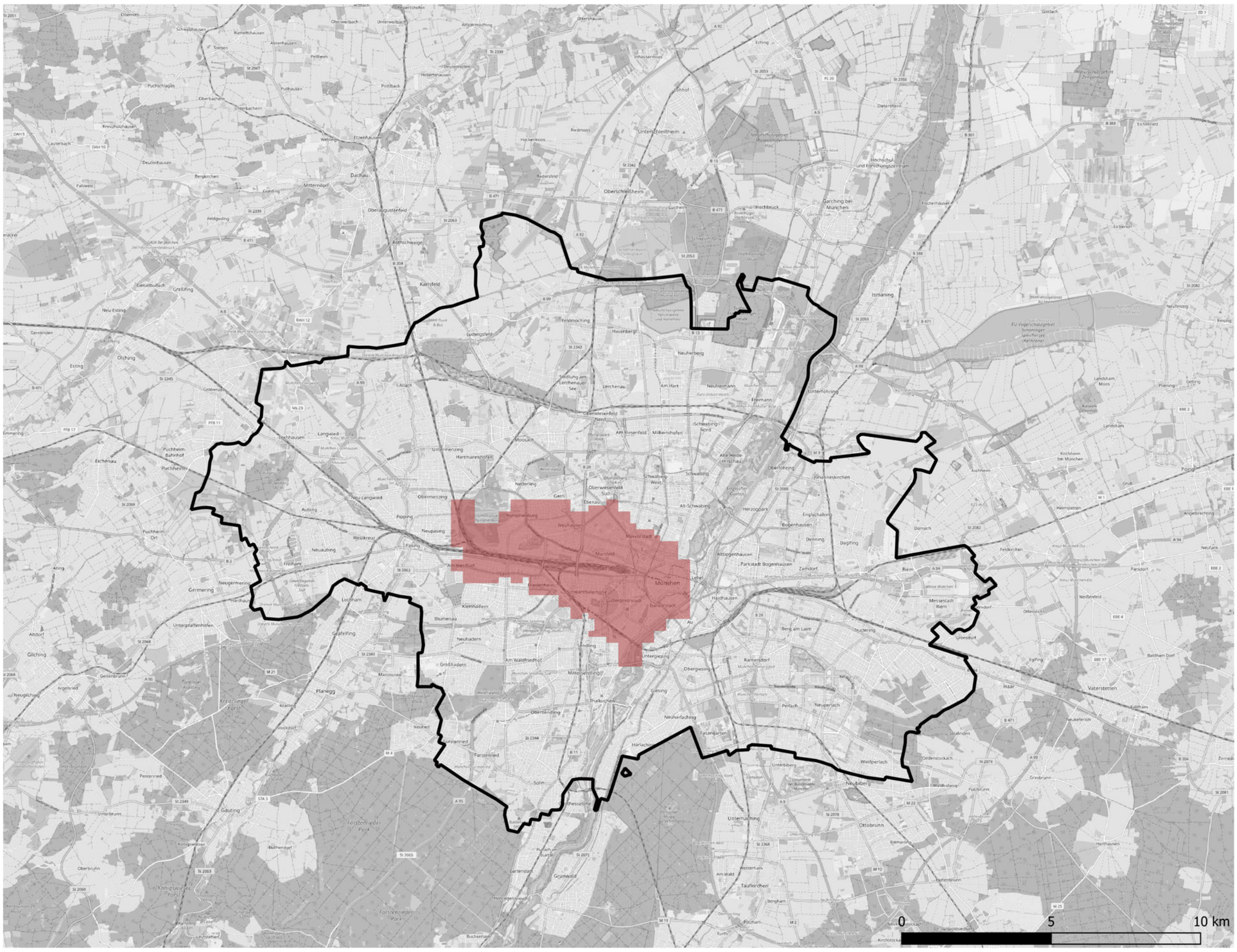


Fig. 3 Boundaries of the city of Munich (Germany). The catchment area of the distribution center is marked in red (background map: OpenStreetMaps.org)

are shipped via parcel shops (80%) or picked-up at business customer locations (20%). No parcels are picked-up at home locations.

- Time windows for deliveries: 8:00 to 17:00.
- Van capacity: 100 parcels.
- Cargo bike capacity: 20 parcels, based on Zhang et al. [49].
- Cargo bike speed: 20 km/h.
- Micro depots for cargo bikes are assumed to be allocated in a grid of 1000 m × 1000 m.

