A Survey-Based Mobility Model of People for Simulation of Urban Mesh Networks

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Abstract

In this paper a mobility model of people in urban areas for mobile wireless network simulation is presented. Unlike most mobility models found in the literature, this model attempts to provide realistic mobility of people in an urban setting. To this end, the model is based on data collected through a number of surveys. The result is a 3-layer hierarchical model where the highest layer is an activity model that determines the high level activity that the node is performing (e.g., working). The second layer is a task model that determines the specific task within an activity (e.g., meeting with three people). And the third layer is an agent model that determines how the person moves from one location to another (e.g., how a node navigates down a crowded hallway). The activity model is based on a recent US Department of Bureau of Labor Statistics time-use study. The task model focuses on mobility of office workers and is based on the current findings by the meetings analysis research community. The agent model is based on the work from urban planning that has extensive knowledge of pedestrian flow. The models presented are implemented in a mobility simulator that is integrated with a propagation model.

I. Introduction

There has been growing interest in urban mesh networks. Recently, the city of Philadelphia has entered the final planning stages for the deployment of a mesh network that intends to provide coverage to the entire 135 sq. mi. city with 4000 fixed base stations [1]. Several other cities are considering similar deployments [2].

While these deployments are proceeding, there remains a large number of unresolved issues relating to the performance of these networks. However, since these networks have yet to be constructed, in order to study them and validate findings related to them, one must utilize simulation. The simulation of urban mesh networks is largely unexplored and quite different from the simulation techniques currently used for mobile ad hoc networks (MANETs). For example, urban mesh networks may be composed of fixed base stations, fixed wireless relays, handheld terminal, and terminals in vehicles whereas MANET research has focused on homogeneous networks in military scenarios. Furthermore, the number of civilians hoped to use such networks far exceeds the numbers of nodes considered in today's simulation of military ad hoc networks. For example, in today's literature, it is not uncommon for MANET simulations to use less than 100 nodes over a 1km^2 region, whereas during the lunch hour, a 1km^2 region in midtown Manhattan has about 10000 people outdoors [3]. Furthermore, today's simulations of military MANETs utilize mobility models such as the random waypoint mobility model that attempts to capture the wide range of mobility that such networks might experience. Such mobility models cannot be applied to urban mesh networks where mobility is more civil.

The principal aspects of urban civilian mobility are that the pedestrians move along sidewalks and inside buildings, while vehicles move along roads. Furthermore, pedestrians and vehicles obey various rules. For example, vehicles and pedestrians, more or less, obey traffic signals. Also, in order for a faster node to pass a slower node, it must go around the slower node. If there is no room to pass, then the faster node must decrease its speed to that of the slower node and follow until there is room to pass. And finally, the mobility of people and vehicles is not necessarily purely random but dictated by the activity that the node is performing. As a result, mobility is not stationary, but varies according to the time of day.

This paper presents a detailed mobility model of urban pedestrians during the workday. This model is based on three mature research areas, urban planning [3], [4], meeting analysis [5], and use of time [6]. The resulting model is a three layer hierarchical model. The top layer is the activity model that determines the high-level types of activities as well as 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 [7]. This study includes interviews with roughly 20,000 people. Furthermore, the BLS determined weightings to account for over sampling 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 over sampled). 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 [5] 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 [8]. 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 [3] 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 the proximity of nodes to other nodes plays an important role in the performance of mesh networks.

The models presented here are part of a set of simulation tools for modeling urban mesh networks. Along with mobility, the simulator includes wireless transmission propagation modeling and tools for designing urban maps including sidewalks, roads, buildings, types of buildings, etc. It is crucial that a simulator of urban mobility is integrated with propagation models. For example, the mobility model may specify that a node moves from indoors to outdoors. However, there are dramatic differences between propagation indoors and propagation outdoors. Merely modeling the mobility of the node without a reasonable propagation model will likely distort the conclusions gained from the simulation.

The paper proceeds as follows. In the next section a brief overview of some related work is provided. Next, some basic ideas about maps and building layout are provided. The model is described in the following three sections: Section IV describes the activity model, Section V describes the task model, and Section VI describes the agent model. Section VII provides some concluding remarks.

