

**Mobility Modeling, Prediction and Resource Allocation
in Wireless Networks**

by

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Abstract

Rapid increase in the number of mobile and wireless users has created greater loads on legacy networks. Also, increased miniaturization of computing devices has led to an influx of handheld gadgets. Mobile users now wish to have seamless roaming across networks and not experience fluctuations in the quality of service. These wireless devices can overwhelm existing networks since these were traditionally not built to handle heavy user mobility across networks.

User mobility influences the performance seen by a mobile device in a wireless network. Prior knowledge of mobility patterns can be exploited to properly allocate network resources and enhance the performance and quality of service experienced by a mobile device for applications and services. Hence, mobility prediction plays an important role in the efficient operation of wireless networks such as WANs and WLANs. In this work we propose a probabilistic model to effectively predict user mobility using wireless trace sets using a Hidden Markov Model (HMM). Access to mobility related information such as user movement provides an opportunity for networks to efficiently manage resources to satisfy user needs. Also, mobility models for simulation and their performance analysis are investigated rigorously.

Adaptive network resource management based on user mobility can reduce network loads. Towards this goal, we propose a generic methodology based on a control theoretic framework. The feedback based controller effectively uses the predicted mobility to allocate resources effectively for mobile users. Incorporation of this engine in a control theoretic framework with feedback from an adaptive controller permits the efficient allocation of network resources to various applications. The effectiveness of the approach using a prediction engine based on HMM is evaluated through simulation experiments. All simulations use real-world wireless traces. The proposed framework is quite general and the HMM based

engine can be replaced by other suitable models such as neural networks and results for these show that the framework is indeed modular as proposed.

Mobility also influences the interference seen by a mobile user. We study the effect of mobility on interference dynamics and the outage perceived by users in a cellular system. Due to the mobility of interfering nodes, the aggregate interference and its statistics are time-varying. Analytical results are obtained for interference statistics by using a Gaussian model and considering the effect of different mobility models. For this purpose, the cross-over probabilities of different edges of a cell and for different mobility models are obtained through simulation and used in the derivation of analytical results.

The main contribution of this dissertation is a generic framework for mobility prediction and resource management. A flexible and generic framework for mobility prediction and resource allocation allows for use of other techniques such as ARMA and machine learning in place of HMM and Neural Networks. The generic model can be used in various network applications such as QoS, seamless handover and jitter-free streaming applications.

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Chapter 1

Introduction

Recent trends in the development of microchip technologies and their miniaturization has caused an explosive spurt in the growth of the hand held device market. Examples of such devices are laptops, PDAs, WiFi enabled cellphones, etc. With ubiquitous wireless connectivity in today's workplaces, social and home environments, these devices are naturally wireless enabled and lead to increased usage at all places. The presence of cellular handsets embedded with WiFi and bluetooth devices, PDAs enabled with multiple kinds of radios, etc can also enable other kinds of networks such as ad hoc networking [1]. These devices support several applications including voice, video, data, etc which are bandwidth intensive.

Even though devices and networking capabilities are ever increasing, there still exist several challenges that can constrict the growth of the hand held wireless market. Some such factors include network connectivity, bandwidth fluctuations and high network costs. Also, available network resources are subject to abrupt changes due to factors such as mobility, environmental variations, etc.

Most access points or home wireless routers are single node networks that are not properly planned before installation. They may be interfering with several other neighboring device channels or may not be installed at the right locations. The increasing availability of public wireless access points with internet connectivity has also increased. Most of these wireless networks are connected to backbone wired legacy systems and wired-wireless networks are still prevalent in several places.

The sudden arrival of a large number of wireless users can lead to a bandwidth crunch and result in network failure. Hence there is a necessity to explore proactive methods to provide guaranteed services to the wireless applications. The huge popularity of wireless

hand held devices have necessitated provisioning distributed resources to a variety of mobile client terminals.

1.1 Motivation

With the availability of contiguous coverage, mobile users now expect to have uninterrupted service. Since most users are highly mobile, there is a need to include mobility as an inherent part of the system [2] [3]. Mobility introduces dynamism in the network. The network, if modeled as a graph with users as vertices and links between the users/network as edges, is ever changing due to the continuous motion of the users. A single network graph snapshot would be stale within a short time and would be worthless to determine the current positions of users. Also, different classes of networks exhibit different flavors of mobility. User mobility in a cellular environment is very different from the mobility of WLAN users. Mobile users on an educational campus move very differently as compared to users on the streets in a city or users in a dense city environment. There may be some level of predictability depending on the topology of the network graph. One way of studying mobility is through designing mathematical models that can model human mobility [4] [5] and these are usually used in simulations. Also, extensive experimental studies have been performed to collect mobility traces of users. However, this requires a lot of resources and becomes mostly specific to the scenario in which the experiments were conducted.

Similar to cellular handoffs, wireless networks also need to hand over the users to an adjacent networks access point (AP) [6]. This is necessary in order to continue active sessions such as voice-over-IP (VoIP) calls, video and audio streaming sessions, file transfers, etc without any disruption of service. This means that their connections are constantly being switched from one wireless access point (AP) to another. A handoff is possible only if resources are made available at the next location and the current AP can inform the next AP before hand. A failure in this process leads to session termination due to any of the reasons such as latency, lack of resources, etc.

In order to ensure timely handoffs, we need to allocate resources at neighboring APs to facilitate the mobile user to join an adjacent AP without interruption to the connection. Reserving resources at several or all neighboring APs causes a definite wastage of resources leading to under-utilization of the network. Moreover, it may not be possible to allocate resources at all neighboring APs to all the current users in the present AP. Hence, some kind of prior knowledge of a mobile user's next destination is helpful in allocating resources. This process is called mobility management.

Cellular providers have performed tracking of user locations to facilitate channel assignment, paging, etc. This kind of continuous real time tracking is necessary in a cellular system since the users are moving at very high speeds. Such continuous tracking is resource intensive and not necessary in a WLAN network since most users move at pedestrian speeds. Slow moving users in a wireless network offer better localization techniques, alternate handover schemes to endure seamless handoffs, etc but offer other challenges such as disjoint WLAN networks and random mobility. In this dissertation, towards this goal of effective resource allocation, we propose a method of predictive mobility management based on a control theoretic approach. We propose a method of mobility prediction, i.e., predicting a mobile user's next location. We make use of a prediction algorithm that can accurately estimate the next location visited by a mobile user, given current and historical movement information. Further, a feedback control system provides information regarding network resource and utilization for better overall resource management. A brief overview of this thesis is presented in the subsequent section.

1.2 Organization of this dissertation

This dissertation is organized as follows.

Mathematical mobility models are an efficient and simple means to validate network protocols and algorithms. In Chapter 2, we lay the groundwork for studying mobility in

networks. We shall discuss the methods of mobility simulation in network models, advantages and disadvantages of existing mobility models and a thorough performance analysis of mobility models under different routing protocols.

Chapter 3 deals with methods of predicting mobility in wireless local area networks (WLAN). In spite of the advantages of using mobility models, we shall use real-world wireless trace data to perform simulations. This chapter provides several methods to perform mobility prediction such as Markovian, Neural Learning methods, etc. We have analyzed the performance of Markovian methods with regard to mobility prediction. A first order and a k^{th} order Markov model are studied. Hidden Markov Model and Neural Network models are proposed to perform mobility prediction.

