# Using SUMO towards Proactive Public Mobility: Some Lessons Learned

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## ABSTRACT

Transportation causes several adverse environmental effects, including the emissions of air pollutants and greenhouse gases. Thus, shifting global mobility towards novel and more sustainable solutions is needed, for instance by enhancing public transports, promoting active modes, or adopting more sustainable technologies. In this context, simulators of urban mobility offer a valuable tool for assessing the impact of new policies, by providing support in designing traffic circulation plans and assessing the effectiveness of new transportation modes. However, building realistic scenarios is challenging due to data reliability issues.

In this paper, we present some lessons learned on the use of the SUMO simulator for sustainable mobility. Through a case study in the city of Genoa, Italy, we described the challenges we faced, which lead us to a significant discrepancy between simulated and real data. Despite manual data cleansing/refinement improved the accuracy, data quality remains still a concern. Thus, in this paper we highlight to the ITS community the need for improving data reliability to preliminary assess eco-friendly transportation solutions.

## CCS CONCEPTS

• **Computing methodologies → Simulation tools**.

## KEYWORDS

Simulation tools, Intelligent Transportation Systems, Sustainable mobility, Proactive Public Mobility

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## 1 INTRODUCTION

It is widely recognized that transportation can have adverse environmental effects, such as releasing greenhouse gases and generating noise pollution. For this reason, there is an urgent need to shift global mobility systems toward more sustainable solutions. Among others, a well-known strategy is to improve public transport systems, making them more attractive and convenient w.r.t private modes, thus reducing traffic congestion, decreasing emissions, and improving overall urban mobility [7, 13]. In this direction, several researches are for example focusing on improving predicting the arrival times of metros and buses (*e.g.* [3, 12, 14]), or the passenger demand, such as [8] and [15]. The aim of these researches is to proactively adapt public services to the dynamic needs of the citizens, also by exploiting the predictions of both the arrival times and the passenger demand.

Evaluating the impact of these new solutions and assessing their sustainability at a city-wide scale is another crucial aspect of urban planning and policy-making. Still, there is a lack of tools for supporting decision-makers in these tasks. Simulators of urban mobility are valuable instruments for conducting comprehensive analyses and performing *what-if* scenarios, to make informed decisions.

For instance, urban mobility simulators can be employed to enhance public transportation systems and reduce reliance on private modes of transportation [2, 9]. They allow to assess the impact of various modifications, such as changes to bus routes, adjustments to train schedules, or the introduction of new modes of transportation like light rail or electric scooters. By simulating different scenarios and analyzing the outcomes, it is possible to identify the most effective strategies for improving the efficiency, reliability, and accessibility of public transportation networks, while minimizing congestion and emissions.

To this purpose, *SUMO (Simulation of Urban Mobility)* simulator[1] has been widely adopted in thousands of ITS researches, being an open source, highly portable traffic simulation package, designed to handle also large networks [10]. For instance, in [4] the simulator is employed for supporting the design of traffic circulation plans in a smart city. More in detail, the scenario of Kuala Lumpur is analyzed, investigating whether one-way roads are more or less effective than two-way roads. According to this work, the best solution

[1] https://sumo.dlr.de/docs/index.html/introduction

highly depends on the traffic conditions. Similarly, in [16] SUMO is used for discussing the effectiveness of the penetration rates of cooperatively controlled vehicles in mixed traffic, by explicitly considering also the emissions. However, both of these works do not consider real mobility demand, which is randomly generated. Instead, in [6], the potential performance of personal rapid transit is examined, in a medium-sized German city, namely Bad Hersfeld. The travel demand for this case study is based on realistic works by Deutsches Zentrum fur Luft-und Raumfahrt (DLR). As shown, a fleet of just 30 vehicles is able to properly serve the mobility demand of the city, guaranteeing passenger wait times below 3 minutes. However, the results of the simulation are not compared to real-world flows, which may be different.

Indeed, as highlighted in [11], building a realistic scenario is not a trivial task. Indeed, in this work, a large-scale agent-based scenario is built and validated for the city of Bologna (Italy), proving that a time-consuming calibration step is needed to obtain realistic simulations. More in detail, the authors run the simulation based on an OD matrix obtained from the 14th population census, conducted by the Italian Institute for statistics (ISTAT) in 2001. Then, they validated the results of the simulation by exploiting observed flows from road-side detectors, showing that several systematic error sources are still present, hindering the accuracy of the results.

