A Comparison of Pedestrian Mobility Prediction Schemes in Wireless Cellular Networks

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ABSTRACT

As the number of mobile technology users in wireless cellular communication increases everyday, the quality of service (QoS) concerns are not totally satisfied. Mobile users are not limited to a fixed location and can move around to other places. Mobility model is a method which is used to predict future location of a mobile user using different techniques. Mobility model is one approach for solving the mobility problem to guarantee the QoS.

In this thesis, we compare two different mobility models for pedestrian movements through simulation using two actual trajectory datasets in the same area with different arrival rates. The first model is called current mobility parameters method, which predicts the future position of mobile user based on current parameters such as current location information, speed and direction. This information is mostly gathered using a positioning system such as GPS. Gauss-Markov mobility model predicts next location using current speed, direction and location information of the user. The second method is called observation histories method, in which prediction is performed based on the historical movement pattern of the user. For this model, a simple second order Markov-Mobility model predicts next position using current and one previous location information of that user. The simulation result shows that the observation histories method has a better performance than the current mobility parameters method for pedestrian movement. The precision rate for current mobility parameters was 99.74 % for first and second dataset, respectively and 99.88 % and 99.87% for observation histories method.

Keywords: Wireless Cellular Network, QoS, Mobility Prediction, Path Prediction, Mobility Model, User Mobility, Next Location Prediction

ÖZ

Kablosuz hücresel iletişim mobil teknoloji kullanıcılarının sayısı her gün arttıkça, hizmet kalitesi (QoS) endişeleri tamamen karşılanamıyor. Öte yandan mobil kullanıcılar sabit bir konumla sınırlı değillerdir ve yer değiştirebilirler. Bir hareket modeli, mobil kullanıcının farklı teknikler kullanılarak gelecekteki bir konumunun tahmin edilmesidir. Hareketlilik modeli, kaliteli servisi güvence altına almak için hareketlilik probleminin çözüldüğü bir yaklaşımdır.

Bu tezde, aynı bölgede olup farklı varış tanımları olan iki gerçek yörüngeli veri kümesi kullanarak, iki farklı hareket modelini yaya hareketi simülasyonu aracılığıyla karşılaştırdık. İlk model, şimdiki hareketlilik değişkenleri yöntemi, hareketli kullanıcının gelecekteki konumunu, konum bilgileri, hız ve yön gibi güncel değişkenlere göre tahmin eder. Bu bilgiler genellikle GPS gibi bir konumlandırma sistemi kullanılarak toplanır. Gauss-Markov hareketlilik modeli, kullanıcının güncel hız, yön ve konum bilgilerini kullanarak bir sonraki konumunu tahmin eder. İkinci model ise gözlem geçmişleri yöntemidir, tahmin kullanıcının geçmiş hareket yapısı baz alınarak gerçekleştirilir. Bu model için, ikinci dereceden bir basit Markov-Hareketlilik modeli kullanıcının şimdiki ve bir önceki konum bilgilerini kullanarak bir sonraki konumunu tahmin eder. Simülasyon sonucuna göre yaya hareketi için gözlem geçmişleri yöntemi, şimdiki hareketlilik değişkenleri yönteminden daha iyi bir performansa sahiptir. Birinci ve ikinci veri kümeleri için doğruluk oranları güncel hareketlilik değişkenleri yöntemi için her ikisi için de %99.74 iken gözlem geçmişleri yöntemi için birinci oran %99.88 ve ikinci oran %99.87’dir.

Anahtar kelimeler : Bağlantısız hücresel ağlar, Qos, Hareket kestirimi, Hareket modeli, kullanıcı hareketliliği, sonraki konum kestirimi

Dedicated to

My father and mother for their endless love and support

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LIST OF ABBREVIATIONS

ACR	Adaptive Channel Reservation
BS	Base Station
DMPM	Destination and Mobility Path Prediction
DPM	Destination Prediction Model
GPS	Global Positioning System
MAE	Mean Absolute Error
MLS	Mobile Location Service
MMM	Mixed Markov-Chain
MMP	Mobile Motion Prediction
MS	Mobile Station
PCR	Predictive Channel Reservation
PPM	Path Prediction Model
QoS	Quality of Service
RWP	Random Way Point

Chapter 1

INTRODUCTION

Wireless communication involves transmission of information between two or more nodes that are connected together without using an electronic conductor (such as cable, wire etc.). This information can be transmitted over any distance, from a few meters (such as television remote control) or a thousand of kilometers (such radio communication). Using wireless communication, these days allows more flexible communication rather the traditional wired models because the user is not limited to a fixed location and is free to move to other places. By increased usage of mobile technology, the quality of service (QoS) criteria may not be totally satisfied because the nodes are mobile and can move or change their places. User movement patterns provide an essential research topic these days for better performance in wireless communication. It is important to make a seamless connection for a mobile user in the wireless network. This leads to the problem of handoff without disruption in communication when moving from one cell to another. Different mobility schemes are proposed to track mobile users and predict future paths of them. Mobility schemes represent the movement pattern of a mobile user with their location, speed and direction, which change over the time.

1.1 Important tasks in Mobility Models

The following is the important tasks to be implemented in wireless networks [9].

1. **Handoff management** which may happen by disordering in signal transmission as the mobile user moves from one cell (i.e., the coverage area of a base station) to the adjacent one.

2. **Flow of control** which prevents overwhelming a slow receiver by a fast sender.

3. **Resource allocation** which allocates available resources (channels) to mobile users, hopefully, optimally.

4. **Congestion control** that prevents performance degradation by sending too many packets to a part of the network.

5. **Call admission control** which will try to regulate the traffic volume in voice communication.

6. **Quality of service (QoS) provisioning** for better performance.

At the application level, the importance of mobility prediction schemes originates from the Mobile Location Service (MLS). Based on the combination of mobile user profile and the current or the predicted location, MLS provides an enhanced wireless service [9]. Examples for such services are online advertising, local traffic information, weather forecast, map adaption and instant messaging for communication with people in nearby localities, mapping or routing guidance and guiding people to reach their destination.

There are several types of mobility models used in simulation of cellular networks. The most common mobility schemes are prediction based on current mobility parameters, prediction based observation histories and prediction based on both current mobility parameters and observation histories. In current mobility parameters schemes, the future position of the mobile user is predicted based on the current location, speed and direction of that user at current time. This information can be collected using a positioning system such as GPS or a sensor.

In the observation histories model, the next position is predicted based on the historical movement pattern of the mobile user. Prediction can be performed using frequently visited locations and/or the previous positions of the mobile user or the place at which the user spends more time. The information collected this way is stored in a database and is used for further prediction.

The current mobility parameters and observation histories method is a combination of the two methods mentioned above. Prediction can be performed using different techniques. Some schemes predict the final or the intermediate destination which the mobile user will visit in future, such as a road segment, highway, home, shopping mall and etc. [13][29][7][23]. Those schemes mostly use the frequently visited location by the mobile user and a spatial map to predict next location. Other schemes, predict the next cell or the next base station for the mobile user. Those schemes are mostly used for the handoff process and for bandwidth reservation in adjacent cells [3] [4] [12] [16]. These schemes mostly use the previously visited cells in their prediction. Some other schemes predict the future path of the mobile user based on coordinate points (longitude and latitude) of the mobile user. This information is collected at a regular time intervals, using a positioning system device such as GPS, sensor, Wi-Fi or RSSI during the movement of the user. These schemes mostly use the previously visited locations information of mobile users, plus speed and direction to predict the future locations of the user [9] [28].

1.2 Problem Statement

In this thesis, we discuss the performance of two different mobility schemes, the current mobility parameters and observation histories models for pedestrian wireless network users with a simulation for both models. We compare the results on two actual trajectory datasets with different arrival rates in the Ostermalm area in Stockholm [31]. For the current parameters mobility model, we used a Gauss-Markov approach in which the next position is predicted based on the current location information, speed and direction of that user as described in Chapter 3. For the observation history mobility model, we used a simple second order Markov-Chain approach which takes the current and previous positions of the mobile user to predict its next position.

The rest of this thesis is organized in the following manner: Chapter 2 presents a review and a classification of the current parameters mobility and observation histories schemes. Chapter 3 contains the current parameters and observation histories models used in simulation in detail. In Chapter 4 we present the simulation dataset, simulation parameters and simulation results of both models, which is performed in Matlab R2011. Chapter 5 concludes the thesis by interpreting the numerical results and discussing future work.

Chapter 2

RELATED WORK

A survey of mobile-oriented channel reservation schemes and their classification is proposed in [1] which employs the user mobility model in resource reservation. These types of schemes predict the future trajectory of a mobile station (MS) and the bandwidth to be reserved for it. Three types of mobility schemes are considered: prediction based on current mobility parameters, prediction based on observation histories and prediction based on both current mobility parameters and observation histories.

For wireless networks, there are various mobility models that are proposed in the literature. Since our study is on pedestrians, we consider two types of popular mobility schemes for pedestrian movements. The first scheme is based on current mobility parameters of the user such as position, speed, and direction at the current time. The second scheme uses the historical movement pattern or the places visited by the mobile node. For the current mobility parameters method, we have considered the Gauss-Markov Mobility Model [2]. Some previous studies in this area are described below.

The simplest form of current mobility parameters models is the Random Walk Mobility Model [24], which is also referred as the Brownian Motion model. In this model, the MS moves from its current location to the next location by choosing a random speed and direction in predefined ranges, [*minspeed*, *maxspeed*] for the speed and $[0,2\pi]$ for the direction. It is easy to implement such a scheme as it requires no information to predict next movements. However, this model may result in inaccurate prediction. Figure 2.1 shows the travelling pattern of a MS using the Random Walk Mobility model.

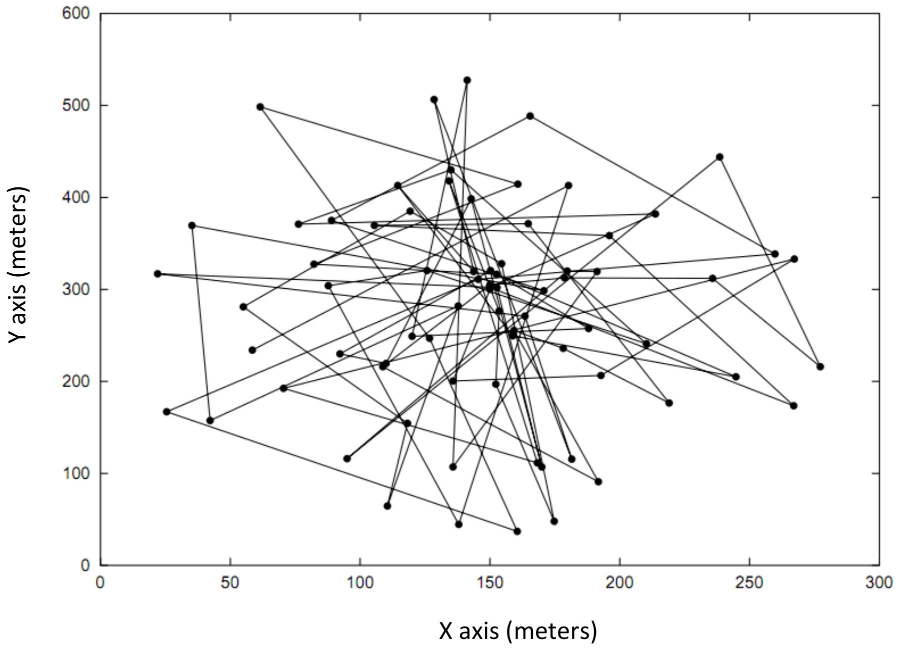

Figure 2.1. Random Walk Mobility Model [2]

In [25], the Random Waypoint (RWP) mobility model is proposed. In the RWP model, the MS moves along a zigzag path, consisting of straight legs from one waypoint to the next. The RWP includes a pause time between changes in direction and speed. After the pause time expires, the direction is selected randomly in the simulation area and a speed value is chosen according to a uniform distribution between [*minspeed, maxspeed*]. Upon arrival at the next location, the MS stops for the pause time and the process continues in the same way.

In the fluid-flow mobility model [26] the individual mobile movements are modulated on a macroscopic level which is representing the aggregate movement patterns of the user. This method ignores the individual mobility behavior, instead, considering the aggregate mobility behavior of all users. It is assumed that the MS direction is uniformly distributed between [0,2π]. This method helps to optimize the total network utilization. However the fluid-flow model is not suitable for smaller scale and doesn't provide prediction for any specific user.

2.1 Mobility Prediction based on current mobility parameters

In [2] the Gauss-Markov mobility model was described with respect to current speed and direction. Gauss-Markov mobility model is suitable for two extreme cases of user movements using a tuning parameter which can vary from 0 to 1. It can represent both constant velocity fluid-flow and random-walk mobility models. The speed and direction of next location in Gauss- Markov-mobility is calculated based on the current speed and direction. The initial position, speed and direction are chosen for each node according to a uniform distribution. In this method, the direction of the MS is calculated probabilistically using a tuning parameter which may or may not be in the same direction of MS. This method will calculate the exact direction of MS in each location update using equations 2.1 and 2.2.

$$s_n=\alpha s_{n-1}+\left(1-\alpha\right)\bar{s}+\sqrt{1-\alpha^2}s_{x_{n-1}} \tag{2.1}$$

$$d_n=\alpha d_{n-1}+\left(1-\alpha\right)\bar{d}+\sqrt{1-\alpha^2}\ d_{x_{n-1}} \tag{2.2}$$

Then, the next location of MS is calculated based on the current speed and direction using equations 2.3 and 2.4:

(2.3)

$$x_n = x_{n-1} + s_{n-1} \cos d_{n-1}$$

$$y_n = y_{n-1} + s_{n-1} \sin d_{n-1} \qquad (2.4)$$

The above formula will be explained in Chapter 3. Figure 2.2 shows a sample Gauss-Morkov Mobility movement pattern for one MS traveling pattern. As illustrated in this Figure, this approach can prevent sudden and sharp turns.

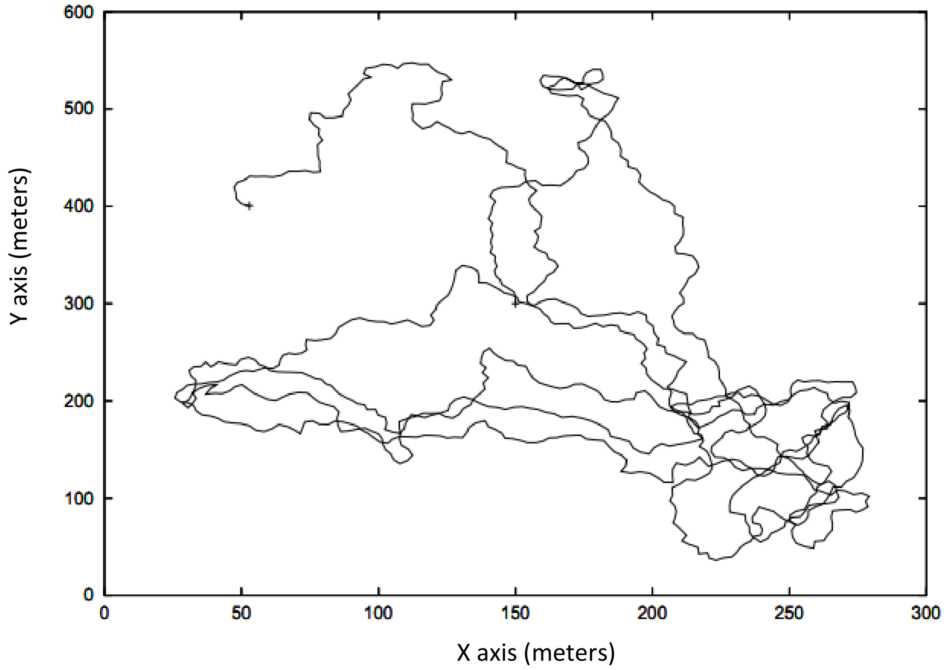

Figure 2.2. Gauss-Markov Mobility Model movement pattern [2]

In [3], a predictive channel reservation (PCR) scheme is proposed, which uses the real time position of MS and a movement extrapolation. This scheme also uses the current position information and direction of MS to predict the future position, and eventually finds the next cell that a MS will enter after later movements. The Current position information is gathered using GPS or any other positioning technique. Orientation can be measured by obtaining two consecutive position measurements in a small time interval. After predicting the neighbor cell (next cell) the base station

(BS) sends a bandwidth reservation request to that neighbor cell. The time required for sending a reservation is calculated based on the threshold distance .Threshold distance is the radius of circle which is smaller than the cell's coverage area and co-centered with the cell. This method is useful for vehicle movement or pedestrians with high speed. If a MS moves with low speed or if it is stationary, the MS may not reach the destination after terminating the call, because the MS may pass the threshold distance but may still remain in the current cell. The main drawback of this method is that it does not consider the speed of MS's and cannot distinguish the pedestrians, vehicles and stationary or mobile MS's from each other.

