Mobility and Traffic Adaptive Position Update for Geographic Routing

Quanjun Chen, Salil S. Kanhere, Mahbub Hassan

School of Computer Science and Engineering,

The University of New South Wales, Sydney, Australia

Email: {quanc, salilk, mahbub}@cse.unsw.edu.au

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Abstract

In geographic routing, nodes need to maintain up-to-date positions of their immediate neighbors for making effective forwarding decisions. Periodic broadcasting of beacon packets that contain the geographic location coordinates of the nodes is a popular method used by most geographic routing protocols to maintain neighbor positions. We contend and demonstrate that periodic beaconing regardless of the node mobility and traffic patterns in the network is not attractive from both update cost and routing performance points of view. We propose the *A*daptive Position Update (APU) strategy for geographic routing, which dynamically adjusts the frequency of position updates based on the mobility dynamics of the nodes and the forwarding patterns in the network. APU is based on two simple principles: (i) nodes whose movements are harder to predict update their positions more frequently (and vice versa), and (ii) nodes closer to forwarding paths update their positions more frequently (and vice versa). Our theoretical analysis, which is validated by NS2 simulations of a well known geographic routing protocol, Greedy Perimeter Stateless Routing Protocol (GPSR), shows that APU can significantly reduce the update cost and improve the routing performance in terms of packet delivery ratio and average end-to-end delay in comparison with periodic beaconing and other recently proposed updating schemes. The benefits of APU are further confirmed by undertaking evaluations in realistic network scenarios, which account for localization error, realistic radio propagation and a practical vehicular ad-hoc network that exhibits realistic movement patterns of public transport buses in a metropolitan city.

Index Terms

C.2.1.k Wireless communication, C.2.8.a. Algorithm/protocol design and analysis, C.2.2.d. Routing protocols

I. INTRODUCTION

WITH the growing popularity of positioning devices (e.g. GPS) and other localization schemes [1], geographic routing protocols are becoming an attractive choice for use in mobile ad hoc networks [2], [3], [4], [5]. The underlying principle used in these protocols involves selecting the next routing hop from amongst a node's neighbors, which is geographically closest to the destination. Since the forwarding decision is based entirely on local knowledge, it obviates the need to create and maintain routes for each destination. By virtue of these characteristics, position-based routing protocols are highly scalable and particularly robust to frequent changes in the network topology. Furthermore, since the forwarding decision is made *on the fly*, each node always selects the optimal next hop based on the most current topology. Several studies [2], [3], [6] have shown that these routing protocols offer significant performance improvements over topology-based routing protocols such as DSR [7] and AODV [8].

The forwarding strategy employed in the aforementioned geographic routing protocols requires the following information: (i) the position of the final destination of the packet and (ii) the position of a node's neighbors. The former can be obtained by querying a *location service* such as the Grid Location System (GLS) [9] or Quorum [10]. To obtain the latter, each node exchanges its own location information (obtained using GPS or the localization schemes discussed in [1]) with its neighboring nodes. This allows each node to build a local map of the nodes within its vicinity, often referred to as the *local topology*.

However, in situations where nodes are mobile or when nodes often switch off and on, the local topology rarely remains static. Hence, it is necessary that each node broadcasts its updated location information to all of its neighbors. These location update packets are usually referred to as *beacons*. In most geographic routing protocols (e.g. GPSR [2], [11], [12]), beacons are broadcast periodically for maintaining an accurate neighbor list at each node.

Position updates are costly in many ways. Each update consumes node energy, wireless bandwidth, and increases the risk of packet collision at the medium access control (MAC) layer. Packet collisions cause packet loss which in turn affects the routing performance due to decreased accuracy in determining the correct local topology (a lost beacon broadcast is not retransmitted). A lost data packet does get retransmitted, but at the expense of increased end-to-end delay. Clearly, given the cost associated with transmitting beacons, it makes sense to adapt the frequency of beacon updates to the node mobility and the traffic conditions within the network, rather than employing a static periodic update policy. For example, if certain nodes are frequently changing their mobility characteristics (speed and/or heading), it makes sense to frequently broadcast their updated position. However, for nodes that do not exhibit significant dynamism, periodic broadcasting of beacons is wasteful. Further, if only a small percentage of the nodes are involved in forwarding packets, it is unnecessary for nodes which are located far away from the forwarding path to employ periodic beaconing because these updates are not useful for forwarding the current traffic.

In this paper, we propose a novel beaconing strategy for geographic routing protocols called *Adaptive Position Updates strategy (APU)* [13]. Our scheme eliminates the drawbacks of periodic beaconing by adapting to the system variations. APU incorporates two rules for triggering the beacon update process. The first rule, referred as *Mobility Prediction (MP)*, uses a simple mobility prediction scheme to estimate when the location information broadcast in the previous beacon becomes inaccurate. The next beacon is broadcast only if the predicted error in the location estimate is greater than a certain threshold, thus tuning the update frequency to the dynamism inherent in the node's motion.

The second rule, referred as *On-Demand Learning (ODL)*, aims at improving the accuracy of the topology along the routing paths between the communicating nodes. ODL uses an on-demand learning strategy, whereby a node broadcasts beacons when it overhears the transmission of a data packet from a *new* neighbor in its vicinity. This ensures that nodes involved in forwarding data packets maintain a more up-to-date view of the local topology. On the contrary, nodes that are not in the vicinity of the forwarding path are unaffected by this rule and do not broadcast beacons very frequently.

We model APU to quantify the beacon overhead and the local topology accuracy. The local topology accuracy is measured by two metrics, *unknown neighbor ratio* and *false neighbor ratio*. The former measures the percentage of new neighbors a forwarding node is unaware of but that are actually within the radio range of the forwarding node. On the contrary, the latter represents the percentage of obsolete neighbors that are in the neighbor list of a node, but have already moved out of the node's radio range. Our analytical results are validated by extensive simulations.

In the first set of simulations, we evaluate the impact of varying the mobility dynamics and traffic load on the performance of APU and also compare it with periodic beaconing and two recently proposed updating schemes: distance-based and speed-based beaconing [14]. The simulation results show that APU can adapt to mobility and traffic load well. For each dynamic case, APU generates less or similar amount of beacon overhead as other beaconing schemes but achieve better performance in terms of packet delivery ratio, average end-to-end delay and energy consumption. In the second set of simulations, we evaluate the performance of APU under the consideration of several real-world effects such as a realistic radio propagation model and localization errors. The extensive simulation results confirm the superiority of our proposed scheme over other schemes. In the third set of simulations we evaluate the performance of the beaconing strategies in a real-world vehicular scenario using realistic movement patterns of buses in a metropolitan city. The results indicate that APU significantly reduces beacon overhead without having any noticeable impact on the data delivery rate. The main reason for all these improvements in APU is that beacons generated in APU are more concentrated along the routing paths, while the beacons in all other schemes are more scattered in the whole network. As a result, in APU, the nodes located in the hotspots, which are responsible for forwarding most of the data traffic in the network have an up-to-date view of their local topology, thus resulting in improved performance.

The rest of paper is organized as follows. In Section II, we briefly discuss related work. A detailed description of the APU scheme is provided in Section III, followed by a comprehensive theoretical analysis in Section IV. Section V presents a simulation-based evaluation highlighting the performance improvements achieved by APU in comparison with other schemes. Finally, Section VI concludes the paper.

II. RELATED WORK

In geographic routing, the forwarding decision at each node is based on the locations of the node's one-hop neighbors and location of the packet destination as well. A forwarding nodes therefore needs to maintain these two types of locations. Many works, e.g. GLS [9], Quorum System [10], have been proposed to discover and maintain the location of destination. However, the maintenance of one-hop neighbors' location has been often neglected. Some geographic routing schemes, e.g. [15], [16], [17], simply assume that a forwarding node knows the location of its neighbors. While others, e.g. [2], [11], [12], uses periodical beacon broadcasting to exchange neighbors' locations. In the periodic beaconing scheme, each node broadcasts a beacon with a fixed beacon interval. If a node does not hear any beacon from a neighbor for a certain time interval, called neighbor time-out interval, the node considers this neighbor has moved out of the radio range and removes the outdated neighbor from its neighbor list. The neighbor time-out interval often is multiple times of the beacon interval.

Heissenbuttel et al. [14] have showed that periodic beaconing can cause the inaccurate local topologies in highly mobile ad-hoc networks, which leads to performances degradation, e.g. frequent packet loss and longer delay. The authors discuss that the outdated entries in the neighbor list is the major source that decreases the performance. They proposed several simple optimizations that adapt beacon interval to node mobility or traffic load, including distance-based beaconing, speed-based beaconing and reactive beaconing. We discuss these three schemes in the following.

In the distance-based beaconing, a node transmits a beacon when it has moved a given distance d. The node removes an outdated neighbor if the node does not hear any beacons from the neighbor while the node has moved more than k-times the distance d, or after a maximum time-out of 5s. This approach therefore is adaptive to the node mobility, e.g. a faster moving node sends beacons more frequently and vice versa. However, this approach has two problems. First, a slow node may have many outdated neighbors in its neighbor list since the neighbor time-out interval at the slow node is longer. Second, when a fast moved node passes by a slow node, the fast node may not detect the slow node due the infrequent beaconing of the slow node, which reduces the perceived network connectivity.

In the speed-based beaconing, the beacon interval is dependent on the node speed. A node determines its beacon interval from a predefined range $[a, b]$ with the exact value chosen being inversely proportional to its speed. The neighbor time-out interval of a node is a multiple k of its beacon interval. Nodes piggyback their neighbor time-out interval in the beacons. A receiving node compares the piggybacked time-out interval with its own time-out interval, and selects the smaller one as the time-out interval for this neighbor. In this way, a slow node can have short time-out interval for its fast neighbor and therefore eliminate the first problem presented in the distance-based beaconing. However, the speed-based beaconing still suffer the problem that a fast node may not detect the slow nodes.

In reactive beaconing, the beacon generation is triggered by data packet transmissions. When a node has a packet to transmit, the node first broadcasts a beacon request packet. The neighbors overhearing the request packet respond with beacons. Thus, the node can build an accurate local topology before the data transmission. However, this process is initiated prior to each data transmission, which can lead to excessive beacon broadcasts, particularly when the traffic load in the network is high.

