Markov based mesoscopic simulation tool for urban freight: SIMTURB

Mathieu Gardrat, Pascal Pluvinet

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Keywords: Urban freight transport, Model, SIMTURB, Multi-agent simulation, Markov process

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Mathieu GARDRAT

Univ Lyon, CNRS, LAET, F-69007, LYON, France

Pascal PLUVINET

Univ Lyon, CNRS, LAET, F-69007, LYON, France

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Laboratoire Aménagement Économie Transports
MSH Lyon St-Etienne
14, Avenue Berthelot
F-69363 Lyon Cedex 07 France

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Abstract

The objective of this paper is to present a mesoscopic simulation model of urban freight transport called SIMTURB. This model is based on the results and is an extension of the FRETURB urban freight model [1]. With an architecture based on a Markov process, this model offers a complement and to some extent an alternative to multi-agent simulation models, since it makes possible to characterise precisely the routes of freight transport vehicles in a conurbation and characterise the movements of each agent (e.g. vehicle).

1. Introduction

Urban freight transport modelling has known for more than 20 years radical evolutions and contributions, from statistical models to optimisation techniques, from very basic spreadsheets to very complex multi-agent models. Today, although the vast lack of knowledge has been partially filled, the need for decision support tools is stronger than ever, given the growing complexity of city logistics and needs for relevant indicators. We present in this paper the contribution of Markov processes in this endeavour with a presentation of the SIMTURB model and its results.

The basis of the modelling process of SIMTURB is the disaggregation of a freight distribution matrix into routes via Markov chains [2], [3]. In this case, the Markov process is used to build routes based on O-D matrices. Thus, routes are Markov chains of varying lengths for which transition matrices are in fact flow distribution matrices. To keep organisational consistency, the goods distribution matrix is subdivided into functionally homogeneous subsets that take into account the vehicle type (3 classes), the management mode (3 classes) and the length of the routes (7 classes). Coupled with geolocalised establishments and a road network, this approach makes it possible to spatially and temporally characterise the vehicle routes, without requiring complex multi-agent approach.

In the first section we present a literature review on urban freight transport modelling and Markov chains. The second section presents the methodology of the SIMTURB model. Section 3 will be dedicated to the confrontation of SIMTURB and results produced by the FRETURB freight generation model. The last section is dedicated to the conclusion and discussion.

2. Literature review

Urban freight modelling, compared to passenger traffic modelling, is often considered as more a complex and less mature topic in transportation sciences [4]. Although the first models designed for urban freight were based on four-step models, their efficiency was quickly questioned [1]. More recent researches have therefore led to alternative methods to the classical four-step models. Most urban freight models now integrate the notion of trips as an output to summarise the intricate structure of urban freight flows [5]. This estimation of trips generated

[1] Corresponding author, LAET (Transport Urban Planning Economics Laboratory)Tel.: +33 4 72 04 82 65 *E-mail address:* mathieu.gardrat@entpe.fr

in a city and their distribution can be done using various methods. These methods are usually based on:

- commodity flows converted into delivery generation, which allows building trip sequences [6]–[11].
- traffic counts, used to deduce vehicle flows or to calibrate the distribution of commodity or trip-based models. These models do not necessarily include freight trip generation but rather a structure for freight trip distribution [12], [13]. This method implies that the characterisation of trips is limited to O-D couples and types of vehicles, but it fails to bring to light data on types of goods or organisational patterns [14].
- establishment surveys in order to include trip generation as a primary step for the estimation of vehicle flows [15]–[19].

Although trips are relevant to quantify the impact of freight flows in cities and provide numerous characteristics on their organisations, this perspective is not suited for all types of urban freight assessments. Indeed, many analyses require specific indicators such as the volume of vehicles or routes (which are indeed related to the number of trips but need further processing to convert trips or commodity flows into vehicles or routes).

To cope with these new needs, multi-agent models in recent years have known a strong development, specifically due to increasing computational capacities [20]. These models are however extremely complex to run and require heavy consumptions of computational resources, furthermore these calculations are often made on a sample of the total amount of the existing agents in a real situation: in order to produce relevant results, multi agent models use a statistically significant sample of agents to represent the reality [21], [22]. Effectively, what is considered as a relevant sample or what categories of actors are modelled, is usually built on strong hypotheses and archetypal behaviours. Some agent approaches usually work for aggregated freight demand and do not specify logistics organisations such as routes and are usually limited to some portions of urban activities, typically retailers and transport operators [23], [24].

It is also important to note that multi-agent models do not necessarily estimate freight flows and routes, but are used for general policy interactions. Although very useful for stakeholders' interactions, this relative simplification of reality fails to take into account the vastness of logistics organisations and extreme but existing transport behaviours [25]–[27], even if some are based on various types of surveys [28].

If we focus on models simulating transportation behaviours, the main question faced is to build realistic routes. In these models, tours are built either using:

- iterative methods based on incremental trip chain or shipment combination [9], [29], [30]. This methods appear relevant but are quite complex to calibrate and implement, using heavy computational resources.
- clustering methods which are less resource consuming but tend to over-optimise routes since they tend to concentrate deliveries based on spatial proximity rather than functional characteristics [31].

Given this state of research, we noticed that very few models use Markov chains in transportation research [32], [33], specifically in logistics, although such choice models offer relevant solutions. In fact, most of the studies using these methods are usually applied in the fields of (including, but not limited to) applied mathematics, biology and physics [34]–[36]. In this context, Markov chain modelling offers an interesting alternative to agent based modelling allowing efficient data processing for rich data sets production, as it will be explained in this paper

3. Methodology

The SIMUTRB model mixes various data sources such as pre-existing models and surveys and relies on several submodules to produce disaggregated results, which are detailed in Figure 1.

