

# A Review on Current Work in Mobility Prediction for Wireless Networks

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## ABSTRACT

The vision of next generation networks (4G & beyond) is to make possible seamless mobility across heterogeneous networks and to support real-time multimedia services. This would require intra/inter-domain handovers and service reconfiguration procedures to be completed with minimum latency. Mobility Prediction has been identified as a key abettor to this goal. The increasing ease of coupling between the mobile user and the network requires that a mobility prediction scheme that is to be deployed in next generation networks be capable of high levels of prediction accuracy despite randomness in user movement. In this work we have presented a survey on mobility prediction schemes that have been proposed for wireless networks. The results of our simulation study focussed on the robustness of different schemes to randomness in user movement are also presented.

## Categories and Subject Descriptors

C.2.1 [Computer Communication Networks]: Network Architecture and Design – *Wireless Communication*

## General Terms

Algorithms, Performance and Design

## Keywords

Mobility Prediction, Handovers.

## 1. INTRODUCTION

Mobility prediction schemes have been proposed to reserve radio resources and to configure cellular wireless networks in anticipation of demand. Accurate mobility prediction can offer a smaller call-dropping probability and lower handover latency in cellular networks. For a mobility prediction algorithm to be easily deployable in a wireless environment it should be efficient in terms of control overhead, not require changes to existing network structure or detailed knowledge of geographical surrounds, be

user specific and adaptable to both regular and random user movements. It is possible to predict the user's mobility based on its velocity and positional co-ordinates with respect to the cell structure, employing location techniques such as GPS. Alternatively we can exploit the record of a user's previous movement patterns stored in Mobility History Bases (MHB), or use stochastic models for mobility prediction. Section 2 presents some recent mobility prediction schemes that have been proposed. We list the salient features of each of these schemes with focus on their robustness to randomness in user movement. Section 3 presents the results of our simulation study and section 4 concludes the article.

## 2. MOBILITY PREDICTION SCHEMES FOR CELLULAR NETWORKS

Basic algorithms making use of individual movement patterns are algorithms employing the Location criterion, Direction criterion, Segment criterion, Baye's rule and Time criterion [1]. A mobile station employing the Location criterion records its next base station as it leaves its present location and keeps a record of the number of times it visits each cell. Based on the regularity of user movements a probability distribution of next moves is formed and is referred to as the departure history. The algorithm identifies the mobile's present location and uses the departure history of this location to predict its next move. The cell that is most frequently visited is predicted as the next move. The direction criterion extends the location criterion by including the mobile's direction of travel in the departure history for increased accuracy. The direction criterion thus incorporates direction information with the departure history. The algorithm identifies the present direction of travel and uses the departure history along this direction to predict the next cell of user residence. The cell in this direction with the highest departure rate is predicted as the next cell. The segment criterion extends the direction criterion scheme further. All previous movements are partitioned into a number of segments and stored. Each segment starts with a stationary cell (i.e., a cell in which the user stays for a sufficiently long time) and ends with a stationary cell, which in turn becomes the start of the next segment. As the user moves across the network its moves are appended as a segment and matched to those already in store. If a match is found then the cell immediately following the matched segment is predicted as the next move. The direction criterion can also be extended such that instead of considering the route already taken; all departure histories along the future direction of travel are considered. Making use of Baye's rule the conditional probabilities of all possible next moves for a destination further down the track can be calculated. For a destination that is two

hops away from the current position the Baye's rule formula is given as: -

$$P(B_x | C_m A_{i-1} A_i) = \frac{P(A_{i-1} A_i B_x) \cdot P(C_m | A_{i-1} A_i B_x)}{\sum_{j=1}^n P(A_{i-1} A_i B_j) \cdot P(C_m | A_{i-1} A_i B_j)} \quad (1)$$

$A_{i-1}$  and  $A_i$  are the previous and present locations,  $B_x$  is the  $x^{\text{th}}$  possible next move,  $C_m$  is the most likely step for visit two hops away and  $n$  is the total number of moves. Once the conditional probabilities of all possible next moves are calculated the one with the highest value is predicted as the next move. The time criterion assumes regularity of user movements with time of day and imposes the time of cell crossing into the direction criterion.

