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Decarbonization policies for last-mile parcels: An adaptable open-data case study for Lyon

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Abstract

Parcel delivery volumes are increasing all over the world and come with an increasingly large footprint in emissions and energy consumption. We describe a replicable modelling pipeline for last-mile parcel deliveries in which all operators of a region are represented as cost minimization problems that are sensitive to the spatial context, vehicle types, and cost structures. For the use case of the Metropolitan region of Lyon, a future scenario for 2030 is faced with various policy interventions. The results suggest that emission levels of 2024 can be maintained by implementing a purchase tax on internal combustion vehicles of more than 50% or a carbon tax of more than 750 EUR/tCO₂eq. Full electrification yields an emission reduction compared to 2024 of 80%. All proposed policy scenarios show lower per-parcel costs compared to 2024 due to scaling effects of increasing parcel demand and density.

Keywords: parcels, urban, last-mile, logistics, optimization, vehicle routing problem, open data

1. Introduction

Parcel delivery volumes are increasing strongly around the world. In France, an increase of 22% in overall parcel volumes has been observed between 2019 and 2022 (arcep, 2022) and distributors expect the market to double compared to volumes of 2019 by 2030 (DHL, 2020). This comes with an economic and environmental impact, as operating the last mile of parcel deliveries is the most costly and environmentally impacting segment of the delivery chain (Gevaers et al., 2011). Furthermore, externalities such as pollution and congestion impact the local environment. Therefore, cities are developing Sustainable Urban Logistics Plans (SULPs) to reduce emissions and meet climate goals (Fossheim and Andersen, 2017). Various strategies for limiting and reducing the negative impacts of urban logistics have been proposed (Patella et al., 2021; Mucowska, 2021), many outlining the large potential of collaboration in the last mile sector (Dolati Neghabadi et al., 2019). However, data scarcity is slowing down respective policies and actions (Buldeo Rai and Dablanç, 2023).

The present paper presents an attempt in understanding better and quantifying the ecological impact of last-mile parcel deliveries in cities. Furthermore, we are interested in the sensitivity of the sector towards specific policies, such as carbon taxing or decentivizing the use of internal combustion vehicles (ICV). In this paper, we document a framework to (1) derive an average parcel demand for a city, (2) model parcel operators

including their warehouse locations, cost structures, and decision-making, (3) run various business-as-usual and policy cases. The approach focuses solely on business-to-customer (B2C) operators on the last mile, which, as will be shown further below, can be modelled using synthetic population methodologies, whereas the generation of B2B demand remains a difficult endeavour as data is scarce.

The developed methodology is presented for the city of Lyon in France and is entirely based on open data. Since operator data is notoriously hard to obtain, keeping the model inputs as open as possible was a primary goal of the approach. Together with various assumptions on the operator behaviour and cost structures, the open-data policy makes the approach fully replicable, which also enables future improvement and extension of the methodology. While the example of Lyon is our focus, the model is sufficiently versatile to be applied to other use cases, and we give hints on doing so throughout the paper.

The paper is structured as follows. Section 2 gives further information on similar research and positions our methodology, which is described in detail in Section 3. The simulation results for various scenarios are presented in Section 4, followed by a thorough discussion on strategic insights and technical aspects of the model in Section 5. A conclusion is provided in Section 6.

2. Background

Models of the entire logistics system of whole cities or regions are increasingly becoming a focus of research in transport planning. Among the few existing examples are MASS-GT (de Bok et al., 2022) and SimMobility Freight (Sakai et al., 2020), which are both agent-based models that describe entities such as shippers, receivers, shipments, or vehicles in detail and individually. On the other hand, there are more aggregate models based on statistical data such as FRETURB (Toilier et al., 2018) in France, which provides valuable policy insights on a zonal level. What these models have in common is that they are based on specific data sets for specific environments, which are often not openly accessible. Hence, while the methodologies are elaborate and highly valuable for their specific environment (USA, Netherlands, France) it is hard to replicate them elsewhere due to the lack of a common input. Further approaches for modelling city-wide logistics have been documented with statistical models that, theoretically, can be applied in other contexts by Comi (2020) and Nuzzolo and Comi (2014). However, the authors also show that the models estimated in one environment are difficult to transfer to other cities (Ibeas et al., 2012).

In search for a common starting point for developing parcel models, the present paper is inspired by agent-based models for passenger transport that are used increasingly all over the world. The key inputs to such models are synthetic populations that represent well the sociodemographic structure of a territory, with persons modelled as individual entities with attributes such as age, gender, or income. Interestingly, such data sets are increasingly published as open data or in the shape of replicable approaches. For instance, Ziemke et al. (2019) propose an openly useable synthetic population for Berlin, and He et al. (2021) propose such a data set for New York City. Hörl and Balac (2021) have proposed an approach that is able to generate synthetic populations for any region in France. It is fully replicable as the open-source framework

is entirely based on open and public available data in France. It has later been adapted for the cases of São Paulo (Sallard et al., 2021) and California (Balac and Hörl, 2021) with the same degree of openness and replicability. As will be shown in this work, such a synthetic population, can be used to generate demand data for B2C deliveries in a city or region. While this is a step back with respect to full logistics models of cities that take into account all flows of goods including B2B, we ensure that the models presented here have a higher degree of transferability for cases where synthetic populations are available.

Another observation that makes our methodology relevant is that even though operators are reluctant to share detailed information on their deliveries, more and more public agencies and private consulting firms take on the effort to collect statistical data on parcel deliveries. In France, ARCEP provides annual statistics on the growth of the B2C parcel market, indicating an average annual growth of about 5% from 2019 to 2022 (arcep, 2022). Furthermore, statistical information on the customer profiles on the receiving end of B2C deliveries are collected. For instance, Gardrat (2019) provide descriptive statistics on the annual parcel demand generated by well-defined sociodemographic groups in the city of Lyon, and Mesaric et al. (2020) provide regression models on the per-household parcel demand in Zurich and Singapore. In our methodology presented below, such statistical information is fused with a synthetic population to obtain a demand data set that represents parcels as individual entities to be delivered. By basing our methodology on such high-level statistical data, we, once more, aim at maintaining as much replicability as possible.

The activities of logistics operators are commonly modelled as Vehicle Routing Problems (VRP). While many forms of VRPs exist (Braekers et al., 2016), we focus on settings in which a set of points to visit (delivery locations) are given, as well as the depot location of the operator. By providing the expected travel times and travel costs between all locations to a VRP solver, the goal is to obtain the cost-minimizing ordered sequence of points to visit of one or more vehicles, such that all deliveries are first picked up at the depot and then brought to their destination. In our model configuration, we use heterogeneous VRPs, which will be specified in detail below.

Since various open-source solvers for VRPs are available, this choice of methodology also supports the replicability of our proposed approach. Furthermore, VRPs are highly sensitive to various inputs, such as the costs for vehicles to move in the network or the costs of individual vehicles. While those inputs need to be well calibrated to provide a realistic baseline case, they can also be modulated on purpose to simulate individual policies, such as cost changes, or even more complex configurations, such as combining deliveries of multiple operators. The choice of VRPs as the basis for our approach, hence, allows for maximum flexibility in testing various policies such as urban consolidation centres (Van Heeswijk et al., 2019) or automated delivery vehicles (Yu et al., 2020) in the future.