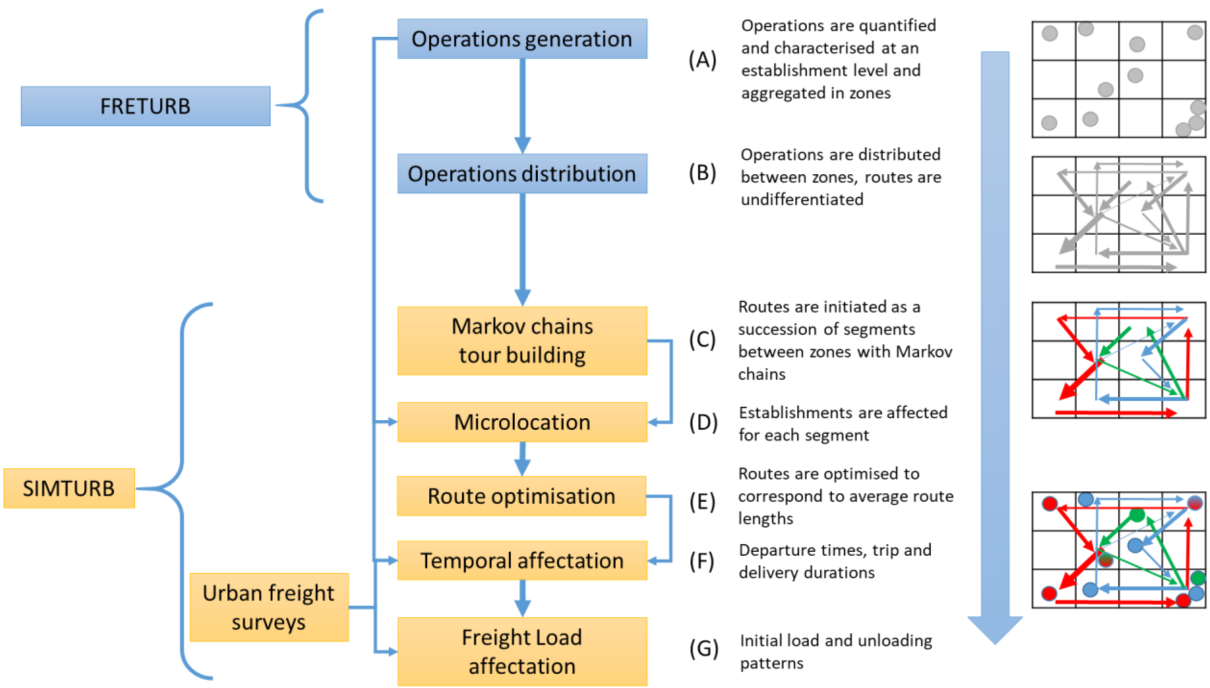

Figure 1 : SIMTURB modelling framework

The next subsections will describe the successive steps of the model, starting with the input data, which are generated by the FRETURB model but also specific surveys on urban freight transport. We then detail how the Markov process is carried out and detail the various functions that allow characterisation of the delivery tours.

Generating operations and OD matrices

The main data input of the model are O-D matrices used to initiate Markov processes. In order to produce these matrices, a generation of movements (step A) has to be processed beforehand. This specific step and further elements on FRETURB and the generation algorithm of the model are detailed in the appropriate references [1], [17].

In this model, the number of operations m_e of firm e is linked to a categorisation of the firms according to C non-empty subsets:

$E = \{E_1, E_2, \ldots E_c, \ldots E_C\}$ such that:

$$e \in E_c \Rightarrow M_e = \varphi(a_c, w_c, p_c) \quad \textbf{[1]}$$

where a is the category of activity of the firm; w designates a class of workforce (based on the number of jobs in the firm e); p is an index that distinguishes different functions of the premises served (4 functions are distinguished: shops, warehouses, offices, head office).

Where a_c, w_c and p_c are particular values of three variables for a firm of category *c*. As mentioned in the above references, the number of operations generated by zone *z* and by logistic category *l* is written as

$$G = M.L = g_{z,c,l} \quad \textbf{[2]}$$

With M a matrix indicating a number of operations by zone z and establishment category *c* and *L* a matrix of logistics structure defining the proportion of operations of logistics category *l*, in each establishment of category *c*. The logistics category *l* is characterised by:

- the type of vehicle used (utility vehicles less than 3.5 tons, rigid trucks, semi-trailers);
- the management mode (own account or third party);
- organisation by "single leg delivery" (or "line haul") with a one stop trip (Figure 2), or by round with several trips. For the rounds, two types of operations are distinguished :
    - Main trips are the first and last trips of a tour
    - Connectors are the trips that link the establishments served by the tour to each other and between the two main trips.

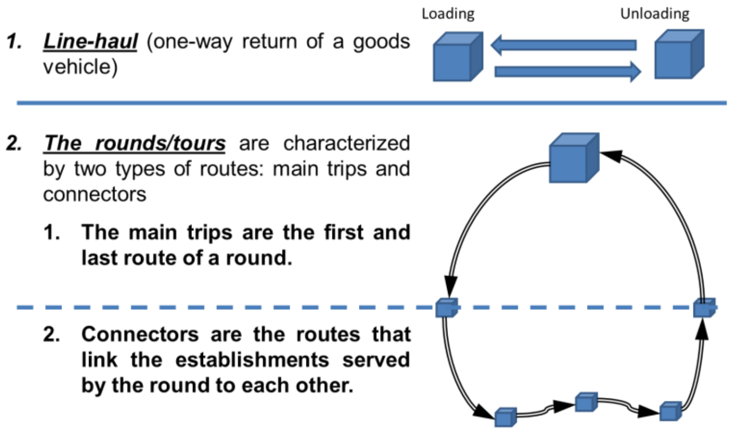

Figure 2 : modes of organisations and types of routes taken into account in SIMTURB

From these volumes of operations characterised by a category *l*, the distribution step carries on thanks to a distance matrix calculated between each pair of zones. It is therefore possible to determine the zones likely to be linked by freight trips. Based on the number of operations of the logistic category *l*, obtained for each vehicle class *v*, management mode *m* and classes of tour lengths *c* in zone *z*, the distribution follows (step B) an attribution process based on:

- The distances of line haul trips and first/last leg of a tour estimated by $\partial^{*}_{z,l}$
- The distance between two connectors estimated by $\partial^{**}_{z,l}$