In [4,] the ACR (Adaptive Channel Reservation) scheme is proposed. Similar to PCR [3], the information related to the current position is gathered using GPS, and orientation is calculated based on two consecutive movements of MS in a small time interval. This scheme uses the threshold time instead of the threshold distance and considers the speeds of MS's. Threshold time is a constant value. Using the MS's current speed, direction and position, BS predicts the time that the MS reach the next cell. If this time is less than or equal to the threshold time, the BS sends a reservation request to the next cell. The difficult problem in this scheme is to select a correct and accurate value for threshold time.

In [5], a single dimensional (1-D) distance based mobility model is proposed, which can predict the future location of a MS using the probability density function of that MS, employing Gauss-Markov mobility with velocity and location information of the last location update. Location update is performed by searching for the MS from the predicted location and outwards, until it is found. In this model, the MS checks its position periodically and updates the location information whenever it reaches some threshold distance away from its predicted position. A multidimensional version of distance based mobility model is proposed in [6]. This model is suitable when there is no real-world map and no additional information about the environment [11].

In [7], the road topology information is incorporated with mobility prediction for better performance. In this scheme, each MS is equipped with a positioning system (GPS) that sends location information periodically to the BS (e.g., every second). The BS maintains a database containing the road information within its coverage area. The roads between two neighboring cells are considered as road segments. The database includes information related to the time that MS will reach the neighbor cell, neighbor segments and the probability that the MS will select that neighbor as the next segment. The calculation of probability for selecting the next segment is done using a second-order Markov process. However, this scheme has a limitation because it assumes that each BS has complete knowledge about road segments. If knowledge of road segments is not available, this model is useless. Also another assumption is that a base station has exact geographical knowledge, using digital maps, about the road network within its coverage area, which is a rare case [8].

Different schemes based on current position parameters and observation histories are proposed in [9] and [23]. In [9], the user movement is predicted based on the environment and user contextual information such as a real-world map, position information, time, user interests, and user's personal information, employing the Damspher Shafer algorithm. The location prediction process is performed in 4 steps. The first step is related to information gathering which is divided into two categories: environment context and user context. Environment context is related to the landscape and environment of MS is represented by the real-world map. The map contains information that describes geographical region information such as buildings, roads, streets and highways. It is assumed that the information related to the map is available in each base station and can be obtained by the MS with a request from BS. User context is related to user contextual information. The second step is evidence extraction which applies the Damspher Shafer algorithm to information gathered in the previous step. The third step is decision making. The result of the second step is a list of locations with degree of support for that location. The highest degree of support is considered as the future location of the MS. The last step is finding the path based on the map information (orientation) from the current position to the predicted location. In one study, the dataset is collected from students in and around Ottawa University campuses using GPS with average speed of 5 km/hr for each MS considering pedestrian movements.

The scheme proposed in [23] is called Destination and Mobility Path Prediction (DMPM) which predicts the final or intermediate destination of the MS within a time period. DMPM consists of two parts. The first part is the Destination Prediction Model (DPM) which predicts the user's destination within the set time period by clustering all possible destinations using the history of the mobile user based on: (1) frequently visited locations, (2) destination from origin to the current location and (3) information related to contextual knowledge (e.g., name, age, position and etc.). The second part is the Path Prediction Model (PPM) which is used to predict the path using current mobility information such as: (1) user habits, (2) current direction of the user to destination, (3) current trajectory/path and (4) spatial conceptual map. The methods which are proposed in [9] and [23] have similar drawbacks [7]. These methods are useful for the cases where a real world map is available and the BS has complete knowledge about roads, streets, and buildings. Supplying BS with complete knowledge about geographical region using spatial map about road network in its coverage area is a rare case Also, the information needed for prediction is not easy to acquire and may change frequently.

The key limitation of the current mobility parameters method is that, the MS's must be equipped with a positioning technology (GPS or etc.) and may need complex mathematical calculation for prediction.

2.2 Mobility Prediction based on observation histories

In [10], a mobile motion prediction algorithm called MMP is proposed which predict the future location of the user movement based on the movement history pattern. The movement patterns are categorized by two models: The movement circle and movement track. In the Movement Circle model, it is assumed that whenever a user moves away from its location, finally it will return to his/her first position. Such a scheme is used for prediction of long-term regular movements. The Movement Track model represents routine movements which include regular and random movements, employing a Markov-chain mobility model. Simulation results presented for the MMP algorithm reports that the prediction accuracy efficiency of this scheme is about 95%.

In [12], a mobility prediction technique is proposed which predicts the BS the MS will visit next, using a simple Markov-mobility model, based on five different prediction algorithms. These algorithms are summarized as:

1. The location criterion: it identifies the previous BS's that MS visited before the current one and stores them in a database. The BS with high probability among mostly visited BS by the MS will be predicted as the next BS.

2. The direction criterion: using current and previous BS's of the MS, it identifies the direction that MS travels between the two BS's.
3. The segment criterion: A segment will start when a MS stays for a long time inside a cell. Segments contain all previous movements. If the current point is same as the initial point of a segment available inside the database, then the next BS is considered by choosing one from the database.
4. Bayes' Rule: used to calculate the probability distribution of all possible next moves. After calculating probabilities of all next moves, the one with the highest value is considered as the next movement.
5. Time criterion: calculates the time that a MS will need to cross to another cell.

In this model, the information related to MS is collected using an Active Badge location system that sends signals every 15 seconds to nearby sensor. An interval of 15 seconds is a very large value for movement prediction of a mobile user. Also, this model needs a large database as it stores a large number of past movements for each MS.

A clustering approach is proposed in [13] which predicts the future location of the MS based on the frequently visited places using a first and second order Markov mobility model. An n^{th} order Markov model means that the probability of next state (next location) is calculated based on current state and the previous n-1 states. In this method, the location information is gathered using a GPS. After collecting locations, the coordinates of significant locations are classified as home, work, grocery and etc. and the rest are removed. Then a unique ID is assigned to each of these locations and they make up a list of locations visited by the user in the past.

The state with highest probability from current state is considered as the future location of the user.

An n^{th} order Markov mobility model is proposed in [14] which predicts the future location of the MS using an optimal data compression method. In this model, it is assumed that the user mobility trajectories have some regularity and they follow some routines, so the users have favorite trajectories and habitual movement patterns. This method holds the real-time database of each MS. (at a specific time, as a Mobile Tree). When a MS makes a call, the predictor sets the current MS as the root of the Mobile Tree. The root contains the cell and time information. Afterwards, it calculates probabilities of all events for the MS using a data compression algorithm.

The drawback of this model is that it needs a large amount of database to store information related to past movements of MS. Also, a huge amount of data must be sent to BS which will verify the feasibility of supporting call over these intervals.

A variant Markov-mobility model called mixed Markov-chain model (MMM) for pedestrian movement is proposed in [15]. This model predicts the future location of MS based on a Markov model belonging to individual MS's with similar behavior, using movement histories. The method takes into account a pedestrian's personality as an unobservable parameter and the effect of pedestrian's previous status. Simulation results presented for the MMM algorithm shows that the prediction accuracy of the proposed method is about 74 %.

The methods proposed in [3] [7] are consider high mobility (vehicular), [9] [14][15] consider low mobility (pedestrian) and [4] [12] [13] [23] consider both for high and low mobility MS's.

The schemes proposed in [16] [17] use data mining approaches in their prediction. The goal of [16] is to predict the next cell of MS using the association rule. It is assumed the architecture of the third generation (3G) mobile network contains a set of cells managed by a BS. It is also assumed that the network core has personal information of MS and BS and a history of the MS movements. The history contains MS user id, source cell, destination cell and data for travel history.

In [18] [19] [20], mobility prediction is performed using neural networks. In [19], a multi-layer neural network is used for prediction of the MS movement. This Multi-layer neural network is based on the back-propagation algorithm which makes prediction using the data obtained from the MS movements. The role of the neural network is to capture an unknown relation between past and future movement patterns of the MS. The prediction accuracy is measured using different movement patterns of the MS.

In [28] a learning automata-based mobility prediction for mobile ad-hoc networks is proposed which predicts the future speed and direction of a mobile user based on Gauss-Markov random process formula [2]. In this model, it is assumed that the mobility prediction parameters (speed, direction and randomness degree) are not obvious (unknown), but can be obtained using a continuous action-set learning scheme to predict the degree of randomness, mean speed and direction for predicting the future speed and direction of the mobile user. The key limitation of the observation histories methods is the overhead to develop and store information which is needed for prediction. If the history of MS is not available, this method will be useless.

Table 2.1 gives a summary of mobility schemes classification.

Table 2.1. Classification of Mobility schemes

	References	Pedestrian	Vehicle	Information Gathering for prediction	Drawbacks
CURRENT PARAMETERS MOBILITY MODEL	[3]	-	✓	GPS	1.Do not consider velocity of the MS 2.select a correct value for Threshold Distance (may cause wrong bandwidth reservation)
	[4]	✓	✓	GPS	Select correct value for Threshold time (may cause wrong bandwidth reservation)
	[7]	-	✓	GPS	1.Base station with exact geographical knowledge, using digital maps, about the road network within its coverage area is rarely case 2. If knowledge of road segment is not available this model is

					useless
	[9]	✓	-	GPS	1.Similar to [7] 2. Information needed for prediction is not easy to acquire and may change frequently
	[23]	✓	✓	GPS	Similar to [9]
OBSERVATION HISTORIES METHOD	[10]	-	-	----------------	High sensitivity to changes in the MS movements
	[12]	✓	✓	Active Badge location system (Sensor)	1. Location update is performed too late (every 15 sec) 2.Needs a large amount of database to store past movements of the MS.
	[13]	✓	✓	GPS	Require the whole dataset of available GPS locations [27]
	[14]	✓	-	Wi-Fi	Needs a large amount of database to store information related to past movements of MS
	[15]	✓	-	GPS	Needs a large amount of database to store information related to past movements of the clustering MSs

Chapter 3

SYSTEM MODELS

The main task of this thesis is using two different types of mobility models (prediction based on current mobility parameters and prediction based on observation histories) for pedestrian movement, making a comparison by simulation using a real-life MS movement trajectory. In this Chapter, we are going to discuss the system models for the two techniques considered.

3.1 Prediction based on current mobility parameters

In this model, we used the current location, speed and direction of the MS to predict its future location. We employed the Gauss-Markov mobility model [2] as discussed in the literature. Gauss-Markov mobility is a well-known mobility model. It can represent both constant velocity fluid-flow and random-walk models through a tuning parameter that varies between 0 and 1.

We assume that the MS is equipped with a positioning system that updates location information, speed and direction over 3 consecutive time intervals. The updated values are then used to predict the next two locations using the Gauss-Markov mobility formulas for speed, direction and location. The speed and direction of the MS is calculated using formulas (2.1) and (2.2) in chapter 2.

$$s_n=\alpha s_{n-1}+(1-\alpha)\bar{s}+\sqrt{1-\alpha^2}s_{x_{n-1}}$$

$$d_n=\alpha d_{n-1}+(1-\alpha)\bar{d}+\sqrt{1-\alpha^2}\, d_{x_{n-1}}$$

In these formulas, s_{n-1} and d_{n-1} are the speed and direction of the MS in a time interval t. The dataset that we have used in these models collected information every 0.6 seconds, but by considering that a conventional GPS provides a position update every 1 second [23] [30] [7], we assume that our data is collected every 1.2 sec (we consider that data is updated after every two observation time intervals of the original data set).

In our simulation model, location information is updated every 3.6 seconds (each 3 time intervals of length 1.2 seconds).α is the tuning parameter which varies between 0 and 1. If it is 0, this indicates the MS follows a random movement (Brownian motion) and when it is 1, the user follows a linear motion. The degree of randomness is obtained by varying α between 0 and 1. $\bar{s}$ and $\bar{d}$ are the mean speed and direction as n goes to ∞. $s_{x_{n-1}}$ and $d_{x_{n-1}}$ have a random Gaussian distribution with mean equal to zero and standard deviation equal to one.

In this method, the direction of the MS is calculated probabilistically which in most cases will not be the same direction as the actual direction. For this purpose, we have calculated the direction of the MS in each location update in a small time interval (0.6 sec) between two consecutive movement measurements. The formula for calculating the direction between two points is described as follows: [21]

$$d = \text{arctangent}\ (\Delta y / \Delta x) \tag{3.1}$$

In formula 3.1, Δy and Δx are the coordinate difference values between two consecutive points, and arctangent function is the inverse of the tangent function. The MS will follow the same direction until the next location update.

The next location coordinates of the MS is calculated using formulas (2.3) and (2.4):

$$x_n = x_{n-1} + s_{n-1} \cos d_{n-1}$$

$$y_n = y_{n-1} + s_{n-1} \sin d_{n-1}$$

Where (x_n, y_n) and (x_{n-1}, yn_{-1}) are the x and y coordinates of MS in n^{th} and $(n-1)^{st}$ time intervals, respectively.

3.2 Prediction based on Observation histories

In this model, we have used the current and the previously visited position coordinates information of the MS to predict its future position. A simple second-order Markov mobility model is used to predict the future position. This means the next position is calculated based on the current and the previous positions.

We limited our model to second–order because using higher order degrees need more space and time requirements (a very large database to store the previous positions information and needs more time for collecting the information).

A sliding window is used to ensure that only the most recent data (the current one and the previous one) are involved for prediction and older data are discarded. For this purpose, we store the first two movement coordinates information of the MS, which are: *P1(x1, y1)*, *P2(x2, y2)*. Then we subtract the first coordinate position from second position to find the difference between these two points. In the third step we added the extracted difference to the second position *P2(x2, y2)* and we predict the next position of the MS as *P3(x3, y3)*. The step is described in the formula given below:

$$\begin{array}{lcl} \text{Diffx} = x2 - x1 & & x3 = x2 + \text{Diffx} \\ & \Longrightarrow & \\ \text{Diffy} = y2 - y1 & & y3 = y2 + \text{Diffy} \end{array} \tag{3.2}$$

In this model, similar to the previous one, the time interval (t) is equal to 1.2 seconds, which means that we are going to predict the next position of the MS after every two observations.

Chapter 4

SIMULATION AND PERFORMANCE EVALUATION

We constructed a simulation model to evaluate the performance for both mobility schemes discussed in Chapter 3. These schemes are implemented in Matlab R2011a program.

4.1 Simulation Dataset

Prediction accuracy of the two mobility models considered was compared using two types of dataset [31] for pedestrian movement. These datasets were collected over an 802.11 ad hoc wireless network from a micro-simulation in an urban area of Stockholm, Sweden called “Ostermalm”. Ostermalm consists of a grid of interconnected streets with 14 passages that connected this area to the other parts of the city. Figure 3.1 shows Ostermalm area map which is shown by yellow color segments. The red dots show passages to outside of this area. The area is 5872 m^2.

In the first dataset, the nodes entered the observed area according to a Poisson process with an arrival rate λ=0.01nodes/s. In the second dataset, the arrival rate was λ=0.05nodes/s. The position of all observed nodes are recorded every 0.6 seconds, but since our models predict future position after 1.2 seconds as mentioned before, we have updated data after every two observations (0.6 + 0.6 sec).

