Mobility Aware Distributed Topology Control in Mobile Ad-hoc Networks with Model Based Adaptive Mobility Prediction

S. M. Mousavi, H. R. Rabiee, M. Moshref, A. Dabirmoghaddam

Abstract— **Topology control in mobile ad-hoc networks allows better spatial reuse of the wireless channel and control over network resources. Topology control algorithms tend to optimize network power usage by keeping the topology connected. However, few efforts have focused on the issue of topology control with mobility. One of the most efficient mobility aware topology control protocols is the "Mobility Aware Distributed Topology Control Protocol". The major problem with this protocol is the future distance predictor which uses mobility prediction to estimate the future distance of neighboring nodes. The efficiency of this estimator varies in presence of different mobility models, sampling rates and different speed ranges. In this paper, we introduce an adaptive mobility prediction method that uses learning automaton to estimate the coefficients of a simple adaptive filter in order to predict the future distance of two neighboring nodes. We evaluated this estimator in the mobility aware distributed topology control protocol. Simulation results show significant improvement in accuracy of the future distance prediction and reduction in power consumption of each node.**

Key Words— **Mobile Ad-Hoc Networks, Distributed Topology Control, Mobility Models, Mobility Prediction**

I. INTRODUCTION

A mobile ad-hoc network (MANET) is a group of mobile wireless nodes working together to form a network. Such networks can exist without a fixed infrastructure working in an autonomous manner and every mobile device has a maximum transmission power which determines the maximum transmission range of the device. As nodes are mobile, the link connection between two devices can break depending on the spatial orientation of nodes. Two mobile wireless devices out of the communication range can use other devices within their communication range to relay packets. Mobile ad-hoc networks have numerous applications in sensor networks, disaster relief systems and military operations. Some of the network constraints in mobile ad-hoc networks are limited bandwidth, low battery power of nodes, and frequent link unreliability due to mobility. The topology of a multi-hop wireless network is a "set of communication links between node pairs used explicitly or implicitly by the routing mechanisms" [1]. A topology can depend on uncontrollable factors such as node mobility, weather, interference and noise as well as controllable factors such as transmission power, directional antennas [2] and multi-channel communications. Inappropriate topology can reduce the network capacity by limiting spatial reuse of the communication channel and decrease the network robustness. For example, if the topology is too sparse then the network can get partitioned. However, topology control can provide better control over network resources such as battery power and reduce redundancy in network communications.

Node mobility causes network topology to change dynamically in mobile ad-hoc networks. Therefore, the topology control in presence of mobile nodes is an important problem to consider. Most of the previous works in topology control have not considered mobility and assume that the network topology is static and there is no change in position of the network nodes. One of the methods that incorporates mobility in topology control is "Mobility Aware Distributed Topology Control" protocol proposed in [3]. Each mobile node in this protocol uses a simple mobility prediction method to predict future distance of two neighboring mobile nodes and attempts to predict future state of the neighborhood topology and to calculate a set of transmission powers required to reach its neighboring nodes. This protocol tries to reach a robust topology by adjusting each node's power to minimum required power to reach all of its neighboring nodes.

But the major problem with this protocol is the assumption that the motion in mobile nodes is nonrandom. If the mobile nodes in an ad-hoc network move in a nonrandom manner then this protocol can easily and accurately predict each nodes future position, and each 2 neighboring nodes future distance. But in real world motion of mobile nodes is not stationary and nodes move in random patterns called mobility models. There are a number of mobility models proposed in the literature to simulate real world motion patterns of mobile nodes in different environments [4,5]. The accuracy of the future distance predictor varies in each of this mobility models. In

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most of mobility models the estimation error is considerable and its predicted future distance between 2 neighboring nodes is much more than the real future distance. Therefore, the selected power for each node is also more than the required power. This inaccuracy can cause serious problems in topology control and power consumption of nodes and also can produce interference and reduce network capacity.

In our proposed scheme we introduce an adaptive estimator that can adaptively change its coefficients in different mobility models, sampling rates and average speeds. This estimator uses a simple learning automaton scheme to achieve adaptation. Simulation results show significant reduction in power consumption of each node using our proposed mobility prediction scheme.

The rest of the paper is organized as follows. Section 2 presents related work regarding topology control in ad-hoc networks. Section 3 explains our proposed scheme to enhance the future distance predictor accuracy. Section 4 provides the performance evaluation and finally in Section 5 we present the conclusion and future work.