In this paper, we are willing to share with the ITS community the positive and negative experiences we gathered in a real-world scenario, where, in an academic-industrial collaboration, we applied a well-known urban simulator, namely SUMO, for the evaluation of different policies, towards proactive public transport demand management.

In particular, we used SUMO to simulate the urban mobility of the city of Genoa, Italy, leveraging the Open Street Map (OSM) road network, the GTFS files reporting public transport schedules, and two datasets about local urban mobility, *i.e.* some Origin-Destination matrices, and real data collected from Genoa buses over more than a year, about passenger load and time of arrival at each stop. From our experience, we found significant discrepancies between simulated and real data, mainly due to a lack of reliability in the open data sources, making results useless. After significant manual data cleansing operations, we were able to obtain simulated data with an accuracy more comparable to the real data.

In the rest of the paper we detail and quantify the issues we found, and we highlight the efforts that the ITS community should carry on to improve the quality of data sources, so that mobility simulations, especially for green-house emission estimation, can be more effective.

# 2 THE INVESTIGATED REAL-WORLD SCENARIO

The objective of our investigation was to set up a simulator of mobility in the city of Genoa, Italy, considering both the private and public transportation modes. Clearly, the usefulness of such a simulator highly depends on its adherence to the reality. For this reason, we validated the accuracy of the simulator by comparing the results of the simulation with real-world data, acquired through sensors installed on board public vehicles. In the following, our deployment experience is described in detail.

## 2.1 Eclipse SUMO

For our experimental project, we employed the SUMO simulator, an open source, highly portable, and widely documented traffic simulation tool, designed to handle also large networks. More in details, SUMO allows two different kinds of simulations, namely microscopic and mesoscopic. The former models each vehicle and its dynamic separately, with a fixed sampling rate, by solving underlying differential equations. For this reason, microscopic simulations are highly time and computational consuming. Moreover, working at a fine-grained resolution, small modeling errors can lead to significant errors in the simulation results [11].

On the other hand, in the mesoscopic view is also provided by SUMO. In this case, the traffic flow is represented as a dynamic queue, where each road-link acts as a FIFO queue. This implementation involves the following specific restrictions:

- Every agent (vehicle or person) must remain on the link for a specific duration, corresponding to the travel time at free flow speed;
- The outflow rate of a link is limited by its capacity, ensuring a controlled flow of agents;
- A link storage capacity is defined, which restricts the maximum number of agents allowed on the link. When this capacity is reached, no additional agents can enter, possibly leading to spillback effects.

In this way, the mesoscopic simulation is a compromise between the aforementioned microscopic and the macroscopic one, which aggregates traffic flow between an origin zone and the destination one, but it is not supported by SUMO as-is. Compared to the microscopic simulation, the mesoscopic one is faster and more robust to network model errors, while being more accurate than the macroscopic simulation. For this reason, in this work we applied the mesoscopic mode.

## 2.2 The Considered Data Sources

In order to simulate urban mobility, considering both private and public transportation modes, we leveraged different datasets, obtained from different data sources:

- network data;
- public transport routes and scheduling;
- urban mobility demand

### 2.2.1 *Network data.*
Such data contain information about roads, footpaths, junctions, traffic lights, and so on. Network data can be freely downloaded by OpenStreetMap (OSM), and then must be converted into the SUMO format. To this purpose, we used the *OSM Web Wizard* tool[2], which allows users to select an OSM excerpt and generate the SUMO networks, based on it. The resulting network, for the city of Genoa, is depicted in Figure 1.