The main drawback of prediction schemes relying solely on the history of individual movement patterns is insensitivity to changes in user behaviour. A recent change in the user behaviour will not reflect significantly on the overall probability distribution of movement regularity. When a mobile user is found in new locations where movement histories do not exist, the algorithm is unable to proceed. To overcome the drawbacks of the basic algorithms, mobility prediction schemes that employ a user's mobility history base and stochastic models for movement prediction have been proposed. Mobility prediction schemes can be classified broadly into those that employ individual user mobility information and those that make use of group mobility patterns as their primary input to the prediction process. The secondary inputs to the prediction process are aimed at increasing the prediction accuracy of the scheme and are unique to each scheme.

## 2.1 Prediction schemes based on user movement history and Markov models

The Mobility Motion Prediction Algorithm (MMP) [2] consists of regularity detection algorithms and a motion prediction algorithm. The motion prediction algorithm uses a database of regular movement patterns and random movement probability information along with constitutional constraints to predict the next movement track of the mobile user. Movements are considered to be a combination of random and regular movements and are defined as a sequence of states that are stored in an Itinerary-Pattern base (IPB). A state is defined as a stationary state if the user has stayed in it for longer than a period of time  $\tau_s$ , a transitional state if it has stayed in that state or cell for less than  $\tau_s$  and a boundary state if the cell is at the boundary of the service area. The regular parts of the movement are modeled using the Movement Circle (MC) and Movement Track (MT) models as in Figure. 1, while stochastic processes and a Markov chain model are used for the random parts of the movement. The random user movements are modelled as a Markov process in which the probability distribution for its future development depends only on its current state. The regularity detection algorithm detects and forms the regular MC's and MT's from the movement tracks of the user. The Motion Prediction Algorithm (MPA) predicts the next states of movement or movement tracks by using correlation analysis of current movement-itineraries with the MC's/MT's in the IPB. By comparing the present itinerary of the user with those stored in the IPB the future regular movements of the user can be

derived. If the predicted itinerary pattern is inaccurate, then a three level matching scheme that consists of state matching, velocity matching and frequency matching is carried out. The matching process selects the best-matched itinerary pattern or predicts the state with the highest probability based on stochastic and Markov process analysis to be the next movement. As reported in the work [2] the performance of the MMP algorithm is accurate for regular user movement patterns but decreases linearly in accuracy with increase in randomness of user movement.

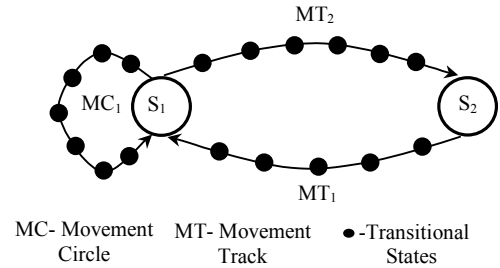


Figure 1. MT and MC model

The Predictive Distance based scheme [3] seeks to exploit the predictability of user mobility patterns in wireless networks. A mobile's future location is predicted by the network based on the information gathered from the mobile's last report of location and velocity. It is supposed that as users generally travel with a perceived destination in mind their future velocity and location are likely to be correlated with their present location and velocity. In systems with correlated velocity mobility patterns (unlike those with random-walk mobility patterns), the largest probability location of a mobile is generally not the last location of tracking update. It is argued [2] that a mobility scheme taking advantage of this predictability of the user's location can perform better. The future location of the user is predicted based on the probability density function of the mobile's location, which is given by the Gauss-Markov model based on the user's location and velocity at the time of the last location update. The prediction information is made available to both the network and the mobile thus enabling the user to be aware of the network's prediction of its location in time. The mobile checks its position periodically and performs location update when it reaches some threshold distance away from the predicted location. In the proposed distance based scheme the mobile reports both its location and velocity as part of the location update process. The model assumes correlation between a mobile's current location and velocity and its future location and velocity.