The APU strategy proposed in this work dynamically adjusts the beacon update intervals based on the mobility dynamics of the nodes and the forwarding patterns in the network. The beacons transmitted by the nodes contain their current position and speed. Nodes estimate their positions periodically by employing linear kinematic equations based on the parameters announced in the last announced beacon. If the predicted location is different from the actual location, a new beacon is broadcast to inform the neighbors about changes in the node's mobility characteristics. Note that, an accurate representation of the local topology is particularly desired at those nodes that are responsible for forwarding packets. Hence, APU seeks to increase the frequency of beacon updates at those nodes that overhear data packet transmissions. As a result, nodes involved in forwarding packets can build an enriched view of the local topology.

There also exist some geographic routing protocols that do not need to maintain the neighbor list and therefore can avoid position updates, e.g. IGF [18], GeRaf [19], BLR [20], ALBA-R [21]. These protocols are commonly referred to as beacon-less routing protocols. The main ideal is that, the forwarding node broadcasts the data packet to all its neighbors who then distributedly decide which node relays the packet. Normally, in these protocols, after receiving a packet, each neighbor sets a timer for relaying the packet based on some metrics, e.g., the distance to the destination. The neighbor that has the smallest timer will expire first and relay the packet. By overhearing the relayed packet, other neighbors can cancel their own timers and ensure that no duplicate packet is transmitted. Hence, the beacon-less routing protocols can certainly avoid position updates. However, these schemes incur longer end-to-end delays, often result in duplicate packet transmissions and are not as effective in sparse networks.

III. Adaptive Position Update (APU)

We begin by listing the assumptions made in our work: (1) all nodes are aware of their own position and velocity, (2) all links are bi-directional, (3) the beacon updates include the current location and velocity of the nodes, and (4) data packets can piggyback position and velocity updates and all one-hop neighbors operate in the promiscuous mode and hence can overhear the data packets.

Upon initialization, each node broadcasts a beacon informing its neighbors about its presence and its current location and velocity. Following this, in most geographic routing protocols such as GPSR, each node periodically broadcasts its current location information. The position information received from neighboring beacons is stored at each node. Based on the position updates received from its neighbors, each node continuously updates its local topology, which is represented as a neighbor list. Only those nodes from the neighbor list are considered as possible candidates for data forwarding. Thus, the beacons play an important part in maintaining an accurate representation of the local topology.

Instead of periodic beaconing, APU adapts the beacon update intervals to the mobility dynamics of the nodes and the amount of data being forwarded in the neighborhood of the nodes. APU employs two mutually exclusive beacon triggering rules, which are discussed in the following.

A. Mobility Prediction (MP) Rule

This rule adapts the beacon generation rate to the frequency with which the nodes change the characteristics that govern their motion (velocity and heading). The motion characteristics are included in the beacons broadcast to a node's neighbors. The neighbors can then track the node's motion using simple linear motion equations. Nodes that frequently change their motion need to frequently update their neighbors, since their locations are changing dynamically. On the contrary, nodes which move slowly do not need to send frequent updates. A periodic beacon update policy cannot satisfy both these requirements simultaneously, since a small update interval will be wasteful for slow nodes, whereas a larger update interval will lead to inaccurate position information for the highly mobile nodes.

In our scheme, upon receiving a beacon update from a node i, each of its neighbors records node i's current position and velocity and periodically track node i's location using a simple prediction scheme based on linear kinematics (discussed below). Based on this position estimate the neighbors can check whether node i is still within their transmission range and update their neighbor list accordingly. The goal of the MP rule is to send the next beacon update from node i when the error between the predicted location in the neighbors of i and node i's actual location is greater than an acceptable threshold.

We use a simple location prediction scheme based on the physics of motion to estimate a node's current location. Note that, in our discussion we assume that the nodes are located in a two-dimensional coordinate system with the location indicated by the x and y coordinates. However, this scheme can be easily extended to a three dimensional coordinate system. Table I illustrates the notations used in the rest of this discussion.

TABLE I: Notations for Mobility Prediction

Variables	Definition
(X_l^i, Y_l^i)	The coordinate of node i at time T_l (included in the previous beacon)
(V_x^i, V_y^i)	The velocity of node i along the direction of the x and y axes at time T_l (included in the previous beacon)
T_l	The time of the last beacon broadcast
T_c	The current time
(X_p^i, Y_p^i)	The predicted position of node i at the current time

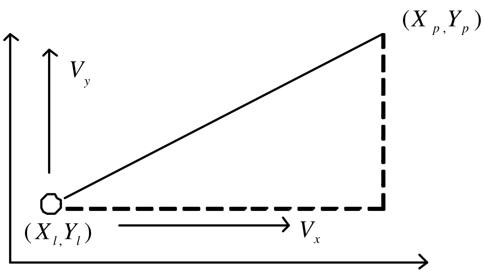


Fig. 1: An example of mobility prediction

As shown in Fig. 1, given the position of node i and its velocity along the x and y axes at time T_l, its neighbors can estimate the current position of i, by using the following equations:

$$\begin{aligned} X_p^i &= X_l^i + (T_c - T_l) * V_x^i \\ Y_p^i &= Y_l^i + (T_c - T_l) * V_y^i \end{aligned} \tag{1}$$

Note that, here (X_l^i, Y_l^i) and (V_x^i, V_y^i) refers to the location and velocity information that was broadcast in the previous beacon from node i. Node i uses the same prediction scheme to keep track of its predicted location among its neighbors. Let (X_a, Y_a), denote the actual location of node i, obtained via GPS or other localization techniques. Node i then computes the deviation D_{devi}^i as follows:

$$D_{devi}^i = \sqrt{(X_a^i - X_p^i)^2 + (Y_a^i - Y_p^i)^2} \tag{2}$$

If the deviation is greater than a certain threshold, know as the *Acceptable Error Range (AER)*, it acts as a trigger for node i to broadcast its current location and velocity as a new beacon.

The MP rule, thus, tries to maximize the effective duration of each beacon, by broadcasting a beacon only when the predicted position information based on the previous beacon becomes inaccurate. This extends the effective duration of the beacon for nodes with low mobility, thus reducing the number of beacons. Further, highly mobile nodes can broadcast frequent beacons to ensure that their neighbors are aware of the rapidly changing topology.

B. On-Demand Learning (ODL) Rule

The MP rule solely, may not be sufficient for maintaining an accurate local topology. Consider the example illustrated in Fig. 2, where node A moves from $P1$ to $P2$ at a constant velocity. Now, assume that node A has just sent a beacon while at $P1$. Since node B did not receive this packet, it is unaware of the existence of node A. Further, assume that the AER is sufficiently large such that when node A moves from $P1$ to $P2$ the MP rule is never triggered. However, as seen in Fig. 2 node A is within the communication range of B for a significant portion of its motion. Even then, neither A nor B will be aware of each other. Now, in situations where neither of these nodes are transmitting data packets, this is perfectly fine since they are not within communicating range once A reaches $P2$. However, if either A or B was transmitting data packets, then their local topology will not be updated and they will exclude each other while selecting the next hop node. In the worst-case, assuming no other nodes were in the vicinity, the data packets would not be transmitted at all.

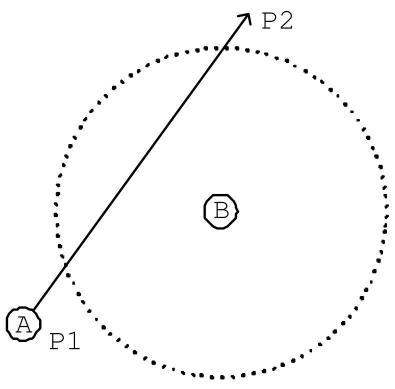


Fig. 2: An example illustrating a drawback of the MP rule

Hence, it is necessary to devise a mechanism, which will maintain a more accurate local topology in those regions of the network where significant data forwarding activities are on-going. This is precisely what the *On-Demand Learning (ODL)* rule aims to achieve. As the name suggests, a node broadcasts beacons *on-demand*, i.e. in response to data forwarding activities that occur in the vicinity of that node. According to this rule, whenever a node overhears a data transmission from a *new* neighbor, it broadcasts a beacon as a response. By a *new* neighbor, we imply a neighbor who is not contained in the neighbor list of this node. In reality, a node waits for a small random time interval before responding with the beacon to prevent collisions with other beacons. Recall that, we have assumed that the location updates are piggybacked on the data packets and that all nodes operate in the promiscuous mode, which allows them to overhear all data packets transmitted in their vicinity. In addition, since the data packet contains the location of the final destination, any node that overhears a data packet also checks its current location and determines if the destination is within its transmission range. If so, the destination node is added to the list of neighboring nodes, if it is not already present. Note that, this particular check incurs zero cost, i.e. no beacons need to be transmitted.

We refer to the neighbor list developed at a node by virtue of the initialization phase and the MP rule as the *basic* list. This list is mainly updated in response to the mobility of the node and its neighbors. The ODL rule allows active nodes that are involved in data forwarding to enrich their local topology beyond this basic set. In other words, a *rich* neighbor list is maintained at the nodes located in the regions of high traffic load. Thus the rich list is maintained only at the active nodes and is built reactively in response to the network traffic. All inactive nodes simply maintain the basic neighbor list. By maintaining a rich neighbor list along the forwarding path, ODL ensures that in situations where the nodes involved in data forwarding are highly mobile, alternate routes can be easily established without incurring additional delays.

Fig. 3(a) illustrates the network topology before node A starts sending data to node P. The solid lines in the figure denote that both ends of the link are aware of each other. The initial possible routing path from A to P is A-B-P. Now, when source A sends a data packets to B, both C and D receive the data packet from A. As A is a new neighbor of C and D, according to the ODL rule, both C and D will send back beacons to A. As a result, the links AC and AD will be discovered. Further, based on the

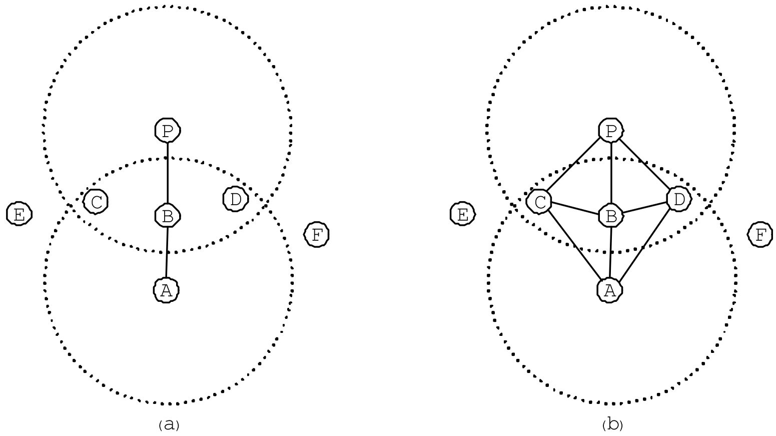


Fig. 3: An example illustrating the ODL rule

location of the destination and their current locations, C and D discover that the destination P is within their one-hop neighborhood. Similarly when B forwards the data packet to P, the links BC and BD are discovered. Fig. 3(b) reflects the enriched topology along the routing path from A to P.

