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Agent-based simulation from anonymized data: An application to Lille metropolis

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Abstract

The availability of transportation scenarios from open data introduces new research motivations, such as route pricing and pollution. Unfortunately, these data are often anonymized to protect the privacy of the survey participants. In this paper, we present a generation of a mobility simulation from anonymized data based on a modal choice model. We show how to reconstruct missing information such as the municipalities of residence and activities and the coordinates of the origins/destinations (O/D) of trips necessary for the estimation of the model. This model integrates an inter-modal alternative mixing car and public transport (pt) for commutes through park and ride (PR) facilities. A first application of the simulation model was made on the perimeter of the European Metropolis of Lille (*MEL*) where the activities zones were blurred and the O/D coordinates of trips were withdrawn from the household trip survey. The preliminary results obtained show that the simulation is capable of reproducing the behaviors of trips performed by combining car and pt. Therefore, this work can serve as a basis for testing inter-modality incentive policies (designated by "car + pt") such as intra-urban tools or the creation of PR facilities.

Keywords: Agent-based model; Open-data; Discrete mode choice; Inter-modality; MATSim; MEL

1. Introduction

The availability of transportation scenarios from open data creates new research perspectives. These scenarios can be used afterward to validate and evaluate different algorithms (e.g., routing, CO2 emissions, and evacuations) and new mobility strategies (e.g., bike sharing, inter-modality, and autonomous vehicle). More and more cities, through open data policies, are making several transport databases available to the public such as household travel surveys,

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public transport schedules, traffic count data. Moreover, with the development of agent-based traffic simulation tools such as *MATSim* [1] and *SUMO* [2], it is possible to perform this type of experiment by taking into account the mobility behavior of users [3, 4, 5]. Therefore, several agent-based simulation scenarios were carried out for different cities [6]. One of the first scenarios using *MATSim* was performed by Kickhofer et al. [7] for the city of Santiago, the capital of Chile. Kamel et al. [8] were the first to propose an open-source synthesis tool for the creation of their *MATSim* model for Île-de-France (France). Ziemke et al. [9] developed the *MATSim* open Berlin scenario. Recently, Hörl and Balać [10] developed an open-source synthesizer by detailing the synthesis process for the generation of transport demand for *MATSim* with a case study on Paris and Île-de-France.

The initial motivation for this work was the study of the capability to simulate inter-modal mobility behaviors i.e., the possibility to combine several transportation modes during the same trip. Inter-modality is presented as one of the solutions to the problems (e.g., congestion, pollution, lack of parking) of population mobility. It is at the heart of mobility policies in large cities in order to reduce the use of private cars [11]. We are particularly interested in the combination of the private car with public transport through the park and ride system. To our knowledge, very few simulation works have focused on the definition and evaluation of inter-modality policies on individuals' travel habits.

Several factors (e.g., professional status, gender, age, travel time, cost of the transport, trip purpose, and weather) have been identified as impacting the modal choice and which must be taken into account for the realization of inter-modal transportation systems [12]. Therefore, in order to estimate the discrete mode choice models, it is necessary to use databases that contain this information. While different data sources exist through household travel surveys, they are mostly anonymized and do not directly integrate inter-modality aspects. In order to preserve the privacy of the survey participants, the spatial information about the places of residence and activity (e.g., work, education, and leisure) are often blurred and the coordinates of the origins/destinations are removed from publicly available data.

In this paper, we present a first scenario of inter-modality simulations from anonymized data. We first describe how to reconstruct the missing information, namely the activity zones and the origins/destinations of the trips. Then, we show how to estimate a modal choice model integrating the combination of the private car and public transport and how to integrate it into a simulation tool. Finally, we present a case of application of the model on the perimeter of the *European Metropolis of Lille* (*MEL*) located in the north of France. This model can be used as a study framework to assess current mobility policies but also to test new ones such as the increase in relay parking lots or even the establishment of intra-urban tolls.