In [9] statistical prediction of user mobility is proposed for mobility based call admission control and bandwidth reservation. Probabilistic prediction of user behaviour is derived from the accumulated behaviour history of the specific mobile. The rationale behind the scheme is that a user's mobility pattern is a reflection of routines and most mobile users exhibit favourite routes and habitual movement patterns. This repetitive nature of the mobility patterns is likened to the stationarity of a sequence of events generated by an  $m^{\text{th}}$  order Markov source. Learning these patterns from the mobility history the next move can be predicted when these patterns reappear. The mobility prediction scheme is derived from data compression techniques and is based on the character-based version of the Ziv-Lempel algorithm [10]. The sequence of events during the lifetime of a call corresponds to a sub-string in the Ziv-lempe algorithm. The mobility database of

every mobile at a specific time holds a Mobility Trie, which is a probability model corresponding to the Ziv-Lempel algorithm. Each node except for the root in the trie preserves handoff related statistics (cell, time & handoff probability) that can be used to predict the probability of following events. The mobility trie is built in an online fashion. When a mobile requests a new call, the predictor sets the current node to the root of the trie according to the mobile, cell and time and calculates the probabilities of all possible events of this mobile. When an event in the trie matches the actual event of the mobile the predictor walks down the trie and is ready to predict again. When an event not in the trie occurs a prediction fault is generated and the event is added to the trie. The scheme is able to achieve a better guarantee of handoff dropping probability while maximizing resource utilization.

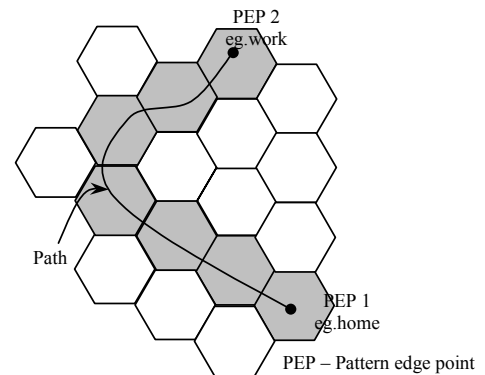
## 2.2 Prediction schemes based on user movement history and non-Markov techniques

The Regular Path Recognition (RPR) Method [11] attempts to exploit regularity in human behaviour in terms of periodic daily activities such as travelling to work etc., which results in probabilities that can be assigned to used paths. Making use of recorded cell patterns, regular user behaviour is divided into pattern edge points (PEP) and paths. PEPs represent static geographical places, such as home or work and are locations (or cells) in which the user stays for a sufficient period of time. Paths on the other hand are connections between two PEPs for which radio network measurements are recorded. The concept is as in Figure. 2. RPR is based on the recording of measurement reports and considering the three strongest received base stations that are sorted according to power levels with handover and idle cell selection criterion. The recording of user measurements and generating user profiles requires GSM measurement equipment making use of a GSM modem, a GPS module and a notebook. Given a user profile is available the algorithm detects if the current reference point is a PEP or part of a path. The PEP or path is compared with previously stored PEPs and paths, which results either in confirmation of the known PEPs and paths or the generation of new ones. Making use of RPR the accuracy of handover prediction has been reported as 60-70%. The accuracy of the algorithm depends on how close the match is between the stored and measured paths.

In [12] a mobility learning and prediction scheme (MLPS) is proposed for restoration of mobility databases in PCS networks. In PCS networks the user's location information is maintained in mobility databases. Locating of users in the event of failure of these mobility databases can be costly. An explicit restoration procedure is required to guarantee continuous service availability to users and prevent large service delays and deterioration in system performance. As a user's mobility dictates its current location, introducing mobility prediction into the restoration process allows systems to locate users after a failure of mobility databases. If systems can accurately predict the probable location of users after a failure it considerably reduces paging costs. This approach to mobility prediction and learning extrapolates probable user locations using the previously known mobility information by a Neural-Fuzzy Inference System (NFIS). The mobility learning and prediction scheme expresses user mobility as the movement velocity and direction. The future location is

predicted from the movement factors of past and current locations. Making use of movement states the NFIS movement function maps the previous and current states onto a future movement state. The probable location of user is obtained from the velocity and direction of the future movement state. Clustering-based techniques that can generate fuzzy rules according to the similarity of movement states are used to construct the fuzzy rule base. The prediction scheme is 80-90% accurate for users that have fairly regular movement patterns. For users with an element of randomness in their movement pattern the prediction accuracy decreases to 20-35%.

