Using Vehicle Trajectory Data to Build and Calibrate Microscopic Traffic Simulation Models

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Lorenzo Sica
Department of Environment, Land and Infrastructure Engineering (DIATI)
Politecnico di Torino
Turin, Italy
lorenzo.sica@polito.it

Matteo Ferraro
Department of Environment, Land and Infrastructure Engineering (DIATI)
Politecnico di Torino
Turin, Italy
matteo.ferraro@polito.it

Francesco Deflorio
Department of Environment, Land and Infrastructure Engineering (DIATI)
Politecnico di Torino
Turin, Italy
francesco.deflorio@polito.it

***Abstract*— To evaluate traffic management policies and new in-vehicle technologies, a digital simulation environment can be useful for testing their functions in virtual experiments. This paper presents a methodology for building a traffic model in a microsimulation environment (SUMO) based on observed vehicular trajectory data. Applying an iterative process, the methodology to refine the traffic model is described to obtain output statistics consistent with observations. In particular, distributions of individual travel times and distances are comparable for most of the simulated and observed vehicles. The main errors detected during the model building phase were fixed, and the solutions adopted were detailed concerning vehicle route selection, traffic light setting, and manoeuvres modelling.**

Keywords— Traffic Micro-simulation, Error checking, Model verification, Trajectories data;

I. INTRODUCTION

The construction of accurate models to support traffic observation and control requires high-quality data, and trajectory data can be one of the recent sources of information. However, their usage can be critical because of the complex model calibration process and synchronisation of different data sources used in the simulation environment. Indeed, collecting and managing such data presents technical challenges related to the large amount of information to be processed and the need to ensure spatial and time consistency between observations and the model. This study explores the opportunity to build a microsimulation model using the OpenStreetMap (OSM) dataset as a network layer and the observed vehicular trajectories for demand and control layers. For our application, a case study in Athens has been selected considering the availability of the pNEUMA dataset [1]. The process of integration of these data into the SUMO [2] model results in a simulation environment consistent with real observations, although critical issues can be identified, and possible solutions are proposed to improve its reliability.

The use of trajectory data for traffic simulation is an area of growing interest. Several studies have focused on collecting these data through technologies such as GPS, radar, LiDAR, and roadside or aerial image acquisition, each with specific advantages and limitations. The pNEUMA dataset [3] used in this paper was collected by drones equipped with high-quality video imaging instrumentation that performed collection campaigns flying over defined urban areas of the city of Athens. Other significant applications include the use of UAVs to monitor traffic flows both in urban environments [4] and on highways or extra-urban contexts, where the wide view allows tracking vehicles on multiple lanes simultaneously [5], [6], [7]. However, the most relevant aspect concerns their applications, which range from driving behaviour analysis to road safety and urban traffic optimisation. Analysis of trajectory data enables accurate modelling of vehicle interactions, such as car-following [8], [9] and lane changing [10], [11], [12] behaviour, which are essential elements for implementing microsimulation models. In addition, the identification of anomalies in vehicular patterns enables the detection of high-risk situations, contributing to the design of advanced safety systems [13], [14]. Several studies have shown how the integration of real data into simulation environments significantly improves congestion prediction capability and traffic management efficiency [15], [16], [17]. In the context of urban simulation, recent experiences have highlighted the importance of using observed data to calibrate digital models that play a crucial role in traffic simulation, enabling real-time modelling of traffic flows, driving behaviours, and mobility strategies, such as the integration of autonomous vehicles. Various studies have proposed different methodologies for building microsimulation models. For instance, in [18] a SUMO-based urban traffic model for Barcelona was developed using OpenStreetMap and origin-destination matrices, differing from our approach, which relies on direct trajectory assignment. Several similar experiments propose constructing microsimulation models for fairly large areas, such as entire urban areas [19], [20], [21], [22]. Other studies [23], [24], [25] instead propose models limited to narrower areas, as in the case of our paper, where a microsimulation model succeeds most effectively. A key advancement is the integration of real-time data to continuously update digital twins of traffic systems, leveraging machine learning and edge computing [26], [27], [28]. These studies highlight the potential of microsimulation scenarios to improve traffic management, although challenges remain in ensuring accuracy and replicability.

