Generating on-demand mobility data for urban vehicles based on bus aggregated data

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***Abstract*—On-demand mobility in urban areas is gaining increasing attention from researchers nowadays. However, human mobility data availability is a real challenge for experiments, because of privacy and commercial concerns, as well as the high cost to deploy sensors and a long time to collect the data. Thus, plausible mobility data generation is an acceptable solution for researchers to conduct their experiments. In this study, we propose a model for generating a set of plausible on-demand mobility requests data from an urban bus aggregated data. A three-step method is introduced to perform data generation for each bus trip. First, the plausible arrival date is computed for every bus stop by using data from OpenStreetMap[1]. In the second step, the total number of passengers served by the trip is distributed appropriately on the stops. At the third and final step, individual passenger requests are generated from each bus stop, using previous results and, a temporal and spatial uniform distribution. The experiments, conducted using the bus company SOTRAL[2] data as source shows that the generated data fits quite well with the activity density levels of the different city areas. A multiplication factor introduced even allows to generate more or less demands than in the source dataset.**

***Index Terms*—Human mobility, dataset generation, urban mobility, mobility data, on-demand mobility, urban bus service, urban areas, spatial-temporal systems.**

I. Introduction

Nowadays, on-demand mobility in urban areas is one among the fields that is gaining the most attention from researchers, especially due to the challenges that cities are facing, such as pollution, traffic congestion, etc. The growing development of intelligent transport systems is increasing this phenomenon. However, one of the major issues encountered by scientific community is the availability of mobility data, especially on-demand mobility. The acquisition of mobility data is not an easy task for three main reasons [1]: 1) People's privacy concerns. Some research works [2], show that people prefer not to share their location information. 2) Commercial concerns. Mobility data are collected and owned by only a few companies that provide popular location-based service applications. As a result, for reasons such as competition, researchers can hardly get access to these data. 3) Deployment expense. Even for the government, it is time-consuming and costly to develop urban sensors and collect data in large scale. This data unavailability is even more true for cities in Sub-Saharan Africa such as Lomé, where mobility infrastructure is less developed and modern. Thus, plausible mobility data generation is an acceptable solution for scientific community to conduct their experiments, among others.

For research on urban ride sharing optimization purposes, we need on-demand mobility data for the city of Lomé. However, we only got aggregated rides data from SOTRAL[3] which is the urban bus company of the city. The provided data includes the number of passengers served by bus rides on each bus line, but there is no way to know which passengers get on the bus on a given stop, not even the number of passengers nor the arrival time of the bus on that stop. It is worth noting that urban bus service is not an on-demand mobility service, as a passenger can't decide its own schedule and its trip origin and destination. However, these data, together with the bus lines and stops data provide a good idea of the mobility demand distribution in the city.

In this research work, we conceived a model to generate plausible on-demand mobility data based on an aggregated urban bus data. For a given ride, the model first determines reasonable arrival time using available geographical data from OpenStreetMap[4] (OSM). Then, the number of passengers served is distributed on the stops of the ride line, considering time slots and density of activities in the different areas of the city. Finally, mobility data is generated, using previous results and uniform temporal and spatial distribution.

[1] https://www.openstreetmap.org
[2] http://sotraltogo.com/
[3] http://sotraltogo.com/
[4] https://www.openstreetmap.org

The remainder of this paper is structured as follows. Section II presents an overview of related scientific works. Section III provides preliminary definitions for the model and describes the source and the target data structure. Section IV details the model that generates simulated data. Section V provides the results of our experiments. Finally, Section VI concludes this paper and opens up perspectives for future work.

II. Related works

The scientific literature is quite rich in the field of urban mobility. Among those we have studied, we found two main groups related to our work, which are presented in the following subsections. The first one summarizes mobility research work, with a focus on the city of Lomé while the second presents mobility data generation papers.

A. Mobility in the city

There is a large body of research work on urban mobility. Recent studies focus, among other domains, on the future of cities, with regard to climate and sustainability challenges. [3] gives an overview about the drivers, feedbacks and constraints of urban mobility and location in a possible future in which transport energy will no longer be abundant and cheap. It asks whether current urban models are able to adequately model the impacts of significantly higher transport costs and demonstrates by an example how it can be done. [4] investigates the role that Urban Planning plays in the long term towards a safer and climate friendlier mobility, highlighting the need for integrated approaches gathering spatial planning and mobility management. [5] propose a rethinking of mobility in cities using automated vehicles; The expected positive impacts derive from the development of car sharing, the reduction of space required for parking vehicles, the possibilities for older people or those with disabilities to use cars, the enhancement of safety, and the improvement of efficiency of the transport system.

