Path Selection Algorithms in Homogeneous Mobile Ad Hoc Networks

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***Abstract*— Because of connectivity richness in mobile ad hoc networks, there often exist multiple paths between a source and a destination. Since many applications require uninterrupted connectivity of a session, the ability to find long-living paths can be very useful. In this paper, we propose three path-selection algorithms and evaluate their performance in a homogeneous network based on two criteria: 1) the selected path is the most likely to meet a target residual path lifetime requirement, and 2) the selected path has the longest residual path lifetime among all the available paths. We also develop two performance metrics (PMs) to compare the proposed algorithms among themselves and with a baseline random-selection algorithm. Our study shows that all three algorithms demonstrate comparable performance in satisfying the first criterion, although the first algorithm performs consistently better than the other two for both criteria. As the path-set size increases, the proposed algorithms yield even greater performance gain over the baseline algorithm. Furthermore, we show that these algorithms perform better in a high-mobility environment than in a low-mobility one.**

I. Introduction

Recent advances in Mobile Ad Hoc Network (MANET) research have generated a growing interest in carrying multimedia-intensive traffic in such a network. Multimedia traffic is known to require more stringent performance of data loss, packet delay, delay jitter, etc., in order to ensure an acceptable quality of service (QoS).

The provisioning of QoS in a MANET presents both challenges and opportunities. On the one hand, the dynamic network topology leads to frequent link breakdowns as all the nodes are mobile. This makes the path maintenance operations such as failure notifications and path rediscovery very costly. Furthermore, if an alternative path cannot be established in a timely manner while a traffic session is ongoing, data loss occurs. On the other hand, because of the relatively high density of mobile nodes in the MANET, and thus connectivity richness, multiple paths often exist between a source-destination pair. This has prompted researchers to study multi-path routing as a promising technique for supporting QoS in MANET (see, for example, [2], [6], [8], [9], [12], and [13]).

A typical path in the MANET consists of multiple hops, and is therefore prone to frequent breakage. In many applications, it may be desirable to judiciously select, from all available paths, one that best serves the requirement to carry data packets. For example, one may wish to choose a path that consists of nodes with the largest average battery power. In our research, we associate the desirability of a path with its remaining (residual) lifetime. In designing the path-selection algorithm, we take into consideration the impact of node mobility (i.e., mobility-induced)[1] on the *residual path lifetime* (RPL), which is defined as the duration from the time the path is first discovered to the time when any one of its links breaks.

This paper is organized as follows. Section II provides relevant background information for our study. Section III proposes three path selection algorithms that base their selection decisions on the mobility-induced residual path lifetime. We then introduce two performance metrics in Section IV and use those metrics for evaluation of these algorithms. Section V discusses some future work we plan to undertake. Finally, Section VI concludes the paper.

II. Background

Many of the proposed MANET routing protocols in the literature have limited provisioning for QoS and use paths discovered without regard to path reliability or longevity. Possessing *a priori* knowledge of the mobility-induced RPL in a path-selection algorithm will reduce the overhead as a result of fewer path failure notifications and of less need for path re-discovery. This in turn will make better use of the scarce bandwidth in the network.

The study of path selection based on mobility-induced RPL is a largely unexplored research field. Because of the difficulty in accurately modeling the multi-hop path, most published work takes the approach of extending the results of individual link lifetime to evaluate the overall path lifetimes. For example, Gerharz et. al. [3] proposed two methods to identify the "stable" links from several available links. Unfortunately, due to the correlation between adjacent links on a path, this approach often does not produce sufficiently good results.

One measure in assessing the stability of a link is the length of the *link age*, defined as the duration between the

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[1] "mobility-induced" means that the residual lifetime of a path is affected only by link breakage caused by nodes moving out of transmission range of each other.

first moment a link is established until the observation time, assuming that at that time the link is still up.[2] There are generally two approaches to selection of links based on their age: one favoring the use of younger links and the other advocating the choice of older ones. Gerharz et. al.[4] examined the relationship between the age of link and its residual lifetime, based on which they proposed several methods to discover a stable path. One of their proposed algorithms finds a path whose age is below a certain threshold, although the threshold in their paper appears to be an arbitrarily chosen one. On the other hand, some routing protocols such as the Associativity-Based Routing (ABR) [14] consider older links to be more stable on the grounds that a link is likely to stay alive for a longer time period if it has already existed beyond a threshold time. However, we note that this assertion may only be applicable to certain mobility models, such as the Gauss-Markov mobility model [7]. In our study, we consider that the choice of a link with an appropriate age, neither too young, nor too old, is very important in assessing its stability.

