EURECOM
Sophia Antipolis

Institut Eurécom
Department of Mobile Communications
2229, route des Crêtes
B.P. 193
06904 Sophia-Antipolis
FRANCE

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On the Average Course Length in Mobility Models for Mobile Ad Hoc Networks

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Jerome Haerri and Christian Bonnet

Tel : (+33) 4 93 00 26 26
Fax : (+33) 4 93 00 26 27
Email : {Jerome.Haerri,Christian.Bonnet}@eurecom.fr

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Abstract

In simulations of Manets, mobile nodes usually move in a random direction until they reach their target, then stop and start heading to another direction. We propose in this paper to study the average course length of mobile nodes, from the moment they start moving to their respective destinations, and the time they stop. Since the knowledge of the time nodes keep on heading to their targets helps adjusting the refreshing period of ad hoc routing and topology control protocols, it becomes possible to obtain an insight of the expected improvements these protocols can get from the use of aperiodic instead of periodical updates. We show in this paper that when using fair metrics, the length of nodes movements following a Random-Waypoint mobility model (RWM) or a Manhattan mobility model (ManM) is situated around 10 seconds in the worst case scenario. Therefore, by fixing a refreshing period to this time interval, it becomes possible to improve the global performance of topology control and routing protocols.

Index Terms

Mobile Ad Hoc Networks, Course Length, Trajectory, Aperiodic Update, Predictability, Prediction-based, Dead-Reckoning.

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1 Introduction

Routing protocols in mobile ad hoc networks must adapt to frequently changing topologies without generating significant overheads. Several strategies exist in order to keep coherent topologies and valid routes. The first one is **non-periodic** route maintenance. It is only triggered from an alert message punctually received either from the physical layer or the network layer. Most reactive protocols use such link maintenance. However, link losses happening unexpectedly, the existence of a particular link cannot be guarantied and make such approach unsuitable for fault tolerance networks. The next strategy is **periodic** route maintenance. Periodically, with the help of beacon messages, the state of nodes neighborhoods, links or routes is refreshed. This strategy is commonly used by proactive protocols and topology control algorithms. Yet, it creates a large communication overhead, decrease the network capacity and make this method non scalable for large scaled networks. Therefore, a better solution should find its existence somewhere between those two strategies. One possibility is to make updates being only triggered when necessary. By the knowledge of a node's position and velocity, it is possible to obtain an area where it is expected to be moving. A recent extension to this approach, called **prediction-based**[1] or **dead-reckoning**[2], adds a motion pattern to the equation in order to extract a node's expected trajectory. Then, whereas the former method gives nodes expected motion area, this model is able to obtain nodes exact positions, conditionally constrained to the hypothesis they did not reach their destinations or unexpectedly changed their trajectories. These methods belong to **aperiodic** route maintenance strategies and their performances, notably those of the dead-reckoning model, highly depend on nodes mobility patterns determined in simulations by mobility models.

Mobile ad hoc networks are often studied through simulations and their performances depend heavily on the mobility model that governs the movement of nodes. In most cases, nodes set initial locations then start moving following some direction and velocity. After a certain time or when nodes have reached a predefined position, they reconsider their situation and head to a new destination, in a new direction and at a different speed. This movement pattern is then repeated until the end of the simulation. Many mobility models have been proposed reflecting particular motion patterns. The most popular one is the Random Waypoint Model (RWM). Another one is the Reference Point Group Mobility Model (RPGM) which tries to reflect group mobilities that can be noticed in human motion. Manhattan and Freeway mobility models (ManM), also called City Section, is purposely developed to reflect mobility patterns found in urban areas. A description of these models can be found in a survey on mobility models [4] or in [3] along with studies of hybrid approaches.

The time between two destination changes, called **course length**, can usually be obtained by dividing the distance between two successive destinations by the motion speed. Yet, the probability distribution of destination locations and velocities usually makes the respective course lengths random and unpredictable. However, the performance of aperiodic maintenance strategies highly depends on those course lengths. Should this course length known or precisely estimated, would aperiodic strategies be optimal.

