Realistic Simulation of Urban Mesh Networks - Part I: Urban Mobility

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Abstract

It is a truism that simulations of mobile wireless networks are not realistic. There has been little effort in developing realistic mobility models. In urban areas, the mobility of vehicles and pedestrians is greatly influenced by the environement (e.g., the location of buildings) as well as by interaction with other nodes. For example, on a congested street of sidewalk, nodes cannot travel at their desired speed. Furthermore, the location of streets, sidewalks, hallways, etc. restricts the position of nodes and traffic lights imapct the flow of nodes. In this paper, simulation of propagation and mobility for urban wireless networks is addressed. Techniques for simulation, models, model parameters, computational complexity, and accuracy are all examined. Nearly all aspects of the mobility models and model parameters can be derived from urban planing and traffic engineering research. Simulation of propagation is discussed extensively in the part II of this paper. The simulation approaches discussed in this paper and in part II of this paper are implemented in a freely available suite of simulation tools that are available for download.

I. Introduction

As of December 2005, the City of Philadelphia was in the final planning stages of deploying a large-scale urban mesh network (LUMNet) [1]. In January 2006, the City of San Francisco began searching for a partner to deploy a city-wide outdoor mesh network [2]. Taipei is establishing wireless access in 5% of the city, which includes the

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city’s most-populated area, and within a year expects to cover around 90% of the city [3]. Several other cities are planning similar LUMNet deployments (others). These deployments are meant to enhance city and emergency services communication as well as to provide city-wide, low-cost, ubiquitous Internet access for residents and visitors. Such networks promise to bring dramatic changes to data accessibility.

While LUMNets are similar to well studied MANETs, there are important differences. One obvious difference is the presence of an infrastructure in LUMNets. However, another important difference between the LUMNets and MANETs (as well as other mobile wireless networks), is that the environment plays an important role in the performance of LUMNets. For example, the layout of the city determines which nodes can communicate, and streets form propagation conduits. Furthermore, urban mobility is quite distinct from mobility for general purpose or military MANETs. For example, as discussed in this paper, there is an abundance of data on the mobility of people and vehicles. This mobility defines, for example, how long a person stays in an office and how long outdoor trips are, as well as node density on sidewalks and roads. Also, people are often more stationary indoors, where propagation is also poor, than outdoors, where propagation is typically good. Thus, LUMNets performance is greatly influenced by mobility and propagation.

While simulation of mobile wireless networks has long been a difficult problem, the influence on propagation and mobility on LUMNets performance requires new effort in simulation. To further motivate the need for mobility and propagation simulation, consider the problem of mobility management for LUMNets (which is necessary for scalability). As is the case for mobile phone networks [4], [5], [6], [7], [8], there are many mobility management techniques that could be applied to LUMNets. However, the performance of these schemes is greatly influenced by node mobility and the base station propagation range. For example, small indoor propagation areas, may result in rapid node migration, whereas good outdoor propagation results in slower node migration when the node is a walking person, but more rapid migration when the person is in a car. To further complicate things, some base stations have coverage that extends both indoors and outdoors. Thus, performance evaluation requires a realistic model of mobility and propagation. Realistic performance evaluation of routing, transport, etc. also requires realistic simulation of mobility and propagation.

This paper examines realistic mobility, and the second part of this paper examined realistic propagation simulation. While mobility and propagation are mostly separate in that they can mostly be simulated independently (except as discussed in the part II of this paper), both are dependent on the city map. Specifically, the mobility simulator must restrict where nodes may be, and the propagation simulator must determine the propagation for all locations that a node may be. Furthermore, a realistic urban mobility model where a node navigates around building is of little use if used with free-space propagation is used that ignores the existence of the buildings. Similarly, the realistic propagation simulation that realistically simulates the grid-like propagation structure that results from streets is of little consequence if the mobility model does not also recognize the significance of streets. For these reasons, models for mobility and propagation in these two joint papers. However, these papers not only discuss techniques to simulate LUMNets, but also discuss how these techniques are implemented in a combined mobility and propagation simulation package.

This first paper discusses urban mobility simulation. This simulation strategy is significantly different from other mobility models in that much of the model is based on surveys. Specifically, the simulator uses surveys on time use from the Department of Labor Statistics, and an extensive set of surveys of pedestrian and vehicle mobility used within urban planning (e.g., [9], [10]). Furthermore, to determine mobility with office buildings, surveys from the meetings analysis research area are used. It should be stressed, that the mobility model is not ad hoc, but based on the findings of mature research communities. For example, time use has been active for approximately 40 years [11] and many aspects of the agent mobility (see Section IV for definition), have been known for 30 years and are integrated into government guidelines on traffic planning [10]. This paper distills the results of these areas and presents the aspects that are important for urban mobility.

Part II of this paper discusses propagation simulation for LUMNets. While further discussion can be found there, that paper provides some details on computationally efficient simulation, but mostly focuses on the issues of propagation simulation, e.g., reflection, transmission, diffraction, scattering, and delay-spread and how these factors affect communication. Hence, some of the material is a tutorial on propagation for urban wireless networking research. Few equations are included (they can be found in the references), rather the goal is to provide an understanding of the various factors that impact propagation. Furthermore, special attention is paid to correcting misconceptions that can be found in the networking literature. In total, these papers present guidelines on simulation of mobility and propagation for LUMNets. These papers also discuss the design decisions made in implementing the simulator.

The simulation strategy discussed focuses on realistic simulation. It is important to distinguish realistic simulation from accurate prediction. By this realistic simulation, we mean that the simulation should provide mobility and propagation similar to what *could* occur in some urban environment, not necessarily what *would* occur in a particular urban environment. As will be discussed, accurate prediction requires substantial knowledge of the modeled urban environment. For example, accurate prediction requires precise knowledge of location and dimensions of buildings and other large to moderate sized structures, as well as knowledge of the building materials used and the layout of building interiors. Furthermore, accurate mobility simulation requires knowledge of details such as the types of establishments within each building (e.g., restaurant, office, shopping, etc.) and origin-destination flow matrices for vehicle traffic. Realistic simulation, on the other hand, merely needs realistic dimensions and locations of buildings, building materials, layout of buildings interiors, and realistic mobility model parameters. Thus motivation for realistic simulation rather than accurate prediction is to reduce the complexity of simulation. That is, to reduce the difficulty in defining the simulated environment. The drawback is that the strategies discussed and the simulation toolbox that implements these strategies cannot necessarily be used to determine the performance of a specific urban network. Thus, this work is more useful for protocol design and evaluation than for network planning.

The goal of the mobility simulator is to model the following realistically.

– node distribution,

– node clustering (i.e., correlation in node location),

– trips including trip lengths, paths, and generation rates,

– and node speeds.

For propagation simulation, the goal is to provide realistic

– propagation range,

– signal strength

– transmission error probability,

– and spatial variation of the link quality.

Together, the mobility and propagation simulators should provide realistic

– topologies,

– and variations of topologies.

Thus, any aspect that may impact the above are included into the simulator.

