Impact of the Gauss-Markov Mobility Model on Network Connectivity, Lifetime and Hop Count of Routes for Mobile Ad hoc Networks

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Abstract - The high-level contribution of this paper is a simulation based analysis of the network connectivity, hop count and lifetime of the routes determined for mobile ad hoc networks (MANETs) using the Gauss-Markov mobility model. The Random Waypoint mobility model is used as a benchmark in the simulation studies. Two kinds of routes are determined: routes with the longest lifetime (stable paths) and routes with the minimum hop count. Extensive simulations have been conducted for different network density, node mobility values and different values of the degree of randomness parameter $\alpha$ ($0 \leq \alpha \leq 1$) for the Gauss-Markov model. In low-density network scenarios, we observe that the network connectivity under the Gauss-Markov model is significantly lower than that obtained under the Random Waypoint model. In moderate and high-density network scenarios, the network connectivity obtained under the two mobility models is almost equal. The minimum hop paths determined under the Gauss-Markov model have a larger number of hops than those computed under the Random Waypoint model. The lifetime of stable paths determined under the Gauss-Markov model is smaller than those determined under the Random Waypoint model. Low-density networks using the Gauss-Markov mobility model attain larger connectivity for intermediate values of parameter $\alpha$ (i.e., $0.4 \leq \alpha \leq 0.8$), while the connectivity of moderate and high-density networks is not significantly dependent on $\alpha$. The minimum hop count of the paths is not much affected by different values of $\alpha$, while maximum lifetime stable paths are obtained for larger intermediate values of $\alpha$ (i.e., $\alpha = 0.6$ and $0.8$), but not for unity.

Index Terms – Mobile ad hoc networks, Route stability, Hop count, Gauss-Markov Mobility Model, Simulation

I. INTRODUCTION

A mobile ad hoc network (MANET) is a dynamically distributed system of mobile wireless nodes. The network bandwidth is limited and the transmitted signals are prone to interference and collision as the medium is shared. The transmission range of a node is often limited because of limited battery power with the nodes. Hence, multi-hop routing is a common feature in MANETs. Due to node mobility, there is unlikely to be a single fixed route throughout the duration of a source-destination session.

Route stability is an important design criterion to be considered in the design of MANET routing protocols. The commonly used route discovery approach of flooding the Route-Request (RREQ) packets can easily lead to congestion in the network and also consume the battery charge of the nodes. Frequent route changes can also result in out-of-order packet delivery, causing high jitter in multi-media, real-time applications. For safety and time-critical applications, it is better to route all the critical data packets through the same path so that the receiver can reassemble the packets and get a consistent view of the network condition.

In [1], we proposed an algorithm called $OptPathTrans$ to determine the sequence of stable routes between a given source-destination pair over the duration of a communication session. Given the complete knowledge of the future topology changes over the entire duration of the communication session between a source $s$ and destination $d$, algorithm $OptPathTrans$ operates as follows: Whenever an $s$-$d$ path is required at a time instant $t$, choose the longest-living $s$-$d$ path from $t$. The above strategy is repeated over the duration of the $s$-$d$ session. The sequence of such longest living stable paths is called the Stable Mobile Path (SMP). The performance of $OptPathTrans$ has been largely studied using the Random Waypoint (RWP) mobility model [2] for MANETs. Note that in this paper, we use the terms ‘path’ and ‘route’ interchangeably. They mean the same.