2.3 Model calibration and validation

We compared the simulated truck volumes with truck counts on major roads in Germany. The traffic counts were downloaded from the Federal Highway Research Institute [5]. Figure 4a shows a comparison between simulated and observed average daily truck volumes in 528 traffic count stations distributed across Germany. The percent Root Mean Squared Error (RMSE) is 32%. The R-squared coefficient of simulated vs. observed counts is 0.72. Similarly, we compared hourly traffic counts. Figure 4b shows the average hourly truck volume in every traffic detector. A departure time distribution was calibrated to resemble the hourly distribution of truck counts on major roads.

After comparing the truck traffic counts, we compared the simulated number of parcels delivered in the study area with the observed values. According to the German association of parcel logistics (BIEK - Bundesverband Paket und Expresslogistik), there were 240,000 delivered parcels in the city of Munich in 2016 [7]. Based on the global growth rate in this period, we extrapolated this value to 184,000 parcels in 2010. The average parcel weight was approximately 7.5 kg. To match the simulation results with this value, we calibrated a parcel weight distribution (used in the step 15 of Fig. 2).

2.4 Scenarios

To understand the impact of electrification of delivery vehicles and the introduction of cargo bikes, we

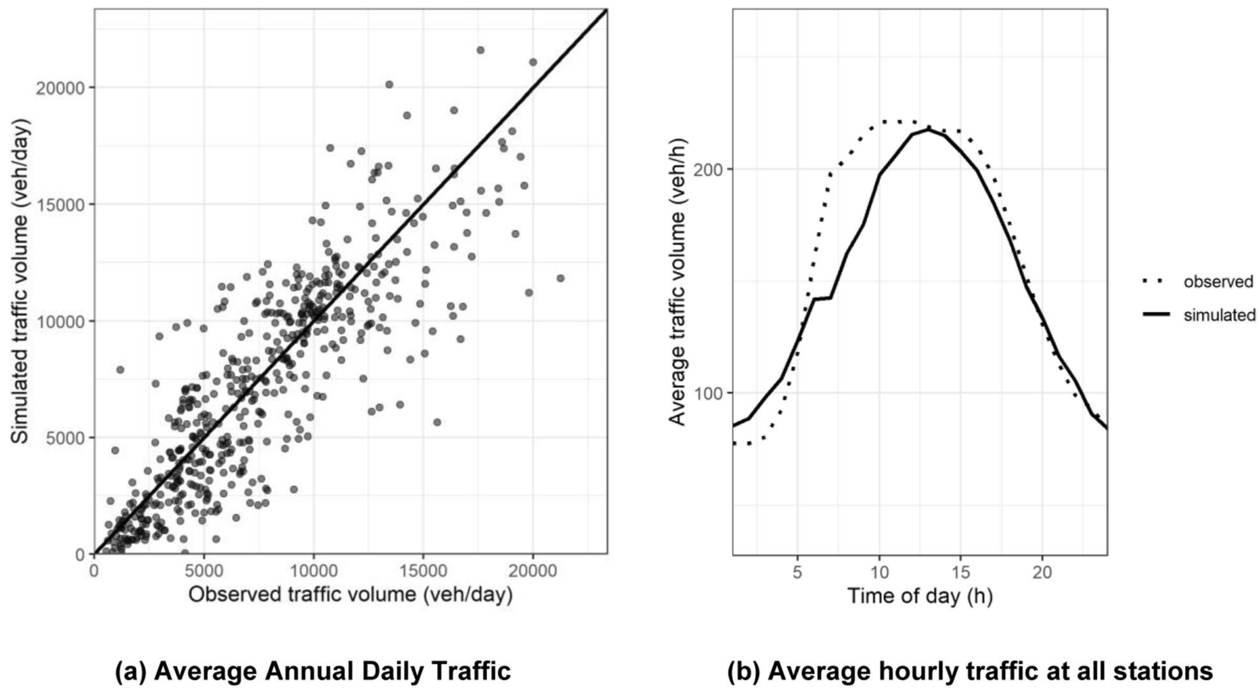


Fig. 4 Comparison of simulated and observed truck counts

Table 1 Scenario definition with shares of cargo bikes and electric vehicle vans and daily delivered parcels