In order for a path-selection algorithm to be applicable to a wide range of mobility scenarios, its decision-making operations should be independent of the mobility attributes. For example, the random waypoint mobility model uses *pause time* for a node as a mobility attribute [1], which dictates how long a node may pause before moving on to the next destination. This attribute value has a significant impact on the dynamics of the network topology [5]. It will not be prudent for the algorithm to make path-selection decisions based on the length of the pause time, since in practice, a mobile node is usually not able to measure this pause time. Similarly, choosing one value for the pause time will cause algorithm to perform unsatisfactorily in a mobility environment with a different pause time. As a guiding principle for our research, a path-selection algorithm should base its path-selection decisions only on information that can be empirically observed by the mobile node. Furthermore, it should be able to do so with rudimentary hardware/software support in each node.

III. Proposed Path Selection Algorithms

We propose three path-selection algorithms that select the best path from a set of available paths. In defining "best", we consider the following two criteria:

1) the chosen path is most likely to meet a target residual path lifetime requirement, or
2) the chosen path has the longest residual path lifetime.

When invoking the algorithms, we assume the paths are discovered *a priori*. At present, we consider only paths that are node-disjoint, that is, paths do not shares common links or intermediate nodes. Such paths have the property that the failure of one path is independent of the others. [3]

Before we introduce the algorithms, we first present a simple statistic-collecting mechanism that would be used in two of the three algorithms.

[2] In our research, we consider that a link is established when two nodes move into the transmission range of each other. The link remains up until the time when the two nodes move out of each other's transmission range.

[3] Of course, the source and the destination nodes are the same in all these paths.

A. A Statistical FLL-Collecting Mechanism

Analytically computing the *full link lifetime* (FLL) in a mobility model is computationally intensive and requires sophisticated HW/SW support(see, e.g., [10] and [11]). Instead, we employ a simple mechanism in each node that collects empirical FLL statistics, based on which an algorithm makes path-selection decisions. A node A periodically broadcasts a beacon to identify itself. A neighbor node B which hears this beacon assumes there is a link from A to B. The FLL is therefore the entire duration between the first and last time Node B hears Node A's beacon. Each node continuously collects FLL statistics in this fashion until a sufficient number of FLLs has been collected. The generated FLL statistic is then used to create a histogram. From this point on, path-selection algorithms may be invoked using this histogram. A similar scheme was also used by Gerharz et. al. [4] in their work.

In our simulations, all the nodes operate under the same mobility model with the same set of mobility attribute values. This makes the network homogeneous, where a similar FLL histogram will be computed at each node. This mechanism is used differently in two of our three proposed path-selection algorithms.

B. Path Selection Algorithm I (PSA1)

During the initial phase of the network deployment, each mobile node collects FLL statistics to construct an FLL histogram. After a set Ψ of disjoint paths is discovered at the destination (using, e.g., Split Multi-path Routing [6]), each upstream node j along an L_i-hop path i, where $i \in \{1, \cdots, |\Psi|\}$ and $j \in \{1, \cdots, L_i\}$, computes the probability that the link with its downstream neighbor k, denoted as $l^i_{(j,k)}$, has a residual lifetime of at least $\tau[sec]$ given its current age t^i_{jk}. The link age is easily obtained by counting the number of times Node j has heard the beacon from Node k. Denote $\tilde{T}^i_{jk}$ as the random variable of the residual lifetime of Link $l_{(j,k)}$ of Path i, and T^i_{jk} the corresponding full link lifetime. The following relation holds: $T^i_{jk} = \tilde{T}^i_{jk} + t^i_{jk}$. The required probability can be computed as:

$$\begin{aligned} p^i_{jk}(\tau) = P\{\tilde{T}^i_{jk} \geq \tau | t^i_{jk}\} &= P\{T^i_{jk} \geq \tau + t^i_{jk} | t^i_{jk}\} \\ &= \frac{P\{T^i_{jk} \geq \tau + t^i_{jk}\}}{P\{T^i_{jk} \geq t^i_{jk}\}} \end{aligned} \tag{1}$$

