Towards a Daily Agent-Based Transport System Model for Microscopic Simulation, Based on Peak Hour O-D Matrices

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Abstract. This paper presents the development of a daily, large scale, agent-based microscopic transport simulation integrating diverse data-structures and including the following transport modes: car, bus, bicycle, motorcycle, and pedestrian. The daily simulation is built upon an already calibrated model for the morning peak hour of the city of Bologna, Italy. The transport supply integrates diverse open-source data such as OpenStreetMap (OSM), traffic light schemes and General Transit Feed Specification (GTFS). On the other hand, the transport demand is based on peak-hour Origin-Destination Matrices (ODMs) and uses traffic flow data extracted from detectors throughout the city to scale rush-hour trips accordingly and disperse their departing times over 24 h. The plan choice model is calibrated based on a simple utility function approach allowing to predict the latest city transport mode split. The model successfully distributes departure times of internal and external trips, compatible with absolute daily traffic flow profile from the detectors. A microscopic traffic simulation is executed at a 10% population demand. The validation process is then conducted by comparing the simulated and observed traffic flows at traffic counts by hour. Finally, total daily travel times by mode of individuals are interpreted and compared. The simulation outputs indicate significant differences in total daily travel time by mode. In particular, bus users have the longest travel time followed by cyclists, car drivers, motorcyclists and pedestrians. Therefore, the developed model is able to evaluate impacts of hypothetical scenarios over a day.

Keywords: daily agent-based model · activity-based model · microscopic simulation · multimodal simulation

1 Introduction

Travel demand estimation is a multifaceted challenge in transport planning. This requires accurate data on population, individuals and household demographic information, daily travel patterns, land-use characteristics, employment distribution, and a well-defined

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transport network to build reliable travel demand models and forecasts. Since the 1950s, traditional four-step travel demand models (FSMs) have been a cornerstone of transportation planning. These trip-based models focus on estimation of travel demand between traffic analysis zones (TAZs) based on Origin-Destination Matrices (ODMs) and comprise four steps: trip generation, trip distribution, modal split, and route assignment. The shortcomings of the FSMs have been identified and discussed in different studies [1, 2]. A key limitation of FSM is its inability to capture individual 24 h trip patterns and trip chaining. Furthermore, new on-demand transport modes and traffic management systems cannot be modeled adequately, which severely limits the ability to predict the respective user behavior.

Activity-based models (ABMs) emerged in the 1970s to address the limitations of trip-based models. ABMs offer significant advancements, including the ability to model the location and timeline of trips made by a synthetic population throughout the day. ABMs can capture the sequential linkages of trips and are also highly sensitive to the changes of other factors that impact the daily travel behavior [3]. ABMs work at a disaggregate person-level rather than at an aggregate zone-level, like most trip-based models do [4]. Major challenges to move from a trip-based model to an activity-based model include the longer model runtimes (as each person needs to be simulated), more sophisticated hardware requirements, more and more detailed data requirements, larger efforts to calibrate, lack of experience with activity-based models, and lack of established software packages [3].

Thanks to the development of advanced computer-hardware and the availability of big-data resources, ABM models have been integrated into various traffic simulation packages as reported in [5]. The most popular modeling platforms are designed for microscopic traffic simulation such as SUMO and AIMSUN, while others are designed for mesoscopic simulation such as TRANSIMS, SimMobiity, BEAM CORE and MATSim. These simulation platforms can estimate significant changes of individual activities and trips, in correspondence to changes of the transport supply, such as the introduction of new transport modes.

In our prior work, a large-scale, activity-based, micro-simulation model has been developed, improved and calibrated for the city of Bologna [6–8]. This peak hour model has been built by using the SUMOPy software, which is an advanced simulation suite for SUMO. The demand model is generated by disaggregating the morning peak hour O-D matrix for a wide variety of transport modes including car, bus, bicycle, motorcycle, and pedestrian. The supply model integrates data from diverse open sources and census data such as OpenStreetMap (OSM), General Transit Feed Specification (GTFS), GPS traces, traffic flow detectors, and traffic surveys.

This study aims at developing a large-scale, daily activity-based model for the city of Bologna. The demand generation leverages the existing peak hour ODMs and incorporates traffic flow data extracted from detectors throughout the city. Microscopic traffic simulation will be implemented using SUMOPy to analyze and validate the generated demand patterns and traffic profile. This model is expected to describe increasingly diversified and complex mobility patterns of every single person. Furthermore, it enables the evaluation of different implemented transport policies and the introduction of new transport modes.