II. RELATED WORK

Topology control has been addressed previously in literature in various settings. In general, the energy metric to be optimized (minimized) is the total energy consumption or the maximum energy consumption per node. In some algorithms, topology control is combined with other objectives, such as increasing the throughput or to meet some specific QoS requirements. The strongly-connected topology problem with minimum total energy consumption was first defined and proved to be NP-complete in [6]. In general, topology control protocols can be classified as: (a) centralized and global vs. distributed and localized and (b) deterministic vs. probabilistic.

The localized algorithm is a special distributed algorithm, where the state of a particular node depends only on states of local neighborhood. However, such an algorithm has no sequential propagation of state information.

Most protocols are deterministic. The work in [1] is concerned with the problem of adjusting the node transmission powers such that the resulting topology is connected or bi-connected, while minimizing the maximum power usage per node.

Li, Hou and Sha [7] devise a distributed and localized algorithm (LMST) for topology control starting from a minimum spanning tree. Each node builds its local MST independently based on the location information of its 1-hop neighbors and only keeps 1-hop nodes within its local MST as neighbors in the final topology. The algorithm produces a connected topology with maximum node degree of 6. An optional phase is provided where the topology is transformed to one with bi-directional links. An extension is given in [8], where the given network contains unidirectional links.

Among probabilistic protocols, the work by Santi, Blough and Vainstein [9] assumes all nodes operate with the same transmission range. The goal is to determine a minimum transmission range in order to achieve connectivity. They use a probabilistic approach to characterize a transmission range with lower and upper bounds of the probability of connectivity.

Hou and Li in [10] present an analytic model to study the relationship between the throughput and adjustable transmission range. The work in [7] puts forward a distributed and localized algorithm to achieve a reliable high throughput topology by adjusting the node transmission power. However, the issue of minimizing the energy consumption has not been addressed in [7] and [10]. Jia, Li and Du [8] are concerned with determining a network topology that can meet the QoS requirements in terms of end-to-end delay and bandwidth. The optimization criterion is to minimize maximum power consumption per node. When the traffic is splittable, an optimal solution is proposed using linear programming.

In other point of view, the topology control algorithms may be categorized as centralized [1,7,11,12,13,14] and distributed. The distributed algorithms are further categorized into three parts (a) Connectivity Aware [1,7,15], which try to optimize network connectivity, (b) Capacity Aware [16,17,18], which try to achieve higher capacity by reducing the contention in the network and (c) Mobility Aware [3,19] which try to make a robust topology while considering mobility in network nodes using mobility prediction.

Mobility prediction is not a new concept and has been used before in mobile ad-hoc networks, for example Link Estimation Time (LET) was previously introduced for estimating link duration and to perform re-routing before the route breaks [20]. In scheme proposed in [3] each node predicts its future distance to each of its neighboring nodes and based on this information it estimates the optimal transmission power required to reach all of its neighbor nodes. It assumes that each mobile node is aware of its location relative to some coordinate system so that it can calculate distances to its neighbors. For that purpose the availability of Global Positioning system (GPS) [21] would be ideal, but for deployment scenarios where the use of global coordinate system is not feasible other mechanisms for node localization such as Relative Positioning System [22] can also be utilized.

The proposed scheme in [3] is divided into two main phases. First, each node sends HELLO packets with maximum transmission power $(P_{\max})$ to learn the future state of neighborhood topology. The HELLO packets comprise node's predicted position and a list of minimum transmission powers that is required to communicate with its one-hop neighbors at some point later in time. Secondly, each node selects an optimal power level $(P_{optimal})$, such that a neighbor demanding higher transmission power can be reached through one that requires lower transmission power level. The main idea of the scheme is illustrated in Figure 1 [3]. In Figure 1(a), the initial topology at some arbitrary time (t_0) is depicted. At this time instant HELLO packets are exchanged among the neighbors with maximum transmission power. Figure 1(b), shows the

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predicted future position of the nodes at time ($t_0+\alpha$). Nodes 5, 4, 3 and 2 are directly reachable from each other. Figure 1(c), shows that each node adjusts the power required to reach its neighbor such that the connectivity in future is retained. For example, node 2 computes the required power for nodes 5, 4, 3 and 1. Based on this neighbor information it sets up the link with nodes 3 and 1. Then at t_0, each node computes a list of minimum transmission powers required to reach its 1-hop neighbors for time $t_0+\alpha$. Time instances t_0 and $t_0+\alpha$ represents current time and new time, respectively and α is the time increment in seconds. The list is constructed as follows.

