A New Realistic Mobility Model for Mobile Ad Hoc Networks

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***Abstract*—Accurately simulating user movements in Mobile Ad hoc Networks (MANETs) is very important to the prediction of actual network and user performance. Therefore, using a realistic mobility model is a crucial factor in enhancing the confidence in the simulation results of these networks. In this paper, we present a new mobility model for MANETs, called Realistic Mobility Model (RMM). In RMM, node velocities and directions of movement are taken from probability distributions that mimic real user mobility behavior. The model is shown to be stationary since it satisfies the conditions of [2]. Simulation results show that RMM produces mobility traces that closely resemble real mobility traces.**

I. Introduction

Wireless ad hoc networks are very attractive since they provide ubiquitous connectivity without the need for fixed infrastructure or centralized control. Mobile Ad hoc Networks (MANETs) is a class of wireless ad hoc networks in which mobile nodes exhibit features of free node mobility in addition to ephemeral node association. Node mobility, in particular, can cause frequent and unpredictable topology changes, while ephemeral node associations may limit the link lifetime, hence affecting the route lifetime. Despite these challenges, MANETs are envisioned to have many applications in both civil and military aspects. As such, innovative solutions for the above challenges are highly needed.

In MANETs, mobile nodes roam around the network area. It is hard to model the actual node mobility in a way that captures real life user mobility patterns. Therefore, many researchers attempted to design approximate mobility models to resemble real node movements in MANETs. A mobility model defines rules that can be used to generate trajectories for mobile nodes. Most of MANET simulations are based on random mobility models used to generate network topology changes due to node movement. Many of these mobility models were embedded in well-known simulators for MANETs, the most popular of which is the Network Simulator (NS-2) [10]. Traditionally, the simplified random Waypoint mobility model [1] is used to capture node mobility in NS-2. The random Waypoint mobility model includes pause times between changes in direction and/or speed (or walk-and-pause cycle). A mobile node begins by staying in one location for a certain period of time (i.e., a pause time). Once this time expires, the node chooses a random destination in the simulation area and a speed that is uniformly distributed between $[minspeed, maxspeed]$. The node then travels toward the newly chosen destination at the selected speed. Upon arrival, the mobile node pauses for a specified time period before starting the process again. It has been shown that the waypoint model has many performance issues that make it unrealistic [1].

The stationary distributions for speed, location, and pause time for a node moving in a rectangular area under the random waypoint mobility model was derived in [3]. It was found that if the initial speed, location, and pause time are sampled from the stationary distribution rather than the uniform distribution, convergence to stationarity is immediate and no data need be discarded. All subsequent node destinations, speeds, and pause times should be sampled from the uniform distribution. A detailed survey of existing mobility models can be found in [1] and the references therein. Another useful survey on advances in mobility modeling for mobile ad hoc network research can be found in [8]. As the results of [1] show, each of the existing mobility models is based on certain intuitions and/or assumptions that might not correctly reflect realistic mobility in the system. In fact, there is no indication that there exists a single mobility model that will accurately capture all the behavior of an ad hoc network. To achieve accurate user mobility prediction, the user mobility model needs to incorporate user behavioral patterns, wireless link characteristics, and the node association decision-making mechanisms. Unfortunately, these are complicated problems. Hence, the problem of designing realistic and reproducible mobility models is really hard. The Mobility Vector Model [7] is a more general framework. It can be used to describe a very large set of scenarios. It is especially useful in a heterogeneous environment where different types of hosts have different mobility patterns.

Another approach for modeling mobility is based on social networks [6] since mobile devices are usually carried by humans. The model is based on the observation that the movement pattern of humans are strongly influenced by the social relationships amongst them. This can be used to mathematically construct more realistic mobility models based on the exploitation of results in social networks theory. The social

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networks are generated using random distributions. After the generation of the social network, it is possible to detect the presence of communities in the network and then place these communities in the simulation area.