In conclusion, there is a lack in system-level information on the economic and ecological impact of logistics systems as a whole. We intend to advance the discussion on last-mile delivery policies by providing first estimates on the overall costs and emissions of such a system for the case of B2C for the specific case of Lyon. Furthermore, we identify a lack of transferability of existing methodologies in the modeling of logistics

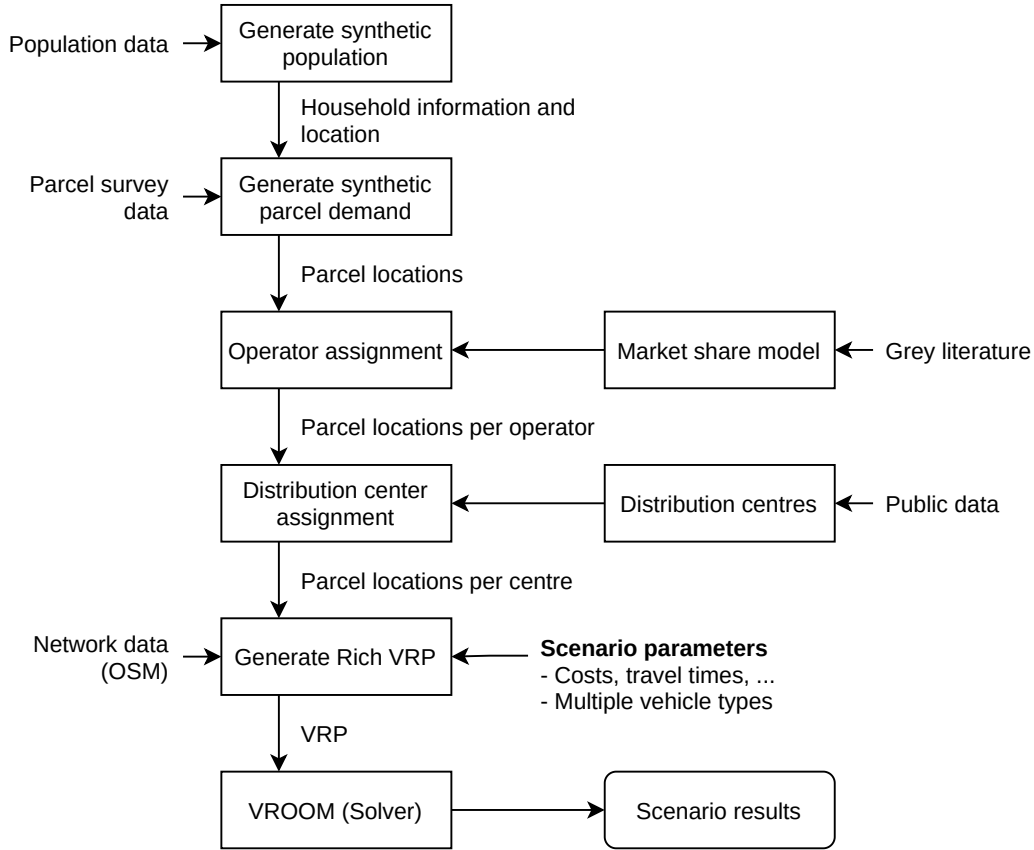


Figure 1: Structure of the modelling process

systems. For that purpose, our model is based on open data and open software, and we document how it can be adapted to other use cases.

3. Methodology

The following sections describe the structure of our simulation model. It consists of various components that are shown in Figure 1. The first component is a synthetic population, which represents in detail the persons living in the territory as individual entities. Second, an average daily parcel demand is established by generating parcels per-person based on statistical information on their purchasing behaviour. Third, we define the operators that are active in the study area by identifying their distribution centres and market shares. Fourth, we assign an operator to each parcel and identify the most likely distribution centre for each parcel. Fifth, the cost structures and other key parameters of the operators are identified and, sixth, the resulting VRPs are prepared and solved. Finally, the outputs are analysed in various key performance indicators (KPIs).

Throughout this section, we will base our presentation on a study area that covers the Lyon Metropolitan region (*Métropole de Grand Lyon*) and some surrounding areas, mainly those that already show rural char-

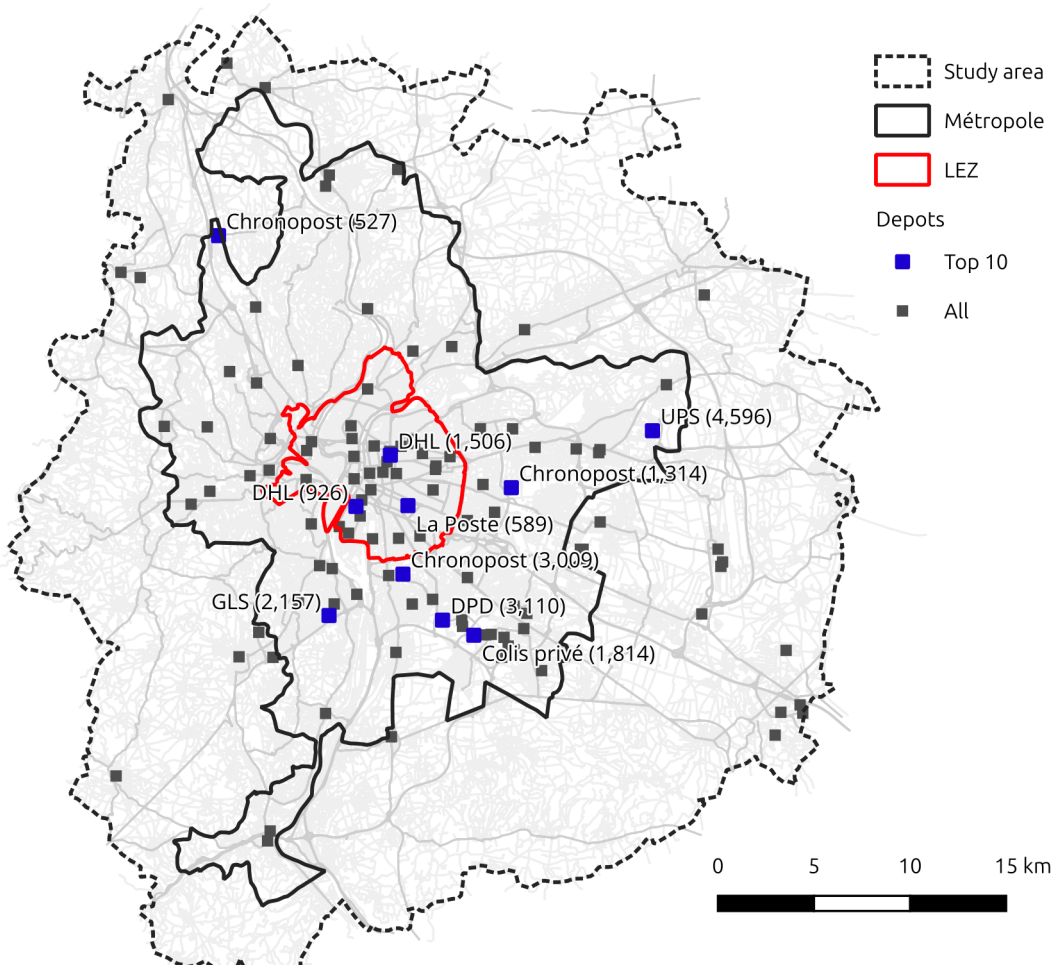


Figure 2: Spatial analysis of the case study

acter but which also house the most relevant distribution centres in the area. The analysis area can be seen in Figure 2. Besides our specific comments on that study area, pathways for generalization of the individual modelling steps are given.

3.1. Synthetic population

As the first step for the generation of a daily parcel demand for the city of Lyon and surroundings, we make use of a framework presented by Hörl and Balac (2021). In that approach, a synthetic population for the Île-de-France region around Paris is generated based on open data in France. The open-source code has been extended several times since and can be applied to any region in France as has been done in various case studies, for instance for Nantes (Hankach et al., 2024), or Lille (Diallo et al., 2023). In the present case, it has been applied to the city of Lyon, yielding a data set that contains individual persons with sociodemographic attributes such as age and sex which are grouped into households with coordinate-based places of residence that correspond to building locations of the open building registry (BD-TOPO) of France. Furthermore, the recent version of the synthetic population pipeline allows making use of population predictions by the

Table 1: Generated households and parcels by year

Year	Households	Parcels
2019	1,049,786	26,984
2024	1,053,130	35,986
2030	1,081,843	54,527

French statistical office (INSEE) based on an Iterative Proportional Fitting Updating algorithm which allows producing synthetic populations for any time in the future, following predicted marginal population counts by age, sex, and department.

In the present case study, we generate synthetic populations for the year 2019 for which all required open data sets (census data, commuters matrices, ...) that are described in (Hörl and Balac, 2021) are available. We then use the projection functionality to create a synthetic population for 2024 to represent the current state of the territory and for the year 2030 to explore future scenarios. Taking into account INSEE’s central population prediction scenario, Table 1 shows the number of households that are generated across the study area (Figure 2).