Scientific studies on mobility in the city of Lomé are mainly done by Togolese or sub-regional researches, generally published in French journals, with English summary. Several of them focus on 2-wheeled vehicles [6]–[9], being primary means of travel in the city[5], and exploring geographical and sociological aspects. In [6], Guézéré compares urban urban sprawl in European cities to African ones, with the city of Lomé as use case. He shows that in contrast to European cities where the car contributed to a fragmented urbanization, the choice to occupy suburban space is not related to the car in Lomé, but poor and medium class people have to build poor habitat on undeveloped spaces in the urban periphery. Therefore motorcycles, used as personal motor bike and as taxi-motor bike, cross these suburban districts and help people to overcome isolation and long distances. He then shows in [7] sociological consequences of these taxi-motor bikes on the city of Lomé, including conflicting relationships with public agents such as police and tax collectors. [8] confirms the importance taxi-motor bikes on suburban areas by another sociological study in two cantons at the edge of Lomé. [10] studies the transformations in users' behaviors induced by an on-demand motorcycle taxi service recently proposed by Gozem[6], through a digital platform.

[11] and [12] performed empiric studies on intermodality and multimodality in urban mobility in the city of Lomé, with means of transport as moto-taxis, car-taxis and urban buses. They found that intermodality and multimodality are mainly improvised by passengers themselves, then outlined the consequences of this state of affairs, and finally highlight the strategic importance of formal transport integration for African city-dwellers, especially in terms of cost and travel times.

More recently, [9] conducted a survey to evaluate the contribution of taxi-tricycles in the mobility of people in Lomé. Taxi-tricycle is lately introduced in Lomé as means of transport, and this work shows that its adoption is growing, responding to the customers' purses, and its drivers most finding it more profitable than car-taxis and moto-taxis.

B. Mobility data generation

There are several scientific works that introduced methods to generate data, especially mobility data. [13] demonstrates a generic, user-configurable toolkit for generating different types of indoor mobility data for real-world buildings, in a three-layer pipeline: an infrastructure layer uses industry-standard digital building information (DBI) files to generate the host indoor environment, then a moving object layer offers the functionality of defining objects or trajectories, and finally a positioning layer generates synthetic signal strength measurements according to the positioning device data and trajectory data generated at relevant layers. [14] presents a procedure to generate mobility dataset for Vehicular Social Networks (VSN) from floating car data. In [1] a method is proposed to generate mobility data for a new target city, by transferring knowledge from mobility data and multi-source data of source cities. City digital twins (CDT) and their potential applications in the context of policy making are explored in [15], and a task-based approach to urban mobility data generation is proposed in the last section of the article.

To offer on-demand mobility services, it is necessary to understand mobility in the city, using real and comprehensive urban mobility traces. If these data are not available or incomplete, we need a tool to generate acceptable simulated data. In this paper, we propose a model to generate an on-demand mobility data from an urban bus aggregated data. To the best of our knowledge, no study has proposed a method for generating from that type of data source.

III. Definitions and data structure

This section presents basic concepts used in this paper. The first subsection defines urban bus rides related terms, while the second describes the structures of the source and the target data.

[5] https://www.ssatp.org/publication/policies-sustainable-mobility-and-accessibility-urban-areas-togo-diagnostic-study

[6] https://gozem.co

A. Definitions

The Lomé urban bus company SOTRAL[7], like most companies providing this type of service, owns buses that perform trips on predefined lines, at more or less regular frequencies during the day, to serve passengers at the various stopping points of the lines. Figure 1 illustrates a structure of a bus line and its stopping points.

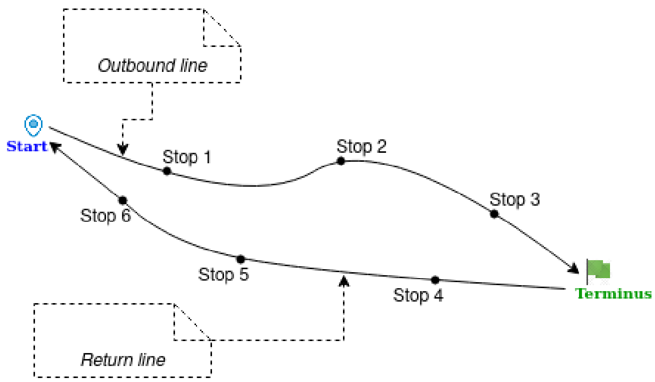

Figure 1. A bus line and its start, terminus, outbound and return lines, and stops

A bus *line* is a predefined route, identified by a number, served by one or more buses. Each bus on this line start a *trip* at a *start* point with passengers, mark small pauses at predefined *stops* to allow passengers to get on or off, then mark a longer pause at a *terminus* point. After that pause, the bus follows a similar path from the terminus point with passengers to the start point. The line section from the start point to the terminus is called *outbound line* while the reverse section is called *return line*. *Start* and *terminus* points are special stops.