Recently, the *random trip* mobility model was introduced in [2] as a generic mobility model for independent mobiles. Several mobility models, such as the random waypoint model, are included as special cases of the random trip model. This model assumes perfect simulation and do not study the convergence of the model to the stationary regime when it exists. For a perfect simulation, all what is required is to sample from the time stationary distribution of the process state, which is defined by four parameters: the phase, the path, the trip duration, and the fraction of time elapsed on the trip. The fundamental relation between these parameters in the random trip model and its stationary distribution were derived in the paper. The Palm calculus was used to study the model and to give a necessary and sufficient condition for a stationary regime to exist. When the stationary regime exists, it was shown that it is unique for all models studied. A sampling algorithm for the stationary distribution over general areas that does not require the computation of geometric integrals was also provided in [2].

In this paper, we present a new mobility model for MANETs, called Realistic Mobility Model (RMM), that is able to capture real mobility of mobile users or nodes. The model is based on a simple, but efficient, probabilistic model that mimics the users' behaviors. In this model, nodes velocity and direction are based on practical probabilistic distributions as will be described later. The model can be also regarded as a special case of the random trip model, and is therefore stationary. Using simulation, we validated the model and compared synthetic traces generated by the model to real traces that were collected and presented in [11]. Results show a convincing correspondence between RMM traces and the real traces. To be specific, trajectories of both location and speed of RMM for variable number of users are shown to mimic those trajectories collected from the real traces. Furthermore, our validation shows that synthetic traces match real traces with a relative mean error of no more than 18%.

The rest of the paper is organized as follows. In section II, the mobility model (RMM) is described in detail. In Section III, the existence of a unique stationary mobility distribution for RMM is shown to hold based on the assumptions of [2]. The performance evaluation of RMM is presented in Section IV. Section V concludes the paper and highlights some future work directions.

II. Realistic Mobility Model for MANETs

In this section, we present the details of the mobility model, namely, the Realistic Mobility Model (RMM). RMM guarantees that we do not stray too much from realistic world. As such, the model represents a general-purpose method that may be used to reliably generate realistic mobility patterns with different characteristics. Initially, the model selects an initial speed, and direction of movement. At discrete time steps, which are determined by the simulation environment, the speed and direction of movement are re-evaluated, based on the current state of the mobile node, and using a Markovian process, which will be described below. We now describe the model in detail.

A. Initialization:

At the start of movement, the location, speed and directions are initialized as follows:

1) *Location:*
The initial and final locations, S and E, defined in terms of the coordinates (x_s, y_s) and (x_e, y_e), respectively, are both chosen from a uniform distribution.

2) *Speed:*
The speed of the mobile node is determined by N phases, where each phase corresponds to a speed zone. The initial phase, or speed zone, is i with probability ν_i, where $\sum_{i=1}^{N} \nu_i = 1$. Note that this speed set can include a speed of zero, which corresponds to pausing. The initial speed of the mobile node in phase i, $i \in \{1, 2, \ldots, N\}$, is a random variable with truncated Gaussian probability density function $f_{V_i}(v)$ with a mean and standard deviation of μ_i and σ_i, respectively. The choice of such a distribution seems to be reasonable since usually most mobile nodes will move around the imposed maximum speed limit, while a few will exceed that speed, and a few others may move at a lower speed. It is also very unlikely that the speed in phase i will exceed a certain maximum value, v_{max_i}, or will be lower than a minimum speed value, v_{min_i}. The probability density $f_{V_i}(v)$ is given by:

$$f_{V_i}(v) = \frac{K_i}{\sigma_i \sqrt{2\pi}} e^{-(v-\mu_i)^2/2\sigma_i^2}, \quad v_{min_i} \leq v \leq v_{max_i} \qquad (1)$$

where K_i is a normalization constant.

3) *Direction:*
The initial direction is chosen out of δ directions, including the direction towards the destination. The directions are separated by segments with equal angles ($\frac{2\pi}{\delta}$), similar to those shown in Figure 1 [1].
The direction towards the destination is chosen with probability d_0, while a direction that is i segments (either in the clockwise, or counter-clockwise direction) away from that leading directly to the destination is chosen with probability d_i, such that $d_0 + 2\sum_{i=1}^{\theta^*} d_i = 1$, where $\theta^* = \lfloor \delta/2 \rfloor$.