We conjecture that values for the critical network and routing protocol performance metrics (e.g., connectivity, hop count, route lifetime, delay per data packet, throughput, energy consumption and etc) are very heavily dependent on the mobility model used in the simulation studies. Most of the simulation studies in MANETs use the RWP model as the node mobility model. Even through the RWP model is easy to simulate, it has some unrealistic assumptions about node movement [3]: sharp turns and sudden stop. Sharp turns occur whenever a node changes its direction after traveling for a random amount of time and sudden stops occur when the node decides to stop at a particular time instant and changes directions. During a direction change, the speed chosen by a node is totally independent of the previous speed. The Gauss-Markov model proposed by Liang and Haas is more realistic compared to the RWP model. It eliminates the twin problems of sharp turns and sudden stops by considering the past speed and direction to influence the future speed and direction. But, the Gauss-Markov model has been very rarely used in MANET simulation studies, mainly due to the relatively larger complexity involved in simulating it compared to the RWP model.
In this paper, we study the performance of algorithm OptPathTrans under the Gauss-Markov mobility model and the RWP model. The RWP mobility model is used as a benchmark to compare and evaluate the relative stability and hop count of the routes. We use the OptPathTrans algorithm to compute the sequence of stable paths (the Stable Mobile Path) with the longest lifetime and use the Dijkstra algorithm [5] to compute the sequence of minimum hop paths (called the Minimum Hop Mobile Path). Simulations have been conducted for different network density, node mobility and degree of randomness (parameter $\alpha$) values for the Gauss-Markov model. For smaller values of $\alpha$, the model allows a node to make random turns, choose random speed and gives less importance to the node’s travel history. With larger values of $\alpha$, the model gives more importance to the travel history of a node to decide the future speed and direction. We could not find such extensive simulation studies on the stable paths and minimum hop paths for MANETs employing the Gauss-Markov mobility model.

The rest of the paper is organized as follows: In Section II, we briefly discuss the Random Waypoint and the Gauss-Markov mobility models. Section III highlights the very few available quantitative analysis results based on the Gauss-Markov mobility model in the literature. Section IV provides an overview of the OptPathTrans algorithm used to determine the sequence of long-stable paths in ad hoc networks. Section V illustrates the simulation results and compares the two mobility models with respect to network connectivity, route lifetime and hop count. Section VI concludes the paper.

II. REVIEW OF THE MOBILITY MODELS

A. Random Waypoint Mobility Model

Initially, the nodes are assumed to be placed at random locations in the network. The movement of each node is independent of the other nodes in the network. The mobility of a particular node is described as follows: The node chooses a random target location to move. The velocity with which the node moves to this chosen location is uniformly randomly selected from the interval $[v_{\text{min}}, v_{\text{max}}]$. The node moves in a straight line (in a particular direction) to the chosen location with the chosen velocity. After reaching the target location, the node may stop there for a certain time called the pause time. The node then continues to choose another target location and moves to that location with a new velocity chosen again from the interval $[v_{\text{min}}, v_{\text{max}}]$. The selection of each target location and a velocity to move to that location is independent of the current node location and the velocity used to reach that location.

B. Gauss-Markov Mobility Model

Initially, the nodes are placed at random locations in the network. The movement of a node is independent of the other nodes in the network. Each node is assigned a mean speed, $\bar{S}$, and mean direction, $\bar{\Theta}$, of movement. For every constant time period, a node calculates the speed and direction of movement based on the speed and direction during the previous time period, along with a certain degree of randomness incorporated in the calculation. The node is assumed to move with the calculated speed and in the calculated direction during the time period. For a particular time period $t$, the speed and direction of a node is calculated as follows:

$$S_t = \alpha S_{t-1} + (1-\alpha)\bar{S} + \sqrt{1-\alpha^2} \alpha_1^G$$

(1)

$$\Theta_t = \alpha \Theta_{t-1} + (1-\alpha)\bar{\Theta} + \sqrt{1-\alpha^2} \Theta_{t-1}^G$$

(2)