The remaining parts of this paper are structured as follows: Sect. 2 reviews relevant existing research; Sect. 3 details the approach and methodology in developing the daily, activity-based microscopic model for the case of Bologna city; Sect. 4 and Sect. 5 present the simulation results and discussion; and Sect. 6 summarizes the conclusions and suggests and future work.

2 Related Work

The temporal dimension of transportation systems plays a crucial role in shaping travel behavior and traffic flow patterns. Traditional transportation models often overlooked the daily cycle, focusing instead on peak periods or average daily patterns. In this context, simulating a daily cycle becomes imperative for a comprehensive understanding of transportation dynamics.

The emergence of large-scale simulation tools and big data has spurred research efforts to refine the modeling of daily activity-based travel demand. These efforts leverage various simulation methodologies, ranging from macroscopic to microscopic scales, implemented by various simulation platforms.

Recent advancements have led to the development of daily activity-based models for entire countries like Switzerland [9] or the Greater Boston Area in the United States [10]. These models leverage mesoscopic agent-based modeling software including SimMobility and MATSim or BEAM CORE to simulate multimodal trips. This capability enables a comprehensive analysis encompassing not only vehicular traffic, but also sustainable transport modes including public transit, cycling, and pedestrian. However, the main limitation of such mesoscopic simulations is the absence of direct vehicle to vehicle interaction in the form of vehicle following algorithms or interactions between pedestrians and vehicles.

The development of large-scale, daily microscopic simulation models remains limited in the scientific literature [11, 12]. It is noteworthy that none of these models incorporate a multimodal approach. The paper of Argota Sánchez-Vaquerizo et al. presents a daily microscopic simulation model of Barcelona but focusing solely on car traffic. Sánchez-Vaquerizo's study shares a similar methodology with the present work, in particular the reconstruction of the daily scenario from a disaggregated peak-hour ODMs uses a similar approach. The difference is that the present study utilizes traffic flow data acquired from induction loops, while the Barcelona scenario uses mobile-phone data to measure traffic intensity over the day.

3 Approach and Methodology

Figure 1 illustrates the methodological framework for developing the daily activity-based model employed in this study, which comprises transport models, key input data, analysis and outputs.

The Bologna metropolitan area, the capital of Emilia-Romagna, a region in northern Italy, is used as a case study. The city covers 3,703 km^2 with 1.02 million inhabitants, whereas the municipality itself covers 141 km^2 with 390,000 inhabitants and 2,769 inhabitants/km^2 in 2022 [13]. The core simulation area in the study is the city of Bologna

and its surrounding towns with a total area of 50 km^2. The road network of the city of Bologna consists predominantly of motorways, major federal roads, provincial roads as well as urban roads, with a higher road density inside the outer ring road.

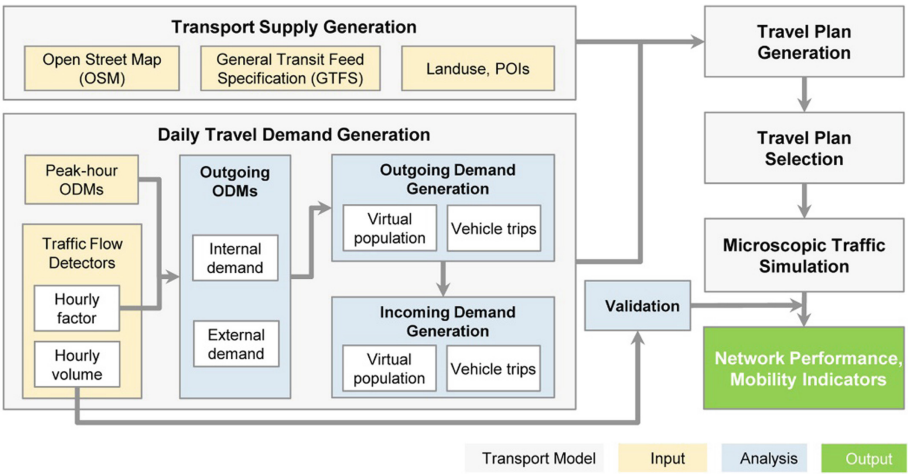


Fig. 1. Framework of developing daily activity-based model

Explanations of the study approach are presented in detail in the corresponding sections.

3.1 Transport Supply Generation

The daily supply model is developed based on the existing peak hour activity-based model [8], which is generated from various open sources and census data. The supply model consists of the road network (i.e. road links, nodes, lanes and associated attributes), the transit network (i.e. routes, stops and timetables) and the land use facilities (i.e. type, location, shape, size).

