Large-scale Agent-based Multi-modal Modeling of Transportation Networks
System Model and Preliminary Results

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Abstract: The performance of urban transportation systems can be improved if travelers make better-informed decisions using advanced modeling techniques. However, modeling city-level transportation systems is challenging not only because of the network scale but also because they encompass multiple transportation modes. This paper introduces a novel simulation framework that efficiently supports large-scale agent-based multi-modal transportation system modeling. The proposed framework utilizes both microscopic and mesoscopic modeling techniques to take advantage of the strengths of each modeling approach. In order to increase the model scalability, decrease the complexity and achieve a reasonable simulation speed, the proposed framework utilizes parallel simulation through two partitioning techniques: spatial partitioning by separating the network geographically and vertical partitioning by separating the network by transportation mode for modes that interact minimally. The proposed framework creates multi-modal plans for each trip and tracks the travelers trips on a second-by-second basis across the different modes. We instantiate this framework in a system model of Los Angeles (LA) supporting our study of the impact on transportation decisions over a 5 hour period of the morning commute (7am-12pm). The results show that by modifying travel choices of only 10% of the trips a significant reduction in traffic congestion is achievable that results in better traffic flow and lower travel times.

1 INTRODUCTION

The performance of transportation systems is a critical factor that affects the human standard of life. The environmental impact of the transportation sector has major effects on human health (Levy et al., 2010). Traffic congestion not only increases fuel consumption and emission levels, but also wastes traveler times. Moreover, the congestion experienced by travelers increases the stress and affects the individual social interactions (Boniface et al., 2015). As a result of all these economic, social, psychological and health impacts, the academic community has devoted significant research efforts to improving transportation system performance. While the majority of these studies use simulation (Osorio and Selvam, 2015), (Zehe et al., 2015), (Zhang et al., 2017), there are significant modeling challenges including scaling, calibrating, and validation issues that impact the accuracy of the results. In this paper, we present a novel agent-based framework for modeling of large-scale transportation systems. The presented framework supports city-level networks with different modes of transportation (cars, buses, railways, walking, biking, and carpooling). The proposed framework utilizes both microscopic and mesoscopic simulation to leverage their respective strengths of accuracy and scalability. The framework spatially partitions the network enabling distinct portions of the region to micro-simulated in parallel, and vertically partitions the network into layers represented loosely interacting modes. In this way, we can utilize the available processing resources either using single or multiple machines. The framework is capable of tracking individual travelers on a second-by-second basis from their origin to their destination across transportation modes. To the best of our knowledge, the proposed framework is the first tool that supports an agent-based city-level transportation system, combining both microscopic with mesoscopic simulations, tracking individual travelers and vehicles on a second-by-second basis, and supporting multi-modal mobility. We instantiate this fra-

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mework into a system to study the impact of routing on travel time and fuel consumption in the Greater LA city from 7am to 12pm. In terms of the paper layout, the paper first introduces the related literature. Because of space limitations, the system is described briefly. The section following the literature review provides an overview of the system architecture, components, and the high-level operations. Subsequently, the last two sections demonstrate the case study on the Greater LA network along with preliminary results.