Determining the initial probability vectors, $\vec{d} = \{d_{\theta^*}, d_{\theta^*-1}, \ldots, d_1, d_0, d_1, d_{\theta^*-1}, d_{\theta^*}\}$, and $\vec{\nu} = \{\nu_1, \nu_2, \ldots, \nu_N\}$ will be described below.

B. Location, Speed and direction updates:

The location, speed and direction of a mobile node are updated at intervals which are chosen from an exponential distribution with rate λ. Such intervals cannot be taken deterministically since in real life, road and traffic conditions

[1]We choose the number of different directions, δ, to be odd in order to simplify the direction update process, which will be described below.

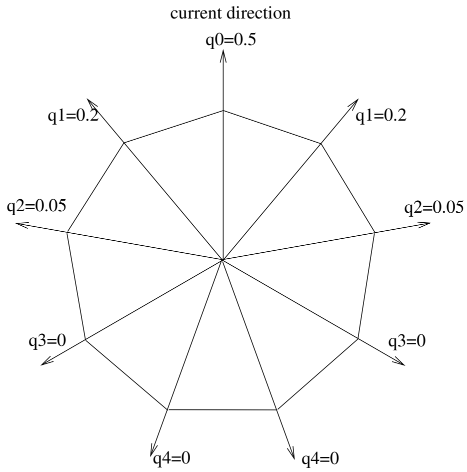

Fig. 1. C process: One-step Markov path model with memory and possible directions probabilities.

which result in changing directions or speed occur at irregular intervals. The update processes are as follows:

1) *Location:*

Assume that the direction of movement is defined by the angle ψ. Also, let the expiring update interval be of duration t. If the previous location was defined in terms of the coordinates, (x_p, y_p), then the current location is calculated as:

$x_c = x_p + t \cdot \cos\psi, \text{ and } \; y_c = y_p + t \cdot \sin\psi$

If x_e and y_e satisfy

$\sqrt{(x_e - x_p)^2 + (y_e - y_p)^2} \leq$

$\sqrt{(x_c - x_p)^2 + (y_c - y_p)^2} \quad \text{and} \quad \theta = 0$

where θ is the number of segments between the current direction and the direction of the final destination, as will be defined below, then, the mobile node has reached the final destination, and we set

$x_c = x_e \quad \text{and} \quad y_c = y_e$

2) *Speed:*

At update times, two processes are invoked:

a) A phase transition process from the current phase, j, to another phase i, with probability n_{ji}, such that $\sum_{i=1}^{N} n_{ji} = 1, \ \forall j$. The transition probability matrix governing the transitions between phases is given by $\mathbf{N} = [n_{ij}]$.

b) If the phase changes, the speed of the mobile nodes is evaluated using equation (1). However, if the phase does not change, i.e., it remains in phase i, the mobile node speed is correlated to the current speed, v_{c_i}. The new speed, v_{n_i}, of the mobile node is taken as a uniformly distributed random variable in the range of $\pm 10\%$ of the current speed. However, the maximum and minimum speed limits within the phase must be observed. Therefore, defining

$\underline{v_{c_i}} = \max(0.9 v_{c_i}, v_{min_i})$,

and

$\overline{v_{c_i}} = \min(1.1 v_{c_i}, v_{max_i})$,

the pdf of the new speed, $f_{V_{n_i}}(v_{n_i})$ is given by

$$f_{V_{n_i}}(v_{n_i}) = \begin{cases} \frac{1}{0.2 v_c} & , \ \underline{v_{c_i}} \leq v_n \leq \overline{v_{c_i}} \\ 0 & \text{Otherwise} \end{cases}$$

This is because users usually maintain a constant speed with small fluctuations around their target speed.

3) *Direction:*

The mobile node direction of movement is also updated at update instants. Similar to the one-step Markov path model [9], our mobility model is also Markovian. However, our model takes two processes into account:

- The current direction of movement of the mobile node, and
- The direction towards the final destination.