### 2.2.2 *Public Transport Routes and Scheduling.*
Public transport information is commonly distributed in GTFS (General Transit Feed Specification) format. Defined by Google in the early 2000s, it consists of a set of text files, containing information about the locations of stops/stations, the routes and the scheduling. The GTFS

[2]https://sumo.dlr.de/docs/Tutorials/OSMWebWizard.html

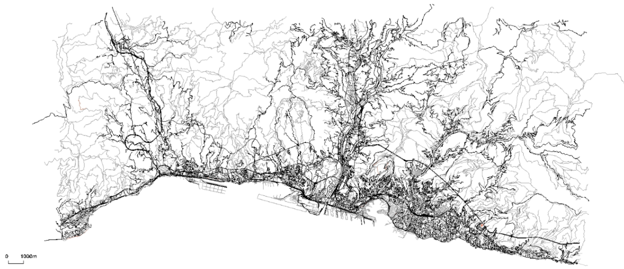


**Figure 1: The road network of Genoa, generated through OSM Web Wizard**

files for the city of Genoa are freely available[3] and can be imported into SUMO via the tool *gtfs2pt.py*[4].

*2.2.3 Mobility Demand.* As for mobility demand data, we leveraged two different datasets, provided by different sources. On one hand, we employed data collected through a smartphone application for public mobility, synthesized in Origin-Destination (OD) matrices. These matrices enable to capture, in a table form, traffic flow information in a region of interest, over a specific time interval. Each value of an OD matrix indicates the number of rides from the origin area to the destination one, in the considered time interval [1].

More in detail, in our experiments, each matrix covers a time slot of 2 hours (leading to 12 matrices a day), where the data are averaged on the months of March, April, and May 2022. Weekdays and weekends, as well as different modes of transport (*i.e.* public transport, private transport, or pedestrian) are summarized by different matrices, resulting in a total of 72 matrices. Let us note that, for the simulation, an OD matrix must be converted to a standard suitable for SUMO. In this work, we employed the *O-Format* [5].

On the other hand, we employed data acquired directly on public buses, about both bus occupancy and its arrival time at each stop. Such data were used for evaluating the accuracy of the simulator. Indeed, at the end of the simulation, the simulated occupancy and arrival time of each bus at each stop were compared with the same data, acquired through the sensors.

## 2.3 Trips Generation

The aforementioned data are used within SUMO for generating the trips made by the citizens, with both private and public transportation modes. To this purpose, the *duarouter* tool[6] was employed. In order to implement the shortest path for each trip, the tool implements Dijkstra's Algorithm. However, the main problem with *duarouter* is that it basically considers each vehicle in isolation, leading to unnatural road congestion. For this reason, we adopted the *automatic routing* approach [7], namely a rerouting strategy that allows some, or all, vehicles to periodically recompile their route. It also considers the current and recent state of traffic in the network, thus preventing traffic jams.

[3]https://openmobilitydata.org/p/amt-genova/1011?p=5
[4]https://sumo.dlr.de/docs/Tools/Import/GTFS.html
[5]https://sumo.dlr.de/docs/Demand/Importing_O/D_Matrices.html/the_o-format_visumvissim
[6]https://sumo.dlr.de/docs/duarouter.html
[7]https://sumo.dlr.de/docs/Demand/Automatic_Routing.html

# 3 RUNNING THE SIMULATION AS-IS

Once the map, public transport and transport demand have been defined, it is possible to run the mesoscopic simulation. Let us note that during the simulation many parameter are randomly generated. For instance, each cell of the OD matrix indicates how many people move from the origin zone to the destination one, but the precise origin and destination positions, within the zones, are randomly calculated, by SUMO. Thus, it is crucial to simulate each scenario a number of times, in order to obtain statistically significant conclusions.

In our experiments, we simulated all the weekdays from the 1st of March to the 31st of May, 2022. For each scenario, 5 repetitions were made.

## 3.1 The Simulation Flow

Figure 2 depicts the simulation flow we employed. More in details, the GTFS files, the OSM network and the OD matrices are given as input to the simulator in order to model, respectively, the public transports, the road network and the mobility demand. Moreover, several configuration files are provided to properly configure and guide the simulation. For instance, in such files the mesoscopic mode is set. The accuracy of the simulator has been validated by leveraging data acquired through sensors installed on real buses. In particular, we compared these real-world data with the simulated results.

