Temporal Behavior Analysis of Mobile Ad hoc Network with different Mobility Patterns

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ABSTRACT

Ad hoc network consists of a set of identical nodes that move freely and independently and communicate among themselves via wireless links. The most interesting feature of this network is that they do not require any existing infrastructure of central administration and hence it is very suitable for temporary communication links in an emergency situation. This flexibility however is achieved at a price of communication hazard induced due to frequent topology changes. In this article we have tried to identify the system dynamics using the proven concepts of time series modeling. Here we have analyzed variation of the number of neighbor nodes of a particular node over a fixed area and for a fixed number of nodes (i) for different values of speed of nodes, (ii) the transmission power, (iii) for different sampling period (iv) for different mobility patterns. We have considered three different mobility models - (i) Gaussian mobility model, (ii) Random Walk mobility model and (iii) Random Way Point mobility model. The number of neighbor nodes of a particular node behaves as a random variable for any mobility pattern. Through our analysis we found that this variation can be well modeled by an autoregressive AR(p) model. The values of p are evaluated for different scenario and we found that the value is in the range of 1 to 5. Moreover we also investigated the relationship between the speed and the time of measurement, and transmission range of a specific node under various mobility patterns.

Keywords

Ad hoc network, mobility modeling, time series analysis, autoregressive modeling.

1. INTRODUCTION

A Multi-hop wireless network [12], commonly referred to as ad hoc wireless networks do not require a fixed infrastructure because the mobile node can relay packets to another node without using base stations. The nodes are mobile and changing locations regularly. A node in Mobile Ad hoc Network (MANET) is moving and its neighborhood is changing constantly with time and place. The number of neighbor nodes of a node is an important information for several applications like routing, congestion control, topology construction etc. Let N = { N_i | 1 ≤ I ≤ n } represents the collection of nodes in the system. The neighbor count NC of a node N_i is changing constantly. At every instant some new nodes are coming into the transmission range of N_i and some old neighbor nodes are leaving the transmission range of Ni. Say node N_i has NC_i number of nodes at t instant of time. After a small amount of time say δt seconds i.e. at t+δt, this number has become $NC_{t+\delta t}$. $NC_{t+\delta t}$ is basically a function of the previous neighbor counts NC_t, $NC_{t-\delta t}$, and so on down to some lags. The reason is that some old nodes have left, some new nodes have come into the transmission range with some old nodes still remaining. How may nodes leave and come is surely a random phenomenon but is dependent on (i) the speed with which node N_i and its surrounding is moving, (ii) the transmission range of nodes N_i and its neighbors, (iii) the time interval after which we are taking the readings and (iv) the mobility pattern [18] followed by node N_i and its surrounding. The number of neighbor nodes of a particular node behaves as a random variable [15] for any mobility pattern. If the nodes are moving very slowly or almost stationary then the correlation between old and new value of Neighbor count NC will be very high. In other words, we can define $NC_{t+\delta t}$ as a function of NC_t, $NC_{t-\delta t}$, $NC_{t-2\delta t}$ and so on.

$NC_{t+\delta t} = f(NC_t, NC_{t-\delta t}, .. NC_{t-p\delta t})$ for some integer p such that $1 \le p < \infty$. The autocorrelation of NC also depends on speed, sampling time, transmission range and mobility patterns. If the speed is low, the nodes cover a short distance during a given duration. Most nodes which were neighbor in earlier instant are expected to remain neighbor again for a fixed transmission range. Very few nodes moves out of transmission range and very few new nodes come in. If the speed is increased, during that interval, the node covers a long distance and may be out of the transmission range. Similarly, several other new nodes may come in the range of the node N_i becoming its neighbor. Since large number of nodes are leaving and joining, with very few old neighbors remaining, the correlation between the old neighbor count value NC_{old} and new neighbor count value NC_{new} does not remain as strong as it used to be in case nodes were moving slowly.

The transmission range defines the area with in which the packet sent by a node can be received correctly by another node. This area usually represented by a circle around the sending node. The radius of this circle is proportional to the square root of the power used to send the packet. If the transmission power of a node is low, i.e. the transmission range is quite small then the neighbor count will vary dramatically. The reason is that if this node moves to a dense region, momentarily its neighbor count will be very high, but a small change in location at next instant may leave this node with very less or even no neighbors. In simple words, we can say that the autocorrelation between NC values will be very low if the transmission power (and hence transmission range) happens to be low. The autocorrelation between NC values increases with increase in the transmission power.