The numerator and denominator in the third equality of Eq. 1 can be numerically computed from the FLL histogram that each node keeps. Node j then reports p^i_{jk} to the source node via the means of RouteReply (RREP) packets. Upon receiving the RREP, the source computes the probability of Path i's residual lifetime being at least τ, denoted $p_i(\tau)$, as follows:

$$p_i(\tau) = \prod_{i=1}^{L_i} \{p^i_{jk}(\tau)\}, \qquad i \in \{1, \cdots, |\Psi|\} \tag{2}$$

Here, we make a simplified assumption that the residual link lifetimes along the path are treated as independent random variables. In reality, this is not true as correlation exists between two adjacent links that are incident on the same node.

Nevertheless, we make this assumption since it is very difficult to incorporate the correlation factor in a multi-hop path.

The decision of selecting the path with the highest probability of meeting the target RPL of $\tau[sec]$ is then given by:

$$i^* = \arg\max_i \{p_i(\tau)\} \tag{3}$$

If more than one path has the same $p_i(\tau)$, the shortest path (in hops) is chosen as i^*.

C. Path Selection Algorithm II (PSA2)

As the destination discovers a set Ψ of paths each with length $L_i[hops]$, for each path it sends back to the source in the reverse direction of a path an RREP packet. Each node that receives the RREP packet includes in it the age of the link between itself and its downstream neighbor. The node then passes on the packet to its predecessor on the path. When the source node receives the RREP, it now knows the age information of the path's constituent links. We define the *path age* of a Path i to be the age of the youngest link of the path:

$$a_i = \min\{a^i_j : j = 1, \cdots, L_i\} \tag{4}$$

The path-selection algorithm then chooses the path with the minimum age:

$$i^* = \arg\min_i \{a_i : i = 1, \cdots, |\Psi|\} \tag{5}$$

This simplistic path-selection algorithm, therefore, is based on the assertion that a younger path should have a longer residual path lifetime. When more than one path has the same path age, the shortest one in chosen as i^*.

D. Path Selection Algorithm III (PSA3)

The third path-selection algorithm is based on the contention that a good multi-hop path should be composed of links that are neither too old nor too young. For each link j on Path i, we know its current age, denoted as a^i_j. The expected full lifetime of Link j given a^i_j is then given by:

$$t^i_j = \frac{\int_{a^i_j}^{\infty} t f_T(t) dt}{\int_{a^i_j}^{\infty} f_T(t) dt}, \tag{6}$$

where $f_T(t)$ is the probability density function of the full link lifetime as observed by Node j, and it can be obtained from the statistical FLL histogram.[4] With t^i_j, Link j is assigned a *link grade* G^i_j. The link grades are assigned with respect to the FLL group that t^i_j falls into, which are defined as follows:

1) if $t^i_j \in (0,\ \tilde{\mu}^i_j - \tilde{\sigma}^i_j/2)$, $G^i_j =$ SOSO;
2) if $t^i_j \in (\tilde{\mu}^i_j - \tilde{\sigma}^i_j/2,\ \tilde{\mu}^i_j + \tilde{\sigma}^i_j/4)$, $G^i_j =$ EXCELLENT;
3) if $t^i_j \in (\tilde{\mu}^i_j + \tilde{\sigma}^i_j/4,\ \tilde{\mu}^i_j + \tilde{\sigma}^i_j)$, $G^i_j =$ GOOD;
4) if $t^i_j > \tilde{\mu}^i_j + \tilde{\sigma}^i_j$, $G^i_j =$ POOR.

In descending order of the link grade, EXCELLENT $>$ GOOD $>$ SOSO $>$ POOR, and $\tilde{\mu}^i_j$ and $\tilde{\sigma}^i_j$ denote the sample mean and standard deviation, respectively, that are computed by using the FLL histogram. Note that the values that we have chosen to define the boundaries of the FLL groups are obtained by observing the distribution of the FLL in simulation scenarios. In practice, how to define the FLL groups is still an open problem that deserves further investigation.