II. Related Work

The fact that mobility plays an important role in MANET performance has been demonstrated in [9]. The specific importance of realistic simulation has been demonstrated in [10] and [11]. These later two papers also demonstrated the importance of integrated mobility and propagation simulation. In this paper, we only describe our mobility model with propagation left for a companion paper.

A review of mobility models of MANETs can be found in [12]. However, MANET research has been dominated by the random way-point mobility model. While such a model may provide valuable insights, it is far from realistic and will likely not give reasonable performance estimates of urban mesh networks. In [9] and [12] mobility models are presented where the nodes are restricted to move along roads of a hypothetical grid-like city. In [13] the graph is not grid-like but based on a Voronoi graph. In [14], a random graph is used. In these cases, the mobility is essentially random way-point, but restricted to a graph. However, [10] illustrated the role that realistic maps play on propagation and network performance.

Recently there has been interest in developing more detailed models along the lines discussed here. For example, [15] and [16] discuss an empirical model based on observations of pedestrian on a university campus, while [17] describes a realistic model of MANET mobility during disasters.

One of the most detailed mobility models is GEMM [18]. 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 here uses parameters derived from surveys, and hence are realistic.

Urban planning, sociology, and architecture have been actively developing mobility models for at least

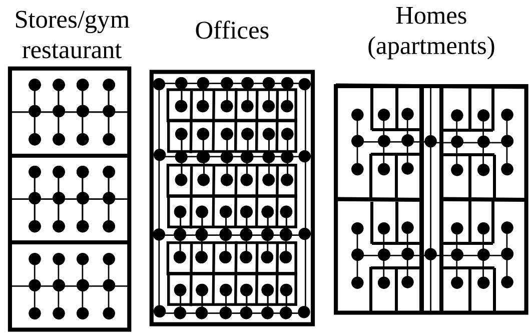

Figure 1. Locations in different types of buildings. Locations are marked with a circle while arcs are indicated by thin lines. The thick lines denote walls. The store/gym/restaurant structure is such that each third of the layout can be any of these options. The apartment building shown has four apartments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

fifty years [19]. As a result, there are far too many approaches and papers to mention here. However, for pedestrian mobility, it appears that the models composed of activity-based model and an agent-based model are the state-of-the-art [20], [21]. This paper utilizes this layered approach to mobility modeling. Furthermore, the model presented here is based on data collected through rigorous surveys.

III. Building and Location Types

The mobility model defines the locations and trajectories of mobile nodes. To this end, the urban region under consideration is modeled as a graph; all locations are vertices and pathways between the locations are arcs. Nodes can only move along the arcs. Locations include offices, hallways, sidewalks, crosswalks, rooms within a residential apartments, seating locations in restaurants, locations within a store, and locations within a gym. As shown in Figure 1, buildings are modeled simply. Our simulation tools require manually generating buildings. The interior layout is automatically generated.

IV. Activity Model

This part of the mobility model is based on the US Bureau of Labor Statistics 2003 time-use study [7]. This study identifies a large number of activities. We focus on those activities that indicate location and group activities together 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 is 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 some one 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 an 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

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	-

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. According to the BLS data, 90% of the people drive to work, 5% walk to work, the remaining 5% take other forms of transportation including subway, bus, and other forms of transportation to work. These parameters can be altered for the simulation of European cities that have significantly fewer people driving to work.

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 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.

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.

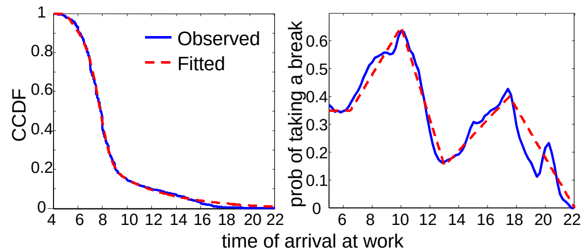

Figure 2. Left. Complimentary cumulative distribution function (CCDF) of the time of arrival at work. Right. The probability of taking a break given the arrival time at work. This includes arrivals after a break.