Note that, though E and F receive the beacons from C and D, respectively, neither of them respond back with a beacon. Since E and F do not lie on the forwarding path, it is futile for them to send beacon updates in response to the broadcasts from C and D. In essence, ODL aims at improving the accuracy of topology along the routing path from the source to the destination, for each traffic flow within the network.

IV. Analysis of Adaptive Position Update

In this section, we analyze the performance of the proposed beaconing strategy, APU. We focus on two key performance measures: (i) update cost and (ii) local topology accuracy. The former is measured as the total number of beacon broadcast packets transmitted in the network. The latter is collectively measured by the following two metrics:

- *unknown neighbor Ratio*: This is defined as the ratio of the new neighbors a node is not aware of, but that are within the radio range of the node to the total number of neighbors.
- *False neighbor Ratio*: This is defined as the ratio of obsolete neighbors that are in the neighbor list of a node, but have already moved out of the node's radio range to the total number of neighbors.

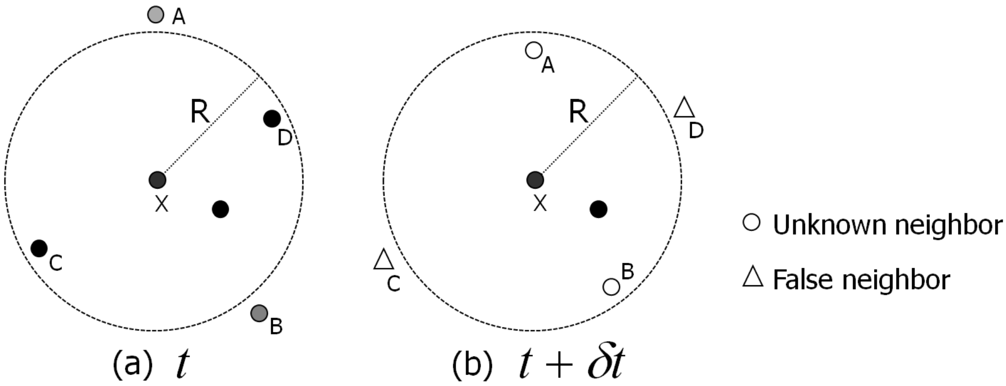


Fig. 4: Example illustrating unknown and false neighbors

The unknown neighbors of a node are the new neighbors that have moved in to the radio range of this node but have not yet been discovered and are hence absent from the node's neighbor table. Consider the example in Fig. 4, which illustrates the local topology of a node X at two consecutive time instants. Observe that nodes A and B, are not within the radio range R of node X at time t. However, in the next time instant (i.e. after a certain period δt), both these nodes have moved into the radio range of X. If these nodes do not transmit any beacons, then node X will be unaware of their existence. Hence, nodes A and B are examples of unknown neighbors.

On the other hand, false neighbors of a node are the neighbors that exist in the node's neighbor table but have actually moved out from the node's radio range (i.e., these nodes are no longer reachable). Consider the same example in Fig. 4. Nodes C and D are legitimate neighbors of node X at time t. However, both these nodes have moved out of the radio range of node X in the next time instant. But, node X would still list both nodes in its neighbor table. Consequently, nodes C and D are examples of false neighbors.

Note that, the existence of both unknown and false neighbors adversely impacts the performance of the geographic routing protocol. Unknown neighbors are ignored by a node when it makes the forwarding decision. This may lead to sub-optimal routing decisions, for example, when one of the unknown neighbors is located closer to the destination than the chosen next-hop node. If a false neighbor is chosen as the next hop node, the transmitting node will repeatedly retransmit the packet without success, before realizing that the chosen node is unreachable (in 802.11 MAC, the transmitter retransmits several times before signalling a failure). Eventually, an alternate node would be chosen, but the retransmission attempts waste bandwidth and increase the delay.

For mathematical tractability, we make the following simplifying assumptions:

- Nodes move according to the Random Direction Mobility (RDM) model, a popular model used in the analysis and simulations of wireless ad-hoc networks. This mobility model maintains a uniform distribution of nodes in the target region over the entire time interval under consideration [22].
- Each node has the same radio range R, and the radio coverage of each node is a circular area of radius R.
- The network is sufficiently dense such that the greedy routing always succeeds in finding a next hop node. In other words, we assume that a forwarding node can always find a one-hop neighbor that is closer to the destination than itself.
- The data packet arrival rate at the source nodes and the intermediate forwarding nodes is constant.

The notations used in the analysis are listed in Table II.

A. Analysis of the Beacon Overhead

Recall, that the two rules employed in APU are mutually exclusive. Thus, the beacons generated due to each rule can be summed up to obtain the total beacon overhead. Let the beacons triggered by the MP rule and the ODL rule over the network operating period be represented by O_{MP} and O_{ODL}, respectively. The total beacon overhead of APU, O_{APU}, is given by,

$$O_{APU} = O_{MP} + O_{ODL} \tag{3}$$

Next, we proceed to separately analyze O_{MP} and O_{ODL}.

1) Beacon Overhead due to the MP Rule (O_{MP}): Recall that, we have assumed that the nodes follow the RDM mobility model. According to this model, a node's trajectory consists of multiple consecutive linear segments. In each segment, the node randomly selects a direction (or heading), a speed and a travel duration from certain predefined ranges. The node moves at the selected speed in the chosen direction until the selected travel duration expires. At the end of the segment, the node pauses for a random time interval and then randomly selects another set of values for the next segment and changes its motion accordingly. For mathematical tractability, we neglect the pause time between successive segments (i.e., we assume that nodes instantly transition to the next segment).

TABLE II: Notations used in the analysis

Symbol	Denotation
N	total number of nodes in network
$A \times B$	dimensions of the region of deployment
ρ	average nodes density, $\rho = AB/N$
Γ	a finite time period
R	radio range
ω	prediction periodicity, i.e. the period after which each node refreshes its neighbor list using the mobility prediction equations
M	number of flows in the network
λ	average packet arrival rate at each data source
$(0, v_{max})$	the speed of the node is randomly chosen from this range
$(0, \tau)$	the travel duration of each linear segment is randomly chosen from this range
$\overline{L}$	average distance between the source and destination nodes
$\overline{H}$	average number of hops between the source and destination nodes
χ	the total number of data packets being forwarded in the network
γ	average beacon overhead for each data packet forwarding operation
$\delta(t)$	The probability that the link between two neighboring nodes ceases to exist after a time interval t

Recall that, according to the MP rule, a node periodically predicts its own location using the motion parameters advertised in the last transmitted beacon, and compares the predicted location with its actual location. If this difference is greater than the threshold AER, a new beacon is broadcast (see Section III-A). Consequently, the threshold AER directly influences the frequency and hence the number of beacon broadcasts. We seek to derive the upper bound of the beacon overhead and hence assume that the AER is zero (the lowest possible value). In this case, a beacon will be broadcast immediately in response to any change in the node's motion characteristics (direction and speed). Since, in the RDM model, a node changes these characteristics at the end of every linear segment, the number of beacons transmitted by the node are equal to the total number of linear segments traversed by the node. Since, the travel duration of each segment is randomly selected from $(0, \tau)$, on average, a node completes traversing a linear segment after an interval of $t/2$. In other words, the average duration between two successive beacon broadcasts is $t/2$. The number of beacons broadcast by a node during a finite time period of Γ is $2\Gamma/\tau$. Therefore, for a total of N nodes in the network, the total beacon overhead triggered by the MP rule, O_{MP} is given by,

$$O_{MP} = \frac{2N\Gamma}{\tau} \tag{4}$$

2) Beacon Overhead due to the ODL Rule (O_{ODL}): According to the ODL rule, whenever a node overhears a data transmission from a *new* neighbor, it broadcasts a beacon as a response (see Section III-B). In other words, beacons are transmitted in response to data forwarding activities. Let χ denote the total number of data packet forwarding operations that occur over the network operating period and let γ be the the average number of beacons that are triggered by each forwarding operation. Now, the total beacons triggered by the ODL rule, O_{ODL}, can be represented by,

$$O_{ODL} = \chi \cdot \gamma \tag{5}$$

Next, we proceed to derive χ and γ.

i. Analysis of χ: The total number of data packet forwarding operations can be represented as the product of the number of packets generated in the network and the number of times each packet is forwarded. The number of packets generated in the network during a finite time period of Γ can be expressed as $\lambda M\Gamma$, where λ is the packet generation rate (packets per second) at each source, M is the number of communication pairs (i.e. source-destination pairs). Let $\overline{H}$ be the average number of hops along the forwarding paths between the source and destination nodes. In other words, each packet is forwarded on average, $\overline{H}$ times, as it progresses from the source to the destination. Hence, χ can be represented as,

$$\chi = \lambda M\Gamma \cdot \overline{H} \tag{6}$$

Since, λ, M and Γ are known network parameters, we only need to derive $\overline{H}$.

In [19], the authors have analyzed the forwarding behavior of greedy geographic routing and derived the average number of hops along a forwarding path, given the Euclidean distance separating the source and destination node in a static multi-hop wireless network. However, in this paper, we consider a mobile ad-hoc network, wherein, due to the mobility of the nodes, the distance between the source and destination nodes of a communicating pair is bound to change with time. This distance can be represented as a random variable. In the following, we first estimate the mean value of the source-destination distance. Then we use the results in [19] to estimate the average hop count, $\overline{H}$.