Modeling and prediction of user mobility is studied in Chapter 3. To use the prediction model effectively to dynamically allocate resources in the network, we propose a control theoretic approach to resource allocation in Chapter 4. A feedback based control system is designed to operate with the network prediction scheme. The proposed scheme is studied both mathematically and experimentally using Monte Carlo simulations. The scheme has the advantage of being incorporated into existing WLAN architectures. To our knowledge, this is the first time control theory is used for studying the effect of mobility on mobile network performance.

Chapter 5 provides a discussion on interference caused due to mobile users in the network. Expressions for aggregate interference on a wireless user from other cells are obtained. Also, effects of mobility average instantaneous number of mobile users in a cell and probability of crossing over to adjacent cells are taken into consideration. Analytical results are obtained for interference statistics under various mobility models.

Chapter 2

Simulation Study of Mobility Models

2.1 Overview

Modeling Mobile wireless networks poses certain challenges that make real prototype implementations very difficult. Some of these are rapidly fading channel characteristics, dynamic topologies, fast user movements, etc. However, these challenges can be addressed by performing a simulation study of such characteristics. Hence a practical method for evaluating the characteristics of networks is through the use of computer simulation methods. Simulation provides researchers with a number of significant benefits, such as parameter abstraction, multi-level views for different tests, etc. A strong simulation based on realistic scenarios provides better insight into understanding the performance of these networks. It is vital for robust network design to understand network performance under different network protocols, varied physical conditions, repeatability in experimental setups and mobility. Also, a large variety of realistic scenarios and network configurations/deployments can be evaluated through simulation. Characterizing these parameters are extremely hard in real network setups. Hence, simulation is the most popular tool for studying and analyzing the performance of networks.

Simulation also has other key advantages such as providing a deeper insight into how parameter changes such as mobility, speed or mobile users, etc impact end user performance. Simulation facilitates parameter isolation which helps study the effects of a single parameter, such as mobility, transmission range, etc. while other metrics may remain unchanged.

A network simulator provides the advantage of simulating network mobility which is the central idea proposed in this dissertation. After the initial placement of nodes, the ‘mobility model’ governs how the nodes move during the course of the simulation. It is this feature

that is useful for our purposes. In this chapter, we discuss the details of several mobility models and their effects on simulation.

2.2 Motivation for using Mobility Models

As discussed in the previous section, mobility models provide benefits in simulating node mobility. They are mathematical algorithms that try to model the behavior of real movement patterns. The mobility model has to be designed to describe the actual movement pattern of mobile users, their geographic location, speed, etc. Since mobility patterns may play a significant role in determining the protocol performance, it is imperative that network protocols [7] [8] [9] be tested for mobile conditions too. Otherwise, the observations made and the conclusions drawn from the studies may be misleading. Hence, when evaluating Mobile Ad hoc Network (MANET) protocols, it becomes necessary to choose the appropriate mobility model for a particular scenario [10].

The mobility model is designed to describe the movement pattern of mobile users, and how their location, velocity and acceleration change over time. Since mobility patterns may play a significant role in determining routing protocol performance, it is desirable for mobility models to emulate the movement pattern of targeted real life applications in a reasonable way. Otherwise, the observations made and the conclusions drawn from the simulation studies may be misleading or erroneous. Hence, while evaluating network protocols, it is of great importance to choose the correct mobility model that suits the real world scenario [11] [12] [13].

2.3 Existing Mobility Models

Mobility models for simulations are implemented as discrete movements of nodes that adhere to certain mathematical rules such as node densities, initial statistical distributions, etc. The initial statistical distribution of nodes may follow uniform, Gaussian or any other distribution. Once the nodes have been initially distributed, the mobility model dictates

the movement of the nodes within the network. Because the mobility of the nodes directly impacts the performance of routing protocols, simulation results obtained with unrealistic movement models may not correctly reflect the true performance of the protocols.

The topology and movement of the nodes in simulation are key factors in the performance of the protocols under study. Initial distributions, node velocities and successive node positions relative to previous locations need to realistically model real-world movements to obtain a true performance metric from the simulation study.

Several mobility models are used in network simulations. Some are very generic and are usually applied to a wide variety of scenarios. Others however may be tailor made for a very specific case and node movements modeled as the case may be. Hence, it is important to understand that there is no one-model-fits-all mobility model. Also, there are other properties of mobility models such as the stationary distribution (i.e., where the nodes spend most of the time) and average velocity that help decide the right model for the simulation.

Mobility models can be broadly divided as random models and dependent models. Random models are those whose parameters such as velocity, direction, etc are based on random processes. On the other hand, dependent mobility models have parameters dependent on geography, location, direction, clustering, etc. A classification of mobility models is shown in Figure 2.1.

To model random mobility in simulations and experiments, random mobility models [14] are extensively used in mobile networks. Other random parameters such as speed, direction, etc [15] [16] [9] have also been considered. Some of the commonly used mobility models in simulation are Random Way Point Model (RWP), Random Walk model (Brownian motion), Random Direction and Random Trip mobility models. However, there is still no way to use these directly on a single users movement to predict a users next position.

In the subsequent sections, we shall discuss the performance of some of the popular mobility models, their mathematical properties, strengths and limitations.