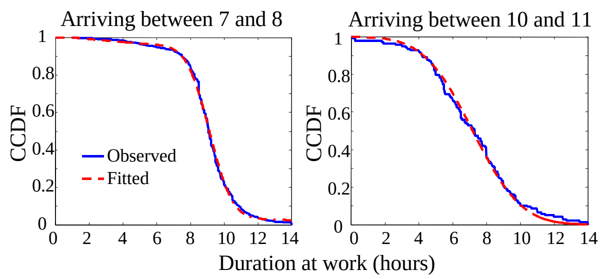

Figure 3. The CCDF of the duration at work for two different arrival times at work.

We fit the probability of taking a break given the time of arrival with a piece-wise linear function.

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

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 $\left(t_1 - t_0\right) \int_{t_0}^{t_1} r\left(\tau\right) d\tau$. The observed rate and fit is shown in Figure (4).

Number of activities performed during a break Figure (5) shows the probability of performing different numbers of activities during a break. We see that over the course of the day, the number of activities

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

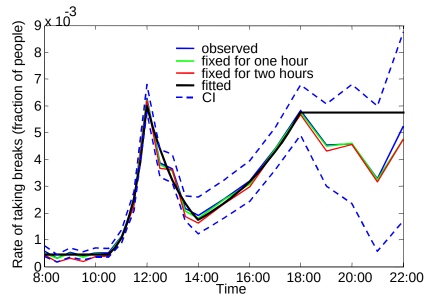

Figure 4. The rate that a person takes a break and leaves work given the current time. Also shown are the rates conditioned on the person being at work for at least one and two hours. These rates are within the confidence intervals that are also shown. Finally, the fitted rate is also shown.

performed varies. However, the variation is small, and hence we take 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

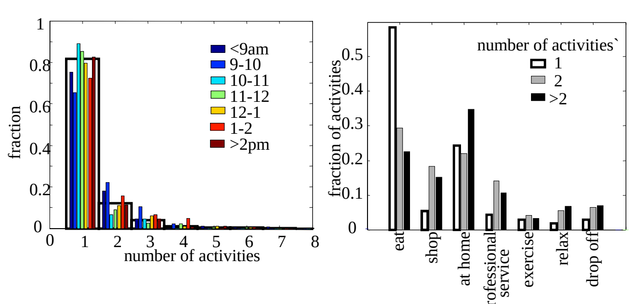

Figure 5. Left: the number of activities done during a break conditioned on the time that the break is started. Right: the fraction of time that a break includes the indicated activity given the number of activities performed within the break.

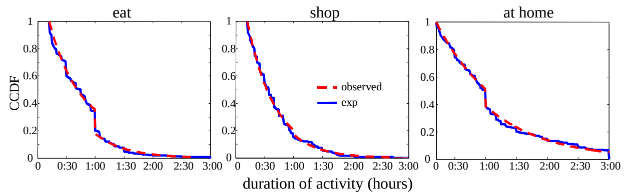

Figure 6. CCDF of the duration of eat, shop, and at home activities.

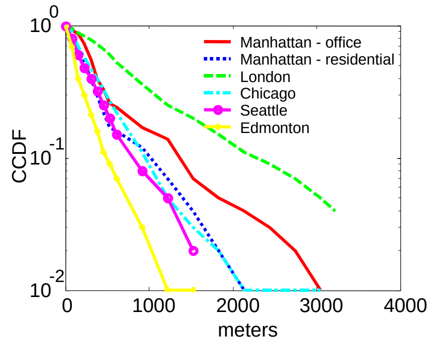

Figure 7. CCDF of Distance Traveled During Outdoor Walking Trips. This data is from [3].

requires 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 [3] 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.

V. 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, work is modeled in a more complicated manner that focuses on modeling meetings. Specifically, [5], [22], [23] have collected data on the frequency, size, and durations of meetings; [22] 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 determined from [5], [22], [23] . 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

VI. Agent Model - Node Dynamics and Interactions

Since the pioneering work of Pushkarev and Zupan [3], 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 people. 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 VI-C, the model is validated by comparing the size of platoons created by the model to those observed by Pushkarev and Zupan.

A. *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 a following vehicle should not be closer than two second behind the vehicle it follows. For both vehicles and pedestrians, these relationships have been extensively studied. Here we focus on the pedestrian case.