The remainder of the paper is organized as follows. In Section 2, we present the open data used in this study and the necessary adjustments to carry out to retrieve the missing information. Section 3 presents the simulation scenario in detail with the demand generation parts, the creation of the multi-modal network, and the estimation of the mode choice model. Afterward, in Section 4, we present the experiments based on *MEL* data by setting up of the simulation with its procedure, first results, and a discussion. Finally, Section 5 concludes and gives different perspectives.

2. Open Data for inter-modal context

In this section, we present the available database on the behavior of individuals in a situation of choice of the transportation mode and how to reconstruct the activities zones (municipalities and coordinates of the origins/destinations (O/D)).

2.1. Available databases

To estimate a modal choice model and build a simulation scenario, it is necessary to have one or more databases to highlight the socio-demographic characteristics of individuals and their mobility behaviors. In France, the main publicly available databases are defined as follows [13]:

- Census data: It contains all the socio-demographic characteristics of individuals (e.g., age and socio-professional category) and the main mode of transport for their commuting (home - work and home - study). Although the sample of this survey is very representative of the population (around 35%), it nevertheless contains very few information on travel habits (e.g., frequency and secondary purposes (e.g., shopping) are not informed). The spatial statistical representation available is at the *Canton-ou-ville* and *IRIS* (at least 200 inhabitants) scale[1].

- Household travel survey (HTS): It provides detailed information on the population's travel habits by informing, for example, on all the daily activities chains (e.g., home, work, education, and shop), the actual transportation mode used, and the possession of transport equipment (e.g. driver's license and public transport ticket or subscription). It also contains some socio-demographic characteristics such as age and socio-professional categories. The main drawbacks of this database are its low sampling rate (between 1 to 2%), the absence of O/D coordinates which are only known at the scale of the *drawing sectors*[2] corresponding to the statistical areas.

In general, it is the HTS that is most often used to estimate modal choice models and generate simulation scenarios. However, it is possible to cross the bases of the census survey with the HTS to obtain a more complete and representative data source (see [10]). In the following, we will only consider the HTS data and we will seek to reconstruct the municipalities and the coordinates of O/D from *drawing sectors*.

2.2. Data reconstruction

To avoid the identification of people indirectly ("identifiable" person), the places (municipalities) of residence and activities are blurred and the coordinates of the O/D of the trips are deleted. We show how to reconstruct this information without betraying the protection of personal data.

2.2.1. Municipalities reconstruction

In general, information relating to the areas of residence and activities are only provided on the level of *drawing sectors* available with survey data. Therefore, to find the municipalities, we superimpose the geographic shapes of the *drawing sectors* with boundary information of the municipalities of the study area. These resulting municipality information are used in the generation of the synthetic population to create the initial demand for transport.

Fig 1 presents an overview of this superimposing of the study case of the *MEL*: the contours of the municipalities[3] are in blue and those of the *drawing sectors* in green. We can see that the center corresponding to the city of Lille (principal municipality) represent several *drawing sectors* while some municipalities (peripheral) belonging to a same statistical area.

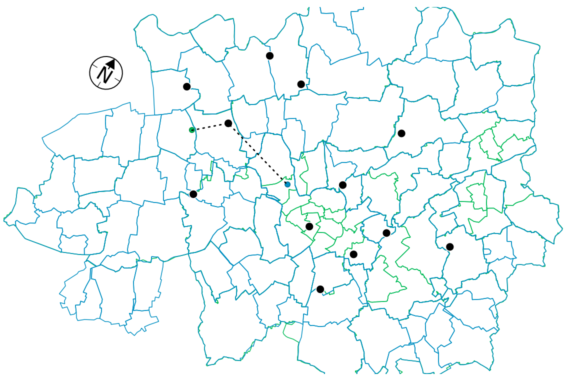


Fig. 1. Contours of the municipalities (in blue) and those of the *drawing sectors* (in green) of the *MEL*

[1] *Canton-ou-ville* is a grouping of one or more entire municipalities. Municipalities with at least 10,000 inhabitants and most municipalities with 5,000 to 10,000 inhabitants are divided into *IRIS*.