In this paper, we provide a fair insight on nodes' course length in a Random Waypoint, a Modified Random Waypoint mobility model and a Manhattan mobility model. We also propose a theoretical model for expected course lengths in general mobility models. The Random Waypoint and the Manhattan models represent trajectory changes in two different manners. The Random Waypoint uses a *distance-based* strategy while Manhattan uses a *probability-based* trajectory change strategy. Indeed, nodes moving following the Random Waypoint mobility model change course every time they reach their destination, while in Manhattan networks, nodes only change their trajectories with a certain probability. Therefore, by varying this probability and increasing the number of destinations, we can simulate a whole range of movement patterns. By using these two models, we manage to show that nodes course lengths using fair metrics never decrease below 10 seconds on average. This result is confirmed by the theoretical model and motivates the use of an aperiodic route maintenance strategy, since updating routes every 10 seconds on average makes the number of maintenance messages drop dramatically. Accordingly, it becomes conceivable to consider prediction-based models to reach optimal aperiodic maintenances.

The rest of the paper is organized as follows. In Section 2, we develop a the theoretical model describing nodes average course lengths. Section 3 shows simulation results and confront them with the theoretical approach. In Section 4, we identify parameters course lengths are depending on and analyze promising improvements to routing protocols in the light of our results . Finally, Section 5 draws some concluding remarks and future works.

2 Theoretical Model

In this section, we expose a theoretical model for nodes' average trajectory length. We divide the global motion of nodes into block-wise linear movements. From the beginning of each block to its end, nodes are moving at constant speed in a known direction. After reaching a block's end, a node changes course with a probability p or keeps its actual trajectory with a probability $1 - p$. The course length, or trajectory length, is then defined as the total number of blocks crossed before a node changes its trajectory. We first define a theoretical model for the Manhattan Mobility Model then extend it to the Random Waypoint, and finally propose a theoretical model for general mobility models.

2.1 Manhattan Mobility Model

In the Manhattan model (ManM), nodes move along the grid of horizontal and vertical streets on the map. At an intersection of a horizontal and a vertical street, mobile nodes can turn left, right or go straight with certain probability. The length of a block, called $\mathrm{block\_L}$, is defined as the distance between two successive intersections and is assumed constant. Therefore, we define the time to cross a block of length $\mathrm{block\_L}$ at a velocity $velo$ as

$$\mathrm{block\_T} = \frac{\mathrm{block\_L}}{\mathrm{velo}}$$

The expected number of blocks crossed during the total simulation time $total\_time$ is defined as

$$\#\mathrm{blocks} = \frac{\mathrm{total\_time}}{\mathrm{block\_T}}$$

Defining $block\_N$ as a random variable representing the block reached by a node and $P(block\_N = i)$ as the probability to reach the i^{th} block, then the average course length is defined as:

$$\begin{aligned} \overline{\mathrm{course\_L}}^{theo} &= \mathrm{block\_T} \sum_{i=0}^{\#\mathrm{blocks}} i \cdot P(block\_N = i) \\ &= \mathrm{block\_T} \left(1 + \sum_{i=1}^{\#\mathrm{blocks}} i(1-p)^i p \right) \end{aligned}$$

2.2 Modified Random Waypoint Mobility Model

The Random Waypoint model (RWM) is the most commonly used mobility model in the research community. In the current implementation, at every instant, a node randomly chooses a destination and moves toward it with a velocity chosen uniformly between [V_min,V_max], where V_min and V_max are the minimum and maximum allowable velocity for every mobile node. After reaching the destination, the node stops for a duration defined by the *pause-time* parameter. Then, it again chooses a random destination and repeats the whole process again until the simulation ends. We define here a block as the interval between two successive destination points.

In order to be able to compare the RWM with the ManM, we modified the way nodes determine their speed. We therefore define a **Modified Random Waypoint Model (**$\mathrm{RWM}^{\mathrm{mod}}$**)** as a modification of the regular RWM where

- The initial velocity is defined as :
  $\mathrm{velo}^{\mathrm{init}} = uniform[\mathrm{velo}^{\mathrm{av}} - \alpha; \mathrm{velo}^{\mathrm{av}} + \alpha]$,
  where α varies from 0 to $\mathrm{velo}^{\mathrm{av}}$.
- No pause time. Nodes do not stop when they reach their destinations.
- Successive velocities are temporally dependent on previous ones :
  $\mathrm{velo}^{\mathrm{next}} = \mathrm{velo}^{\mathrm{prev}} + \mathrm{acc}$,

where acc is a randomly chosen acceleration that increases or decreases nodes' velocity.