A node predicts its own future position given its current position, speed and direction using the following two equations:

$$x(t_{0+a}) = x(t_0) \pm s*(t_{0+a}-t_0)*\cos(\theta)$$
$$y(t_{0+a}) = y(t_0) \pm s*(t_{0+a}-t_0)*\sin(\theta) \tag{1}$$

Here ($x(t_0+\alpha), y(t_0+\alpha)$) denote the position of a node at ($t_0+\alpha$), s is the current speed which is bounded by some maximum value, and θ is the direction. Next, future distance to each of its 1-hop neighbors is calculated using Equation. (2). Assuming that there are two neighbor nodes, node A and node B, then:

$$d(t_{0+a}) = \sqrt{(x_A(t_{0+a})-x_B(t_{0+a}))^2+(y_A(t_{0+a})-y_B(t_{0+a}))^2} \tag{2}$$

Finally, it utilizes two-ray ground path loss model to predict the mean signal strength P_r for an arbitrary transmitter-receiver separation distance d [23, 24] based on wireless propagation model given by the following equation:

$$P_r(d(t_{0+a})_{AB}) = \frac{P_t*G_t*G_r*(h_t^2*h_r^2)}{(d(t_{0+a})_{AB})^{\eta}*L} \tag{3}$$

Using Equation (3), node A estimates the minimum power required to reach node B, provided that transmission power P_t and the predicted distance $d(t_0+\alpha)_{AB}$ are known.

On receiving HELLO packets, each node draws a future topology map in terms of minimum transmission power required to reach its 2-hop neighbors. Each node constructs this topology map by maintaining two data structures. (1) Local view list L consists of two fields, one-hop neighbor's identity and minimum power. (2) Extended view list E includes neighbor's identity, neighbor's-neighbor identity and estimated transmission power. Using both local view and extended view lists the proposed algorithm selects an optimal power $P_{optimal}$, such that a neighbor requiring higher transmission power can be reached through an intermediate neighboring node. Selection of $P_{optimal}$ is done by comparing transmission power required by node itself and its nearest neighbor to reach the farthest one. If the nearest neighbor does not cover the distant ones, the algorithm searches for another neighbor with relatively higher transmission power, such that the connectivity among all neighbors is retained. Pseudo-code for finding the optimal power is formally given in Figure 2.

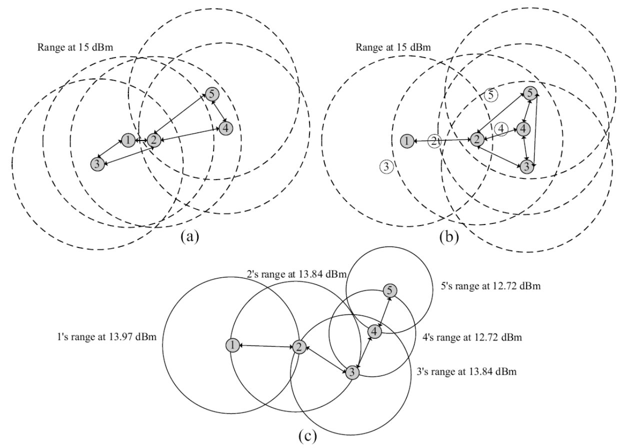

Figure 1. (a) Initial topology. (b) Predicted topology with maximum transmission range. (c) Topology after transmission power adjustment [3].

```
Algorithm OptimalTXTpower(L, E)
comment : Node A recieves HELLO Packet from Node B and P_optimal Selection
RecieveHELLO(p)
UpdateExtendedView(p)
UpdateLocalView(p)
Comment : Sort L in decending order of minimum TX power field.
SortLocalView(L, txPower)
i ← 0
j ← L.Lenght − 1
comment : Initially Optimal Power is set to reach farthest neighbor.
P_optimal ← L_i.txpower
if ( j ≠ i) Then
{
    while ( j ≥ i) do
    {
        x ← L_i.nodeID
        comment : Is Node x reachable from Node L_j.nodeID ?
        if (REACHABLE (x, L_j.nodeID)) then
        {
            if (E(L_j, x).txpower < E(A, x).txpower then
            {
                P_optimal = E(A, L_j).txpower
            else
            {
                j ← j − 1
                Continue
            }
        }
        i ← i + 1
    }
}
return(P_optimal)
```

Figure 2. Power selection Algorithm proposed in [3].

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III. Mobility Aware Distributed Topology Control with Model Based Adaptive Mobility Prediction

Our proposed protocol called "mobility aware distributed topology control with model based adaptive mobility prediction" uses scheme in [3] but with an enhanced future distance predictor which adaptively produces the coefficients of a specified estimator using learning automaton. In the following section we introduce the proposed scheme.