The parameter $\alpha (0 \leq \alpha \leq 1)$ is used to incorporate the degree of randomness while calculating the speed and direction of movement for a time period. The degree of randomness decreases as we increase the value of $\alpha$ from 0 to 1. When $\alpha$ is closer to 0, the degree of randomness is high, which may result in sharper turns. When $\alpha$ is closer to 1, the speed and direction during the previous time period are given more importance (i.e., the model is more temporally dependent) and the node prefers to move in a speed and direction closer to what it has been using so far. Thus, the movement of a node gets more linear as the value of $\alpha$ approaches unity. The terms $S_{t-1}^G$ and $\Theta_{t-1}^G$ are random variables chosen independently by each node from a Gaussian distribution with mean 0 and standard deviation 1. If $(X_t, Y_t)$ are the co-ordinates of a node during the beginning of time period $t$, then the co-ordinates $(X_{t+1}, Y_{t+1})$ of the node at the end of time period $t$ (which is also the beginning of time period $t+1$), are given by equations (3) and (4) shown below. The node thus moves from $(X_t, Y_t)$ to $(X_{t+1}, Y_{t+1})$ during time period $t$ with the speed $S_t$ and in direction $\Theta_t$ determined from equations (1) and (2) respectively.

$$X_{t+1} = X_t + S_t \cos(\Theta_t)$$

(3)

$$Y_{t+1} = Y_t + S_t \sin(\Theta_t)$$

(4)

III. RELATED WORK

Very few quantitative simulation studies involving the Gauss-Markov mobility model are available in the literature. In [3], the authors study the performance of the Ad hoc On-demand Distance Vector (AODV) routing protocol [6] under the Random Waypoint and the Gauss-Markov mobility models. AODV is one of the commonly studied reactive MANET routing protocols. Simulation results in [3] show that when the mobility of the nodes is low, the AODV protocol gave identical performance under both the mobility models. As the mobility of the nodes get high, the AODV protocol obtained a higher throughput and lower end-to-end delay under the Gauss-Markov mobility model vis-à-vis the Random Waypoint mobility model. It has been also observed that the throughput and end-to-end delay of the AODV protocol is not much affected by the degree of randomness parameter $\alpha$ of the Gauss-Markov model.

In [7], the authors study the impact of different mobility models, including the Gauss-Markov mobility model, on the performance of the mobile IP multicast protocols such as Remote Subscription (RS), Bi-directional Tunneling (BT) and the Mobile Multicast...
(MoM) protocols. It has been observed that the tree maintenance overhead produced by the RS protocol under the Gauss-Markov model is nearly 8 times the overhead produced by the protocol under the City-Section mobility model [8]. Under the Gauss-Markov model, the number of link changes in the network increases rapidly as the mobility of the nodes increases. As a result, the throughput of all the three multicast protocols is lower when run under the Gauss-Markov model compared to the City Section model.

In [9], the authors compare the performance of the proactive Optimized Link State Routing (OLSR) protocol [10] and the reactive Dynamic MANET On-demand (DYMO) routing protocol [11] under the Gauss-Markov mobility model. As expected, the proactive OLSR and the reactive DYMO routing protocols incurred a relatively reduced routing load in low speed and high speed scenarios respectively. The packet delivery ratio and end-to-end delay of OLSR were always lower than that of DYMO for all the node mobility values.

In [12], the impact of the Random Waypoint, Manhattan [8] and Gauss-Markov mobility models on the performance of AODV has been studied. The energy-goodput (ratio of the total number of data packets successfully delivered to that of total energy consumed) has been observed to be higher for the Gauss-Markov mobility model and the Random Waypoint model in low mobility and high mobility scenarios respectively. For a given mobility scenario, the control overhead under the Gauss-Markov model is lower than that observed for the Random Waypoint model and higher than that observed for the Manhattan model. The packet delivery ratio of AODV under the Gauss-Markov model is slightly lower than that obtained under the Random Waypoint and Manhattan models for all mobility scenarios. A similar performance study of the impact of mobility models on AODV is also available in [13].