In RWM and $\mathrm{RWM}^{\mathrm{mod}}$, $p = 0$ since nodes changes course with probability equal to 1 when they reach their destinations. Therefore, the theoretical course length is defined as

$$\overline{\mathrm{course\_L}}^{theo} = \frac{\mathrm{block\_L}^{av}}{\mathrm{velo}^{av}}$$

2.3 Reference Point Group Mobility Model

Each group of nodes has a group leader that determines the group's motion behavior. Initially, each member of the group is uniformly distributed in the neighborhood of the group leader. Every node has a speed and direction that is derived by randomly deviating slightly from that of the group leader. Since both the movement of the logical center for each group, as well as the random motion of each individual mobile node within the group, are implemented via the Random Waypoint Mobility Model, course lengths are similar to those obtained by the $\mathrm{RWM}^{\mathrm{mod}}$.

2.4 General Mobility Models

We introduced in the two previous sections a *probability-based* trajectory change model (Manhattan) and a *distance-based* trajectory change model (RWM). By grouping those two models and by varying p and $\mathrm{block\_T}$, results may be obtained for all kind of mobility models. As defined in Section 2.1, $\mathrm{block\_T}$ is obtained by nodes velocity and the distance between two successive destinations. Therefore, mobility models' average course lengths highly depend on fair metrics assigned to these two values. If nodes have a short $\mathrm{block\_T}$, they reach their destination fast thus have a smaller course length. Manhattan-like mobility models experience a limited course length decrease since nodes have trajectory changes only with a certain probability. A theoretical general course length model is defined as

$$\overline{\mathrm{course\_L}}^{theo} \quad = \quad \mathrm{block\_T}_0 + \sum_{i=1}^{\#\mathrm{blocks}} i \cdot \mathrm{block\_T}_i(1-p)^i p$$

where $\mathrm{block\_T}_i = \frac{\mathrm{block\_L_i}}{\mathrm{velo_i}}$ and $\mathrm{block\_L_i}$ and $\mathrm{velo_i}$ representing the block length and speed on the $\mathrm{i^{th}}$ block.

3 Simulation Results

We present in this section results on the average course length of mobile nodes moving following Random Waypoint, Manhattan and Modified Random Waypoint mobility models for different velocities, accelerations and probabilities of trajectory change.

Nodes are assumed to be moving in a flat squared area of $1000mX1000m$. The Manhattan model also contains three horizontal and three vertical streets in the squared area, and the probability to go straight at an intersection is set to $\frac{2}{3}$. Mobility models are simulated for $900[s]$. We make nodes average velocities $velo^{av}$ variate from 5 to 50 $[\frac{m}{s}]$, yet with different variances α around the average velocity. In other words, a node velocity is uniformly distributed between $[velo^{av} - \alpha, velo^{av} + \alpha]$. Three different accelerations are tested: 1, 2, 5 $[\frac{m}{s^2}]$. Finally, for the computation of the theoretical course length, p takes four discrete values: 0, $\frac{1}{3}$, $\frac{1}{2}$ and $\frac{2}{3}$.

We illustrate in Fig. 1 the average course length in Random Waypoint, Modified Random Waypoint and Manhattan models. Since beside p, the average course length depends on blocks length and nodes velocity while moving in these blocks, we plot them in two graphs. In Fig. 1(a), we use $20[\frac{m}{s}]$ for the velocity and vary the average distance between two successive destinations (block length), while in Fig. 1(b) we fix this distance to $500[m]$ and vary the velocity.