The road network was imported from OSM [14] - an open-source project that contains most of the transport network attributes, then converted to a SUMO-compatible XML format by means of the SUMO "netconvert" tool [15]. The SUMO-XML file provides a comprehensive geospatial dataset of the road network, including details on road links/edges, lane configuration, speed limits, access rights for various transport modes, lane connectivity, nodes/junctions, traffic lights and on-street parking. The network was then further refined with SUMO's "netedit" tool [16] based on satellite imagery, street-level view from Google Maps and on-site survey to capture the most up-to-date road network configurations. The road network of Bologna incorporates a detailed road network with 32,409 links, 14,724 intersections (including 530 signalized junctions) and 292,900 on-street parking spaces (see Fig. 2). In the micro-simulation network, each vehicle and person's location are uniquely identified by its road link/edge ID and its position along that edge.

The public transport model was developed based on the GTFS database, a common format used to represent all network and service information of a public transport system including routes, stops and stop-level timetables. The GTFS database was imported to SUMOPy by identifying bus stops ID and names on the corresponding edges. SUMOPy's map-matching procedure then identifies bus routes as sequences of these links and service frequency has been associated. Leveraging GTFS data from the open data of Trasporto Passeggeri Emilia Romagna (Tper) [17], the daily Bologna bus services was created. This resulted in a supply model with 234 urban bus lines, all with service times below 20 min.

Land-use facilities were also imported from the XML file, which was initially extracted from OSM, providing detailed information of land use attributes including type, shape and size. In addition, there are geo-referenced information extracted from the OSM data, which specify buildings or amenities, called "Points of interest" (POI). The POI associated with land-use facilities permits the association between the people's activities and facilities in the simulation area.

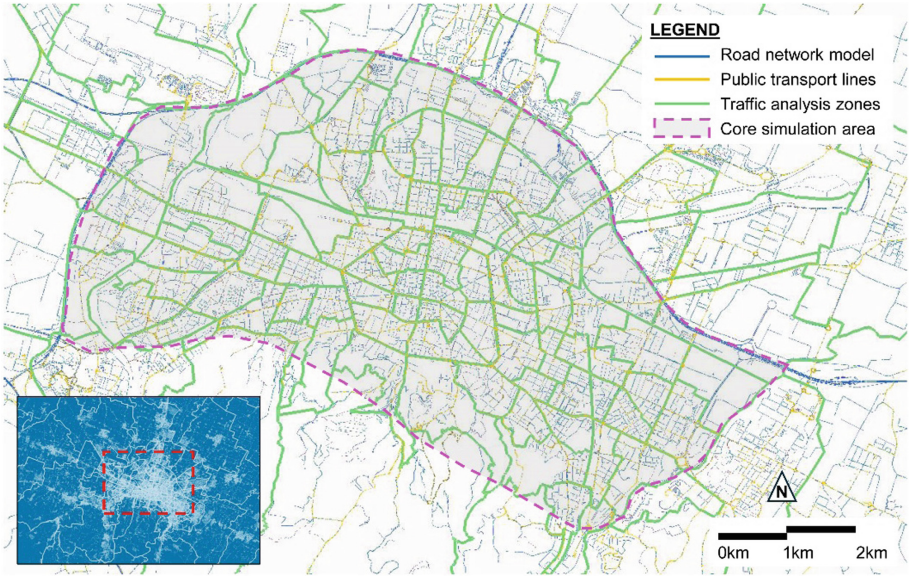


Fig. 2. Map of Bologna road network model and simulation area

3.2 Daily Travel Demand Generation

This section describes how daily travel demand is estimated based on peak hour data. Two key inputs are considered: peak hour ODMs and hourly traffic flows from road-side detectors. In particular, the daily commuting travel demand from 6:00 a.m. to 8:00 p.m. has been generated by disaggregating an updated morning peak hour ODMs (from 7:00 a.m. to 8:00 a.m.) and distributing based on the sum of hourly traffic flows.

The study utilized ODMs for the morning peak hour, obtained from the 14th population census of the city of Bologna [19]. Subsequent updates and disaggregation of these ODMs have been reported in [7, 8]. However, for computational reasons, the entire demand has been scaled down to 10%. In brief, the overall transport demand is composed of external trips (entering, leaving or crossing the study area) and internal travel demand originating and ending within the Bologna core area. The external demand is modeled by vehicular trips while internal demand is represented for active population within the study area.