While the process applied here is specific to France and Lyon, synthetic populations have been published for various other use cases around the world over the last years. An alternative and even more generic approach would be to make use of raster data and generate individual households on the territory. While the level of detail, especially on sociodemographic attributes and spatial precision may be lost, ubiquitously available data sources such as the World grid (CIESIN, 2016) or the 1km² population grid from eurostat (2023) could be used.

3.2. Synthetic parcel demand

Based on the synthetic population, a daily parcel demand is established, following the principle that every household is assigned a discrete number of parcels that are delivered on an average day. For the case of Lyon, we make use of survey data published by Gardrat (2019). In that study, a representative sample of persons living in the Lyon Metropolitan area have been interviewed about the regular purchasing behaviour of their household. The report indicates the annual number of remote purchases performed by the resident households characterized by the sociodemographic attributes of reference persons. The average volumes of purchases are reported by the households’ socio-professional category (SCP), which is an economic and statistical classification system (from white-collar employees to retired persons, here excluding agricultural workers) in seven categories that is frequently used in France (INSEE, 2022). Furthermore, the average number of remote purchases per household are indicated by age and SCP, and by age and household size.

In (Hörl and Puchinger, 2023), an Iterative Proportional Fitting approach has been proposed to impute this publicly reported information to the synthetic population of the territory. Specifically, weight factors $w_{s,a,h} \in \mathbb{R}$ are established for every combination of SCP $s \in \mathcal{S}$, age class $a \in \mathcal{A}$, and household size class

$h \in \mathcal{H}$, which, when multiplied with the population counts $n_{s,a,h} \in \mathbb{N}$ give the marginal annual per-household delivery volumes from the report:

$$\begin{aligned}
\sum_{a,h} n_{s,a,h} \cdot w_{s,a,h} &= T_s & \forall s \in \mathcal{S} \\
\sum_s n_{s,a,h} \cdot w_{s,a,h} &= T_{a,h} & \forall (a,h) \in \mathcal{A} \times \mathcal{H} \\
\sum_h n_{s,a,h} \cdot w_{s,a,h} &= T_{s,a} & \forall (s,a) \in \mathcal{S} \times \mathcal{A}
\end{aligned} \tag{1}$$

The first equation fits the tabulated marginal purchases by the seven SCP given as T_s , the second equation establishes 16 constraints fitting the volumes for the four age categories (18-34, 35-49, 50-64, 65+) and the four household size classes (1, 2, 3, 4+); finally, the last equation fits the weight to the expected volumes by age and SCP (28 constraints). Furthermore, the $7 \times 4 \times 4 = 122$ weights are chosen such that the overall found amount of purchases per year by [Gardrat \(2019\)](#) of $T = 14$ is matched:

$$\sum_{s,a,h} n_{s,a,h} \cdot w_{s,a,h} = T \tag{2}$$

The weights are calculated based on the approach described by [Hörl and Puchinger \(2023\)](#). Furthermore, [Gardrat \(2019\)](#) indicates the share of parcels being home deliveries contrary to being picked up at a shop or a pick-up point. Indicating this probability as $f_{s,a,h} \in \mathbb{R}$, the average daily number of parcels for a household of type (s, a, h) can be defined as

$$\mu_{s,a,h} = \frac{f_{s,a,h} \cdot w_{s,a,h}}{D} \tag{3}$$

with D as the number of effective delivery days. As most operators in France only deliver Monday to Friday, we fix the value to $D = 260$.

While $\mu_{s,a,h}$ gives the daily mean of parcels delivered to each household, it is not yet a discrete number that can be used in a single-day simulation. As no information on the distribution of distinct parcel counts per day is available, we choose a Poisson distribution with mean $\mu_{s,a,h}$ which is the maximum entropy distribution of a random variable that is discrete and non-negative with a known mean. Based on this distribution, a distinct number of parcels per day is sampled for each household of the synthetic population. For a scenario parametrized to 2024 (see below), this process yields about 27,000 parcels to be delivered in the study area (Table 1), with 34,084 households receiving one parcel, 917 two parcels, 20 three parcels and one household with four parcels.

The process presented here ([Hörl and Puchinger, 2023](#)) can be adapted to any descriptive data set on the number of purchases or parcels in relation to the sociodemographic attributes of the population. Such surveys are increasingly performed by researchers, public entities and companies and can be directly transposed to the proposed methodology. However, even without a specific survey, a simplified approach could be followed in this step if the overall number of delivered parcels per person or household (for instance, from national

Table 2: Estimated operator statistics for 2024

Operator	Depots	Parcels
La Poste (Colissimo)	89	14,387
Chronopost	6	5,363
UPS	2	4,953
DPD	3	3,442
DHL	7	3,325
GLS	2	2,461
Colis privé	2	1,978
Fedex	8	77
Σ	119	35,986

statistics) can be obtained or hypothesized. Then such a factor can be applied to the population data and individual parcels can be discretized in an informed best-guess approach.

3.3. Operators and market shares

After establishing the demand data, we cover the modelling of operators. In France, an open registry of all enterprises and their sites is available, including the per-site number of employees. We make use of this data set to identify the distribution centres of the largest logistics operators that are active in the study area. The list of operators has been elaborated based on expert knowledge and comprises Colissimo, Chronopost, DPD, Colis privé, GLS, DHL, Fedex, and UPS. For each of their national enterprise identifiers (SIREN) the respective sites have been identified and checked manually. For the largest operator, La Poste operating the Colissimo service, a large set of sites representing all post offices has been identified. It was filtered to only include offices with more than 15 employees. This heuristic has been obtained by checking the presence of delivery vehicles or garages based on satellite images and then identifying this threshold as a likely limit for an office performing parcel deliveries.

In total, the process yields 119 distribution centres for the eight operators shown in Table 2. The locations of the distribution centres are shown in Figure 2.

To assign the generated parcels to the operators, it is important to know their market share in the parcel delivery sector. Such information is not available. Therefore, assumptions have been developed which are based on two data sources: (1) the annual business reports of the operators where available, and (2) their annual turnover. The respective model can be seen in Table 3, and we give indications on how to read the numbers: It has frequently been reported in grey literature that the market share of La Poste group (including Colissimo, DPD, and Chronopost) is around 65% (a). Based on this information and those services' parcel volumes that can be derived from annual reports (b), we extrapolate to a total of 1,175M parcels delivered per year in France overall (c). Furthermore, we found the volumes of Colis privé to be 63M per year (d),

Table 3: Market share estimation model

Operator	Volume [M]	Turnover [MEUR]	Turnover [%]	Parcels [M]	Market share [%]
La Poste	764	-	-	-	^(a) 65.00
Colissimo	^(b) 471	-	-	-	40.07
Chronopost	^(b) 176	-	-	-	14.97
DPD	^(b) 117	-	-	-	9.95
Colis privé	^(d) 63	-	-	-	5.36
Remaining	^(e) 348	-	-	-	
GLS	-	^(f) 422	23.38	81	6.93
DHL	-	^(f) 545	30.19	105	8.95
Fedex	-	^(f) 13	0.72	3	0.21
UPS	-	^(f) 825	45.71	159	13.55
Σ	^(c) 1175				100.00

leaving 348M parcels (30%) to be distributed over the remaining operators (e). We weight those operators by their published turnover values (f)¹ and distribute the remaining parcels accordingly. This yields our final model of the operator market shares, as shown in the last column of Table 3. With 40% of all parcels, La Poste serves most of them under their Colissimo brand, followed by Chronopost, UPS, and DPD. The ranking of those operators corresponds to anecdotal evidence observed by the authors and peers.

While, in the present case, the goal was to obtain somewhat evidence-based market shares, even coarser assumptions could be made when transposing the modeling pipeline to another use case. Even more, some national or regional regulators, depending on the use case, may have this statistical information such that it could be integrated directly into our proposed modelling chain.

