Agenda Driven Mobility Modeling

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Abstract: Mobility modeling is an essential component of wireless and mobile networking research. It assists planning, developing and evaluating protocols and mobile systems. A simulated mobile world provides flexibility for constructing scenarios that closely resemble the real world. Our proposed mobility model emphasizes humans' social roles when making movement decisions. Our model, the Agenda Driven Mobility Model, takes into consideration a person's social activities in the form of agenda (when, where and what) for motion generation. The paper uses a constructive approach to define functional components of the Agenda Driven Mobility Model for building specific real world scenarios and generating motion steps. A variety of real data sources can be used to populate these components. In this sense, the model provides a framework for translating social agendas into a mobile world. In the paper, we utilize National Household Travel Survey (NHTS) information from the U.S. Department of Transportation to obtain activity and dwell time distributions. As an example, we simulate a mobile ad hoc network in an urban scenario, analyzing the geographic features of the network topology generated by the model and the impact of the model on routing performance. Our simulation results suggest that social roles and agenda activities tend to cause geographic concentrations, significantly impacting network performance. We conclude that the incorporation of social agendas into mobility modeling produces a performance evaluation that better reflects real world scenarios.

Keywords: agenda driven mobility model, mobility model, mobile ad hoc networks, simulation.

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1 Introduction

Mobility modeling has become an important direction in wireless and mobile networking research because it helps in planning, developing and evaluating mobile systems and applications that are under development or have been deployed. Many testbeds or network infrastructure are available for providing understanding about mobility impact. Still, vast amount of research and developments use simulations for performance evaluation. A simulated mobile world is one of the enabling tools that contributes to the research in wireless and mobile networking with which researchers are able to study performance of protocols at all layers of the protocol stack. Research results show that mobility models have a significant effect on the performance of protocols (Camp et al., 2002; Hong et al., 1999). The same routing protocol may produce dramatically different levels of packet delivery capability when evaluated with different mobility models. Thus, the capability and flexibility of capturing key properties of a real mobile node become a critical requirement for a mobility model.

Many mobility models have been proposed recently. Interested readers are referred to (Boukerche and Bononi, 2004; Camp et al., 2002; Zheng et al., 2004) for surveys and modeling issues. Among those existing models, the majority consider the geographical movements of individual mobile communication devices. Those models can be classified into three classes (Zheng et al., 2004) based on the degree of randomness, i.e., total random statistical models, partial random constrained topology based models, and trace based models. Examples include Random Waypoint Model (Johnson and Maltz, 1996), Manhattan Model (Bai et al., 2003), and trace based models (Zhang et al., 2007; Hsu et al., 2007; Kim et al., 2006; Tuduce and Gross, 2005). The statistical and constrained topology based models regard each node as statistically identical and independent. They do not reflect social connections among mobile users nor possible influence of such connections on motion behaviors. Trace based models could include different types of nodes, but they may not explicitly model node roles.

Mobility models taking social connections among mobile users into consideration have also been proposed, where correlated or coordinated motion patterns are identified. Group mobility models were proposed (Hong et al., 1999; Li, 2002) to describe mobility of nodes that tend to move in a group. Mobility models considering real social network have been proposed in (Herrmann, 2003; Musolesi et al., 2004; Musolesi and Mascolo, 2006). These models capture the fact that nodes with stronger social relations tend to move together. Geographic motions are not taken into consideration in these pieces of work.

In this paper, we address the social influence on human's motion behavior from a drastically different angle of mobility modeling, namely, we use a person's social activities as a driving force for his or her movement. To this end, we introduce a key element named *agenda* into mobility modeling: the agenda guides a node's movements. This is based on the observation that people's movements are most likely the explicit or implicit results of their activity agenda. On the other hand, as a mobility model, activities must map to geographical locations and motion steps. In this paper, we introduce a general mobility modeling framework named *Agenda Driven Mobility Model*. The framework contains components that model social activities, geographic locations, and movements of mobile users. It can be used to characterize various wireless network scenarios, e.g., campus wireless networks, urban mesh network coverage, or a regional wireless network that would contain multi-hop wireless networking, vehicular networking and opportunistic connectivity. We use a constructive approach to define functional components for building real world scenarios and generating motion steps. We also instantiate the Agenda Driven Mobility Model in an urban scenario. In such a scenario, the uses of mobile and wireless technologies like UMTS, mesh networks, WiFi or mobile multihop wireless networks are or will be all available. Further, we simulate a Mobile Ad Hoc Network in this scenario to show the spatial statistic properties, the aggregated connectivity graph properties and communications performance. Our simulation results show that the incorporation of social roles and agenda activities into mobility modeling has significant impact on routing protocol performance. Moreover, the idea of agenda has its impact beyond this mobility model. Since agenda provides a certain amount of predictability of a node's whereabouts, it can be used to assist routing (Tang et al., 2007).

An earlier version of this work was presented in (Zheng et al., 2006). This papers extends the work by presenting data analysis results for the National Household Travel Survey (NHTS) (U.S. Department of Transportation, 2007) of the U.S. Department of Transportation. We also analyze the Agenda Driven Mobility Model using a continuous time Markov chain. The model is evaluated with more simulations, and new insight is discussed. The rest of the paper is organized as follows. Section 2 gives a brief review of related work on mobility modeling. Section 3 introduces the Agenda Driven Mobility Model. An overview of the framework and detailed descriptions of the components of the model are given. Section 4 introduces NHTS survey, where the social activities that our model uses are described in great detail. Section 5 analyzes our model by using Markov chain. In Section 6 we use simulation to show the network topology generated by the model and the ad hoc network routing performance impacted by the model. We conclude the paper in Section 7.

2 Related Work

Based on the degree of randomness as nodes move geographically, mobility models can be classified into three classes (Zheng et al., 2004), namely, total random statistical models, partial random constrained topology based models and trace based models. A few representative models are reviewed below.

Random Waypoint Model (Johnson and Maltz, 1996) is a widely used statistical model. In this model, nodes randomly select destinations, speeds, and destination pause durations. In Random Direction Model (Royer et al., 2001), nodes randomly select directions. In these two models, nodes move freely in an open area. To restrict nodes' movements to a more realistic application scenario, several other models were proposed. Obstacle Mobility Model (Jardosh et al., 2003) introduces obstacles to restrict node movements and signal transmission. In City Section Model (Camp et al., 2002), nodes move along street grid to their random destinations. In Manhattan Model (Bai et al., 2003), nodes wander along street grid and make random turns at street crossings. Researchers also proposed mobility models specifically for vehicles on roads (Choffnes and Bustamante, 2005; Saha and Johnson, 2004), where real maps were acquired from the U. S. Census Bureau's TIGER (Topologically Integrated Geographic Encoding and Referencing) database (U.S. Census Bureau, 2007). These pieces of work simulated car-following and traffic control (traffic lights, stop signs, lanes, etc.). Mobility models based on the analysis of user moving patterns from trace data were also proposed (Jain et al., 2005; Kim et al., 2006; Lelescu et al., 2006; Tuduce and Gross, 2005). For example, transition probabilities between physical locations are obtained in (Tuduce and Gross, 2005), the speed and pause time of campus users follow a log-normal distribution (Kim et al., 2006). In the models, nodes move according to these probabilities or distributions. Based on similar trace data, (Hsu et al., 2007) proposed a time-variant community mobility model, where communities were introduced to capture the fact that people tend to visit some places more frequent than others and that people will periodically revisit the same places. In (Zhang et al., 2007), a very interesting set of trace data from a bus-based delay tolerant network was analyzed and models for describing contact process between node pairs were derived. The work provides valuable insight into real world mobile ad hoc networks and the importance of selecting the right granularity for mobility modeling. Nationwide Personal Transportation Survey (NPTS), the predecessor of the National Household Travel Survey (NHTS) (U.S. Department of Transportation, 2007) that we use for this study, was also used in Metropolitan Mobility Model (Lam et al., 1997) which captures the distribution of daily locations visited and the transition probabilities between locations.

