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Multi-Agent Multimodal Transportation Simulation for Mega-cities: Application of Los Angeles

Brian Yueshuai He[a]*, Qinhua Jiang[a], Haoxuan, Ma[a], Jiaqi Ma[a]

[a]*Department of Civil and Environmental Engineering, University of California Los Angeles, Los Angeles California 90095, USA*

Abstract

This paper presents a comprehensive modeling framework for large-scale agent-based multimodal transportation simulation tailored to the complex urban environments of megacities, with a specific focus on the Greater Los Angeles (LA) area. The framework leverages the Multi-Agent Transport Simulation (MATSim) toolkit, which addresses the evolving challenges posed by urbanization and technology-driven shifts in human mobility patterns. The framework enables the generation of explicit travel trajectories for a representative 10% sample population of LA County, comprising over one million individuals. To ensure the model's validity, an efficient network calibration algorithm is proposed with rigorous validation using publicly available traffic count data. This paper underscores the development and configuration of the agent-based simulation model for LA, providing a robust foundation for large-scale urban mobility simulations and advancing our understanding of the intricacies of megacities.

Keywords: Multi-Agent Simulation; Multimodal Transport; Network Calibration; Mega-cities; Los Angeles.

1. Introduction

In light of technology development and economic growth, urbanization is expected to intensify, leading to greater urban population densities [1]. This trend poses increasingly complex challenges for decision-makers and governments

* Corresponding author. Tel.: +1-929-288-2794.
E-mail address: yueshuaihe@ucla.edu

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in terms of urban management and planning. Notably, the dynamics of human mobility have undergone profound transformations in recent years, driven by technological evolution. These shifts encompass the emergence of shared mobility services in the early 2010s [2], the proliferation of micro-mobility services in the mid-2010s [3], and the widespread adoption of electric vehicles (EV) around 2020 [4]. Consequently, understanding “what is happening” and predicting “what will happen” in the context of dense urban areas have assumed paramount importance for decision-makers [5]. In addressing these multifaceted challenges, computational simulation emerges as an innovative and indispensable approach, enabled by the remarkable advancements in computational power. The development of a meticulously calibrated simulation model tailored to the intricacies of megacities offers the potential to function as a virtual testbed. Within this virtual domain, the efficacy of public policies and the impact of novel technologies [6], as well as broader considerations such as accessibility and equity in human mobility, can be rigorously evaluated [7].

A considerable body of research has been devoted to the development of simulation models tailored to the unique complexities of megacities. Within the transportation community, this effort predominantly revolves around two fundamental aspects inherent to transportation systems, namely, travel demand modeling and supply modeling. Travel demand modeling is primarily concerned with elucidating the intricacies of human travel behavior and the concomitant estimation of travel-related patterns. A paradigmatic approach in this domain is the utilization of activity-based models [8-10], which leverage discrete choice models to predict a series of choices pertinent to travel, thus facilitating the formulation of travel demand at the individual level. On the other hand, supply modeling predominantly encompasses traffic assignment, with a specific emphasis on dynamic traffic assignment techniques aimed at simulating the intricate dynamics within the road network. Notable examples include DynaMIT [11] and Dynasmart [12]. In modeling the intricate transportation systems in the context of megacities, a compelling imperative arises to harmoniously integrate both demand and supply models. It is worth noting, however, that certain research endeavors have hitherto relied on the linkage of these two disparate models through the interim file-based information sharing [13]. This approach, while informative, falls short of achieving a comprehensive and seamless integration of demand and supply models.

To address this gap, a prevailing simulation toolkit that integrates demand and supply modeling is the Multi-Agent Transport Simulation (MATSim) [14]. MATSim, an open-source toolkit implemented in Java, adopts a day-to-day iterative adjustment process designed to converge upon the user equilibrium of the transportation system. This iterative scheme captures the nuanced behaviors of individual agents and the intricate interactions among agents within the system. Noteworthy instances of MATSim applications span across global metropolises, including New York City (NYC) [6], Berlin [15], Zurich [16], and Singapore [17]. Notably, these applications extend their purview to encompass larger populations and expansive geographic regions, aligning closely with real-world scenarios. This characteristic renders MATSim a fitting choice for large-scale simulations with heightened realism.