[2] The sample of households is drawn at random without replacement and is geographically stratified. The drawing sectors are zones of the study perimeter from which the survey participants are drawn (at least 70 households and 160 persons per zone, the threshold of statistical representativeness: https://www.cnis.fr/wp-content/uploads/2017/12/DPR_2013_2e_reunion_COM_territoires_enquetes_deplacements_certu.pdf).

[3] https://opendata.lillemetropole.fr/explore/dataset/mel_communes/export/?flg=fr&disjunctive.insee&location=13,50.69483,2.61586&basemap=jawg.streets

2.2.2. O/D reconstruction

The main limitation of the survey is the total absence of the origin/destination (O/D) locations of the trips. Only the euclidean distance and the O/D *drawing sectors* for each trip are available. These locations are necessary to estimate discrete mode choice models. The method we used is as follows: 1) we randomly generate points in the O/D *drawing sectors*, 2) we search a point in the origin zone corresponding to a point in the destination area, such that the distance between these two points is as close as possible to the euclidean distance provided in the survey.

3. Simulation Framework

This section presents the simulation framework, the generation of initial demand and road network, the estimation of discrete mode choice, and the construction of car+pt trips.

3.1. Description of eqasim

In this case study, we are interested in individuals' mobility behaviors in particular their modal choice. We used the *eqasim* simulation framework [14] that integrates a discrete mode choice module into the agent-and-activity-based micro-simulation system *MATSim* [1]. Figure 2 describes the general *eqasim* simulation cycle.

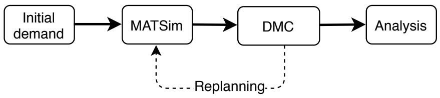


Fig. 2. *eqasim* framework (ref. [14]).

The initial demand is composed of the road network and the daily activities chains (e.g., home - work - shop - home) as well as the relative trips to be performed by each individual (agent). These elements, contained in the agent's plan, will be simulated by the microsimulation tool for a given number of iterations. At the end of each iteration, new travel times and distances are provided to the discrete mode choice (DMC) module where some agents can modify their initial plan by changing the transportation mode based on this information in a re-planning step. Therefore, these agents will seek to optimize their travel time at each iteration until reaching a user equilibrium where no enhancement is possible. It should be noted here that the scoring step in the standard *MATSim* which consists of evaluating executed plans of all agents, is no more used.

3.2. Initial demand and road network generation

The initial transport demand is generally created from a synthetic agent population synthesizer. This population reflects the mobility data, for example from household travel surveys (HTS) and/or census data. To do this, we applied the pipeline initially developed for *Ile-de-France* [10] to generate the transport demand. This synthesizer uses a *statistical matching* between the census and the HTS data to obtain a more completed generic population. The matching process is based on some socio-demographic characteristics (e.g., age, gender, income, and socio-professional category) and the geographic representation (municipality in this case) shared by these two bases.

The multi-modal transportation network is produced from *OpenStreetMap* [4] and *GTFS*[5] data of the study area by using the *pt2matsim* tool [15].

3.3. Modal choice model estimation

Discrete choice models are generally based on the notion of random utility that an individual i has for an alternative (mode) m [16]. Let $U_{i,m}$ and $U_{i,n}$ be the utility perceived by i for m and n respectively, i will choose m instead of n

[4] OpenStreetMap is an open data platform that provides map information of roads, trails, etc.: https:/https://www.openstreetmap.org/about
[5] General Transit Feed Specification (GTFS) is a standard for transit schedules and geographic information: https://gtfs.org/

if and only if $U_{i,m} > U_{i,n}$. However, the utility is a function based on known characteristics (e.g., age and travel time and cost) and unknown (error) to the individual. Therefore, the choice of the individual i is not predicted exactly, but randomly.

In general, the error terms are evaluated either by a *normal distribution* for the *Probit* models (possible correlation between the alternatives) or by a *Gumbell's law* for the *Logit* models (no correlations assumed between alternatives). In this study, we chose a *Multinomial Logit (MNL)* model which is a *Logit* model with more than two alternatives (see Fig. 3).