Daily traffic volume profiles and hourly traffic volume factors within the study area were estimated based on 712 traffic flow detectors from traffic lights distributed across the city [18], as shown in Fig. 3a. The flow detectors measured daily traffic volumes by hour of cars, buses and trucks. The demand profile from traffic counts is computed by simply summing up the traffic counts of all detectors for each hour. Figure 3b shows the daily profile as the accumulated hourly traffic volumes measured by 712 traffic flow detectors on the working days in October 2022. The accumulated daily traffic vehicles passing through all the identified detectors are around 5.76 million vehicles per 24 h. In which, traffic volumes in morning (8:00 a.m. to 9:00 a.m.) and afternoon (5:00 p.m. to 6:00 p.m.) peak hours occupied 7.70% and 7.46%, respectively. The detector flows were further used in the validation process (see Sect. 4).

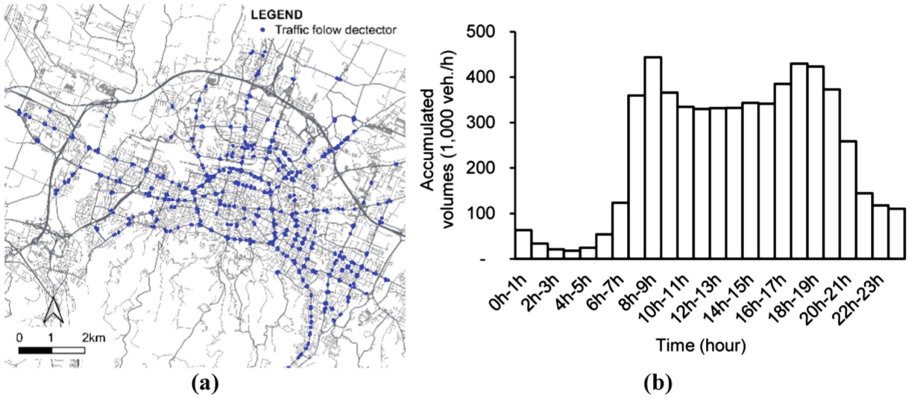


Fig. 3. The distribution of 712 flow measurement detectors in Bologna (a) and accumulated traffic volumes profile (b)

The 10% ODMs have been scaled by a factor equal to 6.37 – the hourly volume factor obtained from the daily traffic profile as shown in Fig. 3b, to generate the outgoing commuting demand during morning hours (i.e. home-to-work trips), matching the absolute traffic flow measured from traffic detectors up to 1:00 p.m. From each destination, an equivalent number of return trips has then been generated as evening incoming demand (i.e. work-to-home trips). This resulted in a replication of daily travel itineraries characterized by the home-work-home sequence as indicated in Fig. 4.

Successively, the outgoing and incoming trips departure times have been adjusted to reproduce the hourly demand profile extracted by the sum of traffic counts. In particular,

we distributed departure times of the outgoing trips in the morning hours and incoming trips in the evening hours over the two respective, intersecting time intervals: the interval for the outgoing traffic has been fixed between 6:00 a.m. and 1:00 p.m., while the interval for the incoming traffic has been set between 10:00 a.m. and 8:00 p.m. The distribution of the number of trips departing during each hour for both intervals has been to match the distribution of the sum of detector flows.

In this way, the observed hourly flow profile is used to define the departure times to outgoing and incoming trips, for both, the trips linked to the internal and external transport demand.

Finally, to account for travel time of vehicles from origins to the traffic detectors, an estimated delay factor of 20 min for internal trips and 30 min for external trips was subtracted from all departure times to approximate the time vehicles required to reach the detectors which are predominantly located in central parts of the city.

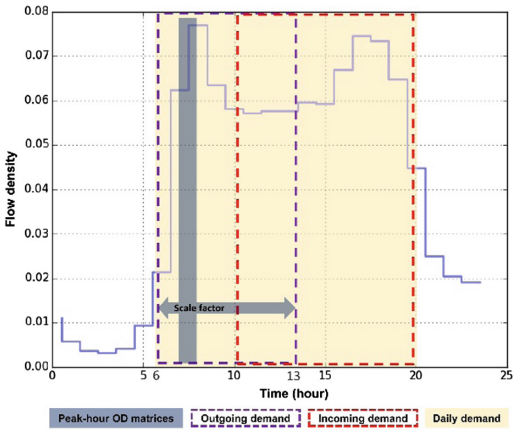


Fig. 4. Distribution of daily travel demand based on peak-hour OD matrix and detected traffic flow profile.

3.3 Travel Plan Generation

Once the departure times have been fixed, travel plans are generated for the internal synthetic population for different transport mode alternatives, based on vehicle availability. A plan is a sequence of elementary movements (e.g. walking, riding) to perform a door-to-door transfer between the location of two successive activities. The transport mode originally specified by the ODMs is initially kept as a "preferred" mode. During a plan choice calibration (see Sect. 3.4) agents can eventually change mode if a different mode will result in shorter (simulated) trips times or higher utilities with respect to the initial mode choice.

