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Transport Research Arena (TRA) Conference

From synthetic population to parcel demand: A modeling pipeline and case study for last-mile deliveries in Lyon

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Abstract

The paper describes an open and fully replicable pipeline to assess the performance of parcel delivery systems. Starting with publicly available data in France, a range of open source tools is used to create a synthetic population of the region from which its parcel delivery demand is derived. Using JSprit for solving the resulting Vehicle Routing Problem and simulating vehicle movements, a test case for automated delivery robots in the Confluence neighbourhood of Lyon is set up and analysed.

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Keywords: last-mile; parcel; delivery; logistics; synthetic; population

1. Introduction

Policy-makers across the world are increasing their efforts in making cities more livable and ecological. While transformation in passenger traffic is mainly driven by modal shift, the case is generally more complicated in the logistics sector as efforts need to focus on restructuring and consolidation of whole supply chains and the aggregation of freight flows. The potential of transformation in city logistics has been underlined by a range of recent literature reviews on the topic (Patella et al., 2021; Mucowska, 2021). Based on modern technology, focus is put on collaboration in the logistics sector, as well as consolidation of flows and last-mile distribution (Dolati Neghabadi et al., 2019). To assess the impact and the efficacy of such measures, as well as to forecast primary, secondary, and rebound effects, models and simulations are needed which focus on policy, planning and technology impacts (Anand et al., 2015).

A large body of logistics research exists in the area of operations research, and sustainability challenges have become a major topic of attention in past years (Bektaş et al., 2019). Only recently, policy-sensitive simulation tools have emerged that consider the behaviour and decision-making of all stakeholders along and across supply chains,

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such as SimMobility Freight (Sakai et al., 2020) or MASS-GT (de Bok and Tavasszy, 2018). In such simulations, the impact of logistics in the context of large-scale traffic systems is of interest. While models of passenger traffic have seen large advances in the past decades from classic four-step models to advanced agent-based simulation tools, demand generation methods for logistics are just gaining inertia as data slowly becomes available and cities and governments adapt respective open data and data sharing policies

A special case for city logistics are business to customer (B2C) parcel deliveries, as they represent a link between logistics and passenger transport models. Today, the latter often feature detailed information on the local population with sociodemographic attributes of persons and households, as well as information on the daily activity schedules of synthetic persons (Hörl and Balac, 2021). Such information can be used as the source for a synthetic parcel demand, which then can be assessed using classic methods from operations research. In this spirit, the paper at hand describes a pipeline from (1) raw survey data, to (2) a large-scale regional synthetic travel demand, to (3) a synthetic parcel demand, to (4) defining a vehicle routing problem to estimate the performance of last-mile logistics services. The pipeline is exemplified for a use case in Lyon, France. The modeling pipeline and example can be fully replicated as they are based on open software and data.

The specific scenario of interest in this paper is the *Confluence* neighborhood in Lyon, France, which is located at the southern tip of a peninsula between the rivers Rhône and Saône and with the old town of Lyon in the north (see Figure 1). The ongoing development of the area and its geographic properties make *Confluence* an interesting object of modeling. One particular topic of interest is the implementation of an Urban Consolidation Center (UCC) to bundle and control logistics traffic flow. To propose a first use case for the modeling pipeline, the present article provides an example where the local demand in parcel home deliveries is covered by a fleet of automated delivery robots. The proposed pipeline permits assessing different scenarios, which will be compared in future work.

2. Background

Recently, research on parcel is emerging (Ducret, 2014). Operators are increasingly forced to redesign their operating schemes (Bruns et al., 2000). From an operator perspective, the largest interest lies in how to deliver a number of parcels cost-effectively and on time. While classic truck-based distribution services can be described by traditional pick-up and delivery problems from operations research (Savelsbergh and Sol, 1995; Berbeglia et al., 2010), more detailed formulations considering the specificities of low-level last-mile delivery services and multi-echelon systems are being developed. For instance, Dalla Chiara et al. (2020) look at the replacement of truck deliveries in Singapore with a combination of trucks to cover longer distances and locally used cargo bikes. As one of the few examples, the study makes use of real demand data to sample respective operating scenarios. A range of other research publications look instead at the combination of trucks and automated delivery robots. While some (Yu et al., 2020; Boysen et al., 2018; Simoni et al., 2020) formulate problems where trucks are steered optimally to pick up and drop off delivery robots, which perform the last-mile deliveries, Jennings and Figliozzi (2019) take macroscopic perspective by proposing a continuous approximation of the problem. These use cases have in common that they focus on the operational aspect of the system and are based on entirely artificially generated demand data.