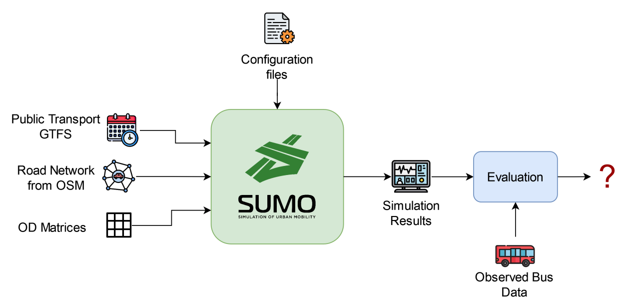



**Figure 2: Simulation Flow.**

## 3.2 Results

Running the simulations as-is (namely without modifying the maps or the OD matrices) produced mobility results far from the real ones, especially in terms of journey time. For instance, Figure 3 depicts the simulated and real average delay of the buses of line 3, for each stop. The real average delay, acquired from GPS sensors installed on board the vehicles, is at most 50 seconds. Instead, the simulated average delay reaches significantly higher values, up to 1500 seconds.

On the other hand, the discrepancy between the simulated and real occupancy of the buses is limited, as shown in Figure 4.

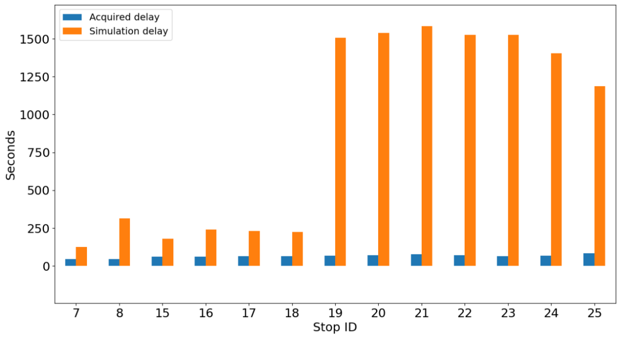



**Figure 3: Average delay for Route 003**

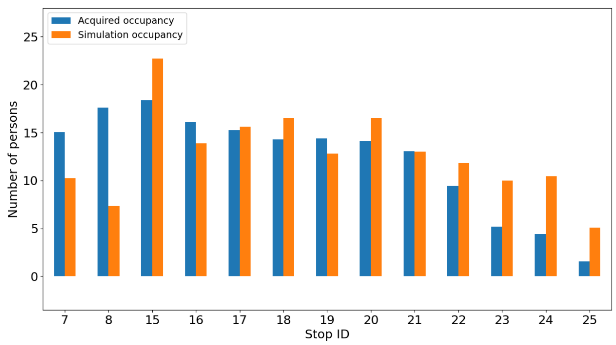
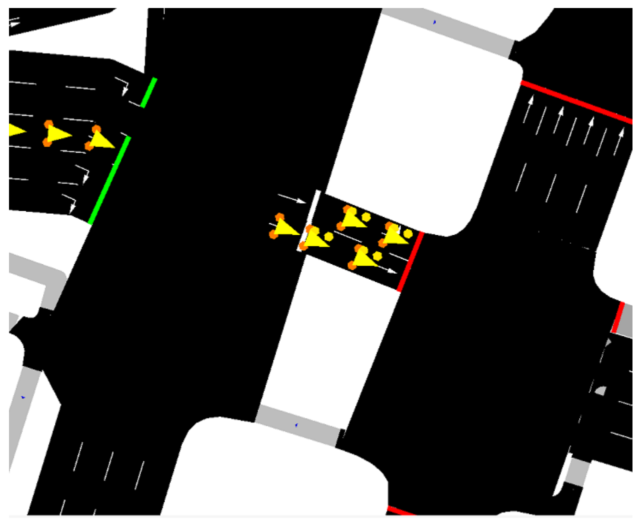



**Figure 4: Average occupancy for Route 003**

(a) A road before manual editing with one lane



(b) A road after adding another lane

**Figure 5: An example of road before and after manual refinement.**

## 4 RUNNING THE SIMULATION AFTER CALIBRATION

By carefully analyzing the simulation via the SUMO GUI, we realized that several traffic jams occurred at certain points on the map, leading to an excessive accumulation of travel delays. Broadly speaking, there are several aspects causing unrealistic behaviors that should be taken into account, when using SUMO. In the following, some of them are discussed.