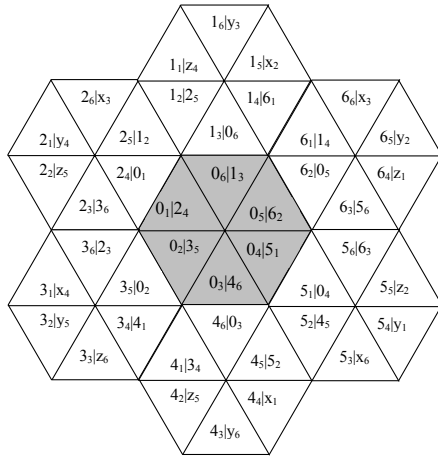
The Sectorized mobility prediction approach [15] is built on the rationale that in order to achieve maximum accuracy in movement prediction the prediction process should be restricted to areas of high handoff probability. To ensure prediction accuracy the process must guard against under-prediction (i.e., commencing the prediction process too late so as to miss a handoff) and over-prediction (i.e., predict too early along a user path). Prediction restricted to the last few movement legs of a mobile user ensures higher accuracy of prediction. To this end the sectorized cell structure to aid in mobility prediction is introduced. The sectorized mobility prediction scheme employs the sectorized mobility history base to aid in regular user movement prediction and makes use of the cell-sector numbering scheme (Figure. 9) to predict random user movements. A method of identifying if the user is moving along a previously stored pattern (regular path) or following a new user path (random path) is also defined. The algorithm does follow traditional methods in that it makes use of previously recorded mobility patterns of the user to predict future movements. User movements are considered to be a combination of regular and random movement patterns. While traditional algorithms store the past movements of the user on a cell-by-cell basis in a mobility history base (MHB), the sectorized mobility history based (SMHB) stores the positions of the user on a sector-by-sector basis. As the sectorized movements of the user are tracked HO points are identified. While the regular movements of the user are predicted using a SMHB once it has been identified that the user is on a random movement track - a method of prediction of the random movements of the user is required. While it is possible to obtain accurate tracking by making the prediction process highly complex the proposed method is computation non-intensive and introduces minimal amounts of additional traffic on the wireless link.



**Figure 2. The Regular Path Prediction scheme**

The cell-sector numbering scheme is used to predict the next handover point. The scheme sits on top of any other cell-

numbering scheme and is only for the purpose of mobility prediction. As shown in Figure. 3, the cell that the user is resident in (greyed) is always identified as the reference cell 0, i.e., if the user moves from cell 0 in the figure to cell 5 then cell 5 is referred as cell 0 for mobility prediction purposes. Each sector of the resident cell is then identified using  $0_i|a_j$  where '0' is the reference cell and 'a' denotes the neighbouring cell to which the users can handoff to from this particular sector of the reference cell. Re-referencing of a neighbour cell is only done if the distance from the original reference cell sector to the present resident sector is at the least 2 cell-sector crossings. The system is robust enough to handle oscillating users between two sectors of different cells without any re-referencing. The sectorized method is found to maintain high levels of prediction accuracy despite randomness in user movement



**Definition :**  
Each sector of cell 0 takes a value  $0_i | a_j$   
where  $i = 1 \dots 6$ ;  $a = 1 \dots 6$ ;  $j = 1 \dots 6$   
further  $a = (i + 1) \bmod 6$  &  $j = (i + 3) \bmod 6$   
And a neighbouring sector takes a value  $a_j | 0_i$