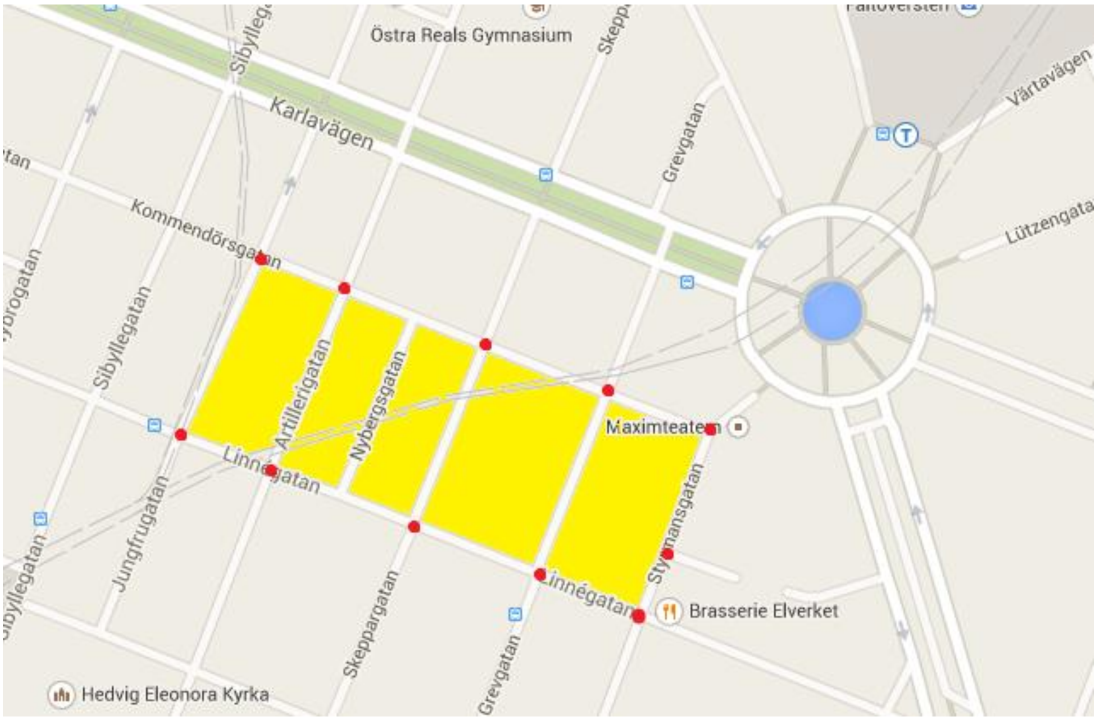

Figure 4.1. Ostermalm Area Map [from Google Maps]

4.1.1 When an MS makes a call

We activate a node with [create, Timestamp, NodeID, X coordinate, Y coordinate, speed] when an MS starts a call. Here, create means that a user starts a call, Timestamp is the current time which is updated every 0.6 sec, NodeID is the ID of MS, Xcoordinate and Ycoordinate are the coordinates of MS at current time instance, and speed is the current movement speed of the MS.

4.1.2 After making a call (after first 0.6 sec)

We record the data set: [Timestamp, NodeID , X coordinate , Y coordinate , Speed] for the MS.

4.2 Simulation Parameters

The simulation time is taken as 10 minutes and the call holding time for each node is 3 minutes. In the first dataset with arrival rate of λ=0.01nodes/s, 72 nodes are observed in the Ostermalm area. In the second dataset with arrival rate of λ=0.05nodes/s, 360 nodes are observed. Table 4.1 shows the simulation parameters for the λ=0.01nodes/s and Table 4.2 shows the parameters for λ=0.05nodes/s.

Table 4.1. Simulation parameters for first dataset [31] [4]

Parameters	Value
Number of Nodes	72
Area	$5872m^2$
Simulation time	600 sec
Location Update time	1.2 s
Call holding time for each node	180 sec
Arrival rate	λ=0.01nodes/s

Table 4.2. Simulation parameters for second dataset [31] [4]

Parameters	Value
Number of Nodes	360
Area	$5872m^2$
Simulation time	600 sec
Location Update time	1.2 s
Call holding time for each node	180 sec
Arrival rate	λ=0.05nodes/s

4.3 Simulation Models in Matlab

The Current parameters mobility scheme is implemented using a Gauss-Markov approach, as described in Chapter 3. Table 4.3 shows the parameter values used in implementing the Gauss-Markov model. A counter is used to check if the MS exceeds 180 seconds (3 minutes) call time and if exceeds, the program will switch to the next node automatically and sets the counter equal to 1. The nodeID is checked in each step. If the MS finishes the call or leaves the area before 3 minutes, the program will switch to the next node automatically and sets the counter equal to 1. For location update, whenever the MS passes over 3 time intervals, the program will assign the MS actual value from the Matlab database and performs the rest of processing. Figure 4.2 shows the flowchart of the current mobility parameters simulation model.

Table 4.3. Simulation parameters for simulating Gauss-Markov model

Parameter	**Value**
α	1
Min speed	0.6 m/s
Max speed	2 m/s
Mean speed	1.3 m/s
direction	0-2π
Mean direction	π

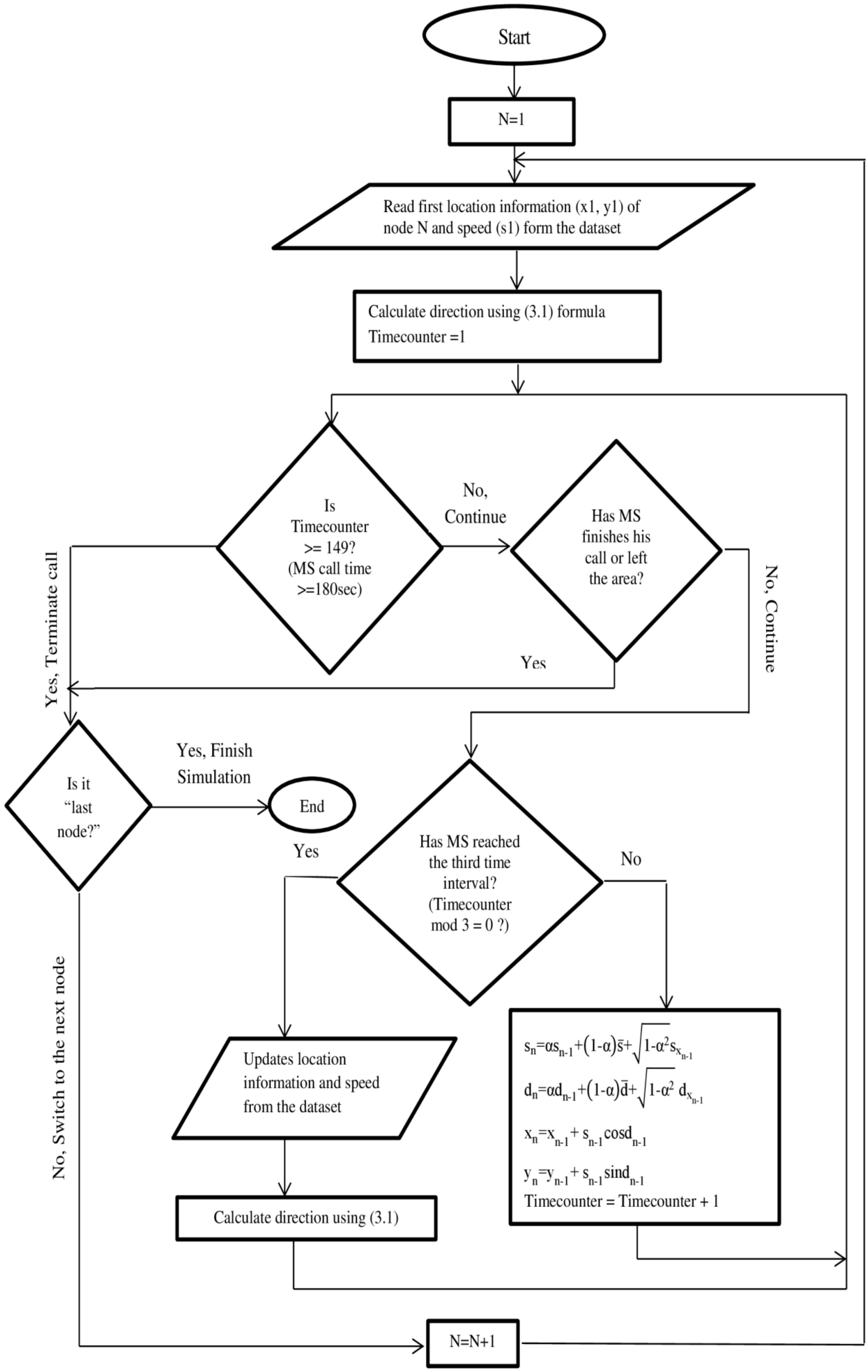

Figure 4.2. Simulation model of Current Mobility Parameters

In the first step of the observation history model, we take the first two movement position coordinates information of the MS, and using the technique which is described in 3.2 in Chapter 3, we predict the next position for the MS. After that, the first movement coordinate of the MS will be discarded and the second coordinate information will assigned as the first coordinate value. We then take the third position information and assign it as the second coordinate value, and calculate the next position information. The procedure continues in this manner until the MS finishes the call or leaves the area. In this method, a counter is also used whenever the user exceeds the call holding time (3 minutes), we assume he/she terminates his/her call and switch to the next node. If he/she leaves the area before 3 minutes, the system will automatically switch to the next node and sets the counter equal to 1. Figure 4.3 shows the flowchart of the observation history simulation model.

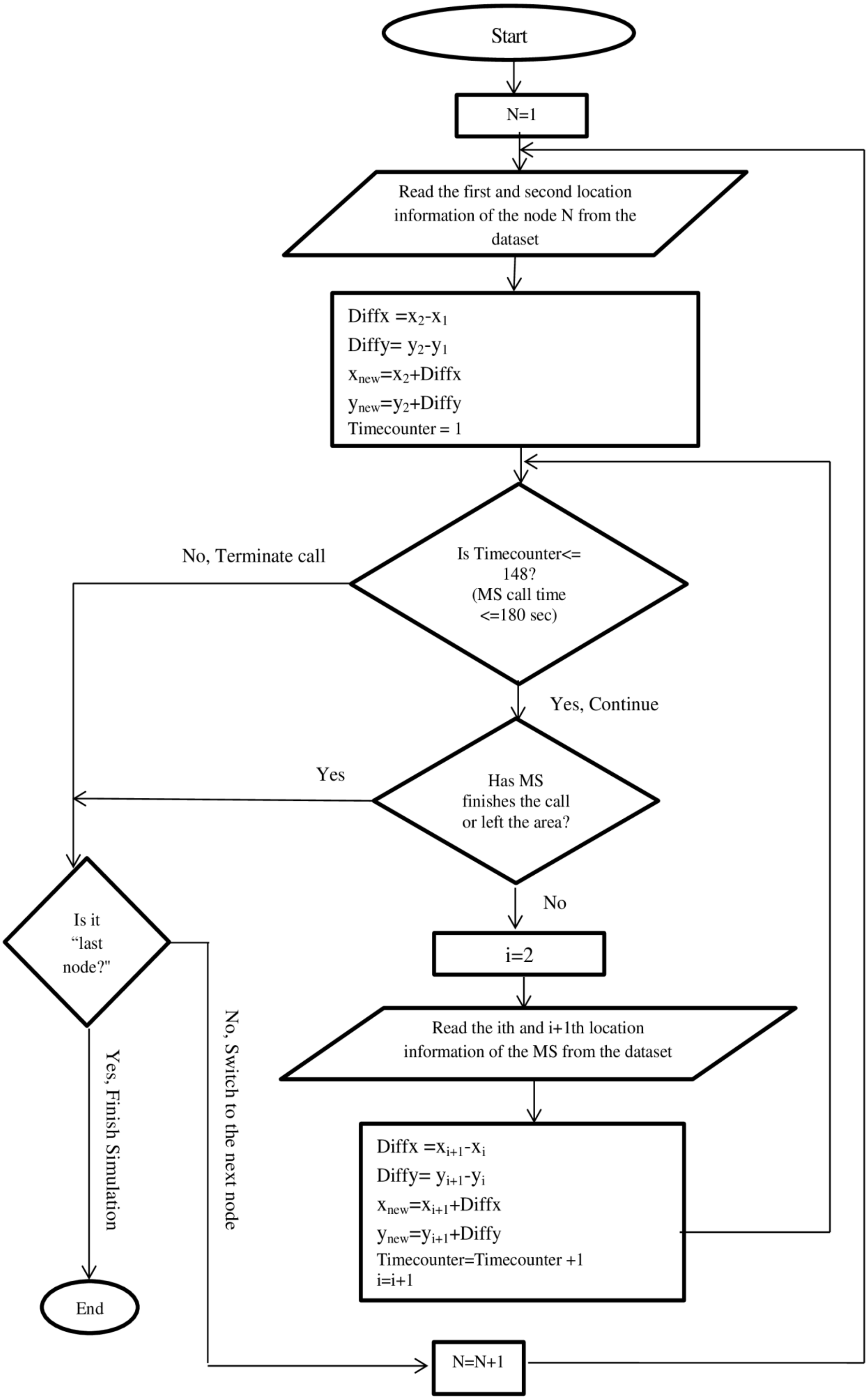

Figure 4.3. Simulation model of Observation histories

4.4 Performance Evaluation

There are several approaches to measuring precision. We have measured precision using the Mean Absolute Error (MAE) approach [22]. Mean Absolute Error is a quality to measure how close a prediction or forecast is to the eventual outcome. It is an average of absolute error over the number of samples. We have used Mean Absolute Error because it is simple, it is fast to compute and shows average error of all nodes in the experiment. Mean Absolute Error is defined as:

$$\frac{1}{M} \sum_{i=1}^{M} \text{absolute}\left(\text{Actual value - Predicted value}\right) \qquad (4.1)$$

In this formula, M is the number of samples (number of position coordinates for each user) until the call terminates. Since the maximum call holding time for a user is 180 sec, and the location information is collected every 1.2 sec, the maximum value for M will be 150 because in 180 sec there are 150, 1.2 sec intervals.

To calculate the difference between two points, we have used the Euclidian distance formula:

$$\text{Difference} = \sqrt{(x(i+1)-x(i))^2+\left(y(i+1)-y(i)\right)^2} \qquad (4.2)$$

In this formula, (x_{i+1}, y_{i+1}) and (x_i, y_i) are the coordinates of the mobile user in $(i+1)^{st}$ and $(i)^{th}$ time intervals, respectively. By combining (4.1) and (4.2) we can conclude:

$$\text{MAE} = \frac{1}{M} \sum_{i=1}^{M-1} \sqrt{(x(i+1)-x(i))^2+\left(y(i+1)-y(i)\right)^2} \qquad (4.3)$$

Figure 4.4 and Figure 4.6 show the Mean Absolute Error for the Current Mobility Parameters method and Figure 4.5 and Figure 4.7 show the Mean Absolute Error for the Observation History for the first and second dataset, respectively.

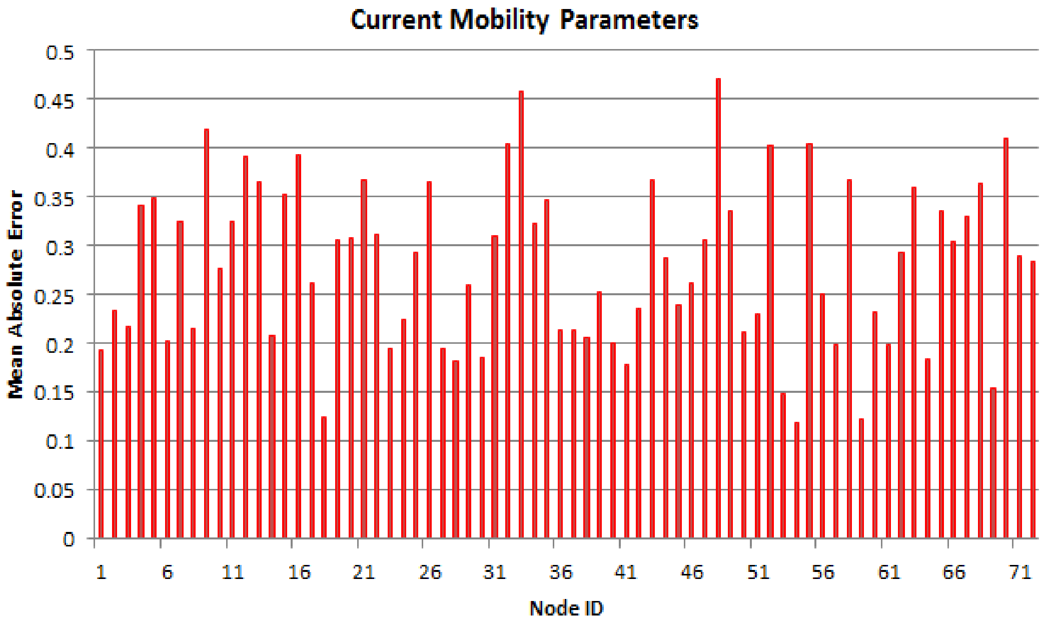

Figure 4.4. Mean Absolute Error for the current mobility parameters method (dataset1)