The remainder of the paper proceeds as follows. In the next section, an overview of the simulation of urban networks is presented. Section III discusses techniques for developing city maps. Clearly, mobility and propagation are greatly effected by the map. Section IV presents the mobility model of people. This model has three parts, namely, the activity model, the task model, and the agent model. These models are discussed in subsections IV-A, IV-C, and IV-D, respectively. Subsection IV-E provides some details on how commuting is implemented, while subsection IV-F discusses how realistic population sizes can be determined. Section V presents a model for car mobility. Related work on mobility modeling is provided in Section VII. Then future directions in realistic mobility modeling are discussed in Section VI and concluding remarks are made in Section VIII.

II. Mobile Wireless Network Simulation Overview

There are several stages to LUMNet simulation. The first step is to define the simulated city map. This step is discussed in Section III. The second step is to determine the propagation matrix for the simulated region. The propagation matrix includes characteristics such as the channel gain, delay spread, and angle of arrival for each source-destination in the simulated region. Propagation is discussed in Part II of this paper. Next, the city map is used to generate one or more mobility trace files. Realistic urban mobility is the focus of this paper. From the mobility trace file and the propagation matrix, the propagation trace file is computed; the propagation trace file provides the propagation statistics between all pairs of nodes at every moment of the simulation. The propagation trace file can then be used by the protocol simulator such as QualNet, ns-2, or OPNET. While computationally complex to determine, the propagation matrix must be found only once for each city. Some propagation matrices are available online. Hence, most simulations only need to generate a mobility trace file and then use the mobility and propagation matrix to determine the propagation trace. Furthermore, several mobility and propagation trace files are also available online. Consequently, if available data is utilized, the computational complexity of simulation with realistic mobility and propagation is similar to that using random way-point mobility and free-space propagation.

III. City Maps

In order to model MANETs over urban areas, it is necessary to have a model of the urban area. There are several ways that maps suitable for MANET simulation can be developed. First, a random city can be built as was done in [12]. In this case buildings are placed at random and a Voronoi diagram is used to construct sidewalks between the buildings. One drawback of such an approach is that important aspects of cities such as long thoroughfares and big intersections are neglected. It is well known that streets play an important role in mobile phone communication and it has been shown that streets play an important role in urban MANET connectivity [13].

A more realistic way to generate cities is to utilize detailed GIS data sets [14]. These data sets include 3-dimensional maps of buildings that provide enough detail for realistic simulation. There is an abundant number of such data sets. For example, there are GIS data sets for most American cites. Our map building suite of tools converts GIS data sets into format suitable for a specialized graphical editor. The graphical editor is used to "touch-up" the GIS map (e.g., remove spurious buildings). The editor is also used to add roads, sidewalks, traffic lights, base stations, subway stations, define the types of buildings (e.g., residence, store/restaurant, office), and define building materials (See Part II of this paper for discussion on the impact of building materials). While GIS data sets have details of building heights and position, they typically do not provide details about the interiors of the building. In lieu of actual interiors, they must be automatically generated. Our suite of tools uses layouts shown in Figure 1.

Another realistic method to generate city maps is to use US Census Bureau’s TIGER data (Topologically Integrated Geographic Encoding and Referencing) [15]. The TIGER data includes roads, railroads, rivers, lakes, and legal boundaries in the US. It also contains information about roads including their location in latitude and longitude, name, type, address ranges, and speed limits. However, it does not include information about buildings. TIGER data is often used for realistic maps for simulating vehicle ad hoc networks [16], [17], and [18].

And finally, there has been some work on generating random, yet realistic cities [19]. Often, these cities can be represented as GIS data sets, and hence are easily used for propagation and mobility simulation. These realistic random cities are often generated to meet certain aesthetic requirements. Further work is required to develop techniques to generate random cities that are suitable for LUMNet simulation.

In general nodes (people or vehicles) may be at a large number of locations within the city. However, a significant computational savings are achieved if the nodes are restricted to a specific graph. In our simulator, we define a large set of locations (vertices) and pathways (arcs). The nodes are restricted to move along this graph. Examples of parts of this graph are shown in Figure 1.

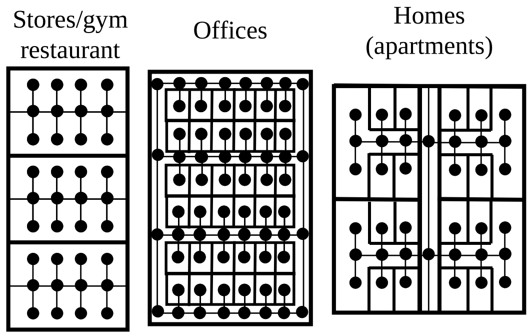

Fig. 1. Locations in different types of buildings. Locations are marked with a circle while arcs are indicated by thin lines. The thick lines denote walls. The store/gym/restaurant structure is such that each third of the layout can be any of these options. The apartment building shown has four apartments each with five rooms. Size of the rooms is approximately constant while larger buildings can accommodate more rooms

IV. Mobility of People

This section presents a detailed mobility model of urban pedestrians during the workday. This model is based on three mature research areas, urban planning [9], [10], meeting analysis [20], and use of time [11]. The resulting model is a three layer hierarchical model. The top layer is the activity model that determines high-level types of activities, the time when people start and end the activities as well as the location where the activity is performed. The data used to develop this model is from the recent US Bureau of Labor Statistics (BLS) use of time study [21]. This study includes interviews with roughly 20,000 people. Furthermore, the BLS determined weightings to account for oversampling of some types of people (e.g., unemployed people tend to be at home at the time of the interview call and tend to be oversampled). Hence, the significance of the study exceeds the 20,000 that were actually interviewed. This study collected detailed data on the interviewee's day included the times that activities were started and stopped, where the activities were performed, and for what reason the activity was performed.

The second layer of the pedestrian mobility model is the task model. While performing a particular activity, a person may carry out many tasks. For example, the model discussed here focuses on office workers. While such nodes are performing a work activity, there are two possible tasks, namely, working at their desk, and meeting with other workers. The basis of this part of the mobility model is several seminal studies of worker meetings performed within the management research community (see [20] and references therein). This part of the model allows one to determine how nodes move within a building and how nodes are clustered within buildings. Mobility within buildings is important if networks utilize relaying by mobile nodes. For example, an outdoor network such as Philadelphia's can greatly increase its indoor coverage if mobile nodes can act as relays [22]. To determine the performance of such relaying, the mobility of indoor nodes must be modeled.

The third layer of the mobility model is the agent model. Such agent models have been investigated within the architecture community and define how nodes navigate walkways to their desired destinations. This model is based on urban planning research, especially the seminal work of Pushkarev and Zupan [9] as well as several other pedestrian mobility studies. A key feature of this part of the mobility model is that it realistically models how nodes form clusters or platoons. Such clusters are important since nodes in close proximity will experience more interference than nodes that are uniformly distributed. On the other hand, the formation of ad hoc or virtual antenna arrays can be enhanced by the presence of clusters of nodes. For these reasons, the model includes several mechanisms that impact platooning.