### 4.1 OSM Quality

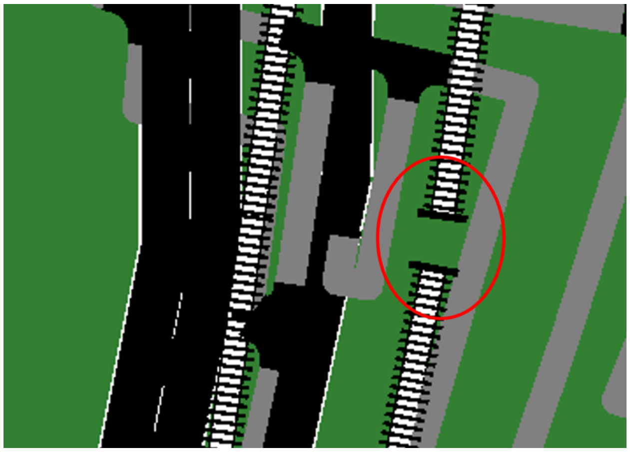
It is well-established that the quality of OSM data is not guaranteed. Indeed, the map provided by OSM is created and editable by thousands of contributors, with no required level of experience [5]. In our experimental campaign, we noticed some inconsistencies, *e.g.* disrupted roads or tracks, missing lanes and stops/stations, and so on. To mitigate these issues, several manual refinements of the imported network were applied with the graphical editor *NETEDIT*[8] [10]. For instance, Figure 5 and 6 depict, respectively, the manual adjustment applied to a disrupted road and track, created in this way by SUMO, probably due to some errors in the OSM network.

### 4.2 Default SUMO Assumptions

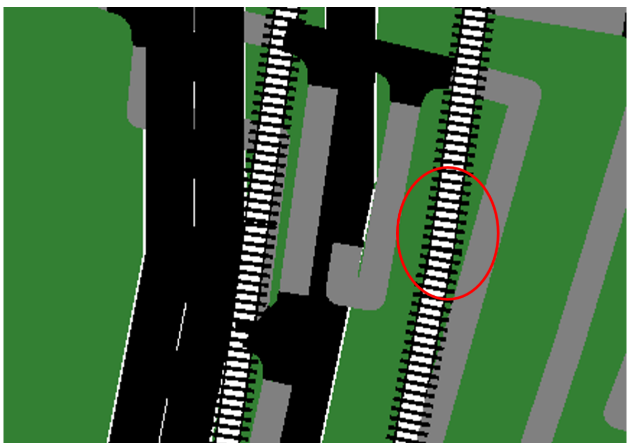
By default, SUMO makes some assumptions which negatively impact the results of the simulation. For instance, since no information on the management of traffic lights was available, SUMO used its default model, in terms of locations and cycle (duration of green and red light). The latter was the same for each traffic light, while it should depend on the criticality of the intersection where the light is located. To solve these issues, several manual refinements were needed, applied again through the NETEDIT tool (see Figure 7).

The precedence model was not realistic either. According to the latter, a priority level is assigned to each road. In the case of junctions between roads with different priorities, all the vehicles on the lower priority road are stopped until the higher priority road is completely free. This means that, if a long traffic jam occurs on the highest-priority road, the cars on the lower priority roads are completely stopped, until the problem is solved. To mitigate this problem, the *ignore junction blocker* attribute of the configuration

[8]https://sumo.dlr.de/docs/Netedit/index.html

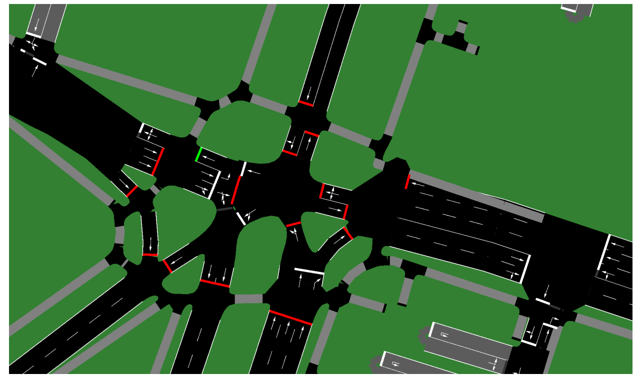


(a) A track before manual editing.