2 PREVIOUS WORK

The benefits of modeling large-scale transportation networks have attracted attention over the last three decades. In 1997, the TRANSIMS simulation tool (Nagel et al., 1996) was used to simulate the traffic in large areas for traffic planning purposes. The research work in (Nagel et al., 1996) uses discrete space modeling for the traffic micro-simulation based on the cellular automaton approach (White and Engelen, 1993), where the road is separated into cells (of length 7.5 meters) which are either empty or occupied by one car. It uses a simple algorithms for car following and lane changing. The use of cellular automaton makes this system fast, however, it cannot accurately capture observed transportation phenomena including car following, lane changing, and gap acceptance. In 2002, TRANSIMS was updated to better include the impact of the congestion on the system performance and it was run on a parallel cluster for fifty iterations to achieve better trip planning (Cetin et al., 2002). TRANSIMS has been used to model the Switzerland network in the morning peak hours using parallel computation (Raney et al., 2003), (Balmer et al., 2004). Then, in 2012, TRANSIMS was used in (Zhao and Sadek, 2012) to evaluate the performance of the transportation network of the Buffalo-Niagara metropolitan area during significant snow events. However, the authors mentioned that extensive efforts are required to make the simulated network realistic in terms of network configuration, lane connectivity, pocket lane and signal locations. In (Guo et al., 2013) the same modeler was used to evaluate the impact of dynamic routing on the fuel consumption. Similar to TRANSIMS, our proposed framework supports the parallel computation either on multi-core or even multiple machines. However, in TRANSIMS the definition of the microscopic simulation is limited to the demand, that is, each trip is simulated individually as an agent. But, the links and the mobility of the vehicles on these links are modeled using a parallel queuing approach (Cetin and Nagel, 2002). These queuing models are inaccurate in estimating the link travel time especially in congestion situations such as the LA morning commute. Furthermore, it cannot capture the accelerations/decelerations events of each vehicle that have a significant impact on the fuel consumption and emissions. In contrast to TRANSIMS, the proposed framework uses continuous space model for the micro-simulation, which is the enabler to capture the many of the mobility parameters. A hybrid traffic modeler was presented in (Burghout et al., 2005), (Burghout and Wahlstedt, 2007), (Yang and Morgan, 2006), (Balakrishna et al., 2009) to model large-scale traffic networks. The hybrid modeler simulates different network links with different fidelity levels (microscopic, or mesoscopic levels), where microscopic simulation was applied to areas of specific interest, while simulating a large surrounding network in lesser detail with a mesoscopic model. In this way, it can provide a customized performance and simulation speed. In our proposed system, we also utilize microscopic-mesoscopic hybrid modeling. However, in our proposed model, we do not have this spatial separation between the microscopic and mesoscopic simulations. In the proposed system, links are assigned to the simulator based on their importance in the network In (Ahn et al., 2012), (Ahn and Rakha, 2013), the authors used the INTEGRATION software to fully microscopically model the dynamic routing on the fuel consumption in the downtown Cleveland and Columbus, Ohio, USA, in the case of different system market penetration rates and congestion levels. The network has about 3,000 links with a traffic demand of 65,000 vehicles per hour during the morning peak hour. Our proposed framework uses parallel INTEGRATION instances enabling our system to capture the morning commute of 1.2M vehicles. In 2015, the authors of (Zehe et al., 2015) proposed the Scalable Electro-Mobility Simulation (SEMSim), an architecture for a cloud-based platform, as a proof of concept to use the cloud for simulation of large-scale transportation systems. The authors used this model to simulate the network of Singapore that has about 500,000 private owned vehicle. However, the model uses simple vehicle characteristics (e.g., kinematic model) and driving behavior models. In contrast (Zehe et al., 2015), our proposed framework is based on mature models that have been validated against observed transportation phenomena and supports travel across different transportation modes. Compared to the MATSIM (Balmer et al., 2009), which is considered the state of the art in simulating large-scale transportation system, our proposed model is not only an agent-based simulation. In addition to that, it utilizes a hybrid simulation approach, it is also capable of microscopically simulating all the transportation aspects including demand, mobility, traffic signals, and road network aspects, as will be described in next section 3.

3 THE PROPOSED MODEL

In this paper, we redefine the state-of-the-art of modeling and simulation of large-scale transportation systems by introducing a new framework that is capable of modeling large city level transportation systems. To achieve both the required accuracy and scalability, the proposed model utilizes both microscopic and mesoscopic modeling techniques. The microscopic simulation defined in this paper includes all the aspects of simulation: demand, mobility, and network. From the demand perspective, our framework models each individual vehicle as an agent in the network that interacts with other vehicles as well as with the traffic signals and road control signs. It also provides dynamic demand modeling, that is, traffic demand changes throughout the simulation. From the mobility standpoint, the proposed framework tracks every individual vehicle at a time resolution of deci-second (0.1 seconds). These features are gained basically from the microscopic nature of the INTEGRATION traffic simulator (Rakha et al., 2012) utilized in proposed model. Based on this time resolution, it captures all the driving events by using validated models for car following, lane changing and gap acceptance. The model also can simulate different stochastic mobility phenomena such as stochasticity in speed calculation, route selection and driver aggressiveness in acceleration/deceleration events. From the network standpoint, many network topological details such as link control methods (stop sign, yield sign, and traffic signals), lane striping, lane prohibition, and high occupancy vehicles (HOV) lanes were modeled in this framework. To the best of our knowledge, none of the current traffic simulators support all these features for large-scale networks. The proposed framework also incorporates other simulators for the modeling of the railway, pedestrian and biking travel modes in addition to buses and carpooling. However, the details of these simulators are beyond the scope of this paper, but will be described in more detail in separate papers. An important advantage of the proposed framework is its ability to track each trip on a second-by-second basis across different modes. Because of the computational cost required for the above-mentioned simulations, the proposed framework uses two partitioning techniques: vertical and spatial. Vertical partitioning combines mesoscopic and microscopic road vehicle simulation along with mode specific simulations for walking, biking, and trains. Spatial partitioning divides the microscopic network into smaller geographic regions. A simulation controller divides each trip into sub-trips to be simulated in different processes and monitors each sub-trip to ensure consistency. Before describing the model, the following subsection gives some definitions that will be used in the model.