The distance-speed relationship for pedestrian is studied in [24] and [25]. Figure 8 shows the distance-speed relationship derived from these observations[1]. We approximate this relationship with $D(S) = S^* D_{\min} / (1.08 \times S^* - S)$ 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 [3].

It has been found that pedestrian desired speeds are approximately Gaussian with mean 1.34 m/s and standard deviation 0.26 [27], [28], [29].

B. *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 [3]. 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 [30]. Such decisions lead to platooning.

[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 [26].

[2] Our simulator includes traffic lights.

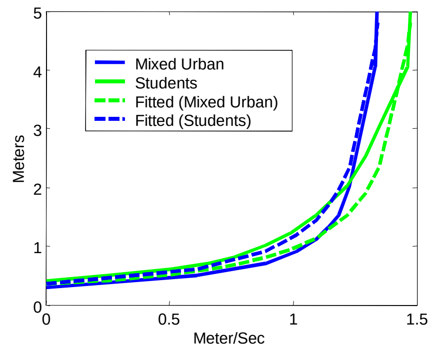

Figure 8. Speed-distance relationship for pedestrians. The mixed urban pedestrian data is adapted from [24] and the student observations are adapted from [25].

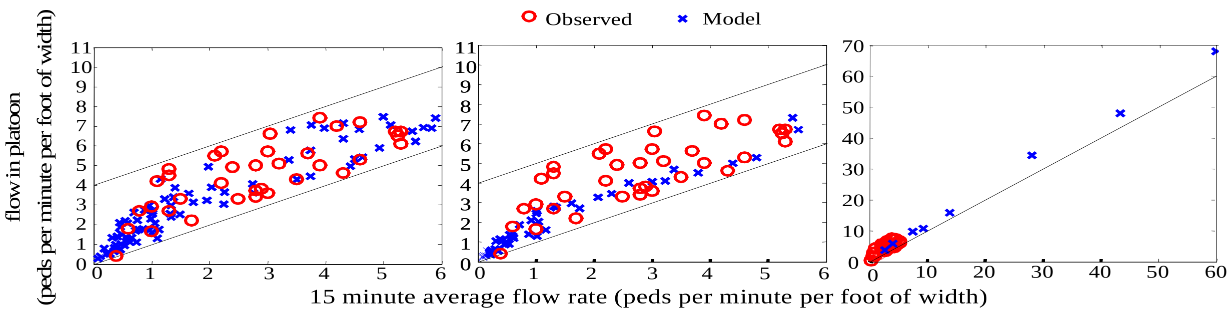

Figure 9. 15 Minute Average Flow Rate versus Flow Rate in a Platoon. The flow rate is the number of pedestrians that pass by the measurement point per minute divided by the width (in feet) of the sidewalk. The black line is the area of realistic values found by Pushkarev and Zupan.

While the dynamics of pedestrian overtaking has been observed, it has not been modeled. However, models for vehicle passing have been developed [31]. 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 lanes and overtake a slower node is

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

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 [31], 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.

C. Validation of Pedestrian Mobility

The burstiness of pedestrians has been investigated by Pushkarev and Zupan [3]. Their work has served as the basis for the pedestrian traffic engineering guidelines set forth in the Highway Capacity Manual [4]. 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 busrty 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 [3]).

VII. Conclusion

We presented a realistic mobility model for use of simulating urban mesh networks. The model is based on extensive data, and hence the model and parameters derived from what has been observed. The model is composed of three sub-models, the activity model, the task model, and the agent model. The activity model is based on a recent US Labor Department study of time-use in America that collected detailed information about how people spend their time. The task model focuses on the mobility of people inside office buildings. This model is based on work in the area of meetings analysis [5]. The agent model determines how mobile nodes interacts with each other as they move toward their destinations. This model is based on the work of Pushkarev and Zupan [3].

While this model is far more detailed and realistic than previous mobility models, the task of modeling and simulating urban mesh networks is far more challenging than simulating ad hoc networks that have been dominated by the random way-point mobility model. This paper includes only a model of pedestrians. While vehicle models have been developed and are included in the simulator that implements the mobility described here, the vehicle and pedestrian models are not yet integrated to the point that the model includes people driving and parking cars.

Due to lack of space, this paper only focused on the mobility model itself. Work is currently underway that demonstrates the importance of such mobility models in terms of network performance.

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