Scenario ID	Share of EV vans (%)	Share of parcels by cargo bike[a] (%)	Parcels delivered directly to the final customer		Parcels to shops (by van)	Total number of parcels
			by cargo bike	by van		
0	0	0	0	12,242	13,330	25,572
1	0	20	1390	10,852		
2	0	40	2727	9515		
3	0	60	4094	8148		
4	0	80	5423	6819		
5	0	100	6783	5459		
6	25	0	0	12,242		
7	25	20	1390	10,852		
8	25	40	2727	9515		
9	25	60	4094	8148		
10	25	80	5423	6819		
11	25	100	6783	5459		
12	50	0	0	12,242		
13	50	20	1390	10,852		
14	50	40	2727	9515		
15	50	60	4094	8148		
16	50	80	5423	6819		
17	50	100	6783	5459		

[a]share of parcels to private and business customers under 10 kg; due to larger parcels that are not delivered by cargo bike, the actual share of cargo bikes may be lower

developed the scenarios defined in Table 1. The scenario zero is a base scenario with only diesel vans and no cargo bikes. The scenarios 1 to 5 assume increasing proportions of cargo bike deliveries, from 20% to 100% of suitable parcels, in 20%-point intervals. In these scenarios, all vans are diesel. Scenarios 6 to 11 assume increasing shares of cargo bikes from 0% to 100%, while 25% of the fleet of vans is electric. Scenarios 12 to 17 are equivalent to the previous ones but assume a 50% share of electric vans. The assumed total weight processed by the distribution center is 212 ton per day. The median density of parcels delivered directly to the final customer is 320 parcels/km^2, with a maximum value of 3048 parcels/km^2 at the densest location. There are 17 micro depots and parcels shops in the catchment area, placed in a 1 km grid.

3 Results

This section compares the simulated scenarios by different indicators to describe the efficiency of the last-mile delivery, the traffic volumes and the environmental impacts within the catchment area of the analyzed distribution center. Results shown in Figs. 5, 6 and 7 focus on the scenarios with different shares of cargo bikes and do not show the differences due to the van fleet composition. Later for the calculation of CO_2 emissions, both the share of cargo bikes and the share of electric vans are considered.

Due to their limited capacity, we assumed that parcels heavier than 10 kg cannot be transported by cargo bikes. As a consequence, the actual share of parcels delivered by cargo bike does not exceed approximately 55%, even in the scenario with a 100% share of cargo bikes for eligible deliveries (Fig. 5a). The number of tours by vehicle type is shown in Fig. 5b. The number of tours by cargo bike increases linearly with the number of parcels that need to be delivered. The same happens for the number of feeder tours, although the absolute number is much lower, because feeders have a larger capacity and are assumed to be fully loaded on their way to micro depots. With an increasing share of cargo bikes, the number of vans decreases. Due to their large capacity, however, the reduction of van tours is smaller than the growth of cargo bike tours.

The share of time spent on parcel deliveries (including travel and service time) develops almost proportionately to the share of parcels by vehicle type (as shown in Fig. 6a). The total time required for delivery (excluding warehouse processing times) increases slightly with a higher share of cargo bikes (the scenario with 100% cargo bikes resulted in 6% more time compared to the scenario without cargo bikes). Due to the slower speed of cargo bikes,