The time after which readings are taken is termed as sampling time in this article. The variation in neighbor count value NC happens due to change of locations by nodes. The distance a node will cover depends on two factors (i) speed and (ii) time. Even for a moderate speed, if the sampling time is increased, several nodes move out of the range of N_i and several other nodes come in the range of N_i. Due to large number of node movement, the correlation with the previous value of NC does not remain very strong. So autocorrelation among NC decreases, as we increase the sampling time.

Currently we have considered three mobility models [1, 5, 9, 18] - (i) Gaussian, (ii) Random Walk and (iii) Random Way Point for our experiment. Surprisingly we found that the effect of mobility pattern is insignificant on the autocorrelation of neighbor count NC values of a node N_i across different time periods. The random walk and random way point mobility models are found to show stronger autocorrelation between NC values at higher speed than Gaussian mobility model. But even that difference is quite low and may be neglected most of the time.

The rest of this paper is organized as follows. Section 2 contains a brief survey of the relevant works. Section 3 covers our proposal for using autoregressive of order p (AR (p)) model and some discussion on that. In Section 4, we present the simulation results to support our proposal of modeling the network dynamics using AR(p) model. In Section 5 describes the techniques to find the order p of AR(p) model. The forecast values using the said model are also described in that section. In section 6 we conclude and sum up the future directions.

2. RELATED WORKS

Time series [7, 10] modeling has been drawing a lot of attention in the modeling of internet traffic, wireless sensor and ad hoc network traffic. Basu and Mukherjee [4] modeled the internet traffic using the AutoRegressive Moving Average Model of order p and q (ARMA(p,q)) model. Using the model they forecast the traffic which was generated by a TCP source using FDDI protocol. They also did develop a system to generate synthetic traffic which can be useful for simulation studies of internet traffic and in resource management algorithms.

C. You and K. Chandra [17] have shown using statistical tests that the aggregate TCP packet arrival process exhibits both non-stationary and nonlinear features. They derived a stationary traffic stream by filtering a subset of the applications exhibiting non-stationary features from the aggregate process. They modeled this filtered traffic process using non-linear threshold autoregressive processes. Their traffic model was found to be in good agreement with real traffic in the packet loss statistics. The model was used in the design of traffic shapers and provided a simple and accurate approach for simulating internet data traffic patterns. Liu et. al. [14] proposed the energy efficiency information collection in sensor nodes. They kept a sensor node from transmitting redundant data. According to them, data is redundant if it can be predicted by the sink node. For prediction, they utilized ARIMA [7] model due to its outstanding performance in model fitting and lightweight computational cost on forecasting. The samples from a specific sensor node arriving at sink node are treated as a time series and the sink maintains a time series for each sensor node. Based on this historical data, prediction is done by sink node for each sensor node. If the difference between the actual data and the predicted data within a pre-defined threshold, then that data is not send from the sensor node resulting in energy savings. Herbert et. al. [13] used ARIMA model to fit the data collected by sensor node. The LEACH [11] protocol was extended to add a verification step at the cluster head. Each member node transmits the ARIMA parameters to its clusterhead which verifies the accuracy of the model by generating a time series with each set of parameters and calculating the mean squared error between them. If the mean squared error is above a fixed tolerance value, the clusterhead request all member nodes to recalculate their respective parameters repeatedly until all models are within tolerance.

Borgne et. al. [6] used a set of Time series models to predict the sensors reading at regular interval of time by the sink node. The sink node transmits this data to every sensor. If sensor nodes find that their reading is different form the sink's prediction by a value greater than a threshold, then sensors send their reading to sink. This approach has shown a great saving in communication cost in sensor networks. Banerjee et. al. [2, 3] modeled the system dynamics using birth and death model. When a node enters in the transmission range of a source node say Ni, that was treated as the birth of that the particular node in the Radio Range of the source node. Similarly when a node was going out of the transmission range, it was identified as the death from the Radio Range of the source node.