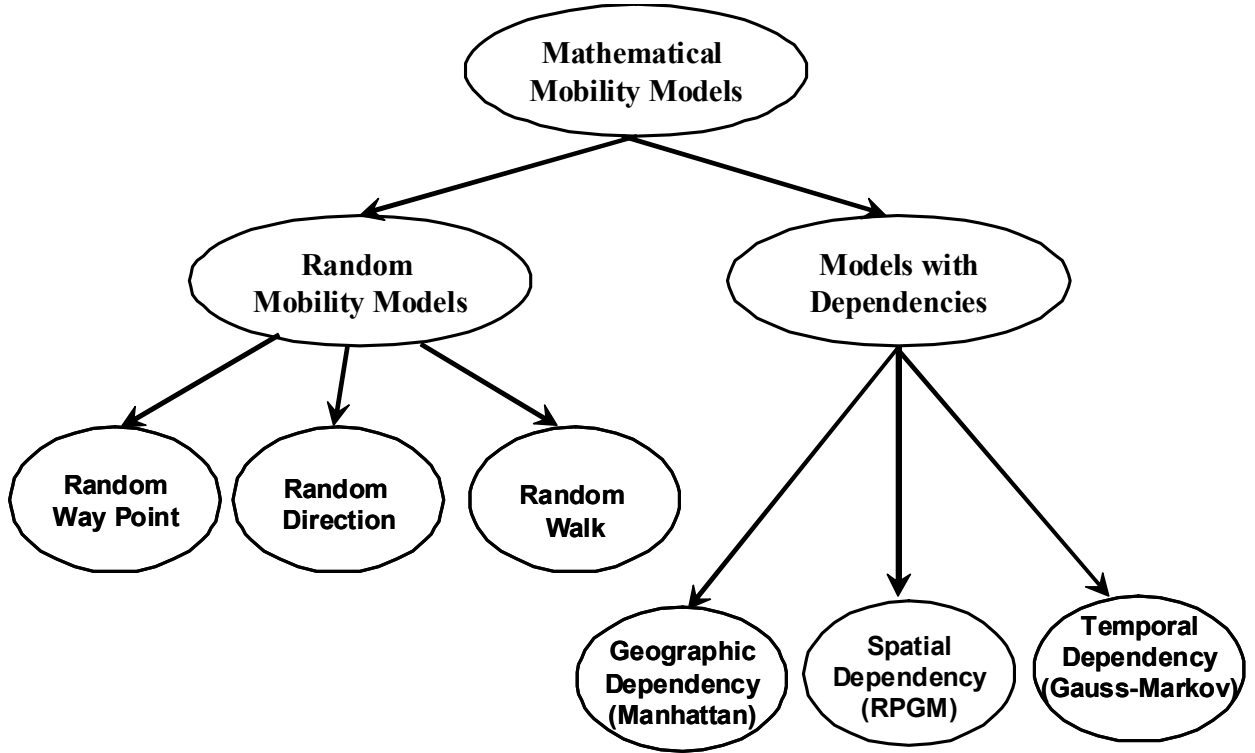


Figure 2.1: A classification of mobility models in literature

2.3.1 Random Way Point Mobility Model

Random Way Point (RWP) mobility model is a simple synthetic mobility model not based on any actual traces. It is very easy to implement, easy to derive analytical results and can be described using very few parameters. The key features of RWP mobility model are random velocity of node movements and pause times between changes in direction and/or speed. A mobile node moves from one location to another for a certain period of time with a random velocity given by a uniformly distributed interval $[0, v_{max}]$. Then, it pauses for a period of time T_p . After this, it once again chooses a random destination in the simulation field and moves towards it at a new velocity. The process repeats again indefinitely to simulate node movement.

The RWP is a random mobility model where the node moves randomly without restrictions. In essence, the destination, velocity, pause time and direction are all chosen randomly

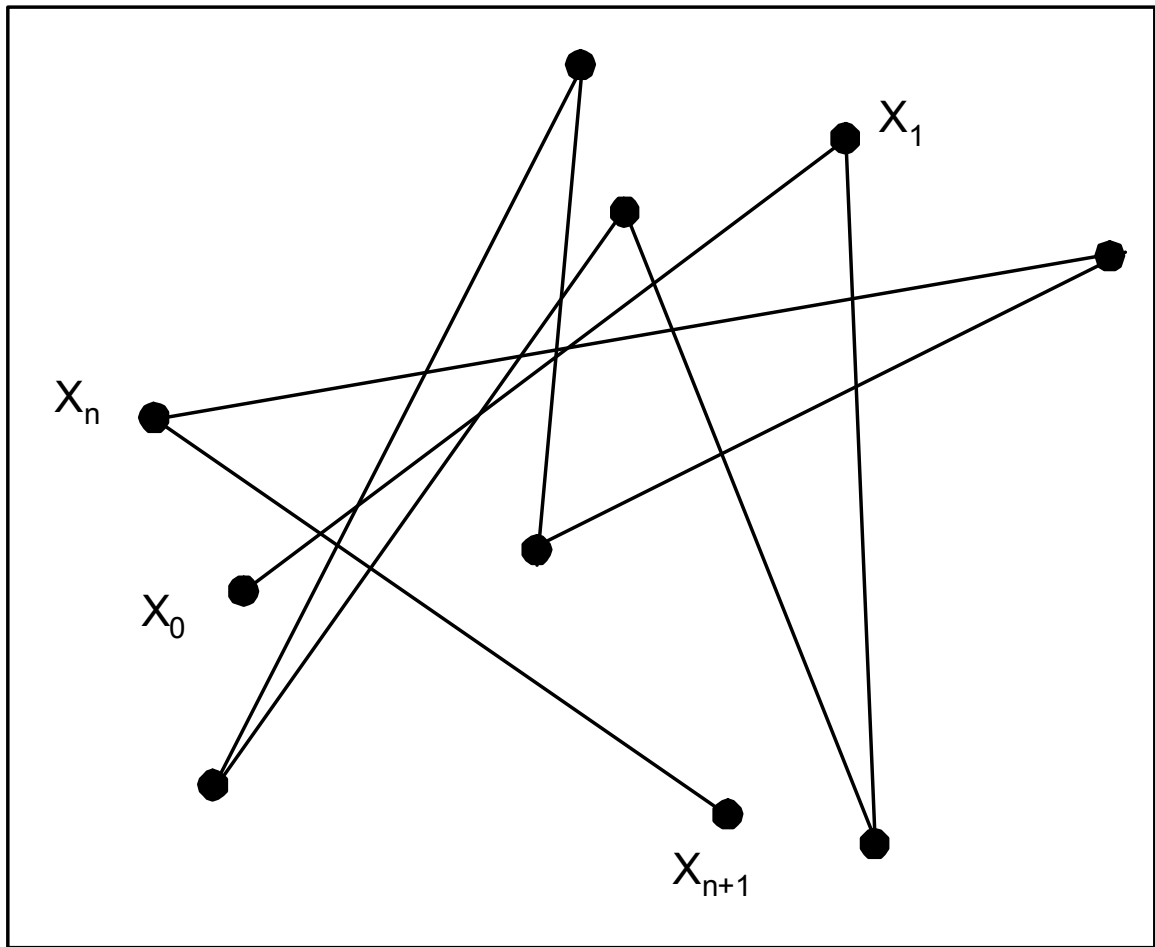


Figure 2.2: Sample movement of nodes in a Random Way Point mobility model

and independently of other nodes. A figure showing an example of random movement of a using following RWP mobility model is depicted in Figure 2.2.

Properties of Random Way Point Model

RWP mobility model is one of the most widely used mobility models in simulation. Since it is extensively used, a thorough analysis of the mathematical properties of the model is presented in this section.

The two main parameters in RWP are V_{max} and T_p . A very low V_{max} coupled with a high T_p results in a reasonably static topology. However, if V_{max} is large and T_p is small,

then the topology is dynamic. This results in frequent changes in routing paths and neighbor node information tables.

RWP Model has some inherent deficiencies, most important of which is non-stationarity as has been recently shown [5] [17] [18] in some research efforts. A key property desired in a mobility model is stationarity. Stationarity means that statistical properties such as mean, variance and the probability distributions remain constant at all times during simulation. However, in RWP model, the average speed of the nodes is consistently decreasing. A common problem with simulation studies using RWP is a misleading choice of velocity distribution, i.e., $U(0, V_{max})$. Often, the model is described as having an average speed of $V_{max}/2$. This model is expected to maintain this average speed as the simulation progresses, and simulation results are almost always in the form of an average over a period of time. Such averages only make sense if the simulation reaches a steady state. Unfortunately, this is not the case. In fact, over a large interval of time, speed decay will cause node velocity to become zero. With increasing simulation time, the speed of the nodes will have an exponential distribution [19] [15]. Hence what started off as a uniform distribution will change with time to an exponential distribution and hence does not satisfy the condition of stationarity [18] [20].

Also, it suffers from border effect which means that nodes pass through the center of the simulation area with a greater probability than any other area. However, it is sometimes still widely used since the decaying effects are only observed during long simulations.