This study aims to develop an urban traffic microsimulation model in which a key role is the individual trajectory data obtained for all of the road users moving in a specific network. Different from more common approaches using aggregated origin-destination matrices, the proposed method relies on disaggregated data to capture the selected routes and vehicular dynamics, including variations in driving behaviours and interaction between different types of vehicles. The proposed methodology provides a process for obtaining realistic traffic models and is applied to a case at a small scale. Realism in traffic modelling can be crucial to simulate critical situations for safety, considering the range of technologies available to support driving tasks (ADAS).

II. Methodology

This study defines a methodology for constructing a digital scenario within a microsimulation environment using observations from real traffic scenarios. The primary input is the pNEUMA dataset [1], which offers high-resolution vehicular trajectories captured via drones for some areas in Athens. The aim is to replicate these dynamics in a model built using the traffic simulation tool SUMO, enabling a realistic and detailed representation of urban traffic flows. Key operations to obtain a valid model include defining vehicle routes, refining intersection layouts, setting traffic light control plans, identifying unexpected vehicular behaviours, and estimating relevant microsimulation parameters.

A. Scenario setting

To generate a preliminary simulation scenario, two basic elements are required: road network and traffic demand. The road network can be generated using OpenStreetMap (OSM) data, whereas traffic demand is derived from vehicle observations based on zone, date, and time slot obtained from [1]. Vehicle trajectories are extracted from the Pneuma dataset, which provides high-resolution data (sampling rate of 0.04s) on vehicle type, position, speed, and acceleration for specific urban zones and time slots. These observations enable the reconstruction of detailed vehicle paths and behaviours. In the case study, data for a specific sampling zone (zone 3) of Athens during peak morning hours (8:30-9:00 a.m.) were extracted, capturing 2112 vehicles in 15 minutes. The road network is downloaded via the OSM Web Wizard, providing a baseline representation of the study area directly importable in the microsimulation environment. To generate traffic demand, vehicle trajectory observations are converted into SUMO-compatible routes by associating each observation position, available by vehicle coordinates, with the nearest road network edge. While importing moving vehicles, SUMO provides different options, and the selected method requires detailed information according to a defined scheme; every trip being part of the traffic demand should be defined by time and position variables, such as the departure instant, edge and lane, initial and final speed, as well as the list of lanes which compose the entire trip.

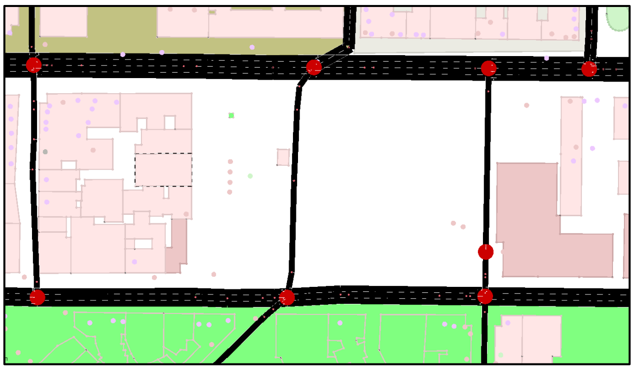

Figure 1: The main arterial in the road network imported in SUMO

Using the processed trajectory data and the extracted road network, preliminary tests were conducted in SUMO to verify data consistency and identify critical issues. Several problems emerged during these tests, including excessive simulation durations, extended congestion phenomena, and numerous teleportation events for vehicles unable to reach their destinations. These issues highlighted general weaknesses in the first version of the road network model that required specific resolution before further simulations. A major issue identified was a geometric error in the road network, particularly at one of the critical intersections that was simplified when imported from OSM. This misalignment impacted traffic flow, leading to severe local congestion and general unrealistic simulation. The network model was corrected using NetEdit, which included refining intersection layouts and adjusting allowed manoeuvres to connect lanes. In addition, it was necessary to evaluate the changes in the recent network that have occurred since the data collection date (2018). The characteristics of some roads have been modified after 2018, for example, by decreasing the number of lanes or adding preferential lanes. For this reason, the network model was readjusted to the conditions it was when the observations were collected. These adjustments significantly improved the accuracy of vehicle routing and overall scenario performance, enabling the first acceptable traffic simulations.