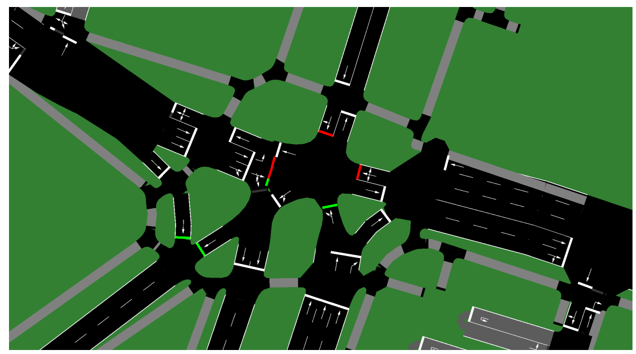


(b) A track after manual editing.

**Figure 6: An example of track before and after manual refinement.**



(a) Traffic lights generated by SUMO



(b) Traffic lights adjusted through NETEDIT

**Figure 7: An example of traffic lights before and after manual refinement.**

file was set to 60 seconds. In this way, the vehicles that are blocking the intersection are ignored, by finding a way around to continue the route.

In addition, by default, the size of the buses and the stops was set to excessively small values. For instance, Figure 8(a) depicts a bus stop as defined by SUMO. Due to the limited length of the stops, passengers were not able to wait at the stops, while for the bus length, they were not allowed to board the bus. To solve these issues, we manually modified the length of the bus stops through NETEDIT (see Figure 8(b)), while the dimension of the vehicles was modified in the configuration options.

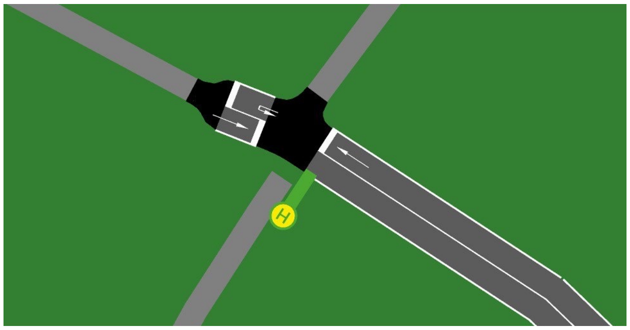
## 4.3 The Simulation Flow

When the accuracy obtained by simulating the scenario as-is is not sufficient, a calibration step is needed. As a consequence, the simulation flow shown in Figure 2 evolves into the one depicted in Figure 9. Here, based on the discrepancy between the simulated and the observed data, several additional refinements have to be performed, during the calibration step. Thus, in this step, both the input data and the configuration files may be modified, also through specific tools (*e.g.* NETEDIT).

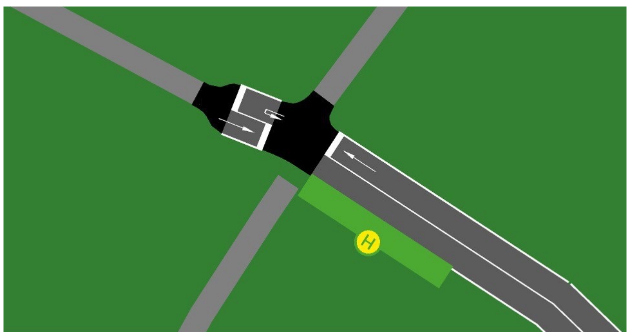
## 4.4 Results

The calibration step ended after 41 simulations. At the end of each simulation, according to Figure 9, the results were compared with data acquired on buses, and based on this comparison further refinements were made to the network or to the configuration files.

Figure 10 depicts the delay obtained for line 003, after the calibration step, w.r.t the delay obtain without calibration (Figure 10(a)) and to the delay acquired from sensors (Figure 10(b)). It can be observed that the calibration step significantly reduced the delays. Indeed, through the manual refinements made on the network with NETEDIT, the unrealistic traffic jams were avoided. However, the results are still not so similar to the real ones. Indeed, while the simulated delay reach peaks of -200 seconds, the real acquired delay ranges from -80 to 80 seconds at most.