Indeed, in order to be paired, and for each logistics category *l*, these zones have to be distant from $\partial^{*}_{z,l}$ (when the trip is the first/last leg of a tour or is a line haul) or $\partial^{**}_{z,l}$ (when the trip is a connector). The pairing procedure is designed to take into account the capacity of each zone to generate operations of a category *l*. For example, the function $\partial^{**}_{z,l}$ indicates that an operation generated by a zone z_i and operated by a third party carrier in a LGV during a *n*-stop tour (defining the category *l*) will induce a given distance between two connectors. The target zones z_j are then selected when they are at a distance $\partial^{**}_{z,l}$ and generate an operation of the same category *l*. If there are no operations of category *l* in this zone z_j, the selection is extended to the neighbouring zones corresponding to a two sided confidence interval. The procedure is repeated for all the zones and all *l* categories of operations, until all operations are paired. z_i and z_j can be the same zone in the case of internal flows. The coherence is insured because the trips between a zone z_i and a zone z_j keep the same logistics characteristics (vehicle, management mode, organisation –single leg delivery or tour- and, when appropriate, size of the tour). According to a 25 class categorisation, the beginning of each *l* type trip which touches the zone z_j matches the movement of *l* type trips generated in z_i. The final O-D matrix T_{ij} is the sum of the O-D $l_{ij}(v, m, l)$ obtained for each vehicle class *v*, management mode *m* and classes of tour lengths c:

$$\boldsymbol{T_{ij}} = \sum_{(v,m,l)} \left[\boldsymbol{l_{ij}}(\boldsymbol{v}, \boldsymbol{m}, \boldsymbol{c}) \right] \quad [3]$$

This method is convergent as it is based on the consistency between the location of activities, types of operations, distances between two consecutive operations and provides us with the distribution matrix *T* which is used to process Markov chains.

Implementation of the Markov process

The core of the SIMTURB methodology is the implementation of a Markov process (step C). We use a discrete-time Markov chain with a finite number of states to simulate freight delivery tour chains. Markov chains respect the Markov property for which the future state of a process only depends on the present state of the same process. The chain describes a set of states noted S with $(X_n)_{n \in N}$ a sequence of random variables.

In this context, Markov property is therefore noted:

$$\mathbb{P}(\boldsymbol{X_{n+1}} = \boldsymbol{x_{n+1}} \mid \boldsymbol{X_{0:n}} = \boldsymbol{x_{0:n}}) = \mathbb{P}(\boldsymbol{X_{n+1}} = \boldsymbol{x_{n+1}} \mid \boldsymbol{X_n} = \boldsymbol{x_n}) \quad [4]$$

A Markov chain needs the construction of a transition matrix, for which transition probabilities are noted p(*x*,*y*) the matrix being formalised as follows:

$$\boldsymbol{P} = (\boldsymbol{p}(\boldsymbol{x}, \boldsymbol{y}))_{x,y \in S} \quad [5]$$

With

$$\boldsymbol{p}(\boldsymbol{x}, \boldsymbol{y}) \geq \boldsymbol{0} \quad [6]$$

$$\sum_{y} \boldsymbol{p}(\boldsymbol{x}, \boldsymbol{y}) = \boldsymbol{1} \quad [7]$$

This transition matrix is therefore a probability matrix with each row summing to 1 and being a measure of the probability S. In the case of SIMTURB, transition matrices are subsets of flows distributions matrices giving the number of operations going from zone i to zone j. Since we use a finite discrete time Markov chain to model sequences of delivery tours, it is necessary to know the actual length of tours depending on the type of tour. In our case a finite Markov chain is an efficient method to know all the states of the chain since each state is a zone delivered. We therefore have to assign to each route a number of stops, corresponding in the Markov process to a chain length corresponding to the number of states on which we want information. This chain length *cl* attribution is carried out using probabilistic choice based on the type of vehicle *v* and management mode *m*.

$$\boldsymbol{cl} = \mathbb{P}(\boldsymbol{v}, \boldsymbol{m}) \quad [8]$$

With

$$\sum_{v,m} \boldsymbol{p}(\boldsymbol{v}, \boldsymbol{m}) = \boldsymbol{1} \quad [9]$$

And

$$\sum \boldsymbol{cl} = \boldsymbol{T_{ij}} \quad [10]$$

Once each route is affected with a tour length, the Markov process is carried out to build the tour to determine which zones are served. In order to keep the coherence in terms of transport behaviour, 63 transition matrices are built as subsets of the matrix T taking into account 3 main parameters:

- 3 types vehicles (vans, rigid trucks, semi-trailers)
- 3 modes of management (own account as a shipper, own account as a consignee or third party)
- 7 classes of tour lengths ranging from line haul routes, with a one stop trip, or by tour with a minimum 3 operations and more

This gives for each combination a transition matrix *P*, in which probabilities is a ratio of the number of operations for each O-D on the total of operations of a *v,m,c* subset *v* being the type of vehicle, *m* the management mode and *c* the class of length of the tour.

$$\boldsymbol{P} = \begin{bmatrix} \frac{l_{11}(v,m,c)}{\sum[l_{ij}(v,m,c)]} & \cdots & \frac{l_{1j}(v,m,c)}{\sum[l_{ij}(v,m,c)]} \\ \vdots & \ddots & \vdots \\ \frac{l_{i1}(v,m,c)}{\sum[l_{ij}(v,m,c)]} & \cdots & \frac{l_{ij}(v,m,c)}{\sum[l_{ij}(v,m,c)]} \end{bmatrix} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,n} \\ \vdots & \ddots & \vdots \\ p_{n,1} & \cdots & p_{n,n} \end{bmatrix} \qquad \textbf{[11]}$$

In order to balance the distribution of flows, each time a Markov chain is processed, the corresponding transition matrix is updated by subtracting the number of operations of the tour for each corresponding O-D generated in the Markov chain.