**Figure 3. The Cell-Sector Numbering Scheme**

### 2.3 Probabilistic mobility prediction schemes

The Shadow cluster scheme [4] has been proposed for resource allocation and call admission control in ATM-based wireless networks. The fundamental concept behind the scheme is that every mobile with an active wireless connection establishes an influence upon the cells in its immediate neighbourhood along its direction of travel. The cells (or base stations) currently being influenced are referred to as the shadow cluster. The influence (or shadow) is strongest near the active mobile and fades as a function of factors such as distance to the mobile, call holding time and priority, bandwidth resources being used and the mobile's current trajectory and velocity as in Figure. 4. The framework of the system can be viewed as a distributed messaging system where a mobile user informs the base stations in its shadow cluster about its requirements, position, and movement parameters to enable the base stations to predict and reserve resources.

In a wireless network implementing the scheme every base station must inform its neighbours about the future location probabilities of each of the mobiles under its control. The location probabilities are calculated based on mobility dynamics (past and present) and call holding patterns. It is further refined using past movement history and detailed knowledge of the geographical surrounds. In high mobility environments there is an increase in the number of messages exchanged between the mobile nodes and the BTSs. Further, reservation of resources (though in proportion to probability of arrival) at BTSs more than one cell crossing away will cause increased dropping of new calls in densely populated networks or cells.

The Most Likely Cluster (MLC) scheme [5] builds on the Shadow Cluster probabilistic approach to determine the most likely location(s) to be visited by the mobile unit. The integration of a mobility model into the service model is proposed to achieve efficient network resource utilization and avoid severe network congestion. In order to deterministically guarantee QoS, exact knowledge of the user's movement path is required. The MLC is defined as a collection of contiguous cells each of which are characterized by a directional probability above a certain threshold. The directional probability of a cell is directly related to its position with respect to the direction of user movement. All users are classified as profiled and non-profiled users. A user profile includes mobility patterns of the user and the services used by the user. The most likely cluster model predicts the user's direction of movement based on this history of its movement. In order for the prediction method not to be affected by small deviations in mobile directions and to converge rapidly to the new direction of movement a first-order autoregressive filter with a smoothing factor is employed. The accuracy of the MLC scheme is directly related to the randomness in user movement. For user movement with a randomness factor of 0.2 the accuracy is between 80-90%. For a randomness factor of 0.6 the accuracy decreases to between 40-50%.

The QoS Adaptive Mobility Prediction (QoSAMP) algorithm [1] is a prediction scheme driven by QoS demand or tariff preference. Its emphasis is on resource reservation and network pre-configuration at appropriate locations in the direction of travel. The Prediction Confidence Ratio (PCR) is introduced to minimise the effect of statistical randomness in user's movements. Effectively random movements are not predicted.

To achieve QoS compliance the QoS requirements of applications or tariff preferences are related to a particular PCR value, which is applied to the adaptive prediction mechanism. A prediction is derived from the probability distribution of all possible next moves. If the first predicted cell does not satisfy the required PCR, additional cells are involved until the probability sum exceeds the PCR. There is a strong dependence on the stored probability values of past user movements with prediction from new locations with a lack of history, being approximated to a group mobility model. Prediction from a new location is based on the movement pattern of the majority in the cell. The algorithm does not deal with the prediction of non-regular individual user movements allowing room for prediction inaccuracies. To ensure prediction accuracy even in the less complex non-random scenario the scheme requires increased PCR. A higher PCR value requires more number of cells to be involved. It is seen that to

achieve a PCR value of 1 (corresponding to 100% accuracy level) the average number of cells involved is 3.