3.4. Parcel assignment

For the next step, the delivery locations, the locations of the distribution centres, and the market shares are known. On the basis of this information, the connection between parcel demand and transport supply can be established. For that, we make use of a detailed road network extracted from OpenStreetMap. In particular, we use a cut-out of the region around Lyon² and process it using the `osmnx` library (Boeing, 2017) to obtain a routing network. We make use of `osmnx`'s standard functionality to impute speed limits and respective lower bound travel times into the network graph.

For the assignment, we first, sample one operator for each individual generated parcel based on the

¹Based on information from <https://www.societe.com>

²We use the cut-out for the Rhône-Alpes region around Lyon from 01/01/2024 provided by <https://www.geofabrik.de/>

derived market shares. Note that households with multiple parcels are disaggregated such that they may receive parcels by different operators. Table 2 shows the number of parcels assigned to each operator for the 2024 case.

Second, we perform a large batch of routing tasks in which we obtain the shortest distance path between every depot (distribution centre) to every customer of each operator. In the 2024 case we obtain 1.2 million routes for the largest operator with 89 depots and 14,387 parcels. They are efficiently processed using the one-to-N implementation of the Dijkstra algorithm in the `networkx` library (Hagberg et al., 2008).

Having obtained all routing information, we select the distribution centre that is the closest in terms of shortest path distance to each parcel. Note that this is a strong assumption as, in reality, operators are likely to group parcels according to various criteria with overlapping or heuristically defined service areas. However, in lack of specific data, we treat the presented mechanism as the best guess (and optimistic) solution. Figure 2 shows the number of parcels assigned to the twenty busiest distribution centres.

3.5. Operator configuration

One goal of our research is to understand how the cost structures of the operators (and policy-induced modulations) affect the use of certain vehicle types, with a specific focus on thermic versus electric and smaller versus larger vehicles. It is, hence, important to define realistic cost structures for the baseline or business-as-usual (BAU) situation. On a daily basis, we assume that a parcel operator has two major cost components: salaries for drivers and vehicle-related costs. The vehicle-related costs can be further broken down into operational expenses and capital expenses related to the purchase of the vehicles. Furthermore, we establish archetypical vehicle types that may be used by parcel operators.

3.5.1. Salaries

Salaries in the parcel delivery sector vary between operators. However, for the sake of simplicity, we assume a generic average monthly salary in the sector. We assume an average gross salary of 1,700 EUR per month. After deduction of income taxes and social security, a net salary of 1,300 EUR per month is achieved. This value is in line with observations from grey literature and discussions with experts. For the employer charges, we assume 50% of the gross salary, leading to salary costs per driver of 2,550 EUR per month. In line with our previous assumption, we divide this value by 22 operating days per month, leading to salary costs of 102 EUR per driver (and thus per active vehicle) per day.

3.5.2. Vehicles

To obtain information on the vehicle costs for a parcel operator, we have investigated a range of long-duration rental contracts for utility vehicles in France. On the one hand, the specification sheets of the vehicles provide valuable information on the consumption (and emissions) of the vehicles. On the other hand, we make use of the rental fees of those contracts as a proxy for vehicle and depreciation costs. Deriving

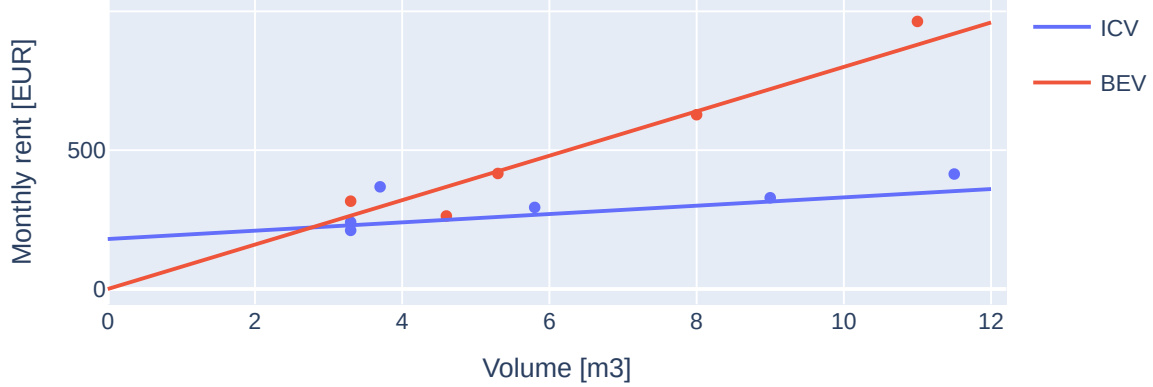


Figure 3: Relation between transport volume and vehicle price for combustion and electric vehicles

the unit costs of the vehicles from these contracts avoids performing a much more complex analysis and reasoning regarding the purchase prices and vehicle lifetime.

A set of data points from French manufacturers has been obtained in early 2022 including the monthly rent, the upfront payment, the transport volume, the fuel or energy consumption per distance, and emissions. The detailed data is documented in [Appendix A](#).

From our data analysis, we derive a linear relationship between price and transport volume, with a steeper slope for electric vehicles, as shown in Figure 3. This means that for the same transport volume, an operator needs to pay disproportionately more for using a Battery Electric Vehicle (BEV) compared to an Internal Combustion Engine Vehicle (ICV). Yet, the difference for smaller vehicles is relatively small.

The obtained vehicle data has been grouped into stereotypical vehicle categories of three sizes (Small 3.3m³, Medium 5m³, Large 10m³) and two engine types, ICV and BEV. The resulting vehicle types, including their per-day unit costs, are summarized in Table 4. Note that for the VRPs introduced further below, a capacity in terms of *parcels* needs to be defined. In lack of data on the average parcel size, we assume a linear relationship of 1m³ representing a transport capacity of 10 parcels. This assumption should be validated with relevant data sources in the future.

For the emissions of BEVs, we assume 90 g/kWh³ which corresponds to the emissions attributed to energy production in France (which is comparably low due to a high share of nuclear energy).

Based on Table 4, we can calculate the operational per-distance cost C_t^V for each vehicle type t as

$$C_t^V = u_t^F \cdot C^F + u_t^E \cdot C^E \quad (4)$$

with u_t^F as the fossil fuel consumption of vehicle type t , C^F the cost of fossil fuel, u_t^E as the electricity consumption, and C^E as the cost of electricity. For the price assumptions of 2024 (see below), Table 4 shows the resulting operating costs in the bottom row.

³<https://www.rte-france.com/eco2mix>

Table 4: Vehicle types used in the simulation

	Small ICV	Medium ICV	Large ICV	Small BEV	Medium BEV	Large BEV
Capacity	33	50	100	33	50	100
Monthly cost [EUR]	210	260	370	260	400	800
Fuel cons. [L/100km]	5	6	8	-	-	-
Elec. cons. [Wh/km]	-	-	-	160	200	300
Range [km]	-	-	-	280	240	120
Emissions [gCO ₂ eq/km]	130.00	160.00	215.00	14.40*	18.00*	27.00*
Cost [EUR/100km]	9.00**	10.80**	14.40**	4.48***	5.60***	8.40***

*Based on 90gCO₂eq/kWh.

**Based on 1.80 EUR/L.

***Based on 28 ct/kWh.

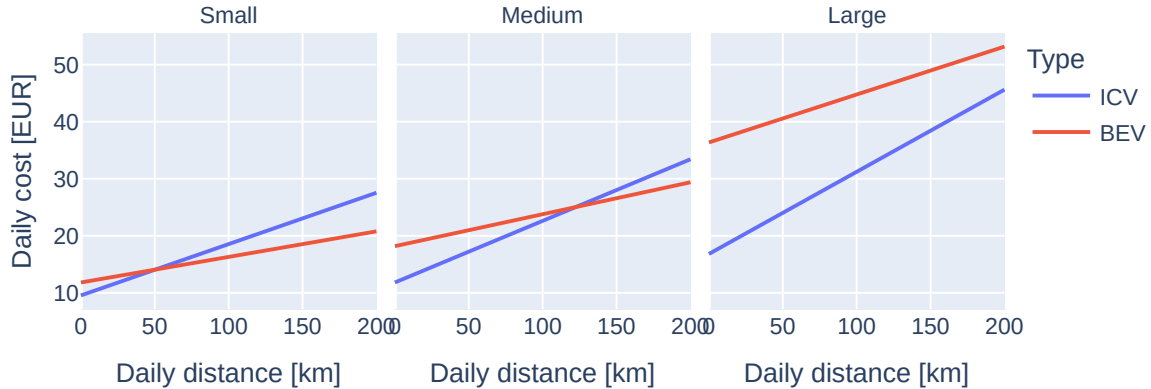


Figure 4: Trade-off between ICV and BEV for different daily driven distances

From Table 4, one can see that the costs for ICVs are one order of magnitude higher than those of the BEVs under those assumptions. Hence, there is an interesting trade-off situation in which the operational costs of BEVs are lower than those of ICVs, but their unit costs are substantially higher, especially for larger vehicles. Following a cost-minimizing approach, an operator would replace a small ICV with a small BEV already if the daily distance exceeded about 50km. However, a medium-sized vehicle would only be replaced at a distance of 120km. Those relations are visualized in Figure 4 and are the key to assessing the policy scenarios presented further below.