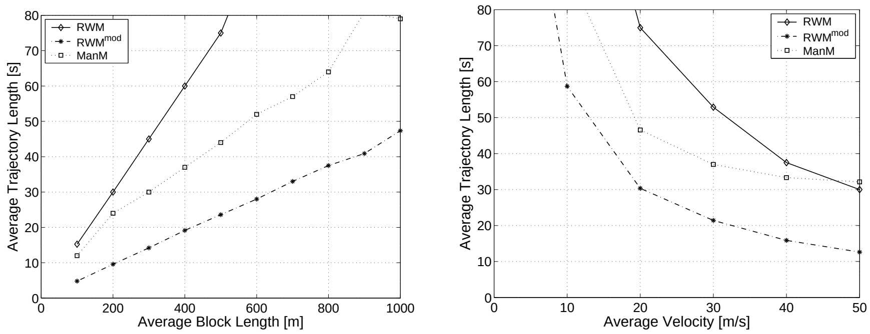
We can see in Fig. 1(a) that the average course length increases as blocks length does, while in Fig. 1(b), the average course length decreases as the velocity increases. When the velocity increases or when the blocks length decreases, nodes reach their destination faster therefore experience a reduced course length. We can see that course lengths are longer for the Manhattan model since at each destination, a node keeps a chance to stay in its present course, whereas in the Random Waypoint or the Modified Random Waypoint model, nodes always change their trajectories when reaching a destination point.

We can also see in Fig. 1(a) and Fig. 1(b) that the Random Waypoint model has longer course lengths than the two other models. This may be explained by the fact that at each destination, nodes' new velocities in the RWM are uniformly distributed between [V_min,V_max], while nodes' new velocities have past dependencies in ManM and RWM^{mod}. Results for the RWM where nodes seem to experience rather long trajectories, are also interesting since this is the commonly used model for simulating mobile ad hoc networks.

Fig. 2 shows that α has a clear influence on the average course length, notably in the Manhattan model. It represents the average trajectory length versus the average velocity of mobile nodes. The first three curves consider nodes moving following a Manhattan model, while the last three ones a Modified Random Waypoint model. For each model, we consider three different values for α.

By analyzing this figure, we notice that the trajectory length decreases as α does. This can be explained as follows. By reducing α, we actually increase the role of the average velocity velo^{av} since nodes' velocities are closer to it. Therefore, the average course length tends to the value

$$\mathrm{course\_L}^{av} = \frac{\mathrm{block\_L}^{av}}{\mathrm{velo}^{av}}.$$



(a) $\mathrm{Velo}^{\mathrm{av}} = 20\frac{m}{s}$.

(b) $\mathrm{Dist}^{\mathrm{av}} = 500m$.

Figure 1: Comparison of the average trajectory length in the RWM, $\mathrm{RWM}^{\mathrm{mod}}$ and ManM.

We can also notice that the average trajectory length is a little bit shorter than $9[s]$ only in unlikely situations where nodes are moving at an average speed of $50\frac{m}{s}$. However, for fairer metrics[1] such as $20[\frac{m}{s}]$, the average course length is $25[s]$ for the Modified Random Waypoint and even $45[s]$ for the Manhattan model. These values are very interesting first because they really express the network mobility and should be used as a factor for comparing protocols performances. It could notably replace the *pause-time* usually used in the literature as a mobility parameter. Secondly, since nodes are highly predictable while they are moving from destination points to destination points, prediction-based models may be considered. The longer is the course, the better is the prediction of future positions of nodes.

Fig. 3 represents the influence of nodes acceleration in nodes average course length. As in Fig.2, nodes average trajectory length are smaller in the Random Waypoint model and the reasons are similar to those expressed for the previous figure. In Fig. 3(a), we can see that the acceleration influences the Manhattan model, but has no impact on the $\mathrm{RWM}^{\mathrm{mod}}$ model. However, when we decrease α in Fig. 3(b) and Fig. 3(c), nodes' acceleration, in other words the difference between previous and next speeds, does not have a major influence on course lengths. This may be explained by the speed limitations induced by α. Since speeds cannot move a lot from the average velocity, the resulting course length is not influenced. Therefore, the acceleration is ignored in the theoretical model.

Finally, Fig. 4 represents a comparison between experimental results obtained through our simulations and theoretical ones computed using the model defined in Section 2. We plotted three experimental values, one for each mobility model.