To propose problem instances which are closer to reality, and to scale up problems to whole cities and regions, a thread of research focuses on the generation of freight demand. Nuzzolo and Comi (2014); Comi (2020) provide a well-documented system of regression models for demand generation, based on survey data for Rome. In a comparison with data from Spain, however, they point out that local influences play an important role in freight modeling and that quantitative models may not be easily transferable between contexts with different habits and policies (Nuzzolo et al., 2016). Similar models are presented by Gonzalez-Feliu and Sánchez-Díaz (2019) based on French data sets, and Toilier et al. (2018) describe FRETURB, a commonly used freight modeling framework that goes beyond demand generation, but also includes regression models on vehicle type use, dwelling time, and other aspects. Most models that have been mentioned so far are zone-based and strongly rely on disaggregation processes if their outputs are to be used in detailed optimization settings as described above. A novel line of models, similar to the trend in passenger transport modeling, is taking a more disaggregate perspective right from the start. MASS-GT (de Bok et al., 2020a, b), for instance, simulates policy-sensitive decisions of shippers that represented as individual agents, based on behavioral data from a continuous freight transport survey in the Netherlands.

3. Modeling Pipeline

The modeling pipeline presented in this paper follows a chain of distinct steps. First, raw data sets are used to generate synthetic travel demand data, describing the households, persons, and their daily mobility patterns in the study area. Second, marginal information on the generation of parcels based on sociodemographic information is used to generate the demand of parcel deliveries on an average day. Finally, a vehicle routing problem (VRP) is defined based on the demand data and solved.

3.1. Travel demand synthesis

The first step in the modeling pipeline is the generation of a synthetic travel demand data set. A general methodology to do so for France has been presented by Hörl and Balac (2021). The approach is based on open and publicly available data sets. They are passed through a chain of processing steps which generate a list of households and corresponding persons with sociodemographic attributes, as well as detailed activity chains. Those chains explain in digital form when and where each of the synthetic persons performs an activity such as working, shopping, or being at home during an average week day.

For the present case, travel demand for Lyon and the surrounding region Rhône-Alpes is created². It contains around 4.3 million synthetic persons in 1.9 million households performing 18 million activities.

3.2. Parcel demand generation

Based on the synthetic travel demand, the parcel demand of the region is created. To do so, we make use of the survey *Achats découplés de ménages* (ADM, Gardrat, 2019) which has been conducted in Lyon in 2017 and 2018. The survey asked a total of about 2,000 respondents about their consumption behavior with respect to remote purchases. While the detailed survey data is not available for this study, the marginal data provided by Gardrat (2019) can be used. It gives the *annual number of remote purchases* of a reference person, which is described by sociodemographic categories. For instance, the report indicates that a person in the stratum of *retired* persons between *50 to 64 years old* performs an average of 12 out-of-home purchases per year. This average number is given for the following strata:

- C_s per socio-professional category $s \in S$. The set S contains the categories *Without activity*, *Retired*, *Worker*, *Employee*, *Intermediate*, *Leading position*, and *Others*.
- $C_{s,a}$ per socio-professional category $s \in S$ and age class $a \in A = \{18 - 34, 35 - 49, 50 - 64, 65 +\}$.
- $C_{s,h}$ per socio-professional category $s \in S$ and household size $h \in H = \{1, 2, 3, 4 +\}$.
- $C = 14$ as the average number of purchases per year for the whole population

Furthermore, the report gives information on how many of the purchases have been realized as home deliveries (and have not been picked up at a store, for instance). This information is given as a probability $d_s \in [0, 1]$ for each socio-professional category.

The parcel demand generation follows two steps: First, an *average number of purchases per year* is obtained per household, based on the sociodemographic attributes of its reference person. Second, a discrete count of parcels is sampled for each household on a reference day.

3.2.1 Disaggregation of purchases

To disaggregate the demand, for each household of the synthetic population, we sample one reference person that is at least 18 years old. Each of the sampled persons falls in a stratum defined by $(s, a, h) \in S \times A \times H$. Counting the number of reference persons in each stratum constructed by the combination of attributes gives a count $n_{s,a,h} \in \mathbb{N}$. Likewise, counts for larger strata can be derived, such as $n_{s,a} = \sum_{h \in H} n_{s,a,h}$.