A *trip* is a bus ride starting at the start point at a given time, following the outbound line to the terminus, then returns back to the start point by the return line, serving passengers at the stopping points of the line. To get in a bus at stop, a passenger needs to buy a ticket.

B. Source and target data

On each trip of every working day, the bus company maintains the following data:

- the line number,
- the bus that ran the trip,
- the departure time (at start point),
- the arrival time (at start point),
- the total number of sold tickets, corresponding to the total number of served passengers on the trip.

Thus, the passengers data we got are aggregated by trip. There is no information on at which stop each passenger get on or off the bus, and the exact times the bus reaches each stop. The company also provides the geographical locations of the stops of each line.

In case of on-demand mobility, we need data on each single passenger:

- the mobility request time (time of day the request was made),
- the mobility request origin (geographical location),
- the mobility request destination (geographical location).

At this point we defined the basic concepts and described the source and target data structures. We will now move the modelling step.

IV. Problem Modelling

Our ultimate goal is to generate a set of mobility demands data that leverages the aggregated data gathered from the bus company. This is performed in three steps for each bus trip:

1) computing the arrival time at each stop;
2) distributing passengers over the stops;
3) generating individual mobility requests.

The following subsections describes these steps, and the last one presents the resulting algorithm.

A. Computing the arrival time at each stop

First, the arrival time at each stop is computed by using data from OSM. In fact, with OSM, we can get vehicles average speed on every road section, and thus the average trip time between two points. However, the sum of all trip times between consecutive stops does not correspond exactly to the real trip time provided by the company for a trip. This is due to the traffic state during a trip which can vary, and thus extends or reduces the real trip time. So to address this issue, the obtained trip times from OSM are used as weighting for the corresponding section.

Formally, a bus line l can be represented as a suite of n stops (see Equation 1). The arrival time $t(s_k)$ at the stop s_k of a trip on the line l can then be computed with the formula of Equation 2, where T_o and T_d are respectively the departure and arrival time of the trip, provided by the bus company, and $\Delta t(s_{i-1}, s_i)$ is the travel time between consecutive stops s_{i-1} and s_i, computed from OSM data.

$$l = (s_1, s_2, ..., s_n, s_1), n \in \mathbb{N} \tag{1}$$

$$t(s_k) = T_o + (T_d - T_o) \cdot \frac{\sum_{i=2}^{k} \Delta t(s_{i-1}, s_i)}{\sum_{i=2}^{n} \Delta t(s_{i-1}, s_i)} \tag{2}$$

At the next step, we seek to plausibly distribute by stop the total number of passengers served by the trip.

B. Distributing passengers over stops

We note that the lines are designed so that the start point is in an extreme suburb of the city, the terminus in a business area, and the line itself passes through areas of varying density of activity. In Figure 2, which shows the SOTRAL lines, the terminus stops are in the administrative district and the entrance to the main market. For instance, it is reasonable to expect more passengers to be served on the outbound line than on the return line, and the reverse in the evening. On that basis, we define a weighting to distribute the total number of passengers on the outbound and return lines, depending on the time slot of the trip. Then we define a second level

[7]http://sotraltogo.com/

of weighting for each stop on the outbound and return lines, which takes into consideration the activity poles of the city of Lomé as shown in Figure 3. These data result from the work of [10]. A weight of 1 to 4 is affected to every stop, according to its location, so that the higher weight for a stop, the more passengers will enter the bus at that stop.