In [14], the authors propose a Partition-Aware Transmission Control Protocol (PAT) for MANETs. The PAT scheme uses the disconnection duration information of nodes with respect to the mobility model deployed in order to reduce the number of retransmissions. The Gauss-Markov mobility model has been one of the mobility models used to compare and study the performance of the PAT scheme with that of the original TCP and Fixed Retransmission-Timeout (RTO) schemes.

IV. ALGORITHM TO FIND THE OPTIMAL NUMBER OF PATH TRANSITIONS

This section briefly reviews the OptPathTrans algorithm [1] to determine the optimal number of path transitions in mobile ad hoc networks. The algorithm uses the notions of mobile graph to record the sequence of network topology changes and mobile path to record the sequence of paths in a mobile graph. A mobile graph [15] is defined as the sequence $G_M = G_1G_2...G_T$ of static graphs that represents the network topology changes over some time scale $T$. A mobile path [15], defined for a source-destination $(s-d)$ pair, in a mobile graph $G_M = G_1G_2...G_T$ is the sequence of paths $P_M = P_1P_2...P_T$, where $P_i$ is a static path between the same $s-d$ pair in $G_i = (V_i,E_i)$, $V_i$ is the set of vertices and $E_i$ is the set of edges connecting these vertices at time instant $t_i$.

The Stable Mobile Path (SMP) for a given mobile graph and $s-d$ pair is the sequence of static $s-d$ paths such that the number of route transitions (change from one static $s-d$ path to another) is as minimum as possible. The constituent static paths of an SMP have the longest possible route lifetime. The SMP for an $s-d$ pair on a given mobile graph is determined by using algorithm OptPathTrans. A Minimum Hop Mobile Path (MHMP) for a given mobile graph and $s-d$ pair is the sequence of minimum hop static $s-d$ paths. The MHMP for an $s-d$ pair on a given mobile graph is determined by repeatedly running the minimum path weight Dijkstra algorithm [5] on the static graphs. We follow the Least Overhead Routing Approach (LORA) [16] for ad hoc networks. Accordingly, a minimum hop $s-d$ path determined by running Dijkstra algorithm on a static graph $G_i$ is assumed to be used in the subsequent static graphs $G_{i+1}$, $G_{i+2}$, ..., as long as the path exists in these static graphs.

Algorithm OptPathTrans (pseudo code in Figure 1) operates as follows: Let $G_M = G_1G_2...G_T$ be the mobile graph generated by sampling the network topology at regular instants $t_1$, $t_2$, ..., $t_T$ of an $s-d$ session. When an $s-d$ path is required at sampling time instant $t_i$, the strategy is to find a mobile sub graph $G(i,j) = G_i \cap G_{i+1} \cap ... \cap G_j$ such that there exists at least one $s-d$ path in $G(i,j)$ and no $s-d$ path exists in $G(i,j+1)$. A minimum hop $s-d$ path in $G(i,j)$ is selected. Such a path exists in each of the static graphs $G_i$, $G_{i+1}$, ..., $G_j$. If sampling instant $t_{i+1} \leq t_T$, the above procedure is repeated by finding the $s-d$ path that exists for the maximum amount of time since $t_{i+1}$. A sequence of such maximum lifetime static $s-d$ paths over the timescale of $G_M$ forms the stable mobile $s-d$ path.

**Input:** $G_M = G_1G_2...G_T$, source $s$, destination $d$  
**Output:** $P_S$ // Stable Mobile Path  
**Auxiliary Variables:** i, j  
**Initialization:** $i=1; j=1; P_S = \Phi$

**Begin OptPathTrans**

1. while ($i \leq T$) do
2. Find a mobile graph $G(i,j) = G_i \cap G_{i+1} \cap ... \cap G_j$ such that there exists at least one $s-d$ path in $G(i,j)$ and no $s-d$ path exists in $G(i,j+1)$ or $j = T$  
3. $P_S = P_S \cup$ {minimum hop $s-d$ path in $G(i,j)$ }  
4. $i = i + 1$
5. end while
6. return $P_S$

**End OptPathTrans**

Figure 1. Pseudo code for algorithm OptPathTrans

The run-time complexity of algorithm OptPathTrans is $O(n^2T)$, where $n$ is the number of nodes in the network, $T$ is the number of static graphs in a mobile graph ($T$ is a measure of the timescale of the communication session.
between the source \(s\) and destination \(d\) and \(\Theta(n^2)\) is the run-time complexity of the minimum-hop path Dijkstra algorithm, which has to be run \(T\) times at the worst case.