3.1 Definitions

Global-network: The global road network includes all the road links in the area of interest. Each link is marked to be in either the micro-network, the meso-network or the train and pedestrian networks.
Meso-network: The meso-network is the connected subset of the links in the global-network that is simulated mesoscopically.
Micro-network: The micro-network is the connected subset of links in the global-network that is simulated microscopically.
Sub-network: A sub-network is a spatial partition of the micro-network. Sub-networks are simulated microscopically using INTEGRATION software.
Zones: Nodes that can act as an origin or destination of the traffic. To have a fully connected network, each zone in the micro-network is mapped to a corresponding zone in the meso-network. However, some zones in the meso-network do not exist in the micro-networks.
Interconnection Zones (IZones): Interconnection zones are correspondences between zones in different networks. For example, for the micro-meso network connectivity, the zones exist in both micro and meso networks are IZones.
Trip: A trip is a travelers planned path from origin zone to destination zone in the global-network. A single trip can go through multiple network layers (multi-modal trips) and/or multiple sub-networks. For example, in the trip shown in Figure 1, a person can drive his/her car on the local road (in meso-network) from his/her home to the main road. Then, he/she continues driving on the main road in the micro-network (where he/she travels through two micro sub-networks). Then he/she parks his/her car and walks (on the pedestrian network layer) to the nearest railway station (rail network) from which he/she takes the train. Then he/she walks again to his/her work.

3.2 Vertical Partitioning

The main roads, the arterial roads and highways are the most influential roadway segments of the city transportation network. These roads can significantly

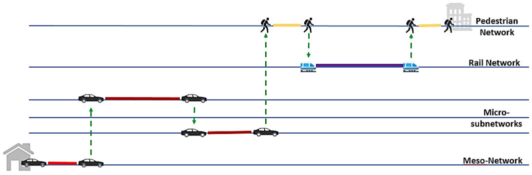


Figure 1: Multimode trip example.

affect the network performance. For example, congestion on a main road can affect thousands of vehicles. On the other hand, the local roads that connect the main roads to residential areas are of low importance because of their low traffic flow rates. However, we cannot totally ignore these local roads because they contribute to the travel time and fuel consumption of the vehicles. In the proposed framework, the critical links (main roads, arterial roads, and highways) are simulated microscopically which gives the highest possible fidelity for this portion of the network. Alternatively, the local roads are modeled mesoscopically to capture their impacts while reducing the modeling and computational requirements. Consequently, the framework has two mandatory layers: the meso-network and the micro-network layers. In addition, the framework supports layers for other transportation modes such as railways and pedestrians. Figure 2 demonstrates the layering concept. A traveler uses more than one transportation mode means moving him/her from one network to another, consequently from one simulator to another. These interactions between different simulators are managed by a simulation controller (SC). Simulations notify the SC when a traveler finishes a sub-trip at an IZone. The SC finds the next sub-trip for this traveler and sends him/her to the appropriate simulator. The IZone must exist in the next network to guarantee the connectivity of the trip.

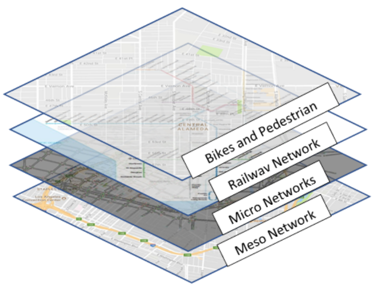


Figure 2: Partitioning the network into different layers.