(a) Stop automatically generated by SUMO



(b) Stop adjusted through NETEDIT

**Figure 8: An example of bus stop before and after manual refinement.**

## 5 DISCUSSION

Running the simulation as-is does not provide completely accurate results, due to both the well-known limitations of OSM and the default assumptions of SUMO. To mitigate these issues, a calibration step is needed. In detail, through the NETEDIT tool, it is possible to make manual refinements to the network obtained from OSM, to the positions of the traffic lights, and to the locations and/or dimensions of the bus stops. Instead, by modifying the configuration files of SUMO, it is possible to adjust the dimensions of the buses, the precedence model, and so on.

The calibration step is definitely not trivial. It requires the execution of several simulation scenarios, a detailed analysis of the results, an accurate manual inspection of the map, and a deep knowledge of the urban scenario under consideration. Nevertheless, despite the improvement of the results obtained after the calibration, several discrepancies, w.r.t the real values, are still present.

Indeed, by further analyzing the simulation, other unexpected behaviors were noticed. For instance, buses do not take always the same route between subsequent stops, since the *shapes.txt* file is not given with the open GTFS of the city of Genoa. As a result, the routing of the buses is not static, but it is dynamically calculated by the *gtfs2pt.py* tool [9].

[9]https://sumo.dlr.de/docs/Tools/Import/GTFS.html

Moreover, let us note that, as mentioned in Section 2.2.3, the OD matrices capture data at coarse-grain. Indeed, since the single movements and trajectories of the citizens are extremely sensitive data, in order to preserve the privacy of the people and meet the GDPR requirements, data aggregation is used as a way for anonymizing this information.

Indeed, in order to preserve the privacy of the citizens mobility data are aggregated in order to anonymize single trajectories. More in detail, in the considered matrices data were aggregated over 3 months, weekdays and bi-hourly time slots, and over large zones. As a result, such aggregation introduces a bias in the data, and thus in the simulation results.

In our opinion, other anonymization techniques should be considered, in order to mitigate the unreliability of data.

## 6 CONCLUSIONS

Nowadays, the urgency to shift global mobility systems towards more sustainable solutions is evident. Among others, improving public transport systems stands out as a promising approach to make them more attractive and convenient w.r.t. private modes. By achieving this shift, the benefits of reduced traffic congestion and lowered emissions can be realized.

Within this context, urban mobility simulators, such as the widely adopted *SUMO (Simulation of Urban Mobility)* simulator, play a significant role in assessing the impact of new solutions, ranging from adjustment in bus routes to the introduction of new transportation modes. Still, the effectiveness of these tools is strictly tied to their adherence to reality.

In this paper, we described our experience in employing the SUMO simulator within the urban landscape of Genoa, Italy, considering both private and public transportation modes. More in detail, leveraging the OSM road network, the open GTFS files for public transport, and the OD matrices for mobility demand, we first tried to run a simulation as-is, which did not provide accurate results. Hence, we introduced a calibration step, aimed at refining both the input data and the configuration files of SUMO, with the aim of obtaining more realistic simulations. Due to the well-known limitations of OSM and the default assumptions of SUMO, such a step was challenging, time-consuming, and required iterative adjustments.

In the end, we obtained more accurate results w.r.t the simulation as-is, but still there are some discrepancies between the simulated outcomes and the empirical data collected from real-world observations.

We believe that the insights gained from our research hold considerable value for the Intelligent Transportation Systems (ITS) community, for understanding the benefits and drawbacks of using SUMO as a tool for assessing urban mobility scenarios. This would also help ITS researchers in making informed decisions about when and how to deploy simulation tools like SUMO.

Finally, our research highlights the importance of continued exploration within the ITS community into alternative methods and tools that can enhance the accuracy and reliability of simulation outcomes.