Therefore, the direction of movement is a composition of two processes.

a) In the first process, C, which is similar to the one-step Markov path in [9], and is shown in Figure 1, we assume that there are δ different directions, including the current direction, as described above, and as shown in Figure 1. The current direction is chosen with a probability that is higher than adjacent directions. We define θ to be the fewest number of segments between the current direction and the direction toward the final destination, with $\theta \in \{0, 1, \ldots, \theta^*\}$, where $\theta^* = \lfloor \delta/2 \rfloor$, as defined above. θ can be measured in either the clockwise, or counter-clockwise direction, in order to arrive at the fewest number of segments. The probability of choosing a direction that is i segments away from the current direction is given by q_i, with $i \in \{0, 1, \ldots, \theta^*\}$, with q_0 being the probability of choosing the current direction. We also enforce $q_i \geq q_{i+1}$, i.e., the probability of choosing a direction decreases as the angle between that direction and the current direction increases. This is because of the fact that a mobile node tends not to drift far away from the current direction, unless it wants to correct its direction towards the destination, which is implemented by the second process to be described next. In the figure, we show nine different directions, and an example of the probabilities that can be assigned to them.

b) The second process, D, which is shown in Figure 2, attempts to correct the direction of movement so that the mobile node will eventually reach the final destination. Given θ, as defined above, we assign the segments, starting from the one next to the current direction, to the one leading to the final destination, the probabilities $m_1^\theta, m_2^\theta, \ldots, m_\theta^\theta$, such that $\sum_{i=1}^{\theta} m_i^\theta = 1$, as shown in Figure 2. In this paper, we choose these probabilities from a uniform distribution. That is,

$$m_i^\theta = \begin{cases} \frac{1}{\theta} & \theta > 0, \text{ and } 1 \leq i \leq \theta \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

For a given θ, the Markovian mobility model uses a probability $p_\theta = \frac{\theta}{\theta^*}$ to choose process D, while it chooses process

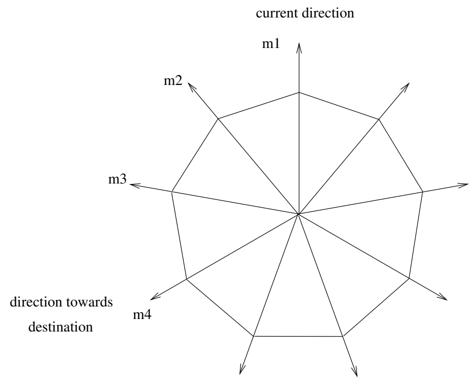

Fig. 2. D process: correction of direction towards the final destination.

C with probability $1 - p_\theta$.

To formally define the Markov process for choosing the new direction at each direction update instant, we define the state of the process, ω, as the number of segments between the current direction and the direction toward the destination, measured in the counter-clockwise direction. That is, $\omega \in \{0, 1, 2, \ldots, \delta\}$. Therefore, the transition probability matrix $\mathbf{R}_{\delta\times\delta}$ can be expressed as

$$\mathbf{R} = \mathbf{PM} + (I - \mathbf{P})\mathbf{Q}$$

where all matrices are of size $(2\theta^* + 1) \times (2\theta^* + 1)$. The matrix $\mathbf{P}$ is the diagonal matrix

$$\mathbf{P} = diag(p_0, p_1, \ldots, p_{\theta^*-1}, p_{\theta^*}, p_{\theta^*-1}, \ldots, p_1, p_0)$$

The elements of the $\mathbf{M}$ matrix are defined by

$$M_{ij} = \begin{cases} 1 & i = j = 0 \\ m^i_{i-j} & 1 \le i \le \theta^*,\ 0 \le j \le i-1 \\ m^{2\theta^*+1-i}_{2\theta^*+1-i} & \theta^*+1 \le i \le 2\theta^*,\ j = 0 \\ m^{2\theta^*+1-i}_{2\theta^*+1-j} & \theta^*+1 \le i \le 2\theta^*,\ i+1 \le j \le 2\theta^* \\ 0 & \text{otherwise} \end{cases}$$