Consider the average speed of a node as V_{av} .

$$\begin{aligned}
 V_{av} &= \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T v(t) dt \\
 &= \lim_{T \rightarrow \infty} \frac{\sum_{n=1}^{N(T)} d_n}{\sum_{n=1}^{N(T)} s_n}
 \end{aligned}$$

$$\begin{aligned}
&= \frac{E[D]}{E[S]} \\
&= \frac{V_{max} - V_{min}}{\ln\left(\frac{V_{max}}{V_{min}}\right)}
\end{aligned}$$

Here $N(T)$ is the total number of trips a node takes in time T and d_n and r_n are the distance and travel time in the n^{th} trip. We notice that $E[S] \rightarrow \infty$ as $V_{min} \rightarrow 0$ and hence $V_{av} \rightarrow 0$ as $V_{min} \rightarrow 0$.

Let us consider the initial average speed as V_{in} . V_{in} may be given by the relation $\frac{V_{max}+V_{min}}{2}$. Now comparing V_{av} and V_{in} , we have

$$\frac{V_{av}}{V_{in}} = \frac{\frac{V_{max}-V_{min}}{\ln\left(\frac{V_{max}}{V_{min}}\right)}}{\frac{V_{max}+V_{min}}{2}}$$

Let

$$\lambda = \frac{V_{max}}{V_{min}} > 1$$

$$\frac{V_{av}}{V_{in}} = \frac{2(\lambda - 1)}{(\lambda + 1)\ln\lambda}$$

This relation shows that $V_{av} < V_{in}$ which means that the average node speed over time is less than that of the initial average node speed, which proves the non-stationarity property of the speed distribution.

We have performed a long simulation using RWP model under the above described conditions. The model is initialized with a velocity distribution $[0, v_{max}]$. The average speed of the nodes at the end of the simulation is shown in Figure 2.3.

A simple workaround to this problem is to set a non-zero minimum speed. Hence, the velocity distribution may be considered to be $[V_{min}, V_{max}]$ where $V_{min} > 0$. Another common problem with the RWP model is zig-zag trajectories. This usually does not correspond to any kind of mobility path in the real world.

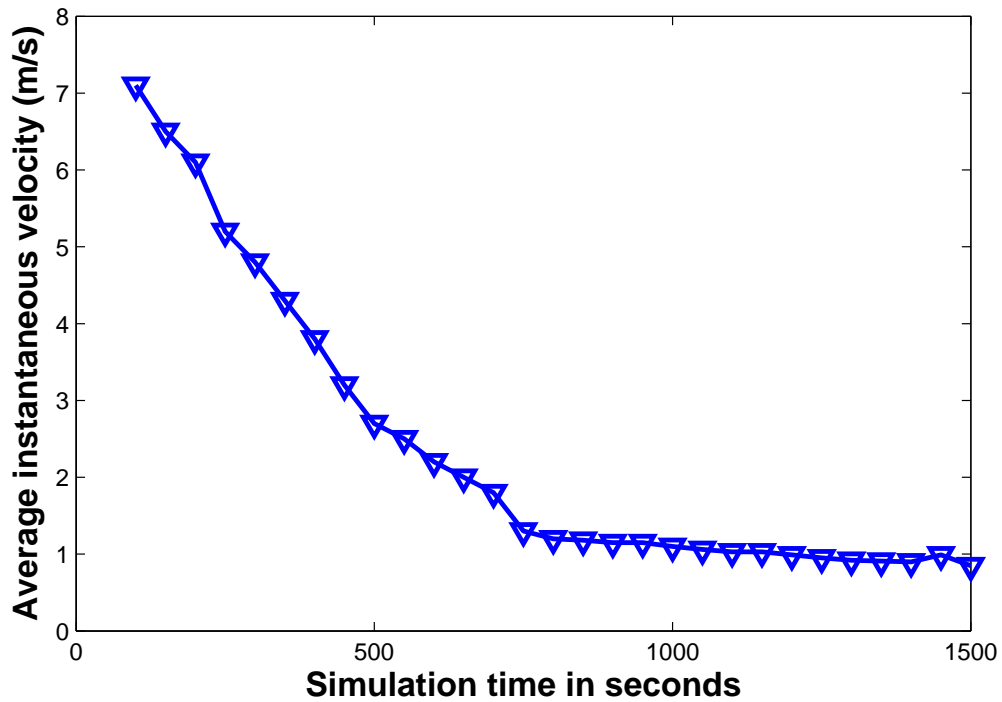


Figure 2.3: Average instantaneous velocity in meters/second as simulation progresses

2.3.2 Random Walk Mobility Model

Random Walk mobility model is a derivative of Brownian motion as formulated by Albert Einstein [21]. Brownian motion [22] describes the movement of particles in a liquid (in 3 Dimensions). For most simulations, the 2-D model is used to represent the motion of mobile nodes in a field.

The Random Walk model is similar to the RWP model in certain ways. The node movement has randomness in both the models. However, the Random Walk model is the RWP model with zero pause time. According to the Random Walk model, a mobile node chooses a random direction and a random speed to travel and moves to a new location. However, the speed and angular direction of motion are dictated by the limits $[v_{min}, v_{max}]$ and $\theta(t)$ from $[0, 2\pi]$ respectively. The speed distribution may be Uniform or Gaussian. Each discrete movement in the Random Walk Mobility Model occurs in a constant time interval

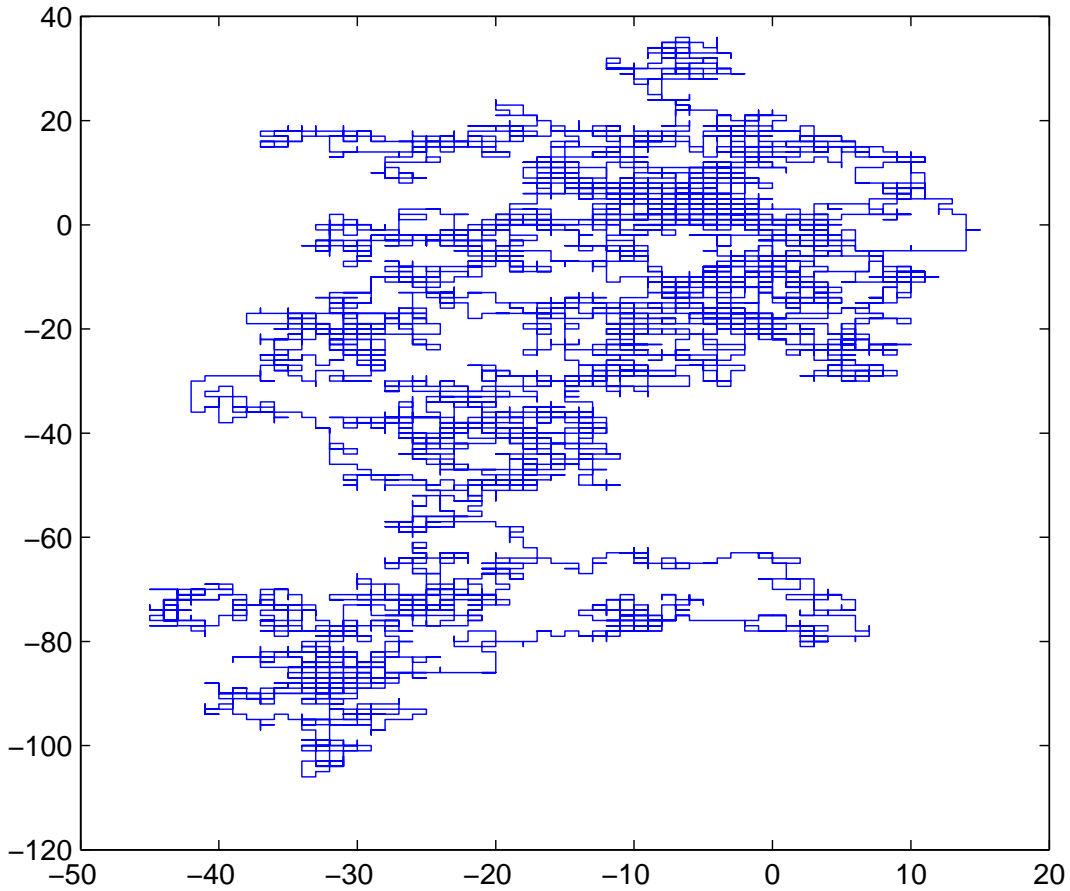


Figure 2.4: Characteristic movement of nodes in a Random Walk mobility model

t or a constant distance traveled d . During the time interval t , the node moves with the velocity vector given by $[v(t)\cos\theta(t), v(t)\sin\theta(t)]$.