This paper introduces a comprehensive modeling framework tailored to the domain of multimodal transportation simulation within megacities. The framework's efficacy is demonstrated through a compelling case study encompassing the Greater Los Angeles (LA) area (LA County)-LA-Sim model, meticulously validated against publicly available datasets. The key contributions of this paper can be succinctly encapsulated as follows:

- We present a modeling framework primed for large-scale agent-based multimodal transportation simulation, catering to the distinctive complexities of megacities.
- Within this framework, we developed the LA-Sim model for a representative 10% sample population of LA County, equating to more than one million individuals.
- The simulation outcomes are rigorously validated against open-source traffic count data, maintaining an acceptable accuracy at the aggregated level.

The rest of the paper is organized as follows. Section 2 introduces the requisite data crucial for the development of the simulation model. Section 3 elaborates on the simulation model's specification, calibration methodology, and the validation results obtained. Finally, Section 4 offers a concise summary of the paper's findings and delineates potential avenues for future research in this domain.

2. Data

In this section, we introduce the requisite datasets for both constructing and calibrating the multimodal simulation model, following by an overview of the data processing tools and packages employed in our study.

2.1. Initial Demand

The travel demand data for Los Angeles County was sourced from the Southern California Association of Governments Activity-Based Model (SCAG ABM) [18]. SCAG, among the most prominent Metropolitan Planning Organizations in the United States, covers six counties in California and encompasses a population exceeding 19 million. We filtered out daily trips for LA residents for this study. Additionally, we aggregated the origin/destinations out of LA County to the nearest zones on the boundary, so that we don't need to simulate the movement of agents outside the area of interest.

2.2. Truck Demand

The truck demand is a unique component of the LA model, since the Port of Long Beach is located in LA, which is the major gateway for US-Asia trade. The truck demand of the LA model is also derived from the SCAG ABM [18]. Three types of trucks are incorporated: light-heavy (8,500 to 14,000 lbs. gross vehicle weight (GVW); medium-heavy (14,001 to 33,000 lbs. GVW); and heavy-heavy (>33,000 lbs. GVW). Each truck is regarded as 3.5 equivalent passenger cars in the simulation [19], considering the impacts of congestion in the traffic flow. The travel demand is estimated in five time periods: morning (6-9AM), mid-day (9AM-3PM), afternoon (3-7PM), evening (7-9PM), and nighttime (9 PM-7AM). Within each time period, the truck demand is uniformly distributed as an individual truck trip.

2.3. Multimodal Network

The multimodal network integrates a road network and a public transit network. The road network was constructed using OpenStreetMap (OSM) data. We employed the open-source Java-based network editing tool, JOSM [20], to procure the OSM road network data for LA County, subsequently converting it into a MATSim format. We maintained the default link attributes identical to those in the original OSM network.

The establishment of our public transit network relied on data sourced from the General Transit Feed Specification (GTFS) [21]. Specifically, we opted for historical GTFS data from September 2016. While MATSim possesses the capability to model shared right-of-way transit modes sharing the same network links with private vehicles, our practical experience indicates that this approach considerably escalates computational expenses. Consequently, we took an alternative approach by treating transit and private vehicle usage as distinct network links. The transit schedule encompasses stop locations, route details, and corresponding timetables for each transit line. We harnessed the pt2matsim extension of MATSim to generate the multimodal network, as depicting in Fig. 1.

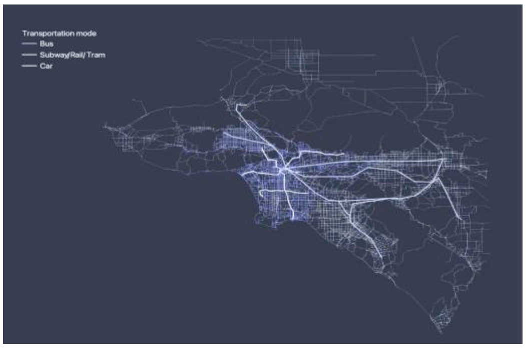

Fig. 1. Multimodal Network of LA County.