3. PROPOSED MODEL

As we pointed out in section 1 that the neighbor count NC of a node N_i number is changing with time and is a function of the values of NC at previous instances. In this article we have tried to identify the system dynamics [16] using the proven concepts of time series. A time series [7, 10] is a sequence of observations that are arranged according to the time of their outcome. By recording and analyzing the data of a time series, we can gain a better understanding of the data generating mechanism and make a prediction of future values. The main characteristic of a time series is that the data are often governed by a trend and they have cyclic components. An important part of the analysis of a time series [7, 10] is the selection of a suitable model (or class of models) fitting that data. Naturally, more appropriate is the model selection, better expected is the prediction. The neighbor count NC of a node N_i is a parameter varying with time and are a suitable candidate to be considered for such modeling. The relation of NC with the previous values is also supported with the corrlelogram of nodes. The plot of experimental data confirms that the autocorrelation is very high at initial lags and is constantly decreasing with higher lags. This implies that the current neighbor count NC is a function of values of NC on previous instances with a white noise with mean zero and variance σ^2. This behavior of data can be represented well with the help of an AR(p) model [7, 10]. An AR(p) model can be defined as

$$r_t = \phi_0 + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \cdots \phi_p r_{t-p} + a_t$$

where p is a non-negative integer and $\{a_t\}$ is assumed to be a white noise series with mean zero and variance σ^2. This model suggests that the past p values $r\{_{t-1}\}$ (i = 1.. p) jointly determine the conditional expectation of given the past data. The series, we obtained through our experiment is stationary since it fulfills the requirements of stationarity [10] which are given below.

(a) $E(r_t) = \mu$, which is a constant and independent of t, and

(b) $Cov(r_t, r_{t-j}) = \gamma_j$, which only depends on lag j, not on time t

Since the series is stationary, the mean and the variance of this series is governed by the formula

$$E(r_t) = \frac{\phi_0}{(1 - \phi_1 - \phi_2 - \cdots - \phi_p)}$$

provided that the denominator is not zero. And the autocovariance are given by

$$\gamma_j = \begin{cases} \phi_1 \gamma_{j-1} + \phi_2 \gamma_{j-2} + \cdots \phi_p \gamma_{j-p} & \text{for } j=1, 2, 3 \ldots p \\ \phi_1 \gamma_1 + \phi_2 \gamma_2 + \cdots \phi_p \gamma_p + \sigma^2 & \text{for } j = 0 \end{cases}$$

The associated polynomial equation of the model, called characteristic equation, is given by

$$x^p - \phi_1 x^{p-1} - \phi_2 x^{p-2} - \cdots - \phi_p = 0$$

The other condition of stationarity is that if all the characteristic roots of this equation are less than unity in modulus, then the series r_t is stationary. The characteristic equation indicates that the plot of the autocorrelations, known as autocorrelation function, (ACF) of AR(p) model would show a mixture of damping sine and cosine patterns and exponential decays depending on the nature of its characteristic roots. This is totally in conformity with our experimental data. One major hurdle in representing data using AR(p) model is finding the proper value of p. In our case we have used the partial autocorrelation function (PACF) to find an idea about the order of AR and then Akeike Information Criterion (AIC) [7] is used to confirm that value of p.

4. SIMULATION AND RESULTS

We have used Omnet++ for node mobility simulation while Minitab is used for the analysis of the results.

4.1 Simulation Setup

The node mobility and traffic generations are simulated using Omnet++ 3.3 discrete event system simulator considering 131 mobile nodes. We have analyzed the neighbor count for three mobility models [1, 18, 5, 8, 9] (i) Gaussian, (ii) Random walk and (iii) Random way point. The nodes are distributed over an area of 600 X 600 m^2. The speed of the node movement is varied between 10 to 170 m/sec. The transmission power is varied from 1000 m to 90000m. The actual coverage area is square root of the transmission power. The number of neighbors of each node is studied at 0.5 sec, 1 sec, 1.5 sec for each speed variation. No