B. Baseline scenario analysis

A new simulation experiment was carried out after obtaining a preliminary road network model. The updated simulation data present statistics (Table 1) that align more closely with real-world observations compared to the preliminary tests. Indeed, almost all vehicles are correctly imported into SUMO, with only 26 undergoing teleportation. Previously, many vehicles failed to import due to network issues, and teleportation cases were widespread, often occurring repeatedly for the same vehicle. However, the simulation time remains significantly high, taking approximately 70 minutes, whereas the actual observation lasted only 12.5 minutes. Several critical issues emerged from the analysis. Notably, the total travel time is approximately three times higher than the observed value of 89,000 seconds. Additionally, the total departure delays, computed using fixed departure times as input, further contribute to discrepancies. Another significant issue is the average waiting time, which is considerably higher than expected; in reality, an average waiting time of around 15 seconds was observed, whereas the simulation produced a much higher value. Moreover, several vehicles were teleported due to congestion, confirming severe traffic bottlenecks within the simulation. Additionally, certain vehicles were not introduced at all, as their planned routes were deemed unfeasible. These factors suggested that further adjustments and refinements were necessary to improve the accuracy and reliability of the simulation model.

Table 1: Baseline scenario simulation statistics

Duration [s]	Loaded veh.	Inserted veh.	Teleports
4207	2112	2105	26
Total travel time [s]	Total depart delay [s]		Average waiting time [s]
265838	380413.4		64.51

The selected analysis to assess the alignment between simulated and observed scenarios compared travel times and distances by vehicles in the two scenarios. Although the travel distances show a general alignment, errors remain high, with an average deviation of 50 %, due to automatic route reassignments made by SUMO for vehicles with unfeasible routes. Travel times are even more complex to analyse because of multiple random factors, such as variability in traffic light behaviour or vehicle interaction. Even by applying a filter to exclude waiting times (defined by SUMO as those at speeds below 0.1 m/s) in the comparison, it is not possible to completely delete some of the stochastic effects, such as deceleration due to traffic, which affects total travel time. The comparison of the distributions in Figure 2 shows important differences, particularly in short trips (<20s) and medium-long trips (>50s), with an overestimation of travel times in simulation. The average deviation between the two distributions is about 55%.

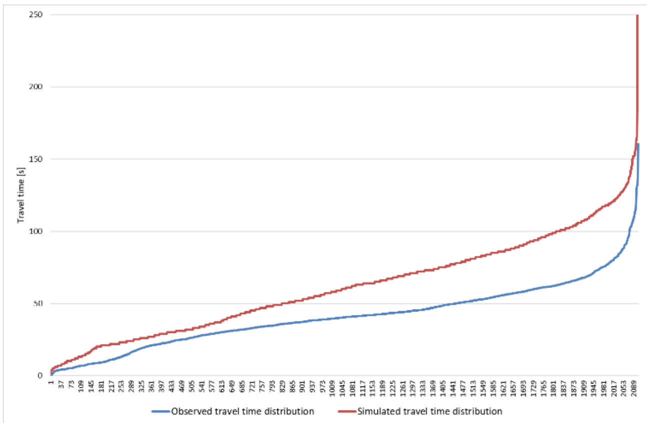

Figure 2: Observed and simulated travel times distributions

In summary, the simulated scenario still has significant discrepancies from the observed scenario, especially in route assignment and congestion modelling. However, it provides a starting point for further improvement.

C. *Scenario adjustment*

After simulating the baseline scenario, several adjustments were made to improve the simulation and reduce discrepancies with respect to the observation. The main objective was to refine the model to obtain a more accurate representation of traffic dynamics. The model refinement focused on three key aspects: vehicle path management, setting traffic light plans, and handling incorrect manoeuvres.

1) Vehicle routing definition

One of the main problems with the simulated scenario concerned an average deviation of 50% between the distances travelled in the simulation and those observed in reality. This error partially resulted from the method of inserting and removing vehicles in the system, which did not consider the exact point of entry and exit in the network. To solve this problem, a distance correction function was implemented in the matching code, allowing SUMO to receive detailed information about the departure and arrival points of vehicles with respect to the start of the edges. Further refinement involved removing the "via" parameter in SUMO, which previously required vehicles to traverse specific network segments, causing excessively long and unrealistic routes due to bias related to improperly associated point detections. Through these operations, in SUMO the generated routes were more consistent with observations, bringing the average deviation below 10%. Figure 3 shows a comparison between the travel distance observed and simulated for each trip included in the scenario. These improvements also had, as a consequence, a positive impact on travel times, reducing the difference between observed and simulated data.