² The detailed technical instructions on how to reproduce the data set are given at <https://github.com/eqasim-org/ile-de-france/blob/v1.2.0/docs/cases/lyon.md>

Given this information, it is possible to define $w_{s,a,h}$ as the average number of purchases made per year by a reference person. Multiplying this number by the count $n_{s,a,h}$ and summing over the product to construct the average count of purchases for the stratum should then correspond to the reference value from the survey. In total, there are $|S| \cdot |S \times A| \cdot |S \times H| + 1 = 64$ constraints. Formally, the weights need to fulfill the following conditions:

$$\begin{aligned} \sum_{a \in A} n_{s,a,h} \cdot w_{s,a,h} &= C_{s,h} & \forall s \in S, h \in H & \quad \sum_{h \in H} n_{s,a,h} \cdot w_{s,a,h} &= C_{s,a} & \forall s \in S, a \in A & \quad (1) \\ \sum_{a \in A} \sum_{h \in H} n_{s,a,h} \cdot w_{s,a,h} &= C_s & \forall s \in S & \quad \sum_{a \in A} \sum_{h \in H} \sum_{s \in S} n_{s,a,h} \cdot w_{s,a,h} &= C_s \end{aligned}$$

The system contains 112 weight variables and 64 equations and, hence, does not have a distinct solution. Note that the joint search for weights is affected by zeros in the constraints. For instance, a worker over 65 years, according to the survey, would generate no purchases, but at the same time, a worker in a four-person household generates 29 purchases. Yet, a person may belong to both strata.

The problem has strong similarity to statistical weighting procedures which are used in survey analysis, for which a standard algorithm is Iterative Proportional Fitting (Deming and Stephan, 1940). In this process, each constraint is looked at iteratively, and the weight is adjusted proportionally as $w'_{s,a,h} = f_{s,a,h} \cdot w_{s,a,h}$ for each stratum that is affected by the given constraint. At the end of the procedure, $w_{s,a,h}$ represent the average number of purchases performed by any household to which belongs a reference person with the given sociodemographic attributes.

To arrive at the number of average deliveries per year for each stratum, the number of purchases $w_{s,a,h}$ is multiplied by the probability of home delivery: $h_s \cdot w_{s,a,h}$. Furthermore, we assume that parcels can be delivered on six days of the week, giving 313 potential days, and an average number of parcels per household per day of $\mu_{s,a,h} = d_s \cdot w_{s,a,h} - 313$. Note that these are fractional numbers. They do not describe the *discrete* number of parcels for each household, but rather the average number of parcels μ_i that a particular household i would receive on a usual day.

3.2.2. Discretization of deliveries

To perform a data-based assignment, one would need to know the distribution of how many parcels are delivered to any household per day. Unfortunately, this information is not available. However, defining k_i as the discrete number of parcels for household i on the reference day, its random variable K_i can be attributed a number of characteristics. It is (1) discrete, (2) non-negative, and (3) has the known mean $E[K_i] = \mu_i$. Given these criteria, the maximum entropy distribution of K_i is identified as the Poisson distribution

$$F(K_i \leq k_i) = \text{Poisson}(\mu_i) \quad (2)$$

As the function is invertible, Inverse Transform Sampling can be used to generate values from it. The distribution is then used to sample a discrete number of parcels k_i for each household i . For one realization of the process we arrive, for instance, at 1,788,848 households in the region that receive no parcel, at 32,709 that receive one parcel, at 480 households with two parcels and five households with three parcels.

3.2.3. Delivery slots

An interesting effect of disaggregating the parcel demand using a synthetic population is that we can determine when people are at home to receive them. For those households which receive a parcel, the activity chains of all household members of a minimum age are examined and the period at which they spend an activity at home are noted down. Based on these periods, a set of slots is derived, indicating when packages could be received. Furthermore, we assume that, although people are at home, parcels will not be received before or after a configurable time.

3.3. Vehicle Routing Problem using JSprit

The aim of the third processing step is to solve a Vehicle Routing Problem (VRP) with pickups and drop-offs. While multiple pickups happen at the consolidation center (depot), the drop-offs take place at the receiver (household) locations. For simplicity, a household with, for instance, two parcels is regarded as one delivery of size two. Furthermore, deliveries need to adhere to the available time windows of each household.

The problem can be described as a VRP with Pickup and Delivery and Multiple Time Windows (VRP-PD-MTW), for which analytical formulations exist. In the present case, we make use of the open-source vehicle routing toolkit JSprit³ to solve the problem. It implements the *Ruin and Recreate* meta-heuristic (Schrimpf et al., 2000).

The delivery locations and time slots of the demand generation stage are converted to the VRP input format, and a depot location is defined. In both cases, locations are snapped to a discrete set of nodes in a routing network. The routing network is created by obtaining OpenStreetMap data for the study area and extracting the road network using *osmosis*⁴. The possible pickup and delivery locations are the nodes of the filtered network.