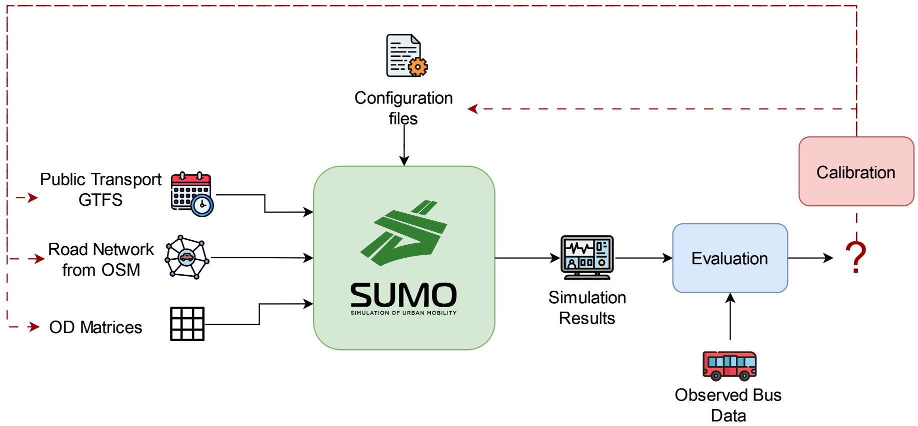
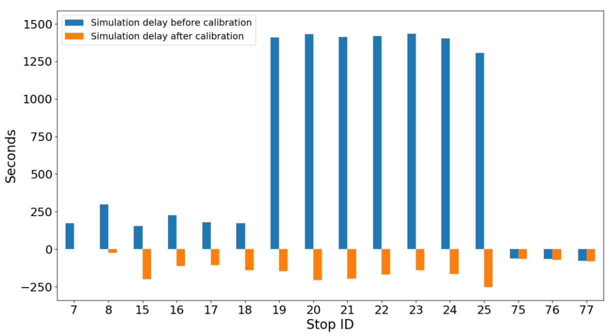
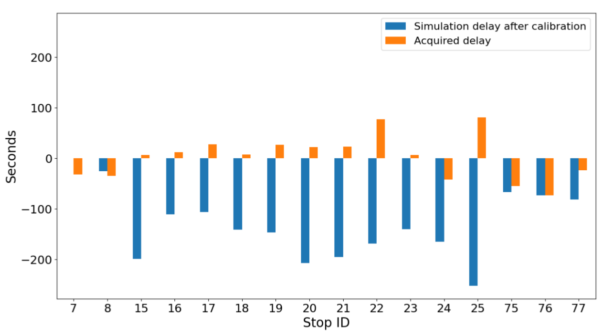



**Figure 9: Simulation Flow with the Calibration Step.**




(a) Delay of line 003, before and after the calibration step




(b) Simulated delay and real one, for line 003

**Figure 10: Delay of line 003 after the calibration step.**

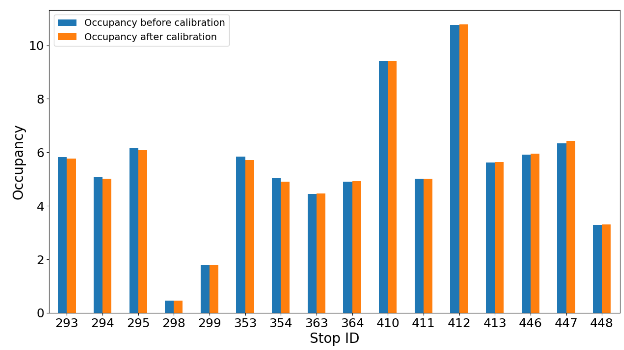



**Figure 11: Average occupancy for line 003, before and after the calibration step.**

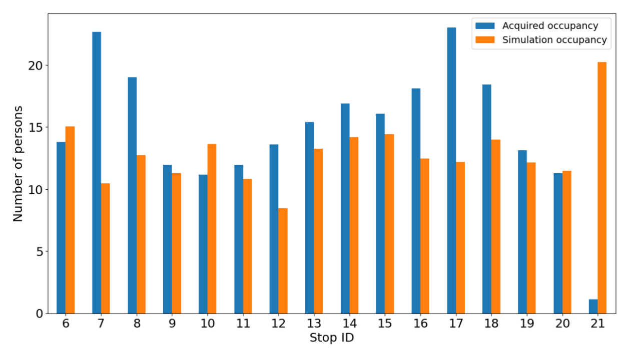



**Figure 12: Simulated occupancy and real one, for line 003. The results are organized for hourly time slots.**

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