[4]Note that for this algorithm nodes on the path are numbered 1 through $L+1$, where L is the path length in hops.

When the source receives the RREP and obtains its computed link grade for the link with its downstream neighbor, it finds the worst link grade (WLG) and best link grade (BLG) and assigns the entire path a path grade G_i. We propose two path-grade assignments. In the first, conservative path-grade assignment, the worse of the two link grades is selected as the path grade. In the second, liberal path-grade assignment, the better of the two is selected as the path grade. Once every path i in Ψ has been assigned its G_i, the source chooses the one with the highest grade:

$$i^* = \arg\max_i \{G_i\}, \qquad \forall i \in \Psi \tag{7}$$

If more than one path has the same path grade, the one with the fewest hops is selected as i^*.

Parameters	Values
Network Size$[m^2]$	800 x 800
Num. of Nodes	100
TX Range[m]	150
Min. Speed [m/s]	42.5(5)
Max. Speed [m/s]	57.5 (20)
Path-set Size [paths/set]	2, 3, 4, 5
Node Velocity Update Interval [sec]	10
Target Residual Lifetime [sec]	1.25 (5)

TABLE I

SIMULATION PARAMETERS FOR PERFORMANCE EVALUATION.

IV. PERFORMANCE EVALUATION

Table I shows the simulation parameters used to construct the simulated network. All the nodes move with the random mobility (RM) model. In this model, each node independently and randomly chooses the speed and direction of the node, then travels for a constant time duration. At the end of this time period, the node, without pause, randomly chooses a new speed and direction, and repeats the above procedures. The node-disjoint path set is discovered by a *multi-path Dijkstra's algorithm* in our simulation. Treating the network from a graph-theoretic point of view, each time a path is found using Dijkstra's algorithm, all the intermediate nodes and links incident on them are removed from the graph, and the Dijkstra's algorithm is employed again to find the next path in the residual graph.

We have shown previously through simulations that from a set of available paths, the shortest path tends to have a longer residual path lifetime than any longer path [5]. A path-selection algorithm that simply chooses the shortest path from all available paths can generally achieve good performance. However, such an algorithm fails to handle situations in which some of the discovered paths are of equal length. Therefore, the performance evaluation below focuses on the special case of equal-length path sets.

A. Performance Metrics

We develop two performance metrics to evaluate the effectiveness of the proposed algorithms. It is worth noting, first of all, that evaluating their ability to find a path that meets the target RPL requirement is not as straightforward as it appears. The target RPL is a system parameter in our simulation. If it is set too high, it is likely that none of the paths would meet this requirement; likewise, if the target RPL is set too low, all the paths would likely meet this requirement. Therefore, some adaptive normalization must be built into the performance metrics in order to compensate for the arbitrary choice of the target RPL and make the evaluation meaningful.

In the first performance metric (PM1), we compare each proposed algorithm with a baseline *random-selection* algorithm to evaluate the former's ability to find a path that meets the target RPL requirement τ. The baseline algorithm arbitrarily selects a path from Ψ *only if* at least one path in Ψ meets the target RPL requirement. We devise two path-selection reward schemes, one for the proposed algorithm, and the other for the baseline algorithm. Denote the path selected by the proposed algorithm as i^*. For the k-th experiment during the simulation, the reward scheme for the proposed algorithm making a path-selection decision is defined as:

$$D_k = \begin{cases} 1 & , \quad T_{i^*} \geq \tau \\ 0 & , \quad o.w. \end{cases} \tag{8}$$

where T_{i^*} denotes the actual residual lifetime of i^*. The reward scheme for the baseline algorithm is defined as:

$$E_k = \begin{cases} 0 & , \quad T_i < \tau \quad \forall i \in \Psi \\ \frac{1}{|\Psi|} & , \quad o.w. \end{cases} \tag{9}$$

Denote N_Ψ as the total number of path-selection decisions for path-set size Ψ made during the simulation. PM1, denoted as γ_1, is therefore defined as follows:

$$\gamma_1 = \frac{\sum_{k=1}^{N_\Psi} D_k}{\sum_{k=1}^{N_\Psi} E_k} \ . \tag{10}$$

The denominator of Eq. 10 is the average number of times the baseline algorithm finds a path that meets the target RPL *in the long run*, thereby making $100(\gamma_1 - 1)\%$ the performance gain of the proposed algorithm over the baseline algorithm. It can be seen that the range of values γ_1 takes on is $0 \leq \gamma_1 \leq |\Psi|$.