[1]Extreme metrics do not represent major cases of possible deployments of mobile ad hoc networks

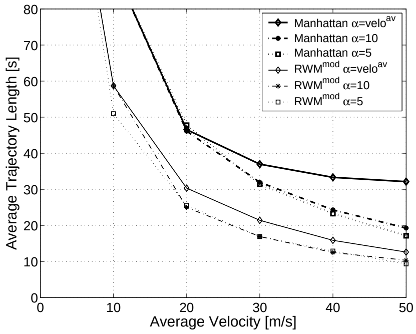
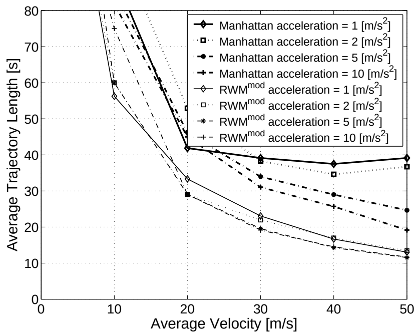
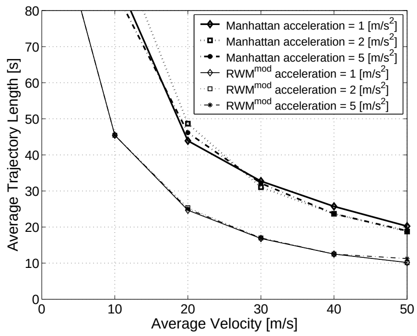


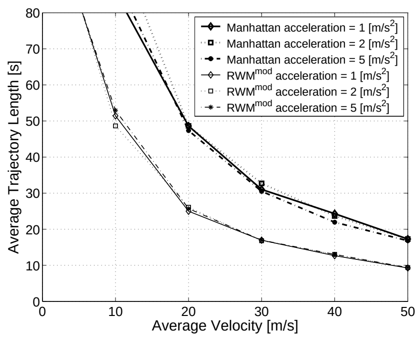
Figure 2: Comparison of the average trajectory length for the $\mathrm{RWM}^{\mathrm{mod}}$ and ManM.



(a) $\alpha = velo^{av}$.



(b) $\alpha = 10$.



(c) $\alpha = 5$.

Figure 3: Comparison of the influence of nodes acceleration on the course length

Then, we added four curves, one for each p used to obtain the theoretical course length. The case where $p = 1$ is not plotted since it would simply represent trajectory lengths equal to the simulation time.

We can first see that the theoretical model is accurate since the curve for the Manhattan experimental trajectory length is similar to the theoretical one for $p = 0.66$. Then, as we increase the probability to change course, the average course length decreases as expected. Then, when $p = 0$, meaning that a node always change course when it reaches an intersection, the curve reaches the experimental values obtained by the $\mathrm{RWM}^{\mathrm{mod}}$.

This graph further shows that by varying p and the average velocity[2], we can obtain the whole array of mobility patterns.

For a fixed speed of $20\frac{m}{s}$ for example, course lengths vary from $45[s]$ for Manhattan when nodes have a probability $\frac{2}{3}$ not to change course at an intersection, to $32[s]$ for $\frac{1}{2}$ and $25[s]$ for $p = \frac{1}{3}$. Finally, in the worst case, when nodes always change course when reaching an intersection, the average course length is still $17[s]$ and similar to the experimental value obtained with the $\mathrm{RWM}^{\mathrm{mod}}$.

Now, by varying the average velocity and keeping a fixed block length, we actually increase the number of trajectory changes since nodes reach an intersection faster. Yet, the average course length never goes below $7[s]$ for the worst case when $p = 0$.

Therefore, by varying those two parameters in the theoretical model, we can model highly mobile or rather static networks, small successive progressions or global directions, and predictable or non predictable motions.

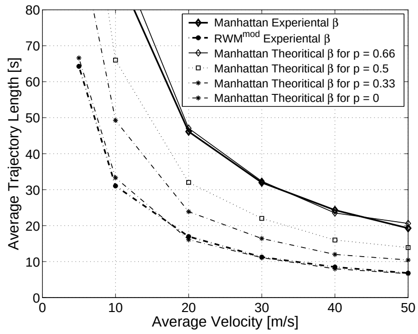


Figure 4: Comparison of the average trajectory length for the RWM and ManM.