Geographical affectation – establishments

Once the zones visited by each tour are defined, the tours have to be more specifically defined with the points visited and their characteristics (e.g. the establishments). This phase (step D) corresponds to an affectation of establishments for each point of the routes simulated through the Markov chains following a two-stage sampling method. The first stage uses as primary sampling unit the establishment category *e* for each zone *z* and type of operation *l* in which the probability *pe* of being chosen is equivalent to:

$$\boldsymbol{pe} = \frac{M_{z,l,e}}{\sum_{z,l} M_{z,l,e}} \qquad \textbf{[12]}$$

Finally establishments are chosen within the strata defined in **[1]** for each operation of tours depending on their category *e* and the number of operations of logistics category *l*. This specific process implemented without replacement guarantees having not the same establishment served twice in the same tour.

Each tour is therefore characterised by a set of successive points having geographical coordinates (longitude, latitude) permitting the estimation of distances thanks to Dijkstra algorithm implemented on the road network.

Following these steps, a Vehicle Routing Problem (step E) algorithm is then used to correct potential aberrations in terms of total distances travelled for the tours. This algorithm is used not to fully optimise the tours in terms of distances, but to render a faithful average distance for each tour in each category of route *v,m,c*. These average distances are derived from data produced from the French urban freight surveys [17], [37], [38].

Freight load affectation

Each of the delivery tour type compiles data about the initial weight loaded and their unloading profile depending on the type of activity delivered (step G). The weight loaded is a function of the number of delivery points in a tour and the type of vehicle. These elements are determined thanks to the French urban freight surveys describing 2200 routes of vehicles and 14000 stops [37].

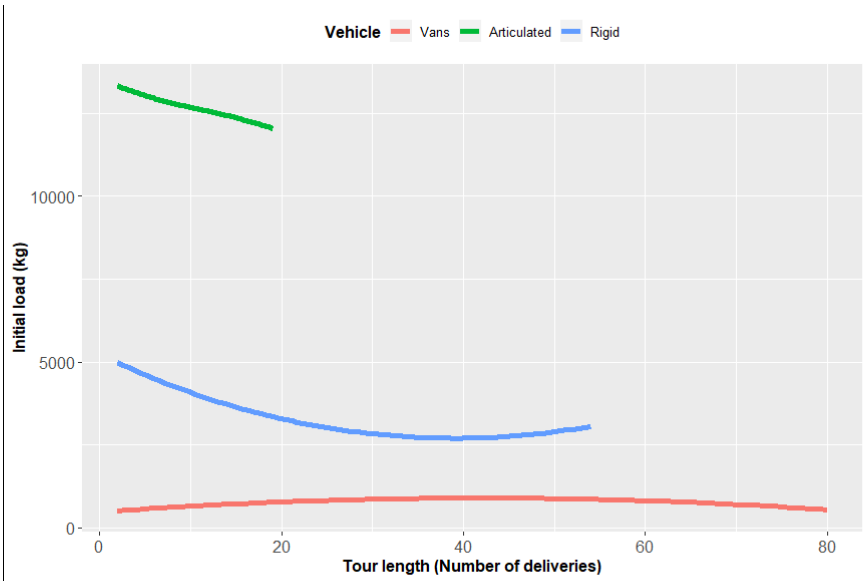

Figure 3 : Initial weight loaded (goods – in kg) according to the number of deliveries in a tour and type of vehicle

During the delivery tour definition, three types of shape for the unloading pattern are applied (Figure 4):

- the "regular" pattern that is defined by a regular unloaded weight all along the delivery tour, which equals to 50% of weight unloaded at mid-route,
- the "hollowed" pattern is characterised by an unloaded weight superior to 50% of the initial weight at mid-route,
- the "rounded" (or bulging) pattern is characterised by an unloaded weight inferior to 50% of the initial weight at mid-route.

These trends were determined thanks to the French surveys on urban goods movements [37], [38]. In order to render these unloading pattern of vehicles, arithmetic functions were formalised using the main characteristics of the routes, such as the number of stops and the initial weight loaded.

The regular unloading function, corresponding to an affine function:

$$\boldsymbol{L}(\boldsymbol{x}) = -\frac{\boldsymbol{I}}{\boldsymbol{n}}\boldsymbol{x} + \boldsymbol{I} \qquad [13]$$

The hollowed unloading curve can be modeled by using the following function:

$$\boldsymbol{H}(\boldsymbol{x}) = \frac{\mathbf{1}}{\boldsymbol{\rho}+\boldsymbol{\alpha}\boldsymbol{x}} + \frac{\boldsymbol{\beta}}{\boldsymbol{n}}\boldsymbol{x} \qquad [14]$$

The rounded unloading curve can be represented by the following function:

$$\boldsymbol{R}(\boldsymbol{x}) = \frac{\mathbf{1}}{\alpha(\boldsymbol{x}-\boldsymbol{n})-\boldsymbol{\rho}} + \left(\boldsymbol{I} + \frac{\mathbf{1}}{\alpha.\boldsymbol{n}+\boldsymbol{\rho}}\right) + \frac{\boldsymbol{\beta}}{\boldsymbol{n}}\boldsymbol{x} \qquad [15]$$

The components being, α a coefficient determining the slope of the curve with 0<α<1 the nearer from 0 the more the curve takes a linear shape; *I* the initial weight loaded in the vehicle; *x* the variable (referring to the stop number); *n* the total number of stops and

$$\boldsymbol{\rho} = \frac{\mathbf{1}}{\boldsymbol{I}} \qquad \textbf{[16]}$$

and

$$\boldsymbol{\beta} = -\frac{\mathbf{1}}{\boldsymbol{\alpha}.\mathbf{n}+\boldsymbol{\rho}} \qquad \textbf{[17]}$$

In order to model loading/unloading patterns, this method needs the initial weight loaded and the number of stops.