A. Activity Model

This part of the mobility model is based on the US Bureau of Labor Statistics 2003 time-use study [21]. This study identifies a large number of activities. We focus on those activities that indicate location and group together activities that are performed in the same location (e.g., all activities performed at home are grouped together into the *at home* activity). While the BLS study also collected coarse location information both activity and location information were used to determine the location used in the modeling effort. We focus on eight types of activities: working, eating not at work, shopping, at home, receiving professional service, exercise, relaxing, and dropping off someone. Note that since we focus on location and mobility, eating at work is counted as work. Eating not at work includes eating at a restaurant and buying food somewhere besides at work. Shopping includes all types of shopping except buying food. Receiving professional service ranges from things such as getting medical attention to receiving household management and maintenance services that are not performed at home.

During the simulation initialization, each node is given an office and home. It is assumed that work is done within the building where the nodes office is (work done at home is included into the at home activity). Eating is done at a restaurant (eating at home is included into at home activity). Shopping is done at one of many stores. Receiving professional service is done at an office that is not the node’s office. Our current model does not specify a location for relaxing and dropping someone off. Dropping someone off includes meeting children at school and taking them home. For the purpose of mobility modeling, we model such activities as a trip home followed by a trip to a random selected office location. The node remains at the office location until the drop off activity if complete. The relaxing activity is modeled as going to an office location (much like receiving professional service).

This model effort focuses on the work day which consists of being at home, going to work, working, and perhaps taking a break and returning to work and then leaving work and returning home. The model neglects activities before and after work. Future work will include the rest of the day.

For each person, the following steps are taken to determine the activities that they perform.

1) Select a home and office.
2) Determine the arrival time at work.
3) Determine the duration at work.
4) Determine if a break from work is taken. (The next 5 steps assume a break is taken.)
5) Determine the break start time.
6) Determine the number of activities performed during a break
7) Determine which activities are performed during the break.
8) Determine the duration of each activity.
9) Determine the arrival time back at work and determined if a break is taken again. If so, steps 5-9 are repeated.

Selection of home and office An office for each node is selected at random. Once an office is selected, a home is selected that is nearby the office. Specifically, a home is selected so that the distance from the home to the office matches the distribution shown in figure 7. This distribution is based on walking distances observed by Pushkarev and Zupan. The model also allows for nodes not to walk to work, but to arrive via the subway or car. Such nodes do not take breaks that go home. The mode of travel to work is discussed in Section IV-E.

Arrival time at work Figure (2) shows the complementary cumulative distribution function (CCDF) of the time of arrival at work. The observed values were fitted with a mixture of exponential and Gaussian distribution. Specifically, with probability of 0.552, the time of arrival is normally distributed with mean 7:46 and standard deviation of 45 minutes. With probability $(1 - 0.552)$, the time of arrival is exponentially distributed with the mean time of arrival of 12:00. The exponential distribution is shifted so that the earliest minimum time of arrival in this case is 5AM. The normal distribution is truncated so that no arrivals occur before 5AM.

Duration at work Figure (3) shows the CCDF of the duration at work for people that arrive at work between 7 and 8 in the morning and for those that arrive between 10 and 11 in the morning. These distributions and ones

TABLE I

DURATION AT WORK MODEL PARAMETERS

time	α	μ	σ	m
≤8AM	0.91	8:09	1:06	9:50
8-9	0.85	7:49	0:56	8:52
9-10	0.81	7:16	1:17	5:52
10-11	1.0	7:11	2:16	-
11-12	0.70	7:16	2:11	5:00
12-1	1.0	6:19	2:40	-
1-3	0.5	7:33	0:55	4:31
3-6	0.83	6:18	1:55	2:07
≥6	1.0	4:30	2:26	-

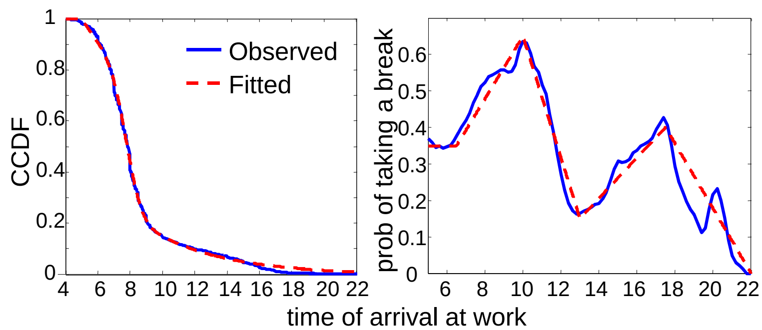

Fig. 2. Left. Complimentary cumulative distribution function (CCDF) of the time of arrival at work. Right. The probability of taking a break given the arrival time at work. This includes arrivals after a break.

for other arrival times at work were fitted with a mixture of a normal random variable and an exponential random variable. These distributions have four parameters, α, the probability of selecting the normal distribution, μ and σ the mean and the standard deviation of the normal distribution and m, the mean of the exponential distribution. Table I shows the value of these parameters for the different arrival times at work. Surprisingly, while the model is simple, the fit shown in Figure (3) is a typical quality of fit throughout the day. On the other hand, from Figure (2) it can be seen that the most important distribution is that for nodes arriving between 7 and 8.

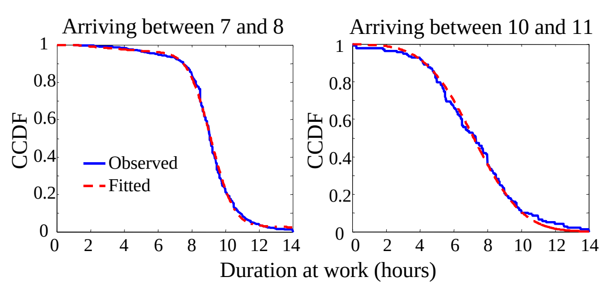

Fig. 3. The CCDF of the duration at work for two different arrival times at work.

Whether a break is taken The probability of whether a break is taken depends on the time of arrival at work. Note that if a break is not taken, the person may still eat lunch, but they do not leave the building. We fit the probability of taking a break given the time of arrival with a piece-wise linear function.

$$P\left(\text{taking a break}\middle|\,\text{arrival time at work} = t\right)$$
$$= \begin{cases} 0.35 \text{ for } t < 6.5 \\ 0.86\left(t - 6.5\right) + 0.35 \text{ for } 6.5 \leq t \leq 10 \\ 0.17\left(t - 10\right) - 0.65 \text{ for } 10 \leq t \leq 13 \\ 0.056\left(t - 13\right) + 0.15 \text{ for } 13 \leq t \leq 17.5 \\ -0.08\left(t - 17.50\right) + 0.4 \text{ for } t \geq 17.5 \end{cases}$$

Note that this equation uses fraction of hours past midnight, not hours and minutes. This model and the observed probability is shown in Figure (2).

The time the break is started Clearly one cannot go on a break before they arrive at work. However, once they arrive at work, the rate that a person goes on a break does not depend on how long they have been at work. Figure (4) shows this rate conditioned on the person arriving at work one hour ago, two hours ago, and unconditionally. It can be seen that the duration at work has only a minor impact of the time to take a break and that this difference is within the confidence intervals. Thus, we assume that the rate of going on a break is independent of arrival time, assuming that the node has already arrived at work. The rate that a person takes a break is approximated by

$$r\left(t\right) =$$
$$\begin{cases} 0.004 \text{ for } t < 10.5 \\ 0.006 \times \exp\left(-1.7\left(12 - t\right)\right) \text{ for } 10.5 \leq 12 \\ 0.006 \times \exp\left(-0.6\left(t - 12\right)\right) \text{ for } 12 \leq t \leq 14 \\ 0.0058 \times \exp\left(-0.3\left(5 - t\right)\right) \text{ for } 14 \leq t \leq 18 \\ 0.0058 \text{ for } t > 18 \end{cases} .$$

By rate of taking a break, we mean that the probability that a node will take a break within the time interval from t_0 to t_1 is $\left(t_1 - t_0\right) \int_{t_0}^{t_1} r\left(\tau\right) d\tau$.