2.4. Traffic Count

Traffic count data was adopted to calibrate the simulation model. We used historical traffic count data from the Performance Measurement System (PeMS) maintained by Caltrans [22]. The top 10 freeways with highest Annual Average Daily Traffic (AADT) were selected as benchmark and the top 10 traffic count stations were selected from each freeway. We used the average hourly volume in September 2016 as the reference.

3. Model Specification and Calibration

In this section, we commence by introducing the model specifications for our multimodal simulation. Subsequently, we delve into the intricacies of our model calibration methodology and present the validation results.

3.1. Modeling Framework

The modeling framework, depicted in Fig. 2, operates as follows: starting with the data introduced in Section 2 as model input, the iterative day-to-day adjustment process for equilibrium searching unfolds on the right side of the diagram. Initially, individual travel demands are executed within the multimodal network (as the Mobility Simulation Module). Within this module, agents possess the autonomy to make multimodal choices.

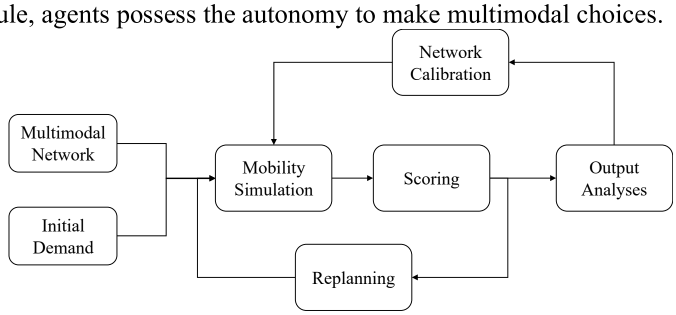

Fig. 2. Framework of Multimodal Transportation Simulation for Mega-Cities.

The quality of daily travel plans is assessed via a comprehensive scoring system, integrated within MATSim [23]. This system factors in the utility associated with conducting activities (typically positive) and travel (typically negative). Parameter values for this scoring system are derived from the SCAG ABM [18], with default values from MATSim serving as a viable alternative in the absence of a suitable reference.

Throughout the simulation, agents retain the flexibility to adjust their travel plans across multiple dimensions, facilitated by the Replanning Module. These dimensions encompass mode choice, route selection, and departure time preferences, all informed by their experiences from previous iterations. MATSim employs a co-evolutionary algorithm to search for equilibrium, employing plan scores as the optimization objective and treating replanning as the mutation operation. Agents are able to change their plans from iteration to iteration until the scores converge after certain iterations. Convergence is inherently challenging to define precisely due to the complexity of the simulation problem. Common practice involves conducting a substantial number of iterations (e.g., 100 or 150) to approach equilibrium.

3.2. Network Calibration

Consider the scale of LA County (10 million population in 2016), it would be reasonable to develop a simulation model for a sample of the whole population. It is a typical practice for large-scale simulation, as Berlin [15], Zurich [16], simulated 10% samples of the population. In this paper, we simulated 10% sample of the LA County population (around one million agents), which is one of the largest simulation models in practice.

To simulate the travel behaviors of 10% population, the capacity of the road network needs to be calibrated accordingly. However, such a relationship is not linear [6]. For instance, simulate the traffic of 10% population with a 10% capacity road network wouldn't have a realistic traffic status. Further calibration is necessary to capture such a non-linear relationship and impacts on road capacities from other factors, such as traffic signals, tourist trips. In this paper, considering the complexity of road network and scale of the population, an iterative proportional adjustment method was proposed to calibrate the road network. The objective of the calibration is defined in Eq. (1).

$$\min_{\theta} f(\theta) = \sum_{i=1}^{I} \sum_{j=1}^{J} \left(y_{ij}^{sim} - y_{ij}^{obs}\right)^2 \tag{1}$$

where θ is a parameter set to be calibrated for freeway links, which includes link speed and capacity factors, y_{ij}^{sim} and y_{ij}^{obs} represent simulated and observed volumes for traffic count station j in time period i. The link speed per hour is calibrated to the average hourly speed from PeMS [22]. The capacity adjustment factor is calibrated by Algorithm 1.