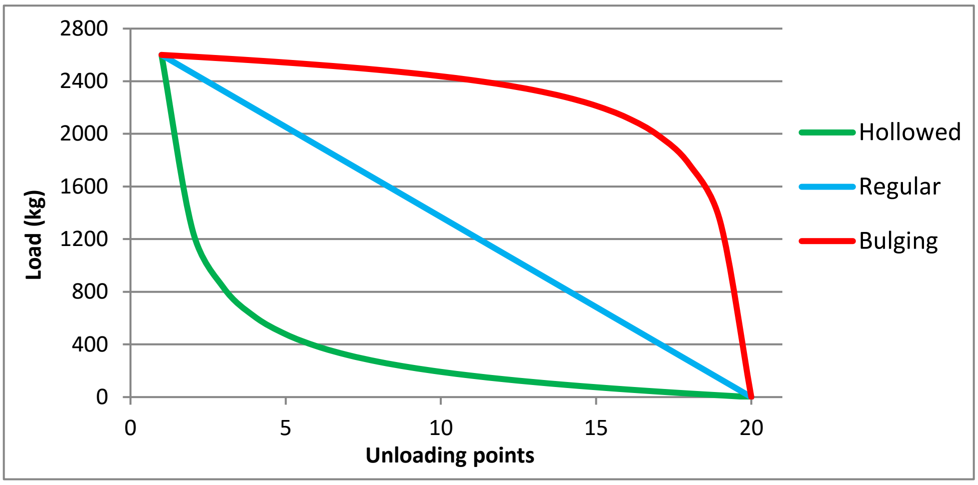

Figure 4: Unloading patterns (example for 20 stops)

Thanks to this modelling process, it is possible to characterise a large variety of dimensions of urban freight routes, encompassing all types of vehicles, modes of organisation, modes of management, types of establishments… with a high level of spatial and temporal resolution (Figure 5, Table 1). We can consider that the level of precision of the model is mesoscopic (and not microscopic) since it is not simulated in real time with other agents and does not take into account behaviours at a vehicle level (such as gear changes, road trajectory, etc.).

The data produced in the model however offer the possibilities to work on a large variety of scenarios concerning public policies (Low Emissions Zones, Off-Hour Deliveries…) or organisational changes (Urban Consolidation Centers, fleet modifications…). It can also be used to calibrate large simulations for multi-agent models thanks to its high level of precision and vehicle based observation unit offering interoperable data input.

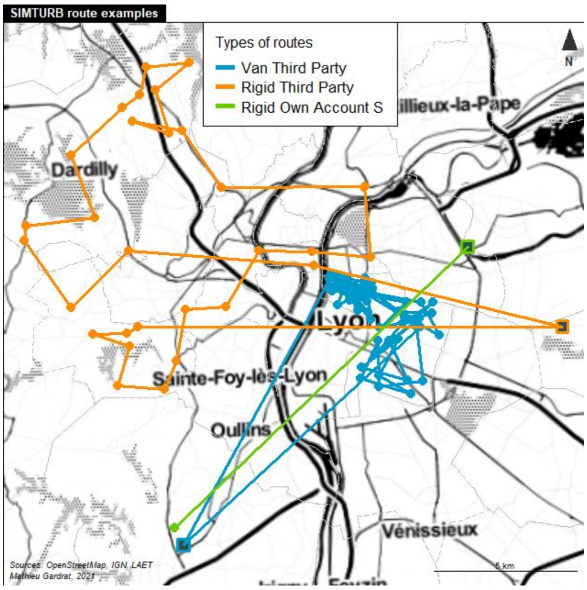

Figure 5 : examples of routes from SIMTURB simulation results in Lyon's urban area

Vehicle	Management mode	Nb points	Length (km)	Total traffic time (h)	Total stopping time (h)	Total load (kg)	Distance between 2 stops (km)	Mean stop time (min)	Total tour duration (h)
Van	Third party	57	124.9	06:05	03:42	779.1	2.2	00:03:54	09:48
Rigid	Third party	31	106.2	04:48	03:32	2088.0	3.4	00:06:51	08:20
Rigid	Own account shipper	2	36.6	01:14	01:00	5476.0	18.3	00:30:00	02:14

Table 1 : examples of routes from SIMTURB simulation results in Lyon's urban area

4. Confrontation to the FRETURB model

In this section, we discuss the use of Markov process to reconstitute urban freight movements and compare it to the data produced by FRETURB and data observed in the French Urban Freight Surveys. We will examine the organisational and spatial dimensions of the routes produced and verify their coherence to these data, which correspond to the state of the art. Simulations carried out to make these comparisons were made on Lyon's urban area (France) for the year 2018.

Organisational structure

As a first indicator of coherence, we compare the characteristics of the movements simulated. The global number of movements distributed by SIMTURB, is relevant with the distribution operated by FRETURB. The number of movements in SIMTURB equals 98% of the initial FRETURB situation. However, if this first global figure is satisfying, the detail and structure shows some deviations. We indeed find some discrepancies specifically concerning the types of vehicles estimated.

First we can observe a strong convergence of SIMTURB for management modes (Table 2), reproducing the practices observed in the various urban freight surveys carried out in France [38]. However, we find an overestimation of articulated trucks in opposition to rigid trucks (Table 3). This deviation is due to variation in the affectation of tour lengths for each type of vehicle. Fortunately these errors compensate themselves in the overall results, moreover these deviations are relatively weakly significant. The SIMTURB simulations are however much closer to the FRETURB results concerning modes of organisations (e.g. types of trips), since the attribution of trip length is entirely dependent of the 7 classes of tour lengths used in the model and guarantee limited deviations.

Management mode	*Freturb flows*	*Simturb flows*	*Difference*	*Deviation (%)*
Third party	114990	114647	-343	-0.3%
Own account	105734	105599	-135	-0.1%

Table 2: Freturb – Simturb comparison for management mode structure

Vehicles	*Freturb flows*	*Simturb flows*	*Difference*	*Deviation (%)*
Vans	146816	146153	-663	-0.5%
Articulated	29045	30906	1861	6.4%
Rigid trucks	44864	43187	-1677	-3.7%

Table 3: Freturb – Simturb comparison for vehicle structure

Type of operation	*Freturb flows*	*Simturb flows*	*Difference*	*Deviation (%)*
Connectors	117710	117536	-174	-0.1%
Main trips	23222	23240	18	0.1%
Line Haul	79793	79470	-323	-0.4%

Table 4: Freturb – Simturb comparison for trip type structure

This organisational structure has to be put into perspective with the distances generated by the model, which is a complementary indicator of coherence for the model. If we compare the results of the model to the data observed in freight surveys and generated through FRETURB, we observe globally similar trends.