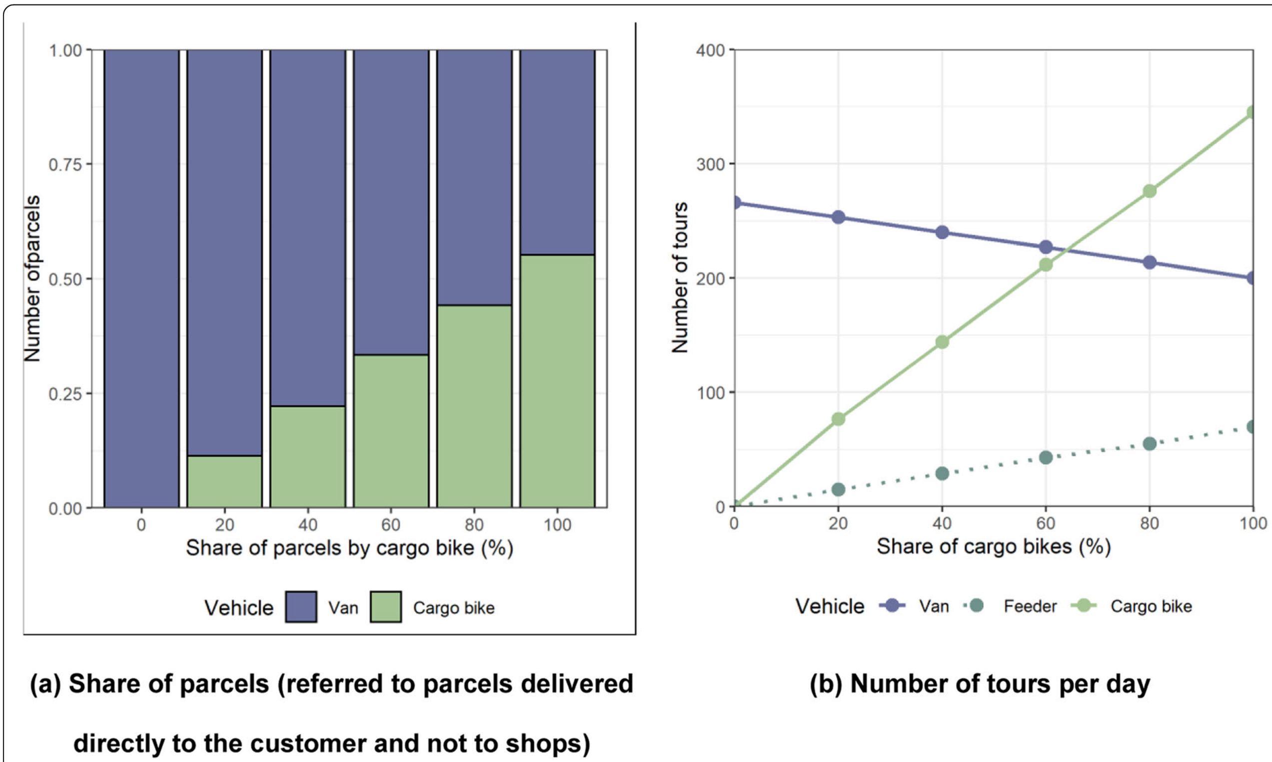
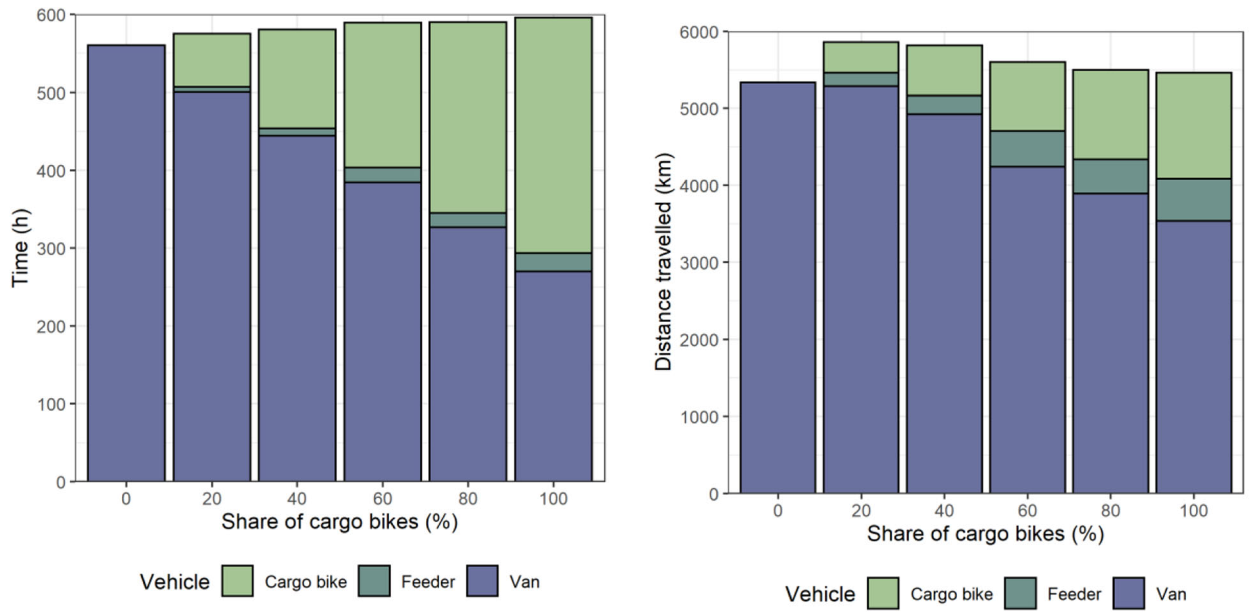