For the next movement, a new angle and speed are chosen. On encountering the simulation boundary, the node moves away from the boundary depending on the incident angle, i.e. with an angle $\pi - \theta(t)$ called boundary effect. Since the Random Walk Mobility Model is memoryless, it has no information of its previous locations and speeds. Hence, this can lead to some impractical mobility patterns.

Figure 2.4 shows a representation of a random walk mobility model.

2.3.3 Random Direction Mobility Model

The random direction mobility is perhaps the most widely used mobility model other than the RWP model. This is because it also considers user movement along straight line paths, constant velocities and pauses in between motion segments. We discussed in the previous section the RWP model, the spatial distribution of mobile nodes changes from a uniform distribution to that of a non-uniform distribution during the simulation. At the end of the simulation, the density of nodes is much higher at the center of the simulation area and almost non-existent at the boundaries.

The Random Direction mobility model has been designed to overcome the non-stationarity problem in the RWP Mobility Model. In this model, instead of a random destination as in RWP model, nodes only choose a random direction in which to travel. After choosing a random direction, a node travels to the border of the simulation area in that direction. When the boundary is reached, the node pauses for a certain period of time, chooses another angular direction in the interval $[0, \pi]$.

For a movement area of size A , the sojourn density by one node using this model is $\rho(x) = \frac{1}{A}$ for the whole movement area and the mean user movement is zero since all movement directions are equal and hence cancel each other. Hence the mobility model possesses the desired property of stationarity. This model is used for simulation studies of mobile cellular networks since the design of cells and mobile hot spots within the node movement area does not affect the simulation results. However, one of the drawbacks of the random direction is its behavior at the boundary of the simulation area. Realistically characterizing the movement at a boundary is a complicated process. Analysis of the model is difficult due to the non-linear factors introduced by such movements.

There also exist several other variations of the random direction mobility model. The way these versions vary from one another is the method in which they generate the subsequent movement segment. One version proposes [23] a method that models a cell structure with users passing the cell in straight lines. They choose new directions at cell borders. Other

versions model direction changes happening anywhere in the movement area with minor differences to suit other scenarios [24]. Some approaches characterize the direction change with absolute angles while some others determine relative angular changes with respect to the current direction [25].

2.3.4 Other Mobility Models

There are several other mobility models that have been proposed to suit certain specific scenarios. In this section, we shall discuss some of the dependent mobility models as shown in Figure 2.1 and their benefits in simulation.

Group Mobility Models

Real world scenarios usually involve cases where groups of users move together. There is a high correlation in the relative spacing of the nodes which can determine that it is group common. This is called group mobility. An example is a group of soldiers on the battlefield where they move together on the same mission. Other simple examples include a group of students taking the same classes or a family on a outing, etc where they usually move in groups.

In a group mobility model, the node movement is relative to a reference point amongst the group of nodes it belongs to. An example of a group mobility model is the Reference Point Group Mobility model (RPGM).

However, there are certain difficulties in realistically using group models for simulation. Most group mobility models such as RPGM implicitly assume permanent group affiliation. In most cases, it is also understood that each node only belongs to a single group. But in reality, to model more complex scenarios, a more comprehensive model is required. Some nodes move in groups while others move independently. Some nodes may even be stationary. Moreover, the group affiliation is not permanent. A good realistic mobility model must capture all these mobility dynamics in order to yield realistic performance evaluation results.

Manhattan Mobility Model

Manhattan mobility model is a grid-based mobility model that attempts to mimic the movement of users in a city section. This mobility model was mainly proposed for modeling node movement in urban areas where the streets are organized as a grid. This are used widely for vehicular movement modeling in city scenarios.

In this mobility model, the mobile nodes move in horizontal or vertical direction on an urban map. The Manhattan model employs a probabilistic approach in the selection of node movements. At each intersection, a node continues to keep moving in the same direction or takes a turn based on some probability distribution. However, the model may be altered to suit different scenarios where probabilities to choose certain streets over others may be higher.

The Manhattan mobility model is an example of a geographic mobility model. It can be overlaid over a city map and made to accurately model the movements of mobile users in a city. Figure 2.5 shows an example of a layout of movements according to Manhattan mobility model.

2.3.5 Shortcomings of Mobility Models

Mobility Models have been designed primarily using mathematical properties such as stationarity. Some of these models may not reflect any realistic scenarios. RWP model and other random based models model provide perfectly random movements. However, users in the real world may not move so randomly at all. Also, most research has focused on designing protocols and network designs based on synthetic mobility models. Hence, results and designs emanating from these efforts may also be misleading or erroneous.

There are also other parameters in the real world that are difficult to create in a mobility model. Obstacles are a difficult deterrent for user movement. However, realistic obstacle creation and modeling user movement when they encounter obstacles is not as easy in a