The second performance metric (PM2) evaluates the ability of the proposed algorithm to choose the path with the longest residual lifetime. Since all the paths in Ψ are node-disjoint, the probability of randomly selecting a path from Ψ that has the longest residual lifetime is $1/|\Psi|$. In the simulation, an algorithm selects a path i^* from Ψ, and all the nodes continue moving until the last path breaks. If it is i^* that breaks the last, the selection decision made by the algorithm is called a success. Denote $N_{\Psi,s}$ as the number of successes for path-set size Ψ in the simulation. PM2, denoted by γ_2, is defined as:

$$\gamma_2 = \frac{\frac{N_{\Psi,s}}{N_\Psi}}{\frac{1}{|\Psi|}} = \frac{|\Psi| N_{\Psi,s}}{N_\Psi} \ . \tag{11}$$

The range of PM2 is $0 \leq \gamma_2 \leq |\Psi|$, with a larger value indicating a greater gain of the proposed algorithm over the baseline algorithm.

B. Simulation Results

We generate a number of simulation scenarios that apply the PMs to each of the three proposed path-selection algorithms. For each scenario, $10,000$ statistics are collected to compute the PMs. In order to maintain consistency of the results, all the algorithms perform path-selection operations using the same statistical data as input. Note that in evaluating PSA3, the conservative approach, as explained in Section III-D, is adopted to assign path grades.

Figs. 1, 2, and 3 plot the PM1 of PSA1, PSA2, and PSA3, respectively, as a function of $|\Psi|$, for path lengths $2[hops]$, $3[hops]$, and $4[hops]$, with node speed uniformly distributed between $42.5[m/s]$ and $57.5[m/s]$ (i.e., a high-mobility environment), and a target RPL of $1.25[sec]$. Given a fixed path length, each proposed algorithm achieves more substantial performance gain with increasing $|\Psi|$ (e.g., PSA1 achieves a gain of 100% for three-hop paths when $|\Psi| = 4$). The increased gain is contributed by the inability of the baseline algorithm to make better decisions as the path-set size grows. On the other hand, as the path length increases, the performance of the proposed algorithms degrades. For longer paths, the performance of each of the proposed algorithm approaches that of the baseline algorithm. Of the three proposed algorithms, PSA1 outperforms the other two to meet the target RPL requirement as $|\Psi|$ increases, and PSA2 slightly performs better than PSA3 for paths three hops and longer.

Figs. 4, 5, and 6 demonstrate the behavior of PM2 in the three PSAs with increasing path-set size. For PSA1 and PSA2, there is a discernable trend that these two algorithms' performance increases with increasing Ψ. When $|\Psi| = 5$, both algorithms have a performance gain of over 50% and 40%, respectively, over the baseline algorithm. Again, PSA1 outperforms PSA2 and PSA3 in achieving the greatest gain over the baseline algorithm. Furthermore, its performance gain is least impacted by path length. PSA3 performs the worst compared with the other two. This is because of the non-optimized partitioning of the FLL groups used in the simulation, which is a source of future research.

We also evaluate the performance of the proposed algorithms by comparing γ_1 and γ_2 obtained in simulation with their theoretical upper bounds (i.e., $|\Psi|$). We define the ratio of γ_i to $|\Psi|$, where $i = 1, 2$, to be the *metric efficiency* of Performance Metric i. Using Fig. 1 as an illustration, when the path length is fixed at $2[hops]$, the efficiencies for PM1 with $|\Psi| = 2, 3, 4, 5$, are 75.21%, 67.5%, 64.4%, and 63.4%, respectively. That is, although the proposed algorithm performs better compared with the baseline algorithm with increasing $|\Psi|$, at the same time the metric efficiency deviates further from the upper bound of the performance. Similarly, by fixing the path-set size, the metric efficiency decreases as the path length increases.