## 2.4 Hierarchical mobility prediction schemes

A two-level approach to mobility prediction is introduced in the Hierarchical Position Prediction (HPP) scheme [6] by defining user mobility at the global and local levels. HPP aims to improve connection reliability and overall system performance by accurate user movement pattern prediction. At the global level, approximate pattern matching is applied to determine the mobile's overall inter-cell movement direction, and at the local level an optimum self-learning Kalman estimator makes use of real-time signal strength measurements to estimate the mobile's intra-cell movement direction and velocity. Global level mobility is in terms of inter-cell movements, the cell sequence the user might achieve during its connection lifetime. The mobility model is motivated by the assumption that most mobile users exhibit regularity in their movements and such regularities can be characterized by a number of user mobility patterns (UMPs), recorded in a profile for each user and indexed by the most possible occurrence time. The UMPs proposed here have a decreased sensitivity to small deviations of actual user path while retaining the ability to explore inter-cell moving intention by approximate pattern matching. At the local level, resolution is in terms of intra-cell movements modeled as a stochastic process with state variables that vary dynamically with time. The motivation for the local level modeling is to reduce the uncertainty of inter-cell mobility by tracking the user's intra-cell movement. Reported results of the HPP algorithm show that it remains reasonably accurate (83%) despite the influence of random movements. The time taken for the Kalman filter to stabilise is attributed to the initial inaccuracy in prediction.

The combined prediction system [13] is a hierarchical prediction mechanism that extends the Profile based Next-Cell Prediction algorithm [14] based on a location classification and individual user movement history. The combined prediction system uses two prediction techniques, namely signal strength prediction and next-cell prediction. The combined approach aims to eliminate incorrect handoff requests and provide destination driven handoff patterns for MSs. The rationale behind the scheme is that if it were possible to determine a candidate base station in advance and then predict the signal strength values from this base station to the mobile station a considerable reduction in the mean number of handoffs can be achieved. This involves extension of the next cell prediction scheme to mask out BSs that do not meet the criteria for a candidate base station consideration, and signal strength prediction for obtaining instances in time for handoff, based on priority levels. Once a candidate base station is selected, handoffs to it are determined by LMS adaptive prediction of received signal strength. Handoff priorities are assigned, with a higher value indicating a strong handoff request to the base station. The combined prediction system is approximately 80% accurate for handoff prediction.

## 2.5 Mobility prediction based on group mobility

The Neural-Network Based Prediction Algorithm [7] proposes a prediction scheme that takes into account both global and user level information while performing the prediction. The first level

is a neural global predictor (NGP) that keeps track of all the users in a cell. An accurate prediction will be given by the NGP based on paths of users within the cell. The second level is a user track predictor (UTP) that keeps track of user specific movement history. The model is designed with the assumption that all mobile users will move along pre-set paths such as along roads, streets etc. The NGP consists of a 2-hidden layer neural network with back propagation error correction learning. The x-y coordinates, the distance from base station centre and moving direction of a user within a cell are fed periodically into the NGP as the input of the neural network. The NGP predicts the next cell crossing at a global level and reserves resources at the predicted cell. In order to eliminate the effect of some small disturbance of movement such as a sudden stop, moving backwards and then forwards, the input data is filtered and smoothed. The proposed method requires the design of a neural network as well as prior detailed geographical knowledge of the cellular structure. The analysis of this method stresses that the next cell is predicted accurately based on movement paths within the cell and that prediction is user independent.

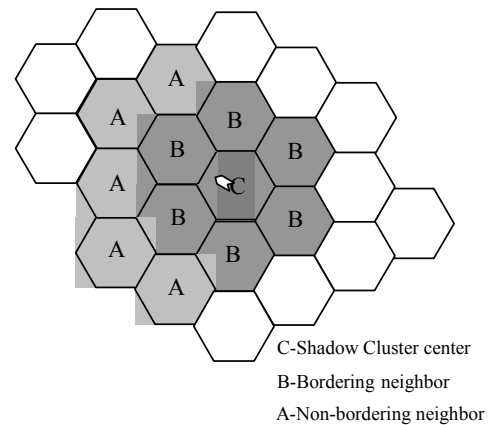


Figure 4. The Shadow cluster concept

A "user movement tendency" is introduced by the user movement tendency prediction scheme [8] to characterize user behaviour by making a judgement of whether the user is moving or not. It is assumed that the user's movement tendency is stationary within a certain time period before commencing an active communication. The algorithm aims to determine the movement tendency during the stationary time-period, which is then used to predict user's movements during the active communication period. The required inputs to the information processing system are user's location and velocity estimation records, local geographical features and statistical traffic information as in Figure. 5. The output is the movement tendency of the mobile user – which road it is moving along and its direction. The algorithm works on the assumption that the traffic speed distribution is constant for each road and that the speed of the user is constant. The user's movement tendency is predicted by tracking the sequence of roads and moving directions that the user follows in a certain time period. A trellis-like diagram is employed to evaluate the metric value for different paths a mobile user may follow during a certain time period. The metric value of each line represents the likelihood of the user movement tendency along a specific path. By calculating the metric values of all possible paths, one path, which has the highest metric value, can be chosen as the survivor path and all