Mobility models considering real social network have been proposed in (Herrmann, 2003; Musolesi et al., 2004; Musolesi and Mascolo, 2006). They are based on the observation that people's relation with each other heavily influences their mobility patterns and motion correlations. In (Herrmann, 2003), a graph is created where edges represent that two persons will meet each other. A set of nodes that must meet each other forms a clique. Nodes in each clique meet at an anchor (a location). The movements of nodes are generated from anchor to anchor. In (Musolesi and Mascolo, 2006), the authors used interaction matrix to represent the strength of interactions between nodes (persons). Communities are then extracted based on that matrix. A node chooses a region as its destination with the highest social attractivity, the value of which depends on the interactions between this node and the nodes already in that region. A group mobility model was proposed in (Hong et al., 1999) to describe mobility of nodes that tend to move in a group, where correlated or coordinated motion patterns are identified. The focus of that model is on the relation between individual mobility and the mobility of the group he or she belongs to. A further group mobility model (Li, 2002) was able to determine group membership dynamically at runtime based on each node's current state. It has the very nice property of deciding group membership by similarity of mobility pattern rather than physical distance.

In all, these models use different modeling approaches from the activity-driven approach we present in this paper. In our model, both social and geographical factors are considered. The social factors and their influence on motions are reflected implicitly through agenda items.

3 The framework of Agenda Driven Mobility Model

We aim at not only developing a concrete mobility model but also providing a general framework which allows us to build various scenario-oriented mobility models to meet different network applications and research demands. This framework defines functional components for building more specific motion scenarios and generating motion steps. In this model, nodes move with purposes (not randomly) and different nodes have different moving behaviors. To model his or her social role, each node has an individual agenda which specifies his or her activities at various times and locations corresponding to his or her role. The movements of the node are totally determined by this agenda. The geographical aspect of the model is supplied by geographic maps with roads and addresses as basic elements. More specifically, while *agenda driven* being a core concept, we introduce it and materialize it in a constructive way, especially when the association between an agenda and a geographic location is concerned. We instantiate the Agenda Driven Mobility Model in an urban scenario. In this section, we first present an overview of the framework, then we describe the key elements of our model.

3.1 The general framework

This framework has three key components: personal agenda, geographic map, and motion generator. They will be elaborated in this section. It also includes knowledge bases of activity profiles for job related and social connection related activities. Fig. 1 illustrates the architecture of the framework.

An agenda defines a person's activities based on his or her social role. It includes "what, when and where" elements of the activities. The agendas drive the movements of nodes. The National Household Travel Survey (NHTS) (U.S. Department of Transportation, 2007) data is used to obtain various distributions to generate agendas, including activities and dwell times.

A geographic map contains location information of possible activities and road information that connects all the locations. Our model presents the map with its geographic addresses that are associated with activities. This gives the framework great flexibility in being populated using various geographic data sources, e.g., program generated random locations, significance statistics of locations from WLAN traces, or real maps from GIS database like TIGER (the U. S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing database) (U.S. Census Bureau, 2007).

With inputs from an agenda and a map, a motion generator generates nodes' physical movements, i.e., how nodes move along the map to reach their destinations, including moves, turns, and pauses.

In addition to these three key components, there are global knowledge bases that will be used to help generate the personal agenda. Global knowledge bases include job-related activities, social events calendar, social relationships, area maps at different detail levels and common senses.

Based on the framework, different scenarios can be constructed by using different maps and activities as inputs. In the rest of the section, we build a concrete Agenda Driven Mobility Model for activities in an urban area.

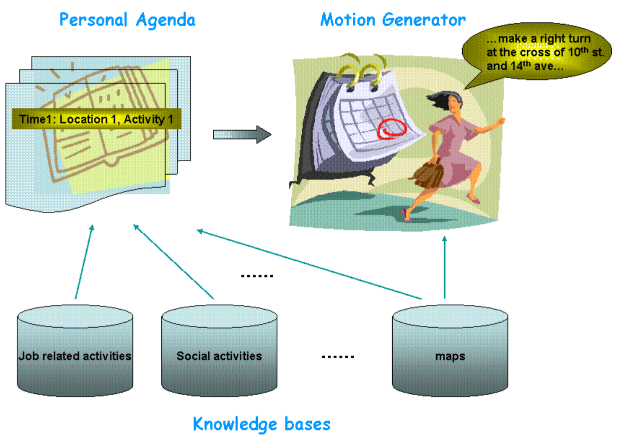

Figure 1: Agenda Driven Mobility Model

3.2 NHTS survey data

An important step we take to model the mobility *realistically* is to use measurements from the real world. We use data from the National Household Travel Survey of the U.S. Department of Transportation. "The *National Household Travel Survey* (NHTS) is the national inventory of daily and long-distance travel. The survey includes demographic characteristics of households, people, vehicles, and detailed information on daily and longer-distance travel for all purposes by all transportation modes. NHTS survey data are collected from a sample of U.S. households and expanded to provide national estimates of trips and miles by travel mode, trip purpose, and a host of household attributes" (U.S. Department of Transportation, 2007). A sample record of the data from NHTS would read like this: a student, on a specific weekday took a trip; the purpose of the trip was to go to school; she used her personal vehicle to travel a distance of four miles, which took her 10 minutes; she then stayed at school for six hours.

The large number of records in the database presents many useful statistics, e.g., people's various occupations, their activity features, such as the mode of transportation, the duration, distance and purpose of a trip, dwell time at the destination, etc. From the NHTS repository, we extract the distributions of address type, activity type, dwell time, etc., to be used in our model. In the particular urban scenario that we build in the paper as a case study, we do not include all the possible distributions. Rather, we pick a set of representative occupations and use only associated distributions. This allows us to focus on the descriptions of the model. To illustrate the usefulness of the NHTS data in mobility modeling, we will describe our analysis methods and results in a later section.

3.3 Geographic map

Geographic topology is a key component in our model. In our Agenda Driven Mobility Model, the geographic map consists of streets and avenues. These streets and avenues are the routes where real motion takes place. To capture the fact that human activities are conducted at certain locations on streets and avenues which can be identified by addresses, we base our mobility model on road addresses. Each activity on a person's agenda then links to a specific address.

Earlier synthetic mobility models like Random Waypoint Model allow nodes to move freely in an open area by picking a random location and moving straight towards it. Criticizing Random Waypoint Model as unrealistic, a later model named Obstacle Mobility Model (Jardosh et al., 2003) constructs map and confines node movements on roads. In that model, the construction includes two steps: first, buildings are randomly scattered in an area; second, roads are built according to Voronoi diagram of these buildings.

Our approach of constructing map differs from the above practice. We define roads first and place buildings (addresses) second. The buildings are represented by their addresses. People move along the roads and stay at those addresses for the activities listed in their agendas. This approach allows great flexibility in populating the map: users can use real digital map like that from the TIGER database, or use synthetically generated roads and addresses as we do in our implementation.

In our implementation we use synthetic approach to generate a map consisting of roads with addresses. We take the example of Manhattan type of city scenario. The map in our implementation consists of streets that run east-west and avenues that run south-north. Distances between neighboring streets (or avenues) are randomly chosen; they are not equally separated. The lengths of streets and avenues are also randomly chosen within a certain range. The generated streets and avenues are indexed (and also named) numerically, e.g., from south to north, streets are numbered $0, 1, 2, ...$; and from west to east, avenues are numbered $0, 1, 2, ...$ Fig. 2 shows a typical urban area generated by our model. Addresses are notated with '+'.