As a result of this initial demand generation, the down-scaled internal demand consists of 79,382 persons, which represents 10% of the active city population. In which, 205,500 plans were generated for 79,382 people, consisting of 18.52% car plans, 25.31%

bus plans, 11.53% bicycle plans, 6.01% motorbike plans and 38.63% walking plans. Note that plans are door-to-door and might involve multi-modality; for example, a bus or car user may also walk to a public transport stop or access a parked car before riding it. However, each plan has a dominant mode, so that plan choice and mode choice are interchangeable in the present context.

The down-scaled external demand is generated including 15,373 car and 1,075 motorcycle trips between the urban and extra-urban areas, as well as between extra-urban areas passing through the core city area. These trips are modeled by a simple disaggregation of the relevant mode's OD matrix, with the distribution of edges within the zone of origin and destination determined by their length.

3.4 Travel Plan Selection

The mode choice model employed in this study seeks to accurately estimate mode shares as door-to-door timeframes become known as simulation result. The model assumes that a person's activity locations remain constant for the present calibration, except for travel times, which change depending on the mode choice. A maximum utility model has been used, with each mode's utility consisting of a mode-specific attribute and a time-dependent component, as summarized below:

$$U_{s,i} = \alpha_s - \beta \mathrm{T}_{s,i} \tag{1}$$

where: $U_{s,i}$ is the utility function of mode s for single person i; α_s is utility constant using mode s; $\mathrm{T}_{s,i}$ is the door-to-door travel time using mode s of person i; and β is a value of time (VoT) for all people and modes.

The plan choice model is calibrated to reflect the latest mode share statistics of the city as reported in [13]. The calibration approach developed in [8] is utilized. In short, the calibration process involves two steps. In the first step, the travel times for all feasible mobility strategies for each individual are determined (either estimated free-flow travel times or executed travel times). This allows individuals to select feasible plans based on the utility function. In the second step, the model is iteratively calibrated to maintain the observed mode shares by swapping the selection of feasible mobility plans for each person. The utility parameters are then determined to minimize the difference between modeled and observed mode shares. Consequently, the utility function parameters are determined as presented in Table 1. The β value of 0.002 €/second has been used, based on relevant studies in Italy [20, 21].

Table 1. Parameters of the utility function to calibrate mode share model.

No	Mode	Car	Bicycle	Bus	Walking	Motorcycle
1	Utility constants α_s	0	−0.2604	1.855	2.016	−0.0761
2	Observed mode shares	35.60%	6.90%	25.60%	21.30%	10.60%
3	Calibrated mode shares	36.81%	6.70%	25.59%	20.41%	10.49%

3.5 Microscopic Traffic Simulation

The study uses the microscopic simulation suite SUMOPy/SUMO, basically the ones described in [8], which is able to track movements and interactions of every individual vehicle and person from origin to destination in desired time steps. The microscopic simulation models vehicle movements by considering factors like the vehicle speed, distance to the leader and desired speed to determine acceleration or deceleration as well as how vehicles interact with pedestrians at designated crossing points or shared areas. Given the low demand in the 10% population micro-simulation scenario, the shortest time routing approach was used to determine vehicle routes for all modes except buses, which have their fixed routes. In specific, the route of each vehicle and person is stochastically pre-determined before simulation by assigning shortest travel time with some randomness in the free-flow edge travel times.

4 Simulation Results

In this study, due to computational reasons, only 10% of the total demand has been simulated with an internal demand of 79,382 people and 6,448 external vehicles. During one microsimulation run in the relevant period from 6:00 a.m. to 8:00 p.m, the entire daily plan of each individual is simulated. One simulation run took approximately 12 h on a single core Intel i7 processor.

Figure 5 illustrates the successful distribution of departure times prior to simulation execution for the external trips and internal trips as modeled by virtual population compared to the accumulated traffic flow data collected from 712 actual detectors across the city. The values were normalized to constitute a consistent probability distribution. Travel demand exhibited a bimodal distribution, with peaks concentrated during the morning commute (7:00 a.m. to 10:00 a.m.) and the afternoon commute (4:00 p.m. to 8:00 p.m). These peak periods accounted for approximately 6% to 8% of the total daily demand. In contrast, the afternoon off-peak hours (10:00 a.m. to 4:00 p.m.) experienced a lower demand, ranging from 5% to 6% of the daily demand. Travel demand was lowest before the morning commute (prior to 7:00 a.m.) and after the evening commute (after 8:00 p.m.), constituting less than 5% of the total daily demand.