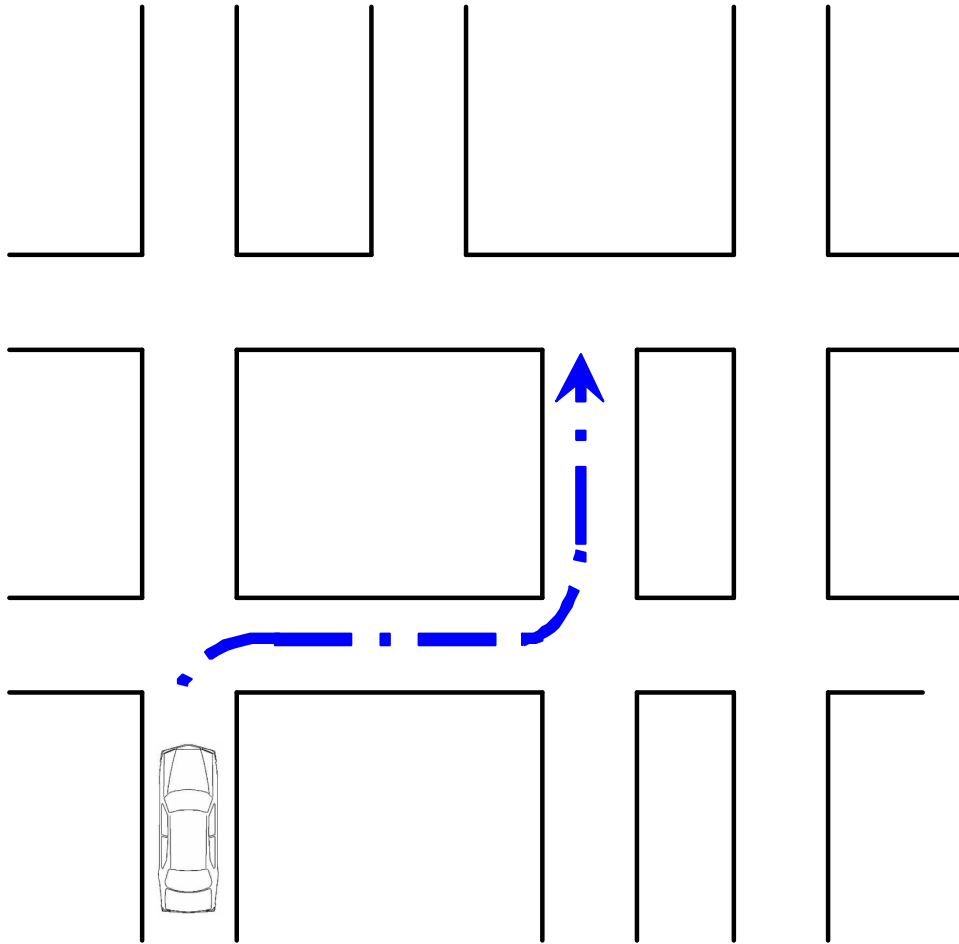


Figure 2.5: Characteristic movement of nodes in Manhattan mobility model

mathematical mobility model. However, Geographic Information Systems (GIS) may provide real terrain data that may be overlaid onto a simulation scenario.

Perhaps the most important problem with synthetic mobility models are incorporating temporal and spatial correlation amongst users. As we discussed, not all user movement is random. The way users move may be dependent on other nearby nodes, the time of the day and the location they are in. Hence memoryless mobility models defeat the purpose when simulating such scenarios.

In spite of all these shortcomings, mobility models do provide an easy way to test network protocols. Also, other issues such as scalability and traffic flow characteristics which cannot be realistically tested in a real-world deployment may be tested in a simulation setup.

2.4 Performance Analysis of Mobility Models

The mobility models discussed in the preceding sections have been used extensively in simulations. In this section, we discuss some of the network models used to test the protocols and mobility models and the performance issues involved in using the models.

We use ns2 (version 2.28) [26] to simulate the effects of node mobility. The network architecture for simulation is described below.

Several mobile nodes are randomly distributed in a square geographical area. These nodes are equipped with radios that can communicate with other nodes using one of several protocols such as Ad Hoc On Demand Distance Vector routing(AODV) [27] or Dynamic Source Routing (DSR) [9].

To better connect the nodes in the network, a backbone comprising of better equipped nodes to perform back end operations is assumed to exist. We assume sparsely distributed powerful radios in the same region to provide a backbone network to the mobile nodes. These are stationary and are better powered, long lasting and more robust. Nodes are categorized into groups called clusters. They act as cluster heads, coordinating local node activities, inter-cluster communications, etc thereby providing some scalability to the network.

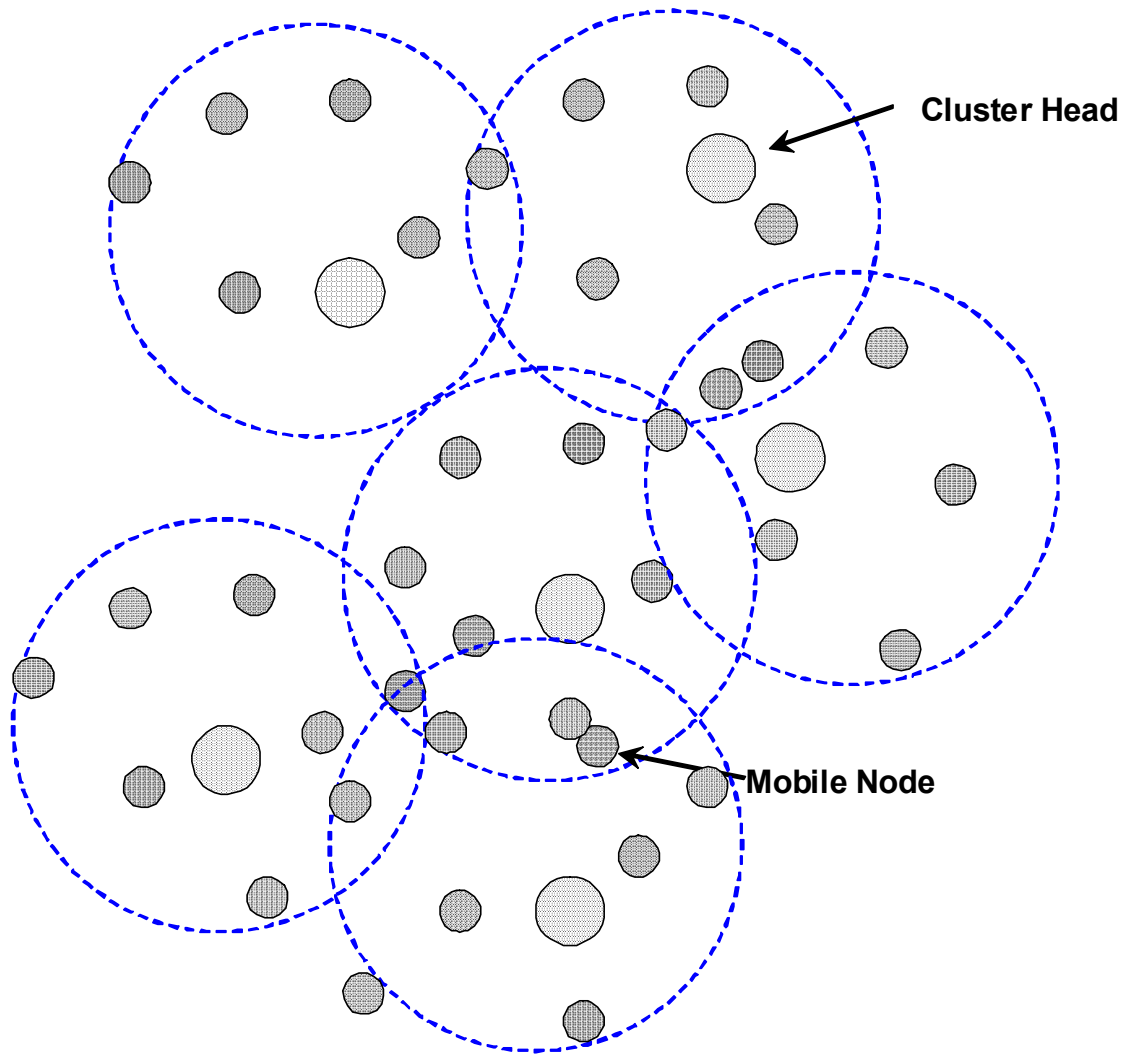


Figure 2.6: Network architecture comprising of mobile nodes, clusters and cluster heads

When the network is initialized, the mobile nodes identify the nearest cluster heads as shown in Figure 2.6 and are associated with that cluster. Hence all mobile nodes belonging to a particular cluster only transmit to the cluster head. In turn, the cluster head transmits to neighboring cluster heads and hence propagates information to the sink.