The average Mean Absolute Error for 72 nodes in Figure 4.4 is calculated as:

$$\frac{\sum_{i=1}^{72} \mathrm{MAE}(i)}{72} = \frac{20.2165}{72} = 0.280785$$

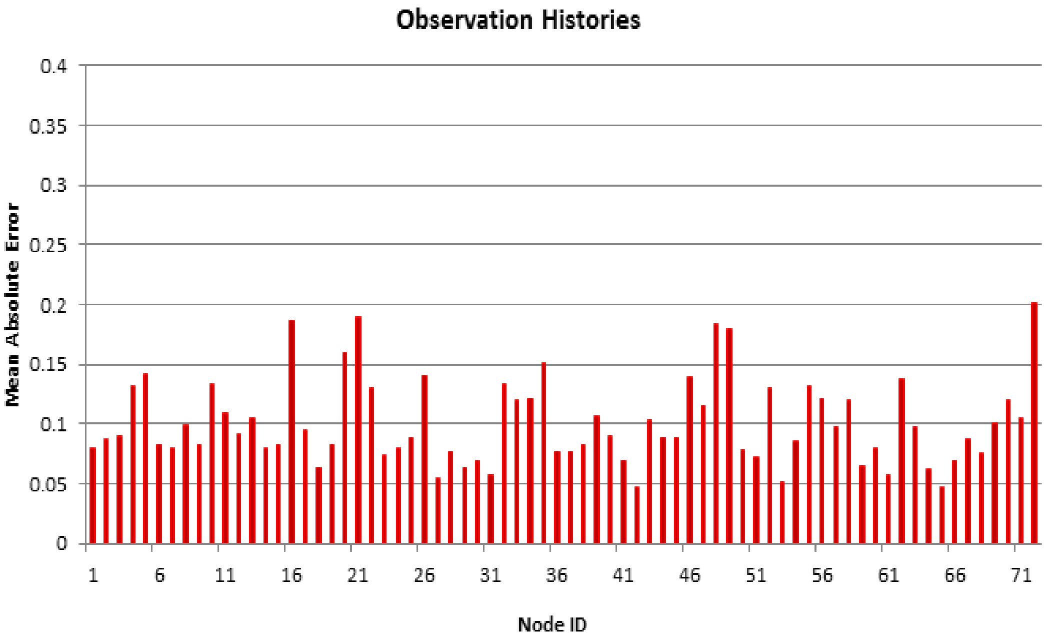

Figure 4.5. Mean Absolute Error calculation for the Observation History method (dataset1)

The average Mean Absolute Error for Figure 4.5 for 72 nodes is calculated as:

$$\frac{\sum_{i=1}^{72} \text{MAE(i)}}{72} = \frac{7.2694}{72} = 0.100964$$

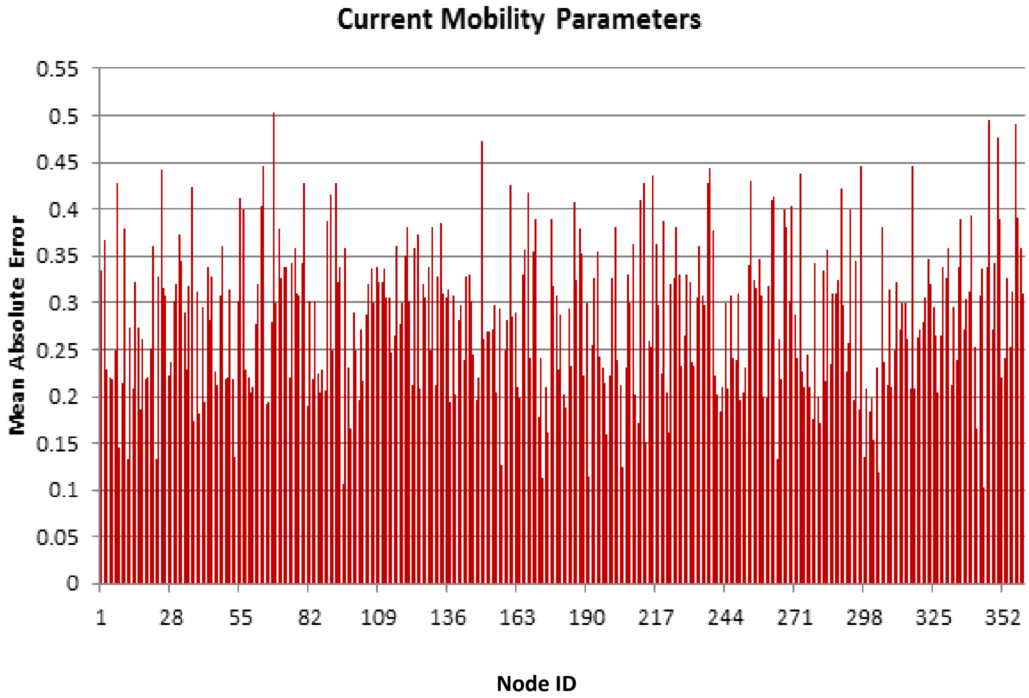

Figure 4.6. Mean Absolute Error calculation for the current mobility parameters method (dataset 2)

The average Mean Absolute Error for 360 nodes in Figure 4.6 is calculated as:

$$\frac{\sum_{i=1}^{360} \mathrm{MAE(i)}}{360} = \frac{102.8613}{360} = 0.282446$$

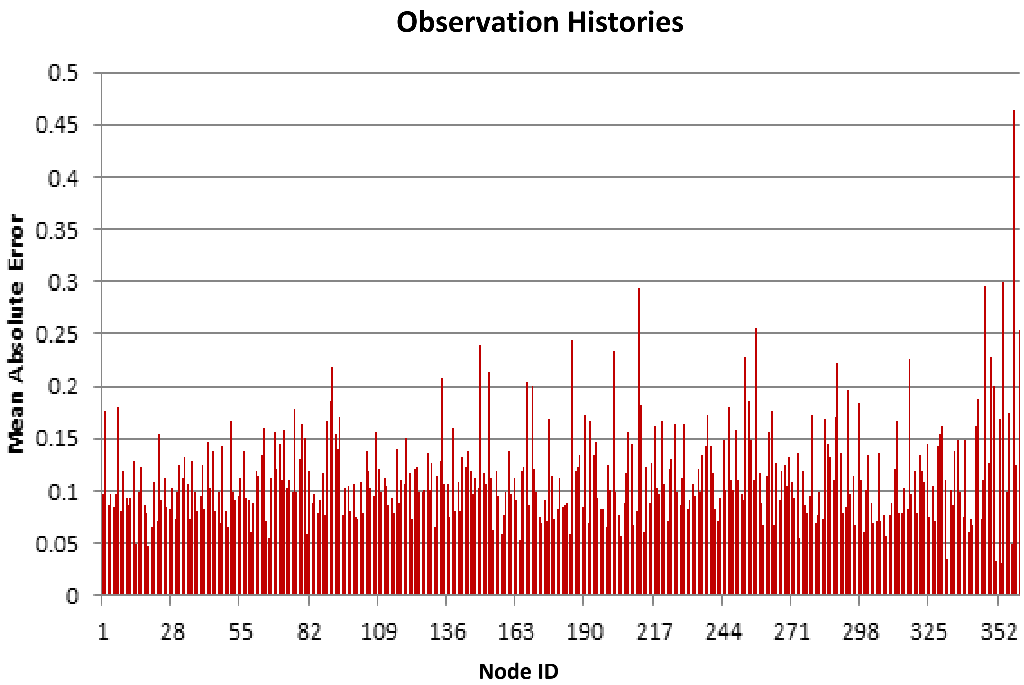

Figure 4.7. Mean Absolute Error calculation for Observation History method (dataset2)

The average Mean Absolute Error for 360 nodes in Figure 4.7 is calculated as:

$$\frac{\sum_{i=1}^{360} \mathrm{MAE}(i)}{360} = \frac{41.6775}{360} = 0.115771$$

By comparing Mean Absolute Error in both datasets outlined in Figure 4.4 to Figure 4.7, we observe that the observation histories method has a better performance than the current mobility parameters method. The observation history method is suitable for movements that have some regularity in their trajectory. The performance of such schemes can be decrease as the speed goes through changes or as there are sharp turns in movement directions (MS changing its speed or direction frequently). Since most pedestrians follow some regularity in their movements, this scheme has a better performance than the current mobility parameters method. There are some variations in the nodes' performance for example: Node 48 in Figure 4.4 has the highest error in the current mobility parameters method (≈ 0.47). In our analysis we found that this is caused by the high speed of node 48 (with an average speed ≈ 1.94 m/s), which is much greater than the mean speed value (Mean speed = 1.3 m/s). Node 54 has the lowest amount of Mean Absolute Error (=0.12) in Figure 4.4. This node moves with a low speed (average speed ≈ 0.72m/s). In Figure 4.5, node 72 has the highest value of error in observation histories method. This is caused by changes in its direction, much more frequently than other nodes. Node 48 also has a high value of error because of frequent changes in the user speed. Nodes 65 and 53 have low Mean Absolute Error value because node 65 didn't changed its directions until terminating the call and node 53 has changed its speed rarely without too much difference between previous speeds.

Similar patterns were observed in Figure 4.6 and Figure 4.7 for the second dataset. Node 68 in Figure 4.6 has the highest value of error (≈0.50) with an average speed = 2.032 m/s and node 345 has the lowest error (≈ 0.10) with an average speed ≈ 0.7 m/s in the current mobility parameters method. In Figure 4.7, node 358 has the highest value of error (≈0.46) as the speed goes through changes and direction has sharp turns. Node 353 has the lowest value of error (≈0.03) because the speed is not too much changed during movement period and the direction was constant until terminating the call.

One problem with observation histories method is when the user changes its speed and direction frequently. For example, if a node passes 2 movements without changing its direction and after that because of some physical restrictions or barrier such as a wall, he/ she changes its direction or speed, the scheme follows the previous direction until the next update. In such cases, the current mobility parameters method has better performance since it works with direction and speed at the current instance of time. However, this scheme needs more mathematical calculation which is also more complex than the observation histories method. The problem of Gauss-Markov mobility approach is when the user moves with a speed much more above the mean speed. In this situation, the error will increase rapidly. We present some actual and predicted paths graphs for some selected nodes below.

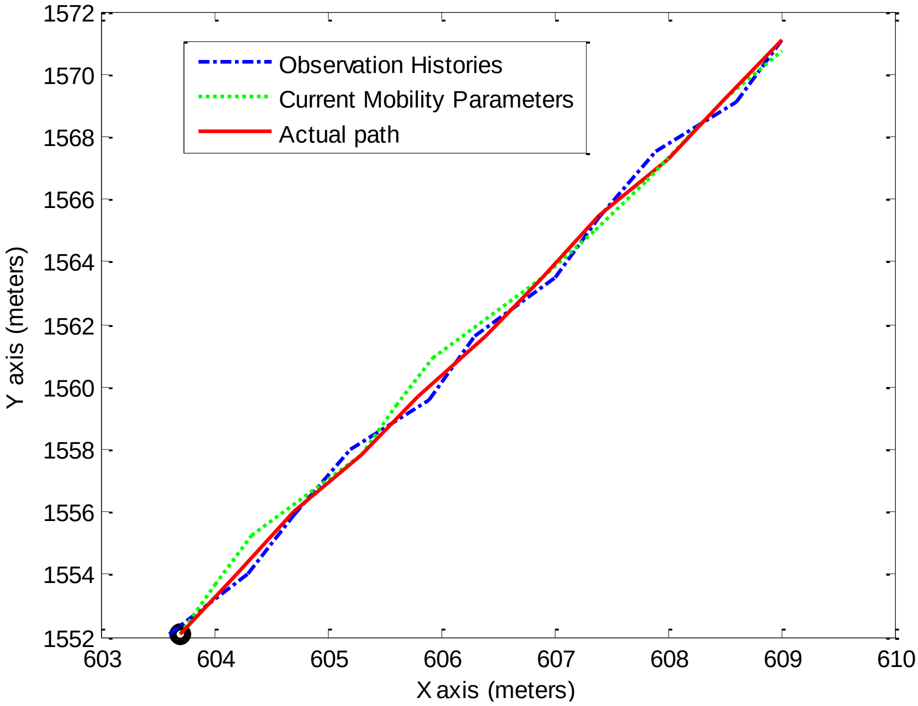

Figure 4.8. Actual trajectory versus predicted trajectories of node 26 (52-62 time intervals)

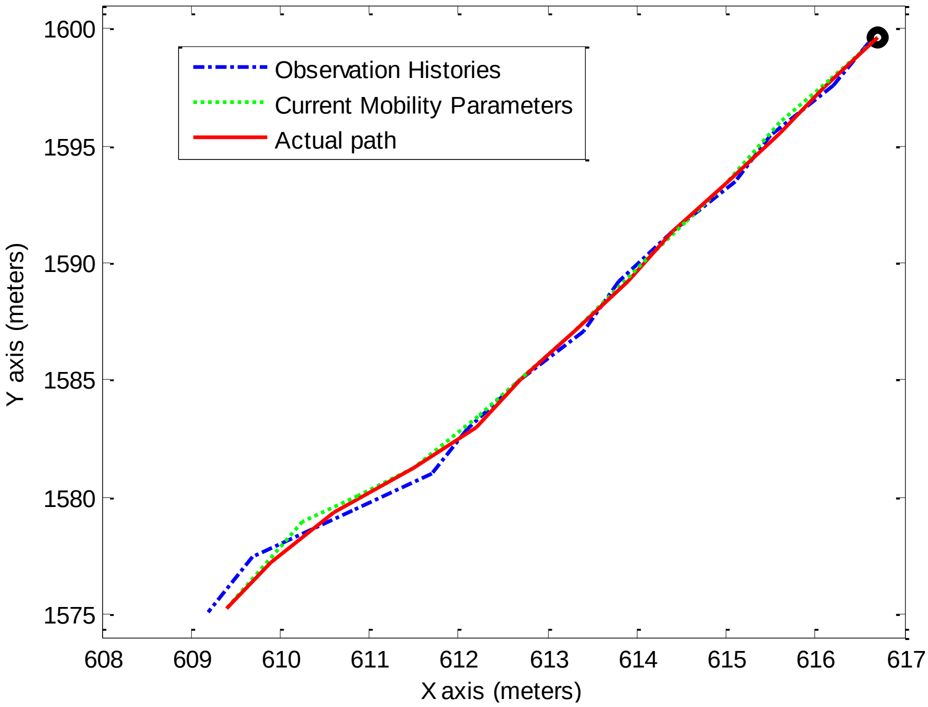

Figure 4.9. Actual trajectory versus predicted trajectories of node 52 (130-142 time intervals)

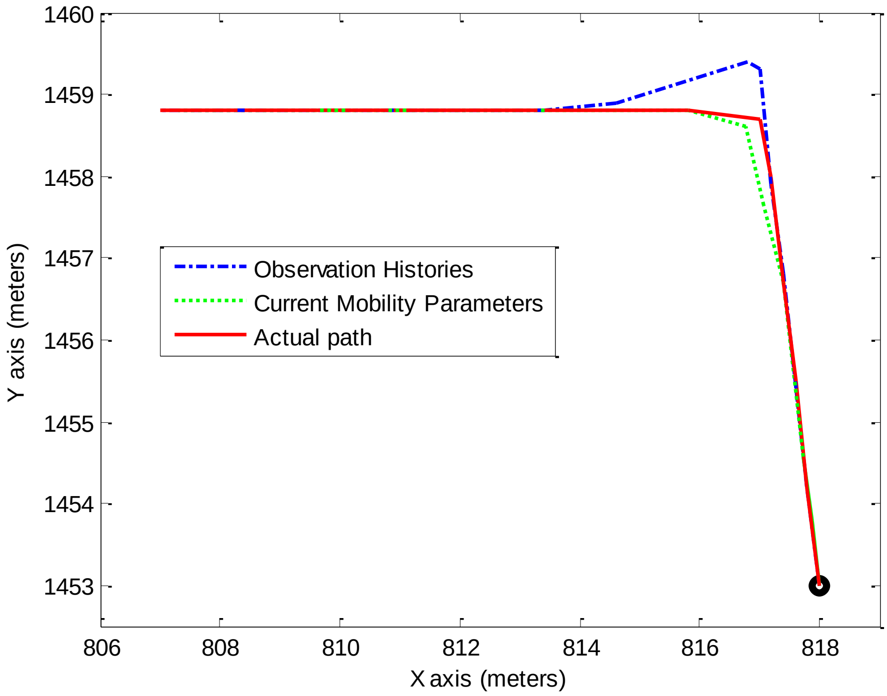

Figure 4.10. Actual trajectory versus predicted trajectories of node 1(1-13 time intervals)