The validation procedure is carried out by comparing the simulated and observed hourly traffic flows across 712 network edges, in correspondence with the physical flow-detector locations. A linear regression is performed for hourly time intervals throughout

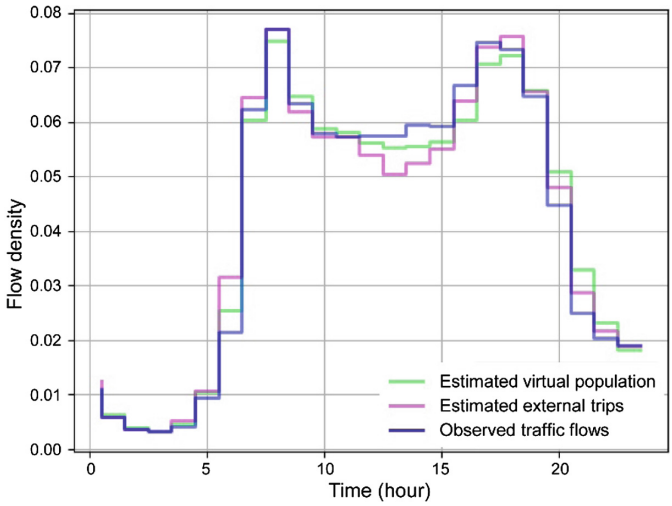


Fig. 5. Distribution of estimated external trips and virtual population departure time in comparison with detected flows over time.

the day. Table 2 illustrates the results of the regression analysis, while Fig. 6 shows the linear regression diagrams of different periods in a day. The results indicated that the slope (m) ranges from 0.082 to 0.129 and the intercept has relatively low values varying between 19 and 33 vehicles per hour. The variance between simulated and detected flows is relatively large, with typical values of R^2 between 0.28 and 0.35. An exception is the transition intervals at the beginning and end of the simulation period, with R^2 values below 0.2.

Table 2. Linear regression indicators of the simulated and observed traffic flows by hour.

No.	Time	Slope	Intercept	R^2
1	6:00–7:00	0.0904	23.788	0.1950
2	7:00–8:00	0.1165	32.471	0.3236
3	8:00–9:00	0.1268	30.073	0.3378
4	9:00–10:00	0.1283	26.265	0.3344
5	10:00–11:00	0.1260	25.607	0.3347
6	11:00–12:00	0.1169	26.233	0.3128
7	12:00–13:00	0.0940	19.161	0.3526
8	13:00–14:00	0.1022	22.602	0.3085
9	14:00–15:00	0.1116	25.380	0.3051
10	15:00–16:00	0.1297	25.839	0.2937
11	16:00–17:00	0.1105	23.927	0.2879
12	17:00–18:00	0.0901	24.419	0.3350
13	18:00–19:00	0.0959	23.324	0.2803
14	19:00–20:00	0.0822	21.607	0.3280