Furthermore, the algorithm outcomes are affected by the following problem parameters: (1) vehicle speed, (2) parcel pick-up time, (3) parcel drop-off time, (4) vehicle capacity, (5) fleet size. In order to let JSprit find the optimal routes, a cost matrix between all nodes need to be provided. This cost matrix is calculated by performing the shortest distance path routing between all nodes, and the obtained distance is used as the cost. Furthermore, a matrix of travel times must be provided, which is obtained by dividing the values of the distance matrix by the defined vehicle speed. The optimization problem is set up using an infinite fleet size, i.e. the number of vehicles is variable and optimized along with the vehicle movements.

Finally, the output of JSprit is a list of pick-ups and deliveries with their respective vehicle identifier and time.

4. Results

The following sections show (1) results on the generated demand, and (2) how it is served by a fleet of automated delivery robots, given a specific scenario of configuration parameters. While only one realization of the synthetic population is used, the remaining steps of the pipeline are executed with 10 random seeds to observe the statistical variation of the model.

4.1. Demand synthesis

The demand generated by the modeling pipeline can be seen in Figure 1. On the left, households which receive at least one parcel in the Rhône-Alpes region are shown as dots. For the whole region, we arrive at around 39,500 parcels and 38,800 households with deliveries. Reducing the extent of the scenario to the Confluence peninsula (Figure 1b) gives about 112 households with 113 parcels that must be delivered per day (Table 1).

Looking at the delivery slots of the population in the Confluence area, Figure 2a shows the percentage of households with at least one person available to receive the deliveries at the given time of day. For the specific use case, the pipeline has been parameterized such that at least one 14 years old person must be at home for a household to receive a package. Also, without having more accurate knowledge on the potential willingness of people to use the proposed service, we assume that deliveries are only accepted after 7:00 am in the morning and before 11:00 pm. The analysis shows that early in the morning and late in the evening about 90% of households can receive parcels, while availability drops to shares as low as 45% during the afternoon.

³ <https://github.com/graphhopper/jsprit>

⁴ <https://wiki.openstreetmap.org/wiki/Osmosis>

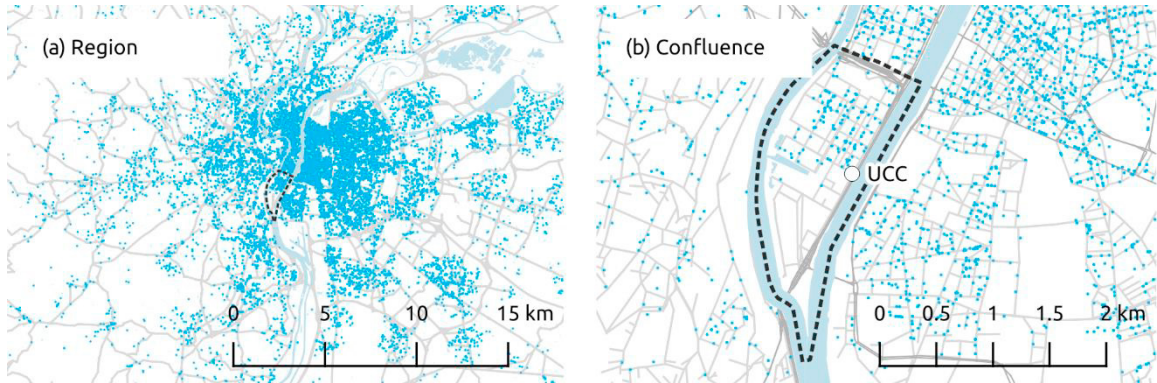


Fig. 1. Parcel demand for the whole region surrounding Lyon (a) and the Confluence peninsula (b). Background network is derived from OpenStreetMap