A. Enhanced Future Distance Predictor

Instead of using the future position predictor used in equation (1), we used an adaptive estimator which is similar to the old one but it has the term $(1/alpha)$ as the scaling coefficient of the estimator. This coefficient adaptively varies in different mobility models, speeds and sampling rates. The term sampling rate is the time between to prediction points which the protocol does the Hello packet transmission and selects optimal power in each node. Using a lower sampling rate causes lower overhead in topology control protocol because each node does not need to send hello packets and it does not run the radio range selection algorithm at each instance of time. This scheme causes much lower topology control overhead to the network. But using lower sampling rate causes considerable distance prediction error in future distance predictor shown in equation (1). Because the predictor used in [3] assumes non-random motion in mobile nodes. It means that in each sampling time the predictor receives node position, speed and motion angle from GPS and assumes that the speed and angle of each node is static until the next sampling time. But in the real world, because of random motion in mobile nodes, speed and angle of each mobile node can vary between two sampling times. This randomness is different in different mobility models. For example, in the RPGM mobility model, each node changes its speed and angle in each instance of time. But in Manhattan mobility model this randomness is much lower. Therefore, future distance prediction error in Manhattan mobility model is much lower than RPGM mobility model. To solve this problem and to achieve a more accurate future distance predictor we propose an adaptive future distance estimator which can adapt itself to different mobility models, speeds and sampling rates using a simple learning automaton scheme to estimate the estimator coefficients $(alpha)$.

The term sampling rate is shown with $(t_{0+a} - t_0)$ in equations (1) and (4). The following equations show the proposed future position estimator.

$$\begin{aligned} x(t_{0+a}) &= x(t_0) \pm 1/alpha * (s * (t_{0+a} - t_0) * \cos(\theta)) \\ y(t_{0+a}) &= y(t_0) \pm 1/alpha * (s * (t_{0+a} - t_0) * \sin(\theta)) \end{aligned} \quad (4)$$

Similar to the scheme proposed in [3], future distance between each 2 nodes in the future is calculated by equation (2) and each node's transmission power is calculated by equation (3).

In the following section we introduce the simple learning automaton scheme that we have used to adaptively select the estimator coefficients.

B. The Learning Automaton

In this section, we present the fundamentals of the learning automaton model [25]. This involves the definition of the automaton itself and the environment with which it interacts.

An automaton can be regarded as a finite state machine. Mathematically, it can be described by:

$$SA \equiv \{\alpha, \beta, F, G, \phi\} \quad (5)$$

Where

$\alpha \equiv \{\alpha_1, \alpha_2, ..., \alpha_r\}$ is the set of actions of the automaton;

$\beta \equiv \{\beta_1, \beta_2, ..., \beta_r\}$ is the set of inputs to the automaton;

$F \equiv \phi \times \beta \to \phi$ is the function that maps current state and input into next state;

$G \equiv \phi \to \alpha$ is the output function mapping the current state into the next output.

The Krinsky$_{(2N,2)}$ automaton has 2N states and 2 actions and attempts to incorporate the past behavior of the system in its decision rule for choosing the sequence of actions. For every unfavorable response, the automaton switches its state from state ϕ_i to ϕ_{i+1} and in state ϕ_N and ϕ_{2N} it changes the action. But for favorable response any state ϕ_i :

$(for\ \mathrm{i} = 1,..., \mathrm{N})$ passes to the state ϕ_i and any state ϕ_i

$(for\ \mathrm{i} = \mathrm{N}+1,...,2\mathrm{N})$ passes to the state ϕ_{N+1}

The random environment can be mathematically described bythe triple:

$$E \equiv \{\alpha, \beta, c\} \quad (6)$$

Where

$\alpha \equiv \{\alpha_1, \alpha_2, ..., \alpha_r\}$ is the set of inputs;

$\beta \equiv \{\beta_1, \beta_2, ..., \beta_r\}$ is the set of outputs;

$c \equiv \{c_1, c_2, ..., c_r\}$ is the set of penalty probabilities;

The input of the environment is one of the r actions selected by the automaton. The set c of penalty probabilities characterizes the environment and is defined as

$$c_i = prob[\beta(n) = 1 \mid \alpha(n) = \alpha_i] \ \text{for}\ i = 1,2,...,r. \quad (7)$$

The values of c_i are unknown and it is assumed that $\{c_i\}$ has a unique minimum. When dealing with stationary environments, the penalty probabilities are fixed, while in non-stationary environments the penalty probabilities vary with time. Figure 3 shows a simple Krinsky Automaton system.