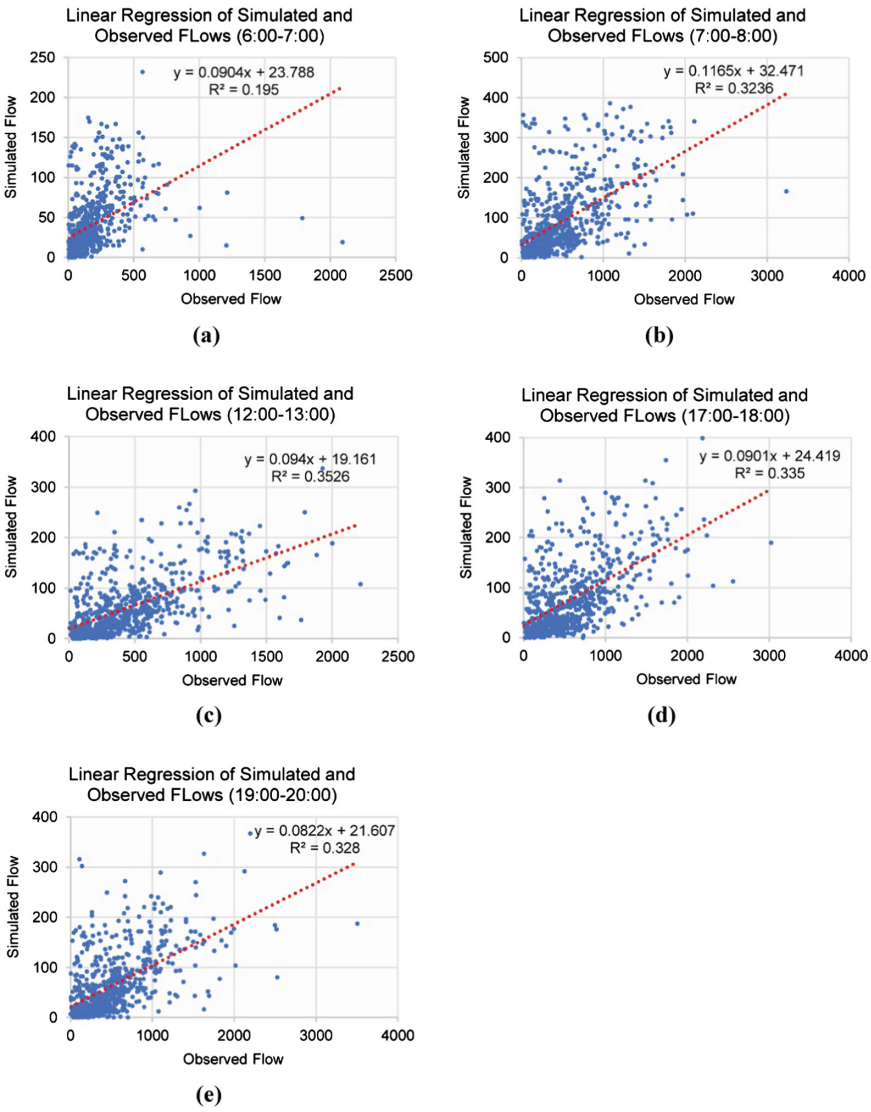


Fig. 6. The regression diagrams show the simulated traffic flow compared to the observed flow (vehicle/h) in early morning (a), morning peak (b), afternoon off-peak (c), afternoon peak (d) and early evening (e)

The door-to-door travel times of individuals in the simulated area were then compared. Table 3 presents the total finished trips associated with the mean, median and standard deviation of daily travel time of individuals by mode, while Fig. 7 shows the distribution of total travel times in interquartile ranges (IQRs). A total of 47,972 population trips were completed within the micro-simulation timeframe, representing a completion rate of 60% among the simulated population of 79,382 individuals.

Table 3. Number of simulated trips and total daily travel time by modes of individual in the daily simulation model

No.	Mode	Simulated trips (trip)	Mean (min/trip)	Median (min/trip)	Std. Deviation
1	Bus	7,342	70.4	67.5	27.7
2	Bicycle	3,295	51.5	44.5	27.6
3	Car	21,234	35.1	31.6	18.8
4	Motorcycle	5,254	20.5	19.5	8.2
5	Walking	10,847	12.9	4.9	16.6

It is noteworthy that the differences in total daily travel time of individuals by transport mode were significant. The simulation results showed that bus users have the longest travel time (mean: 70.4, IQR: 49.6–87.6 min/trip), followed by cyclists (mean: 51.5, IQR: 30.8–64.5 min/trip), car drivers (mean: 35.1, IQR: 24.1–40.9 min/trip), motorcyclists (mean: 20.5, IQR: 14.6–25.3 min/trip) and pedestrians (mean: 12.9, IQR: 2.5–17.9 min/trip).

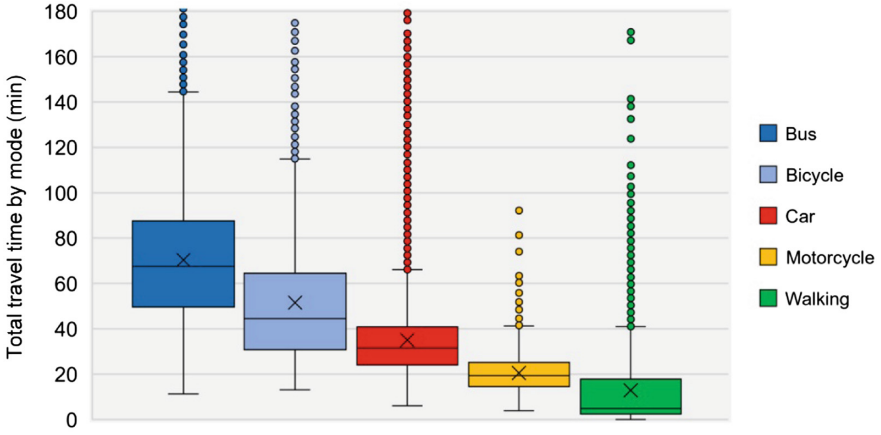


Fig. 7. The door-to-door travel time by modes of individuals in core simulation area

5 Discussion

The rich database leveraged from OSM and GTFS enables the generation of digital twins of the transport supply models. This is the foundation for building activity-based, agent-based transportation models. In particular, the combination of peak-hour ODMs and traffic flows from detectors has been used to determine the departure times over one day for both external trips and internal trips (e.g. the virtual population). This approach

ensures that the distribution of departure times align with the city's daily traffic-flow profile. A plan choice model has been calibrated, which successfully reproduces the latest city modal split of the city of Bologna [13], thus providing a baseline for further analysis.