other paths discarded. Prediction is in terms of the possible physical locations of the mobile user and not in terms of the possible connection points on the network.

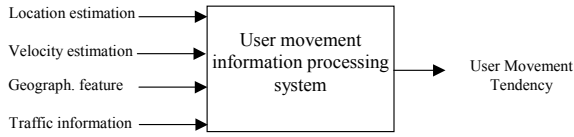


Figure 5. User Movement Tendency Prediction

### 3. SIMULATION STUDY

Performance study of the MMP, MLPS, MLC and the sectorized mobility prediction scheme was performed in a cellular environment using the OPNET modeler 9.0 simulation tool. The focus of the simulation study was to evaluate the performance of each of the algorithms with respect to their extensibility to next generation networks. The scheme would need to exhibit compliance to foundational protocol principles for both hybrid and completely ad hoc network environments as next generation networks will employ the wide area cell-based concepts along with hot-spot (WLAN) and ad hoc networking. Emphasis on the robustness of the prediction scheme to randomness in user movement is required. With this focus our points/metrics of interest were: -

**Prediction Accuracy:** The ratio of the number of handoffs actually executed by the user to the number of handoffs predicted by the scheme. To be incorporated successfully into a resource reservation scheme the prediction process should guard against over-prediction.

**Prediction Accuracy**

$$= \frac{\text{Number of user executed handoffs} - \text{No. of prediction misses}}{\text{Number of user executed handoffs} + \text{No. of overpredictions}}$$

**Randomness Factor ( $R_f$ ):** The ratio of random handoffs executed by the user (i.e., handoffs not previously stored) to the total number of handoffs executed by the user. The scheme should be able to adapt to high degrees of randomness in user movement without compromising the prediction accuracy.

**Randomness Factor ( $R_f$ )**

$$= \frac{\text{Number of user executed handoffs not previously stored}}{\text{Total number of user executed handoffs}}$$

**User Mobility Support:** The scheme should be able to support different user types with the same level of prediction accuracy and control overhead.

The simulation model consists of a cluster of hexagonal cells. The base station for each cell resides in the centre of the cell. In order to maintain consistency of results and ensure that all cells have equal handoff probabilities user executed handoffs from outlying cells are not included in the simulation results. To maximize the number of handoffs executed on the network each mobile user was assumed to maintain a call for the entire simulation interval. The movement of the mobile user was not restricted in relation to direction or step size. The simulation environment allowed users to move in any arbitrary direction (between  $0$  &  $2\pi$ ) and vary their speed at random intervals. Depending on the user category

there exists [MinSpeed, MaxSpeed]. Simulation runs were conducted for pedestrian or low-speed users with a speed of 4 km/hr - 6 km/hr, medium-speed users with a speed of 15 km/hr - 55 km/hr and, high-speed users of speed 100 km/hr - 130 km/hr. The diameter of each cell was set approximately to 1000 meters. Simulation runs were conducted with different random seeds and the results were averaged over all these iterations.

Figure. 6 reports the comparative performance of the four prediction schemes in terms of robustness to randomness in user movements. MMP and MLC both make use of constitutional constraints to increase the accuracy of prediction. In our studies the MMP (0%) and MLC (0%) corresponding to when no constitutional constraints are in place and the MMP (92%) and MLC (91%) scenario when maximum constitutional constraints are in place were used. It is observed that the sectorized scheme is the least affected by the increase of randomness in user movement. The prediction accuracy of the MMP, MLC and MLPS are found to almost linearly decrease with increase of randomness in user movement. The accuracy of the sectorized scheme, even in the case when there is a 20% error introduced in the specification of the Hi-HO region is still considerably higher than the other schemes. The decrease in accuracy is partly attributed to over prediction in which case all handoffs executed by the user are still predicted accurately.