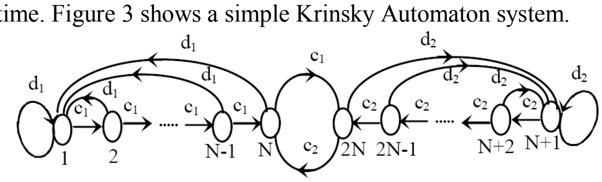

Figure 3- Krinsky$_{(2N,2)}$ Automaton[25]

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C. *Adaptive Estimator Coefficient Selection*

According to the automaton principles introduced in the previous section, we define the environment, inputs and actions of our automaton. The environment of our automaton is the movement of mobile nodes and the estimated distance between the position of each node in current and the future point of time. The action of automaton is the estimator coefficient $(alpha)$ used in equation (4). The automaton changes its state and actions according to the award and penalty that it receives from the environment as follows.

At the first point of time (t_0), the automaton sets the coefficient $(alpha)$ to 1, predicts the future position of the mobile node and sets the current position and predicted future position in place of the specified variables. At time ($t_0 + \alpha$) the node receives its real position using GPS and calculates its distance between last position at t_0 and current position at ($t_0 + \alpha$). Then it calculates the distance between its last position ($x(t_0)$, $y(t_0)$) and predicted position ($x(t_0 + \alpha)$, $y(t_0 + \alpha)$). If the difference of these 2 values is above or below a specific threshold, then the automaton gets a penalty, changes its state and chooses a new action $(alpha)$. But if the difference is between upper and lower thresholds, the automaton receives an award and changes its state and chooses current alpha as the action. These steps continue until the optimum value for alpha is learned adaptively for the mobility model, sampling rate and average speed of the environment. In each point of time each node calculates its distance to its neighbors using equation (2).
According to our simulation results this method can enhance the distance estimator accuracy and eliminate the effect of sampling rate estimator inaccuracy in all mobility models, sampling rates and speeds.

IV. SIMULATION RESULTS

We used Mobisim [26] to generate mobility traces for our simulations. Mobisim can generate mobility traces which may contain each node's position, speed and motion direction angle at anytime in various mobility models, speeds and other mobility model configurations. Using this graphical simulator we generated mobility traces for 20 mobile ad-hoc nodes. Our simulation region is [500*500] meters and the average speed of each mobility trace varies from 20m/s to 90m/s. Simulation time is 50000sec and sampling rate is 1/50 which means that in protocol each node predicts its future position, sends hello packet and runs power selection algorithm at each 50 seconds. We used Matlab to implement our proposed method and learning automaton. In these simulations, Matlab uses mobility traces generated by Mobisim and implements exact, simple and enhanced predictors. Exact predictor uses future mobility traces to fetch future position of each node from mobility traces. Simple predictor uses equation (1) to estimate future position of each node and Enhanced predictor uses our proposed method to estimate future position of each node by using an adaptive estimator.

We also implemented the proposed algorithm in [3] with our graphical topology control simulator called Toposim [27]. This simulator can use traces by Mobisim and implement topology control algorithms. Also it can evaluate performance of topology control protocols with various parameters.

A. *Enhanced Future Distance Estimator*

We implemented our proposed scheme using Matlab. Figure 4 shows the convergence diagram of the mobility models. In Figure 4, the first part (A) shows real future distance between 2 specified neighbor nodes, the second part (B) shows predicted future distance between two neighboring nodes using simple future distance predictor proposed in [3], and the third part (C) shows predicted future distance using our proposed enhanced predictor. As we can see in the third part of each figure, our estimator causes significant improvement in future distance prediction accuracy in comparison with the simple predictor in part (B).

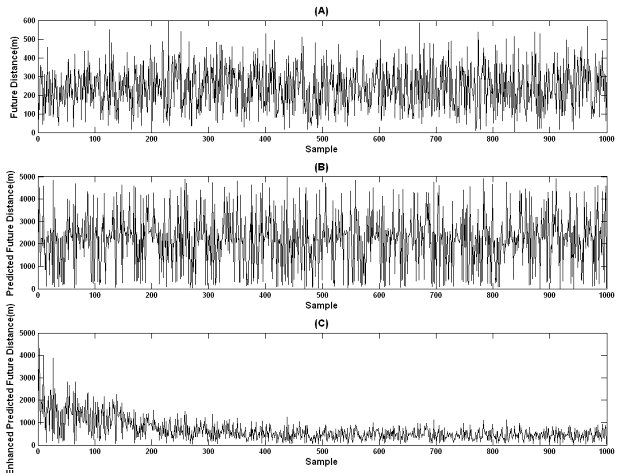
We also used Toposim simulator [27] to implement Mobility Aware Distributed Topology Control Protocol and evaluate performance of our proposed adaptive estimator and compare it to simple estimator proposed in [3].