Since, the nodes are uniformly distributed in the network (a property of the RDM model [22]), the distance between a source-destination pair is equivalent to the distance between two randomly selected points. In [23], Bettstetter et al., have analyzed the distance between two randomly select points, and formulated the average distance ($\overline{D}$) as,

$$\overline{D} = \frac{1}{15}\Big[\frac{A^3}{B^2} + \frac{b^3}{B^2} + \sqrt{A^2+B^2}(3 - \frac{A^2}{B^2} - \frac{B^2}{A^2})\Big] + \frac{1}{6}\Big[\frac{B^2}{A}\text{arccosh}(\frac{\sqrt{A^2+B^2}}{B}) + \frac{A^2}{B}\text{arccosh}(\frac{\sqrt{A^2+B^2}}{A})\Big] \tag{7}$$

, where $A \times B$ denotes the network dimensions. Based on work [19], given the Euclidean distance $\overline{D}$ between the source and destination node, the average number of hops between these nodes can be represented as follows,

$$\overline{H} = \frac{\overline{D}}{R \cdot \left[1 - \int_0^1 1 - \exp(\rho R(\arccos{(t)} - t\sqrt{1-t^2}))dt\right]} \tag{8}$$

, where ρ is the average node density, which is given by, $A \cdot B/N$.

Combining Equations (6), (7) and (8), we obtain the total number of data packet forwarding operations, χ.

ii. Analysis of γ***:*** According to the ODL rule, when a node forwards a data packet, the new neighbors that have moved in to the radio range of this forwarding node (and are hence unaware of the existence of the node forwarding the packet), broadcast beacons upon overhearing the packet transmission. This allows the forwarding node to maintain an up-to-date view of the local topology. Thus, the average number of beacons triggered by each packet forwarding operation, i.e. γ, is equal to the number of new neighbors that have entered the radio range of the forwarding node in the time interval between two successive data forwarding operations.

Recall that, one of the assumptions in our analysis is that the packet arrival rate at the source nodes and the intermediate forwarding nodes is constant, and is represented by λ. Thus, the time interval between two consecutive data forwarding operations at a node is $1/\lambda$. Since the nodes are uniformly distributed in the network, on average each node has the same number of one-hop neighbors, which is given by $\rho\pi R^2$ (where ρ is the nodes density). In steady state, the average number of new neighbors that enter the radio range of a node during the interval $1/\lambda$ is equal to the average number of neighbors that leave this region (this has been validated by simulations but have been omitted for brevity). Therefore, γ is equal to the average number of neighbors that move out of the radio range of the forwarding node during the interval $1/\lambda$.

Let $\delta(t)$ be the probability that a neighboring node moves out the radio range of a node during a small interval t. In other words, $\delta(t)$ denotes the link breakage probability. Given that a node has an average of $\rho\pi R^2$ neighbors, the number of neighbors that move out of the radio range of a node during the time $1/\lambda$ follows[1],

$$\gamma = \rho\pi R^2 \cdot \delta(\frac{1}{\lambda}) \tag{9}$$

Next, we derive $\delta(t)$. Intuitively, $\delta(t)$ is a function of the mobility pattern of the nodes. The faster the nodes move, the higher is the link breakage probability. We prove the following theorem:

Theorem 1: The probability that the link between two neighboring nodes ceases to exists after a small time interval t, is given by,

$$\delta(t) = \frac{1}{\pi a R^2} \int_0^R l \cdot \Big[\int_0^{2\pi} \int_0^a g(r, \theta, l) dr d\theta \Big] dl \tag{10}$$

where $a = v_{max} \cdot t$, and $g(r, \theta, l)$ is defined as,

[1]Note that, Eq. (9) only holds as an approximation. The correct way to calculate γ is $\int_0^{+\infty} \rho\pi R^2 \delta(t) \lambda e^{-\lambda t} dt$. However, numerical comparisons have shown that the approximation is quite accurate. These results are omitted for reasons of brevity.

$$g(r,\theta,l) = \begin{cases} 1-\alpha a+u\sin\alpha-\int_{\pi-\alpha}^{\pi}\sqrt{R^2-u^2\sin^2 v}dv \\ \qquad u\geq\sqrt{(R+a)^2}, \\ 1-\alpha a+u\sin\alpha-\int_{\pi-\alpha}^{\pi}\sqrt{R^2-u^2\sin^2 v}dv \\ \qquad -2\int_{\pi-a\sin\frac{R}{u}}^{\pi-\alpha}\sqrt{R^2-u^2\sin^2 v}dv \\ \qquad \sqrt{(R+a)^2}>u\geq R, \\ 1-\alpha a+u\sin\alpha-\int_{0}^{\pi-\alpha}\sqrt{R^2-u^2\sin^2 v}dv \\ \qquad R>u\geq R-a, \\ 0 \qquad R-a>u \end{cases} \tag{11}$$

where $u=\sqrt{(l-r\cos\theta)^2-r^2\sin^2\theta}, \alpha=\arccos\frac{u+a^2-R^2}{2ua}$,

Proof: A link between two neighboring nodes ceases to exist if the distance between the two nodes becomes greater than the radio range, R. Hence, the link breakage probability can be obtained by evaluating the probability that the distance between two adjacent nodes after time t becomes greater than R. Let L be the original distance between the two random neighboring nodes (e.g. node A and its random neighbor B) at the start of the interval, as shown in Fig. 5. Since node B is the one-hop neighbor of node A, node B is uniformly distributed within the radio coverage of node A. Therefore, the distance L is a random variable and we calculate its distribution as follows.

The probability that the distance L is less than a value l, is the probability that the node B is located within the circular region of radius l. Therefore, the cumulative density function (cdf) of L is given by,

$$F_L(l) = Prob(L\leq l) = \frac{\pi l^2}{\pi R^2} = \frac{l^2}{R^2} \tag{12}$$

The probability density function (pdf) of L follows,

$$f_L(l) = \frac{d}{dl}F_L(l) = \frac{2l}{R^2}, \qquad 0<l\leq R \tag{13}$$

Let L' be the new distance between the two nodes after the small interval t. Thus $P(L'>R|L=l)$ is the link breakage probability given the original distance between the two nodes is l. By law of total probability, the link breakage probability over all possible values of l is,

$$\delta(t) = P(L'>R) = \int_0^R f_L(l)P(L'>R|L=l)dl \tag{14}$$

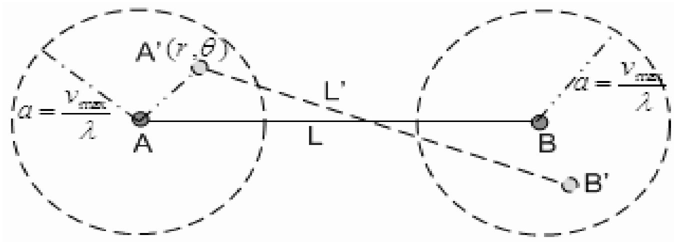


Fig. 5: Example used to prove Theorem 1

We now compute $P(L' > R|L = l)$. Without loss of generality, we assume that node A is located at the origin $(0, 0)$ at the start of interval. Recall that, in the RDM mobility model, a node is assumed to be moving along a randomly selected direction (represented as an angle) from $(0, 2\pi)$ and a randomly selected speed from $(0, v_{max})$. The maximum distance that a node can traverse during interval t is $v_{max} \cdot t$. We assume that nodes do not change their moving velocity during the small interval of t. Therefore, the possible new location of node A after interval t forms a circular area with a radius of $v_{max} \cdot t$, as shown in Fig. 5.

Let $a = v_{max} \cdot t$. Using the polar coordinates system, the *pdf* of the distance r to the new location is $1/a$, and the *pdf* of angle θ is $1/(2\pi)$. Therefore the joint pdf of the new location (r, θ) of node A is given by,

$$f(r, \theta) = \frac{1}{2\pi a} \tag{15}$$

Given that the original distance between node A and B is l, and the new location of node A is at (r, θ), we denote $g(r, \theta, l)$ as the link breakage probability over all possible new locations of B. The overall link breakage probability given the original distance of l can be expressed as

$$P(L' > R|L = l) = \int_0^{2\pi} \int_0^{a} f(r, \theta) g(r, \theta, l) dr d\theta \tag{16}$$

By some tedious calculations, the function $g(r, \theta, l)$ can be expressed as equation (11). The details are omitted here for brevity.

Finally, combining Equations (14), (13), (16) and (15), Theorem 1 is proved. ■

Given the link breakage probability $\delta(t)$, we can use Equation (9) to estimate γ, i.e. the average number of beacons that are triggered by each data packet forwarding operation. Since, we have derived the total number of data packet forwarded ξ earlier, we can calculate the beacon overhead triggered by ODL rule using Equation 5.

Finally, according to Equation (3), the total beacon overhead generated by APU (O_{APU}) follows,

$$O_{APU} = O_{MP} + O_{ODL} = \frac{2N \cdot \Gamma}{\tau} + \chi \cdot \gamma \tag{17}$$

B. Analysis of the Local Topology Accuracy

Recall that, we have defined two metrics that collectively represent the neighbor table accuracy - (i) unknown neighbor ratio and (ii) false neighbor ratio. The neighbor table maintained by a node is only referenced when the node has to forward a packet. Consequently, it only makes sense to calculate the neighbor table accuracy at the time instants when the node is forwarding a data packet.

We first analyze the unknown neighbor ratio. In our earlier analysis (see analysis of γ), we have shown that, according to the ODL rule,the average number of new neighbors that enter the radio range of a node between two successive forwarding operations (i.e. the interval $1/\lambda$) is given by γ. The node will only become aware of these new neighbors when it forwards the next packet, since these neighbors will broadcast beacons announcing their presence in response to the packet transmission. According to Equation (9), on average $\rho\pi R^2 \cdot \delta(1/\lambda)$ new neighbors enter the radio range of a forwarding node during the interval $1/\lambda$. The number of actual neighbors is the total number of nodes within the radio range of the forwarding node, which is $\rho\pi R^2$ on average. Therefore, the unknown neighbor ratio, represented by Λ^m_{APU}, can be computed as follows,

$$\Lambda^m_{APU} = \frac{\rho\pi R^2 \cdot \delta(\frac{1}{\lambda})}{\rho\pi R^2} = \delta(\frac{1}{\lambda}) \tag{18}$$

We now proceed to evaluate the false neighbor ratio. As per the MP rule, a node periodically estimates the current locations of its neighbors using Equation (1). Let ω denote the periodicity of this operation. At the beginning of each period, the node updates its neighbor list by removing all the false neighbors (i.e. those nodes that are estimated to have moved out of its radio range). Since, data packets arrive at the forwarding node at random during the interval ω, the average time of arrival of a packet is given by $\omega/2$. The number of false neighbors at time $\omega/2$ is the number of neighbors that have moved out of the radio range during $\omega/2$. Therefore, according to Equation 9, the false neighbor ratio, denoted by Λ^f_{APU}, is given by,

$$\Lambda_{APU}^{f} = \frac{\rho \pi R^2 \cdot \delta(\frac{\omega}{2})}{\rho \pi R^2} = \delta(\frac{\omega}{2}) \tag{19}$$

V. Simulation Results

In this section, we present a comprehensive simulation-based evaluation of APU using the popular NS-2 simulator. we compare the performance of APU with other beaconing schemes. These include PB and two other recently proposed adaptive beaconing schemes in [14]: (i) Distance-based Beaconing (DB) and (ii) Speed-based Beaconing (SB) (see Section II). We conduct three sets of experiments. In the first set of simulations, we demonstrate that APU can effectively adapt the beacon transmissions to the node mobility dynamics and traffic load. In addition, we also evaluate the validity of the analytical results derived in Section IV, by comparing the same with the results from the simulations. In the second set of experiments, we consider the impact of real-world factors such as localization errors, realistic radio propagation and sparse density of the network on the performance of APU. In the third set of experiments, we evaluate the performance of APU in a practical vehicular ad-hoc network (VANET) scenario that exhibits realistic movement patterns of public transport buses in a metropolitan city. This enables us to investigate if the benefits exhibited by APU still hold in a practical scenario.