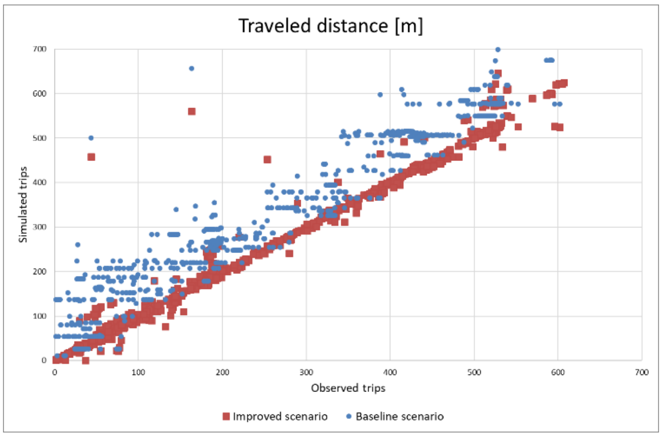

Figure 3: Observed vs simulated travel distance for each trip before and after routing definition improvement

2) Setting traffic lights

Further inaccuracy in importing the road network from OpenStreetMap was caused by the introduction of unrealistic traffic light plans, which are generally defined according to default SUMO rules (e.g., fixed-cycle programs with equal green times for roads of the same priority level). This led to congestion problems in the model because of the numerous signalised intersections along the urban arterials (Figure 4).

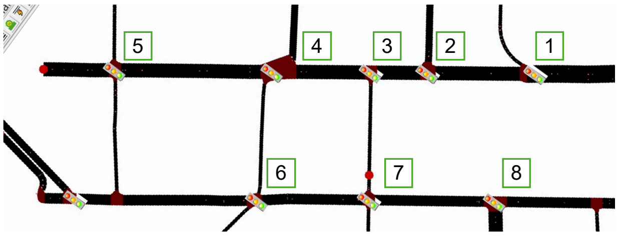

Figure 4: Signalised intersection in the study area road network

Vehicle trajectory data were analysed to improve the model to estimate the traffic light plans along the main arterials. Through the use of time-space diagrams, it was possible to identify the vehicles in a queue and the phase duration of traffic lights along major arterial roads. An example of traffic light timing identification using time-space diagrams is reported in Figure 5.

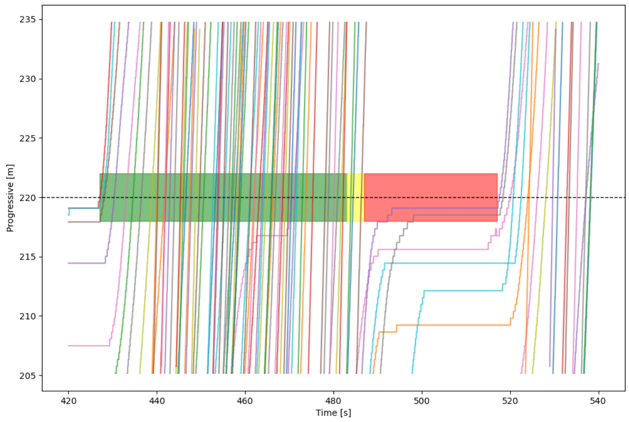

Figure 5: Example of traffic light cycle identification

Therefore, a fixed cycle of 90 seconds was adopted, with 56 seconds of green, 4 seconds of yellow, and 30 seconds of red for the approaches along the main road. In addition, the offsets between traffic light plans were calculated to obtain a model consistent with observations. The new traffic light setting significantly reduced travel time and departure delays, further improving the consistency of the simulation model with observations.