Figure 5 shows our simulation results using Toposim. Each part of Figure 5 shows average estimation error in each of the Exact, Simple and Enhanced estimators and each mobility model with different average speed. The mobility traces are same as mobility traces used in the previous simulation using Matlab. As we can see average estimation error in exact predictor in all traces is zero and our enhanced predictor estimation error is much lower than estimation error of simple predictor proposed in [3].

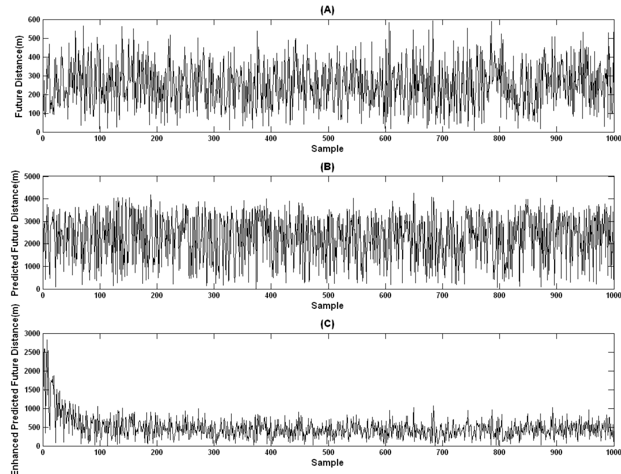
B. *Power Selection Using Enhanced Future Distance Estimator*

In our simulations using TopoSim, we used 3 different future distance estimators to implement the Mobility Aware Distributed Topology Control Protocol.

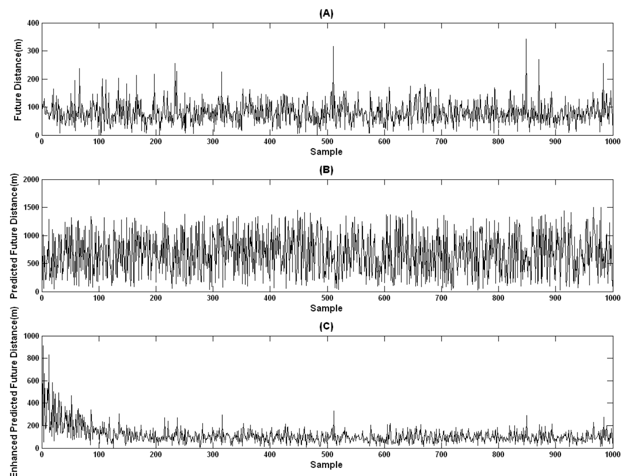
The average selected radio ranges using each of the estimators (Exact, Simple, Enhanced) is shown in Figure 6. As we can see, because of more accurate predicted distance between 2 neighboring nodes, in all mobility models average radio range of our enhanced predictor is much lower than the simple predictor and it is near the exact predictor's average selected radio range. It can cause lower average power consumption and lower interference cost in media access layer and improve capacity of the network. Using our proposed method, each node in protocol can predict its future position, send hello packets and adjust its power in lower sampling rates. This can cause improvement in protocol performance and reduce topology control overhead while reducing power consumption.



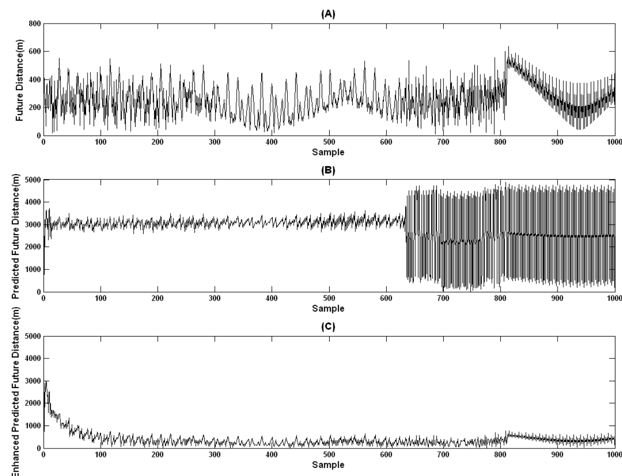
(A) - Random Waypoint Mobility Model, Average Speed = 40m/s, Sampling Rate = 1/50, Average Convergence Alpha = 5.6