Fig. 5 General indicators for parcel distribution by vehicle type



(a) Operating time (including travel and services) **(b) Vehicle-km traveled by vehicle type per day**

Fig. 6 Operational indicators for parcel distribution by vehicle type

however, the share of distance traveled by cargo bike does not reach the same percentage as time, and reaches no more than approximately 25% (Fig. 6b). The scenarios that required the highest number of vehicle-km were those with a 20% and 40% share of cargo bike share. In these scenarios, the distances traveled by van do not decrease significantly, but cargo bikes and feeders add extra distance. When the share of cargo bikes is high (80% or 100%), the total distance traveled is not much longer than in the base

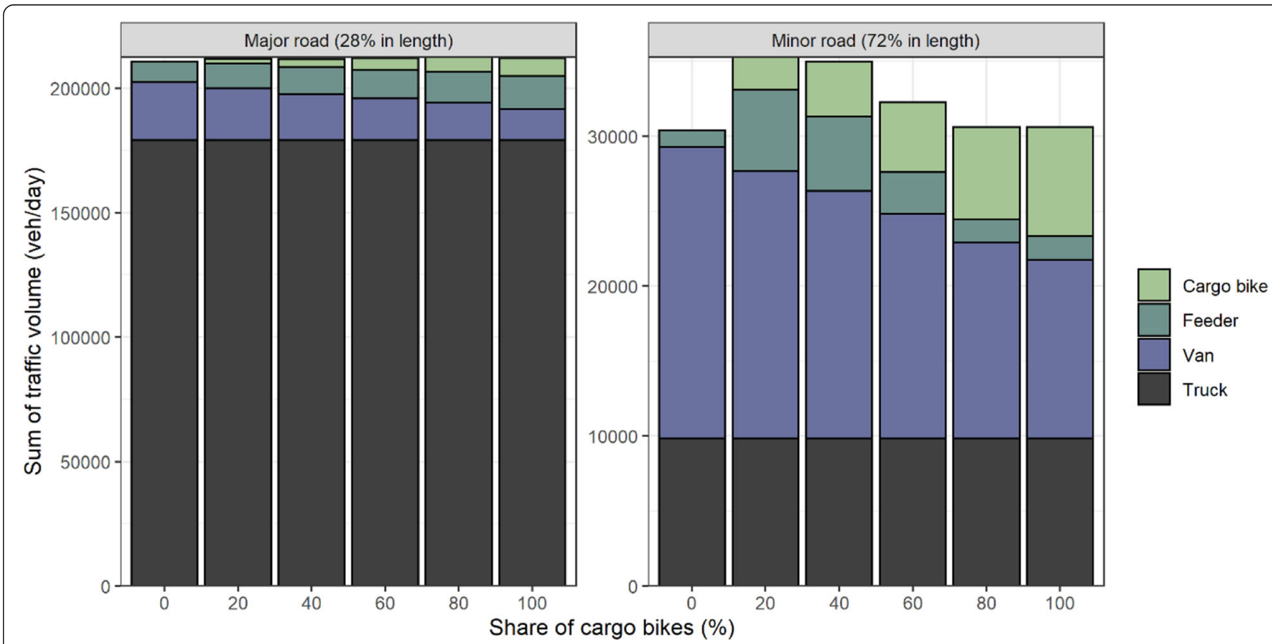


Fig. 7 Link counts of urban freight vehicles by road type and freight vehicle type in the catchment area of the analyzed Munich distribution center

scenario without cargo bikes, though the share of distance by mode is affected.