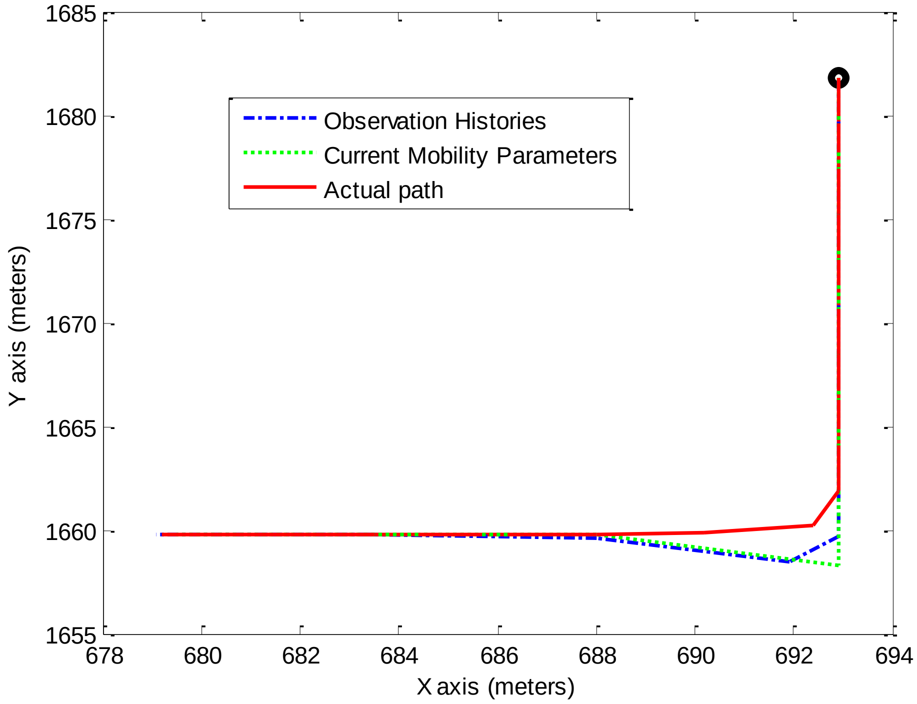

Figure 4.11. Actual trajectory versus predicted trajectories of node 32 (88-104 time intervals)

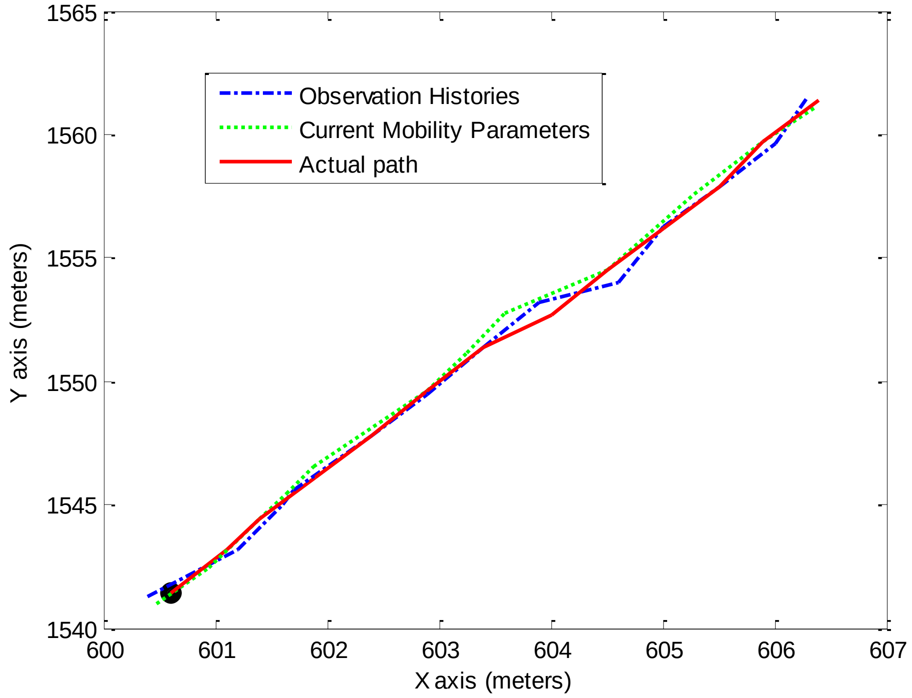

Figure 4.12. Actual trajectory versus predicted trajectories of node 132(50-64 time intervals)

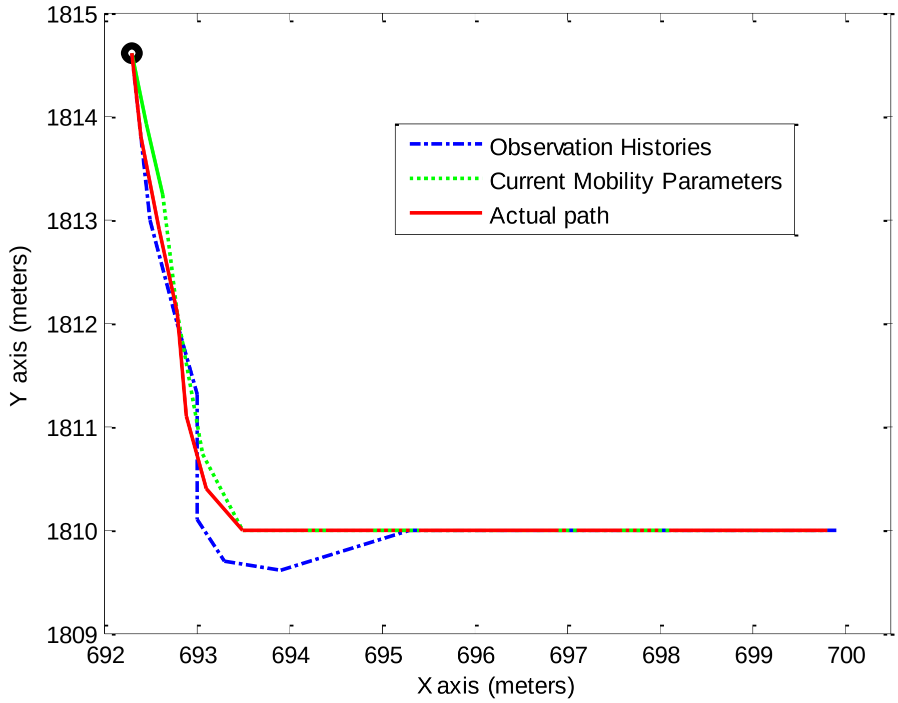

Figure 4.13. Actual trajectory versus predicted trajectories of node 8 (1-13 time intervals)

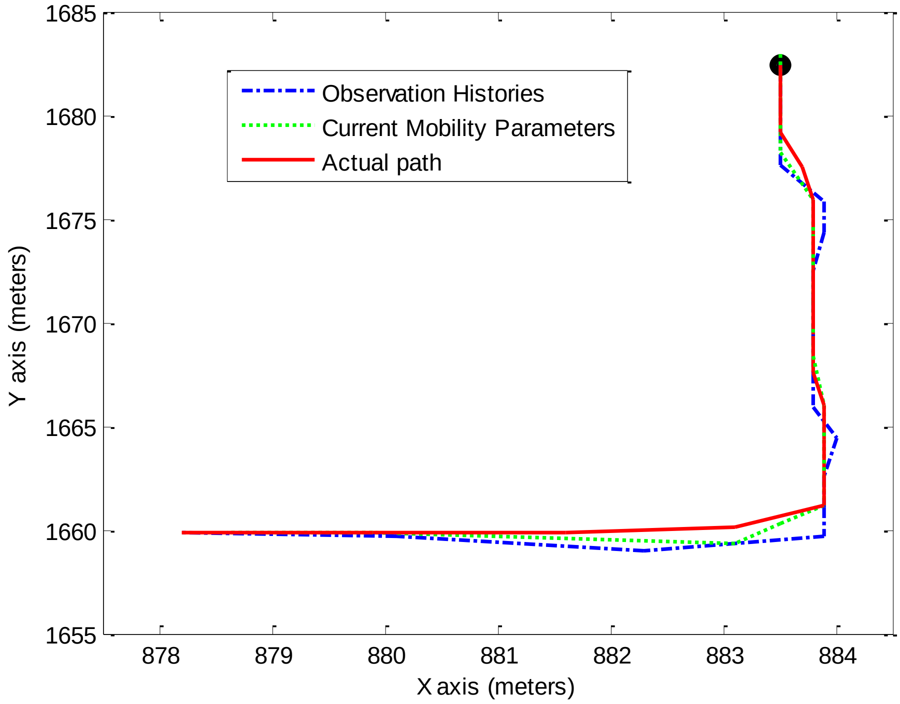

Figure 4.14. Actual trajectory versus predicted trajectories of node 229 (81-98 time intervals)

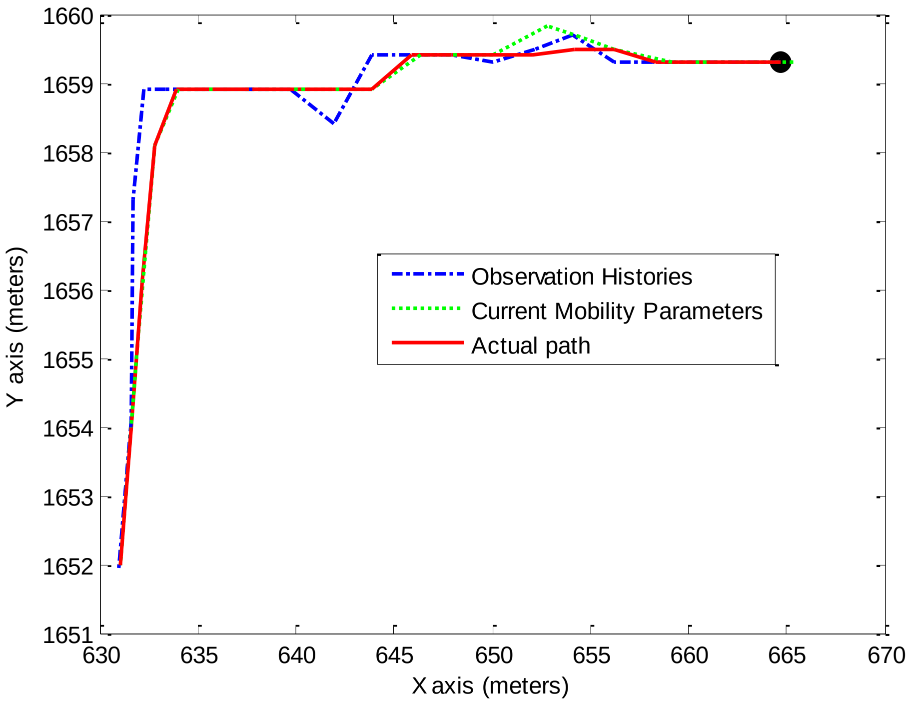

Figure 4.15. Actual trajectory versus predicted trajectories of node 63 (87-106 time intervals)

Figure 4.8 to Figure 4.11 consider an arrival rate = 0.01 nodes/sec and Figure 4.12 to Figure 4.15 consider an arrival rate = 0.05 nodes/sec for the first and second datasets respectively. These figures indicate a comparison between the actual trajectory and the trajectories predicted of several selected nodes in Ostermalm area using current mobility parameters and observation histories methods. The solid red lines represent the actual trajectory. Black dashed and green dotted lines show predicted trajectories belonging to observation histories and current parameters mobility methods, respectively and ● indicates the starting point of the node trajectory. As seen in these figures, when the direction of the MS is changed slightly during the movement pattern (Figures 4.8, 4.9 and 4.12) both methods have almost the same trajectory with the actual path. When there is a sharp turn in the MS movement (for example turns by 90 degrees or more) (Figures 4.10, 4.11, 4.13, 4.14, 4.15) the performance of observation histories is lower than the current mobility parameters method.

For the observation histories method, as it is depends on the current and the previous position, the MS will continue in the same direction but will start following the correct direction after some movements. For the current mobility parameters method, if the turn occurs just after the location update, the MS will continue with the same direction without turning until the next location update (Figure 4.11). If turning occurs one or two movements before location update of the MS (Figures 4.10, 4.13, 4.14, 4.15) the method can realized it and turns immediately after the MS turns. The percentage precision of our model is measured using a formula described in [9] which calculates the ratio between Mean Absolute Error and the length of actual trajectory:

$$P = \left(1 - \frac{MAE}{\sum_{i=1}^{n} \|a_{i+1} - a_i\|}\right) \times 100 \qquad (4.4)$$

Table 4.4 gives the precision percentage rate of above figures at the intervals calculated using formula 4.4.

Table 4.4. Precision rate of mobility prediction schemes

Node #	Distance (m)	Precision Percentage Current Mobility Parameters (%)	Precision Percentage Observation Histories (%)
26	19.7338	98.15	99.39
52	25.5108	98.34	99.40
1	14.4959	98.48	98.33
32	37.0946	98.50	99.41
132	24.4854	98.53	99.13

8	10.3315	98.12	97.91
229	27.4914	98.50	99.23
63	36.5057	98.99	99.26

We have reached an average of 99.74 % and 99.89 % accuracy for current mobility parameters and observation histories methods for the first dataset and 99.74 % and 99.88 % for the second dataset.

Chapter 5

CONCLUSION

Mobility prediction using a certain mobility model is an approach to predict the future location of a mobile user. In this technique, we use the location, speed and distance of a mobile user over a period of time to predict its next location, speed, and direction. Mobility model techniques may be used to make an effective means of quality service guarantees and may be used to decrease the amount of call dropping and call blocking probabilities for a seamless communication for mobile users.

In this thesis, we presented two types of popular mobility models for the prediction of the future position of mobile user in pedestrian movements. We compared the result of both methods through a simulation study, which is conducted in Matlab R2011 program.

The first model considered is the mobility prediction based on current mobility parameters model, which predicts the future location of mobile user based on the current speed, direction and location information at the current instance. We have used a Gauss-Markov mobility approach, which is useful for both random walk and fluid-flow patterns using a tuning parameter.

The second model is prediction based on observation histories of mobile user. This model uses the historical movement pattern of mobile user to predict the future position of that user. In this case, we used a simple second order Markov-Mobility model.

We compared these models with two actual trajectories datasets of pedestrian movement in the Ostermalm area of Stockholm, Sweden, with arrival rates of 0.01 nodes/sec and 0.05 nodes/sec, respectively. Simulation results indicate that the observation histories model has better performance than the current mobility parameters model, with an average Mean Absolute Error equal to 0.1 and 0.11 and percentage error equal to 99.89 % and 99.88 % for the first and second datasets.

The observation histories model is suitable for movements that have some regularity in their travelling patterns and the accuracy of this model decreases as the direction or speed constantly goes through changes. For such a situation, the current mobility parameters model will be more effective than the observation histories since it works with the current speed and direction of the mobile user.

The observation histories method also has overheads as it needs a large database to store the previous position information of mobile user for prediction purposes. When the history of movements for a mobile user is not available, this model will be useless. Since pedestrian nodes usually follow some regularity in their movements without too much change in their speed and directions, with real-time data, this method has better performance than the current mobility parameters method. Also, implementation of this model is easier than the current mobility parameters scheme as the current mobility parameters model needs more mathematical calculation to calculate the future speed, direction and the position of the mobile user. Also we may expect that when the arrival rate increases (higher arrival rate) the prediction performance in both models may decrease as the users will be constantly forced to change their location due to crowdedness.

Both methods can be combined to predict the future location of a user based on: 1) the displacement of the user between the first and second coordinate movements using the observation histories method and 2) the direction of the user which is calculated at each location update using the current mobility parameters method. However, as our results show very high (99%) performance for individual methods, the combination of these two methods can be considered to be unnecessary from practical point of view.

As future work, we are planning to investigate in more detail the role of proposed approaches in enhancing network resource reservation and providing better QoS. Later work may consider MS movements not just limited to pedestrians, but also vehicle speeds may be considered. The results we have reached in this study were for the pedestrian dataset in the Ostermalm area, which is rectangular with 90 degree turns, mostly containing regular movements. We have in mind to implement our models for other areas with more irregular changes in MS movement patterns.