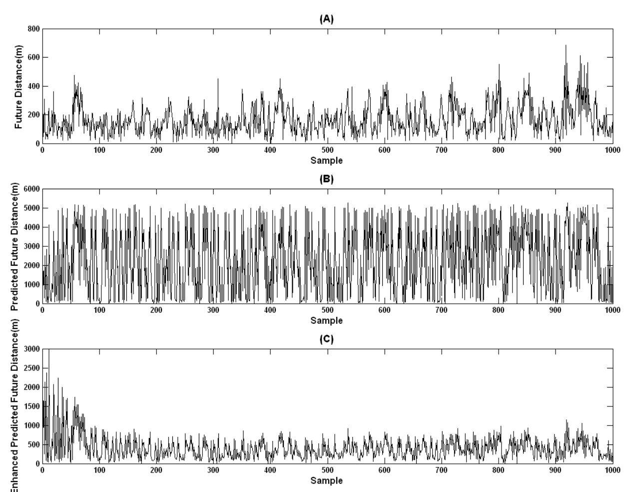
(B) - Randomwalk Mobility Model, Average Speed = 40m/s, Sampling Rate = 1/50, Average Convergence Alpha = 6.81



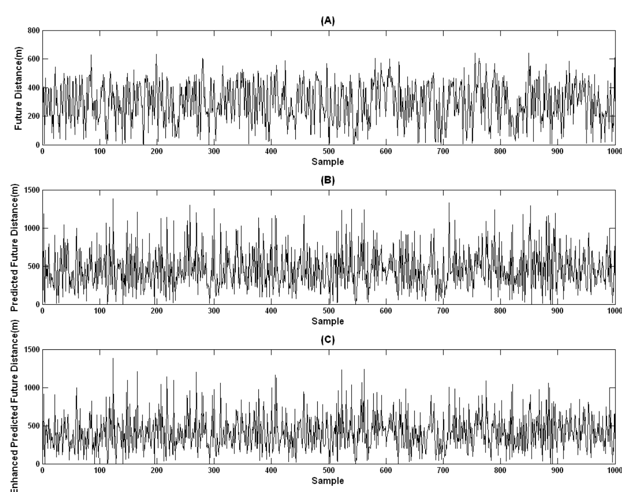
(C) - RPGM Mobility Model, Average Speed = 40m/s, Sampling Rate = 1/50, Average Convergence Alpha = 15.75



(D) - Gauss-Markov Mobility Model, Average Speed = 40m/s, Sampling Rate = 1/50, Average Convergence Alpha = 21.47



(E) - Freeway Mobility Model, Average Speed = 40m/s, Sampling Rate = 1/50, Average Convergence Alpha = 8.15



(F) - Manhattan Mobility Model, Average Speed = 40m/s, Sampling Rate = 1/50, Average Convergence Alpha = 1.25

Figure 4 – Convergence Diagram of Enhanced Future Distance Estimator

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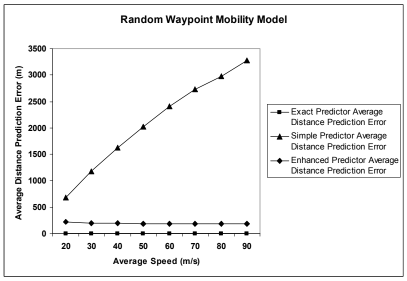
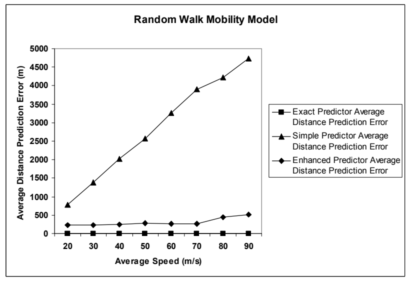
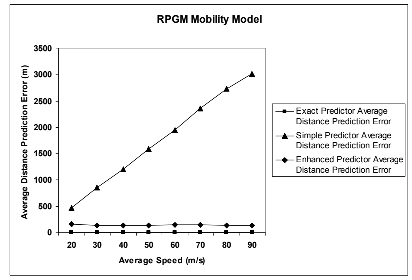


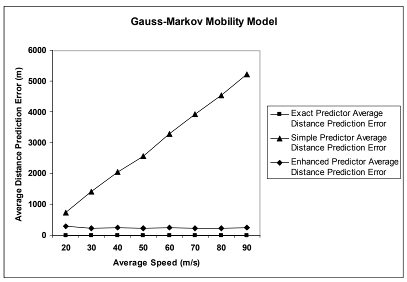
(A) – Random Waypoint Mobility Model,
Sampling Rate = 1/50



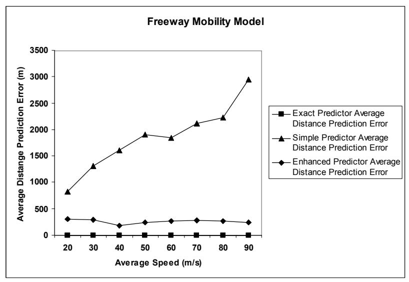
(B) – Random Walk Mobility Model,
Sampling Rate = 1/50