Apart from the previously mentioned changes in distance and time, we assessed the differences in traffic counts on all links of the catchment area of the analyzed distribution center. Figure 7 divides the road links intro two groups: major roads include urban segments of motorways, primary, secondary and tertiary roads (based on the classification obtained from OpenStreetMaps.org). Minor roads include residential roads. In Fig. 7, we included the truck flows transporting other commodities (e.g. construction materials, food, etc.) in the bars filled in dark gray. The truck volumes of other commodities that are not parcels remain constant in all scenarios. According to Fig. 7, the traffic volume increases significantly, but only on minor roads and when the share of parcels by cargo bikes is low (20% to 40%). It remains similar to the base case (0% cargo bikes) when the share of cargo bikes is high (80% to 100%). On minor roads, the vans for parcel delivery are the most frequent freight vehicle, while trucks are the dominant freight mode on the major road network.

The FOCA model also reports the distance traveled by long-distance trucks to transport the parcels between this distribution center and distribution centers of other cities. That distance is not included in the figures, as it is the same for all scenarios, and is equal to 6245 km. By comparison, the total distance traveled for the last-mile delivery tours ranges from 5000 km to 6000 km, representing approximately the same distance.

To analyze the CO_2 emissions, we multiplied the distance traveled by vehicle type with average emission factors according to the following assumptions:

- Diesel vans' fuel consumption of 10 l/100 km (based on Krause et al. [25]
- Electric vans' electricity consumption of 30 kWh/100 km (based on Weiss et al. [48])
- Cargo bikes' electricity consumption of 3 kWh/100 km (based on Saenz et al. [43])
- CO_2 emissions of fuel-powered vehicles of 3.170 kg/l (based on DIN EN 16258:2012 [11])
- CO_2 emissions for electricity consumption in Germany in 2018 of 0.518 kg/kWh (based on Icha and Kugs [23])

Given the above-mentioned data, the emission factors for the different vehicles are 317 g CO_2/km for diesel vans, 155 g CO_2/km for electric vans and 16 g CO_2/km for electric cargo bikes. Using these emission factors, we calculated the emissions generated by the delivery tours. In Fig. 8 we assessed the scenarios with different shares of cargo bikes (x-axis) in combination with a different share of electric vans (3 subplots). The comparison with Fig. 6b reveals a linear relationship between distances traveled by vans and emissions (due to the use of simplified emission factors in g CO_2/km). The use of cargo bikes represents, in all cases, a relevant reduction of emissions in comparison to the base scenario with no cargo bikes. The emissions generated by electricity consumption of cargo bikes are almost irrelevant, despite