Spatial structure

The previous sub-section showed strong organisational convergence between FRETURB and SIMTURB. We however noted hints of deviation concerning the spatial structure of flows specifically concerning the types of vehicles involved, which in turn have an influence on how the flows are distributed on a territory. We therefore start with an analysis of the distances generated by the model.

We observe that SIMTURB generates longer routes in some cases, specifically for vans and tours with a high number of points to deliver. This deviation is due to slightly longer inter-stop distances than usually observed which consequently has an influence on the total length of the route (Figure 7, Figure 6). These trends are identical for management modes and types of vehicles (although they tend to concentrate most on vans).

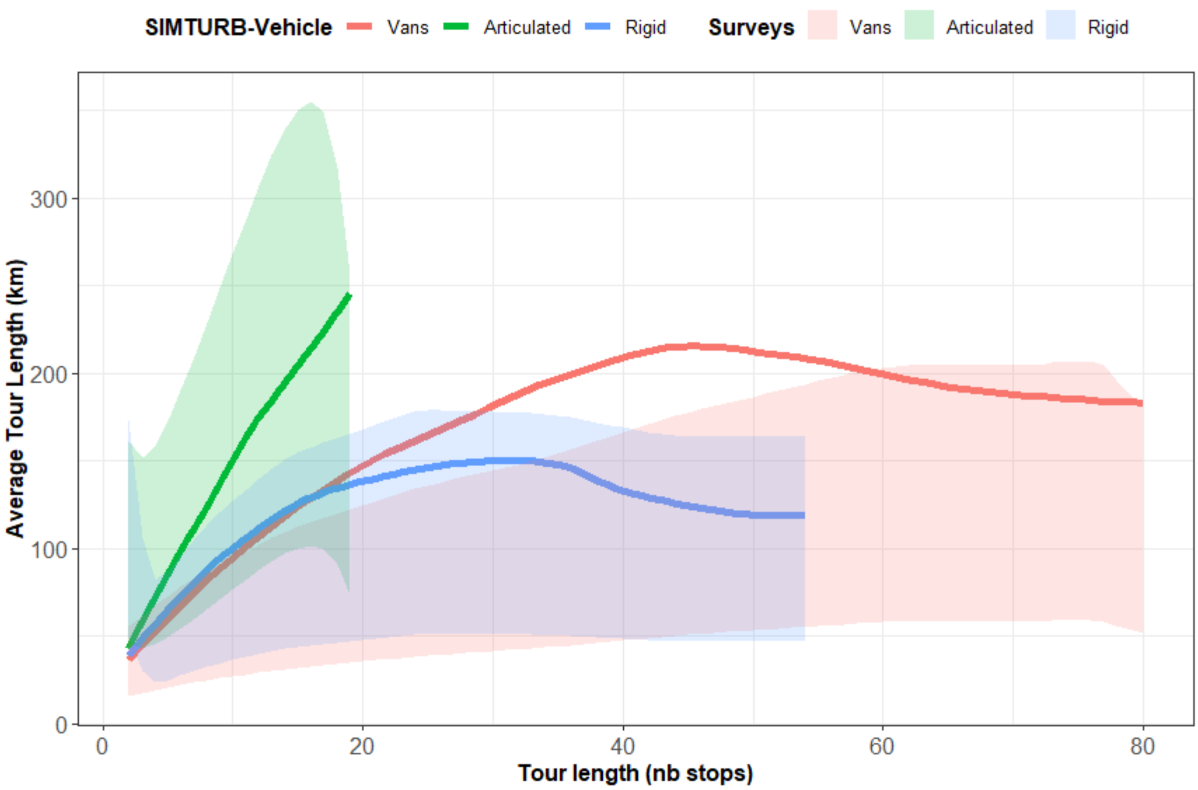

Figure 6 : total distance of a tour according to the number of points for types of vehicles, envelopes for survey values