Based on the scale of the area of interest, the micro-network can be divided into a set of sub-networks. Each sub-network can run individually. In this way, we can utilize the available resources, and increase the simulation speed. There is a trade-off between modeling speed and accuracy. The larger the sub-network size, the slower the simulation speed, but the higher the accuracy of the simulation results. Within a subnetwork, the simulator models impacts between all connected road links (e.g., spilling the vehicles queue back from one link to its upstream link, and the interactions between vehicles in the intersection). Selecting the appropriate sub-network sizes depends on the total network size and the available computational resources.

3.3 Traveler Types

In our framework, there are two types of travelers; background and controlled.

Background Travelers: background travelers create the network traffic conditions in each network, such as congestion levels in the micro-network and meso-networks; and vehicle loading on public transit vehicles, etc. In the micro-network, INTEGRATION tracks every individual traveler (both background and controlled). In the other simulators, the travelers of the background traffic are not tracked individually, instead they are used to estimate the network state (e.g., congestion levels, train loads) in order accurately calculate the travel time and fuel consumption.

Controlled Travelers: Each controlled traveler represents a person traveling from an origin to destination at a particular time. A planner creates a trip for each controlled traveler and the simulation controller ensures the traveler traverses the networks in the appropriate simulators. Each controlled trip is tracked on a second-by-second basis in all the transportation modes. Moreover, the controlled trip can be re-routed or re-planned, while the person is traveling.

3.4 System Architecture and Components

Figure 3 shows the general architecture of the proposed framework. A basic idea is separating the system software components from the hardware components. The communication layer is the enabler to transparently run this system on different infrastructures with minimal configuration changes. The communication layer utilizes the RabbitMQ implementation (Videla A., 2012) of the Advanced Message Queuing Protocol (AMQP) (Fernandes et al., 2013). The execution layer of the system consists of two plans: (1) the planning and simulation plan which is responsible for simulating trips and creating the multimodal routes for the controlled trips (2) the control plan which is responsible for controlling and managing the different system components. The framework has the components shown in in Figure 4. The input data repository

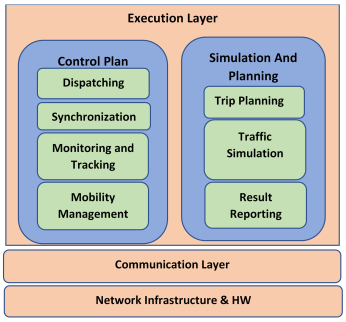


Figure 3: System architecture.

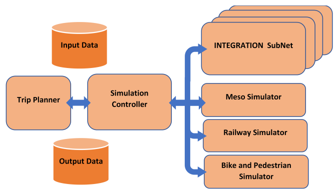


Figure 4: System components.

contains all the required input data to be used by the system components. For example, the road maps for both the meso-network, micro-network and the sub-networks are stored in this database along with the OD inputs that represent the traffic demand, transit schedules, energy models and transit loading. The SC manages the different simulations. When started, each simulation module imports the corresponding input files from the input database then it initializes its environment and starts its internal synchronization procedure that communicates to the SC. Due to space limitation, we will give a brief overview of the operation for only the basic components including micro-simulator, meso-simulator, planner and the SC focused on additions not reported in previous research.

3.5 INTEGRATION and Micro-Models

Micro-simulation using INTEGRATION software is the focus our framework. INTEGRATION is a discrete-time continuous-space trip-based microscopic traffic simulation and optimization model which is capable of modeling networks with thousands of cars. It is characterized by its accuracy that comes from its microscopic nature and its small time granularity. INTEGRATION provides 10 traffic assignment/routing options with a full support of five vehicle classes, each class has its own parameters and routing trees.