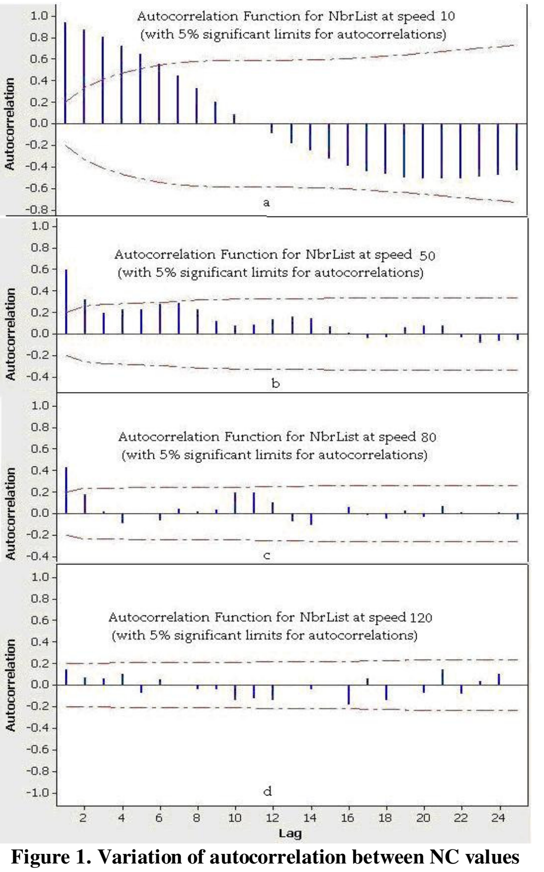

Figure 1. Variation of autocorrelation between NC values with speed

standard network protocol has been used for the total simulation. The results are then taken to Minitab version 14 for carrying out necessary statistical analysis.

4.2 Analysis under varying speed for a fixed sampling rate

Our first experiment deals with finding the relationship between the autocorrelation of NC and speed of moving nodes. For our experiment, we have assumed that all nodes are moving with the equal speed and readings are taken after 1 sec. At low speed, NC shows a nice autocorrelation with several previous lagged values. But as the speed is increased, the nodes starts leaving and joining region rapidly and so the autocorrelation with the previous values starts diminishing.

We calculated the autocorrelations among NC data for nodes moving with the speed of 10. The speed was varied from 10 to 120 with an increment of 10. The sample is taken after 1 sec in each case. Some of the sample correlations at speed 10 m/sec, 50 m/sec, 80 m/sec, and 120 m/sec are shown in figure 1. As evident from figure 1.a, the NC values for nodes moving with the speed of 10m/sec have shown nice autocorrelation with high peaks at initial lags but decreasing at higher lags. But when the speed has gone to 120 m/sec, then no significant autocorrelation exists as evident from figure 1.d. Figure 1 shows a snapshot of autocorrelation of nodes following Gaussian mobility model. For other two models the results are very similar. The autocorrelation become insignificant at a speed of 130 m/sec for Random Way Point mobility pattern whereas for Random Walk mobility pattern, it remains significant up to the speed of 200 m/sec. So

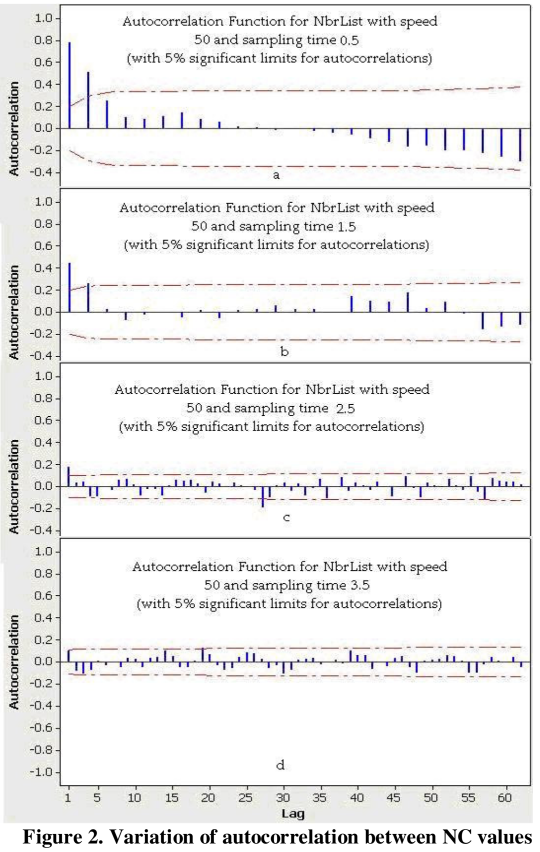

Figure 2. Variation of autocorrelation between NC values with sampling time

Random Walk mobility model shows strong autocorrelation between NC values at higher speed than other two considered mobility models.