Equation (3) shows an example of $\mathbf{M}$. The matrix $\mathbf{Q}$ is given by

$$\begin{bmatrix} q_0 & q_1 & \cdots & q_{\theta^*-1} & q_{\theta^*} & q_{\theta^*} & q_{\theta^*-1} & \cdots & q_2 & q_1 \\ q_1 & q_0 & \cdots & q_{\theta^*-2} & q_{\theta^*-1} & q_{\theta^*} & q_{\theta^*} & \cdots & q_3 & q_2 \\ q_2 & q_1 & \cdots & q_{\theta^*-3} & q_{\theta^*-2} & q_{\theta^*-1} & q_{\theta^*} & \cdots & q_4 & q_3 \\ \vdots \\ q_1 & q_2 & \cdots & q_{\theta^*} & q_{\theta^*} & q_{\theta^*-1} & q_{\theta^*-2} & \cdots & q_1 & q_0 \end{bmatrix}$$

The matrix $\mathbf{Q}$ consists of a first row (row number 0) that is given by the $[q_0, q_1, \ldots, q_{\theta^*-1}, q_{\theta^*}, q_{\theta^*}, q_{\theta^*-1}, \ldots, q_2, q_1]$. Row i is then obtained by rotating row 0 i times to the right. It is to be noticed that element M_{00} can assume any value, including 0, since it is only used when the mobile node is moving in the direction toward the destination, in which case $p_0 = 0$ and $\mathbf{M}$ will not be chosen. However, it was chosen to be 1 in order to make $\mathbf{M}$ a stochastic matrix.

Note that although the matrix $\mathbf{Q}$ represents a one-step Markov process similar to the one-step Markov path model in [9], RMM attempts to stear the mobile node back on track towards its final destination. This property ensures that the final destination is reached within a finite time.

Note also that the probability of reversing the direction of movement is set to 0. As the moving direction and the speed of mobile nodes are non-deterministic processes, the path of a mobile node will be a random trajectory. Figure 3 shows the movement in most probable directions of a mobile node. The movement is within a square area of 36 square zones, which are organized as a 6×6 grid. A mobile node roams for one hour, and updates its direction and speed after an exponentially distributed time with a mean of 10 minutes. The direction is chosen according to the model shown in Figures 1 and 2, and according to the values of m^θ_i given in equation (2). The figure also shows a sample trajectory paths collected from simulation experiments for six users wandering in the network area with starting points (S) and ending points (E). The path trajectories resemble a smooth movement of each user, which may represent a more realistic movement pattern. The changes in direction occur in time steps that are exponentially distributed with an average value of one minute.

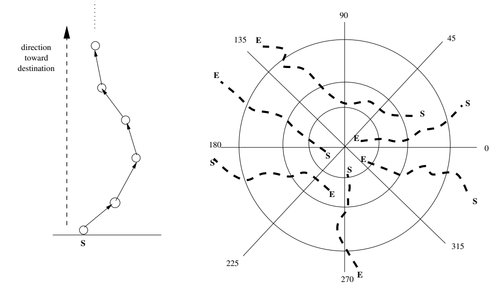

Fig. 3. (a) Movement in most probable directions, and (b) path trajectory trace of six mobile nodes (S and E: Start and End points).

III. Stationary Distribution of the Mobility State of RMM

For the mobility state of RMM to be stationary, and to have a unique stationary distribution, it needs to satisfy three conditions [2], which are slightly rephrased to fit our model:

1) Condition **H1**: *The trip selection rule depends on all past only through the current mobile location, and the state of the one-step Markov chain controlling the direction and speed.*
2) Condition **H2b**: *The distribution of the location at a direction and speed update instant is independent of the Markov chain state to be chosen at this instant, and future trip duration and state depend on the current Markov chain state.*
3) Condition **H3**: *The Markov chain is positive recurrent.*