Number of activities performed during a break Figure (5) shows the probability of performing different

TABLE II
DURATION OF ACTIVITY MODEL PARAMETERS

activity	μ	$\underline{d}$	ρ
eat	0:31	0:20	0.18
shop	0:28	0:20	0.03
at home	1:00	0:20	0.12
professional	0:44	0:10	0.04
exercise	0:35	0:20	0
relax	0:27	0:15	0.01
drop-off	0:19	0:10	0.02

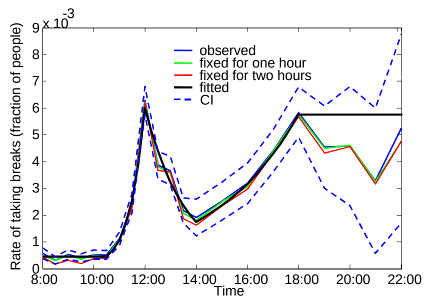

Fig. 4. The rate that a person takes a break and leaves work given the current time. Also shown are the rates conditioned on the person being at work for at least one and two hours. These rates are within the confidence intervals that are also shown. Finally, the fitted rate is also shown.

numbers of activities during a break. We see that over the course of the day, the number of activities performed varies. However, the variation is small, and hence we model the probability to be independent of the time of day.

Which activities are performed during a break The types of activities performed during a break strongly depend on the number of activities to be performed. Figure (5) shows the fraction of breaks that include the indicated activity. Note that if more than one activity is performed, the fractions sum to more than one.

The duration of activities The time spent performing an activity depends on the type of activity. Figure (6) shows the CCDF of the duration of three activities. The distribution of the duration of eating shows a jump at 1 hour. Smaller jumps are noticeable in the distribution of other activities. The duration of these and the other activities are modeled as a mixture of an exponentially distributed random variable conditioned on the duration being larger than a minimum duration along with deterministic duration of one hour. Thus, the distribution of the duration of each activity has three parameters, μ, the mean of the exponential distribution, $\underline{d}$, the minimum duration, and ρ, the probability of the duration lasting exactly one hour. Table II shows the value of the model parameters for the different activities considered.

Once the activity has been selected, the location of the activity must be determined. Specifically, eating requires

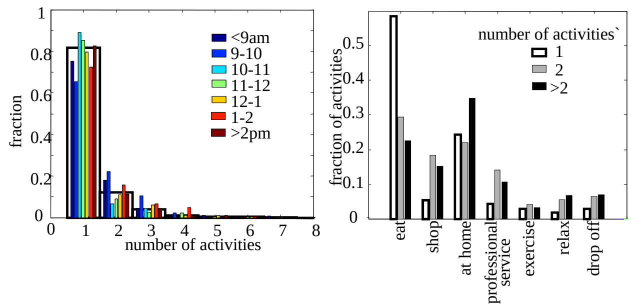

Fig. 5. Left: the number of activities done during a break conditioned on the time that the break is started. Right: the fraction of time that a break includes the indicated activity given the number of activities performed within the break.

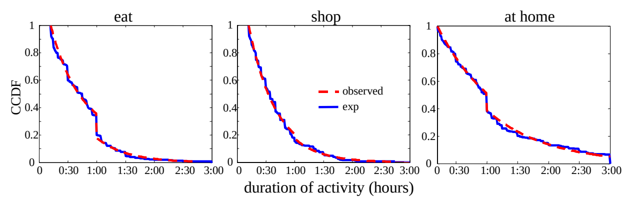

Fig. 6. CCDF of the duration of eat, shop, and at home activities.

selecting a restaurant, exercising requires selecting a gym, getting professional service requires selecting an office location, shopping requires selecting a store, dropping someone off requires selecting an office location to drop them off at. We assume that people walk to the location that is required to perform the activity. Future work will include the case where people take other forms of transportation. Pushkarev and Zupan [9] observed the distribution of the distance that pedestrians walk (see Figure 7). We see that the distance is well modeled by an exponential distribution with means 554 m, 380 m, 403 m, 344 m, 813 m, and 216 m for Manhattan from office buildings, Manhattan from residences, Chicago, Seattle, London and Edmonton respectively. We see that the US cities have approximately the same mean. Thus, we select a location of the correct type (e.g., a store for shopping) at random such that the walking distance is exponentially distributed with mean 400 m.

B. Activity model of people who did not work

On a particular work day, about 8% of people interviewed did not work. While these people have a wide variety of activities, an approximate model is as follows. With a probability of 0.54, a sequence of trips is started at a time with the same distribution as the arrival time to work given above. Upon arriving at the desired destination (which we model as a random office in the region), the time that the person remains at the location is exponentially distributed mean 56 minutes. Then, with probability 0.37, the person begins another trip, and with probability 0.63, the person

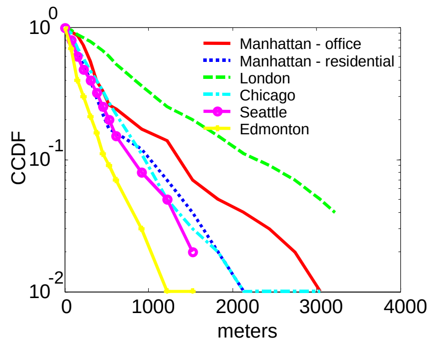

Fig. 7. CCDF of Distance Traveled During Outdoor Walking Trips. This data is from [9].

returns home. A second sequence is trips is started with probability 0.72 at a time that is normally distributed with mean 14:27 and standard deviation of 118 minutes. These sequence of trips has the same distribution as the morning trips.

C. *Task Model*

Some activities consist of a single task. For example, eating consists of going to a restaurant. However, shopping and working consist of multiple tasks. We model shopping as a simple random walk inside the store. However, this model is based on intuition; future work is required to verify this model. The work activity is modeled in a more complicated manner that focuses on modeling meetings. Specifically, [20], [23], [24] have collected data on the frequency, size, and durations of meetings; [23] includes two person meetings. These studies allow the model to include worker interactions. Thus, we model mobility while at work as a sequence of meetings followed by working in the node's office. This process repeats until the work activity is complete.

More specifically, meetings are simulated as follows. The time between meetings is *assumed* to be exponentially distributed. When a meeting begins, a random number of people are selected to attend the meeting. Based on the number of people attending, the duration of the meeting is determined. The duration is *assumed* to be exponentially distributed.

The model parameters of the model are the mean time between meetings, the distribution of the size of meetings, and the relationship between number of meeting participants and the mean meeting duration. These parameters are derived from [20], [23], [24] . Specifically, the mean time between meetings is 18 minutes while Table III gives the remaining of the model parameters.