4.3 Analysis under constant speed for varying sampling rate

Our second experiment is concerned with the variation of number of neighbors with the time at which we are recording the data, called as sampling time. Since the nodes are moving very slowly at low speed, the neighborhood is also undergoing change very slowly. In this case if we sample data very frequently, we ought to get nearly similar number of neighborhood. For this experiment, we have sampled the network for a time period of 0.5sec to 5sec with a sampling period of 0.5sec. For our data we have fixed the speed to 50m/sec and the sampling time was varied from 0.5 sec to 5 sec in increments of 0.5sec. The autocorrelation diagram ACF for nodes following Gaussian movement is shown in figure 2 for each case. With sampling time of 0.5 sec, we get an ACF which is sinusoidal in nature having higher autocorrelation value at initial lags. But for sampling time of more than 3.5, no autocorrelation value is significant enough as evident from ACF shown in figure 2.d. The autocorrelation appears significant up to 4 sec for Random Walk mobility model and 6 sec for Random Way Point mobility models respectively.

4.4 Analysis under varying radio range

The radio range is determined by the transmitting power of a node. For our experiment, we have defined the range as the square root of the transmitting power. We have varied the transmitting power form 1000 to 90000.

For low transmitting power, no significant autocorrelation is observed among nodes because few nodes are expected in the transmission range. A node moving very slowly will also change neighborhood rapidly. So no correlation exists. But as we increase the transmitting power, the autocorrelation between the nodes starts exhibiting a sinusoidal pattern with high peaks at the start as shown in figure 3. From figure 3.a, we can see that the autocorrelation is not significant for neighbor count NC data when the transmission power is 1000 for Gaussian node mobility. It becomes significant only after the transmission power is beyond 9000. The autocorrelation becomes significant beyond the transmission range of 6000 for random walk and beyond 7000 for random way point respectively.

4.5 Analysis under varying speed and varying sampling rate

Our next experiment was conducted with the combined effect of speed and sampling time on the autocorrelation of neighbor count NC values for Gaussian mobility model. The speed was varied from 10m/sec to 100m/sec in increments of 10m/sec and the sampling time was varied from 0.5sec to 5sec in increment of 0.5sec. The findings are enlisted in table 1. Due to space limitation, we are not listing the table for other two mobility models. As evident from table 1 that the neighbor count NC data moving with speed of 10m/sec has significant autocorrelation for each sampling period i.e. from 0.5 sec to 5 sec. When the speed becomes 50m/sec, the autocorrelations are significant only up to the sampling period of 3.5 but after that interval, no significant autocorrelation is found. This behavior is expected because the distance covered by a node is product of speed and time. So for a moderate speed, if the time is allowed to increase, several nodes move out of range and similarly several nodes move in thereby manifesting lower autocorrelation with the values at previous lags.

Table 1. Changes in autocorrelation with time and speed

Sampling Time →

Speed	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5
10	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
20	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
30	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
40	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
50	Y	Y	Y	Y	Y	N	N	N	N	N
60	Y	Y	Y	N	N	N	N	N	N	N
70	Y	Y	Y	N	N	N	N	N	N	N
80	Y	Y	N	N	N	N	N	N	N	N
90	Y	Y	N	N	N	N	N	N	N	N
100	Y	Y	N	N	N	N	N	N	N	N
110	Y	N	N	N	N	N	N	N	N	N
120	N	N	N	N	N	N	N	N	N	N

5. RESULTS

As evident from the previous simulation that within a threshold value of speed, sampling period, and transmission power, the neighbor count NC data shows a nice autocorrelation with high peaks at initial lags and decreases at higher lags. This property of data confirms that within that threshold, it is justified to model the neighbor count NC data with Autoregressive model. Autoregressive modeling requires the order p of the model to be specified. In the next section we outline the process of ascertaining the order of AR. The chosen AR(p) model is then used to forecast the next value of neighbor count.