It is to be noted that assumptions **H1** and **H2b** above are satisfied by the construction of RMM. Notice that in this case the phase of the process is the Cartesian product of the set of speed phases, and the set of direction states. To satisfy assumption **H3**, we have to make sure that the involved Markov processes are stationary. This can be simply guaranteed by making sure that the matrices $\mathbf{N}$ and $\mathbf{R}$ are stochastic, and they correspond to irreducible and aperiodic Markov chains. Since the Markov chains are finite and irreducible, then they are positive recurrent, and are therefore ergodic. Choosing

$$M = \begin{bmatrix} 1 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ m_1^1 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ m_2^2 & m_1^2 & \dots & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ \vdots & & & & & & & & & \\ m_{\theta^*}^{\theta^*} & m_{\theta^*-1}^{\theta^*} & \dots & m_1^{\theta^*} & 0 & 0 & 0 & 0 & \dots & 0 \\ m_{\theta^*}^{\theta^*} & 0 & \dots & 0 & 0 & 0 & m_{\theta^*-1}^{\theta^*} & m_{\theta^*-2}^{\theta^*} & \dots & m_1^{\theta^*} \\ m_{\theta^*-1}^{\theta^*-1} & 0 & \dots & 0 & 0 & 0 & 0 & m_{\theta^*-2}^{\theta^*-1} & \dots & m_1^{\theta^*-1} \\ \vdots & & & & & & & & & \\ m_2^2 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & \dots & m_1^2 \\ m_1^1 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & \dots & 0 \end{bmatrix} \tag{3}$$

appropriate transition probabilities, which also reflect real life situations can lead to the satisfaction of this assumption.

In order make sure that the simulation generates samples from the stationary RMM, and not from its transient behavior, the initial direction and speed vectors need to be selected from the stationary process. Notice that if the number of update intervals until the mobile node reaches its final destination, E, is given by k, then the direction probability vector when the node reaches E, $\vec{d_e}$ is given by

$$\vec{d_e} = \vec{d}\ \mathbf{R}^k$$

If k is large enough, then $\vec{d_e}$ is very close to the steady state probability vector of the embedded Markov process described by the transition probability matrix $\mathbf{R}$. Therefore, in order to ensure the stationarity of the paths generated by RMM, we set $\vec{d}$ to be the steady state probability vector of $\mathbf{R}$.

Using a similar argument, we set $\vec{\nu}$ to the steady state probability vector of the transition probability matrix $\mathbf{N}$.

IV. Performance Evaluation of RMM

In this section, we demonstrate and validate RMM as a realistic mobility model by comparing it to real traces of user movement. We compare the performance of RMM model to a real trace scenario available at [11] in terms of mobility patterns. We consider a network of mobile and heterogeneous mobile nodes that are randomly deployed in the network field (bounded region of 500 $\times$ 500 m^2). The network area was divided into 36 zones (6 x 6) with an average of 36 mobile nodes per zone using the VGA clustering approach [2] [12]. The trace duration is about 4 hours. Each mobile node is allowed to move for a duration of 30 minutes. Start points of mobile nodes were generated to correspond to the beginning and end points of the trace. In the simulations, the initial speed of a mobile node follows a truncated Gaussian pdf with an average of 50 Km/h, and standard deviation of 15 Km/h. There 11 phases, and 18 possible directions. Changes in direction occur in time steps that are exponentially distributed with an average value of one minute. The velocity increments of a mobile node is taken to be uniformly distributed in the range of 10% of the current velocity, such that the minimum and maximum speeds are 0 and 100 Km/h, respectively. Then we vary the average initial speed of a mobile node, μ, as well as the standard deviation, σ in order to study the effect of node speed on the network performance.

In Figure 4, we plot the real trace mobility pattern for two users wandering in the grid. In the same figure, we compare the mobility pattern of users under RMM model and the trajectories derived from the real traces. The mobility shows that RMM model is almost capturing the same real mobility pattern of the two users. We experimented with different mobility traces, and they showed the same trend of mobility pattern[3]. In most experiments, the mean difference between user locations under RMM and the real traces, taken over the entire experiment, was limited to no more than 18%. This indicates that the RMM model is able to mimic actual and realistic movement patterns.

Next, we study the effect of the simulation time on the mobility of the generated scenario. The mobility characteristics of the RMM should be independent of the simulation time. In Figure 5, we depict the average relative speed[4] of the mobile nodes plotted against simulation time. As shown, the first 300 seconds is too short for the model to display the mobility characteristics of MANETs. The average relative speed stabilizes at about 600-800 seconds of simulation time.