3.5.1 INTEGRATION Car Following Model

INTEGRATION updates the vehicle speed and location every decisecond based on a user-specified steady-state speed-spacing relationship along with the speed differential between the subject vehicle and the heading vehicle. INTEGRATION uses the variable power vehicle dynamics model to estimate the vehicle's tractive force. Consequently, it implicitly accounts for gear-shifting on vehicle acceleration, which ensures a realistic estimation of the vehicle acceleration. More specifically, the model computes the vehicle's tractive effort, aerodynamic, rolling, and grade-resistance forces, as described in details in the literature (Rakha et al., 2001), (Rakha and Lucic, 2002). In INTEGRATION, the car-following model computes the speed$u_n(t+t)$ of the following vehicle (n) at the new time step t+t as (Rakha et al., 2012):

$$
\begin{aligned}
u_n(t+\Delta t) = min\Big\{ & u_n(t)+a_n(t)\Delta t\ , \\
& \frac{-c_1+c_3u_f+\bar{S}_n(t+\Delta t)-\sqrt{A}}{2c_3}, \\
& \sqrt{u_{(n-1)}(t+\Delta t)^2+d_{max}(\bar{S}_n(t+\Delta t)-\frac{1}{k_j})}\ \Big\}
\end{aligned}
\tag{1}
$$

where

$$
\begin{aligned}
A = & \big(c_1-c_3\,u_f\,\bar{s}_n(t+\Delta t)\big)^2 \\
& -4c_3\big(\bar{s}_n(t+\Delta t)u_f-c_1\,u_f-c_2\big)
\end{aligned}
\tag{2}
$$

and c_1, c_2, and c_3 are the model constants which are computed as:

$$c_1 = \frac{u_f}{k_j\,u_c^2}(2u_c-u_f) \tag{3}$$

$$c_2 = \frac{u_f}{k_j\,u_c^2}(u_f-u_c)^2 \tag{4}$$

$$c_3 = \frac{1}{q_c}-\frac{u_f}{k_j\,u_c^2} \tag{5}$$

and the vehicle $\bar{s}_n(t+\Delta t)$spacing is computed as:

$$
\begin{aligned}
\bar{s}_n(t+\Delta t) = & x_{(n-1)}(t)-x_n(t)+ \\
& \lfloor u_{(n-1)}(t)-u_n(t)\rfloor\Delta t+0.5a_{(n-1)}(t+\Delta t)\Delta t^2
\end{aligned}
\tag{6}
$$

Here $a_n(t)$ is the acceleration of the vehicle n; u_f is the free-flow speed of the roadway; u_c is the roadway speed-at-capacity; q_c is the roadway capacity; k_j is the roadway jam density; $x_n(t)$ and $x_{(n-1)}(t)$ are the positions of the subject vehicle the lead vehicle at time t; d_{max} is the maximum acceptable deceleration level (m/s^2).

3.5.2 Delay Computation

Within INTEGRATION, the delay D_n^l experienced by the vehicle n is computed for each traveled link l , as the difference between the vehicles simulated travel time and the free flow speed speed travel time for this link (Dion et al., 2004). And the total delay D_n experienced by the subject vehicles is computed as:

$$\begin{aligned} D_n &= \sum_{(l \in \textit{the vehicle path})} D_n^l \\ &= \sum_{(l \in \textit{the vehicle path})} \int_{t_0^l}^{t_1^l} (u_f - \frac{u(t)}{u_f}) dt \end{aligned} \tag{7}$$

where t_0^l and t_1^l are the times at which the vehicle enters and exits the link l respectively.

3.5.3 Fuel Consumption and Emissions

Computing the fuel consumption and emission levels is important to capture the travel costs and environmental effects of transportation decisions. The INTEGRATION software is capable of computing the second-by-second fuel consumed; vehicle emissions of carbon dioxide (CO2); carbon monoxide (CO); hydrocarbons (HC); oxides of nitrogen (NOx); and particulate matter (PM). The micro-simulator uses the VT-Micro model (Rakha et al., 2004) to calculate the second-by-second fuel consumption and emissions for each vehicle in the micro-network.

3.6 Meso-simulator

The meso-simulator is implemented as a discrete event simulation (M.H., 1989). The events represent the instant of reaching a network node through some link, at which moment a new event is generated for the next link and is added to the discrete event queue. The discrete event queue is an ascending sequence of events ordered by the time of their occurrence. The meso-simulator is given paths in the meso-network to be simulated together with the initial start time. The first event for each path then consists of the first node in the path and the start time, while all other events are generated as a consequence of the initial event. In the meso-simulator, each road link has its configuration parameters such as free-flow speed, speed-at-capacity, and jam density. In addition, each road link has state information which includes the number of vehicles on this link, and a queue that has these vehicles. This state information is updated by the events happening on the subject link, such as a vehicle enters the link or a vehicle exits the link. The average speed and travel time for each individual vehicle are calculated based on the current state of the link at the time the vehicle enters that link. The arrival of a vehicle to a given link triggers the meso simulator to calculate its average speed and travel time, subsequently, to schedule another event at the time in which vehicle expected to exit that link. At the exit time, the meso-simulator estimates the fuel consumption of the vehicle on this link and adds it up to the vehicles total fuel consumption.