3) Identification of incorrect maneuvers

Detailed analysis of the simulation and comparison with the real data revealed that some vehicles, particularly motorcycles, were travelling stretches of road in the opposite direction of travel, which could not be replicated in the simulation because of the traffic rules implemented in the one-way edges of the model. An extreme example showed a vehicle with a real travel distance of 90 meters but a simulated distance greater than 900 meters due precisely to the circulation rules for travelling from one point to another available in simulation (Figure 6).

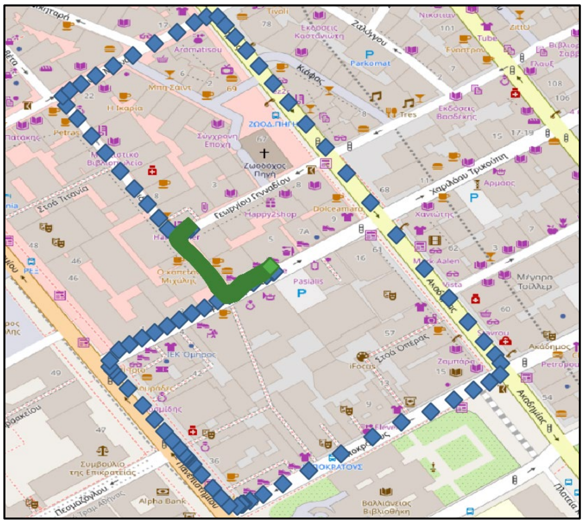

Figure 6: Observed (green) and simulated (blue) paths for trip 660

To avoid such errors, it was decided to exclude vehicles that did not comply with the road traffic rules (approximately 15, mostly motorcycles) from the simulation. This choice further reduced the discrepancies between simulated and observed data, improving the overall reliability of the model.

D. Setting vehicle simulation parameters

A crucial step in building the traffic model is defining vehicle simulation parameters to capture their real-world traffic behaviour accurately. This aspect is essential to ensure that different vehicle types exhibit realistic behaviour, as their driving characteristics can vary significantly. For example, the driving dynamics of a heavy vehicle are entirely different from those of a motorcycle. Due to its size and weight, a truck has slower acceleration, longer braking distances, and a more conservative lane-changing strategy. In contrast, a motorcycle is highly manoeuvrable and has a much higher acceleration. To reflect these differences, vehicle differentiation was implemented, considering real-world variations in size, acceleration, deceleration, and maximum speed. Table 2 presents these characteristics for each vehicle category. Without considering these distinctions, the simulation would risk oversimplifying interactions between different vehicle types, reducing its realism and reliability.

Table 2: Setting of parameters per vehicle types

Vehicle typology	Max speed (km/h)	Accel (m/s^2)	Decel (m/s^2)
Bus	85	1.2	7
Car	200	2.6	9
Heavy vehicle	130	2.5	7
Medium vehicle	200	2.6	9
Taxi	200	2.6	9
Motorcycle	200	6	10

Additionally, other specific simulation parameters were carefully configured to enhance accuracy. The “actionStepLength” parameter, which determines the time interval between two consecutive updates of a vehicle’s actions (driver’s reaction time), was set to 0.1 seconds for all vehicles to simulate an ideal situation without any delay in vehicle reaction, leaving a more adequate setting to further calibration process. This resolution ensures that even rapid adjustments in speed and position are captured. Lane-changing behaviour was also refined using the “lcStrategic” and “lcCooperative” parameters, both set to 1. This configuration allows vehicles to balance strategic lane changes—needed for executing specific manoeuvres—with cooperative decisions considering surrounding traffic conditions. Another key parameter is “tau,” set to 0.5 seconds for all vehicles, representing the target driver’s time gap to the leader. This value influences the simulated safety distances, contributing to overall traffic stability and flow characteristics.

III. Results

A. Global model output

After various iterations in the refining process of the model, the updated version provides an acceptable reproduction of the observed scenario. The modifications introduced have led to interesting improvements, as shown by the aggregated statistics by simulation in Table 3. The duration of the experiment is indeed consistent with the actual observation time (12.5 minutes), and the total travel time is also comparable to the real-world data, with a value of approximately 89,000 seconds. Teleportation episodes due to routing or congestion issues are not observed either. The average waiting time has decreased, even with lower values than the observed situation, while remaining within expected limits. A significant reduction is also observed in departure delays, although rare errors persist. These residual discrepancies may be due to complex situations of the selected case that are difficult to manage in a simulated environment, such as vehicle overlaps that result in delayed insertions, an effect influenced by blind spots during observation.