According to the logic presented above, the operator-level assumptions from Table 4 can be adapted to other environments when transposing our methodology to other use cases.

3.6. Vehicle Routing Problems

The information presented in the sections above is combined into VRP instances which each represent an average day of one distribution centre, of which one operator can have multiple. Optimizing the depots individually drastically reduces the size of the problems, which is necessary for some operators so that solutions can be obtained in an acceptable time.

The multi-trip VRPs (Cattaruzza et al., 2016) set up in this research have the following characteristics. The goal is to minimize the overall costs per distribution centre, which is the sum of the unit cost per vehicle including the driver’s salary and the operational cost based on the driven distance. Each distribution centre can freely choose the number of active vehicles of each available vehicle type, as listed in Table 4. Each vehicle can perform multiple round-trips per day and needs to return to the distribution centre at the end of the day. All parcels need to be transported from the distribution centre to their specific delivery location. Each pick-up at the depot takes 60 seconds, which is our assumption, while each delivery takes four minutes, which is in the order of magnitude reported in literature (Van Heeswijk et al., 2019; Buldeo Rai and Dablanc, 2023). Each vehicle and driver have a maximum active time (stopping, driving, including return) of ten hours. This assumption has been derived from grey literature reports. Electric vehicles, additionally, must adhere to their maximum range between subsequent visits to the depot.

The major input to the VRP is a set of large matrices. For each distribution centre, we calculate $(N+1) \times (N+1)$ shortest paths by travel time, including all delivery locations and the depot. The travel times are based on the speed-limit-based traversal times from network conversion. The values are inflated by a factor to represent averaged congested conditions in Lyon. The factor consists of an assumed +30% increase to obtain free-flow conditions compared to speed limits and another +30% taking into account congestion averaged over an entire day, based on the TomTom congestion index (Cohn et al., 2012) for Lyon⁴. Furthermore, we impose a maximum speed limit of 120 km/h for all vehicles. In total, routing all point-to-point matrices for 2019 took about 24 hours on a standard 12-core virtualized infrastructure.

All input data and constraints are transformed into the format of the open-source VRP solver VROOM (Coupey et al., 2024). It requires a list of vehicle definitions, a list of cost and travel time matrices (per vehicle profile), and a list of shipments with pick-up and delivery locations in JSON format. The tool is actively developed and has been used in various real-world use cases for grocery and parcel operators in France. Figure 5 shows the runtime performance on the highest configurable solution quality as a function of the number of parcels per instance for all scenarios described below.

The fleet selection mechanism is implemented such that each instance, initially, has 40 vehicles of each type available from which some are assigned tasks by the solver or not. In case the solution indicates that indeed 40 vehicles of one type are used, the instance is rerun with double the number of vehicles, as indicated by the number of retries in Figure 5. Furthermore, it should be noted that the consideration of the range

⁴<https://www.tomtom.com/traffic-index/lyon-traffic>

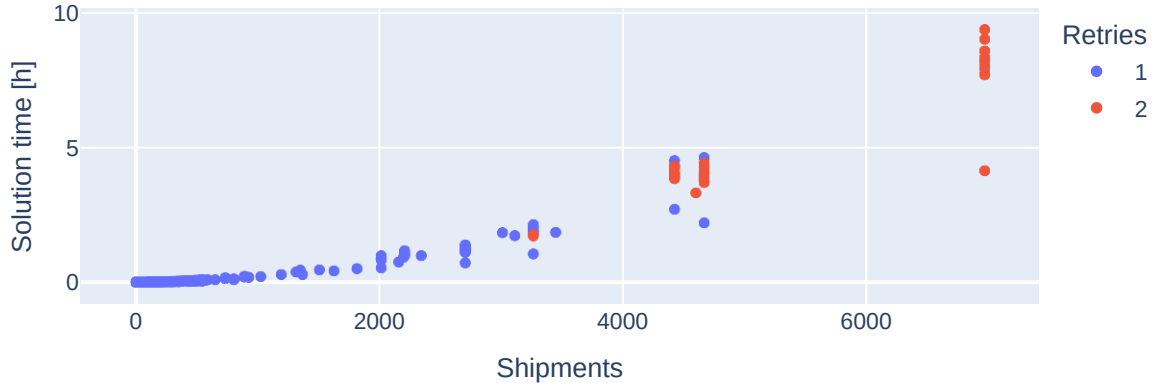


Figure 5: Runtime results for the solved instances

constraint between two visits to the depot is a custom development that has been performed for the present research. In total, for the baseline and policy scenarios presented below, 1,889 VRPs have been solved with a total runtime of 342 hours.

The output of VROOM (also in JSON format) is then processed to obtain values on relevant indicators such as distance, emissions, costs per movement, per tour, per vehicle, per distribution centre, per operator, and overall.

4. Simulations

The presented modelling pipeline has been used to simulate various policy scenarios for the city of Lyon. The goal is to observe the operators' reaction to changing demand scenarios and external influences on the cost structures. The following section describes how the scenarios have been configured inside the pipeline, followed by an analysis of different demand scenarios and policy cases.

4.1. Scenario configuration

We define two sets of scenarios. The first are business-as-usual (BAU) scenarios, in which our goal is to provide a realistic representation of various points in time. We are interested in observing how the operators react to the parcel demand that has been and is increasing year by year. It is then interesting to understand what vehicle types operators choose without any specific incentive towards one or the other option, and we can derive the resulting infrastructure use in terms of distance driven as well as the caused emissions. Second, we define external influences through policies that are either quantitative by influencing the cost structure of the operators or qualitative by introducing additional constraints. We can then observe the environmental impact and economic effects of such measures.

The BAU scenarios are evaluated for the years 2019, for which the baseline version of all source data is available, 2024, to model the current situation, and 2030 to perform a future projection. To set up those scenarios, three dimensions are varied:

Table 5: Assumptions for the business-as-usual scenarios

Year	2019	2024	2030
Demand factor	1.00	1.35	2.00
Electricity price [ct/kWh]	10.15	27.56	27.56
Fuel price [EUR/L]	1.45	1.80	1.80

1. During population generation, we apply the population growth factors from the central projection scenarios of the French statistical office. Those result in an increase of persons by about 0.3% per year.
2. The mean number of parcels generated per household μ is inflated by a demand factor ξ_D . The updated mean $\mu' = \xi_D \cdot \mu$ is then used for demand generation. To represent the demand for 2024, we apply a factor of 1.35 taking into account the average annual growth reported by (arcep, 2022). For 2030, we double the demand by imposing $\xi = 2$, following the business projection by various parcel operators (DHL, 2020).
3. For each year, we assume different electricity and fuel prices. For the ICVs, we assume Diesel prices of 1.45 EUR/L in 2019 and 1.80 EUR/L in 2024 based on time series on fuel prices in France⁵. For electricity prices, we use information from Eurostat⁶ for non-household consumers, and impose 10.15 ct/kWh in 2019 and 27.56 ct/kWh in 2024. The prices represent the strong shifts between 2019 and 2024. For the case of 2030 we don't make additional assumptions on their development, but keep the values for 2024.

The BAU assumptions are summarized in Table 5.