At last, we define a multiplication factor f so that we can generate more or less requests than the number of requests provided. So if P represents all passenger requests served by the trip, P_o and P_r represents respectively the passengers that entered the bus on the outboud line and the return line, and ts a time slot of the day, Equation 3 shows how the number of passengers on outbound and return lines are computed, $\alpha(ts)$ and $\beta(ts)$ being respectively the coefficients of the outbound and return lines according to the time slot ts.

$$\begin{cases} |P_o| = \alpha(ts) \cdot f \cdot |P| \\ |P_r| = \beta(ts) \cdot f \cdot |P| \\ s.t., \alpha(ts) + \beta(ts) = 1 \end{cases} \tag{3}$$

Equation 4 defines how the number of passengers $p(s_k)$ getting on the bus at stop s_k is computed, $P(s_k)$ being equal to P_o if s_k belongs to the outbound line, P_r otherwise; w_i is the weight of the stop s_i.

$$|p(sk)| = \frac{w_k \cdot |P(s_k)|}{\sum_{i=1}^{n} w_i}, 1 \leq k \leq n \tag{4}$$

At the third and final step, we generate individual plausible mobility requests.

C. Generating individual mobility requests

The plausible arrival time and number of passengers getting on the bus at a stop are computed at the previous steps. For the request origin, it is reasonable that a passenger getting on a bus at the time $t(s_k)$ needs to travel within a few minutes before $t(s_k)$, and its current location should be in a spatial radius close to the stop s_k. This is also valid for the request destination which will be in a radius close to the passenger destination stop. These are modelled as follows, for a stop s_k:

- A fixed time radius Δt_{radius} is defined, a single passenger request is determined randomly on the time interval $[t(s_k) - \Delta t_{radius}, t(s_k)]$, using uniform distribution;
- A circle centered on s_k with a predefined space radius $radius$ is defined, a single passenger plausible request location (origin or destination) is determined randomly within the circle, using uniform distribution.

Uniform distribution is preferred to the normal one for the spatial distribution, because there is no other information on the distribution of the population around the bus stops. Therefore, uniform distribution in a $radius$ around the stop is more reasonable. For temporal distribution, it should be acceptable to use normal distribution around the mean/expectation of $t(s_k)$, for a stop s_k, if we are generating data for the bus mobility; this is because bus arrival times at each stop are generally known in advance by customers. However, in our case we are generating data for on-demand mobility for taxi-like vehicles, where a customer expresses its request immediately when needed, not at determined times. We therefore consider reasonable to use a uniform distribution.

Thus, $|p(sk)|$ requests are generated for each stop $p(sk)$. The destinations of these generated requests are distributed on the stops following s_k to the terminus if on outbound line, to the start stop if on the return, and using each stop defined weight. A constraint is however introduced so that the origin and destination are not too close for a vehicle trip : the real trip distance between request origin and destination should be above a threshold. A request is represent as $r(t, O(x_o, y_o), D(x_d, y_d))$, with t the request time, $O(x_o, y_o)$ the request origin and $D(x_d, y_d)$ the request destination. Equation 5 shows how r values are computed. The terms ϵ_1, ϵ_2 and ϵ_3 are random variables derived with uniform distribution, $s_{ko}(x_{ko}, y_{ko})$ and $s_{kd}(x_{kd}, y_{kd})$ are respectively the determined origin and destination stops of the requests. $d(O, D)$ is the real trip distance between O and D and Δd_{min} is this distance threshold.

$$\begin{cases} t & = & t(s_{ko}) - \epsilon_1 \cdot \Delta t_{radius} & 0 \leq \epsilon_1 \leq 1 \\ x_o & = & x_{ko} + \epsilon_2 \cdot radius \cdot cos(2 \cdot \pi \cdot \epsilon_2) & 0 \leq \epsilon_2 \leq 1 \\ y_o & = & y_{ko} + \epsilon_2 \cdot radius \cdot sin(2 \cdot \pi \cdot \epsilon_2) & 0 \leq \epsilon_2 \leq 1 \\ x_d & = & x_{kd} + \epsilon_3 \cdot radius \cdot cos(2 \cdot \pi \cdot \epsilon_3) & 0 \leq \epsilon_3 \leq 1 \\ y_d & = & y_{kd} + \epsilon_3 \cdot radius \cdot sin(2 \cdot \pi \cdot \epsilon_3) & 0 \leq \epsilon_3 \leq 1 \\ s.t. & & d(O, D) >= \Delta d_{min} & \end{cases} \tag{5}$$

D. Algorithm summary

Finally, the resulting algorithm is summarised in Algorithm 1.

Algorithm 1 Data generation algorithm

```
Load lines, stops and weights
Initialize generated passenger requests set P as {}
for all trip in trips do
    Compute trip arrival at every stop (Equation 2)
    Compute passenger requests count at every stop (Equations 3 and 4)
    for all stop s_k in stops do
        Generate individual |p(s_k)| passenger requests (Equation 5)
        Add generated passenger requests to P
    end for
end for
```

Now that the model is well defined, in the next section, we will present and discuss our experiments and results.