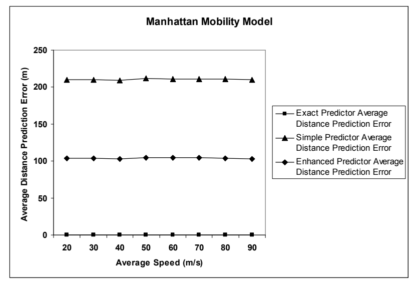
(C) – RPGM Mobility Model,
Sampling Rate = 1/50



(D) – Gauss-Markov Mobility Model,
Sampling Rate = 1/50

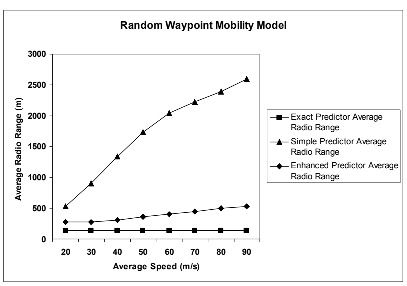


(E) – Freeway Mobility Model,
Sampling Rate = 1/50

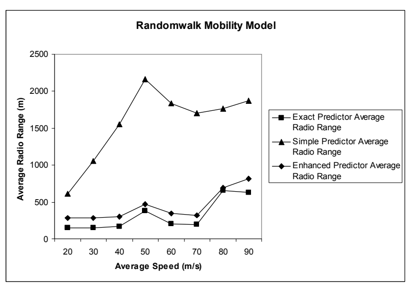


(F) – Manhattan Mobility Model,
Sampling Rate = 1/50

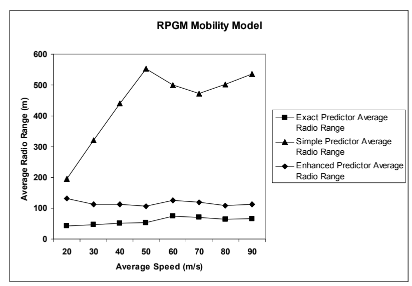
Figure 4 – Average Distance Prediction Error in Exact, Simple and Enhanced Estimators



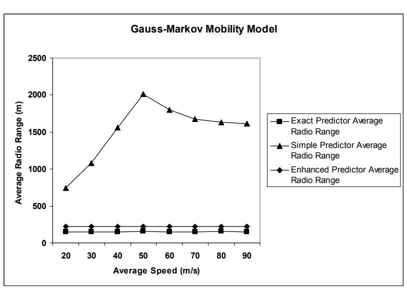
(A) – Random Waypoint Mobility Model,
Sampling Rate = 1/50



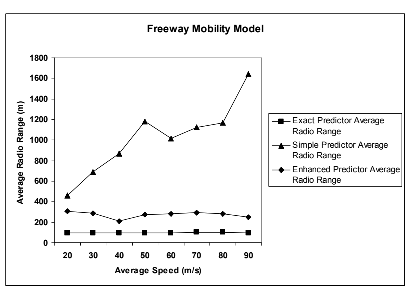
(B) – Random Walk Mobility Model,
Sampling Rate = 1/50



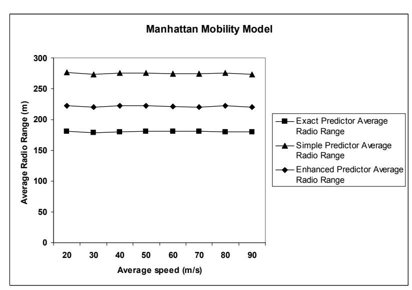
(C) – RPGM Mobility Model,
Sampling Rate = 1/50



(D) – Gauss-Markov Mobility Model,
Sampling Rate = 1/50



(E) – Freeway Mobility Model,
Sampling Rate = 1/50



(F) – Manhattan Mobility Model,
Sampling Rate = 1/50

Figure 5 – Average Selected Radio Ranges in Exact, Simple and Enhanced Estimators

V. Conclusion

In this paper we introduced the Mobility Aware Distributed Topology Control Protocol along with a new future distance estimator. In fact, we introduced a new adaptive future distance estimator which uses learning automaton to estimate its coefficients. Based on the value of these coefficients, the estimator can adaptively predict the future distance between 2 neighboring nodes for different mobility models, speeds and sampling rates. Our simulation results showed significant enhancement in accuracy, for the proposed adaptive future distance estimator in comparison with the simple future distance predictor proposed in [3].

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