The model has been built and validated with only 10% of the city population demand. Literature suggests acceptable slope (m) values between 0.9 and 1.1 for a 100% demand scenario [22], which would translate into a range from 0.09 to 0.11 for a 10% demand. With these considerations, the found range shows plausible results, even though not entirely in the suggested interval.

The values of R^2 are expected to be low, as there is a systematic difference between the 100% demand and the 10% simulated demand, which increases the squared residuals in the R^2 function. Furthermore, the simulated network is almost uncongested, meaning that the vehicle's route choices correspond typically to the fastest route – which is in stark contrast with the real, congested network where edge travel times are increased and traffic flows are closer to a state of a user-equilibrium, especially during rush hours.

It is expected that the R^2 will improve considerably as the simulated demand approaches 100%. However, the simulation times for such a full-scale scenario are currently unacceptably long. Moreover, simulation time increases disproportionately when congestion occurs more frequently and the vehicle following algorithm needs to be executed more often for an increased number of vehicle-to-vehicle interactions.

SUMO is currently limited to a single core and several threats can be configured. However, in this case, the simulation has been unstable until recently. In any case, the computation time of the microsimulation should improve by an order of magnitude in order to be able to simulate daily multi-modal scenarios of large-scale urban areas. One possibility is the parallelization of the simulation kernel while using Graphical Processor Units (GPU), as demonstrated in [23].

The developed microscopic traffic simulation offers a significant advantage over classical, macroscopic traffic assignment methods because it outputs door-to-door travel times for various transportation modes, encompassing active mobility. This capability of accurately simulating daily door-to-door travel times facilitates the evaluation of the impacts of diverse transportation policy scenarios as well as the feasibility for individuals to make use of new, hypothetical transport modes.

6 Conclusion and Future Work

The present research addresses the current research gap in developing a daily, agent-based microscopic transport simulation for multiple transport modes including car, bus, bicycle, motorcycle and pedestrian. The daily macroscopic traffic simulation has been built upon an already calibrated model for the morning peak hour of the city of Bologna, Italy.

The model, based on the open-source micro simulator SUMO, incorporates transport supply, which has been created from various open-source data. OSM has been used to build the initial attribute-rich road network including traffic light schemes. The public transit services, including stops and timetables, have been built from the open access GTFS data of the local bus operator.

The daily transport demand has been generated based on peak hour ODMs and traffic flow data extracted from detectors located throughout the city to scale up and disperse their departing times. The disaggregated ODMs are used to generate a synthetic population and to determine the origins and destination of external trips. The daily trips are classified as outgoing trips (i.e. home-to-work as represented by the peak ODMs) and incoming trips (i.e. work-to-home as represented by the transposed ODMs) to represent the chained daily commuting patterns as home-work-home sequence. An estimated delay factor, subtracted from all departure times, for both internal and external trips has been applied to account for travel time of vehicles from origins to the traffic detectors. The model successfully distributed departure times of the synthetic population and external trips, compatible with absolute daily traffic flow profile from the detectors.

Travel plans for the internal synthetic population have been generated based on vehicle availability. The plan choice model has been calibrated based on a simple utility function approach, able to predict the latest city transport mode split. A microscopic traffic simulation has been executed at a 10% demand level. The validation process has been carried out by comparing the simulated and observed traffic flows from traffic counters on an hourly basis. The slope of the respective linear regression is between 0.082 to 0.129, which has been found reasonable for a 10% demand level. The R^2 values are generally low (between 0.28 and 0.35) because of the lower demand level and the absence of congestion effect of the simulated scenario. A simulation model of 100% travel demand expects to significantly improve these indicators. However, the simulation times for such a full-scale scenario are relatively high.

In order to use the microsimulation model also for congestion-sensitive applications, it is necessary to attempt to approach 100% demand levels. But at high demand levels, the computation time would become very high, even though multithreading will be possible with SUMO to a certain extent. However, another interesting development would be a complete parallelization, using hundreds or thousands of processors on a graphical processing unit.

Finally, the outputs of the model enabled to measure the door-to-door travel times for various transportation modes including active mobility. Total daily travel times of individuals are interpreted and compared for each transport mode. The simulation outputs indicate significant differences in total daily travel time by mode. In particular, bus users have the longest travel time followed by cyclists, car drivers, motorcyclists and pedestrians.

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