TABLE III
MEETINGS MODEL PARAMETERS

meeting size	mean duration	prob.
2	21 (min)	0.65
3	19	0.12
4	57	0.04
5	114	0.02
6	37	0.04
7	50	0.03
8	150	0.01
9	75	0.02
10	150	0.01
15	30	0.025
20	30	0.025

D. Agent Model - Node Dynamics and Interactions

Since the pioneering work of Pushkarev and Zupan [9], it has been known that pedestrians are not uniformly distributed but tend to be group into clusters or, in the terminology of urban planning, platoons. Since the distribution of nodes plays an important role in the performance of mesh networks, the mobility must also model platoons. This part of the model is known as the agent model and is responsible for determining the trajectory of the node as it moves from one location to the next. In our simulator, nodes take the shortest path, hence path finding is not an important part of the agent model. Rather, the agent model focuses on the dynamics and interaction between moving nodes. More specifically, the agent model consists of enforcing a distance-speed relationship between nodes and lane changing rules. These are discussed in the next two sections. In Section IV-D.3, the model is validated by comparing the size of platoons created by the model to those observed by Pushkarev and Zupan. As will be discussed in Section V, with some small changes, the node interactions described here are also applicable to vehicles.

1) Inter-node Speed-Distance Relationship: When a node with a higher desired speed catches up to a slower moving node, it will either follow or pass. To understand the dynamics of catching up, it is necessary to understand the distance-speed relationship. The impact of this relationship is that nodes will be tightly packed (i.e. high density) if their speed is low (congestion), but if the speed is higher, then the nodes must be further apart (low density). Since the density of nodes plays an important role in the performance of mesh networks, the distance-speed relationship must be understood and realistically modeled. For vehicles, the distance-speed relationship, which we denote as $D(S)$, is closely related to the "two-second rule" that specifies that for safe driving, a vehicle should not be closer than two second behind the vehicle in front of it. For both vehicles and pedestrians, these relationships have been

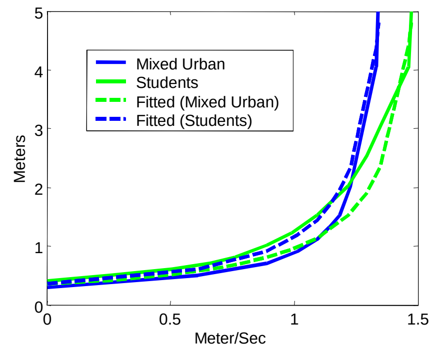

Fig. 8. Speed-distance relationship for pedestrians. The mixed urban pedestrian data is adapted from [25] and the student observations are adapted from [26].

extensively studied. Here we focus on the pedestrian case.

The distance-speed relationship for pedestrian is studied in [25] and [26]. Figure 8 shows the distance-speed relationship derived from these observations[1]. We approximate this relationship with $D\left(S\right) = S^{*}D_{\min}/\left(1.08 \times S^{*} - S\right)$ where $D_{\min}$ is the minimum distance between people without touching and S^{*} is the desired speed of the pedestrian. $D_{\min}$ was found to be at least 0.35m [9].

It has been found that pedestrian desired speeds are approximately Gaussian with mean 1.34 m/s and standard deviation 0.26 [28], [29], [30].

2) Lane changing: While traffic lights are an important cause of platooning[2], the passing or not passing of slower walkers also plays an important role [9]. People will certainly not overtake slower walkers if there is no room (e.g., if the other lanes are full). Even if there is room, pedestrians (as well as vehicles) might not pass out of choice and select to slow down and follow the node ahead [31]. Such decisions lead to platooning.

While the dynamics of pedestrian overtaking has been observed, it has not been modeled. However, models for vehicle passing have been developed (e.g., [32]). We borrow from this model. It has been found that lane changing depends on the difference between the speed that results from not changing lanes and the speed that could be achieved if the lane was changed. Specifically, a slightly simplified model for the probability of wanting to change

[1]The plot shown is based on area-speed relationships with the assumption of 0.75 meter of lateral space between people as found by Oeding [27].

[2]Our simulator includes traffic lights.

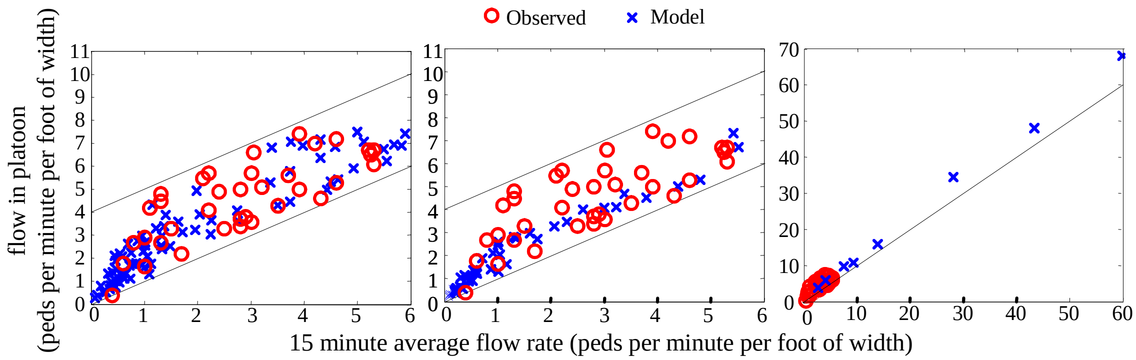

Fig. 9. A validation of the pedestrian agent model. The black lines are the ranges that Pushkarev and Zupan considered realistic. The circles are values that Pushkarev and Zupan observed and the x-marks are the values generated by the simulator. The left-hand frame shows the results of the full simulator. The middle frame shows the results when no probabilistic passing model is used; instead a node always passes. The right-hand plot is when no inter-node dynamics are used, e.g., two nodes can occupy the same location.

lanes and overtake a slower node is

$$\begin{aligned} & P\left(\text{desire to change lanes}\right) \qquad (1) \\ = \quad & 1/\left(1+\exp\left(A+B\left(V_{*}-V^{*}\right)\right)\right) \end{aligned}$$

where V_{*} is the speed that the node would achieve if it remains in the current lane and V^{*} is the speed that would be achieved if the node changes lanes. Since speeds may experience short-term variation, instantaneous determinations of V_{*} and V^{*} leads to erratic behavior. Instead, letting ν denote the node that is considering changing lanes, we define V_{*} to be the average speed of all nodes between ν and the next intersection, and define V^{*} to be the minimum of the desired speed of ν and the average speed of the nodes in the target lane that would be between ν and the next intersection. Scaling the parameters found in [32], we set $A_{Pedestrian} = -0.225$, and $B_{Pedestrian} = 1.7$.

While this model has not been verified for pedestrians, in the next section we will see that it does give rise to realistic platooning.

3) Validation of the Agent model: The burstiness of pedestrians has been investigated by Pushkarev and Zupan [9]. Their work has served as the basis for the pedestrian traffic engineering guidelines set forth in the Highway Capacity Manual [10]. The metrics of burstiness for pedestrian platoons is different from the ones typically used in studying data networks. Specifically, Pushkarev and Zupan compare two flow metrics, the 15 minute average flow rate (AFR) and the flow rate during a platoon (PFR). A node is in a platoon if the local density of nodes exceeds the average density. As is shown in Figure 9, the PFR is higher than the AFR. According to Pushkarev and Zupan, the larger the PFR is as compared to the AFR, the more bursty the pedestrian traffic. The study of Pushkarev and Zupan was not focused on finding the frequency of specific flow rates, but to examine what combinations of AFR and PFR occur on urban sidewalks. Thus, we use this data as a baseline with which we compare the pedestrian mobility model described above.