Node mobility models such as RWP, random walk and random direction are implemented in the simulator. All node movement is characterized by the mobility model. Due to mobility, the nodes move out of range of the nearest cluster head node and hence move into a new cluster. The overhead in joining the cluster and configuring new routes to the cluster head

node lead to more delays and dropped packets. To simulate the overhead of joining a new cluster, the mobile nodes have a fixed latency which is used to configure to the new cluster head. This includes the time required for local broadcasts, route requests, route configuration, etc. High mobility involves frequent joining and leaving several clusters.

2.5 Results

The algorithm performance is evaluated through a simulation study using some of the mobility models. We test various routing protocols and their performance under different mobility conditions.

Mobility models are studied under the influence of the overlying network routing protocols. The first study involves using the Dynamic Source Routing (DSR) protocol [9] and testing various mobility models. In this experiment, the effects of Random Direction, Random Way Point and Random walk on DSR are studied. The nodes move anywhere from 5 to 25 meters per second. As we can see from Figure 2.7, Random Direction performs the best while Random Way Point performs the worst. However, the delay associated with the Random Way Point model is low and it provides almost 90% packet delivery rate at lower speeds. In Figure 2.8, we see that the delay is normalized and RWP performs very well. Also, it still performs better than the other random models at higher speeds. Random direction model performs the worst with the highest number of packets dropped even at very low speeds. However, the DSR protocol is ideal in cases where the node remains in a cluster for sufficient amount of time to determine the routing paths.

Since RWP is widely used in many simulation studies, we analyze the effects of RWP on multiple routing protocols. DSR and AODV routing protocols are implemented to relay information to the sink. The node mobility model used is the RWP mobility model. Simulation is performed for 1000 seconds of simulation time and results are averaged over several runs. As we see in Figure 2.9, in spite of the cluster identification overhead and delay, DSR performs best with RWP model. However, the throughput drops noticeably if

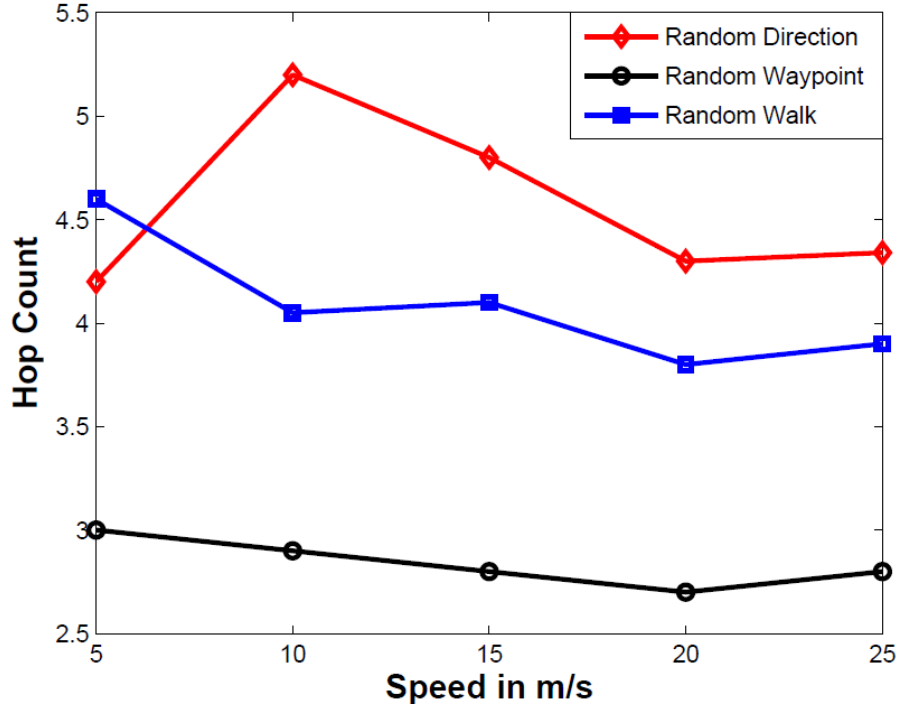


Figure 2.7: Performance of DSR protocol for various mobility models; RWP gives best hop count in simulation results for DSR

the number of hops increases. This is because of the increase in packet size since the whole path has to be prefixed to the data payload. These results are in slight variation compared to the non-hierarchical network architecture. Due to constant association and disassociation with clusters and routing overhead, these protocols perform only slightly worse than in non-hierarchical networks.

Next, we compare RWP and Random Walk mobility models using DSR and AODV protocols. DSR performs well for both mobility models achieving a throughput of about 90% in both cases. However, AODV performs the same as DSR for Random Walk model. The performance of these routing protocols in a cluster also depends on the cluster size. A higher node density in a cluster leads to more latency for DSR. This is due to the proactive nature of DSR which requires every node to broadcast periodically and store routes in cache. With fast mobility, the cache routes become stale leading to frequent broadcasts. Hence AODV performs better if there are more nodes.

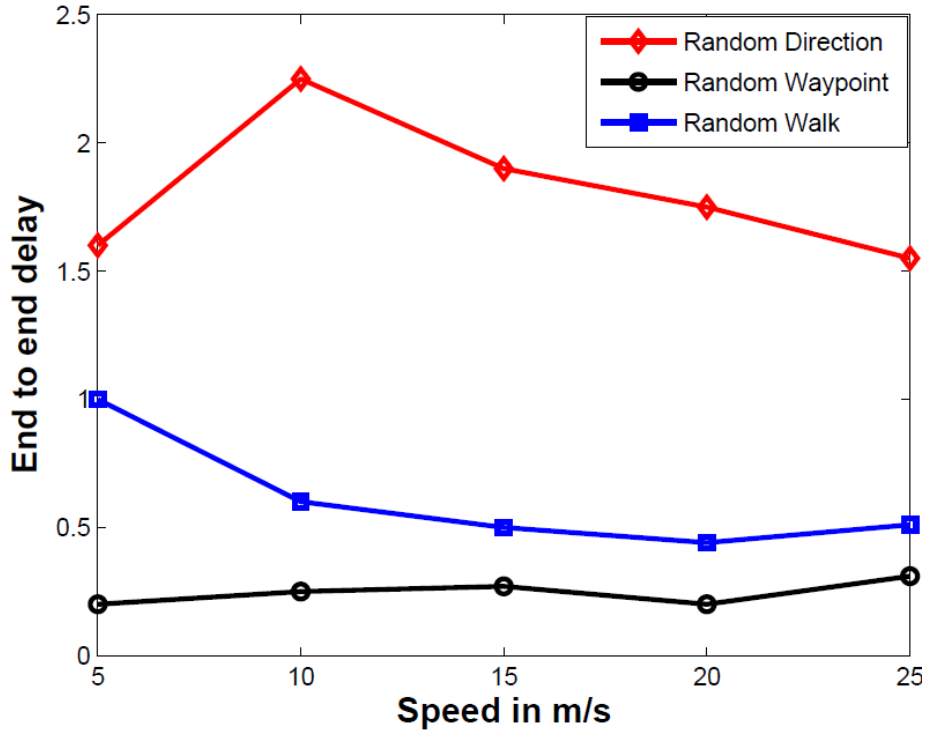


Figure 2.8: End to end delay packet transport for Dynamic Source Routing protocol