V. SIMULATIONS

The simulations were conducted in a discrete-event MANET simulator developed by the author in Java. This self-developed MANET simulator has also been recently used to study the performance of the multicast extensions [17] of the Location Prediction Based Routing (LPBR) protocol [18] and the performance of a density and mobility-aware energy efficient broadcast strategy [19] vis-à-vis flooding.

The network dimensions are 1000m x 1000m. The wireless transmission range of a node is 250m. The node density is varied by performing the simulations with 25, 50 and 75 nodes representing respectively low, moderate and high density networks. For the Random Waypoint mobility model, we assume \(v_{\text{max}} = v_{\text{max}} \text{ and 0 second pause time. The values of } v_{\text{max}}\text{ (for the RWP model) and } \Theta\text{ for the Gauss-Markov mobility model are 5, 15 and 30 m/s, representing scenarios of low, moderate and high node mobility respectively. In the case of the Gauss-Markov model, each node is initially assigned a random value for the mean direction of movement, } \Theta\text{, chosen from the range } [0\ldots360^\circ]\text{. When a node travels beyond the boundaries of the simulation field, the mean direction of movement of the node is forced to flip } 180^\circ\text{ so that the node can remain within the field boundaries. We update the speed and direction of movement of the nodes under the Gauss-Markov model for every 1 second.}

We obtain a centralized view of the network topology by generating mobility trace files for 1000 seconds under both the mobility models. The network topology is sampled for every 0.25 seconds to generate the static graphs and the mobile graph. Two nodes \(a\) and \(b\) are assumed to have a bi-directional link at time \(t\), if the Euclidean distance between them at time \(t\) (derived using the locations of the nodes from the mobility trace file) is less than or equal to the wireless transmission range of the nodes. Each data point in Figures 2 through 6 is an average computed over 5 mobility trace files and 20 randomly selected \(s-d\) pairs from each of the mobility trace files. The starting time of each \(s-d\) session is uniformly distributed between 1 to 20 seconds.

The following performance metrics are evaluated:

- **Percentage Network Connectivity**: This metric indicates the probability of finding an \(s-d\) path between any source \(s\) and destination \(d\) in the network for a given density and a mobility model. Measured over all the \(s-d\) sessions of a simulation run, this metric is the ratio of the number of static graphs in which there exists an \(s-d\) path to the total number of static graphs in the mobile graph.

- **Average Hop Count**: This metric is the time averaged hop count of a mobile path for an \(s-d\) session, averaged over all the \(s-d\) sessions. For example, if a mobile path comprises of a 2-hop static path \(p_1\), a 3-hop static path \(p_2\), and a 2-hop static path \(p_3\), existing

in static graphs at time 1-2, 3-5 and 6-10 seconds respectively, the time-averaged hop count of the mobile path would be \((2*2 + 3*3 + 2*5) / 10 = 2.3\).

- **Average Route Lifetime**: This metric is the average of the lifetime of all the static paths of an \(s-d\) session, averaged over all the \(s-d\) sessions.