We use two sets of metrics for the evaluations. The first set includes the metrics used in our analysis, viz., beacon overhead and local topology accuracy (false and unknown neighbor ratio), which directly reflect the performance achieved by the beaconing scheme. Note that, the beaconing strategies are an integral part of geographic routing protocols. The second set of metrics seek to evaluate the impact of the beaconing strategy on the routing performance. These include: (i) packet delivery ratio, which is measured as the ratio of the packets delivered to the destinations to those generated by all senders (ii) average end-to-end delay incurred by the data packets. and (iii) energy consumption, which measures the total energy consumed in the network. We adopt the widely used energy consumption model, which estimates the energy consumption for each basic operation (e.g. transmitting, receiving and overhearing in promiscuous mode) based on empirical data collected from commercial wireless cards (Table III in [25]). We also measured the average hop count traversed by the packets. However, we found that this metric is not an effective tool for comparing beaconing schemes (please refer to Appendix A for the details). In the simulations, we have implemented GPSR [2] as an illustrative example of a geographic routing protocol. We simulate IEEE 802.11b as the MAC protocol with wireless bandwidth of 11Mbps and assume a two-ray ground propagation model unless otherwise stated.

A. Impact of Node Mobility on Beaconing Schemes

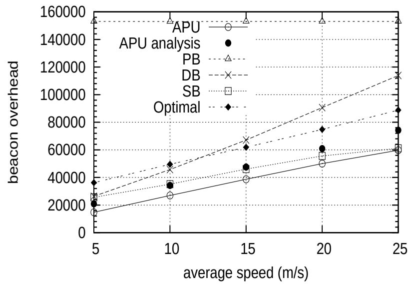
We first evaluate the impact of varying the mobility dynamics of the nodes on the performance on APU. In addition, we compare the performance of APU with other beaconing schemes. The simulations are conducted in NS-2 with each experiment being run for 1000 seconds. The results represented here are averaged over 30 runs (the standard deviation achieved is on average less than 5% of the mean value). In each simulation, 150 nodes are randomly placed in a region of size 1500m*1500m. The radio range for each node is assumed to be 250 meters (thus the average number of one-hop neighbors for each node is 12). We use Constant Bit Rate (CBR) traffic sources with each source generating four packets per second. We simulate 15 traffic flows and randomly select nodes as source-destination pairs as the traffic flows. We have assumed that the nodes move according to the RDM model, to be consistent with our analytical results. First, we study the impact of changing the mobility dynamics of the nodes on the performance of APU and PB. Note that, the faster the node moves, the more frequently it changes its mobility parameters (i.e. speed and direction). We vary the average speed of the node from 5m/s (18km/hr, representing low dynamism) to 25m/s (90km/hr, representing high dynamism). This range is consistent with typical vehicular mobility scenarios. The travel duration for each segment in RDM (see Section IV-A1) is randomly selected from (0,40s).

We assume that the prediction period in APU (ω) is 1s. The parameter of AER is 40m. We have studied the impact of AER values on the performance of APU. Please see Appendix B for the details. The beacon period (ϵ) in PB is also assumed to be 1s, which is the default value in NS2 and also is recommended in [14]. The neighbor timeout interval in PB is set to 3s. In DB [14], assuming that the distance parameter is d, and a node is moving at speed v, the beacon interval is given by, d/v. We have set the distance parameter, $d = 20m$ and the neighbor time-out interval as twice the beacon interval, as suggested in [14]. In SB, if the speed of the node is v, then its beacon interval is given by $B = a+(b-a)\cdot(\frac{v_{max}-v}{v_{max}-v_{min}})^n$, where

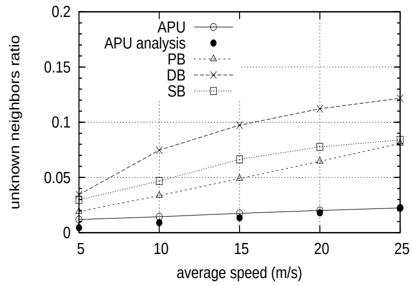
$[a, b]$ is pre-defined beacon interval range; v_{min} and v_{max} are the minimal and maximal node speeds. We assume that the beacon interval range is [1s, 5s] and $n = 4$, as suggested in [14]. Since, the average speed is varied from 5m/s to 25m/s in the simulations, $v_{min} = 0$ and $v_{max} = 50$. Note that, in the simulations, PB scheme does not use promiscuous mode while all other schemes piggyback beacon information in data packets and employ promiscuous mode.

We also include the optimal performance that be achieved in terms of delivery ratio as a performance benchmark. The best possible delivery ratio can be achieved if each node can select the optimal next hop node according to geographic routing. This would require each node to be always aware of the exact location of its current neighbors. We simulated such a hypothetical scheme and refer to it as *optimal*. Note that, in simulating the above we did not actually generate any beacons, since the simulator has a global view of the entire network topology. However, we can readily estimate the minimum beacon overhead incurred by the optimal scheme. The minimum possible beacon overhead can be achieved if a forwarding node (i.e. a node that currently holds a packet that it needs to forward) is immediately informed about a change in the position of its next hop node. At least one neighbor of the forwarding node should broadcast a beacon to reflect the change. Therefore, the minimum beacon overhead incurred by the optimal scheme is equal to the number of times that forwarding nodes change their next hops, which can be readily computed in simulations by observing the dynamics of the network topology.

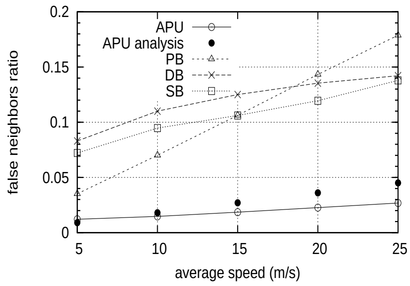
We initially focus on the first set of metrics, i.e., the beacon overhead and the unknown and false neighbor ratios. Fig. 6(a) shows that the beacon overhead of APU increases linearly as a function of the average speed. This behavior is primarily attributed to the ODL rule. Recall that, in the OLD rule, when a node forwards a data packet, all of its new neighbors that overhear the data packet respond with beacons. When the network topology is highly dynamic, the local topology of a node frequently changes with several new neighbors entering the radio range. As a result, APU generates more beacons in order to keep up with the frequent changes of topologies. With DB, we observe a similar linear increase. This is expected, because, the beacon periodicity in DB is inversely proportional to the node speed. Finally, with SB, the beacon overhead also increases with increase in average speed, though not linearly. The beacon overhead tends to saturate as the average speed increases. This is because of the polynomial relationship that exists between the beacon update period and the node speed. In contrast, observe that PB results in



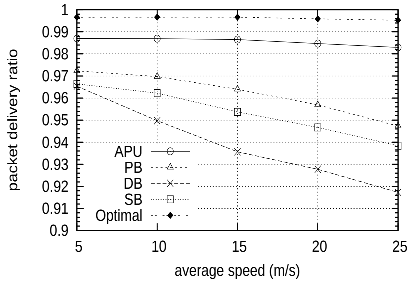
(a) Beacon Overhead (packets)



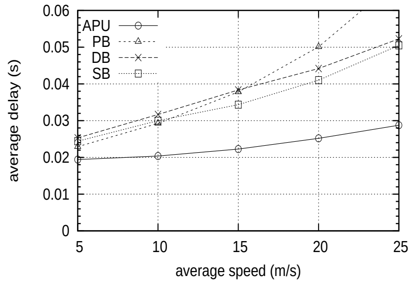
(b) Unknown neighbors Ratio



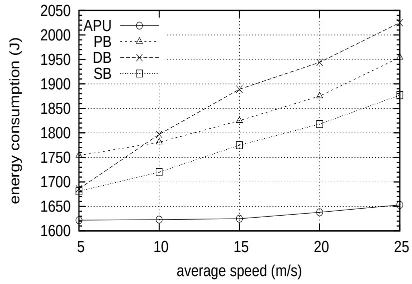
(c) False Neighbors Ratio



(d) Packet Delivery Ratio



(e) Average End-to-End Delay



(f) Energy Consumption

Fig. 6: Impact of node speed on the performance of beaconing schemes

very high beacon overhead, which does not vary significantly with the node speed. This is because in PB, the beacon broadcasts are independent of the node mobility.

Fig. 6(b) shows that APU can achieve a similar unknown neighbor ratio as that of PB, despite the fact that APU generates significantly less beacon overhead. Recall that, the beacon broadcasts in APU are more concentrating around the routing paths due to the ODL rule. Therefore, these beacons are highly effective in maintaining an up-to-date view of the the local topology at the nodes involved in forwarding most of the traffic. On the contrary, both DB and SB exhibit higher unknown neighbor ratio as compared to APU. In particular, when the average node speed is 25m/s, the unknown neighbor ratio for DB and SB is more than twice as that of APU. We attribute this increase in the unknown neighbors to the fact that in both DB and SB, when a fast moving node passes a slow node, the fast node may not detect the slow node due to the infrequent beacon transmissions by the slow node. Note that, in APU, due to the ODL rule, if either of these nodes are involved in forwarding packets, beacons would be exchanged, thus reducing the likelihood of unknown neighbors.