The above evaluation method may also be applied to compute the metric efficiency for PM2. Since the best that any

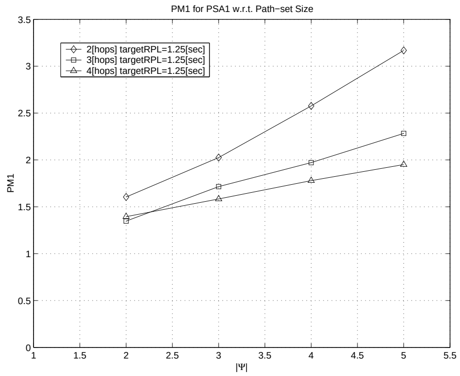

Fig. 1. Performance Metric 1 for Path Selection Algorithm 1

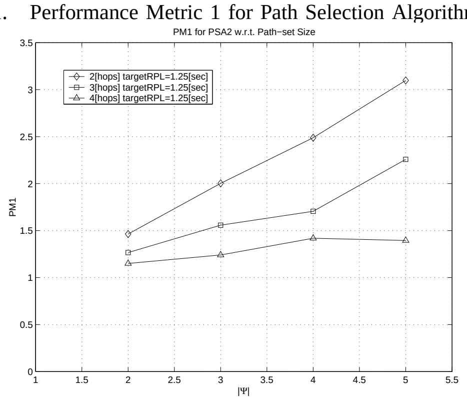

Fig. 2. Performance Metric 1 for Path Selection Algorithm 2

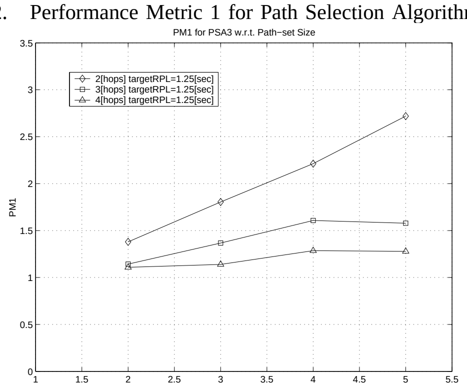

Fig. 3. Performance Metric 1 for Path Selection Algorithm 3

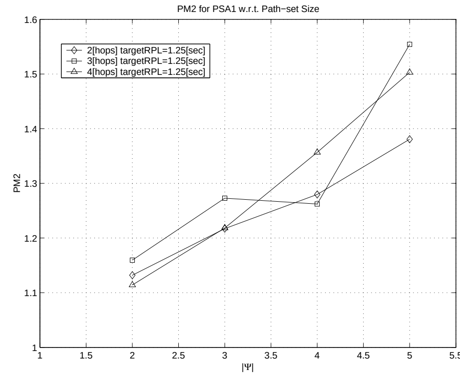

Fig. 4. Performance Metric 2 for Path Selection Algorithm 1

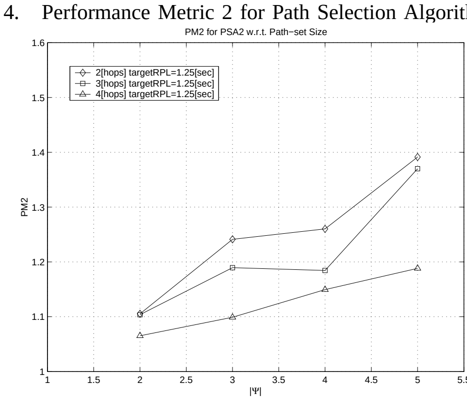

Fig. 5. Performance Metric 2 for Path Selection Algorithm 2

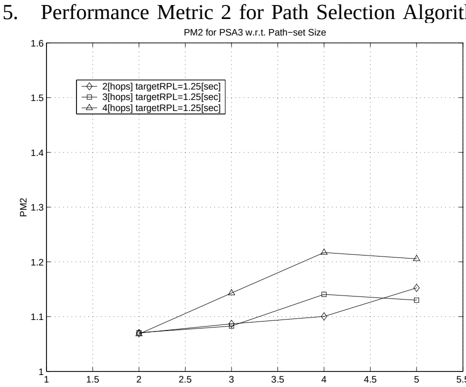

Fig. 6. Performance Metric 2 for Path Selection Algorithm 3

algorithm can do is to achieve 55% performance gain over the baseline algorithm Fig. 4 with $|\Psi| = 5$ and path length $3[hops]$), which is greatly below the theoretical upper bound, it implies that it is much more difficult to select a path that has the longest RPL than to select one most likely to meet the target RPL requirement.