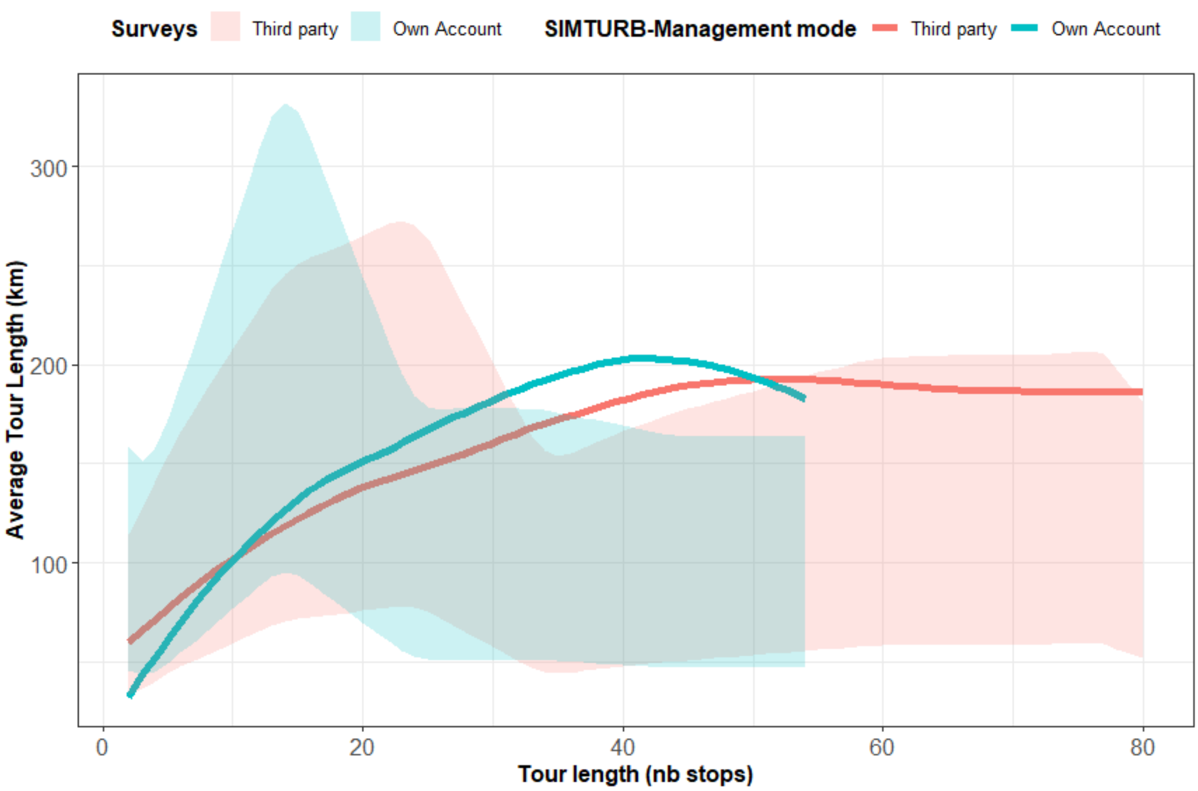

Figure 7 : total distance of a tour according to the number of points for management modes, envelopes for survey values

The overestimation of total tour length is however compensated by shorter movements for line-haul and short tours than those measured in freight surveys. This difference is explained by the distribution of flows: movements generated in the model stay in the simulation area (the urban area) without exchanging with outside zones (regional, national and international flows – which are taken into account in surveys although in limited proportions). Although typically representing long distance transport at regional, national or international levels, line haul trips in SIMTURB are limited to the area of study, consequently being shorter. We can effectively see that movements in shorter tours and line haul generate less distance than those observed in FRETURB and freight surveys.

Moreover short tours and line haul represent the most common types of movements (Figure 8). Since more than 50% of movements in the model are affected to line-haul and tours shorter than 10 movements, these deviations compensate themselves in the overall results.

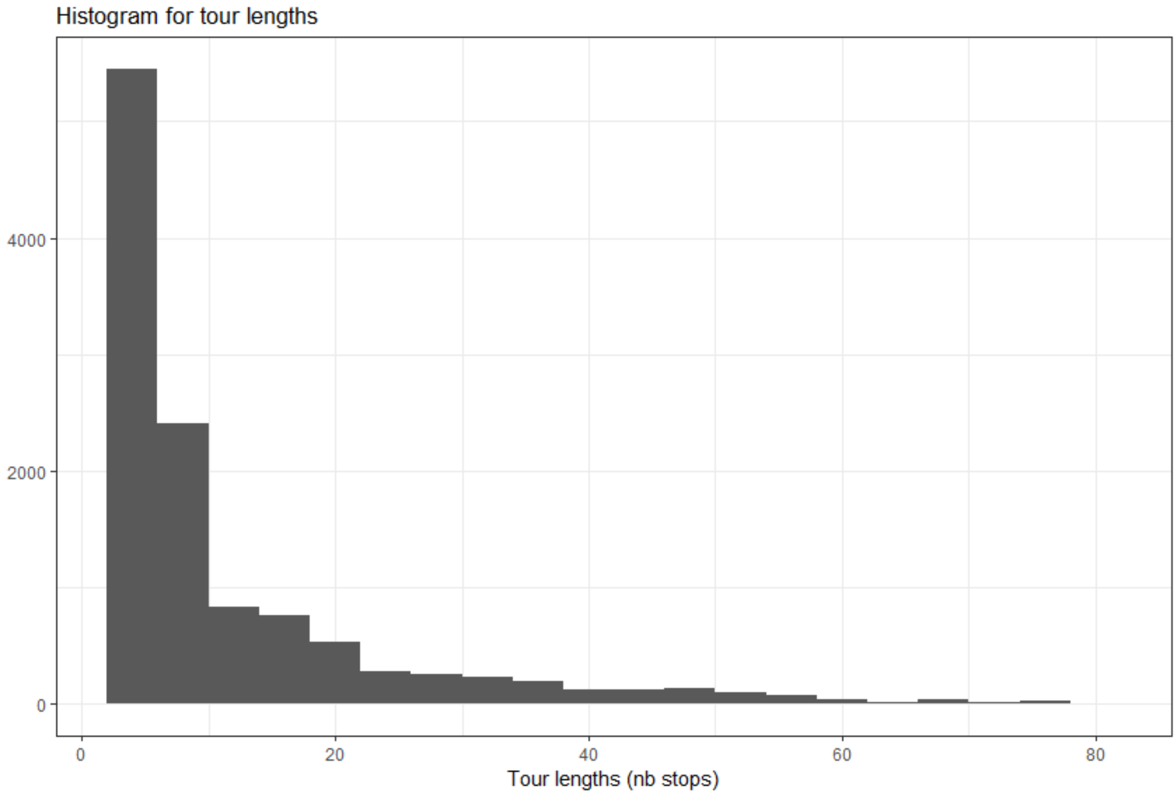

Figure 8 : histogram of tour lengths (line haul -2 stops- are evicted for better readability)

The comparison of the Origin-Destinations flows compared to the original O-D matrices generated by FRETURB is not entirely correspondent. In this section we analyse the deviation of SIMTURB when we use the Markov chains as they are originally produced (but with a strong deviation to urban freight surveys in terms of tour length) and routes optimised by a VRP algorithm. In order to measure the deviation of SIMTURB we carry out an analysis of the difference of flows according to the distances between each zone (Figure 9).

We can notice strong deviations for short O-D distance. With the original Markov process these deviations are however smaller than the VRP optimised Markov process. The optimised tours tend to overestimate flows (relatively to the FRETURB model) for O-D couples distant from 5 to 12 kilometers.

On the opposite, the model tends to slightly underestimate flows for more remote O-D couples (between 12 kilometers and more). On the overall, the errors are compensated and the models converge for longer O-D distances.