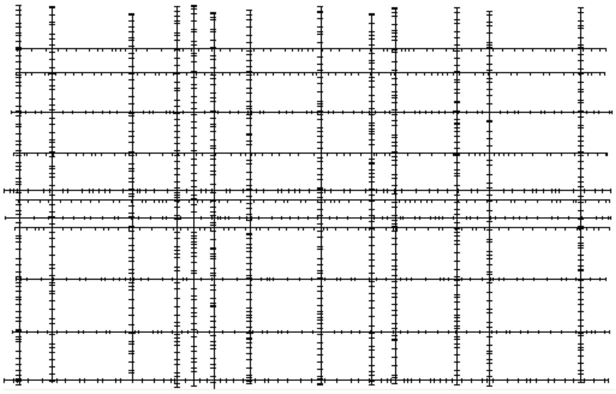

Figure 2: Map generated by the Agenda Driven Mobility Model. Addresses are marked. Each address serves a different function, e.g., restaurant, school, super market.

3.3.1 Address

An important element in our Agenda Driven Mobility Model is the addresses. Addresses are used to locate the places where people will stay for certain activities. The address distributions can be either acquired from real road data or randomly selected.

Each address is associated with one type of activities that people will conduct at that place, e.g., a restaurant, a library, etc. The importance of address type is that it decides how long people will stay there, i.e., the dwell time at that location. Dwell times are different for different types of activities, and hence different at different types of addresses. For example, a gas station has a shorter average dwell time than a restaurant. From the NHTS database, we obtain mean durations of many types of activities. We call it mean activity duration. For example, activity 'go to gym exercising' takes an average of 91 minutes, activity 'ice cream break' takes an average of 25 minutes.

The actual duration a person staying at an address is mainly decided by this mean activity duration (travel time will also be considered as shown in later section). This approach of deciding dwell time ensures a realistic meaning - compare that to the approach of randomly picking a dwell time as used by many existing mobility models like Ranom Waypoint Model, Obstcle Mobility Model, etc.

The NHTS database provides a large collection of address types (28 in total). From those, we are able to derive the occurrence ratio of each address type. For example, 1.7% addresses are theaters. The NHTS database also provides mean activity duration. We will discuss this later.

3.3.2 Speed table

We take into consideration the fact that a node's speed is decided by road traffic which is out of the traveler's control. Thus, each street or avenue is associated with another important property - speed limits. Each street or avenue is assigned a speed table which contains the estimated speed ranges for nodes moving along this road at different times of the day. Any node entering this road has to move according to the speed limit of that time.

3.4 Agenda

The *agenda* of a node is the core of our Agenda Driven Mobility Model. It organizes all the whereabouts of this node. The places he or she stays, the time he or she travels and all the details regarding a trip to his or her next destination. For example, in a college student's schedule for a certain weekday, he or she records which classes he or she is going to take and in which building, when and where he or she is going to have lunch, and when and where he or she is going to exercise. He or she will then move according to this schedule. Thus agenda well captures the social aspect of human activities. In our model, each node carries a unique agenda. Agenda describes his or her whole day journey. Each item of the agenda indicates when and where the node will be, and what activity he or she is going to participate. The node moves only according to his or her agenda. Please note that in our model, the time associated with each activity is the time the activity is expected to begin, e.g., the time for an interview. Thus, a node has to calculate the time to start to move towards the next activity according to the destination's address, the roads' average speeds, and the time that he stops the current activity.

3.4.1 Activities

Each agenda item will specify an activity the person will participate. The NHTS data records 35 different types of activities (purposes of trips) in total. Examples include 'go to work', 'shopping', 'hang out', etc. Each activity has a corresponding mean activity duration. NHTS data also gives the distribution of frequency of these activities. For example, it tells us that 2.3% activities are 'buy gas'. In agenda generation, we use this distribution to select the activity for next agenda item. Each activity will be performed at a corresponding address and the node will stay at that address for a time period around the mean activity duration. For example, the activity of 'buy gas' will result in a node staying at a gas station for about 9 minutes.

3.4.2 Occupation types

It is natural to assume that people with different occupations will have different activities and people with the same occupation have similar activities and agendas. NHTS data shows a total of 14 occupations together with their corresponding percentages. Our model allows a predefined profile agenda template for each occupation type. A node with the occupation will derive his or her own agenda based on the profile (and add his or her own randomness).

3.4.3 Agenda generation

Our implementation of the Agenda Driven Mobility Model creates an agenda for each node at initialization that covers all day long activities. The type of the activity for the next agenda item is picked according to NHTS's activity distribution; its address is picked randomly from the many addresses of the corresponding address type (notice that there will be many addresses bearing the same address type).

The time recorded in the agenda for each item is the time the activity expected to occur. Thus the time for the next activity has to consider the current activity's mean activity duration, and the longest possible travel time from current address to next address. More specifically, the current activity will last for a period around the mean duration (select from an appropriate distribution); the longest possible travel time will take the shortest path from the current location to the next location using the slowest speed of each road segments. So the next activity's starting time equals to the current activity's starting time plus the current activity's lasting time and the longest possible travel time to the next address.

3.5 Motion generator

Motion generator chooses a motion path for a node to move towards its next activity location according to the agenda. This path is the shortest distance path between current activity location and the next activity location (using Dijkstra's algorithm). It also calculates the time that a node starts this movement. Let us suppose the starting time of current activity is T_1, the starting time of next activity is T_2, the trip duration is D_t. Notice that given T_2, next address, current address, and speed tables of roads that the node will travel from current address to next address, the trip duration D_t is acquired accurately by counting backwards from T_2 (as the node takes the shortest path). Then the dwell time at current address is $T_2 - T_1 - D_t$. The node starts its movement at $T_2 - D_t$. It will arrive at next address just in time at T_2. Since in our agenda generation we use the longest possible travel time from current address to next address to decide the starting time for next activity, a node will always have enough time to finish its current activity and travel to the next location before the scheduled starting time of next activity. Current model doesn't consider extreme travel cases.

4 NHTS data analysis

4.1 The Survey data

NHTS survey data serves various purposes, for example, transportation safety (U.S. Department of Transportation, 2007). Mobility modeling is one of its many uses. As cited earlier that the National Household Travel Survey of U.S. Department of Transportation includes demographic characteristics of households, people, vehicles, and detailed information on daily and longer-distance travels for all purposes. It collected travel data from a national sample of the civilian, non-institutionalized population of the United States, not including people living in college dormitories, medical institutions, military bases, etc. The available 2001 NHTS dataset includes approximately a total of 66,000 households. About 26,000 households are in the national sample, while the remaining 40,000 households are from nine add-on areas, including Baltimore metropolitan area, Des Moines metropolitan area, etc. Four datasets are provided in the original survey data, describing the household information, personal information, vehicle information, and the information of each day trip. In our study, we use the data that provides profiles of day trips.

A portion of the database is shown in Table 1 (the actual database has more fields. We excluded those fields that are not directly related). For each field, data records are marked with different code values. Some fields have a large set of values that finely categorize the fields. Many of the subcategories are useful for other statistics information but not necessary for mobility modeling. For the convenience of analysis, we processed the database to aggregate some codes that only have a small amount of records associated with them. For example, code for 'attend funeral/wedding' and 'family personal business/obligations' are combined into one. Only limited bias could be introduced to the related fields due to the small portion of the data affected.

We give a brief description of the fields in Table 2. The listed `OCCAT` codes are the occupations of the persons who take the trips. `WHYTRP01` has a large collection of codes and is the source of the activity types in our model. NHTS has provided aggregated `WHYTRP1S` field which simply groups similar purposes of `WHYTRP01` into larger category. For example, code 3 ('shopping') of `WHYTRP1S` includes not only `WHYTRP01` code 41 ('buy goods: groceries/clothing/hardware store'), but also `WHYTRP01` code 43 ('buy gas'), among others.