Fig. 6(c) illustrates that APU can achieve a very low false neighbor ratio as compared with the other three schemes. This can be explained as follows. Since each node in APU uses mobility prediction to track the locations of its neighbors (MP rule), the node can always quickly remove the obsolete neighbors, which have moved out of its radio range, from the neighbor list. On the contrary, a node in PB, DB or SB only passively removes an obsolete neighbor when the node has not heard any beacons from the neighbor during a certain time window . Therefore, the removal of obsolete neighbors is delayed resulting in a higher false neighbor ratio. In summary, APU succeeds in maintaining an accurate view of the local topology in the network, while keeping the beacon overheads to a minimum.

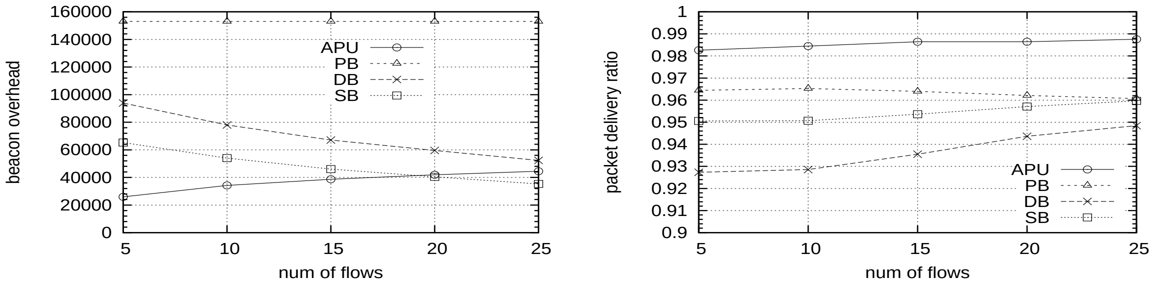
We also seek to validate the results from our analysis in Section IV. We obtain the analytical results for the beacon overhead, false neighbor ratio and unknown neighbor ratio for APU by substituting the simulation parameters in the corresponding equations. These results are compared with the corresponding simulation results in Figs. 6(a)-(c). One can readily observe that the analytical model can provide an upper bound for the beacon overhead and false neighbor ratio, and provide an accurate approximation for the unknown neighbor ratio. There are several reasons for the inconsistency between the analysis results and simulation results. First, as explained for Equation 4, our analysis seeks to derive an upper bound for the beacon overhead generated by MP rule. Second, in the analysis, we have assumed that the packet arrival rate at all intermediate nodes is constant (λ). However, this assumption may not hold if multiple flows share some common forwarding nodes. For example, if an intermediate node forwards data packet from multiple flows, the packet inter-arrival duration at such nodes would be less than $1/\lambda$. Consequently, in this shorter interval, fewer new neighbors would enter the radio range of these nodes. As a result, the number of beacons transmitted according to the OLD rule would be lower as compared to when the routing paths for multiple flows are completely disjoint (as assumed in the analysis). Hence, our analytical results overestimate the beacon overheads for APU. Third, when we estimate the link breakage probability for two neighboring nodes in Theorem 1, we implicitly assume that, for any two pairs of neighboring nodes, their link breakage probabilities are independent. However, this is not true in practice. For example, assume that node A has two neighbors: B and C. The link breakage probability of nodes A and B cannot be independent of the node pair A and C, since they share a common node, A. This dependency is increased in higher mobility scenarios, which leads to the inconsistency between the analysis results of false neighbor ratio and the corresponding simulation results, as shown in Fig. 6(c).

Next, we focus on the second set of metrics, which evaluate the impact of the beaconing strategies on the performance of the geographic routing protocols (GPRS in this case). These metrics include the packet delivery ratio, end-to-end packet delay and energy consumption. Since, APU is successful in maintaining an up-to-date view of the local network topology, it also achieves a consistently high packet delivery ratio as illustrated in Fig. 6(d), independent of the speed, since each node involved in forwarding a packet is almost always able to find an appropriate next hop neighbor. Fig. 6(d) also shows that APU can achieve comparable packet delivery ratio as the optimal scheme. However, the beacon overhead generated by APU is considerably lower than that of the optimal scheme, as shown in Fig. 6(a). Since, in APU most packets are forwarded along the optimal paths than other schemes, APU achieves lowest end-to-end delay, as can be seen from Fig. 6(e). In comparison, all the other three schemes (i.e. PB, DB and SB) exhibit a decrease in their packet delivery ratio as the average speed of the nodes increases (Fig. 6(d)). Further, as seen from Fig. 6(e), the average end-to-end delay also increases as a function of speed for these three schemes. This can be attributed to the fact that the false and unknown neighbor ratios are considerably higher in all these schemes as compared to APU.

Fig. 6(f) compares the total energy consumption for the different schemes. The energy consumption depends on the beacon overhead and the total number of data packets transmitting. Fig. 6(f) shows that, despite the use of promiscuous mode, APU can achieve the lowest energy consumption. The reason is two-folds. First, comparing promiscuous mode to non-promiscuous mode, the extra energy consumption used for data packet overhearing is not significant, as shown by Table III in [25]. Second, APU generates less beacon overhead and, since packets are more likely to follow optimal routing paths than other schemes (evidenced by Fig. 6(d)), the total number of data packets transmitted is also smaller than other schemes. As a result, APU achieves the lowest energy consumption.

B. Impact of Traffic Load on Beaconing Schemes

In the second set of simulations, we evaluate the impact of varying the traffic load on the performance of APU and also compare APU with the three beaconing schemes under consideration. We use the same scenario as in the first set of experiments. We fix the average node speed to 15m/s. We vary the number of flows from 5 (low load) to 25 (high load). As the number of traffic flows increase, more nodes in



(a) Beacon Overhead (packets)

(b) Packet Delivery Ratio

Fig. 7: Impact of traffic load on the performance of beaconing schemes

the network are involved in forwarding packets. Since, the ODL rule in APU aims at maintaining an accurate view of the local topology for nodes involved in forwarding packets, we expect the beacon overhead to increase with the traffic load. Fig. 7(a) confirms our hypothesis. On the contrary, the beacon overhead for DB and SB decrease with an increase in the traffic load. This is because, in these schemes the beacon information is piggybacked with data packets whenever possible. When the traffic load is high, the opportunities for piggybacking increase, thus reducing the explicit transmission of beacons. However, the beacon overhead of APU is still lower than that of PB, which is constant over the traffic load variation (since we do not use promiscuous mode in PB). For low traffic load, the beacon overhead of APU is also lower than that of DB and SB. However, when the traffic load is high, DB and SB outperform APU. As seen from Fig. 7(b), APU achieves better packet delivery ratio than all other schemes, due to that APU can maintain a more accurate local topologies for the nodes around routing paths. Note that, the packet delivery ratio in APU, DB and SB increases slightly with the traffic load. This is because that the larger number of data packet forwarding can piggyback more beacon information, which leads to a more accurate local topology and therefore better packet delivery ratio. However, it is expected that the packet delivery ratio will fall if the traffic load is high enough to saturate the network. Note that, we only present the key results (omitting other performance metrics) here and also in the rest of evaluations for the brevity.

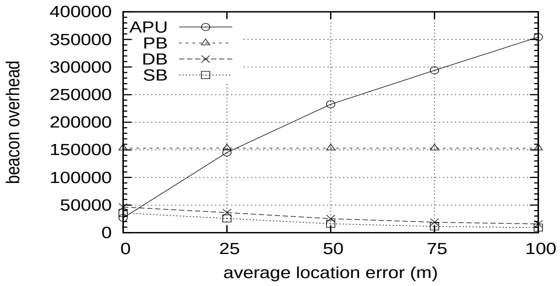
Overall, the simulation results show that APU is significantly better at adapting to network mobility and traffic load as compared to PB, DB and SB. The fundamental reason for this is that the beacons generated in APU are more concentrated in the network hotspots, where they are most useful in maintaining an accurate representation of the local neighborhood.

C. Impact of Localization Errors, Fading Channel and Node Density on Beaconing Schemes

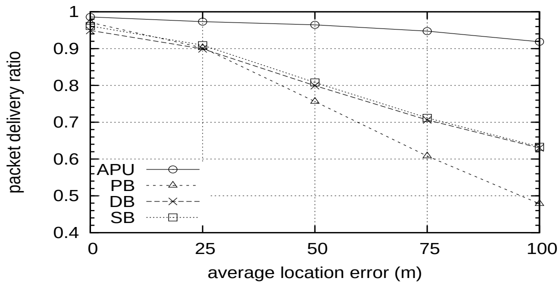
In this set of simulations, we study the performance of APU and the other three beaconing schemes in a more realistic simulation environment that takes into account several real-world effects such as localization error, fading wireless channel and sparse node densities. Nodes move according to RDM model and the speed is randomly selected from (0,20m/s). The number of flows is fixed at 15. Other parameters are same as those used in previous simulations, unless explicitly noted.

First, we study the impact of localization errors on the performance of beaconing schemes. We define the average localization error as the mean distance from the estimated location to the actual location. A direct consequence of this error is that a node has inaccurate information about the location of its neighbors. We vary the average localization error from 0 to 100m (in steps of 25m) and observe the impact on the beacon overhead and packet delivery ratio. Fig. 8(a) shows that the beacon overhead of APU increases significantly as the localization error increases. This is because, a packet is more likely to take a longer path towards the destination, which involves more hops and thus more transmissions. On the contrary, the beacon overhead of DB and SB decrease marginally. The greater number of transmissions due to the packets taking a longer path, allows these schemes to piggyback more beacons in the data packets and therefore reduces the beacon overhead. However, the increased beacons generated by APU ensures that the nodes frequently refresh their view of the local topology. This increases the likelihood that a forwarding node is able to find an appropriate next hop towards the destination, which in turn results in a higher packet delivery ratio. One can observe from Fig. 8(b) that this is indeed the case. There is only a marginal drop in the packet delivery ratio for APU. On the contrary, all other schemes experience a sharper drop in delivery ratio. In summary, the increased beacon overhead in APU counters the negative effect of localization errors and thus maintains a high delivery ratio.