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APPENDICES

Appendix A: Simulation results for both Mobility Models

A1. Current Mobility parameters method for first dataset

Node #	Number of Movements(Each 1.2 sec)	Sum of all differences	Mean Absolute Error($\sum_{i=1}^{n}$ diff/n)	Distance	Accuracy %
1	150	29.0673	0.1938	187.796	99.9
2	144	33.7228	0.2342	161.528	99.86
3	150	32.6768	0.2178	158.047	99.86
4	75	25.6684	0.3422	123.623	99.72
5	68	23.7148	0.3487	122.666	99.72
6	150	30.528	0.2035	171.857	99.88
7	150	48.6023	0.324	308.445	99.89
8	101	21.7602	0.2154	135.296	99.84
9	150	62.977	0.4198	347.25	99.88
10	67	18.5232	0.2765	121.744	99.77
11	150	48.6486	0.3243	293.278	99.89
12	150	58.8248	0.3922	350.067	99.89
13	124	45.4136	0.3662	257.866	99.86
14	150	31.2735	0.2085	155.126	99.87
15	150	52.8357	0.3522	268.595	99.87
16	37	14.5767	0.394	65.6595	99.4
17	113	29.6915	0.2628	163.004	99.84
18	150	18.7675	0.1251	105.747	99.88
19	142	43.4566	0.306	277.946	99.89
20	51	15.73	0.3084	77.7284	99.6
21	39	14.3631	0.3683	67.5841	99.46
22	46	14.3544	0.3121	68.8103	99.55
23	150	29.2742	0.1952	187.191	99.9
24	150	33.7003	0.2247	189.427	99.88
25	150	44.0841	0.2939	235.88	99.88
26	112	41.0018	0.3661	220.292	99.83
27	150	29.2057	0.1947	162.46	99.88
28	121	22.109	0.1827	132.871	99.86
29	150	39.1273	0.2608	225.726	99.88
30	150	27.8576	0.1857	188.711	99.9
31	150	46.635	0.3109	269.274	99.88
32	128	51.6727	0.4037	281.026	99.86
33	124	56.7876	0.458	281.536	99.84
34	150	48.4844	0.3232	287.222	99.89
35	150	52.0872	0.3472	294.84	99.88

36	102	21.8283	0.214	132.867	99.84
37	150	31.9749	0.2132	208.355	99.9
38	150	31.0071	0.2067	199.579	99.9
39	90	22.7961	0.2533	123.172	99.79
40	150	30.1129	0.2008	189.362	99.89
41	150	26.8385	0.1789	191.234	99.91
42	150	35.3	0.2353	164	99.86
43	121	44.4893	0.3677	250.11	99.85
44	150	43.2369	0.2882	264.449	99.89
45	107	25.7296	0.2405	131.994	99.82
46	50	13.0569	0.2611	67.3598	99.61
47	85	26.0538	0.3065	134.52	99.77
48	59	27.8338	0.4718	135.61	99.65
49	81	27.2029	0.3358	134.665	99.75
50	150	31.8577	0.2124	171.01	99.88
51	150	34.585	0.2306	220.807	99.9
52	150	60.5027	0.4034	319.555	99.87
53	145	21.6	0.149	130.407	99.89
54	132	15.7	0.1189	111.518	99.89
55	130	52.4912	0.4038	275.624	99.85
56	60	15.0033	0.2501	73.5614	99.66
57	102	20.2571	0.1986	135.828	99.85
58	116	42.7135	0.3682	247.181	99.85
59	112	13.7024	0.1223	80.5742	99.85
60	106	24.5655	0.2317	123.39	99.81
61	102	20.3	0.199	120.8	99.84
62	49	14.4184	0.2943	68.9663	99.57
63	78	28.1081	0.3604	141.916	99.75
64	65	11.9226	0.1834	75.1294	99.76
65	63	21.2	0.3365	117.7	99.71
66	58	17.6328	0.304	100.903	99.7
67	49	16.1713	0.33	77.0726	99.57
68	37	13.486	0.3645	61.5902	99.41
69	33	5.1	0.1545	29.6246	99.48
70	33	13.544	0.4104	69.3235	99.41
71	22	6.3704	0.2896	24.1571	98.8
72	8	2.2741	0.2843	10.2057	97.21

A2. Observation Histories method for first dataset

Node #	Number of Movements(Each 1.2 sec)	Sum of all differences	Mean Absolute Error($\sum_{i=1}^{n}$ diff/n)	Distance	Accuracy %
1	148	11.8662	0.0802	185.264	99.96
2	142	12.4004	0.0873	161.5284	99.95
3	148	13.2603	0.0896	155.947	99.94
4	73	9.5876	0.1313	123.6234	99.89
5	66	9.4127	0.1426	122.6656	99.88
6	148	12.206	0.0825	169.5574	99.95
7	148	11.7375	0.0793	304.3445	99.97
8	99	9.759	0.0986	135.2959	99.93
9	148	12.1705	0.0822	342.65	99.98
10	65	8.6297	0.1328	121.744	99.89
11	148	16.1685	0.1092	289.1781	99.96
12	148	13.5207	0.0914	345.3669	99.97
13	122	12.785	0.1048	257.8664	99.96
14	148	11.8303	0.0799	153.0261	99.95
15	148	12.3421	0.0834	264.8947	99.97
16	35	6.5563	0.1873	65.6595	99.71
17	111	10.5381	0.0949	163.004	99.94
18	148	9.5064	0.0642	104.2467	99.94
19	140	11.5948	0.0828	277.9455	99.97
20	49	7.8175	0.1595	77.7284	99.79
21	37	7.019	0.1897	67.5841	99.72
22	44	5.7131	0.1298	68.8103	99.81
23	148	10.989	0.0743	184.7744	99.96
24	148	11.7858	0.0796	186.8266	99.96
25	148	13.1965	0.0892	232.7799	99.96
26	110	15.511	0.141	220.2916	99.94
27	148	8.1752	0.0552	160.2599	99.97
28	119	9.2169	0.0775	132.8712	99.94
29	148	9.498	0.0642	222.6264	99.97
30	148	10.3548	0.07	186.1113	99.96
31	148	8.5583	0.0578	265.7743	99.98
32	126	16.7857	0.1332	281.0259	99.95
33	122	14.7197	0.1207	281.5362	99.96
34	148	18.0784	0.1222	283.2223	99.96
35	148	22.3345	0.1509	290.8404	99.95
36	100	7.6629	0.0766	132.8669	99.94
37	148	11.3624	0.0768	205.5546	99.96
38	148	12.305	0.0831	196.8788	99.96
39	88	9.359	0.1064	123.172	99.91

40	148	13.2973	0.0898	186.8621	99.95
41	148	10.3447	0.0699	188.6337	99.96
42	148	7.1	0.048	161.8	99.97
43	119	12.3105	0.1034	250.1096	99.96
44	148	13.2149	0.0893	260.9487	99.97
45	105	9.3317	0.0889	131.9939	99.93
46	48	6.7104	0.1398	67.3598	99.79
47	83	9.5954	0.1156	134.5203	99.91
48	57	10.5032	0.1843	135.6098	99.86
49	79	14.1433	0.179	134.6648	99.87
50	148	11.6442	0.0787	168.8095	99.95
51	148	10.7035	0.0723	218.1033	99.97
52	148	19.2401	0.13	315.1867	99.96
53	143	7.4472	0.0521	130.4071	99.96
54	130	11.1521	0.0858	111.518	99.92
55	128	16.801	0.1313	275.6235	99.95
56	58	7.0623	0.1218	73.5614	99.83
57	100	9.8049	0.098	135.8282	99.93
58	114	13.6097	0.1194	247.1808	99.95
59	110	7.1307	0.0648	80.5742	99.92
60	104	8.3265	0.0801	123.3895	99.94
61	100	5.7	0.057	120.8	99.95
62	47	6.4991	0.1383	68.9663	99.8
63	76	7.4332	0.0978	141.9164	99.93
64	63	3.9243	0.0623	75.1294	99.92
65	61	2.9	0.0475	117.7	99.96
66	56	3.9236	0.0701	100.9029	99.93
67	47	4.1042	0.0873	77.0726	99.89
68	35	2.6621	0.0761	61.5902	99.88
69	31	3.1236	0.1008	29.6246	99.66
70	31	3.7203	0.12	69.3235	99.83
71	20	2.117	0.1059	24.1571	99.56
72	6	1.2119	0.202	10.2057	98.02

A3. Current Mobility parameters method for second dataset

Node #	Number of Movements(Each 1.2 sec)	Sum of all differences	Mean Absolute Error($\sum_{i=1}^{n}$ diff/n)	Distance	Accuracy %
1	96	32.0439	0.3338	157.6633	99.79
2	59	21.6636	0.3672	144.3938	99.75
3	150	34.4187	0.2295	214.4421	99.89
4	150	33.1611	0.2211	208.7783	99.89
5	150	32.6691	0.2178	159.5065	99.86
6	150	37.3323	0.2489	210.2022	99.88
7	40	17.1068	0.4277	66.5113	99.36
8	150	21.8899	0.1459	131.7597	99.89
9	150	31.9947	0.2133	191.1274	99.89
10	150	56.9174	0.3794	317.9367	99.88
11	144	19.0594	0.1324	123.6941	99.89
12	150	40.9456	0.273	221.3428	99.88
13	67	13.9186	0.2077	66.9286	99.69
14	150	48.2561	0.3217	300.426	99.89
15	135	36.8635	0.2731	199.6642	99.86
16	59	10.9401	0.1854	67.3701	99.72
17	150	39.1582	0.2611	224.2227	99.88
18	150	32.8122	0.2187	164.4934	99.87
19	150	32.9099	0.2194	207.1788	99.89
20	150	37.6911	0.2513	222.7578	99.89
21	150	54.2073	0.3614	293.1753	99.88
22	150	20.0924	0.1339	120.1184	99.89
23	150	49.2896	0.3286	272.2408	99.88
24	150	66.437	0.4429	328.8075	99.87
25	150	47.3428	0.3156	239.7392	99.87
26	150	46.3157	0.3088	244.0052	99.87
27	150	33.4591	0.2231	145.0232	99.85
28	116	27.4255	0.2364	162.7412	99.85
29	150	45.3015	0.302	272.1473	99.89
30	150	47.9841	0.3199	240.6538	99.87
31	67	24.9774	0.3728	135.3988	99.72
32	150	51.5278	0.3435	251.8133	99.86
33	57	16.4859	0.2892	81.2287	99.64
34	150	34.4233	0.2295	212.4532	99.89
35	150	47.8345	0.3189	268.7029	99.88
36	150	63.6317	0.4242	325.5822	99.87
37	150	26.1612	0.1744	141.0312	99.88
38	119	37.0745	0.3116	222.5803	99.86
39	150	27.1561	0.181	143.4054	99.87

40	150	44.4823	0.2965	252.3774	99.88
41	150	29.1	0.194	205.1	99.91
42	122	41.2159	0.3378	220.5496	99.85
43	150	42.1716	0.2811	216.925	99.87
44	76	24.952	0.3283	132.6966	99.75
45	150	34.1105	0.2274	201.9172	99.89
46	100	21.2928	0.2129	136.5232	99.84
47	150	46.0396	0.3069	298.2382	99.9
48	150	54.2228	0.3615	318.2471	99.89
49	131	28.5679	0.2181	158.1263	99.86
50	150	32.9921	0.2199	179.0722	99.88
51	50	15.6935	0.3139	73.363	99.57
52	150	32.7028	0.218	187.9507	99.88
53	150	20.3873	0.1359	127.9102	99.89
54	120	36.2915	0.3024	179.5369	99.83
55	150	61.6964	0.4113	323.6373	99.87
56	150	59.888	0.3993	321.0374	99.88
57	150	34.392	0.2293	213.4763	99.89
58	150	32.9893	0.2199	169.9162	99.87
59	150	30.4872	0.2032	150.0494	99.86
60	150	31.5604	0.2104	188.5918	99.89
61	150	41.6421	0.2776	254.737	99.89
62	150	48.0882	0.3206	258.7002	99.88
63	150	60.6284	0.4042	315.566	99.87
64	150	67.0613	0.4471	366.2853	99.88
65	150	28.7651	0.1918	154.1531	99.88
66	150	29.2	0.1947	197.2	99.9
67	150	41.8974	0.2793	220.3998	99.87
68	150	75.4133	0.5028	364.8435	99.86
69	150	44.9634	0.2998	283.0627	99.89
70	150	56.9353	0.3796	305.0937	99.88
71	115	37.5849	0.3268	219.8248	99.85
72	150	50.6488	0.3377	294.7983	99.89
73	150	50.7949	0.3386	267.3058	99.87
74	150	32.9755	0.2198	181.0921	99.88
75	150	51.3523	0.3423	275.2152	99.88
76	48	17.2527	0.3594	79.16	99.55
77	150	46.6107	0.3107	273.3758	99.89
78	150	46.0502	0.307	269.3155	99.89
79	41	14.0157	0.3418	67.0265	99.49
80	56	23.9508	0.4277	134.7288	99.68
81	150	28.4912	0.1899	164.6814	99.88
82	86	25.9259	0.3015	158.8699	99.81
83	150	32.7762	0.2185	180.2013	99.88
84	150	45.1425	0.301	242.3381	99.88

85	150	33.7864	0.2252	169.7544	99.87
86	150	30.5778	0.2039	200.0476	99.9
87	150	34.4147	0.2294	152.9622	99.85
88	150	30.8977	0.206	150.722	99.86
89	150	58.1274	0.3875	311.7125	99.88
90	150	62.3862	0.4159	323.4532	99.87
91	38	9.419	0.2479	65.5172	99.62
92	150	64.1209	0.4275	330.6641	99.87
93	51	16.3994	0.3216	73.0537	99.56
94	94	31.7568	0.3378	144.3665	99.77
95	150	16.0243	0.1068	121.4125	99.91
96	101	36.3088	0.3595	209.5256	99.83
97	150	34.6445	0.231	217.0642	99.89
98	64	10.6421	0.1663	69.1902	99.76
99	150	43.4877	0.2899	258.0163	99.89
100	150	37.3022	0.2487	222.9889	99.89
101	140	27.4436	0.196	135.4584	99.86
102	150	40.8074	0.272	222.2444	99.88
103	150	32.5732	0.2172	182.1139	99.88
104	54	15.55	0.288	80.5895	99.64
105	94	30.0262	0.3194	162.9084	99.8
106	81	27.2685	0.3366	136.3468	99.75
107	150	44.8424	0.2989	247.7481	99.88
108	150	50.6645	0.3378	263.1339	99.87
109	89	28.5772	0.3211	135.3119	99.76
110	150	48.2833	0.3219	294.7354	99.89
111	150	50.44	0.3363	248.5085	99.86
112	150	45.887	0.3059	256.6734	99.88
113	150	45.779	0.3052	269.4533	99.89
114	150	37.0641	0.2471	220.4562	99.89
115	150	39.8184	0.2655	248.9455	99.89
116	65	23.5039	0.3616	134.8323	99.73
117	150	41.6588	0.2777	225.6841	99.88
118	150	45.0071	0.3	234.7529	99.87
119	150	52.4377	0.3496	241.4071	99.86
120	150	57.1172	0.3808	303.9565	99.87
121	150	45.1782	0.3012	283.9578	99.89
122	150	31.826	0.2122	205.7844	99.9
123	84	30.168	0.3591	158.1611	99.77
124	150	56.0624	0.3737	292.9619	99.87
125	117	24.3856	0.2084	158.5892	99.87
126	150	48.1346	0.3209	263.0361	99.88
127	100	30.5086	0.3051	161.9884	99.81
128	72	24.3163	0.3377	122.9434	99.73
129	63	15.6989	0.2492	81.8955	99.7

130	78	29.6627	0.3803	162.8012	99.77
131	150	31.728	0.2115	165.8301	99.87
132	150	49.2455	0.3283	271.2949	99.88
133	115	44.3228	0.3854	223.0133	99.83
134	36	11.131	0.3092	67.7527	99.54
135	136	41.6456	0.3062	210.9449	99.85
136	130	40.9041	0.3146	222.1098	99.86
137	150	29.0828	0.1939	185.2461	99.9
138	42	12.9007	0.3072	67.5777	99.55
139	150	30.3518	0.2023	198.3436	99.9
140	104	29.2341	0.2811	158.7265	99.82
141	115	34.2242	0.2976	181.1047	99.84
142	65	15.5344	0.239	77.818	99.69
143	150	49.2294	0.3282	248.2058	99.87
144	150	49.5217	0.3301	267.1511	99.88
145	150	45.3761	0.3025	256.2915	99.88
146	150	36.784	0.2452	175.3396	99.86
147	150	29.5145	0.1968	186.5069	99.89
148	142	31.192	0.2197	180.6357	99.88
149	33	15.5677	0.4717	73.903	99.36
150	135	35.2391	0.261	194.4824	99.87
151	150	40.5043	0.27	225.9276	99.88
152	150	40.2402	0.2683	206.2924	99.87
153	150	40.7423	0.2716	229.7765	99.88
154	150	44.537	0.2969	237.4878	99.87
155	150	30.7019	0.2047	139.0161	99.85
156	150	44.1579	0.2944	260.2568	99.89
157	150	18.9897	0.1266	115.9436	99.89
158	150	37.2319	0.2482	210.4892	99.88
159	150	42.0896	0.2806	223.933	99.87
160	75	31.8806	0.4251	163.0889	99.74
161	150	42.7195	0.2848	232.6015	99.88
162	124	35.9045	0.2896	219.8372	99.87
163	150	31.6505	0.211	188.8984	99.89
164	150	29.7099	0.1981	149.805	99.87
165	143	47.1062	0.3294	220.7172	99.85
166	80	28.5462	0.3568	134.4345	99.73
167	33	13.8183	0.4187	66.7678	99.37
168	133	32.0894	0.2413	180.5704	99.87
169	35	12.427	0.3551	62.1567	99.43
170	114	44.2499	0.3882	219.078	99.82
171	141	25.1634	0.1785	159.1079	99.89
172	150	36	0.24	213.4849	99.89
173	150	16.8	0.112	115.1	99.9
174	150	31.4517	0.2097	174.6677	99.88