On top of the BAU scenario for 2030, we add two quantitative and two qualitative policy (and technology) scenarios. The first quantitative policy represents a specific tax on the purchase of ICVs. Technically, we increase the unit cost for all respective vehicle types by the factor ξ_{ICV} . The tax is varied between 20%, 50% and 100%. The second quantitative policy is a classic carbon tax. For that policy, we assume that the tax is impacting the operators through the use of fossil fuel and electricity. Hence, we add another component to the operating costs (via the cost matrices) for all vehicle types. For both ICVs and BEVs, the emission rate per kilometre is calculated as documented above (Table 4) and multiplied by the carbon tax, represented by ξ_{CO2} ranging from 100 to 2,000 EUR/tCO₂eq.

The qualitative scenarios explore driving restrictions for ICVs. The first scenario assumes that ICVs are not allowed any more to enter the existing low-emission zone (LEZ) of Lyon (see Figure 2). The second scenario is more extreme in that it forbids ICVs altogether. Technically, the second case is easier to implement in the VRPs, as the ICV types are simply removed from available vehicles. In the VROOM solver, so-called skills are used to differentiate between different vehicle capabilities and can be used to require vehicles to

⁵<https://www.tolls.eu/fuel-prices>

⁶[tps://ec.europa.eu/eurostat/cache/infographs/energy_prices/enprices.html](https://ec.europa.eu/eurostat/cache/infographs/energy_prices/enprices.html)

Table 6: Business-as-usual results

	Baseline 2019	Today 2024	Future 2030
Delivered parcels	26,984	35,986	54,527
ICV	22,627	32,358	51,573
BEV	4,357	3,628	2,954
Vehicles	351	437	610
ICV	286	384	570
BEV	65	53	40
Distance [km]	16,432	19,612	24,898
ICV	10,836	14,809	21,405
BEV	5,596	4,803	3,493
Cost per day [EUR]	46,602	58,603	82,202
Cost per shipment [EUR]	1.73	1.63	1.51
Fuel [L]	809	1,085	1,604
Electricity [kWh]	925	776	566
Energy [kWh]	9,017	11,628	16,602
Emissions [kgCO ₂ eq]	2,250	2,972	4,345

have a certain skill to visit certain customers. For the electric LEZ, BEVs receive a specific skill to enter the zone, while all deliveries located inside the zone require vehicles to have that skill in order to be assigned to them. Furthermore, ICVs are routed on a reduced network that excludes road links inside the LEZ or those crossing its boundaries.

4.2. Business-as-usual results

Table 6 shows the results of the BAU scenarios from 2019 to 2030. While the parcels more than double between 2019 and 2030, the driven distance only increases by about 50% indicating that a higher density of parcels leads to a higher efficiency in delivering them because newly added demand can be integrated along sparser routes from the earlier scenarios.

In terms of the transition from ICVs to BEVs, we can observe that in 2024 about 18% of vehicles are electric, a number that drops to 12% in 2030 due to the increased parcel volumes. Table 7 confirms those results by showing that especially Large ICVs are added to fulfill the demand while Small BEVs are abandoned.

Accordingly, we observe that our model results show an increase of fuel consumption and a decrease of electricity consumption from 2024 to 2030 with a net increase in energy demand of 42%. To compare the scenarios, the total used energy is calculated as the sum of consumed electricity in kWh and the energy

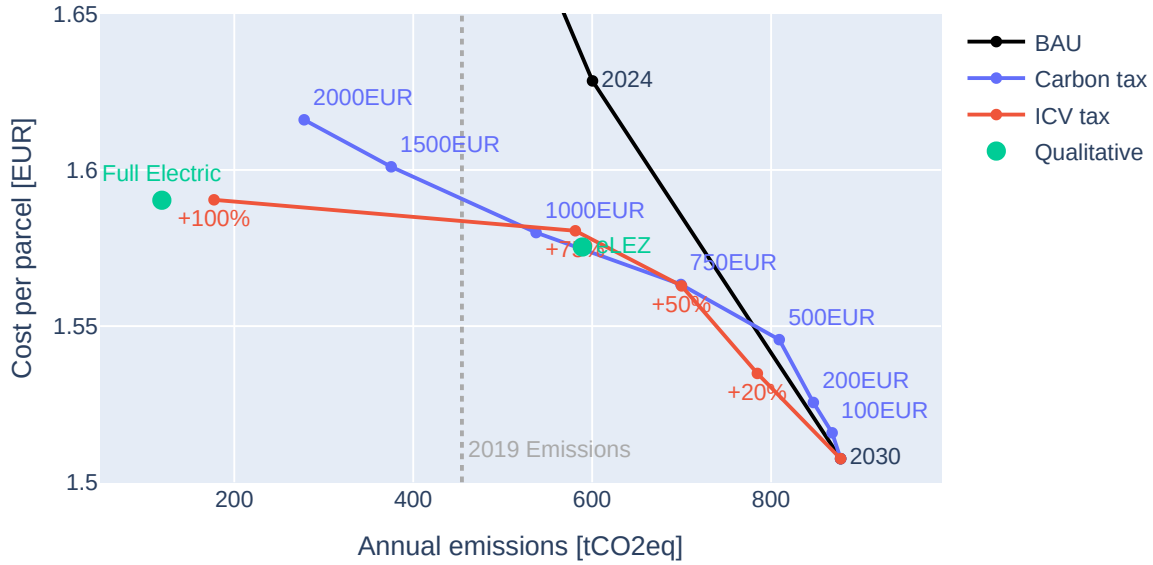


Figure 6: Results of the policy scenarios

content of the used fuel with a conversion rate of 10 kWh/L (Diesel). Emissions increase by 46% between 2024 and 2030.

Finally, Table 6 indicates that economy-of-scale effects due to increased efficiency reduce the per-unit parcel delivery cost by about 7%.

4.3. Policy results

Figure 6 shows the *annual* emissions that have been scaled from the daily results in relation to the per-parcel delivery costs in the simulated scenarios. The black graph represents the BAU results from the previous section, indicating a decrease in delivery costs coupled with a strong increase in emissions. Note that the data point for 2019 (1.73 EUR per parcel at 455 tCO₂eq) is outside the shown range and only the emission level is indicated.

After tracing the BAU scenarios until 2030 in the lower right corner, the respective policies are introduced. Starting at the 2030 BAU case, the blue graph traces increasing levels of carbon tax, while the red graph indicates the effects of increasing vehicle tax levels. In both cases, one can see that the policies push down the annual emissions (shifting left) while increasing the per-parcel cost (shifting up). In particular, a carbon tax of about 1,000 EUR/tCO₂eq pushes emissions back to a similar level as in the year 2024, and the same effect is obtained by implementing a vehicle tax of 75%. The emission level of 2019 is reached at a carbon tax of about 1,400 EUR/tCO₂eq and a vehicle tax of about 85% when interpolating linearly between the data points.

As a reference, Figure 6 also shows the qualitative policy scenarios as green dots. Implementing the electric LEZ in the city of Lyon yields similar emission levels to the 2024 BAU scenario in the study area. A full electrification of the fleet pushes emissions further below the level of 2019. A vehicle tax of 100% yields

Table 7: Fleet composition results across scenarios

	Small ICV	Small BEV	Medium ICV	Medium BEV	Large ICV	Large BEV
Baseline 2019	131	61	0	4	155	0
Today 2024	177	52	4	1	203	0
Future 2030	220	39	2	1	348	0
Carbon tax (100 EUR)	206	53	1	0	350	0
Carbon tax (200 EUR)	192	65	3	2	349	0
Carbon tax (500 EUR)	164	108	0	3	336	0
Carbon tax (1000 EUR)	113	182	0	9	254	57
Carbon tax (1500 EUR)	80	214	0	11	184	125
Carbon tax (2000 EUR)	60	238	0	9	139	169
ICV tax (20%)	56	217	2	1	335	0
ICV tax (50%)	0	328	0	4	284	0
ICV tax (75%)	0	390	0	4	223	6
ICV tax (100%)	0	489	0	3	44	101
Electric LEZ	104	207	3	4	150	151
100% Electric	0	427	0	13	0	188

about the same emission and cost characteristics as full electrification.