A. Percentage Network Connectivity

The Random Waypoint model provided the maximum connectivity (close to 90%) among the nodes for low-density networks compared to the Gauss-Markov model. The connectivity provided by both the mobility models is almost the same for moderate and high-density networks. In low-density networks, relatively larger network connectivity is attained for intermediate values of the degree of randomness parameter \(\alpha\) \((0.4 \leq \alpha \leq 0.8)\). This illustrates that a mix of both temporal dependency and randomness in the selection of speed and direction of movement is better than completely relying on either of these strategies. When a node is 100% temporal dependent (i.e., \(\alpha = 1\)), there is no randomness associated with its motion and the node continues to travel in a linear fashion. If each node moves in a linear fashion in their initially chosen direction of movement, then the network connectivity is heavily dependent on the direction values initially assigned to each node and the distribution of the nodes in the network. Also, when the nodes randomly change directions without considering the previous direction of movement, the neighborhood of a node changes too often, affecting network connectivity.

![Figure 2.1. Node Velocity = 5m/s](image1)

![Figure 2.2. Node Velocity = 15m/s](image2)

![Figure 2.3. Node Velocity = 30m/s](image3)
For a given node mobility, as we increased the number of nodes in the network, the network connectivity provided by the RWP model increased from 90% to 99%-100% and the network connectivity provided by the Gauss-Markov model increased from 63%-71% to 98%-100%. As we add more nodes to the network, the probability of finding $s$-$d$ routes increases significantly and network connectivity does not depend on the parameter $\alpha$. Network connectivity (refer Figure 2) is mainly influenced by the number of nodes in the network and their initial random distribution. Node velocity and direction of movement of nodes are not significant factors influencing network connectivity as we increase the number of nodes in the network. Note that the network connectivity values plotted in Figures 2.1 through 2.3 is an average of those obtained for both the Minimum Hop Mobile Path and the Stable Mobile Path.

B. Minimum Hop Mobile Path

We now discuss the time averaged hop count per minimum hop path (refer Figure 3) and the average route lifetime (refer Figure 4) of the minimum hop paths determined as the constituent paths of the Minimum Hop Mobile Path under the two mobility models.

B.1 Average Hop Count per Minimum Hop Mobile Path

The average hop count per minimum hop path determined for the Gauss-Markov model is considerably larger than the hop count per minimum hop path determined under the Random Waypoint model. The relatively larger hop count for all values of parameter $\alpha$ can be attributed to the tendency of the nodes to consider staying on close to an initially chosen direction and speed with a tinge of Gaussian randomness associated with the decision during each time period. The minimum hop paths in networks with such a dependence on randomness and past history are most likely not to exist on a straight line between the source and destination nodes.

We also observe that with increase in network density, the average hop count per path for the Random Waypoint mobility model and the Gauss-Markov mobility model decreases (by a factor of 5 – 10%). This can be attributed to the increase in the number of $s$-$d$ paths in the network and the chances of finding the $s$-$d$ paths with the smallest possible hop count increases.

The degree of randomness in the Gauss-Markov model does not significantly influence the average hop count of the minimum hop paths in the network. Such an observation is consistent with the simulation results obtained in [3], wherein it has been concluded that the degree of randomness of the Gauss-Markov mobility model has no significant influence on the throughput and end-to-end delay per data packet.
determined under the Gauss-Markov model. For a given level of node mobility, we observe that as we increase the network density, the lifetime of the minimum hop routes under both the mobility models decreases. The decrease is attributed to the decrease in the hop count of the paths with increase in node density. It was possible to get the source and destination connected through paths of lower hop count, but the physical distance between the constituent nodes of the hops in such minimum hop paths is close to the transmission range of the nodes in the network. For a given level of node mobility, as we triple the number of nodes in the network from 25 to 75, the lifetime of the minimum hop routes determined under the Gauss-Markov model decreases by 18%-22%; whereas the lifetime of the minimum hop routes determined under the RWP model decreases by 12%-14%.

C. Stable Mobile Path

We now discuss the average route lifetime (refer Figure 5) and the time averaged hop count (refer Figure 6) of the stable paths determined as the constituent paths of the Stable Mobile Path under the two mobility models.