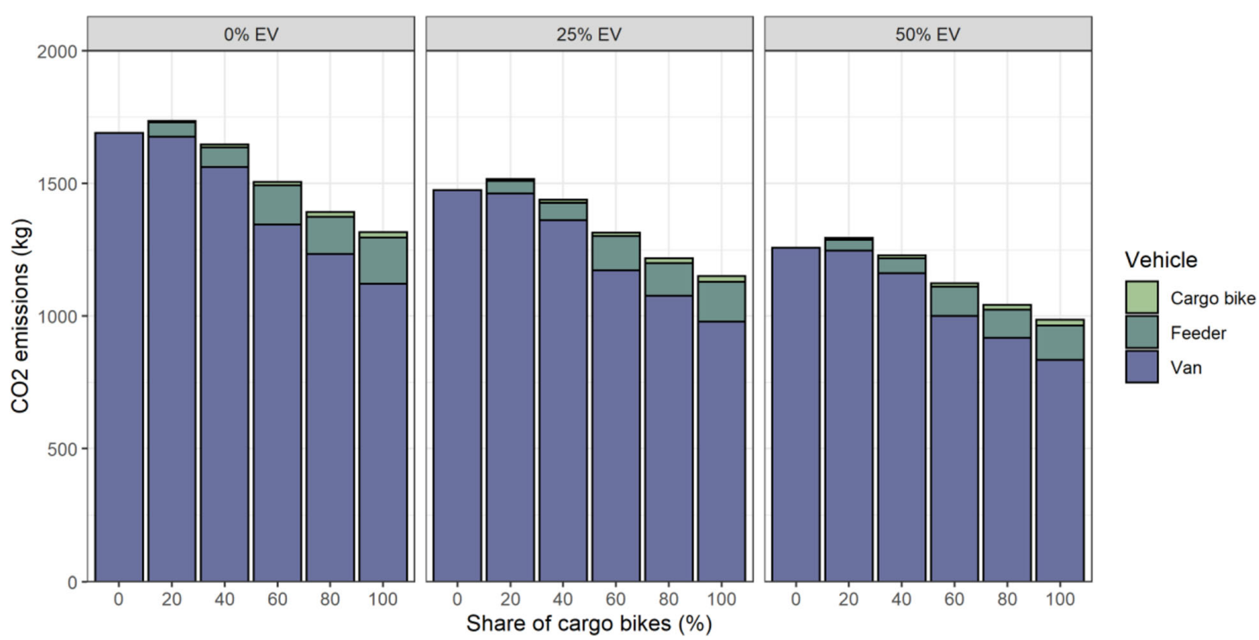


Fig. 8 CO_2 emissions per day

the long operating times and distances. The contribution of feeder trips is also small in relative terms. A replacement of 50% of diesel vans with electric vans (without the use of cargo bikes) is similar in terms of CO_2 emissions to the use of cargo bikes for as many parcels as possible.

The long-distance diesel trucks that transported the parcels from (or to) the analyzed distribution center produced under these assumptions approximately 3960 kg of CO_2.

4 Discussion and conclusions

One of the challenges of freight modeling is the lack of good data [9, 16, 41]. This affects the availability of accurate information about the number, the spatial and temporal distribution and the size of delivered parcels. These data are known to logistics companies who consider this information as a business secret. Unfortunately, these data are commonly not accessible for research purposes. In this paper, we present the development of a model for freight mostly based on openly accessible data. The model is solely based on data sources that can be downloaded by request or are directly open data. The model disaggregates national commodity flow data in tons to the finer scale of vehicles (for all commodities) and individual transported shipments (for parcels).

The number of parcels in a certain analysis area matches the observed data, although the model results may deviate if a very small geographical area is analyzed. While the modeled spatial distribution, which is proportional to population and employment density, seems reasonable, further work is needed to fine-tune the temporal distribution: currently, the model represents an average day and ignores seasonal effects. In absence of systematic data of parcel volumes by time, it could be useful to analyze online shopping or parcel tracing related web search trends. This information could be also used to extrapolate the volumes of 2011 (when the last commodity flow data was released) to the present.

The use of a freight model at different scales and levels of detail allowed us to analyze the scenarios related to the last-mile delivery within the entire supply chain [10]. The results confirmed that the urban distribution of parcels is a relevant component of the entire parcel distribution in terms of vehicle-km traveled (and consequently also emissions). Although the share of volumes and number of vehicles of this commodity is relatively low in comparison to the other commodities, its impact is relevant particularly in urban areas.

The impacts of the introduction of cargo bikes were identified in the paper. The smaller size of cargo bikes requires the introduction of a reasonable weight threshold, as the heaviest parcels cannot be delivered by cargo bike. We assumed this threshold to be 10 kg, and it resulted in an actual share of parcels transported by cargo bikes of up to 55%. As a result, a relatively high number of van tours is still required. As the heavier parcels are assumed to be uniformly distributed in the catchment area, the van tours remain somewhat long and the distance traveled by vans does not decrease drastically (although the time is cut to 50% due to the reduced number of stops). On the other hand, the presence of cargo bikes results in a high number of tours (the cargo bike tours are short) and a relative low number of feeder trips (from large distribution centers to micro depots). The distance traveled and operating time of feeder trips is minor, compared to the delivery tours of either vans or cargo bikes.

Without cargo bikes, the model estimates that there are 266 van tours with an average distance of 20 km (the dimensions of catchment area of the distribution center are approximately 7×4 km). The average tour duration is 2:06 h. Assuming 8 h of service operation, at least 90 vehicles per day are required (the loading at the distribution center is not included in the calculations). When we simulate the use cargo bikes for as many parcels as possible, the number of van tours is reduced to 200, but 345 additional cargo bike tours and 70 feeder tours are required. The duration of a van tour is reduced to 1:20 h. Cargo bike tours are, on average, 0:51 h long, while feeder tours last only 0:21 h. For the same operation time of 8 h, the minimum number of vans drops to 40 with the introduction of cargo bikes, and up to 38 cargo bikes are required to serve the entire demand. Approximately 3 additional vans would be needed for the feeder tours. As derived from the previous calculations, cargo bikes may be used to distribute every parcel lighter than 10 kg, resulting in a decrease of the number of vans from 90 to 43, but adding 38 cargo bikes. The total person hours required increase by 6% for the cargo bike scenario. The results are obtained with cargo bikes with a capacity of 20 parcels. However, due to many different cargo bike designs there is no consensus with value should be, ranging from 10 [3] to 40 parcels [44]. Further work needs to explore the sensitivity to this parameter.