`STRTTIME` and `ENDTIME` are the starting and ending time of the trip. `TRPMILES` is the mileage of the trip. `DWELTIME` is how long the person stays at the trip destination, counted in minutes. We define trip duration `DURATION=ENDTIME-STRTTIME`, which represents how long this trip lasts. The histograms of `DURATION` (trip duration), `TRPMILES` (trip mileage) and `DWELTIME` (dwell time)

Table 1: Simplified sample NHTS data records

OCCAT	WHYTRP01	WHYTRP1S	STRTTIME	ENDTIME	TRPMILES	DWELTIME
3	60	4	1000	1015	6	235
3	1	6	1410	1425	6	45
1	11	1	815	825	5	515
4	41	3	1100	1105	0.77	20
4	11	1	1125	1128	0.22	47

Table 2: Selected categories in simplified sample NHTS data

Field names	Meaning	Code
OCCAT	occupation	1 = Sales or Service 2 = Clerical or administrative support 3 = Manufacturing, construction, maintenance, or farming 4 = Professional, managerial or technical 91 = Other
WHYTRP01	purpose of a trip	1 = home 11 = go to work 41 = buy goods: groceries/clothing/hardware store 60 = family personal business/obligations ...
WHYTRP1S	larger category of purpose	1 = work 2 = school 3 = shopping 4 = personal 5 = social 6 = others

for different trip purposes are shown in Figs. 3, 4, and 5.

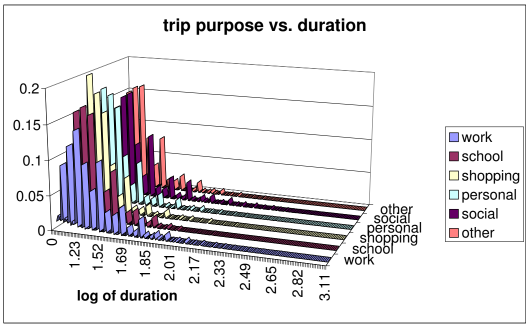

Figure 3: Trip duration distribution

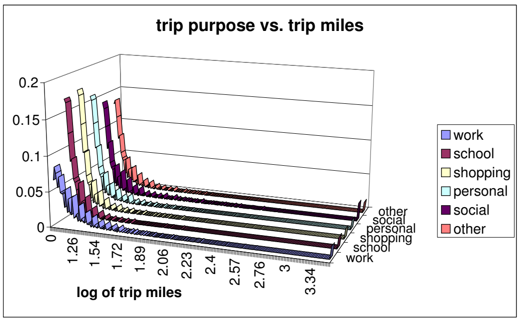

Figure 4: Mileage distribution

4.2 Data analysis

In this section, we present our analysis on the survey data using statistics tools for the distributions of trip duration, mileage, and dwell time. All of these results are important for mobility modeling. We examine the histograms obtained from the raw data presented in Figs. 3, 4, and 5 (secondary distributions are removed in this analysis).

We use a statistics tool called DFITTOOL in MATLAB (MathWorks, 2007) to fit the data to different distributions. DFITTOOL draws Cumulative Distribution Function (CDF) of the data. It also shows CDFs of those different distributions together in one graph, allowing us to decide which distribution fits the data best. In determining the closeness of fitted distributions against the real data, we use AIC (Akaike's Information Criterion) (Burnham

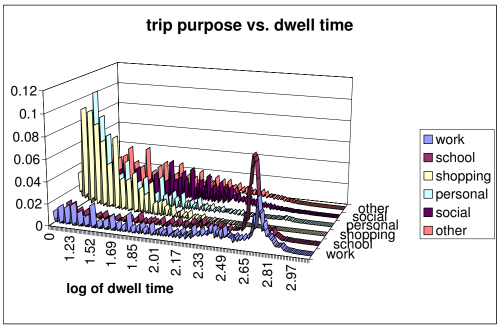

Figure 5: Dwell distribution

and Anderson, 1998) method. AIC is defined as:

$AIC = -2 * (\text{log likelihood}) + (\text{number of parameters}) * 2$

In this formula, *number of parameters* is the number of parameters in the distribution. For example, the normal distribution has two parameters, μ and σ, thus, number of parameters = 2. The *log likelihood* is provided by DFITTOOL as an output. So for each candidate distribution, we can compute its AIC. The one with the smallest AIC is the best fit for the data.

4.2.1 trip mileage

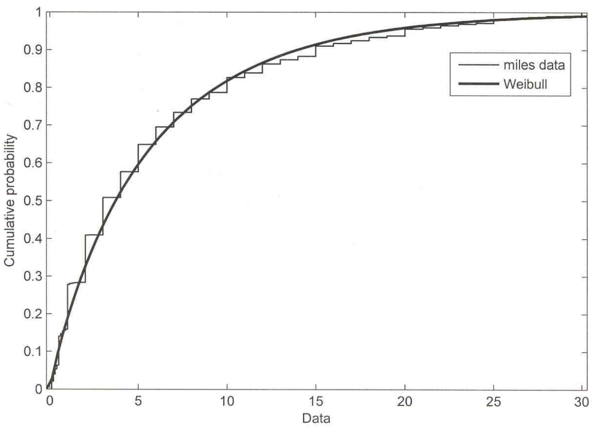

Figure 6: Fit Weibull distribution to trip mileage data

Initial observation of the raw data shows that the mileage of 94.9% trips are under or equal to 30 miles. Of the remaining records, some mileage is exceptionally large. Those large milage comes from long distance travelers. The data could be helpful in a separate study to analyze long distance motion patterns. Here, we exclude all the records whose mileages are larger than 30 miles (the threshold is selected partly due to convenience and partly due to a reasonable good fit to the majority of the data). Using the method we described above, we find that the best fit for trip mileage data is a Weibull distribution (Sa, 2003):

$$w_{\alpha,\beta}(x) = \frac{\alpha}{\beta}(x/\beta)^{\alpha-1}e^{-(x/\beta)^{\alpha}}$$

with shape parameter $\alpha = 0.91$, and scale parameter $\beta = 5.56$. See Fig. 6.

4.2.2 trip duration

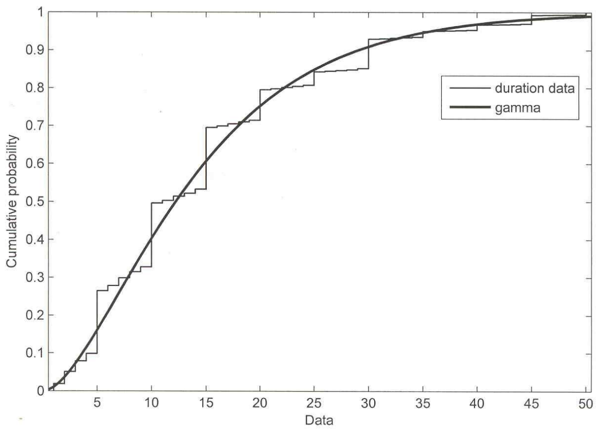

Figure 7: Fit Gamma distribution to trip duration data

Similar to mileage data, 95.0% trips have a duration under or equal to 50 minutes. Of the remaining records, some duration is exceptionally large. Thus, we exclude the records whose durations are above 50 minutes in order to have a reasonable good fit to the majority of the data. The best fit for trip duration is a Gamma distribution (Sa, 2003):

$$\gamma_{a,p}(x) = \frac{1}{a^p\Gamma(p)}e^{-x/a}x^{p-1}$$

with shape parameter $p = 1.87$, and scale parameter $a = 7.87$. The Gamma function is defined as $\Gamma(p) = \int_0^{\infty} e^{-t}t^{p-1}dt$. See Fig. 7.

4.2.3 dwell time

A Weibull distribution (Sa, 2003) can be used to depict the distribution of dwell times that are under 500 minutes (covering 92.7% data):

$$w_{\alpha,\beta}(x) = \frac{\alpha}{\beta}(x/\beta)^{\alpha-1}e^{-(x/\beta)^{\alpha}}$$

with shape parameter $\alpha = 0.77$, and scale parameter $\beta = 82.17$. See Fig. 8.