3.7 Planner

Each controlled traveler has an origin, destination and a travel window. The main task of the planner is the planning of these multi-modal routes for the controlled trip. The planner also is responsible for updating or changing these routes whenever needed. During a window that begins 30 minutes before the earliest possible departure time for the controlled traveler, the planner starts planning the trip by using the up-to-date cost and timing information reported from each individual simulator. It also uses the connectivity information between the different sub-networks and/or layers in order to create the optimal route for the subject trip. The trip can be replanned or rerouted after the trip starts. For example, if the traveler can not catch the train at the scheduled time, or he/she can not board the scheduled bus because the bus is full, the responsible simulator notifies the SC which requests the planner to find an alternative route for the traveler.

3.8 Simulation Controller

The SC is the core component of the model which is responsible for:

- Initializing the simulation,
- Synchronizing the different simulators,
- Moving travelers between layers/sub-networks,
- Tracking the individual controlled trips.

In the initialization process, the SC reads parameters such as the simulation duration and the locations of the input files for each simulation component. Then it reads in the network files, builds the required graphs for the networks, and checks for the appropriate connectivity among the different layers/sub-networks. It also builds a list of all the controlled trips. Then, it starts the different simulators (INTEGRATION, meso-simulator, bike and pedestrian simulator (BPSim), and railway simulator (RailSim)) and waits for all of them to initialize. When a simulator starts, and initializes its own environment, it must send the first synchronization request to the SC and wait for the simulation start messages from the SC. When all the simulators are ready, the SC allows them to start the simulation. During the simulation, all the simulators must be synchronized at pre-specified intervals. This period is defined as the maximum synchronization interval, which is a system-wide variable., its defualt value is 1 second. After this time interval, the simulator can not progress the simulation process until permitted by the SC. When the SC identifies that all the simulators reached the same simulation time, it allows them to run the next interval. During the simulation, the SC receives the state information about each controlled trip or sub-trip from each simulator. Consequently, it can track every individual controlled trip in different networks/layers and is responsible for moving the traveler from one sub-network/layer to another. By doing so, the SC establishes the connectivity between different sub-networks/layers. For example, when a driver finishes his/her sub-trip on the meso-network (say, IZone1) and needs to be moved to the micro network, the meso simulator informs the SC to 1) update the trip information (travel time, fuel consumption, current location, , etc.); 2) pull the trip information from its database and find the destination of the next sub-trip on the micro sub-network (say, Z2); and 3) request the corresponding INTEGRATION instance to start a new sub-trip in its network from IZone1 to Z2 and passes the initial route for this sub-trip ot INTEGRATION. In this case, INTEGRATION may defer the start time of this vehicle if the link to which the vehicle should enter is at jam density.

4 CASE STUDY: LA NETWORK AND PRELIMINARY RESULTS

We use this system to model the overall city of LA in the peak hours. This section describes the network and the preliminary simulation results.

4.1 LA Networks

To build the micro-network and meso-network, we used three different data sources: (1) NavTeq is used for generating nodes and links, (2) OpenStreetMap is used for intersection traffic control information, and (3) Google Maps are used for validating road attributes including the number of lanes, one-way streets, speed limits, bus lane locations, etc. The global-network has 62,984 nodes and 181,840 links, as shown in Figure 5-a. The LA area is divided into five sub-networks shown in Figures 5-b through 5-f. The walking and biking simulators use the meso-network as input. Our system model includes the largest operator of public rail and buses in LA, LA Metro. LA Metro bus service includes 170 lines, 15,967 bus stops, and 854,693 boardings/day. LA Metro rail service includes 6 passenger rail lines, 93 stations, and 359,861 boardings/day. Station level boarding data were provided by LA metro along with specifications of the vehicle fleet.