Algorithm 1: link capacity factor calibration

Input: link capacity factor set θ^c
Output: calibrated link capacity factor set $\hat{\theta}^c$
Initialization: set every element in θ^c to be 0.8 as θ_k^c;
for $k \in K$ do:
  launch simulation with θ_k^c and calculate the y_{ij}^{sim}
  compute $f(\theta)$ according to Eq. (1)
  if $f(\theta) < threshold$
    stop calibration and output θ_k^c
  else
    update θ_k^c according to Eqs. (2) – (3)
  end
end

$$\theta_{i,k}^{c} = \frac{\sum_{j=1}^{J} y_{ij,k-1}^{sim} * 10}{\sum_{j=1}^{J} y_{ij,k-1}^{obs}} \tag{2}$$

$$c_{i,k} = c_{i,k-1} * f_{i,k} \tag{3}$$

where $\theta_{i,k}^c$ is the capacity factor in time period i in the calibration iteration k, $y_{ij,k-1}^{sim}$ and $y_{ij,k-1}^{obs}$ stand for the simulated and observed traffic volumes in time period i for count station j in the calibration iteration k. $c_{i,k}$ is the freeway link capacity in time period i in calibration iteration k.

3.3. Model Validation

The simulation model was set up on a Dell workstation with Intel(R) Xeon(R) Gold 6240R CPU @ 2.40GHz 2.39 GHz (2 processors) and 512 GB memory. Each MATSim run is set as 100 iterations to reach the equilibrium. The computation time for each run is about 94 hours. After 6 iterations of calibration, the comparison of aggregated results between simulation and observations is shown in Fig. 3 (a) and comparison across calibration iterations is presented in Fig. 3 (b). We can find that the simulated volumes match the real traffic volumes very well at the aggregated level among all period, which is acceptable comparing to other simulation models in practice [6]. After 6 iterations of calibration, we found that the relative differences between simulated and observed volumes in four time periods are below 5%, which is a reasonable performance for large-scale simulation models. The only exception is the Nighttime, however, considering that most of trips happen before 9 PM, such a derivation is acceptable.

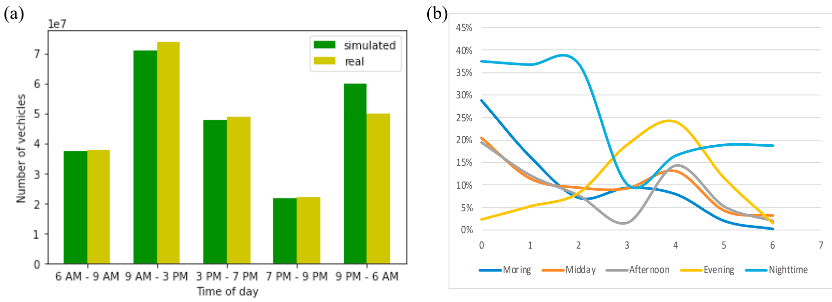

Fig. 3. (a) Comparison of aggregated simulated and real traffic volumes; (b) Relative difference between simulated and observed volumes across calibration iterations.

4. Conclusion

This paper proposes a modeling framework for developing and calibrating multi-agent multimodal transportation simulation models for megacities. We also illustrate the LA-Sim model as a case study of real-world application. The future directions of the proposed modeling framework are in two aspects: model calibration and model extensions. Next step would be incorporating a spatial-temporal capacity adjustment factors to further improve the model performance. For the model extensions, MATSim integrated many additional features from the open-source community. One potential direction could be incorporating the traffic signals into the road network so that the output can present more realistic travel trajectories.

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