175	150	24.304	0.162	130.3551	99.88
176	150	58.4758	0.3898	363.4498	99.89
177	138	43.8487	0.3177	257.8267	99.88
178	150	46.0325	0.3069	240.9586	99.87
179	150	34.1996	0.228	191.7483	99.88
180	150	43.2353	0.2882	229.2125	99.87
181	122	24.5391	0.2011	132.7525	99.85
182	150	28.0614	0.1871	137.8293	99.86
183	150	44.1943	0.2946	252.997	99.88
184	150	34.8518	0.2323	162.5045	99.86
185	29	11.8121	0.4073	66.4709	99.39
186	150	48.6644	0.3244	278.2457	99.88
187	80	30.2997	0.3787	134.7408	99.72
188	150	52.9477	0.353	283.0232	99.88
189	150	33.514	0.2234	208.8939	99.89
190	73	21.8082	0.2987	122.5692	99.76
191	150	17.0619	0.1137	108.1069	99.89
192	56	14.2612	0.2547	74.5687	99.66
193	89	29.0246	0.3261	163.119	99.8
194	44	15.6138	0.3549	69.8272	99.49
195	150	36.3234	0.2422	212.3326	99.89
196	150	34.6289	0.2309	207.5311	99.89
197	128	27.4876	0.2147	181.2781	99.88
198	150	23.9494	0.1597	135.5667	99.88
199	52	11.5277	0.2217	68.065	99.67
200	150	48.8565	0.3257	283.7292	99.89
201	65	24.7319	0.3805	132.0596	99.71
202	150	35.7323	0.2382	213.905	99.89
203	150	31.9254	0.2128	162.8294	99.87
204	150	18.8037	0.1254	120.0407	99.9
205	150	34.5673	0.2304	154.9893	99.85
206	150	49.4207	0.3295	278.1509	99.88
207	150	45.0705	0.3005	260.5567	99.88
208	150	54.4548	0.363	300.5627	99.88
209	150	30.456	0.203	147.6713	99.86
210	150	25.8464	0.1723	141.0077	99.88
211	32	13.1111	0.4097	68.2092	99.4
212	101	43.1874	0.4276	220.5608	99.81
213	150	22.7519	0.1517	129.7	99.88
214	150	38.9577	0.2597	193.6197	99.87
215	150	37.923	0.2528	160.0178	99.84
216	88	38.2892	0.4351	181.2866	99.76
217	150	54.3363	0.3622	299.751	99.88
218	150	44.5484	0.297	263.3836	99.89
219	150	33.5249	0.2235	151.2058	99.85

220	78	30.2246	0.3875	132.1414	99.71
221	150	30.5182	0.2035	198.6568	99.9
222	150	24.2638	0.1618	136.0365	99.88
223	100	31.9612	0.3196	162.4137	99.8
224	150	49.0247	0.3268	293.7881	99.89
225	101	38.5561	0.3817	210.6362	99.82
226	150	49.5165	0.3301	250.0097	99.87
227	123	28.5007	0.2317	161.6651	99.86
228	150	39.7617	0.2651	219.3893	99.88
229	150	49.5731	0.3305	229.5333	99.86
230	150	48.3185	0.3221	268.7351	99.88
231	99	23.469	0.2371	124.5226	99.81
232	94	21.9222	0.2332	135.1692	99.83
233	150	45.8419	0.3056	256.9891	99.88
234	150	53.9778	0.3599	306.3907	99.88
235	150	46.0721	0.3071	280.6472	99.89
236	150	44.6709	0.2978	262.8052	99.89
237	150	64.0898	0.4273	357.0802	99.88
238	150	66.6172	0.4441	364.7075	99.88
239	150	56.4135	0.3761	264.4747	99.86
240	150	33.435	0.2229	189.2168	99.88
241	150	30.3479	0.2023	182.2481	99.89
242	150	27.6315	0.1842	139.3801	99.87
243	150	31.5416	0.2103	204.5458	99.9
244	150	44.9777	0.2999	268.7448	99.89
245	150	31.1075	0.2074	169.8743	99.88
246	150	46.0323	0.3069	208.0035	99.85
247	150	36.1768	0.2412	217.7425	99.89
248	92	22.0296	0.2395	123.6036	99.81
249	52	16.0736	0.3091	82.197	99.62
250	54	10.5842	0.196	68.3707	99.71
251	129	26.348	0.2042	158.6236	99.87
252	149	34.4701	0.2313	211.8013	99.89
253	148	50.4776	0.3411	207.7804	99.84
254	93	40.0564	0.4307	219.4255	99.8
255	147	47.7088	0.3245	269.8569	99.88
256	143	45.2442	0.3164	230.2475	99.86
257	143	49.4437	0.3458	281.8741	99.88
258	131	40.4265	0.3086	209.4189	99.85
259	141	28.1831	0.1999	175.8478	99.89
260	141	27.8	0.1972	137.322	99.86
261	97	30.8187	0.3177	181.175	99.82
262	139	56.8126	0.4087	325.1362	99.87
263	139	57.4055	0.413	309.3557	99.87
264	138	18.3696	0.1331	106.3383	99.87

265	137	35.8011	0.2613	188.8576	99.86
266	136	29.5651	0.2174	156.0894	99.86
267	134	53.5801	0.3999	312.8216	99.87
268	108	41.1046	0.3806	220.3041	99.83
269	133	40.1974	0.3022	217.7457	99.86
270	105	42.3592	0.4034	223.3109	99.82
271	126	36.3075	0.2882	191.6177	99.85
272	126	30.2653	0.2402	154.6214	99.84
273	126	55.122	0.4375	281.2801	99.84
274	126	28.4262	0.2256	149.9103	99.85
275	124	25.9979	0.2097	163.7857	99.87
276	122	29.9556	0.2455	155.5613	99.84
277	120	25.116	0.2093	116.3626	99.82
278	118	20.7062	0.1755	110.9143	99.84
279	62	21.2789	0.3432	123.1456	99.72
280	118	23.5178	0.1993	147.4042	99.86
281	116	19.9551	0.172	103.002	99.83
282	116	38.8639	0.335	206.5469	99.84
283	114	24.5479	0.2153	154.627	99.86
284	111	39.6635	0.3573	196.2154	99.82
285	111	26.0086	0.2343	124.7505	99.81
286	109	33.7446	0.3096	191.7861	99.84
287	108	33.3846	0.3091	169.5473	99.82
288	105	33.9763	0.3236	169.4134	99.81
289	105	44.3088	0.422	209.6166	99.8
290	103	30.7585	0.2986	170.2503	99.82
291	102	23.1	0.2265	111.8	99.8
292	100	25.6222	0.2562	144.2759	99.82
293	100	39.9927	0.3999	206.6612	99.81
294	99	19.4974	0.1969	103.5016	99.81
295	98	33.7174	0.3441	165.6177	99.79
296	96	17.921	0.1867	97.485	99.81
297	63	28.1557	0.4469	136.9048	99.67
298	95	12.7658	0.1344	74.8906	99.82
299	94	19.6	0.2085	104.4	99.8
300	92	16.9613	0.1844	87.3621	99.79
301	61	12.1305	0.1989	63.0779	99.68
302	89	13.5822	0.1526	74.563	99.8
303	89	20.6	0.2315	111.1166	99.79
304	88	10.3667	0.1178	69.4898	99.83
305	87	33.2108	0.3817	153.3413	99.75
306	84	19.8316	0.2361	112.7257	99.79
307	78	16.5755	0.2125	107.4154	99.8
308	78	24.5416	0.3146	124.0825	99.75
309	78	16.4361	0.2107	97.78	99.78

310	77	19.12	0.2483	96.2402	99.74
311	74	23.8451	0.3222	144.7582	99.78
312	48	13.0184	0.2712	66.3077	99.59
313	74	22.2473	0.3006	116.3658	99.74
314	73	21.8105	0.2988	114.0641	99.74
315	73	19.0233	0.2606	109.9083	99.76
316	72	14.9926	0.2082	94.3595	99.78
317	72	32.1344	0.4463	149.6364	99.7
318	71	14.8242	0.2088	74.9853	99.72
319	66	17.3242	0.2625	99.9956	99.74
320	65	17.6368	0.2713	97.2397	99.72
321	63	17.5424	0.2785	98.6	99.72
322	62	18.9929	0.3063	113.143	99.73
323	58	20.115	0.3468	89.0983	99.61
324	55	17.6507	0.3209	91.4316	99.65
325	53	15.6571	0.2954	81.9031	99.64
326	49	13.0385	0.2661	68.2074	99.61
327	48	9.8	0.2042	66.4	99.69
328	47	12.4356	0.2646	63.6651	99.58
329	46	15.5252	0.3375	69.2555	99.51
330	43	14.0431	0.3266	72.7619	99.55
331	43	15.4356	0.359	75.1226	99.52
332	41	8.7	0.2122	45	99.53
333	40	11.8322	0.2958	59.6962	99.5
334	38	9.0916	0.2393	42.7572	99.44
335	33	11.1503	0.3379	48.9777	99.31
336	33	12.8438	0.3892	59.3329	99.34
337	32	8.6515	0.2704	46.2345	99.42
338	31	9.4	0.3032	60.4	99.5
339	29	9.053	0.3122	43.7585	99.29
340	28	11	0.3929	63.2	99.38
341	28	7.0981	0.2535	36.1307	99.3
342	27	4.458	0.1651	22.2557	99.26
343	26	7.9885	0.3072	37.0264	99.17
344	25	8.4068	0.3363	49.3909	99.32
345	23	2.365	0.1028	17.0449	99.4
346	23	7.7934	0.3388	33.5663	98.99
347	22	10.899	0.4954	37.1548	98.67
348	22	5.9619	0.271	24.3443	98.89
349	18	6.1502	0.3417	35.2925	99.03
350	18	8.5723	0.4762	43.4835	98.9
351	17	6.6	0.3882	35.2	98.9
352	17	3.7484	0.2205	16.1662	98.64
353	15	3.6	0.24	16.4	98.54
354	13	4.235	0.3258	21.0737	98.45

355	12	3.0472	0.2539	13.118	98.06
356	11	3.4214	0.311	13.3708	97.67
357	10	4.9	0.49	22.1	97.78
358	9	3.5293	0.3921	17.2255	97.72
359	9	3.2243	0.3583	15.8161	97.73
360	8	2.4767	0.3096	7.0369	95.6

A4. Observation Histories method for second dataset

Node #	Number of Movements(Each 1.2 sec)	Sum of all differences	Mean Absolute Error($\sum_{i=1}^{n}$ diff/n)	Distance	Accuracy %
1	94	9.1428	0.0973	154.3391	99.94
2	57	10.0035	0.1755	144.3938	99.88
3	148	13.7364	0.0928	211.9178	99.96
4	148	14.3354	0.0969	205.9783	99.95
5	148	12.3824	0.0837	157.4065	99.95
6	148	14.167	0.0957	207.3022	99.95
7	38	6.8488	0.1802	66.5113	99.73
8	148	11.9775	0.0809	129.9597	99.94
9	148	17.7104	0.1197	188.5303	99.94
10	148	13.8472	0.0936	313.6367	99.97
11	142	12.4823	0.0879	123.6941	99.93
12	148	13.6351	0.0921	218.4428	99.96
13	65	8.3628	0.1287	66.9286	99.81
14	148	7.3886	0.0499	296.426	99.98
15	133	13.1672	0.099	199.6642	99.95
16	57	7.05	0.1237	67.3701	99.82
17	148	12.8143	0.0866	221.2227	99.96
18	148	11.6498	0.0787	162.2934	99.95
19	148	7.6831	0.0519	204.8	99.97
20	148	9.5988	0.0649	219.8578	99.97
21	148	16.1454	0.1091	289.2753	99.96
22	148	10.6893	0.0722	118.4184	99.94
23	148	23.767	0.1606	269.438	99.94
24	148	13.6779	0.0924	324.5028	99.97
25	148	16.7205	0.113	236.4392	99.95
26	148	12.8126	0.0866	240.8528	99.96
27	148	12.1506	0.0821	143.0232	99.94
28	114	11.7079	0.1027	162.7412	99.94
29	148	10.9595	0.0741	268.5473	99.97
30	148	14.5375	0.0982	237.4538	99.96
31	65	8.0582	0.124	135.3988	99.91
32	148	16.6332	0.1124	248.4133	99.95
33	55	7.324	0.1332	81.2287	99.84
34	148	15.8449	0.1071	209.6532	99.95
35	148	10.8223	0.0731	265.0029	99.97
36	148	19.0115	0.1285	320.9822	99.96
37	148	14.5057	0.098	139.1312	99.93
38	117	9.5965	0.082	222.5803	99.96
39	148	14.0152	0.0947	141.6054	99.93

40	148	18.3308	0.1239	249.0774	99.95
41	148	12.3	0.0831	202.5	99.96
42	120	17.6501	0.1471	220.5496	99.93
43	148	15.3259	0.1036	213.925	99.95
44	74	10.3265	0.1395	132.6966	99.89
45	148	12.1546	0.0821	199.1172	99.96
46	98	9.7741	0.0997	136.5232	99.93
47	148	10.1758	0.0688	294.2382	99.98
48	148	21.4381	0.1449	314.8471	99.95
49	129	10.4086	0.0807	158.1263	99.95
50	148	9.6567	0.0652	176.6722	99.96
51	48	7.9789	0.1662	73.363	99.77
52	148	14.6806	0.0992	185.4507	99.95
53	148	13.3844	0.0904	126.2102	99.93
54	118	11.3318	0.096	179.5369	99.95
55	148	16.5956	0.1121	319.3373	99.96
56	148	20.2855	0.1371	316.6374	99.96
57	148	13.5547	0.0916	210.5763	99.96
58	148	13.5021	0.0912	167.6162	99.95
59	148	9.5196	0.0643	148.0494	99.96
60	148	12.9743	0.0877	186.0918	99.95
61	148	17.4454	0.1179	251.337	99.95
62	148	16.9411	0.1145	255.6002	99.96
63	148	20.0952	0.1358	311.4021	99.96
64	148	23.8997	0.1615	361.2638	99.96
65	148	10.6349	0.0719	152.2987	99.95
66	148	8.3	0.0561	194.5	99.97
67	148	16.8184	0.1136	217.4998	99.95
68	148	23.4539	0.1585	360.441	99.96
69	148	18.1142	0.1224	279.1627	99.96
70	148	21.3656	0.1444	301.041	99.95
71	113	12.4283	0.11	219.8248	99.95
72	148	23.4856	0.1587	290.9983	99.95
73	148	15.2917	0.1033	263.7058	99.96
74	148	16.3811	0.1107	178.6871	99.94
75	148	14.5745	0.0985	271.5993	99.96
76	46	8.2146	0.1786	79.16	99.77
77	148	14.5761	0.0985	269.6758	99.96
78	148	19.4626	0.1315	265.7155	99.95
79	39	6.44	0.1651	67.0265	99.75
80	54	8.1062	0.1501	134.7288	99.89
81	148	8.7476	0.0591	162.4011	99.96
82	84	10.0594	0.1198	158.8699	99.92
83	148	13.1532	0.0889	177.7013	99.95
84	148	14.4984	0.098	240.0381	99.96