Table 3: Simulation statistics of the improved scenario

Duration [s]	Loaded veh.	Inserted veh.	Teleports
828.3	2092	2092	0
Total travel time [s]	Total depart delay [s]		Average waiting time [s]
87135.7	9565.1		7.7

B. Detailed vehicle statistics

The analysis of distances travelled by vehicles shows a good alignment between simulated and observed values, with an average deviation of less than 2%. This result demonstrates that the routes were properly identified and reproduced after improvements were made to the input provided to SUMO (accurate lane departure and arrival positions and unforced routing) and the handling of vehicles with non-replicable routes. Regarding travel times, although some degree of variability remains due to the stochastic nature of this measure, there is a good consistency between the simulated and observed time distributions (Figure 7). The improvement is also confirmed by the reduction in the mean deviation, which is less than 35% in this version, compared to the value of more than 100% recorded in the initial configuration before the optimisation of vehicle routing and traffic light calibration. In particular, this improvement can be observed by comparing travel time distributions among vehicles travelling along the main arterial road of the scenario. The simulation now slightly underestimates the travel times but achieves high quality, particularly by comparing values related to cars and filtering observations related to the other vehicle types, such as buses along lines, for which further improvements in the model can be implemented.

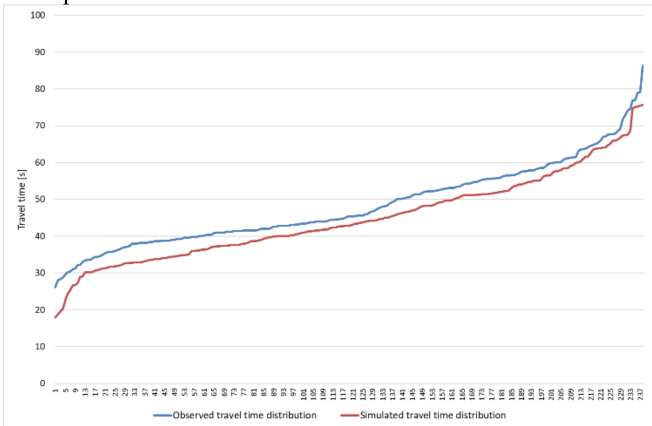

Figure 7: Observed and simulated travel time distributions for car trips in the main arterial road of the network

In summary, the modifications implemented in the preliminary version of the model have achieved a good degree of accuracy, minimising the large discrepancies revealed in preliminary experiments between simulated and observed scenarios. Simulation statistics on travel patterns and travel times confirm the level of consistency reached. Although further refinements can be applied to the scenario to account for additional aspects that would contribute to increasing its realism, the obtained simulation model traffic can be considered an adequate baseline scenario to be used for performing experiments to test and calibrate car-following and lane-changing models in a signalised multilane urban arterial with mixed traffic.

IV. Conclusions

This paper presents and analyses a methodology for building reliable microsimulation traffic scenarios based on real observations of vehicle trajectories. A key aspect of this work was the availability of high-resolution vehicle data and the extraction of a basic road network from open-source maps. Various refinement operations were carried out, impacting traffic assignment procedures and the road network layout to be consistent with reality. A significant example is the identification of traffic light phase durations derived by traffic observation by analysing vehicle trajectories without the availability of the implemented traffic light plans in real life. Moreover, the setting of vehicle parameters to control their interactions in simulation revealed their role in the output statistics. The results obtained after the refining process of the model are consistent with the observation in terms of individual travelled distances and travel time distributions.

Future developments will further improve the model's realism for vehicle interactions. Among the key advancements planned are: the integration of public transport lines because simulated buses are currently modelled as other vehicles; the implementation of a sub-lane model for more detailed management of lateral dynamics, improving the representation of overtaking manoeuvres and vehicle interactions; the refinement of vehicle parameters for enhancing their behaviour, including randomness.

Nevertheless, these further improvements can be applied only if a reliable simulation scenario is available in which vehicle routes, distance, and travel time are consistent with observations. Therefore, the proposed methodology can be considered a first step that can evolve into an even more accurate model after the expected fine-tuning.

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