The left-hand plot in Figure 9 shows two sets of data. The generated data from the mobility model is from a variety of configurations including counting pedestrians on a block with and without buildings, various sizes of sidewalks (from 4 lanes to 32 lanes), various traffic light timings (from 60 seconds to 120 second periods), and various rates of pedestrians flowing into the street. As can be seen from the left-hand plot in Figure 9, the mobility model described above generates combinations of PFR and AFR that are realistic.

The center plot in Figure 9 shows the data set collected by Pushkarev and Zupan and a set of data generated by the mobility model but where nodes pass whenever there is room to pass, i.e., $P\left(\text{desire to change lanes}\right) \equiv 1$ as oppose to what is given in (1). Clearly, increasing the propensity to change lanes acts to decrease the burstiness so that some realistic levels of burstiness never occur. Finally, the right-hand plot in Figure 9 shows Pushkarev and Zupan's data compare to data generated by the mobility model but where there are no inter-pedestrians dynamics, i.e., nodes move along lanes irrespective of other nodes. Such mobility allows, for example, nodes to disobey the distance-speed relationship. As shown in Figure 9, ignoring inter-node dynamics results in unrealistic levels of congestion (extreme discomfort occurs when the flow rate exceeds 7 [9]).

E. Mode of Travel During Commute

Rush hour is an important aspect of urban mobility. One characteristic of rush hour is the fraction of people who drive or take mass transit during rush hour. Our simulator supports people traveling to and from work via car, subway, and, for people who live within the simulated area, walking. In the case of traveling to work by car, the trajectory of the person and a car matches until the car arrives at a parking lot that is located close to there final destination. Currently, street parking is not implemented in our simulator, but is considered by some other traffic micro-simulators (e.g., [33]). Once the person reaches the parking lot, they walk to their destination. More discussion of car travel is discussed in Section V.

On the other hand, during subway travel, the person's trajectory starts at the subway stop and the person walks from the subway to their destination. We assume that subway trains arrives at Poisson distributed times, and hence during rush hour people exit the subway in bursts. As mentioned in [9], subway train arrivals can lead to platooning or clusters of pedestrians. Realistic mean times between subway arrivals is 3 - 10 minutes [34].

In American cities, the fraction of people who take mass transit widely varies, hence our simulator allows this fraction to be adjusted. Realistic fractions are as follows. The national average of people who take mass transit to work in the US is 10.4 [**?**], but 87% or the people who enter Manhattan use mass transit [**?**].

F. Urban Population Size

It is well known that the number of users has a major impact on the performance of the network. Thus, realistic node population sizes are an important part of realistic simulation. While the number of nodes in a network depend on the number of people in the simulated region, it also depends on the fraction of people that subscribe to the network. Today, mobile phone penetration in Europe exceeds 80% while in the US the fraction of subscribers is approximately 60%. Of course, in the early period of mobile phone deployment, the fraction of subscribers was much smaller. Hence, a wide range of penetration rates are realistic.

As expected, realistic populations size in an urban region can be quite large. For example, 1 km^2 of Manhattan may contain 10,000 people outdoors [9], a number that is far larger than most simulations currently found in the literature. However, in a less dense city, if 10% of the population participates in the network, then a nine block region of Chicago would contain about 4000 nodes, a number that can be supported by protocol simulators such as QualNet [35]. The following presents guidelines for determining the population size in an urban region.

In the urban core, most of the indoor space is used for commercial purposes, including offices, stores, and restaurants, with office space being the most prevalent. As one moves away from the core, a larger fraction of the indoor space is used for residences. However, it is assumed that the map specifies which buildings are office, retail, residential, or mixed usage. For office space, a survey of office use in the UK found that typical densities are approximately 15 m^2 per person [36]. Thus the total working population can be determined by computing the total area of office space and dividing by 15.

The US Census American Housing Survey finds that in urban areas there is approximately 1 person per 65 m^2 of residential space. The size of the residential population can be found by determining the total area of residential space and dividing by 65. However, in simulation, we assume that 92% of the people that live in the city will also work within the city, and hence are counted in the working population.

The simulator sets the population as follows

$$\begin{aligned}
\text{Number of office workers} &= \frac{\text{total office area}}{15}, \\
\text{Number of people living locally} &= \min\left(\frac{\text{total residential area}}{65}, \frac{\text{number of office workers}}{0.92}\right), \\
\text{Number of people simulated} &= \text{number of office workers + number of people living locally} \times 0.08 \text{ + number c} \\
\text{Number of people who commute via subway} &= \text{(Number of office workers - Number of people living locally} \times 0.92) \times \text{ MassT} \\
\text{Number of people who commute via car} &= \text{(Number of office workers - Number of people living locally} \times 0.92) \times \text{(1-Mas}
\end{aligned}$$

where the values are such that the office worker density is maintained even if there is an abundance of residential space. Note that we allow for some nonworking visitors. These people follow the same mobility as nonworkers that live within the city. However, further work is required to determine realistic sizes of the nonworking visitor populations. The MassTransitRatio is the fraction of commuters that take the subway, as discussed in Section IV-E.

Remark 1: Some population density statistics focus only on the number of residences per geographic area, not per square foot of indoor space. Furthermore, in the urban core, workers will commute to work, and hence are not counted in the residence population densities that are commonly cited.

V. Vehicle Mobility

Vehicle mobility has been widely studied for urban planning and sophisticated simulators exists (e.g., [37]). However, these simulators focus on highway traffic and often require more detailed information than is easily accessible to network researchers. On the other hand, simulation of vehicles along urban streets is more simple than simulation of highways where complicate processes such as rubbernecking can have a dramatic impact on traffic.

In general there are two types of vehicles, namely, commercial vehicles such delivery vehicles and busses that make frequent stops, and private vehicles that make few stops. The current version of the simulator only considers private vehicles. For private vehicles, two types of trips are considered, trips where the car simply passes through the simulated region, and trips where the vehicle carries a person into or out of the simulated region. We first examine the case when the car simply passes through the simulated region.