85	148	11.6044	0.0784	167.474	99.95
86	148	13.3858	0.0904	197.2476	99.95
87	148	17.231	0.1164	150.9962	99.92
88	148	11.4453	0.0773	148.622	99.95
89	148	24.5808	0.1661	307.5125	99.95
90	148	27.5932	0.1864	319.0532	99.94
91	36	7.8493	0.218	65.5172	99.67
92	148	22.6844	0.1533	326.1641	99.95
93	49	6.8557	0.1399	73.0537	99.81
94	92	15.7681	0.1714	144.3665	99.88
95	148	11.2828	0.0762	119.8125	99.94
96	99	10.1395	0.1024	209.5256	99.95
97	148	15.3726	0.1039	214.1642	99.95
98	62	5.0672	0.0817	69.1902	99.88
99	148	15.8582	0.1072	254.6163	99.96
100	148	11.0552	0.0747	219.9889	99.97
101	138	10.0977	0.0732	135.4584	99.95
102	148	16.1342	0.109	219.2444	99.95
103	148	11.8175	0.0798	179.5139	99.96
104	52	7.1889	0.1382	80.5895	99.83
105	92	10.8497	0.1179	162.9084	99.93
106	79	8.0679	0.1021	136.3468	99.93
107	148	14.1584	0.0957	244.4481	99.96
108	148	23.9908	0.1621	260.439	99.94
109	87	10.5947	0.1218	135.3119	99.91
110	148	14.8454	0.1003	290.6354	99.97
111	148	16.6832	0.1127	245.2085	99.95
112	148	15.5576	0.1051	253.2734	99.96
113	148	12.8785	0.087	265.8533	99.97
114	148	13.6895	0.0925	218.1092	99.96
115	148	11.7759	0.0796	245.6455	99.97
116	63	8.873	0.1408	134.8323	99.9
117	148	13.1991	0.0892	222.5841	99.96
118	148	16.3435	0.1104	231.5529	99.95
119	148	15.6184	0.1055	238.1071	99.96
120	148	22.2602	0.1504	300.5505	99.95
121	148	17.087	0.1155	280.1578	99.96
122	148	11.1911	0.0756	203.2308	99.96
123	82	9.9398	0.1212	158.1611	99.92
124	148	18.2237	0.1231	288.9619	99.96
125	115	11.4842	0.0999	158.5892	99.94
126	148	14.6155	0.0988	259.5361	99.96
127	98	9.8059	0.1001	161.9884	99.94
128	70	9.5819	0.1369	122.9434	99.89
129	61	6.1915	0.1015	81.8955	99.88

130	76	9.6461	0.1269	162.8012	99.92
131	148	9.4719	0.064	163.6301	99.96
132	148	16.9065	0.1142	267.6949	99.96
133	113	14.458	0.1279	223.0133	99.94
134	34	7.1002	0.2088	67.7527	99.69
135	134	14.2731	0.1065	210.9449	99.95
136	128	13.6992	0.107	222.1098	99.95
137	148	11.1773	0.0755	182.7461	99.96
138	40	6.4329	0.1608	67.5777	99.76
139	148	12.0289	0.0813	195.9256	99.96
140	102	11.0136	0.108	158.7265	99.93
141	113	9.1615	0.0811	181.1047	99.96
142	63	8.3423	0.1324	77.818	99.83
143	148	18.1342	0.1225	244.8058	99.95
144	148	20.3652	0.1376	263.5109	99.95
145	148	17.6115	0.119	252.7915	99.95
146	148	14.2856	0.0965	172.9396	99.94
147	148	16.6125	0.1122	184.0051	99.94
148	140	14.2816	0.102	180.6357	99.94
149	31	7.4082	0.239	73.903	99.68
150	133	15.5372	0.1168	194.4824	99.94
151	148	15.807	0.1068	222.9276	99.95
152	148	31.4342	0.2124	203.4762	99.9
153	148	16.694	0.1128	226.5765	99.95
154	148	9.2341	0.0624	234.2878	99.97
155	148	17.4329	0.1178	137.1942	99.91
156	148	13.9882	0.0945	257.3568	99.96
157	148	8.6831	0.0587	114.6436	99.95
158	148	11.4506	0.0774	207.5892	99.96
159	148	14.6741	0.0991	220.933	99.96
160	73	10.1611	0.1392	163.0889	99.91
161	148	14.2271	0.0961	229.5015	99.96
162	122	13.8174	0.1133	219.8372	99.95
163	148	13.5425	0.0915	186.3984	99.95
164	148	7.7828	0.0526	147.805	99.96
165	141	16.6974	0.1184	220.7172	99.95
166	78	9.5432	0.1223	134.4345	99.91
167	31	6.3327	0.2043	66.7678	99.69
168	131	11.3314	0.0865	180.5704	99.95
169	33	6.5857	0.1996	62.1567	99.68
170	112	13.6137	0.1216	219.078	99.94
171	139	13.8896	0.0999	159.1079	99.94
172	148	11.1541	0.0754	210.5849	99.96
173	148	10.3	0.0696	113.5	99.94
174	148	13.4658	0.091	172.3677	99.95

175	148	10.6494	0.072	128.5551	99.94
176	148	25.3177	0.1711	358.7571	99.95
177	136	15.5574	0.1144	257.8267	99.96
178	148	10.6982	0.0723	237.7586	99.97
179	148	12.3125	0.0832	189.1483	99.96
180	148	16.556	0.1119	226.1125	99.95
181	120	10.2006	0.085	132.7525	99.94
182	148	12.8324	0.0867	136.0293	99.94
183	148	13.1891	0.0891	249.797	99.96
184	148	8.8	0.0595	160.4045	99.96
185	27	6.6056	0.2447	66.4709	99.63
186	148	17.6359	0.1192	274.7457	99.96
187	78	9.5676	0.1227	134.7408	99.91
188	148	20.0265	0.1353	279.2232	99.95
189	148	12.6026	0.0852	206.0939	99.96
190	71	12.2936	0.1731	122.5692	99.86
191	148	10.081	0.0681	106.6069	99.94
192	54	8.947	0.1657	74.5687	99.78
193	87	11.6985	0.1345	163.119	99.92
194	42	6.1888	0.1474	69.8272	99.79
195	148	13.7084	0.0926	209.5326	99.96
196	148	12.1053	0.0818	204.7311	99.96
197	126	10.4467	0.0829	181.2781	99.95
198	148	9.9195	0.067	133.8667	99.95
199	50	6.2765	0.1255	68.065	99.82
200	148	14.7204	0.0995	279.9265	99.96
201	63	14.6917	0.2332	132.0596	99.82
202	148	14.5345	0.0982	210.9732	99.95
203	148	11.5586	0.0781	160.7294	99.95
204	148	8.3064	0.0561	118.4407	99.95
205	148	13.1472	0.0888	152.9893	99.94
206	148	17.2349	0.1165	275.0392	99.96
207	148	23.2664	0.1572	257.0567	99.94
208	148	21.5043	0.1453	296.5627	99.95
209	148	9.9405	0.0672	145.6713	99.95
210	148	11.9893	0.081	139.1077	99.94
211	30	8.8237	0.2941	68.2092	99.57
212	99	18.0975	0.1828	220.5608	99.92
213	148	9.1	0.0615	127.9	99.95
214	148	18.2576	0.1234	191.7197	99.94
215	148	13.335	0.0901	157.954	99.94
216	86	10.9592	0.1274	181.2866	99.93
217	148	23.7561	0.1605	295.451	99.95
218	148	15.2353	0.1029	259.8652	99.96
219	148	14.3528	0.097	149.1058	99.93

220	76	12.6521	0.1665	132.1414	99.87
221	148	15.7277	0.1063	196.0568	99.95
222	148	10.4378	0.0705	134.2365	99.95
223	98	11.8289	0.1207	162.4137	99.93
224	148	19.2723	0.1302	289.6881	99.96
225	99	16.2137	0.1638	210.6362	99.92
226	148	14.4794	0.0978	246.6097	99.96
227	121	10.4805	0.0866	161.6651	99.95
228	148	16.659	0.1126	216.4893	99.95
229	148	24.1934	0.1635	226.3333	99.93
230	148	12.4868	0.0844	265.2351	99.97
231	97	8.8775	0.0915	124.5226	99.93
232	92	9.7903	0.1064	135.1692	99.92
233	148	14.1905	0.0959	253.4891	99.96
234	148	17.8549	0.1206	302.2907	99.96
235	148	14.51	0.098	276.8472	99.96
236	148	19.9274	0.1346	259.3052	99.95
237	148	23.6624	0.1599	352.3244	99.95
238	148	25.4341	0.1719	359.9075	99.95
239	148	20.971	0.1417	260.8747	99.95
240	148	17.4217	0.1177	186.7429	99.94
241	148	12.3495	0.0834	179.9316	99.95
242	148	10.6115	0.0717	137.5801	99.95
243	148	14.0295	0.0948	202.2236	99.95
244	148	21.9113	0.148	265.0448	99.94
245	148	14.7044	0.0994	167.5743	99.94
246	148	26.5492	0.1794	204.8035	99.91
247	148	16.4131	0.1109	214.8425	99.95
248	90	9.1229	0.1014	123.6036	99.92
249	50	7.8818	0.1576	82.197	99.81
250	52	5.7658	0.1109	68.3707	99.84
251	127	12.2514	0.0965	158.6236	99.94
252	147	13.2528	0.0902	210.4013	99.96
253	146	33.2995	0.2281	207.7804	99.89
254	91	16.9884	0.1867	219.4255	99.91
255	145	21.4109	0.1477	269.8569	99.95
256	141	15.7175	0.1115	230.2475	99.95
257	141	35.9817	0.2552	281.8741	99.91
258	129	15.1298	0.1173	209.4189	99.94
259	139	12.3752	0.089	175.8478	99.95
260	139	9.4532	0.068	137.322	99.95
261	95	10.9453	0.1152	181.175	99.94
262	137	21.41	0.1563	325.1362	99.95
263	137	24.1181	0.176	309.3557	99.94
264	136	9.1249	0.0671	106.3383	99.94

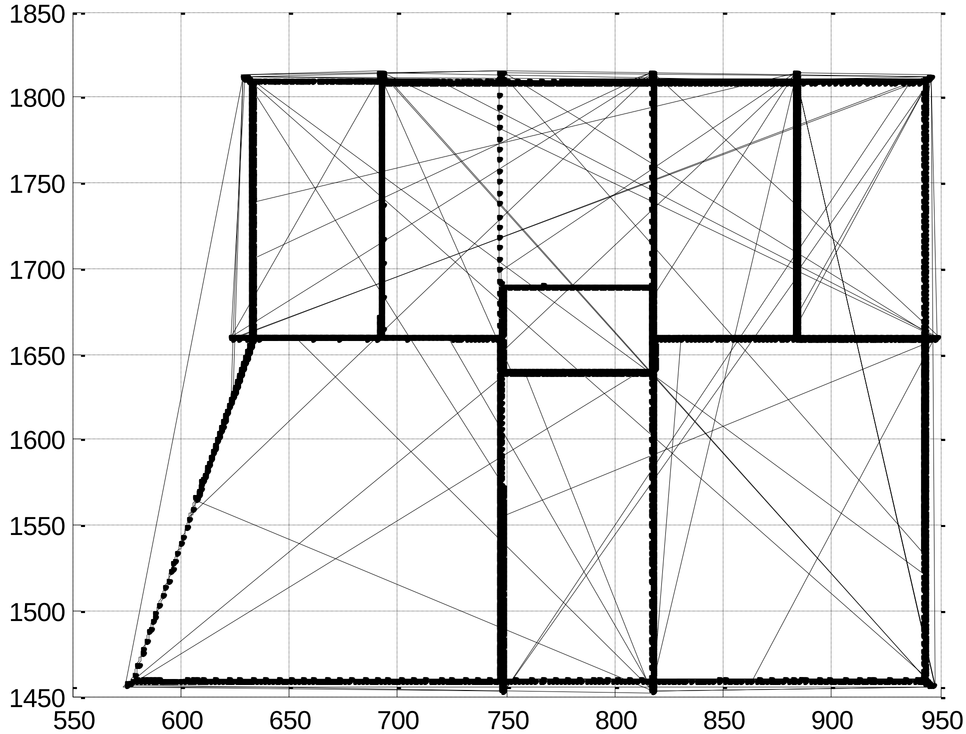
265	135	17.0073	0.126	188.8576	99.93
266	134	12.0973	0.0903	156.0894	99.94
267	132	15.7506	0.1193	312.8216	99.96
268	106	13.1754	0.1243	220.3041	99.94
269	131	13.7904	0.1053	217.7457	99.95
270	103	13.6097	0.1321	223.3109	99.94
271	124	13.4638	0.1086	191.6177	99.94
272	124	11.4359	0.0922	154.6214	99.94
273	124	17	0.1371	281.2801	99.95
274	124	6.8218	0.055	149.9103	99.96
275	122	14.4996	0.1188	163.7857	99.93
276	120	10.4664	0.0872	155.5613	99.94
277	118	9.3147	0.0789	116.3626	99.93
278	116	10.9767	0.0946	110.9143	99.91
279	60	10.3787	0.173	123.1456	99.86
280	116	8.0414	0.0693	147.4042	99.95
281	114	8.7339	0.0766	103.002	99.93
282	114	11.2923	0.0991	206.5469	99.95
283	112	8.1414	0.0727	154.627	99.95
284	109	18.4593	0.1694	196.2154	99.91
285	109	15.7363	0.1444	124.7505	99.88
286	107	14.2077	0.1328	191.7861	99.93
287	106	11.7934	0.1113	169.5473	99.93
288	103	17.5408	0.1703	169.4134	99.9
289	103	22.9141	0.2225	209.6166	99.89
290	101	13.7763	0.1364	170.2503	99.92
291	100	7.9	0.079	111.8	99.93
292	98	8.3303	0.085	144.2759	99.94
293	98	19.1628	0.1955	206.6612	99.91
294	97	9.4182	0.0971	103.5016	99.91
295	96	11.1027	0.1157	165.6177	99.93
296	94	6.365	0.0677	97.485	99.93
297	61	11.247	0.1844	136.9048	99.87
298	93	10.2795	0.1105	74.8906	99.85
299	92	5.7	0.062	104.4	99.94
300	90	9.1563	0.1017	87.3621	99.88
301	59	7.9675	0.135	63.0779	99.79
302	87	7.7867	0.0895	74.563	99.88
303	87	6	0.069	111.1166	99.94
304	86	6.0877	0.0708	69.4898	99.9
305	85	11.6022	0.1365	153.3413	99.91
306	82	5.8657	0.0715	112.7257	99.94
307	76	5.8991	0.0776	107.4154	99.93
308	76	4.3245	0.0569	124.0825	99.95
309	76	5.8848	0.0774	97.78	99.92

310	75	6.7175	0.0896	96.2402	99.91
311	72	8.6795	0.1205	144.7582	99.92
312	46	7.697	0.1673	66.3077	99.75
313	72	5.74	0.0797	116.3658	99.93
314	71	5.6593	0.0797	114.0641	99.93
315	71	7.3799	0.1039	109.9083	99.91
316	70	5.8485	0.0836	94.3595	99.91
317	70	15.8565	0.2265	149.6364	99.85
318	69	6.7142	0.0973	74.9853	99.87
319	64	7.5999	0.1187	99.9956	99.88
320	63	5.0259	0.0798	97.2397	99.92
321	61	8.2526	0.1353	98.6	99.86
322	60	7.0924	0.1182	113.143	99.9
323	56	6.1509	0.1098	89.0983	99.88
324	53	7.6792	0.1449	91.4316	99.84
325	51	3.8414	0.0753	81.9031	99.91
326	47	4.9349	0.105	68.2074	99.85
327	46	3.3	0.0717	66.4	99.89
328	45	6.4471	0.1433	63.6651	99.77
329	44	6.7899	0.1543	69.2555	99.78
330	41	6.7043	0.1635	72.7619	99.78
331	41	4.5372	0.1107	75.1226	99.85
332	39	1.4	0.0359	45	99.92
333	38	3.8515	0.1014	59.6962	99.83
334	36	3.1162	0.0866	42.7572	99.8
335	31	4.2909	0.1384	48.9777	99.72
336	31	4.6363	0.1496	59.3329	99.75
337	30	2.9915	0.0997	46.2345	99.78
338	29	2.2	0.0759	60.4	99.87
339	27	4.0303	0.1493	43.7585	99.66
340	26	1.6	0.0615	63.2	99.9
341	26	1.9194	0.0738	36.1307	99.8
342	25	1.665	0.0666	22.2557	99.7
343	24	3.8889	0.162	37.0264	99.56
344	23	4.3285	0.1882	49.3909	99.62
345	21	1.5472	0.0737	17.0449	99.57
346	21	2.3262	0.1108	33.5663	99.67
347	20	5.9153	0.2958	37.1548	99.2
348	20	2.5402	0.127	24.3443	99.48
349	16	3.6391	0.2274	35.2925	99.36
350	16	3.2164	0.201	43.4835	99.54
351	15	0.5	0.0333	35.2	99.91
352	15	2.5363	0.1691	16.1662	98.95
353	13	0.4	0.0308	16.4	99.81
354	11	3.287	0.2988	21.0737	98.58

355	10	0.9828	0.0983	13.118	99.25
356	9	1.5646	0.1738	13.3708	98.7
357	8	0.4	0.05	22.1	99.77
358	7	3.2521	0.4646	17.2255	97.3
359	7	0.8768	0.1253	15.8161	99.21
360	6	1.5187	0.2531	7.0369	96.4

Appendix B: Traveling pattern of all MS

B.1. Traveling pattern for first dataset with arrival rate 0.01nodes/sec for 72 nodes



B.1. Traveling pattern for second dataset with arrival rate 0.05nodes/sec for 360 nodes