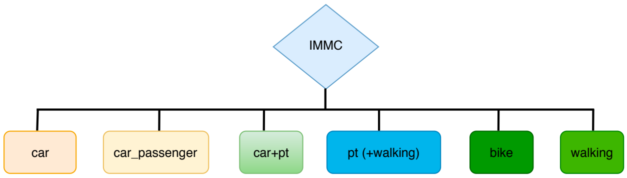


Fig. 3. MNL model of inter-modal mode choice (IMMC)

The utility U for all alternatives are inspired by those proposed in [14] and defined as follows:

$$U_{i,car} = \beta_{ASC,car} + \beta_{inVehicleTime,car} \times x_{inVehicleTime,car} + \beta_{inVehicleTime,car} \times \theta_{parkingSearchPenalty} + \beta_{accessEgressWalkTime} \times \theta_{accessEgressWalkTime} + \beta_{cost} \times x_{cost,car} \tag{1}$$

$$U_{i,pt} = \beta_{ASC,pt} + \beta_{inVehicleTime,pt} \times x_{inVehicleTime,pt} + \beta_{accessEgressTime,pt} \times x_{accessEgressTime,pt} + \beta_{numberTransfers} \times x_{numberTransfers} + \beta_{transferTime,pt} \times x_{transferTime,pt} + \beta_{cost} \times x_{cost,pt} \tag{2}$$

$$U_{i,bicycle} = \beta_{ASC,bicycle} + \beta_{travelTime,bicycle} \times x_{travelTime,bicycle} + \beta_{highAge,bicycle} \times \begin{cases} 1 & if \quad a_{age} \geq 60 \\ 0 & else \end{cases} \tag{3}$$

$$U_{i,walk} = \beta_{ASC,walk} + \beta_{travelTime,walk} \times x_{travelTime,walk} \tag{4}$$

From the utilities for *car* and *pt*, we can also define the utility for the mode *car_pt* as the sum of the utilities of these two alternatives, added by the *ASC*. This utility function is not used in model estimation, but only in the following mobility simulation.

$$U_{i,car\_pt} = \beta_{ASC,car\_pt} + U_{i,car} + \theta_{exchangeTime} \times x_{inVehicleTime,car} + U_{i,pt} - \theta_{parkingSearchPenalty} \times \theta_{inVehicleTime,car} - \beta_{ASC,car} - \beta_{ASC,pt} \tag{5}$$

Where, i: individual, β: parameters of the model to estimate, x: trip attribute, ASC: *Alternative Specific Constants* include terms that we cannot explain using only the explanatory variables, and a: attribute related to the individual, in this case the age. It is assumed here that the use of the bicycle can be painful for certain age groups. Therefore, its utility may be less attractive to this category of individuals.

The costs of using the car are evaluated per km traveled and include the "use" costs, fuel costs and motorway toll costs (if applicable) [13]. The cost of the trip by public transport depends on the possession of a valid transport ticket.

Tab. 1 presents the estimated model parameters from a third of the data from the *MEL* household travel survey. The model was estimated with *PandasBiogeme* [17].

3.4. Construction of car+pt trips

The current version of *MATSim* does not directly take into account trips performed by car+pt. As above-mentioned, the car and pt commutes depend on the PR facilities. Thus, we create a trip performed by car+pt, which is described by: 1) to find the closest PR facility from home, 2) to perform the routing by car between the home and the PR, 3) to perform the routing by pt between the PR and the destination. For the return, we proceed in the same way but this time starting with the trip in pt. An example of a PR trip is presented by the dashed black line in Fig. 1. The 12 PR facilities are represented by the black dots. This trip starts with the green point (home) to the blue one (a shop location is this case) through a PR. This approach always ensures to go through the same PR to perform the car and pt commutes.

Table 1. Estimated model parameters.