In summary, Figure 6 shows that all policy cases increase the per-parcel costs compared to the 2030 BAU situation. However, the per-parcel cost stays consistently below the estimated levels of 2019 and 2024. Compared to 2024, the cost of delivering a parcel on the last mile is about four cents cheaper, even in the full electrification scenario or with a vehicle tax of 100%. This effect is achieved due to the scaling effects due to increased parcel volumes and higher density.

4.3.1. Fleet analysis

Table 7 provides a more in-depth analysis of the policy effects with respect to the used vehicle fleet.

For the carbon tax policy, we observe that mainly small ICVs are exchanged gradually for their electric counterpart with increasing tax values. This result is congruent with the observation that with the lower investment cost for small vehicles, the per-distance costs have a higher importance in the cost minimization process than for larger vehicles. Only starting at a carbon tax of 1,000 EUR a noticeable effect on large vehicles can be observed. While at lower tax values, some larger vehicles may be exchanged for medium-size ones, only at that value large BEVs become cost-efficient.

The adaptation effects are different for the vehicle tax policy. Already at a tax of 20% the entire fleet of

small ICVs is exchanged against electric vehicles. An adaptation of large BEVs is only observed at a vehicle tax of 100%.

Looking at Figure 6, three very comparable scenarios are the electric LEZ scenario, a carbon tax of 1,000 EUR and a vehicle tax of 75%. While the first case is heavily influenced by the geographic restrictions for ICVs, the two quantitative policy cases show different fleet characteristics at roughly the same emission and cost levels. The vehicle tax strategy yields a complete transition towards BEVs for small vehicles, which also has implications on other factors such as noise in city, while at a carbon tax of 1,000 EUR still about 43% of the small vehicle fleet are ICVs. On the contrary, the carbon tax scenario leads to 18% of the large vehicles being electric, while almost none are transformed at a vehicle tax of 75%.

Comparing the full electric scenario with the 100% vehicle tax, we observe that similar emission and cost levels are reached, but that ICVs remain in the latter case. The emissions caused by large ICVs in that scenario are compensated by a higher number of small BEVs. A similar system configuration can, hence, be reached either by forbidding electric vehicles altogether or imposing a very high vehicle tax, which, however, still allows carriers to use ICVs in specific demand configurations.

Finally, Table 7 indicates that the stereotypical medium-sized vehicle is used very rarely in our study, as it fills only a narrow niche of demand configurations. We can deduct that the operators in our study are either densely distributed throughout the territory (for instance, with their post offices) and prefer smaller vehicles, while others have one or two individual depots that require long driving distances. The ratio between operational and investment costs for medium vehicles seem to fall in between the distance ranges commonly observed in this scenario.

4.3.2. Policy effects

In the following, we investigate the relative effects of the individual 2030 policy scenarios compared to the 2024 and 2019 BAU cases. The relevant numbers are shown in Table 8.

In terms of emissions, the full electrification scenario shows a decrease of about 80% in emissions compared to 2024 and 74% compared to 2019. The emissions of the two quantitative policies only lead to decreased emissions at relatively strong policy settings.

Interesting differences can be observed in terms of energy consumption. The largest decrease in the overall energy used can be observed for the full electrification scenario, with a reduction of 44% compared to 2024. The strongest evaluated scenarios for the vehicle tax (100%) and the carbon tax (2,000 EUR) yields reductions of 37% and 26%, respectively. At the same time, cost reductions are 2.3% and 0.7%, respectively. The vehicle tax strategy, therefore, provides relatively higher reductions in energy with respect to the per-parcel costs. Furthermore, it can be observed that benefits in emission reduction are generally achieved quicker than energy reductions when tracing the policies towards higher intervention levels. Compared to the 2019 scenario, only the full electrification scenario, a vehicle tax of 100%, and a carbon tax of 2,000 EUR are able to lead to a net reduction of energy consumption.

Finally, distance is an important system indicator, because it is directly linked to congestion and the

Table 8: Changes in key indicators compared to reference scenarios [%]

	$\Delta 2024$				$\Delta 2019$			
	Dist.	Energy	Emissions	Cost	Dist.	Energy	Emissions	Cost
Future 2030	26.95	42.77	46.19	-7.43	51.52	84.12	93.15	-12.71
Carbon tax (100 EUR)	27.38	41.70	44.61	-6.92	52.03	82.73	91.06	-12.23
Carbon tax (200 EUR)	27.11	38.95	41.11	-6.32	51.71	79.19	86.44	-11.67
Carbon tax (500 EUR)	28.44	34.31	34.77	-5.09	53.30	73.20	78.05	-10.50
Carbon tax (750 EUR)	31.55	21.74	16.45	-4.00	57.01	56.99	53.85	-9.48
Carbon tax (1000 EUR)	32.43	3.39	-10.50	-2.98	58.05	33.33	18.25	-8.52
Carbon tax (1500 EUR)	32.55	-14.88	-37.47	-1.69	58.21	9.77	-17.39	-7.30
Carbon tax (2000 EUR)	32.79	-26.00	-53.68	-0.76	58.49	-4.57	-38.81	-6.43
ICV tax (20%)	27.69	31.09	30.69	-5.75	52.40	69.06	72.67	-11.13
ICV tax (50%)	34.73	21.09	16.58	-4.03	60.80	56.16	54.03	-9.51
ICV tax (75%)	44.60	7.46	-3.20	-2.95	72.59	38.58	27.90	-8.48
ICV tax (100%)	69.01	-37.02	-70.46	-2.34	101.72	-18.78	-60.97	-7.91
Electric LEZ	35.50	10.36	-1.88	-3.27	61.72	42.32	29.63	-8.78
100% Electric	57.09	-43.69	-80.17	-2.35	87.50	-27.39	-73.81	-7.92

intensity of logistics movements in the city. Table 8 shows that the driven distance in 2030 increases by 27% compared to 2024 and by 52% compared to 2019. For the carbon tax policy, this distance remains relatively stable for increasing policy values, although a slight increase can be observed. In contrast, there is a strongly noticeable effect on the driven distance for the vehicle tax policy. At a level of 100% an increase of 70% compared to 2024 can be observed and even a doubling of distance compared to 2019. The vehicle tax policy, hence, induces additional distance by forcing the operators to perform more and longer round-trips using fewer (expensive) vehicles. A similar pattern can be observed for the full electrification scenario, with a slightly lower increase in distance of 57% compared to 2024.

5. Discussion

In the following, we discuss the results obtained in our simulation study, potential improvements for the modelling components and aspects of reproducibility and transferability of the approach.

5.1. Policy results

The results obtained with our modelling pipeline depend on a multitude of assumptions that have been documented further above. While each of them may impact the final output, we have attempted to thoroughly define and plausibilize them by presenting them to domain experts. Clearly, all assumptions can be improved as data becomes available and more knowledge gets collected on the functioning of last mile deliveries in the urban context. The values provided in Section 4 should, hence, not be considered as solid predictions, but rather as likely outcomes driven by best guess inputs. In that regard, what is rather of interest are the general magnitudes in terms of key performance indicators and policy intensity. Furthermore, the overall model dynamics provide valuable inputs for understanding the system on an abstract level.

In particular, we see that the last-mile parcel delivery system needs relatively high levels of policy intervention in order to observe a substantial effect on the structure of the underlying planning logic. Especially the carbon tax required to recover 2024 or 2019 levels at future states of the system is substantially higher than the 100 EUR/t applied in the European Union Emissions Trading System (EU ETS) with transport emissions only being covered by EU ETS2 starting 2027.

Furthermore, we observe that the same emission effects as a full restriction of ICVs can be achieved by introducing a ICV tax of 100%. While both measures seem politically highly improbable, the latter still allows for a higher degree of freedom on the operator side.

When comparing the two quantitative policies, we observe that the carbon tax strategy generally yields similar emission levels as the vehicle tax at slightly higher costs. The vehicle tax policy is, hence, more cost-effective. Another observation is that the carbon tax strategy gradually drives small vehicles at first, then large electric vehicles out of the market. In contrary, the vehicle tax strategy works abruptly on the smaller vehicles and only at relatively high interventions large vehicles are affected. A side effect of the vehicle tax strategy is that it is more cost-efficient for the operators to switch from larger ICVs to a larger number of

smaller BEVs, which, in turn, leads to a disproportionate increase in driven distance compared to the carbon tax strategy at similar emission reduction levels.