V. Experiments, results and discussion

This section presents the experimentation setup and the obtained results. The first subsection presents the source dataset and the tools used, the second one presents the experimentation and the results. In the final subsection, we discuss some identified limitations of our approach.

A. Source dataset and tools

The original data we got from the urban bus company SOTRAL are in CSV format, aggregated by bus trips, for every working day of years 2015, 2017, 2018, 2019, 2020, 2021. We imported these data to a Prostgresql[8] database and cleaned them before use as source data. We also got lines and stops data, represented in Figure 2. The stops are weighted with regard to the activity poles of the city of Lomé depicted on the map of Figure 3.

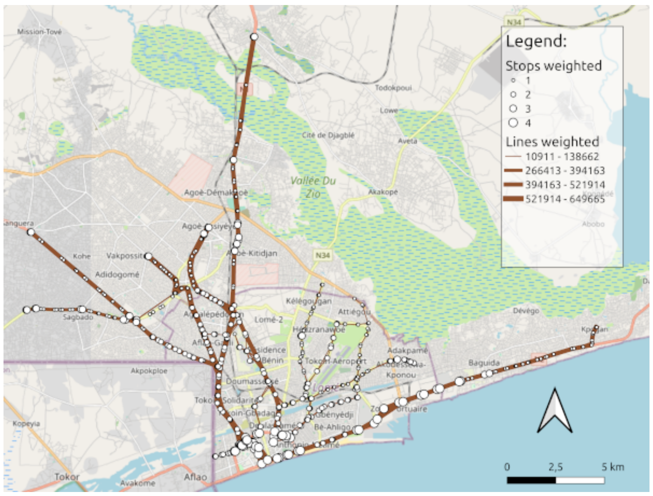

Figure 2. SOTRAL bus lines and stops

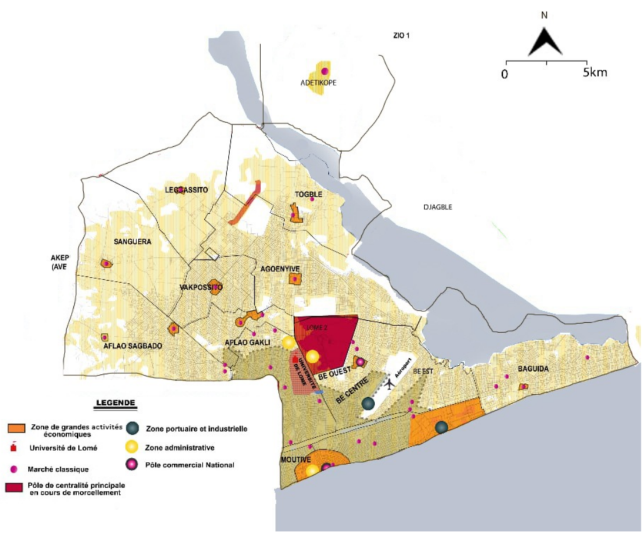

Figure 3. Lomé and its 13 communes with the different major activity poles Source: SDAU (Schéma Directeur d'Aménagement Urbain) of Lomé, 2010, redrawn by Yao SAGNA [10])

The geographic information system software QGIS[9] is used for visualisation. All implementations are done with Python version 3.10. More specifically, these python libraries are used:

- osmnx [10]: to manipulate geographic data, including real distance, real trip time and shortest route between two locations; it uses data from OpenStreetMap[11];
- pyshp[12]: to create shapefiles for visualization in QGIS.

B. Experiments and results

The implemented model was applied on several days of the source dataset. In this section, we present results for the day 04-29-2021 having a total of 8721 passengers served.

For proper operation, our generation model needs to take several predefined variables as input. Table I summarizes the appropriate values of these variables. SOTRAL lines run from 06:00 AM to 08:00 PM, so we believe that there will be more passengers on the outbound lines in the morning than the return lines, passengers mainly going to work. We will have the reverse situation in the afternoon. Thus, we defined two time slots: $morning$, before 12:00 and $afternoon$, after 12:00.