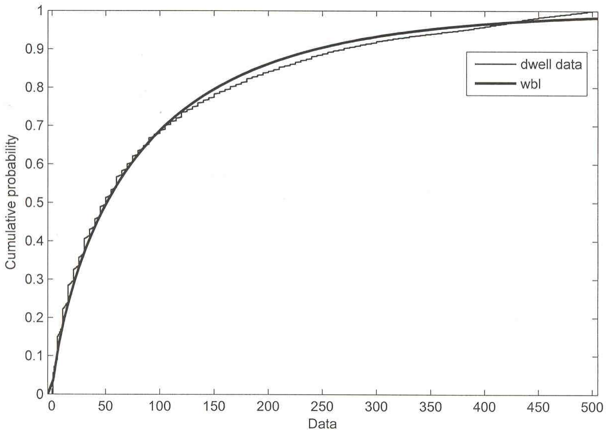

Figure 8: Fit Weibull distribution to dwell time data

Table 3: The Mean of Sample Activities

code	meaning	mean (min)	r	p
21	go to school as student	355	2.38	0.007
30	medical/dental service	67	1.24	0.018
40	shopping/errands	33	0.58	0.020
53	visit friends/relatives	121	0.90	0.007
80	meals	55	1.18	0.021

4.3 Dwell time of different activities

For the purpose of our Agenda Driven Mobility Model, we'll take a look at the distribution and the mean of lasting time of each *individual* activity in `WHYTRP01` (notice that the distributions in previous sections are aggregated distributions). For example, for activity code 83 ('coffee/ice cream/snacks'), the mean time is 26 minutes. Negative binomial distribution describes the dwell time of each activity (with different parameters). The probability mass function of negative binomial distribution with parameters p $(0 < p < 1)$ and r $(r > 0)$ is defined as:

$$f(k; r, p) = \frac{\Gamma(r+k)}{k!\Gamma(r)} p^r (1-p)^k$$

for $k = 0, 1, 2, ...$, where Γ is the gamma function.

The mean values and parameters of negative binomial distribution of some example activities are shown in table 3.

5 Model Analysis

In this section we use a Markov chain to analyze our Agenda Driven Mobility Model. Using a slightly different assumption (exponential staying at an address or location), we are able to get the limiting probabilities of a node staying at various addresses (or locations). The certain amount of predictability of a node visiting a location is an important character of agenda.

Suppose there are n locations, noted as $1, 2, ..., i, ..., n$. Once the node enters location i, it will stay there for a duration obeying exponential distribution with mean $1/\lambda_i$. There is also home h. The node stays at home for a duration obeying exponential distribution with mean $1/\lambda_h$. There are m activities in the node's agenda, named $A_1, A_2, ..., A_i, ..., A_m$. For each activity A_i, there are several possible locations for the node to choose. For example, if the activity is dining, the node has many restaurants to select from. Suppose the corresponding location set of activity A_i is $S_i, i = 1, 2, ..., m$. We assume none activity in the agenda is same as another, so all location set S_i's are disjoint. Suppose these sets cover all locations, that is, $\bigcup_{i=1}^{m} S_i = \{1, 2, ..., n\}$. The size of S_i is denoted as $|S_i|$. After the node finishes all m activities, it returns home. This procedure loops.

A continuous time Markov chain (Ross, 1995) can be set up for analysis. A state is denoted as (i, j) where i is the node's current location, j is the number of steps the node has taken so far. When the chain leaves state (i, j), it will next enter state $(i', j+1)$ with probability $p_{(i,j),(i',j+1)}$. See Fig. 9. If $j = m$, it will next enter state $(h, 0)$ with probability 1. This chain is irreducible and positive recurrent (Ross, 1995).

Thus the limiting probability $p_y = \lim_{t\to\infty} p_{xy}(t)$, which can be rewritten as $p_{(k,l)} = \lim_{t\to\infty} p_{(i,j),(k,l)}(t)$, can be found. Here $p_{(i,j),(k,l)}(t)$ is the probability that the chain, currently in state (i, j), will be in state (k, l) after time t.

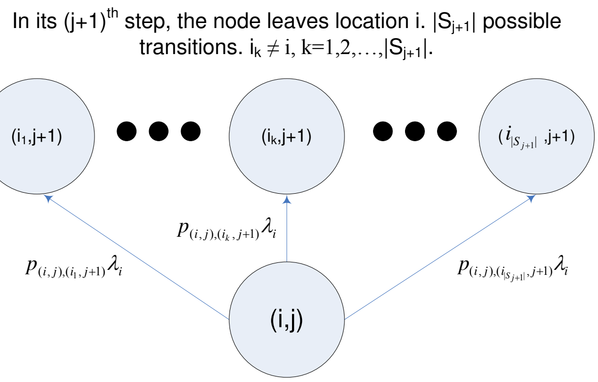

Figure 9: State transition when number of steps $j < m$.

We give an example here. Suppose a node has an agenda consisting of only two activities: A_1 and A_2. Its corresponding location sets are $S_1 = \{1, 2, 3\}, S_2 = \{4, 5\}$. See Fig. 10. Parameters of exponential distributions of staying at each location are shown in the figure. We draw state transition in Fig. 11. Transition rates are shown in the figure. We use Kolmogorov equations (Ross, 1995) to obtain numerical results. Fig. 12 shows the state probability of each of the states $p_{(h,0)}(t)$, $p_{(1,1)}(t)$, $p_{(2,1)}(t)$, $p_{(3,1)}(t)$, $p_{(4,2)}(t)$, $p_{(5,2)}(t)$. Given any time t, the Figure gives the probability of staying at any of these 6 locations. We further calculate the following limiting probabilities for each state: $p_{(h,0)} = 0.68$, $p_{(1,1)} = 0.07$, $p_{(2,1)} = 0.02$,

$p_{(3,1)} = 0.03$, $p_{(4,2)} = 0.11$, $p_{(5,2)} = 0.09$.

System-wide behavior can be deducted henceforth. Recall that location sets are disjoint and no repeated visits in one agenda circle, we take the example that there are M nodes in the network. The M nodes may visit location i in their different step, e.g, node A in its gth step, node B in hth step; Or they may not visit location i at all. We use I_k as an indicator variable ($I_k = 1$ when node k is at location i, 0 otherwise). If the limiting probability of node k at location i (in its jth step) is $p^k_{(i,j)}$, counting these M nodes, we have the expected number of nodes (X) at location i as

$$\begin{aligned} E[X] &= E[I_1 + ... + I_M] \\ &= E[I_1] + ... + E[I_M] \\ &= \sum_{k=1}^{M} p^k_{(i,j)} \end{aligned}$$

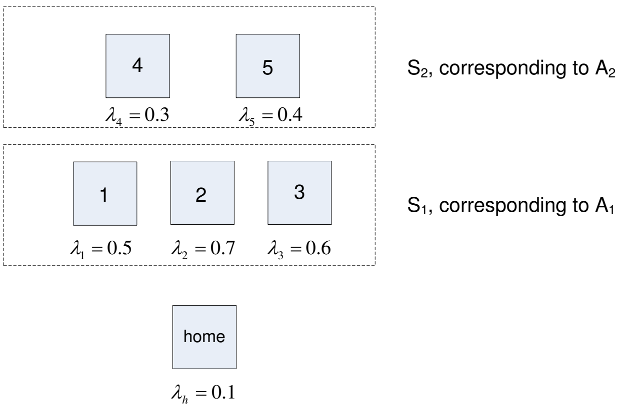

Figure 10: A node starting from home has an agenda consisting of activities A_1 and A_2. There are 5 locations (plus home). To conduct activity A_1, the node select one (and only one) location from location set $S_1 = \{1, 2, 3\}$; to conduct activity A_2, it selects one from set $S_2 = \{4, 5\}$. The node staying at location i for exponential time with parameter λ_i. It returns home after it finishes activity A_2. This procedure loops.