	Parameters	Value	Rob. Std err
Car	$\beta_{ASC,car}$	−0.816	0.405
	$\beta_{inVehicleTime,car}$	−0.00146	0.00975
PT	$\beta_{ASC,pt}$	−1.75	0.557
	$\beta_{inVehicleTime,pt}$	0.0035	0.00186
	$\beta_{accessEgressTime,pt}$	−0.0186	0.0409
	$\beta_{numberTransfers}$	−0.207	2.21
	$\beta_{transferTime,pt}$	−0.914	0.403
Bicycle	$\beta_{ASC,bicycle}$	−1.27	0.44
	$\beta_{travelTime,bicycle}$	−0.107	0.0157
	$\beta_{highAge,bicycle}$	0.00905	0.00472

	Parameters	Value	Rob. Std err
Walking	$\beta_{ASC,walk}$	2.16	0.418
	$\beta_{travelTime,walk}$	−0.135	0.00677
Other	β_{cost}	−0.298	0.038
Calibration	$\theta_{parkingSearchPenalty}$	4	–
	$\theta_{accessEgressWalkTime}$	4	–
	$\theta_{exchangeTime}$	5	–
	β_{ASC,car_pt}	2	–
	Number of parameters	14	
	Sample size	5,114	
	Init log likelihood	−8,668.555	
	Final log likelihood	−5,086.149	

4. Experiments based on *MEL* data

This section gives general information of the study area and the first results of simulation.

4.1. *General information of the* MEL

The Lille metropolis is a French metropolitan-type inter-municipal authority located in the center of the *Nord* department. In 2020, the *MEL* is composed of 95 municipalities with 1.2 million inhabitants in an area of 672 km^2.

The *MEL* has undertaken several investments to develop modal transfers to active modes and encourage intermodal travel combining the car and public transport (pt). Today, the public transport network includes two metro lines (43.6 *km*), two tram lines (22 *km*), and around 90 bus lines. The *MEL* has 12 park and ride (PR) lots corresponding to 5,005 parking spaces for connecting with the bus, metro and train and for carpooling. These different transport offers and the resulting investment projects make the *MEL* an interesting case study for the analysis of alternative transport policies at the metropolitan scale.

The *MEL* household travel survey (*EMD*) was carried out in 2016, are been used. The *EMD* (French acronym for *Enquête ménages déplacements*) provides information on the mobility practices of people at the level of a municipality or an agglomeration community at a given time. The survey participants are 5 and above years old and were composed of 9,479 persons belonging to 4,539 households. A version of the data from this survey is available in open access on the open-data website of the *MEL*[6].

4.2. *Simulation procedure*

We present here some details of the simulation procedure such as the size of simulated population, the number of iterations, the share of agents allowed to change the transportation mode, and some road network parameters.

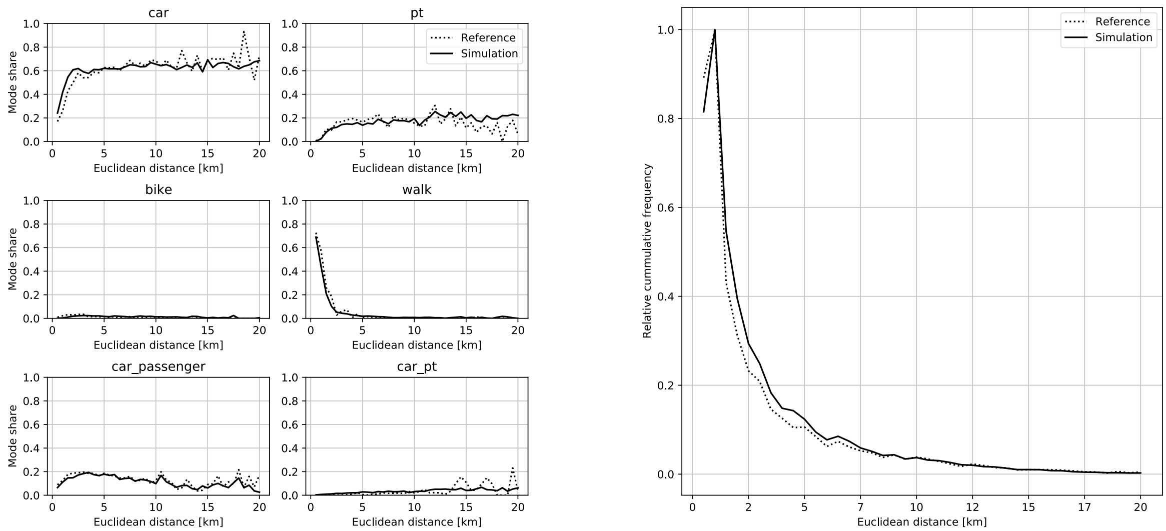
The *MATSim* synthetic population generated in this study represents a 10% sample of the actual population which correspond to 87,057 agents with a total of 370,446 trips. The *EMD* represents 0.8% of the population with 24,629 trips. To take into account this sampling on traffic flow on the actual road network, the flow and storage capacities of all the links in the car network are multiplied by 0.08. The number of iterations is set to 100 and the share of agents allowed for the re-planning, is set to 10%.