Table I
INPUT PREDEFINED VALUES

Variable	Description	Value
Δt_{radius}	Time radius	3 min
$radius$	Space radius	900 m
Δd_{min}	Minimum request distance	1.5 km
$\alpha(morning)$	weight of outbound line in the morning	0.75
$\beta(morning)$	weight of return line in the morning	0.25
$\alpha(afternoon)$	weight of outbound line in the afternoon	0.25
$\beta(afternoon)$	weight of return line in the afternoon	0.75

Figure 4 illustrates a heat map of generated mobility data origins. One can observe that the resulting map fits quite well with the density levels of the different areas of Figure 3, especially the area of high activity density in the south formed by the administrative area and the main market.

Table II summarizes the number of generated mobility data over the multiplication factor f. We obtained 8721 generated requests when the multiplication factor $f = 1$, and more broadly a value of $f \cdot 8721$. The heat map in Figure 4 remains roughly the same for all values of f, showing the stability of the model over the multiplication factor.

Nevertheless, we identified some limitations which will be discussed in the next subsection.

Table II
GENERATED REQUESTS OVER MULTIPLICATION FACTOR

f	Date	Number of generated requests
1	2021-04-29	8 721
10	2021-04-29	87 210
20	2021-04-29	174 420
50	2021-04-29	436 050
100	2021-04-29	872 100
250	2021-04-29	2 180 250

C. Limits

Figure 2 highlights the existence of an area in the north-west area of the city which is not served by the bus lines

[8]https://www.postgresql.org
[9]https://www.qgis.org
[10]https://github.com/gboeing/osmnx
[11]https://www.openstreetmap.org
[12]https://pypi.org/project/pyshp/

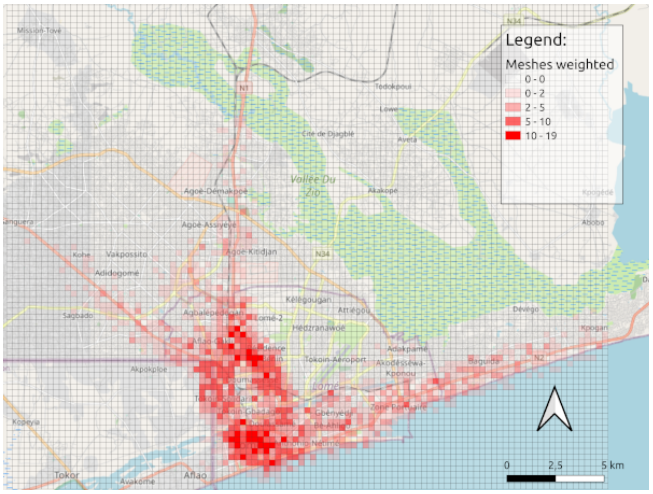

Figure 4. Heatmap of generated mobility origins

of the SOTRAL company, although there are residences and human activities in that area, according to the map at Figure 3. Consequently, our model does not generate mobility data for this area (Figure 4) which is a problem if we need mobility data for all areas of the city.

Thus, we believe our model will provide acceptable data in these two scenarios:

1) mobility data is not needed over all the city, solely plausible data on some areas;
2) mobility data is needed over all the city and the bus lines serve all areas of the city sufficiently.

VI. Conclusion and Future Work

Today, the availability of human mobility data is a real challenge for researchers' experiments, for the sake of privacy and commercial concerns, as well as the high cost of sensor deployment and the long time required to collect data. Thus, plausible mobility data generation is an acceptable solution to compensate the lack of real data. In this research work, we defined a model to generate a set of plausible on-demand mobility requests data from an urban bus company aggregated data. A three-step method is used to perform data generation for each bus trip. First, the plausible arrival date is computed for every stop. Then, the total number of passengers served by the trip is distributed appropriately on the stops. Finally, individual passenger requests are generated from each stop, using previous results and a spatio-temporal uniform distribution.

Experiments are conducted on the city of Lomé, using the bus company SOTRAL dataset as source. The results show that the generated data fits quite well with the density levels of the different areas. The multiplication factor introduced even allows to generate more or less data than in the source dataset. However, if we want to generate comprehensive mobility data on the whole city, we need bus lines to serve all areas sufficiently, which is not the case with the dataset used. Fortunately, the model produces acceptable mobility data for all bus lines covered areas.

In our future work, we aim to improve the model by making the temporal radius Δt_{radius} and the spatial radius $radius$ dynamic for each stop. The first one can be determined based on the bus arrival times at the adjacent stops, and the second one based on the distances between the bus stop and its adjacent ones. We believe this should produce an even more realistic result.

We also aim to experiment other models for the distribution of requests, such as gravity model. We will continue to look for ground truth data to improve the model validation.

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