C.1 Average Lifetime per Stable Path

When we aim for the maximum route lifetime and determine the Stable Mobile Path using algorithm OptPathTrans, routes determined under the RWP model are relatively more stable (i.e., have a longer route lifetime) for all the simulation conditions. This can be again attributed to the unconstrained mobility of the nodes in all directions and the algorithm makes best use of this feature. For a given level of node mobility, the average lifetime of the stable routes determined under the RWP model is about 50%-65% and 35%-50% more than the lifetime of stable routes determined under the Gauss-Markov model in low density and high density networks respectively. The relatively higher stability of the routes under the Gauss-Markov model in high-density networks can be attributed to the increased chances of finding nodes that travel in a temporally dependent fashion.

For a given level of node mobility, the lifetime of the stable routes under both the mobility models improves as the network density is increased. Algorithm OptPathTrans makes use of the increased availability of nodes in the network to find stable paths that exist for a relatively longer time. The physical distance between the constituent links of a hop in such stable paths is only about 50%-70% of the transmission range of the nodes. The constituent nodes of the hop are likely to remain as neighbors for a longer time, leading to increase in the route lifetime, but at the cost of increase in the hop count.

With the Gauss-Markov model, long-living routes are obtained by adopting larger intermediate values of $\alpha$ (i.e., $\alpha$ values of 0.6 to 0.8), but not unity. Thus a small level of randomness is required to occasionally deflect nodes from their linear path so that the nodes continue to remain as neighbors with a larger probability and do not move far away from each other. If the nodes strictly take a linear path, it is possible for them to move away from each other relatively sooner. For lower values of $\alpha$, the degree of randomness increases and the number of link changes increases significantly. Nevertheless, the lifetime of stable routes determined for lower values of $\alpha$ is not significantly smaller than those obtained for $\alpha$ values in the range of 0.6 to 0.8 and is almost close to the lifetime values obtained when $\alpha$ is unity.

C.2 Average Hop Count per Stable Mobile Path

As we aim for highly stable routes, algorithm OptPathTrans makes use of the less dynamic nature of the low and moderate node mobility networks and determines paths with relatively longer lifetime. The physical distance between the constituent nodes of every hop in the stable paths determined for the Random Waypoint model is about 50%-60% and for the Gauss-Markov model is about 60%-70% of the transmission range of the nodes at the time of route determination. As a result, more intermediate nodes with a relatively longer link lifetime have to be accommodated in order to connect the source and destination. Thus, in networks of low and moderate mobility, paths with longer lifetime are determined at the expense of hop count. This illustrates the tradeoff between route stability and hop count. But, in high node mobility networks, the chances of finding long-living stable paths by accommodating intermediate nodes with longer link lifetime decreases. Hence, we observe a relative decrease in the hop count of the stable paths determined for high node mobility networks.

For a given level of node mobility, the average hop count per path increases with increase in network density. As we add more nodes to the network, algorithm
OptPathTrans attempts to make use of these additional nodes and find more stable paths. This coincides with the relatively longer lifetime of the stable paths determined by the algorithm in high-density network conditions. In low-density networks, for a given node mobility, the average hop count of the stable routes determined under the Random Waypoint mobility model is about 10% more than that incurred with the Gauss-Markov model. On the other hand, for moderate and high-density networks, the average hop count of the stable routes determined under the Random Waypoint model is about 10%-15% less than those incurred with the Gauss-Markov mobility model.

D. Route Lifetime – Hop Count Tradeoff

We observe a tradeoff between the objectives of optimizing route lifetime and hop count for both the mobility models. Both of these performance metrics cannot be optimized at the same time. For a given simulation condition of network density and node mobility, the average hop count of a Minimum Hop Mobile Path is smaller than the average hop count of a Stable Mobile Path; the average route lifetime of a Stable Mobile Path is more than the average route lifetime of a Minimum Hop Mobile Path.