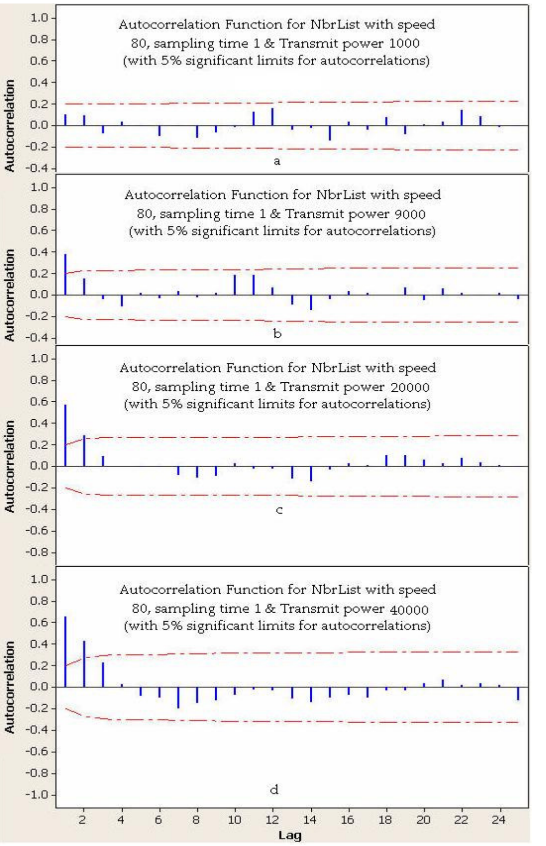

Figure 3. Variation of autocorrelation between NC values with transmission power

5.1 Finding the order of AR

To calculate the order of AR process, we have to find the PACF, which gives us an indication of probable value of p. Then we have used AIC to confirm on that. PACF and table 2 of AIC [7] values are given below. The PACF in figure 4 tells us that this data can be modeled with an AR(2) process. When we find the AIC values, the value is smaller for 3, but the difference is very low. So we may stick with 2 for p value.

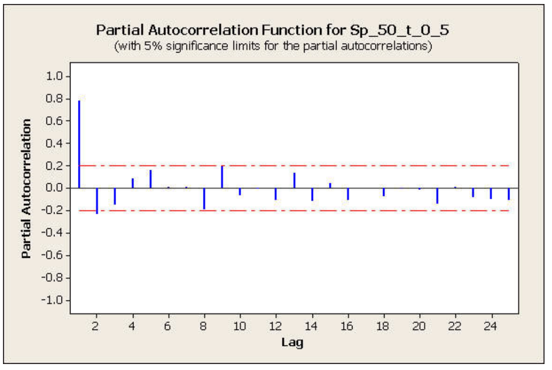

Figure 4. PACF of sample data values of neighbor counts

5.2 Forecasting with AR(2)

We have used our model to forecast the next NC value. For forecasting we have used an AR(2) model. The comparison of forecast and original data obtained from our experiment is shown in figure 5. It is evident from the figure 5 that the actual data and the forecast data value are very close to each other. The chi-square test confirms the above statement.

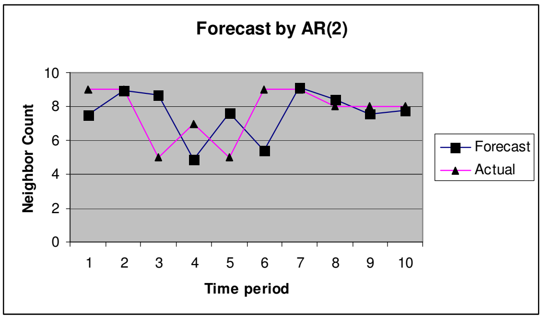

Figure 5. Forecast offered by AR(2) model

6. CONCLUSION

In this article, we have modeled the temporal neighbor distribution of a node using a popular Time series model Autoregressive AR(p) model. We found through our experiment that node distribution under a threshold value of speed, range and sampling time for all three mobility models considered in this article are well correlated and can be represented by AR(p) model for suitable choice of p. But above a threshold value, the autocorrelation of node distribution does not remain significant enough. The thresholds for different parameters are also determined in this article. The threshold value of speed is 170m/sec or 612 km/hr and range is 77 m for random walk mobility model and very similar for other mobility models. The threshold obtained is surely very suitable for any practical deployment for ad hoc network. We have also predicated the number of neighbor nodes in future time frames and found that the prediction is close enough to the real value. These predicated values of neighbor nodes can be used for different application which relies on number of neighbor nodes like multi-path routing, topology construction, congestion control, traffic prediction etc.

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