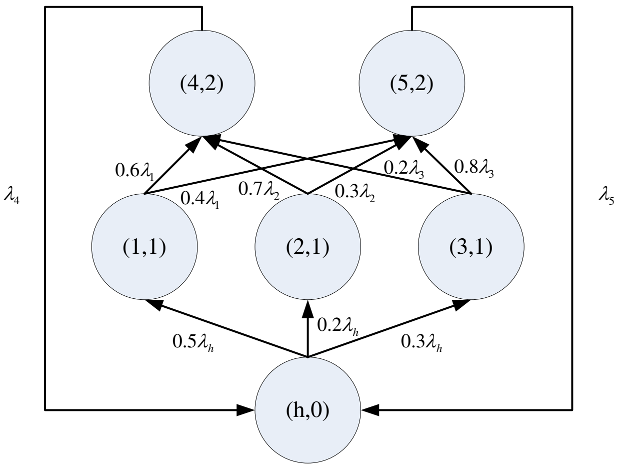

Figure 11: Continuous Time Markov Chain state transition.

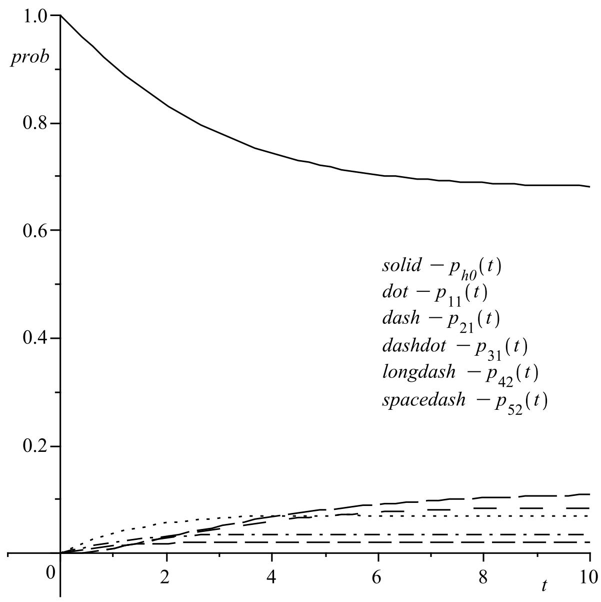

Figure 12: Numerical solution: state probabilities.

6 Simulation

In this section, we simulate the Agenda Driven Mobility Model (Agenda Model in short). The main objective of the simulation is to understand the impact of agenda and map in a simulation environment. The simulation shows that the introduction of map (with addresses) and agenda into the model has significant impact on both network topology and routing performance. The Agenda Model is implemented in a well known network simulator Qualnet (Scalable Network Technologies, 2007). Through simulation, we first test node movements and geographic distributions. Then, as a case study, we simulate a Mobile Ad Hoc Network in an urban environment where activities and motion steps are generated using the model we implemented. The nodes run routing protocol AODV (Perkins and Royer, 1999) for connectivity and data forwarding. We evaluate topological metrics and routing performance to show mobility influence. Since Agenda Model depicts motion and relocation of nodes continuously over a long time, we present the results in both short and long periods of time so as to illustrate how social roles and activities impact network connectivity.

In our simulation scenario, we aggregated node types to three broader categories: the first type is *employee* whose first activity must be ‘go to work’; the second type is *student* whose first activity must be ‘go to school’; the third type is *other* whose first activity could be any of those 35 activities in NHTS except 'go to work' and 'go to school'. The percentages of the three types are 60%, 10% and 30% respectively after the aggregation. The starting time of the first activity of any nodes is between 8:00AM and 9:00AM. As a comparison, we also simulate Random Waypoint Model (RWP). The Random Waypoint Model chooses destinations randomly from the field. Nodes move in a speed picking up randomly from the range between the minimum and the maximum of the street speed limits that match the Agenda Model. They then pause at destinations for a time period that is randomly picked up from the interval between the minimum and maximum mean dwell times of all the addresses.

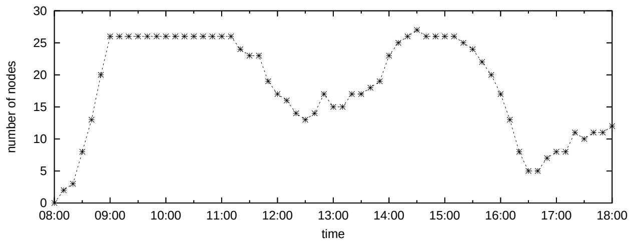

Figure 13: Number of nodes at a workplace (address 0 4th st., or (35, 1533)).

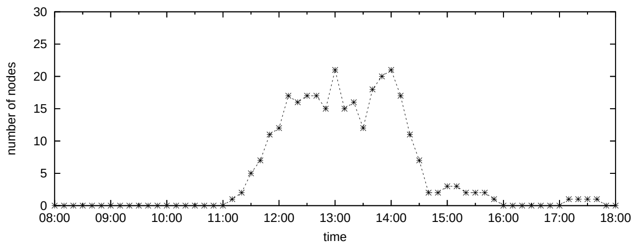

Figure 14: Number of nodes at a restaurant (address 17 3rd av., or (1168, 2638)).

6.1 Geographic distribution

We simulate an area of 4000m $\times$ 4000m with 2000 nodes. There are 478 addresses in the map. The simulation runs from agenda time $08:00$ to $18:00$, lasting 10 hours. We assume that every node will go out for lunch (mainly around $12:00$ to $14:00$), but he or she usually goes back to home for his or her dinner as one day's activities end. We want to see that at an address, as time flows, how the node density changes. From our simulation results, we pick two addresses to show their node density variations. The first one is a workplace, whose address is 0 4th st. with coordinates $(35, 1533)$. We observe in Fig. 13 a pattern very close to real life. Employees arrive at the workplace randomly around $08:00$ to $09:00$, then they stay there and work. During the lunch period, they leave workplace to take their lunch. The curve goes down during that period. After lunch they come back to work and the curve goes up again. When its time to be off duty, people leave. Some hard-working employees may come back again after some break. In the second address - a restaurant with address 17 3rd av. and coordinates (1168, 2638), curve shown in Fig. 14 - we observe a surge of nodes during the prime lunch time and very few nodes during other times. This is also very close to real world. On the other hand, Random Waypoint model shows little node density variations (at those destinations) and all destinations are statistically identical. The results thus are not included here. This is because that the model randomly picks a destination, without making a difference on address types nor considering the time in a day.

6.2 Network performance

We simulate a mobile ad hoc network running routing protocol AODV in an area of 2000m $\times$ 2000m. The map is the same as in Fig. 2. We set 100 nodes as being able to communicate while moving, representing the reality that only a portion of population would be a part of the mobile ad hoc network . The distributed coordination function (DCF) of IEEE 802.11 is used at the MAC layer and the two-ray ground reflection is the radio propagation model. The channel capacity is 2Mbps with the default transmission range $370m$ in Qualnet. This density generates 11 neighbors on average which is an acceptable density. On the other hand, we intend to use a less dense network in order to observe the influence from mobility more easily. We have 5 CBR (constant bit rate) flows with randomly selected sources and destinations. Each CBR sends 4 packets per second with a packet size of 1000 bytes. This configuration is used to generate all the following results.

We show two simulation runs, one in short time period and the other over a long time period. The short simulation runs for 900 seconds (15 minutes), corresponding to the agenda time $8:45$ AM - $9:00$ AM. Some figures below extract data of the last 400 seconds from this run. The long run simulates a 15 hour period, starting from agenda time $7:45$ AM. A sample travel trace of seven nodes is given in Fig. 15. The travel paths are the results of using Dijkstra's shortest path algorithm. The figure shows various routes. It also includes a node that stays at its original location(the little black dot in the middle). Fig. 16 shows the position changes of three nodes during the 15 hour period of time. Notice that the lines between points are not the real travel traces. They simply indicate the connections between a node's locations every two hours, starting at 8 AM from his or her home. Here, every trace is closed - since during this period, each node leaves home in the morning and returns home at the end of the day.