These deviations can be explained by two reasons. The first is the difference between FRETURB built O-D matrices, which are distributed on a continuous basis, and the Markov chains, which are based on a discrete and finite process. In this case, O-Ds with very low flows equal to very low probabilities in the Markov process, which tends to build chains on O-Ds with larger flows. On the contrary, O-Ds with less flows (which incidentally are usually more distant) are less likely to be drawn in the process.

The second reason is the use of a VRP, which necessarily modifies OD flows. The VRP emphasises deviations between the unoptimised tours produced through the Markov process and optimised tours: the algorithm keeps the number of points for each tour and the zones served, only rearranging the order in which the deliveries (points) are done in order to keep distances travelled consistent with observed tours in freight surveys.

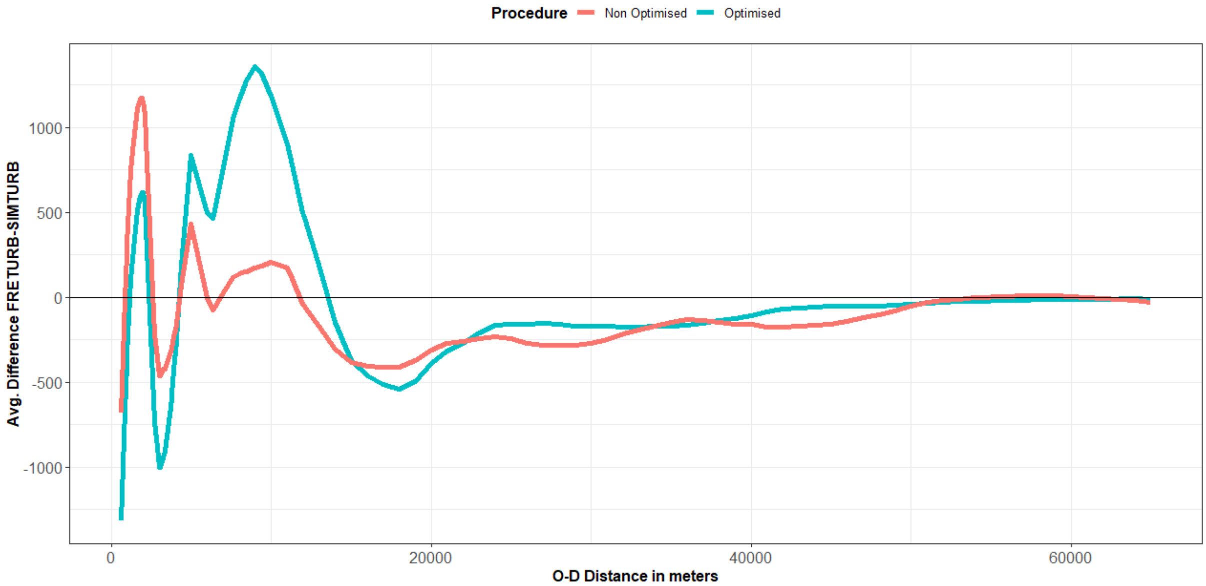

Figure 9: Deviation to Freturb in O-D flow structure according to O-D distances

The number of movements therefore stays unchanged between unoptimised and optimised procedures, but the distances travelled and OD structures can evolve drastically (more than 300,000 daily kilometres travelled).

Model	*Flows (daily operations)*	*Total Distance (km)*	*Average distance/trip*	*Deviation to Freturb(%) - Flows*	*Deviation to Freturb (%) - Distances*	*Deviation to Freturb (%) - Avg dist/trip*
Freturb	220725	2934681	13.30	NA	NA	NA
Markov non optimised	220246	3154969	14.32	-0.2%	7.5%	7.7%
Markov optimised	220246	2812140	12.77	-0.2%	-4.2%	-4.0%

Table 5: Comparison of distances generated with Freturb – Simturb

We can however see that although the flows generated by non-optimised Markov processes have a better convergence with FRETURB flow structure, this process estimates longer distances, showing that the VRP is relevant, reducing the deviations in terms of distances generated, which is more relevant for evaluating pollutant emissions and congestion.

5. Conclusion

This paper presented an original method to simulate urban freight delivery tours using Markov chains at a mesoscopic level. After describing the general method, we analysed the deviations of the model to pre-existing data and models used for freight transport diagnosis and simulation (FRETURB and Urban Freight Surveys).

We noted that the overall organisational structure and volumes estimated by SIMTURB corresponded to FRETURB simulations and data observed in Urban Freight Surveys. However, the spatial structure of flows estimated by the model could show some deviations because of the transition between a continuous and discrete process and the use of VRP algorithm. Although deviations to FRETURB are in some case rather significant, these differences do not necessarily mean that the model itself is not efficient in realistically reproducing urban freight tours. Therefore, the next steps to validate the model will be to confront the SIMTURB modelled data with samples of routes operated by freight carriers.

Thanks to its ability to account for the structures at stake in urban freight transport, the use of SIMTURB allows to work on a wide variety of scenarios useful for both local authorities and private operators. For instance, it can be used to examine the impact of LEZ, off-hour regulations, use of UCCs or the implementation of new types of vehicles [39]–[41].

The model has indeed been used in various studies concerning the use of new vehicles [42], Low Emission Zones, and other researches studying the impacts of UCCs and new urban distribution technologies (studies produced under non-disclosure agreement and not freely available).

For now, the model only takes into account B2B flows, but some modifications in the modelling process, coupled with behavioural data collected on household deliveries [43], [44] will allow the integration of such flows. This specific calibration will however call for new typologies of movements and freight generation points (not only establishments, but also households and their characteristics).

Other enhancements will include commodity modelling based on establishments' generation. The current loading functions are based on the initial load at the starting establishment, which is a rough estimate of the demand for goods. The model does not in fact produce data on the types of goods, packaging and the receiving establishments themselves do not generate the demand for goods. Incidentally, the model is limited to delivery tour generation and does not take into account pick-up tours or mixed organisations (alternating deliveries and pick-ups in the same tour). A modification of the modelling framework should allow taking into account pick-ups in conjunction with the goods generated by the points served by tours. This work however needs the modification of O-D matrix generation with a functional perspective on deliveries and pick-ups.

6. References

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