Next, we study the impact of fading channel on the performance of beaconing schemes. Note that, in all previous simulations, we have assumed the two-ray ground radio model. In this radio model, the radio coverage of each node is a perfect circle, which is often not true in real-world scenarios [27]. Therefore, in this simulation, we consider a more realistic radio model, i.e., log-normal shadowing [26],



(a) Beacon Overhead (packets)



(b) Packet Delivery Ratio

Fig. 8: Impact of localization error on the performance of beaconing schemes

which captures the random multi-path (or reflections) fading between two nodes. Due to random fading, there exists a transition region near the border of the radio coverage of a transmitter. For the nodes that lie inside this transition region, the existence of a link with the transmitter is a random variable. Further, there is also a high probability that this link exhibits asymmetry (i.e. the link may exist in one direction but not in the other) [27]. In order to cope with this issue, the authors in [27] propose *bounded distance Forwarding*, which excludes nodes in this transition region from being considered as possible forwarders. In other words, a node only includes those neighbors in its neighbor list that are located less than a certain *distance threshold* away from the node. In this set of simulation, we simulate bounded distance forwarding. We vary the distance threshold from 150m to 250m (in steps of 25m) and evaluate the corresponding performance of the beacon schemes. For the shadowing radio model, we assume that both the path loss rate and the standard deviation of the random signal are equal to 3. Fig. 9 shows that APU can still achieve better packet delivery ratio than other schemes, since it allows nodes to maintain a more accurate view of their local topology along the routing path. Note that, comparing the different distance thresholds, the optimal performance occurs at 225m. This is because, when the distance threshold is too small, only a few neighbors can be included in the neighbor list, which often leads to routing failure. When the distance threshold is too large, the neighbors in the transition region are considered as potential forwarders and the associated randomness and link asymmetry affects the performance.

Finally, we study the impact of node density on the performance of beaconing schemes. In our previous simulations, we have assumed a sufficiently dense network, such that a node can always find a neighbor

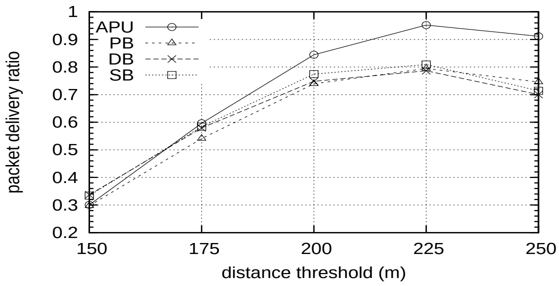


Fig. 9: Impact of fading channel on the performance of beaconing schemes

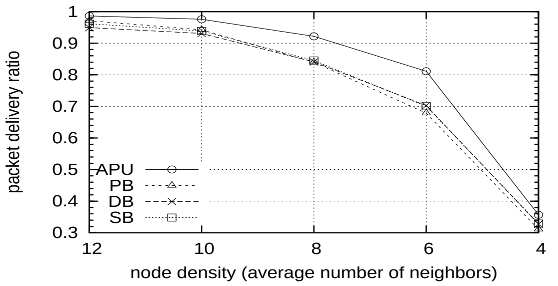
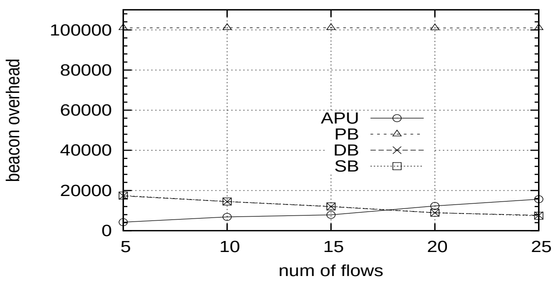


Fig. 10: Impact of node density on the performance of beaconing schemes

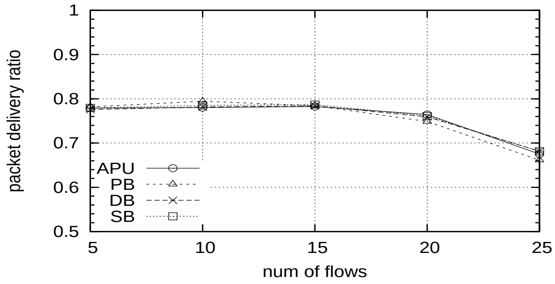
that is closer to the destination than itself. In the following simulation, we evaluate the impact of sparser topology on the performance. We vary the total number of nodes in the network such that the average number of neighbors for each node varies from 12 to 4. As expected, Fig. 10 shows that the performance of all schemes degrades as the node density reduces. This is because geographic routing experiences more frequent route failures in sparser networks as forwarding nodes are more likely to not find a suitable next hop node towards the destination. However, Fig. 10 illustrates that APU can still achieve relatively higher performance than other schemes.

D. Results for a Realistic VANET Scenario

In the previous set of simulations, we have assumed that the nodes move according to the RDM mobility model. However, in a real-world scenario, the mobility dynamics of the nodes can be significantly different. We conduct a second set of simulations using a real-world Vehicular Ad hoc Network (VANET) to confirm if the findings from our previous experiments with synthetic mobility models hold true in a realistic scenario. We use realistic movement patterns of public transport buses in a metropolitan city to simulate the VANET. We have used mobility traces that capture the actual movement of public transport buses



(a) Beacon Overhead (packets)



(b) Packet Delivery Ratio

Fig. 11: Impact of traffic load on the performance of beaconing schemes (realistic VANET scenario)

from the King County Metro bus system in Seattle, USA [28]. This transport network consists of close to 1163 buses plying over 236 distinct routes covering an area of 5100 square kilometers. The traces were collected over a three week period in November 2001. The traces are based on location update messages sent by each bus. Each bus logs its current location, its bus id and route id along with a timestamp. The typical update frequency is 30 seconds. We have not simulated the entire bus network. This is because the network is quite sparse (for example, only 1 or 2 buses) in several regions of the city, which would not lead to meaningful results. Rather, we focus on the downtown area, which has a consistently high density of buses. We focus on a rectangular region of size 4km x 6km in the downtown. We create three scenarios from a weekday trace (Thursday, Nov 8, 2001), each lasting for 1000 seconds, but at different times of the day; 8am (morning peak), 12pm (afternoon off-peak) and 5pm (evening peak). The simulations were conducted in NS-2 with the node movement patterns being read from a file. We assumed a radio range of 1km, which is consistent with that for the DSRC (Dedicated Short Range Communications) [26] standard proposed for vehicular communication. We used shadowing radio model at Phy layer to simulate realistic radio propagation. As discussed in Section V-C, we employed bounded distance forwarding to exclude neighbors in the transition region. The distance threshold is assumed to be 800m. We used CBR traffic sources with the sender transmitting at 4 packets per second. We study the impact of varying the traffic load from 5 to 25 flows on the performance of the beaconing schemes. The source and destination nodes were randomly selected. The results presented here are averaged over 30 runs, with each scenario being executed ten times with different random seeds of traffic load. Note that, since we use real vehicular traces to simulate the node mobility, we are unable to systematically study the impact of mobility dynamics on the performance. However, the traces capture the typical dynamism that would exist in a typical urban VANET scenario.

Fig. 11(a) illustrates that in low traffic load, APU achieves significantly lower beacon overhead as compared to the other three beaconing schemes. For example, with 10 traffic flows, APU reduces the beacon overhead by 50% as compared with distance-based beaconing. However, with an increase in the traffic load, we notice a slight increase in the beacons exchanged in APU. This is primarily due to the ODL rule, which tries to maintain an accurate topology along the forwarding paths. On the contrary, with DB and SB, since the beacons are piggybacked on the data packets, the number of explicit beacon packets that need to be broadcast decreases with an increase in the load. Fig. 11(b) shows that APU can achieve comparable packet delivery ratio as other schemes. These simulations illustrate that even in a real-world scenario, APU significantly outperforms all other beaconing schemes when the traffic load is low.

VI. Conclusions

In this paper, we have identified the need to adapt the beacon update policy employed in geographic routing protocols to the node mobility dynamics and the traffic load. We proposed the *Adaptive Position Update (APU)* strategy to address these problems. The APU scheme employs two mutually exclusive rules. The MP rule uses mobility prediction to estimate the accuracy of the location estimate and adapts the beacon update interval accordingly, instead of using periodic beaconing. The ODL rule allows nodes along the data forwarding path to maintain an accurate view of the local topology by exchanging beacons in response to data packets that are overheard from new neighbors. We mathematically analyzed the beacon overhead and local topology accuracy of APU and validated the analytical model with the simulation results. We have embedded APU within GPSR and have compared it with other related beaconing strategies using extensive NS-2 simulations for varying node speeds and traffic load. Our results indicate that the APU strategy generates less or similar amount of beacon overhead as other beaconing schemes but achieve better packet delivery ratio, average end-to-end delay and energy consumption. In addition, we have simulated the performance of the proposed scheme under more realistic network scenarios, including the considerations of localization errors, a realistic Phy layer radio propagation model and the realistic movement patterns of public transport buses within Seattle city. The results confirm the superiority of our proposed scheme over other schemes.

REFERENCES

[1] J. Hightower and G. Borriello. ”Location Systems for Ubiquitous Computing”, in IEEE Computer, vol. 34, no. 8, pp. 57-66, August 2001.

[2] B. Karp and H. T. Kung. ”GPSR: Greedy Perimeter Stateless Routing forWireless Networks”, in Proceedings of ACM Mobicom 2000, pp. 243-254, Boston, MA, USA, August 2000,

[3] S. Basagni, I. Chlamtac, V. R Syrotiuk and B. A Woodward. ”A Distance Routing Effect Algorithm for Mobility (DREAM)”. In Proceedings of ACM Mobicom 1998, pp. 76-84, Dallas, TX, USA, October 1998.

[4] L. Blazevic, S. Giordano, J-Y. LeBoudec. ”A Location Based Routing Method for Mobile Ad Hoc Networks”, in IEEE Transaction on Mobile Computing, Vol. 3 No. 4, December 2004.

[5] Y. Ko and N. H. Vaidya. ”Location-Aided Routing (LAR) in Mobile Ad Hoc Networks”, in ACM/Baltzer Wireless Networks, vol. 6, no. 4, pp. 307-321, September 2002.

[6] T. Camp, J. Boleng, B. Williams, L. Wilcox and W. Navidi. ”Performance Comparison of Two Location Based Routing Protocols for Ad Hoc Networks”. In Proceedings of IEEE Infocom, pp. 1678-1687, NY, USAL, June 2002.

[7] D. Johnson, Y. Hu and D. Maltz, “The Dynamic Source Routing Protocol (DSR) for Mobile Ad Hoc Networks for IPv4”, RFC4728, February 2007.