4.2 Traffic Calibration

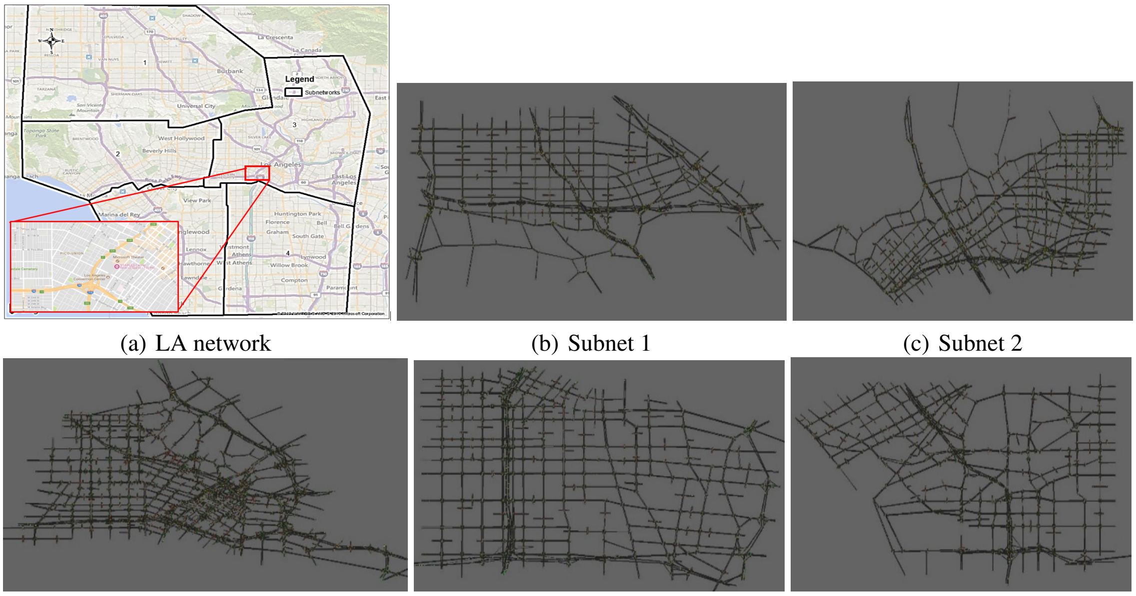
The traffic is created based on real data from Performance Measurement System (PEMS) database. The count and speed data from PEMS database are aggregated and the traffic demand between each Origin-Destination (OD) pair is estimated using the QueensOD (Aerde et al., 2003) software which utilizes the Maximum Likelihood Least Relative Error (LRE) approach. A portion of these trips is used as controlled travelers, while the remaining are modeled as the background. The background travelers are modeled in each network separately based on the calibrated traffic for each sub-network as shown in Table 1. The vehicle count in Table 1 is the total traffic on each sub-network that includes both the controlled and the background traffic.

5 SIMULATION RESULTS

We created the system model to enable assessing potential system-wide effects of individual transportation decisions across the LA region. We ran two scenarios for the LA area. In the base scenario, all the travelers make travel decisions by themselves. In the controlled scenario, the controlled travelers (10% of the driving population) are given directions regarding modes and routes by the planner. Our hypotheses are that the controlled case will result in an energy reduction and a reduced network congestion level. So, in the micro-network routing configuration, the Sub-population Feedback Eco-Assignment (ECO) (Ahn and Rakha, 2013) is used for the controlled traffic, while the Time-Dependent Sub-Population Feedback Assignment (SFA) (Rakha et al., 2012) is used for the background traffic. In the base scenario, since it does not have controlled traffic, only the

Table 1: Sub-network sizes.

Sub-net	Nodes	Links	Signals	Vehicles
1	743	1691	256	404,191
2	940	2251	361	447,948
3	1625	3561	459	592,343
4	741	1724	237	445,857
5	647	1507	203	362,415
Sum	4696	10734	1516	2,252,754



(a) LA network (b) Subnet 1 (c) Subnet 2

(d) Subnet 3 (e) Subnet 4 (f) Subnet 5

Figure 5: LA total network and micro-subnetworks.