Finally, we compare the average relative speed of RMM and other mobility models when we vary the maximum speed (v_{max}) of mobile nodes. Figure 6 shows the comparison results. For the same v_{max}, it is observed in Figure 6 that the average relative speed for CRM and PRWM is higher than RWP, which is in turn higher than RMM. This means that even if the maximum nodal speed is increased, the RMM model reaches steady state faster and hence the network performance can be obtained with high accuracy.

V. Conclusions

This paper presented a new mobility model called Realistic Mobility Model (RMM) for MANETs. The model is able

[2]When the same simulation scenarios are run for different network area sizes and different numbers of zones, similar error values between traces were exhibited.

[3]The trace can also be generated in terms of the location and not the zone number. However, the same behavior can also be noticed.

[4]The average relative speed is the average speed with respect to the speed of the initial phase.

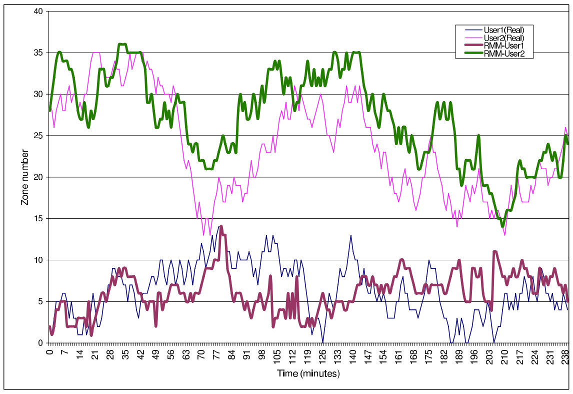

Fig. 4. Mobility pattern of users under RMM model and real trace scenarios.

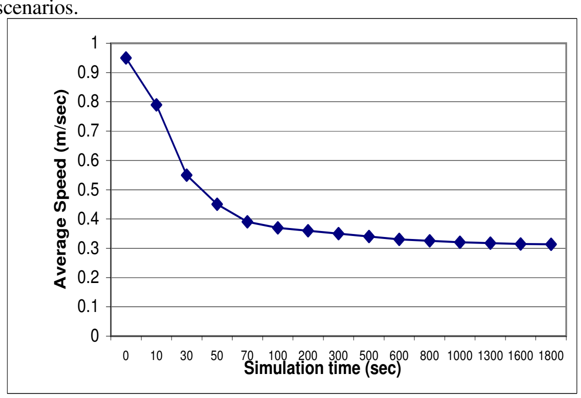

Fig. 5. The average relative speed versus simulation time.

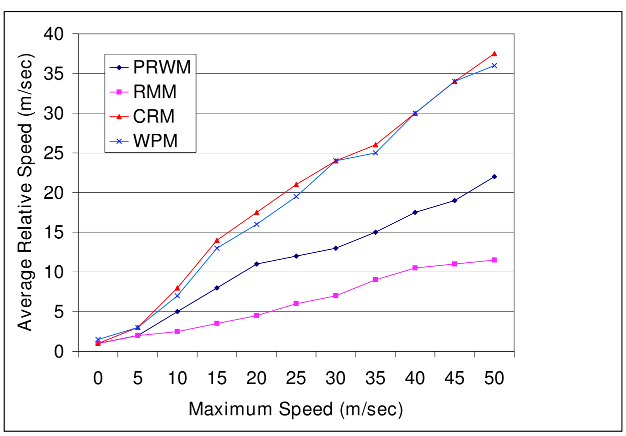

Fig. 6. The average relative speed versus maximum speed.

to capture the node mobility based on a simple but efficient probabilistic model. When compared to real mobility traces, RMM is able to trace closely the real user behavior. As such, RMM becomes a more practical and efficient mobility model for MANETs research. The question whether a fine tuning of RMM parameters will enhance its performance is still under investigation. While RMM is aimed specifically at MANET, the work does have its applications in simulating user mobility in general mobile networks. As a future work, we intend to investigate the extension of the model to incorporate obstacles or different street layouts such as sharp curves or semi-circles.

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