6.2.1 Topological metrics

Through topological metrics we directly examine how the motions generated by the Agenda model affect nodes' interconnections, i.e., the topology of the networks. We

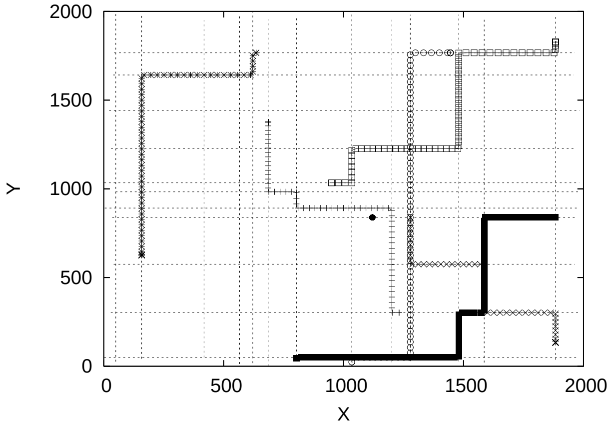

Figure 15: Travel traces of 7 nodes

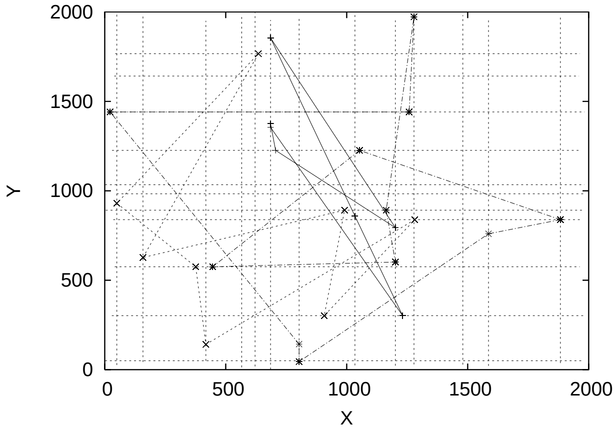

Figure 16: A whole day journey of 3 nodes. Locations are recorded every 2 hours.

choose 75, 100 and 130 nodes respectively. The topological metrics include the average numbers of partitions and unreachable pairs. The calculation is based on snapshots taken every 5 seconds for the short run and 5 minutes for the long term simulation respectively.

Number of partitions

From time to time, due to the limited transmission range, the network could be disconnected and partitioned into many sub networks. We call such sub networks *partitions*. In a partition, all nodes can reach any other nodes in the same partition over one or multiple hops. However, there is no way to organize a route, over one-hop or multi-hops, from a node in one partition to another node in a different partition. Let P be a partition and $D(x, y)$ be the minimum number of hops of any possible routes between node x and node y, we conclude that $\forall x, y \in P, D(x, y) \neq \infty$. Our metric *number of partitions* describes the extent of this phenomenon. Specifically, suppose the number of partitions is n, and the partitions are $P_1, ...P_n$, we have $\{\forall x \in P_i, \forall y \in P_j | i \neq j, D(x, y) = \infty\}$. The simulation results are given in Fig. 17. Clearly, the network partitions; and the number of these partitions fluctuates. The figure also shows that as network density increases, the number of partitions decreases. This is natural as nodes will have more chances to connect to other nodes. Not only that, a sparser network increases the fluctuation level. For example, for a 130 nodes network, the number of partitions is either 1 or 2; but for a 75 nodes network, the number of partitions fluctuates between 2 and 7. Fig. 18 shows the number of partitions in the long time of 15 hours.

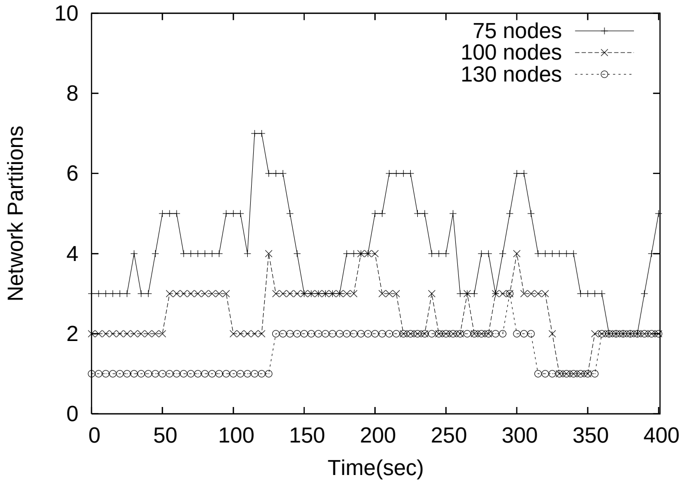

Figure 17: Number of partitions in 15 minutes, from 8 : 45 AM to 9 : 00 AM

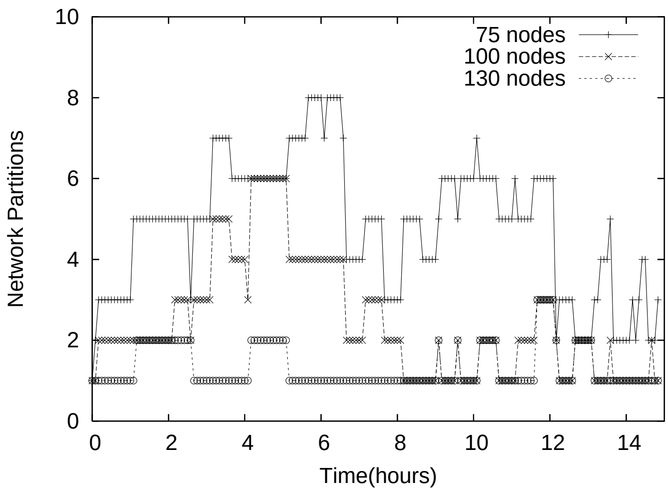

Figure 18: Number of partitions in 15 hours

Unreachable pairs

Because of partitioning, a pair of nodes each belonging to a different partition can not establish a route between them. We call such node pairs *unreachable pairs*. In a fully connected network of n nodes, each node can reach every other node, the total reachable pairs is $n(n-1)/2$.

The unreachable pairs can be represented as the cardinality of the set $\{(x, y)|x \in P_i, y \in P_j, i \neq j\}$. Fig. 19 shows the percentage of pairs that is unreachable. It is obvious that as the number of nodes increases, the number of unreachable pairs decreases. The curves fluctuate but the overall ratios of unreachable pairs are kept at a low level since this is the time period corresponding to a time interval prior to nodes' first agenda item. Nodes are roughly evenly distributed at their homes before they move to their first destinations. Compare to Fig. 20, which shows the ratio of unreachable pairs in the long simulation run, the overall ratio there is much higher. That is because during the long period of a whole day, at many times nodes will concentrate at various addresses (e.g. grocery store), thus increase the ratio of unreachable pairs (nodes at two different addresses are likely not to reach each other if these two addresses are far apart). When we compare these two figures to the number of partitions figures 17 and 18, we can see that they roughly fluctuate at the same time - when there are more partitions, there are more pairs that cannot reach each other.