SFA traffic assignment was run. All the other simulator use the energy as the routing metric. Furthermore, we expect a controlled travel mode distribution to be dominated by driving in the micro and meso-networks. The global network traffic calibration showed that there were approximately 1.3 million vehicle trips in Greater LA area. When calibrating these ODs for the micro-networks, it generated 2.25 million trips as shown in Table 1. The reason for this large difference is that a portion of the global trips pass through multiple sub-networks, being divided into multiple sub-trips across the sub-networks. Table 2 shows the system-wide comparison for the traveled distance, we can notice that the traveled distance decreases for the micro-network, while it increases for other modes as the 10% of controlled trips are planned over multiple transportation modalities. Combining the results in Tables 2 and 3 together, we can notice that in the micro-network the vehicle's average traveled distance

Table 2: System wide traveled distance comparison.

Transportation Mode	Traveled Distance (Km)	
	Base	Controlled
Walking	0	1,418.6
Cycling	0	147,246.8
Riding Bus	0	3,886.4
Riding Train	0	9,230.5
Driving on Micro	18,298,072.8	17,760,530.8
Driving on Mesok	616,105.2	791,424.0
Carpooling	0	356,549.1
Total	18,914,178.0	19,070,286.2

is about 8 km and the vehicle average travel time is about 39 minutes in the base case. In the controlled case, the vehicle's average traveled distance remains approximately the same while the vehicle average travel time is reduced to approximately 23 minutes demonstrating that by controlling 10% of the traffic, the vehicles moving on the main roads and highways (micro-network) achieved a 40% saving in the total travel time. Table 3 also shows that those vehicles achieved about an 18% saving in the fuel consumption, and their average delay is reduced by about 46%. Shifting the controlled trips to the public transit system is energy efficient because the increases in the energy consumption by the buses and trains due to the extra passenger loads is less than the savings accrued as a result of a reduction in the traffic congestion. However, some of these savings come at the cost of an increment of energy consumption in other transportation modes. Specifically, the energy consumed in both the meso-network and the public transit increased by 110% from 270028 to 568737 KW-hr. We have to mention that the system wide comparison of the fuel/energy is not possible in the current version because some of energy/fuel consumption models have not been implemented in the various sub-models.

6 CONCLUSION

The paper proposes and describes a novel multi-modal large-scale agent-based transportation network

Table 3: Micro-network results for base and controlled scenarios.

Subnet Number	Number of vehicle Trips		Total Travel Time (*s*)		Total Delay (*s*)		Fuel Consumed (*Liter*)	
	Base	Controlled	Base	Controlled	Base	Controlled	Base	Controlled
1	404,191	399,298	1,425,241,984	737,314,176	725,780,800	223,516,944	839,149	580,246
2	447,948	399,301	716,592,000	370,059,488	374,176,480	201,135,536	580,276	448,206
3	592,343	539,949	1,466,868,736	907,472,448	702,194,240	437,199,680	901,559	714,016
4	445,857	402,510	1,126,294,656	602,945,728	544,548,864	318,766,464	704,458	544,593
5	362,415	337,392	588,823,424	306,889,216	295,441,600	126,577,376	499,629	383,526
Sum	2,252,754	2,078,450	5,323,820,800	2,924,681,056	2,642,141,984	1,307,196,000	3,525,071	2,670,588
Sub-network Average/veh			2363.25	1407.15	1172.85	628.93	1.56	1.28

modeling system that has a wide spectrum of application. The proposed system is capable of modeling large urban cities including different transportation modes of travel (driving, biking, walking, riding a bus, riding a train, and carpooling). This system is tested by modeling the Greater LA Area during the morning peak period. The preliminary results show that the network is currently very congested, with an average speed of approximately 12.3 km/hr. The results also show that by re-planning 10% of the trips, the performance of the network can be significantly improved. An important future effort is to improve the system to achieve faster simulation speeds. Currently, the average simulation speed is approximately half real-time, i.e. every virtual second is simulated in 2 actual seconds. We also plan to improve the mesoscopic traffic simulator to achieve better estimates of energy consumption, delay, and travel time. It is also important to study the complexity of the system by quantifying its simulation speed and memory usage for different demand levels. An advantage of a detailed system model, like the one proposed in this paper, is that it enables modeling mode changes for different scenarios including traffic incidents, construction, and special events. We intend to explore potential savings that could result from informed decision-making by groups of travelers in these scenarios.

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