Fig. 7 demonstrates the difference in PM1 when PSA1 is used for two different mobility scenarios of the random mobility model: in one, the average node speed is $50[m/s]$ (in solid lines in the figure), and in the other, the average node speed is $12.5[m/s]$[5] (in dash lines), and the target RPL for the latter is $5[sec]$ (a four-fold increase because the average node speed is one-quarter that for the former). The algorithm's performance is consistently better at high average speed than at low average speed. Similar results are observed for the other two algorithms as well. This shows that these algorithms perform better in a high-mobility environment than in a low-mobility one.

Another interesting observation from the simulation results above is that PSA2 has comparable performance to PSA3 in both the path-selection criteria. Although its performance suffers a little compared with PSA1, PSA2 is a very simple and straightforward algorithm that, unlike PSA1 and PSA3, does not rely on the construction of a FLL histogram in each node; all it requires is the beacon mechanism. This means that PSA2 can be invoked as soon as the network is deployed, without undergoing the initial FLL-collecting phase.

[5]The relevant simulation parameters for the $12.5[m/s]$ average speed are parenthesized in Table I.

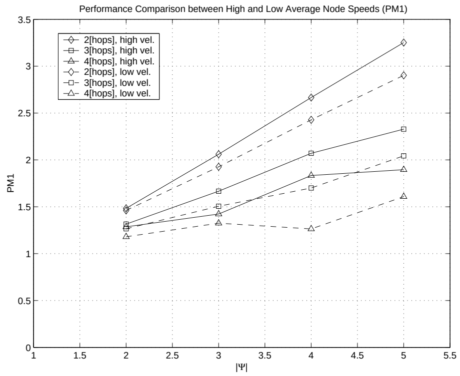

Fig. 7. Difference in PM1 using PSA1 with different average node speeds

V. Future Work

Selecting the best path from all the available paths based on mobility-induced residual path lifetime is, to the best of our knowledge, a largely unexplored area of study in MANET research. One of the strengths of the proposed algorithms is that it does not require any sophisticated HW/SW. This simplicity, however, imposes some fundamental limitation on their performance. Our preliminary investigation shows this limitation may be related to the shape of the probability density function of FLL, in which the density of a very large range of FLLs may be approximately modeled by the memoryless exponential distribution, which implies that any prediction for FLL that falls in this range given current link age may not be possible. The true cause of this fundamental limitation is currently under further research.

For the PSA3, where we consider a path that consists of links neither too old and too young, there are some open issues to be studied. In particular, we wish to study how to optimally define the boundaries of different FLL groups in a mobile environment that would allow PSA3 to yield better performance.

Furthermore, we are studying new approaches to collect empirical link lifetime statistics that will aid the decision making of path selection, and are working on a new algorithm to investigate its performance potential. We are also developing a testing mechanism that would allow us to evaluate the performance of the class of age-based path-selection algorithms expediently over a wide range of mobility scenarios.

VI. Conclusion

Selecting the best path from all the available paths based on mobility-induced RPL is a relatively unexplored new area of study. In this paper, we propose three simple, implementable path-selection algorithms that are aimed at making intelligent path-selection decisions to choose the best one from a path set. By "best," we mean either a path is most likely to meet a requirement for desired residual path lifetime, or that it is most likely to have the longest residual lifetime among all paths in the path set.

We evaluate the performance of the proposed algorithms with respect to two path-selection criteria which we have introduced, by introducing two performance metrics for the criteria. The algorithms are compared with each other and with a baseline random-selection algorithm, which arbitrarily chooses any one of the available paths. Our simulations show that the proposed algorithms have comparable performance among themselves, with PSA1 achieving the best performance with respect to the two criteria. The performances of all three algorithms over the baseline algorithm improve as the size of the path set increases. Furthermore, we showed in simulation that these algorithms perform better in a high-mobility environment than in a low-mobility one.

For future work, we wish to improve the performance of PSA3 presented in this paper. We also want to investigate the cause of the fundamental limitation on the performance of the proposed algorithms. Furthermore, we are designing a new path-selection algorithm with a different technique of utilizing link lifetime statistics collected empirically by each node.

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