[2]The velocity can be used to represent the time to reach an intersection since the blocks length is constant in average

4 Discussion

In the previous section, we obtained values for the average trajectory length in Random Waypoint, Modified Random Waypoint and Manhattan mobility models. Although very interesting, these values depend on nodes average velocity and on the distance between two successive destinations.

Let us first consider the case of nodes average velocity. It is not easy to have a good estimate on their values in real situations. We can only propose some assumptions. First, if an average velocity should be obtained for nodes attached to people (such as sensors or mobile phones), a fair value would more be around $5[\frac{m}{s}]$ since the major part of the human species experiences only limited movements. Yet, the average velocity is highly evoluting and may have a large variance. It can indeed vary from 0 in the office, to $20[\frac{m}{s}]$ in a car and to $200[\frac{m}{s}]$ in commercial airplanes. Finally, we can find a dual behavior for personal motions. When nodes move fast, they usually follow predefined routes and their trajectories may be predicted. But when nodes experience random walks, they usually move at lower speeds and results obtained in this paper gives estimates on their average course lengths. Therefore, nodes mobility depends on the application for the deployment of mobile ad-hoc networks.

When considering the distance between successive destinations, we simply argue that when nodes have a small distance between each intersections, the average course length drops dramatically. Yet, by having fast randomly distributed trajectory changes, a node effectively remains in the same position and the network does not really needs to update nodes position at each trajectory change. For mobility models describing nodes globally moving following a reference direction yet experiencing minor random trajectory changes around the reference direction (see Fig. 5), it is conceivable to look at the reference motion and not at the specific ones. Trajectories are therefore considered as a global movement between two destinations and minor trajectory changes which do not add sufficient information on nodes mobility are discarded.

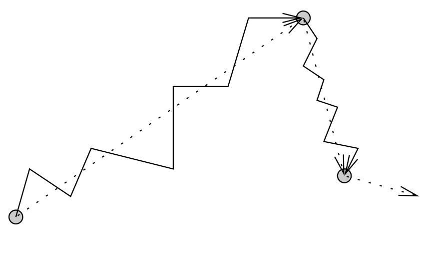


Figure 5: Reference Point Model.

Finally, as we gave some insight on nodes average trajectory length in commonly used mobility models, we bring justifications to the pertinence of prediction-based models. Thanks to nodes position, speed and motion pattern, these models are able to predict nodes exact future position without the need of periodical beacon messages, conditionally constrained to the hypothesis nodes did not unexpectedly change their trajectories. Therefore, the longer the course length is, the more accurate the prediction is. Lets consider the worst case result obtained in the previous section. The average course is more or less $7[\mathrm{s}]$. Let us consider the proactive OLSR[5] routing protocol. It keeps the state of its neighbors by sending Hello messages every $500[\mathrm{ms}]$. Therefore, the expected benefit obtained from the use of a prediction-based approach for this protocol is a reduction by a factor of 14 of the number of messages compared to the regular OLSR. Now, in better situations where trajectory lengths are longer than $7[s]$, we can imagine further improvements.

5 Conclusion and Future Work

We proposed in this paper a study of the average trajectory length of mobile nodes in mobility models. We obtained results for Random Waypoint, Modified Random Waypoint and Manhattan models. We showed that the average trajectory length is never shorter than $7[s]$ in the worst case scenario when using fair metrics. In better situations, this value is rather situated around $30[s]$. Therefore, by fixing a refreshing period to this time interval, it becomes possible to improve the global performance of topology control and routing protocols.

We also proposed a theoretical model for the average course length of mobile nodes and prove that it is consistent with experimental results. This model is able to compute the expected course length for highly mobile or rather static networks, considering small successive progressions or global directions, and in predictable or non predictable motions.

Finally, to the light of our results, we expressed justifications to prediction-based models which are emerging as the next stage to the evolution of routing protocols.

In our future work, we plan to perform a thorough study on practical trajectory lengths in real environments. Now that we obtained an insight of the average course lengths in mobility models, it is interesting to see if those results hold in practical situations.

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