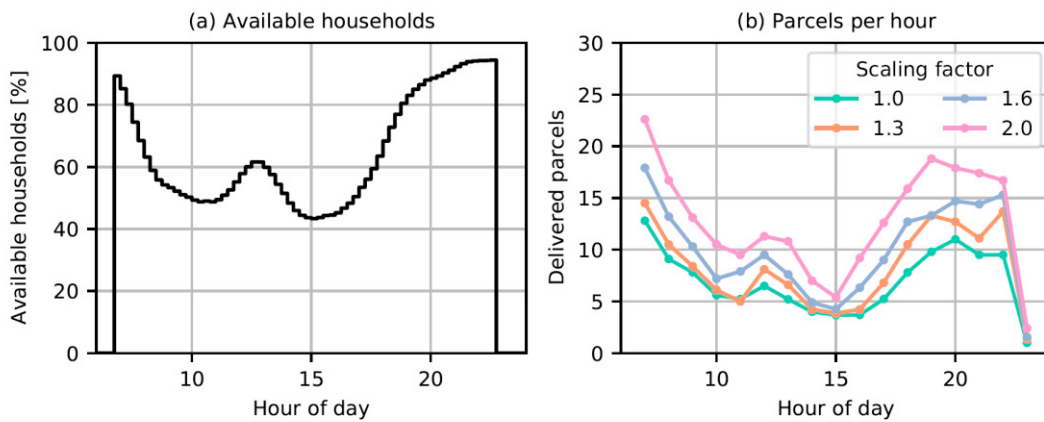


Fig. 2. Temporal analysis of the demand and parcel deliveries

4.2. Delivery simulation

The required fleet to serve the demand based on the available time slots is shown in Table 1. The problems are configured with a vehicle speed of 5 km/h (similar as Simoni et al. (2020)), capacity of 4 parcels, a duration of 60s for pickups at the depot, and 5 min for each delivery. JSprit has been run with a maximum of 2,000 iterations.

Furthermore, the sensitivity of the metrics on the demand is tested by scaling the average number of parcels μ_i by a factor from 1.0 to 2.0.

Table 1 shows that in the base case (without upscaling) on average four vehicles are needed. However, for at least one realization, six vehicles were needed. In total, the robots cover a distance of about 67km per day to deliver all parcels. These values increase with higher demand. With twice the number of parcels and households to serve, also the distance doubles roughly. The fleet size, in the mean, increases by 3.3 vehicles.

Figure 2b shows how parcels are delivered over the course of an average day, where many parcels are delivered in the morning hours. Afterwards, the delivery rate decreases, with another peak during the evening hours.

Table 1. Pipeline results with mean values and range based on 10 realizations

		Scaling factor	1.0	1.3	1.6	2.0
Households	Mean		112.20	138.30	167.90	217.80
	Min.		101.00	121.00	147.00	186.00
	Max.		129.00	158.00	190.00	249.00
Parcels	Mean		113.50	142.30	172.30	225.40
	Min.		101.00	125.00	151.00	190.00
	Max.		129.00	165.00	198.00	259.00
Vehicles	Mean		4.10	5.00	5.40	7.40
	Min.		3.00	3.00	3.00	6.00
	Max.		6.00	6.00	7.00	10.00
Distance [km]	Mean		67.64	82.95	102.42	125.02
	Min.		62.37	74.56	88.25	112.87
	Max.		76.22	96.23	127.54	150.31

5. Discussion

The results obtained above show a fleet size estimate for the Confluence area in Lyon, based on a consistent step-by-step modeling pipeline with clearly defined assumptions. In fact, the major result is that the parcel demand for the peninsula could be covered in combination of a UCC and fleet of automated delivery robots consisting of only 6 vehicles. However, the study does not analyze how parcels are moved to the UCC in the first place.

Hence, the results should be understood as a conceptual test case for the modeling pipeline. A couple of other components, which may be improved in the future, obfuscate the picture:

- Parcels all have the same size. Unfortunately, no information is currently available on the distribution of parcel sizes or weights, which could make the model more realistic. In a first step, basic assumptions could be taken.
- Operator cost is the driven network distance. This is an unrealistic assumption, as cost functions for logistics operators are more complex, including at least a component of fixed costs for the vehicles. This can be improved by performing a detailed literature review on existing parcel delivery robots or other vehicle types and their cost structures.
- Currently, only the road network of *Confluence* has been extracted from OpenStreetMap. However, delivery robots may also run on sidewalks, which may give them an advantage over classic distribution schemes. A more detailed differentiation and definition of the network would be beneficial.

6. Conclusion

To summarize, we have presented a pipeline from raw data sets to the final performance assessment results for a parcel delivery system with automated robots, based on a population and parcel synthesis procedure and a VRP solver.

It is noteworthy that all tools involved, as well as the used data sets, are open. The study at hand, hence, poses a rare example of a completely replicable simulation pipeline in the context of logistics that will be further detailed in future publications.

In terms of practical (though preliminary) results, we find that a fleet of six automated delivery robots could serve the parcel demand in the Confluence neighborhood in Lyon, France, under the assumptions taken and if delivery slots are synchronized with the receiving population.

Future applications of the system will refine the assumptions underlying the model parameters and look at qualitatively different scenarios, including urban growth and development and alternative distribution schemes such as cargo bikes. Furthermore, they will compare the obtained results to a well-defined baseline case.

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