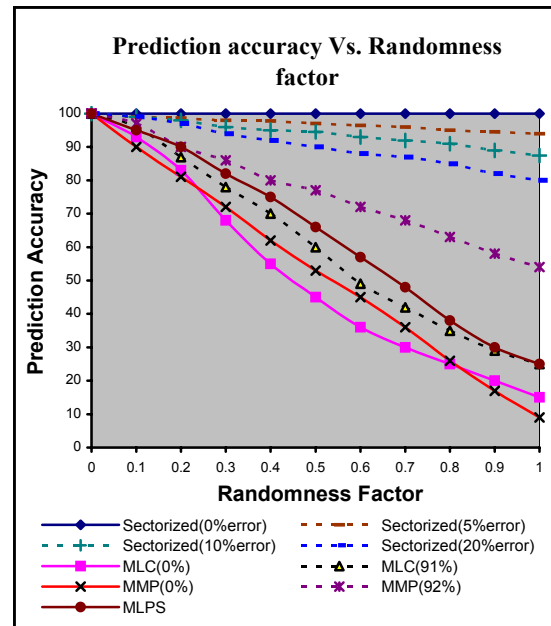


Figure 6. Accuracy Vs. Randomness Factor.

Figure. 7 reports the efficiency of the sectorized method with relation to different user types. It can be seen the maximum prediction accuracy is achievable for all three types of users with significant reduction the area of tracking that is required. The results presented are for area for user movement randomness value  $R_f = 1$ . In this scenario the scheme is required to function independent of the SMHB as there are no recorded user movement patterns. It is observed that the scheme is capable of accurate prediction in the completely random movements scenario with critical areas of tracking being 40%, 47% and 54% of the cell area for the slow moving, medium-speed and high-speed user

respectively. Since a record of user movement patterns cannot be maintained in an ad hoc network environment, the scheme by offering maximum accuracy independent of the SMHB exhibits potential to be extended into the ad hoc networking domain. Achieving high prediction accuracy with reduction in the area of tracking augurs well for the scheme in comparison to traditional schemes that require tracking in the complete cell area.

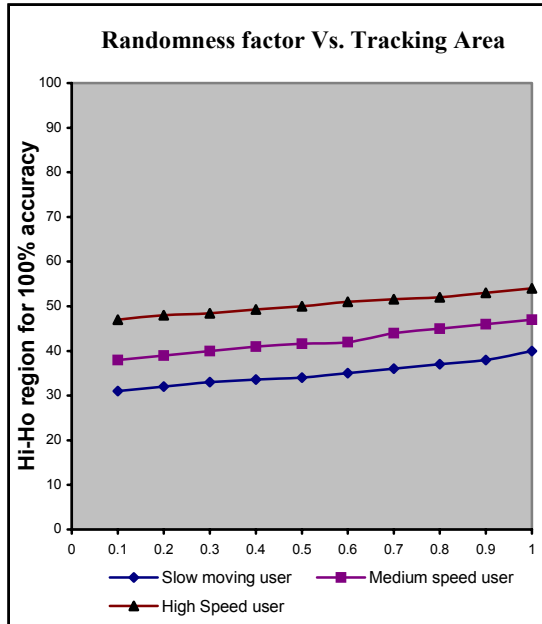


Figure 7. Randomness Factor Vs Tracking Area

#### 4. CONCLUSION

In this article we have presented a review of recent work on mobility prediction in wireless networks. While mobility prediction can assist in achieving handovers and service reconfiguration with minimum latency in cellular networks they offer support to route discovery and reconstruction procedures in ad hoc networks. A classification of mobility prediction techniques has been attempted along with simulation study of the MMP, MLPS, MLC and Sectorized approaches to mobility prediction in wireless networks.

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