[8] C. Perkins, E. Belding-Royer and S. Das. ”Ad hoc On-Demand DistanceVector (AODV) Routing”. RFC3561, July 2003.

[9] J. Li, J. Jannotti, D. S. J. D. Couto, D. R. Karger, and R. Morris. ”A Scalable Location Service for Geographic Ad Hoc Routing”, in Proceedings of ACM Mobicom 2000, pp. 120-130. Boston, MA, August 2000.

[10] Z. J. Haas and B. Liang, ”Ad Hoc Mobility Management with Uniform Quorum Systems”. IEEE/ACM Transactions on Networking, vol. 7, no. 2, pp. 228-240, April 1999.

[11] A. Rao, S. Ratnasamy, C. Papadimitriou, S. Shenker and I. Stoica. “Geographic routing without location information”, in Proceedings of ACM Mobicom 2003, pp. 96-108. San Diego, CA, USA, September 2003.

[12] S. Lee, B. Bhattacharjee and S. Banerjee. “Efficient geographic routing in multihop wireless networks”, in Proceedings of ACM MobiHoc 2005, pp. 230-241, Urbana-Champaign, IL, USA, May 2005.

[13] Q. Chen, S. S. Kanhere, M. Hassan and K. C. Lan. ”Adaptive Position Update in Geographic Routing”, in Proceedings of the International Conference on Communications (ICC 2006), pp. 4046-4051, Istanbul, Turkey, June 2006.

[14] M. Heissenbuttel, T. Braun, M. Walchli and T. Bernoulli. “Evaluating of the limitations and alternatives in beaconing”, in Ad Hoc Networks, vol. 5, no. 5, pp. 558-578, 2007.

[15] Y. Kim, R. Govindan, B. Karp and S. Shenker. “Geographic routing made practical”, in Proceedings of the 2nd Conference on Symposium on Networked Systems Design and Implementation, pp. 217-230, Berkeley, CA, USA, May 2005.

[16] F. Kuhn, R. Wattenhofer, Y. Zhang and A. Zollinger. “Geometric ad-hoc routing: of theory and practice”’, in Proceedings of the 22nd Annual Symposium on Principles of Distributed Computing, pp. 63-72, Boston, Massachusetts, July 2003.

[17] F. Kuhn, R. Wattenhofer and A. Zollinger. “Worst-Case optimal and average-case efficient geometric ad-hoc routing”’, in Proceedings of the ACM MobiHoc 2003, pp 267-278. Annapolis, Maryland, USA, June 2003.

[18] B. Blum, T. He, S. Son, and J. Stankovic. “IGF: A state-free robust communication protocol for wireless sensor networks”. tech. rep., Department of Computer Science, University of Virginia, USA, 2003.

[19] M. Zorzi and R. Rao. “Geographic random forwarding (GeRaF) for ad hoc and sensor networks: energy and latency performance”, in IEEE Transactions on Mobile Computing, vol. 2, no. 4, pp. 349-365, 2003.

[20] M. Heissenbuttel, T. Braun, T. Bernoulli et al. “BLR: Beacon-Less Routing Algorithm for Mobile Ad-Hoc Networks”, in Computer Communications, vol,27, pp. 1076-1086, July 2004.

[21] P. Casari, M. Nati, C. Petrioli and M.Zorzi. “Efficient Non Planar Routing around Dead Ends in Sparse Topologies using Random Forwarding”, in Proceedings of IEEE ICC, pp. 3122-3129. Scotland, UK, June 2007.

[22] P. Nain, D. Towsley, B. Liu and Z. Liu. “Properties of random direction models”, in Proceeding of IEEE Infocom 2005, pp. 1897-1907, Miami, FL, USA, March, 2005.

[23] C. Bettstetter, H. Hartenstein and X. Prez-Cos. ”Stochastic Properties of the Random Waypoint Mobility Model”, in Wireless Networks, vol. 10, no. 5, pp. 555-567, September 2004.

[24] Q. Chen and S. S. Kanhere and M. Hassan. “Mobility and Traffic Adaptive Position Update for Geographic Routing”. CSE, UNSW, Sydney, Australia. UNSW-CSE-TR-1002, 2010. Available: ftp://ftp.cse.unsw.edu.au/pub/doc/papers/UNSW/1002.pdf

[25] L. M.Feeney and M. Nilsson. “Investigating the energy consumption of a wireless network interface in an ad hoc networking environment”. in Proceedings of IEEE Infocom, pp. 1548-1557, 2001.

[26] C. Bettstetter. “Connectivity of wireless multihop networks in a shadow fading environment”, in Wireless Network, vol. 11, no. 5, pp. 571-579, 2005.

[27] G. Zhou, T. He, S. Krishnamurthy and J. A. Stankovic. “Impact of radio irregularity on wireless sensor networks”, in Proceedings of ACM MobiSys, pp. 125-138, 2004

[28] J. G. Jetcheva, Y.-C. Hu, S. PalChaudhuri and D. B. Johnson. ”Design and Evaluation of a Metropolitan Area Multitier Wireless Ad Hoc Network Architecture”, in Proceedings of 5th IEEE Workshop on Mobile Computing System and Applications (WMCSA 2003), pp. 32-43, Monterey, CA, October 2003.

[29] Dedicated Short Range Communications (DSRC), http://wireless.fcc.gov/services/its/dsrc/

APPENDIX A

THE STUDY OF HOP COUNT METRIC

When conducting simulations, we have considered the hop count metric as a means for evaluating the performance of our scheme. However, after analyzing our simulation results, we found that this metric is not well-suited for comparing different beaconing schemes.

Intuitively, it may appear that if a beaconing scheme allows nodes to maintain an accurate view of their neighboring topology, then this scheme should be able to find better routing paths and thus achieve a smaller average hop count. Therefore, a smaller average hop count should ideally indicate a superior beaconing scheme. However, this is not true in practice, since the hop count metric only accounts for packets that were successfully delivered to the destination. For example, consider a source and destination pair which are several hops away. It may so happen that when an inferior beaconing scheme is employed, geographic routing is unable to find the end-to-end path and the corresponding packet is dropped along the way. However, when a superior beaconing scheme is used, the intermediate nodes may succeed in routing the packet towards the destination. In the former case the average hop count is unchanged since the packet was not successfully delivered. On the other hand, in the latter case, the large hop count will be accounted for in the final statistics, which may actually result in a larger average hop count.

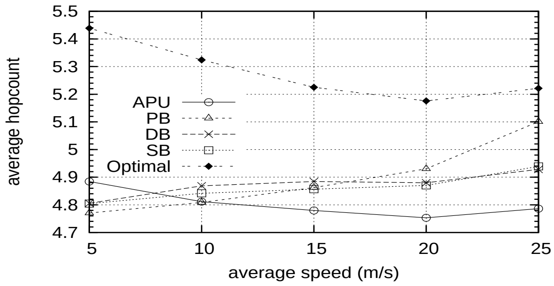


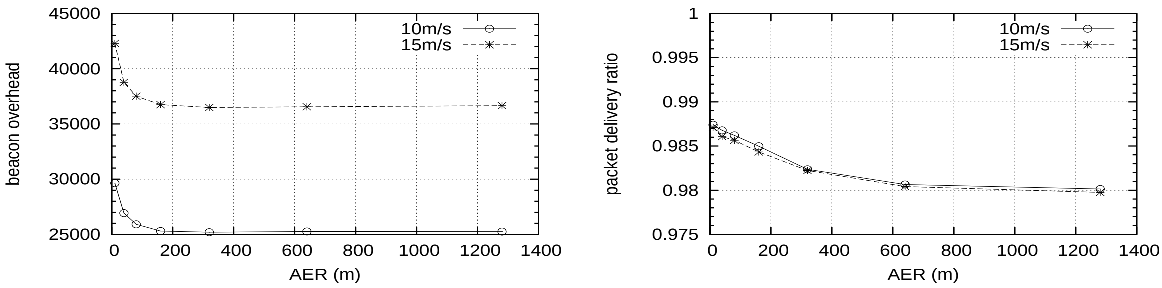
Fig. 12: Comparison of average hop count

Fig. 12 plots the average hop count for different beaconing schemes for the simulations described in Section V-A (i.e. corresponding to Fig. 6). We have included the *Optimal* scheme, which assumes that nodes have perfect knowledge of their neighbors without requiring beacons, as a benchmark. One can readily observe from Fig. 12 that the average hop count for the optimal scheme is significantly greater than all other schemes. This despite the fact that the optimal scheme leads to close to 100% packet delivery (see Fig. 6(d)). Consequently, we have not used the average hop count metric in our manuscript.

Appendix B

The Impact of AER on the Performance of APU

Recall that, in MP rule, we have a parameter called *Acceptable Error Range (AER)*, which determines when to send the next beacon. According to MP rule, a node i sends the next beacon when the error between the predicted location of i in its neighbors and node i's actually location is greater than the threshold of AER. In this section, we simulate the impact of AER on the performance of APU.



(a) Beacon Overhead (packets)

(b) Packet Delivery Ratio

Fig. 13: Impact of AER the performance of APU

The simulation setups are similar as the ones presented in Section V-A. We randomly select 15 communicating pairs and consider two mobility scenarios, one with average speed of 10m/s and another with average speed of 15m/s. We vary the value of AER from 10m to 1280m. Fig. 13 shows the performance of APU with varying AER. As expected, when AER is 10m (the smallest value), APU generates the highest amount of beacons in each mobility case (see Fig. 13(a)) since a smaller threshold AER can be more frequently reached and triggers more beacon broadcast. With the increase of AER, beacon overhead is decreasing dramatically and then slowly converges to a certain value. This is because, when the AER is large enough (e.g. 360m), MP rule is more tolerant to the prediction errors and it rarely triggers beacon broadcast. If we further increase AER, the beacon overhead generated by MP keeps around zero and stays unchanged. The similar pattern is also found for packet delivery ratio, as shown in Fig. 13(b). With the increase of AER (or the decrease of beacon overhead), APU maintains a less accurate local topology, which leads to the decrease of of packet delivery ratio. The selection of appropriate AER depends on the requirement of application. The higher value of AER achieves better packet delivery ratio but generates more beacon overhead and vice versa. If the application aims to achieve the highest packet delivery ratio, we should select 10m for AER. In our simulation in Section V, we choose AER as 40m, which can achieve a good trade-off between packet delivery ratio and beacon overhead.