4.3. *Results*

Fig. 4a presents a comparison between mode shares as given in the *MEL* survey (Reference in dotted) and the simulated one (Simulation in full line). The modal shares for each mode are presented on the ordinate while the

[6] https://opendata.lillemetropole.fr/explore/dataset/enquete-deplacement-2016/information/?location=10,50.65641,3.03338&basemap=jawg.streets

euclidean distances of the displacements are on the abscissa. This representation allows a better appreciation of the modal distributions. For example, we can see that the share of walking is very important for small distances and tends to zero for larger distances.



(a) Mode shares by distance class from the simulation (full line) and the *MEL* survey (dotted line).

(b) Distribution of trips distance from the simulation (full line) and the *MEL* survey (dotted line).

Fig. 4. Simulation results

The simulation results match very well with the baseline data for all transportation modes with only a third of the HTS data used to estimate the discrete mode choice model. It should be noted here that the modal split does not depend only on the DMC module but also on the travel times by car and pt that change from iteration to iteration and recursively dependent on the mode choice.

The combination of car and pt is well represented after the necessary manual calibration of β_{ASC,car_pt} to 1.25. This calibration was necessary as the combined mode is not used frequently enough in the survey to obtain robust results when estimating the discrete choice model. However, there are some deviations for the long distances (more than 12 km) trips performed by car, pt, and car+pt. This is mainly due to the lack of reference data on these types of trips which are mostly occasional. Fig. 4b gives an overview of the distribution of trips distance from the simulation and the *MEL* survey. We can see here that the generated trips for the synthetic population match very well with the *EMD* data. Moreover, the most important part of trips has less than 12 km of distance.

4.4. Limitations

The main points of discussion on our method of creation a scenario from anonymized open data are: the reconstruction of O/D and the resulting discrete mode choice model. The precision of the O/D coordinates reconstruction algorithm relies both on the size of the area and on the number of points to be generated randomly. The smaller the size of the area, the better the quality of the reconstructed points. In addition, the greater the number of random points, the more chance we have of finding O/D points whose distance is closer to the reference distance. However, this generates a very large amount of computation time. For example, to reconstruct the O/D coordinates of the 24, 630 trips in the survey with 500 random points, the algorithm takes 15 hours on a machine *i*7 with 16 GB of RAM.

Regarding the discrete choice model, the utility function of the *car_pt* alternative is essentially based on those of the car and the pt. However, trips combining the car and pt are heavily dependent on the park and ride facilities. Therefore, it may be interesting to take into account the attributes relating to the park relay such as price (subscription), accessibility, and transfer time. Unfortunately, to our knowledge, there is no database to have this information. Moreover, it may be interesting to build a nested *MNL* as proposed in [18] to take into account the dependencies between the car and the pt in the combination of the two modes. If the estimation of such a model is straightforward, its integration in *MATSim* can be more complicated.

5. Conclusion

In this paper, we presented a creation of a reproducible agent-based scenario of the *MEL* from open data. These data being anonymized, we proposed a method to reconstruct the blurred information, namely the municipalities of activities and O/D coordinates. From there, we developed a discrete mode choice model that takes into account the private car and public transit combination which has been integrated into the micro-simulation platform *MATSim*. The simulation results relating to modal shares match well to the reference data of *MEL* household travel survey.

As future works, we plan to investigate the impact of urban tolls and the optimization of relay parking locations on modal shares. The aim is to make the combination of private cars and public transport more attractive.

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