The paper analyzed the potential changes in traffic volumes with the introduction of cargo bikes. The results do not show relevant changes in volumes of freight vehicles, especially on major roads and arterial streets. On residential streets, the scenarios with a low share of cargo bikes result in an increase of total volumes compared to a scenario without cargo bikes. With a high share of cargo bikes, this effect is no longer relevant. However, despite the low impact on the total vehicles volume, the introduction of cargo bikes represents an average change in the vehicle composition: the share of cargo bikes increases up to 25% of all freight vehicles. However, the share of freight vehicles was, on average, only 1% of the total number of vehicles, including cars and motorcycles. Therefore, the impact of different scenarios on the overall urban traffic is small. However, selected locations may be affected noteworthy by changes in the last-mile delivery processes.

Regarding the impacts on CO_2, the use of cargo bikes has the potential to reduce total emissions. The reduction is almost proportional to the reduction of distance traveled by vans (the emissions caused by the electricity production to run cargo bikes are much smaller). Alternatively, the same effect in emission reduction could be achieved if part of the diesel vans was substituted by battery-powered electric vans. In the paper, it was assumed that the logistics of the parcel delivery by van does not change (diesel vs. electric), which seems plausible given the relatively short length of tours that are within the usual range of electric vans. The results of the emission assessment are an additional data point to reduce emissions caused by last-mile parcel deliveries.

The paper simulated various scenarios with increasing cargo bike shares. However, we exogenously assumed the share of cargo bikes of each scenario (with the exception of the fact that parcels heavier than 10 kg could be only delivered by van) and analyzed the effects on delivery tours, distance traveled, traffic and emissions. The actual choice between cargo bikes and electric vans depends, however, on a combination of many factors. From the point of view of logistic providers, the introduction of cargo bikes may increase labor costs (longer operation times with same wage according to Sheth et al. [44]) and at the same time, additional fixed costs to build micro depots (including rent of space). On the other hand, purchase and maintenance costs of cargo bikes are significantly lower than for vans, but more cargo bikes are required to substitute one van (According to the American Transportation Research Institute [1], operational costs of cargo bikes are around one fourth of vans). From the point of view of the city administration, the presence of cargo bikes (or electric vehicles) can contribute to reduce emissions (note that this research modeled CO_2 emissions, but similar results would be obtained if local NO_x, PM or other emission factors were calculated). On the other hand, if the bicycle infrastructure is insufficient, the use of cargo bikes is unlikely to benefit traffic conditions (as bikes will occupy motor vehicle lanes and probably reduce the average travel speeds). While the paper presents a model that can be used to assess those indicators under different assumptions, further cost-benefit analyses that include many points of view are needed. In any case, the results this paper suggest that in absence of specific policies for the promotion of cargo bikes or without restrictions or pricing measures for motorized traffic, the attractiveness of cargo bikes is not obvious compared to other measures, such as the introduction of electric vans.

The results of the paper cannot be extrapolated to other geographical areas without proper adaptations. If the distance between the distribution center and the served area is higher (in our example the distribution center was inside the served area), the average trip length of van tours and feeder tours would be higher as well (this is not the case for cargo bike tours, as long as micro depots are located close to the zones they serve).

Another limitation of the model is the simplified definition of the bicycle network, which is motivated by the use of the software MATSim. Road links that allow the access to bicycles do not differ much from each other in our model. However, a more realistic approach should include additional link attributes, such as the type of infrastructure, the maximum speed or the possibility of overtaking slower bicycles.

Despite the above-mentioned limitations, the FOCA model provides a framework that is suitable for policy analyses in a field where observed demand data commonly are unobtainable. Further research will apply this model to test alternative scenarios, including road pricing, emission fees or parking restrictions for freight vehicles.

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Authors' contributions
CL, RM: study design, CL: model development, CL, RM: result analysis, CL: manuscript writing. The authors read and approved the final manuscript.

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Availability of data and materials
The model developed in this paper is an open-source model that can be downloaded directly from the GitHub repository https://github.com/msmobility/foca. Input data and simulation results are available from the authors on request.

Competing interests
The authors declare that they have no competing interests.

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