Like the pedestrian model, a hierarchical model is used. However, only two tiers are used. The highest tier

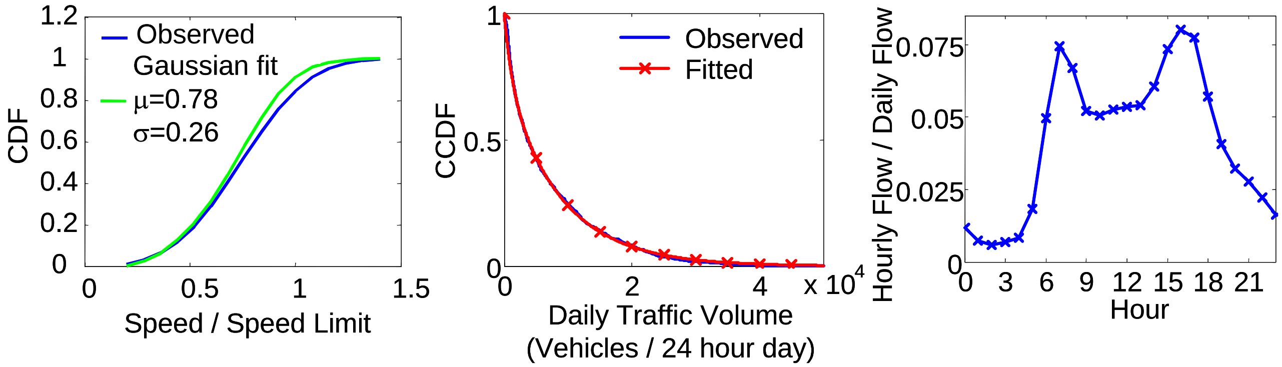

Fig. 10. Left, Cumulative Distribution Function (CDF) of the Vehicle Speed in Urban Areas and a Fitted Gaussian CDF. Middle, Complementary Cumulative Distribution Function of the Vehicle Traffic Volumes on San Francisco Streets. Right, Ratio of Hourly Voume to Daily Volume.

controls the flow of vehicles into the simulated region, while the lower tier controls the mobility of the vehicles. The lower tier is discussed next.

A. *Vehicle Agent Model*

This lower tier is similar to the pedestrian mobility in that it includes the same structure for node interaction; specifically, the same framework for passing and speed-distance relationship is used. The distance-speed relationship is given by $D(S) = \alpha + \beta S$. For dry driving conditions, it has been found that (α, β) ranges from $(1.78, 10.0)$ to $(1.45, 7.8)$ [38]. These values also agree with the observations presented in [39] and [40]. The probabilistic passing model is discussed in Section IV-D.2, but the parameters in (1) are $A_{Vehicle} = -0.225$, $B_{Vehicle} = 0.1$.

For vehicles, the ratio of the vehicle's desired speed to the speed limit presented in [41] can be modeled as Gaussian with mean 0.78 and standard deviation 0.26 (see Figure 10).

Traffic engineering provides guidance on modeling the paths cars take through the modeled area. Traffic simulators /congestion prediction models such as CORSIM [37] allow vehicle trips to be generated in two ways, with origin-destination (O-D) flow matrices or with turning probabilities. O-D matrices are much like the traffic matrix used in data network provisioning. The rate at which vehicles enter the simulated region at a origin O with desired destination D is given by the (O,D) element of the O-D matrix. If only turning probabilities are used, vehicles enter into the modeled area at one of a pre-selected locations and proceed until the vehicle arrives at any exit location, which is at the edge of the modeled area or a parking location. At each intersection, vehicles turn or go straight according to the turning probabilities assigned to that intersection. O-D matrices yield a more accurate simulation, however, accurate O-D matrices are difficult to determine, whereas turning probabilities can be determined by simply counting vehicles turning at each intersection. Thus, both approaches are used for urban traffic engineering.

Drawbacks of turning probabilities are that vehicles might travel in long loops or meander through the city of extended periods of time. However, since cars typically go straight (turning probabilities are typically between 0.1 and 0.3 [42], [43]) such unrealistic behavior is rare; most trips would proceed through the city with only a few turns. Our simulator currently uses homogeneous turning probabilities.

B. Vehicle Flow Rates

Each road that reaches the edge of the simulated area may have vehicles enter or exit at that point. Following the findings of [44], it can be assumed that vehicles enter the region as if they have just passed through a traffic light (i.e., in bursts), and that the number of vehicles in a burst is distributed according to a Poisson distribution. The mean number of vehicles per burst is not the same for each road. The distribution of flow rate for San Francisco streets is shown in middle frame of Figure 10 [45]. As is also shown, this distribution is well modeled the mixture of two exponentials, specifically, $P\left(\text{Number of cars per day } > r\right) = 0.74\exp\left(-r/8.9\cdot 10^3\right) + (1-0.74)\exp\left(-r/1.3\cdot 10^3\right)$. To convert the daily average flow shown in Figure 10 to hourly flow, the scale factor from [46] is shown in the right-hand frame of Figure 10 is used. Note that a simple way to scale the amount of traffic that enters a city is to scale the distribution of daily volume, but leave the scale factor unchanged to get realistic variability of traffic flow.

While many vehicles may pass through the city, they may also carry people into or out of the city (currently, we ignore the possibility that people use a car to travel within the city). In our simulator, when a person desires to exit the city via a car, they merely walk to their parking lot. Upon reaching the parking lot, the person enters a car and then proceeds to drive through the city as described above until exiting the city. While driving, the trajectory of the car is the same as the trajectory of the person. Furthermore, depending on the transmitter and propagation, communication with the person may be possible. However, once a person or a car exits the simulated area, they are no longer reachable as all channel gains are set at $-\infty$ dB.

The implementation of a person entering the city by car is more complicated. When a person desired to enter the city, they enter a virtual buffer at the parking lot near to their destination. When a car that was traveling through the city and is not carrying a person out of the city reaches the parking lot, it turns into the parking lot with a specified probability. The first person in the buffer is then assigned to this car, i.e., the person's trajectory becomes that of the cars from when the car entered the city to when the car reached the parking-lot. At this point, the person walks to their destination.

In the ideal case, the virtual queue should never become too full. For example, during rush hour, the rate that vehicles enter into the city increases, and hence more commuters are accommodated. However, in case that the various modeling parameters are such that the queues become large, the rate at which the vehicles enter into the city is adjusted. Specifically, the rate that cars enter the city is increased by $kQ\left(t\right)$ where k is a gain factor and $Q\left(t\right)$ is the total number of people waiting in all virtual queues. While k is a user parameter, it is important that $k < \pi/\left(2TpN\right)$, where T is the average time it takes for a car to travel from the edge of the city to a parking lot, N is the number of parking lots, and p is the probability that a car passing a parking lot with a non-empty queue will turn into the parking lot. If this constraint holds, then it is likely that the rate that cars enter the city is stable, whereas if k is too large, then the rate that cars enter the city may oscillate with large bursts of cars enter the city. Briefly, the stability of the virtual queues can be seen as follows. $\frac{d}{dt}Q\left(d\right) = -pNkQ\left(t-T\right) + u\left(t\right)$, where u is the nominal rate that cars enter the city. Thus, $Q\left(s\right) = \frac{1}{s+kpN\exp(-sT)}U\left(s\right)$. The denominator can be written as $\left(a + kpN\exp\left(-aT\right)\right)\cos\left(bT\right) + j\left(b - kpN\sin\left(aT\right)\right)$, where $s = a + jb$. For $a > 0$ (i.e., s in the right-half plane), the smallest b that could result in the real part being zero is $b = \pi/2T$. However, if $\pi/\left(2T\right) > kpN$, then, whenever the real part is zero and $b > 0$, the imaginary part is larger than zero. Similarly, if $b < 0$ and the real part is zero, then the imaginary part of less than zero. Hence, the denominator can never be zero.