Overall, the general trend of the lifetime-hop count tradeoff is that for a given node mobility condition, when we increase the network density, the static paths of an SMP have a relatively longer route lifetime at the expense of an increase in the hop count. Figure 7 captures this tradeoff for both the mobility models by illustrating the range of the ratio of the average hop counts of the SMP and MHMP and the range of the ratio of the average route lifetime of the static paths in SMP and MHMP. Larger the ratio, the larger the stability-hop count tradeoff. As observed in the figure, the ratio of the hop counts is relatively lower under the Gauss-Markov model in low-density networks and almost matches with that of the RWP model in high-density networks. The ratio of the route lifetimes is lower under the Gauss-Markov mobility model and higher under the Random Waypoint model in both low and high density networks.

VI. CONCLUSIONS AND FUTURE WORK

The Random Waypoint mobility model provided larger connectivity among nodes in low-density networks compared to the Gauss-Markov mobility model. The connectivity provided by both the mobility models is almost the same for moderate and high-density networks. In low-density networks, relatively larger network connectivity is attained for intermediate values of the degree of randomness parameter \( \alpha \). The average hop count per minimum hop path determined for the Gauss-Markov mobility model is considerably larger than those determined under the Random Waypoint mobility model. The degree of randomness in the Gauss-Markov model does not significantly influence the average hop count of the minimum hop paths in the network. The minimum hop paths determined under the Gauss-Markov mobility model are relatively less stable (i.e., have a smaller route lifetime) compared to those determined under the Random Waypoint model. The stable routes determined under the Random Waypoint model have a relatively longer lifetime for all the simulation conditions.

We observe a tradeoff between the objectives of optimizing route lifetime and hop count for both the mobility models. It is unlikely that both of these performance metrics can be optimized at the same time. For a given simulation condition of network density and node mobility, the average hop count of a Minimum Hop Mobile Path is smaller than the average hop count of a Stable Mobile Path; the average route lifetime of a Stable Mobile Path is more than the average route lifetime of a Minimum Hop Mobile Path. We also observe that in the
case of the Gauss-Markov model, one can determine long-living routes by adopting larger intermediate values of $\alpha$ (i.e., $\alpha$ values of 0.6 to 0.8). A certain degree of randomness is required for the nodes to get deflected and move in the vicinity of each other for relatively little longer. If the nodes strictly take a linear path, they could move away from each other relatively sooner.

As future work, we plan to conduct an extensive simulation analysis of the well-known minimum hop-based and stability-based MANET routing protocols under the Gauss-Markov mobility model and the Random Waypoint mobility model and establish a ranking of these protocols with respect to different performance metrics. It would be interesting to observe whether the protocol rankings for different performance metrics remain the same or not under both the mobility models.

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BIOGRAPHY

Dr. Natarajan Meghanathan is currently working as Assistant Professor of Computer Science at Jackson State University, Mississippi, USA, since August 2005. Dr. Meghanathan received his MS and PhD in Computer Science from Auburn University, AL and The University of Texas at Dallas in August 2002 and May 2005 respectively. Dr. Meghanathan’s major area of research is ad hoc networks. He has more than 40 peer-reviewed publications in leading international journals and conferences in this area. Recently, Dr. Meghanathan received a 3-year grant from the National Science Foundation (NSF) to host a Research Experiences for Undergraduates (REU) site at Jackson State University in the area of Wireless Ad hoc Networks and Sensor Networks. He also received a 1-year grant from the Army Research Laboratory (ARL) to develop routing protocols that would minimize the number of route disconnections in mobile ad hoc networks. Dr. Meghanathan won the best paper award for his paper on the stability of multicast Steiner trees at the 2006 ACM Southeast Conference in Melbourne, FL. Besides ad hoc networks, Dr. Meghanathan is currently conducting active research in the areas of network security, sensor networks, graph theory and bioinformatics. He is also serving in the Editorial Board of several international journals and in the Technical Program Committee of several international conferences in the area of Computer Networks.