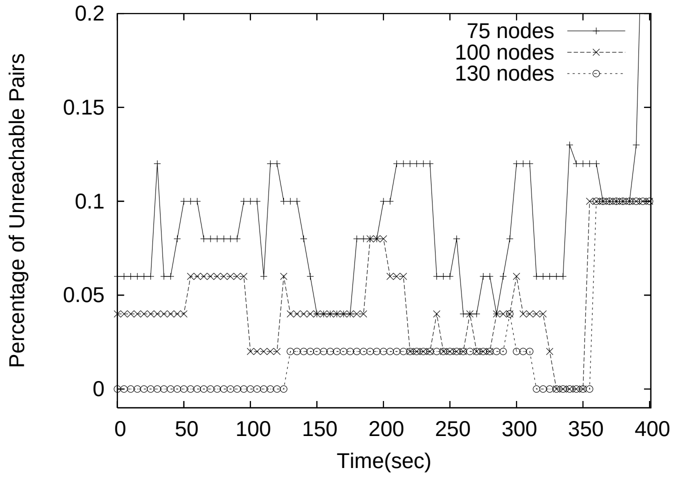

Figure 19: Unreachable pairs in 15 minutes, from 8 : 45 AM to 9 : 00 AM

6.2.2 Routing performance metrics

Here we examine the network performance in terms of delivery ratio and average path length. In order to show the influence on the topology change of the two mobility models through time, we sample the metrics based on a time slot of 5 seconds, i.e., counting all of the packets received and sent in every 5-second time slot. Thus the delivery ratio is the ratio of the number of packets received and sent during the time slot. For the path length, we take the packets arrived during the slot. On average, there will be 100 packets in total during each time slot. Since some packets may not be generated and received within the same time slot, the delivery ration may be larger or smaller than real cases, e.g., more than 100%. Thus, we take an average

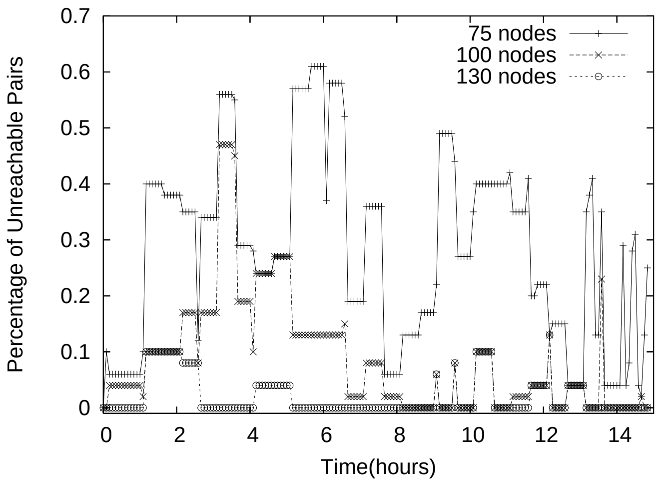

Figure 20: Unreachable pairs in 15 hours

using the current, the previous and the succeeding slots. This method is different from early work which mostly calculate average at the end of the simulation. While the latter approach is common in evaluating stationary behavior, the way we adopt here can highlight the nonstationary behavior of mobility better. As demonstrated in our measurement, the connectivity variations we demonstrated in previous Figures will significantly affect these two performance metrics. Further, in comparing the two mobility models, we refer to previous research (Camp et al., 2002; Hong et al., 1999) which has shown that mobility models have vital impact on routing protocol performance, without necessary indications on which model tops the rest models nor which routing protocol reacts better to all the different mobility models. We expect our results validate these observations.

Delivery ratio

The result of delivery ratio is shown in Fig. 21. The two curves vary a lot because our measurements are calculated based on different time slots. Thus they are affected by the highly dynamic connectivity as shown in the previous Figures. Comparing the delivery ratios of the two models, Agenda Model can be higher than that of Random Waypoint Model because when nodes in Agenda Model confine to roads, they tend to have better connectivity, while in Random Waypoint Model nodes can be at any place in the area. On the other hand, Agenda Model can also create more partitions when nodes concentrate, leading to lower delivery ratio than that of Random Waypoint Model. This shows that the influence of mobility model on routing performance is significant. The choice of mobility model in performance evaluation is important.

Average path length

Path length counts the number of hops of the AODV routing path between the source and the destination for the successfully delivered packets. The average path lengths

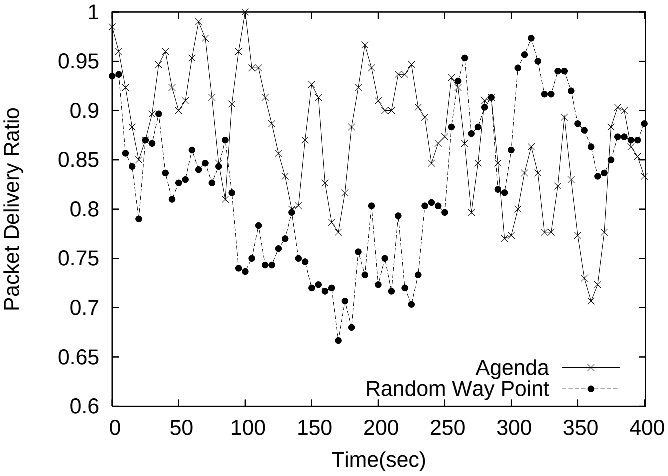

Figure 21: Delivery ratio

vary over time as shown in Fig. 22. Same as delivery ratio, the curves vary a lot for Agenda Model and Random Waypoint Model. For Agenda Model, because nodes are confined to limited places (roads), the distance between them show less arbitrary pattern then that in Random Waypoint Model. In addition, nodes in Random Way-point Model can move anywhere. The routing paths then can cut corners when possible. This results in shorter path lengths in many cases.

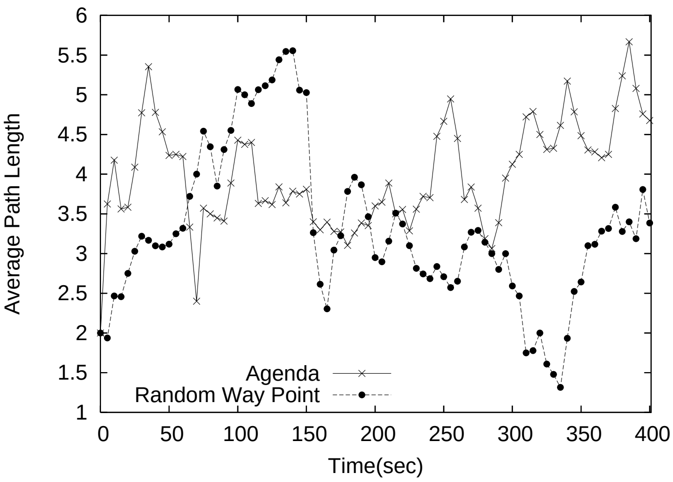

Figure 22: Average path length

6.3 Summary

Our simulation study shows that the Agenda Model generates uneven distributions of node concentrations around the addresses, as a demonstration of nodes' social roles and activities. Such a result is close to the observation of a real world. The direct influence of the geographic concentration is the partitioning of the network. The partition fluctuates as time passes and as nodes move to participate different activities. We also show that the use of map (with addresses) and agenda has a significant impact on routing protocol performance, using Random Waypoint Model as a comparison. It shows that different mobility models would diverge on predicting the performance of the same routing protocol. This validates the results from early study (Camp et al., 2002; Hong et al., 1999) that the selection of mobility models is crucial for accurate performance evaluations. By generating realistic scenarios, Agenda Model is expected to provide more realistic results.

7 Conclusions

We have presented an Agenda Driven Mobility Model. The key contribution of the work is using a person's social roles and activities as a driving force for his or her motion. We use agenda to describe a person's activities and to determine his or her whereabouts. The proposed model is a general framework that can be used to produce various scenarios. In the paper, we simulated an example of an urban area. With a comparison to a popular statistic mobility model, we show that our model is able to reduce the unrealistic randomness. The performance results confirm that different mobility models affect performance differently. Our results suggest that social roles and agenda activities tend to cause geographic concentrations, which impact network performance significantly. Agenda model has its advantage in producing a performance evaluation that reflects situations in a real world. In addition to the simulated example of an urban area, the model can be used to generate a variety of realistic scenarios, such as campus networks where people tend to walk rather than drive cars.

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