VI. Future Work in Mobility

There are several areas of realistic urban mobility simulation that require further effort. One important area is mobility during disasters, crisis, and other events (e.g., Independence Day celebrations). Disasters and crisis mobility requires mobility models not only of the civilians, but also of emergency personnel. Note that both Philadelphia and San Francisco specify that their mesh network will be used to enhance emergency communication. Also, the discussion above and the current version of the simulator only considers cars. However, buses and commercial trucks should also be considered. For example, network protocols for such commercial vehicles are already under development (e.g., [47], [48], [49].

The mobility models develop above are mostly derived from statistics collected in the US. However, use of time and the agent models of both vehicles and people depend on the country. Much of the data used here is also available for other countries. Hence, future work will develop mobility models for cities in other countries besides the US. Similarly, the focus of the model is mostly on office workers and nonworkers, the dynamics of nonoffice workers still needs to be explored and incorporated into the simulator.

Group mobility is a popular class of mobility models. However, there has been little work in realistic group mobility. One situation where group mobility commonly occurs in the urban setting is when groups of office workers go to lunch. An informal study performed in Philadelphia found that the number of people in a group followed the Zipf distribution with shape parameter of 2.18, i.e., $P\left(\text{Group size} \geq g\right) = 1/g^{2.18}$. However, further study of group sizes and group mobility dynamics is required.

VII. Related work

There are several mobility models used for MANET simulation. The most popular is the random way-point model [50]. There are many variations of such random mobility models (see [51] for details and references). However, these models are obviously not realistic. In [52], several scenario based mobility models were considered. However, as mentioned in [52], these mobility models are not meant to be realistic. In [53], the Manhattan mobility model is introduced where nodes are restricted to a grid that resembles the street map of Manhattan. This model does not include any realistic node mobility dynamics (e.g., node interaction, traffic lights) or realistic trip generation. While Manhattan used idealized grid-cities, several researchers have used actual cities maps from the TIGER data sets [15] (e.g., [16], [17], and [18]), whereas [54] uses a random graph. In many of these graph constrained cases, the mobility is essentially random way-point, but restricted to a graph. In [55], mobility patterns from multi-user games were used, but did not verify that the mobility of characters in games to resemble the mobility of pedestrians or vehicles.

In [52], [12] and [56] obstacles were included, and mobile nodes avoid the obstacles. In [12] and [56], the obstacles were randomly located buildings. As was mentioned in Section III, as well as in Part II of this paper, streets play an important role in connectivity. Hence, the random placement of buildings will result in non-realistic topologies.

Recently there has been interest in developing more detailed models along the lines discussed here. For example, [57] and [58] discuss an empirical model based on observations of pedestrian on a university campus, while [59] describes a realistic model of communication usage during disasters.

One of the most detailed mobility models is GEMM [60]. GEMM is an agent-based model where several factors impact the mobility of the node. For example, GEMM includes attraction points as well as habits to influence the mobility. A noted drawback of this work is that realistic values of the model parameters are not known. The model presented in this paper uses parameters derived from surveys, and hence are realistic.

Metropolitan Adhoc Network Simulator (Madhoc) is scenario-based simulator that allows simulation of several different urban scenarios. The Madhoc simulator is currently under development [61].

In [62], a type of trace-based urban mobility is presented. This algorithm takes as input the flow edge rates of a simulated area, i.e., the rate that pedestrians enter or exit the simulated region at each walkway that crosses the edge of the simulated region. From these values, mobility within the simulated region is estimated. Since this scheme uses actually mobility measurement, it is inherently realistic. However, it is difficult to extend the data to other scenarios for which data was not collected. Furthermore, the approach is best suited for mobility in a small region, e.g., mobility within a large urban mass transportation station.

In [63], node mobility is based on a predefined social network; nodes tend to move towards nodes with which they have a strong social connection. Such a mobility model could be incorporated into the task model in Section IV-C so that the nodes that take part in meetings are those that have strong connections in a social network. This approach could also be used in group mobility.

In [17], a realistic mobility model of vehicles is developed. While the model does not include realistic flow rates, it does include a realistic distance-speed relationship as well as a realistic desired speed distribution (i.e., Gaussian, as is discussed in Section V). However, a probabilistic passing model such as the one described in Section IV-D.2 is not included. The model also makes use of realistic maps via TIGER [15].

While realistic mobility within mobile wireless networking is a new area of interest, within disciplines such as urban planning, architecture, transportation engineering, and sociology, mobility modeling is a mature field with early efforts dating back nearly fifty years [64]. While these areas have produced refined techniques, the objectives of this previous work are different from what is required for modeling mobile wireless networks. Thus, it is not possible to simply copy these other efforts. Rather, techniques, observations, and results have been be taken from this large body of work and adapted to the specific needs of mobile wireless networks. While it is not possible to provide a complete review of these active research areas, a brief overview is as follows.

Much of this previous work in mobility can be classified into flow based [65], [66], [67], [68], [69], mesoscopic [70], [71], cellular automata [72], [73], [74], agent-based [75], [76], [77], [78], [79], [80], or activity-based [81], [82], [83], [84] methods. Flow-based methods do not model individual mobile nodes, but model the density of nodes in continuous flows. Mesoscopic models aggregate nodes into groups. Cellular automata discretize space and model the node density in each cell. Since mobility modeling requires each node to be modeled individually, these three methods are not appropriate for networking. Thus, the methodology presented here incorporates the activity-based and agent-based approaches.

The data for vehicle agents is spread throughout the literature [42], [85], [86], [87], [88], [89], [71]. For pedestrian mobility, observations can also be found in the literature (e.g., [90], [91], [68], [92], [93], [84], and [81]), but Pushkarev and Zupan [9] and Fruin [94] have compiled a collection of their own observations as well as other researchers' observations. Their work is the authoritative work on pedestrian mobility and forms the basis for the pedestrian mobility in the US Highway Capacity Manual [95].

CORSIM (corridor simulator) [37] is by far the most widely used traffic simulator for high and traffic planning [96]. CORSIM is used for accurate traffic prediction. As a result, CORSIM is more realistic than the vehicle mobility discussed here, but it is also far more difficult to configure and use.

VIII. CONCLUSIONS

A methodology for realistic simulation of urban mobility was presented. The techniques described have been implemented in a suite of simulation tools that are available for download [refff]. The techniques presented are based on data collected from a wide range of sources. For example, the activities that people perform are derived from the 2004 US Department of Labor Statistics survey on time use. The detailed mobility model of people and vehicles is derived from modeling methodologies and data collected by the urban and traffic planning community. Vehicle traffic flows are derived from data collected by the City of San Francisco and the State of Connecticut. The density of people are derived from surveys of office space use and the US Census American Housing Survey. Other aspects of the model are derived from other data. In all, much of the model is based on observation of the mobility of people and vehicles.

While the mobility model presented here is considerably more realistic than models often used in mobility wireless networking research, realistic mobility alone will not produce realistic simulations. Along with realistic protocol and physical layer simulation, it is critical to model the channel realistically. Furthermore, mobility simulation and channel simulation are linked by the virtue that they both use the same city map. Furthermore, since the time varying nature of the channel is due to both propagation and mobility, realistically simulating one without the other does not result in realistic simulation. Therefore, the techniques discussed here are incorporated into a simulation package that includes propagation simulation. A discussion of propagation simulation and our simulator can be found in a companion paper [ref].

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