Such an increase of driven distance can be observed for all policy scenarios, mainly driven by the fact that cost differences between small and large electric vehicles are substantially higher than those between their internal combustion counterparts, which favours smaller vehicle sizes. Since the imposed cost structure is based on today’s electric vehicle market, this relation may change in the coming years with potential gains in the efficiency of battery production.

Finally, we observe that the higher demand and density in future scenarios leads to per-unit cost reductions in the delivery system. As a key insight, our model results suggest that the costs incurred by the relevant policies to keep emissions at the level of 2024 or even drive them substantially below 2019 are most likely compensated by the cost reductions due to efficiency gains and scale effects.

5.2. Model components

Several limitations of the current model structure are discussed. These elements may be improved and point towards potential future work.

Currently, only B2C flows are considered and B2B activities are completely left out. However, in reality, operators are very likely to combine both types of customers to optimize their routes and overall expenses. This means that the values presented above generally present a rather abstract perspective on B2C activities. In consequence, the efficiency regarding solely B2C is likely to be lower in reality than presented here. The analysis is, hence, expected to be rather optimistic in terms of distance, emissions, and energy consumption.

Furthermore, only home deliveries have been considered while a certain share of parcels should be delivered to parcel lockers or pickup points. In the future, it would be interesting to also integrate these highly bundled flows into the model. The implementation is rather straight-forward; one could generate the respective parcel demand additionally to the already modelled items and then place their delivery location on the locker or pickup point that is closest to the respective household. Another element of analysis could then be to determine the distance of those households to the lockers to estimate emissions induced by the persons picking up their parcels themselves. Even further, the detailed synthetic population would allow exploring more complex scenarios in which lockers closest to the work or any other daily activity could be chosen. Such a perspective would also allow assessing the overall efficiency and impact of different locker placement strategies.

An important point for future research will be to apply the present methodology to explore collaborative city logistics strategies. In particular, Urban Consolidation Centres (UCCs) are of interest. The goods destined for the operating area of such a UCC would be first delivered to the centre and then delivered locally by an aggregated last-mile service that could furthermore be operated using low-emission modes such as cargo-bikes. Such collaborative scenarios can be implemented relatively small effort in our modelling framework, as the parcels of selected operators with destination in a UCC’s operating area could just be

redirected to that centre in the individual VRPs of the operators. Then, a new operator would be created which represents the delivery of those parcels from the UCC to the final destination.

Our proposed model is based on computing detailed vehicle routes for every operator to deliver every parcel. It could be interesting to compare it with continuous approximation models (Figliozzi, 2009) and further investigate their usefulness in our context.

5.3. Transferability

The whole methodology described above is fully replicable for the case of Lyon. The main feature of the technical implementation is that the whole process is encoded in a data processing pipeline based on Python and Snakemake (Köster and Rahmann, 2012) that runs all modelling steps from the raw data to the final results. Since all data for the Lyon use case is openly available, all results are fully reproducible. The detailed instructions on how to collect or generate the open input data sets, set up the runtime environment, run the models and perform the analyses are provided in the code repository for the present paper⁷.

Based on this initial implementation, further use cases can be set up. The sections above have described alternatives and simplifications for each modelling step that can be followed to apply the method to other study areas. For instance, the approach is currently being applied to a European capital where certain assumptions as outlined above are taken: For the synthetic population, a third-party input is used in which such a data set has been created using other methods than for our use case of Lyon. Furthermore, the overall parcel volumes in the city have been estimated by experts and the depots of the largest operators have been extracted using online map services. The cost structures, as no specific study for the county has been performed, have been copied from the Lyon use case and slightly adapted. These additions can easily be integrated into the step-by-step simulation pipeline.

6. Conclusion

The present paper describes a modelling framework based on open data and software to understand the decision-making process of operators in the last-mile transport sector for B2C deliveries. The central goal of the model is to understand the evolution of the key indicators distance, energy consumption, emissions, and costs until a future state and how specific policies can offset unwanted effects. Specifically, the model is applied to the use case of Lyon and four policies are tested: (1) implementing a carbon tax acting on fuel consumption, (2) implementing a tax for internal combustion vehicles, (3) restricting electric vehicles to the low-emission zone of Lyon, and (4) fully electrifying the logistics fleet.

Since the model is based on various assumptions documented above, the individual values should be considered with care. With an increase of about 48% in parcel volumes until 2030, emissions for last-mile

⁷<https://github.com/sebhoerl/last-mile-parcel-paper>

deliveries are found to increase by 46% and energy consumption by 43% with a decrease of 7% in per-parcel delivery costs. The cost reduction is achieved due to higher delivery density induced by the added demand.

For the policies, we observe that in 2030 emission levels of 2024 can be reached at a ICV tax between 50% and 75% and a carbon tax on fossil fuel between 750 and 1,000 EUR/tCO₂eq. This value is substantially higher than real market values in 2024. In comparison, the vehicle tax provides emission reduction at slightly lower costs than the carbon tax. However, the former strategy has a tendency to disproportionately increase the driven distance in the city due to the use of smaller vehicles.

Restricting access for ICVs in the low-emission zone of Lyon in 2030 leads to emission levels of 2024 in the study area, while a full restriction of ICVs leads to emission reductions of 80% compared to 2024. Such a reduction can also be reached with an ICV tax of about 100% while maintaining flexibility in the choice of vehicles for the operators or a carbon tax of more than 1,5000 EUR/tCO₂eq. While full electrification and 100% ICV tax yield the same costs for the operators, they are noticeably higher for the carbon tax.

A key insight of our study is that the added costs of implementing any of the tested policies are compensated by the cost reductions due to increasing parcel demand and density. This observation suggests that effective policies with the aim to reduce emissions in the last-mile logistics sector can be implemented without losses in profit for the operators, and, dependent on the reduction level, even with profit gains in the longer term.

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Appendix A. Collected long-duration rental and vehicle information

Table A.9 shows the information on long-distance utility vehicle rental contracts in France in the beginning of 2022. Additionally, the vehicle characteristics are documented.

Table A.9: Collected data on long-duration contracts and vehicle types

Source	Brand	Type	Monthly rent	First month rent	Duration	Average monthly rent	Volume	Fuel cons.	Emissions	Elec. cons.	Battery	Range
			[EUR]	[EUR]	[months]	[EUR]	[m ³]	[L/100km]	[gCO ₂ eq/km]	[Wh/km]	[kWh]	[km]
(b)	Renault	Expres Van	139	4,471	60	211	3.3	5.1	134	-	-	-
(b)	Renault	Kangoo Van	159	5,063	60	241	3.3	5.4	143	-	-	-
(a)	Citroen	Jumpy	366	466	48	368	3.7	6.2	162	-	-	-
(b)	Renault	Trafic	189	6,483	60	294	5.8	6.7	176	-	-	-
(b)	Renault	Master Fourgon	209	7,388	60	329	9.0	8.4	221	-	-	-
(a)	Citroen	Jumper	412	512	48	414	11.5	7.8	206	-	-	-
(a)	Citroen	E-Berlingo	301	1,036	48	316	3.3	-	-	187	51.24*	274
(c)	Renault	Kangoo E-Tech	259	499	60	263	4.6	-	-	152	33.00	270
(a)	Peugeot	E-Expert	329	4,510	48	416	5.3	-	-	230	54.74*	238
(c)	Renault	Master E-Tech	629	553	60	628	8.0	-	-	275**	33.00	120
(a)	Peugeot	Boxer	899	4,005	48	964	11.0	-	-	361	42.24*	117

*Not indicated. Derived by multiplying cons. and range.

**Not indicated. Derived by dividing battery capacity by range.

Sources accessed in February 2020:

(a) <https://www.free2move-lease.fr/nos-offres/nos-vehicules-utilitaires>

(b) <https://professionnels.renault.fr/offres-vehicules-utilitaires.html>

(c) <https://professionnels.renault.fr/offres-vehicules-hybrides-pro.html>

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