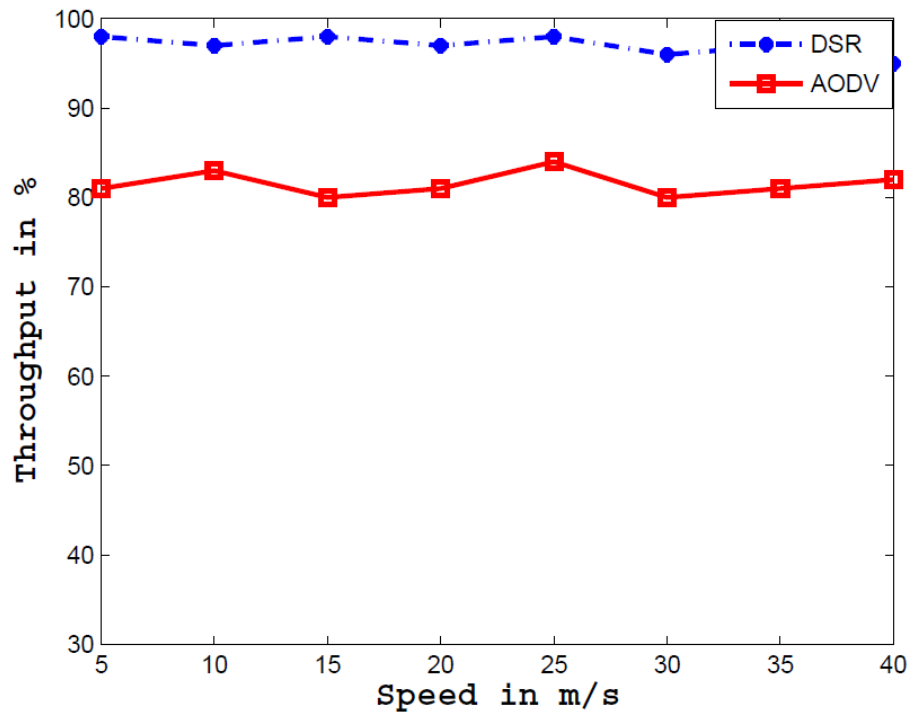


Figure 2.9: Packet delivery ratio for Random Way Point mobility model

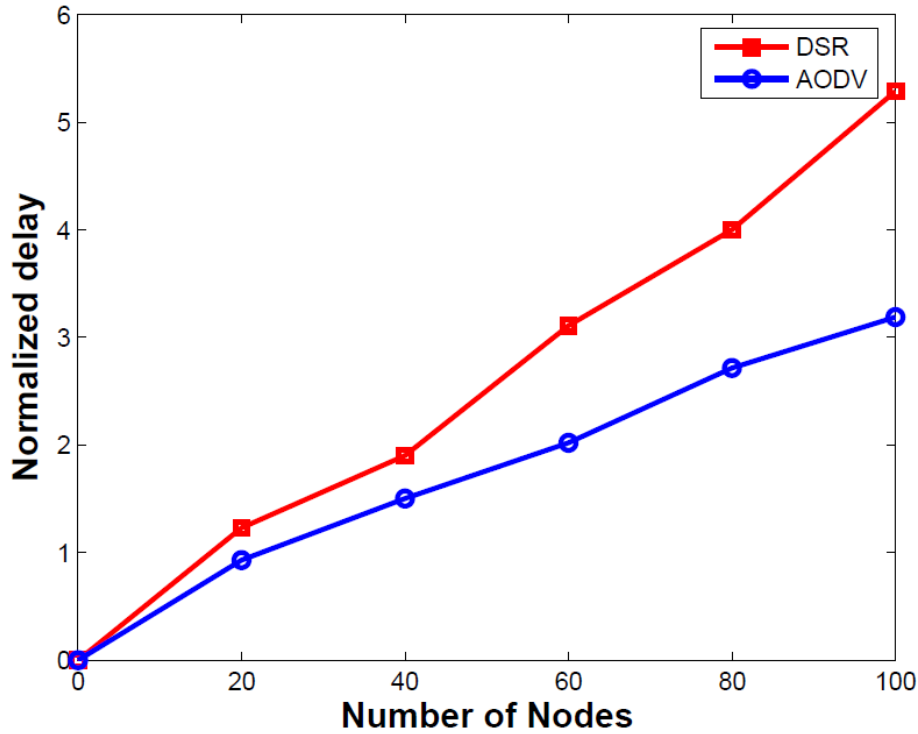


Figure 2.10: Effect of node density on network delay

To compare the effect of high mobility on packet delivery rate for different mobility models, we simulate Constant Bit Rate (CBR) traffic in the network. As we see in Figure 2.12, DSR performs best at lower speeds and its performance degrades drastically at higher speeds. At much higher speeds, the packet delivery ratio is almost the same for many protocols and is very bad at about 50%. However, DSR performance suffers from simultaneous traffic flows. With multiple CBR traffic flows, each flow being 32Kbps, in the same cluster with a high density of nodes, DSR performance drops below that of AODV.

Compared to a static network, we observe a significant drop in network throughput when adopting DSR and AODV protocols with the speed of the mobile nodes. If the speed is low, then DSR works better due to valid routes in the cache. Higher mobility leads to obsolete route caches very often. Hence as we see in Figure 2.10, AODV performs better in cases of higher mobility.

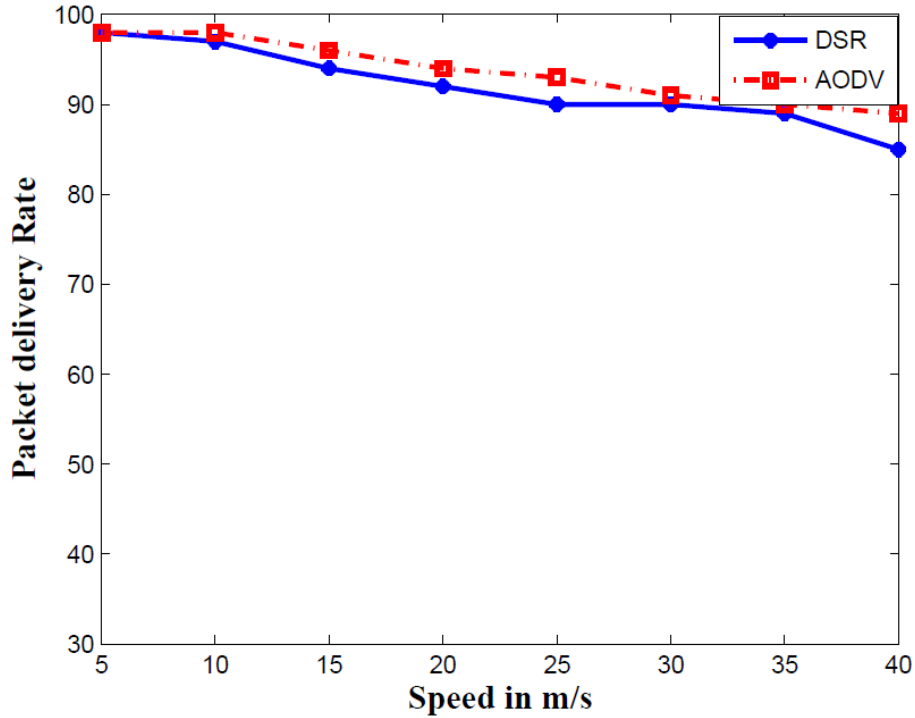


Figure 2.11: Packet delivery ratio for Random Way Point mobility model

Figure 2.11 shows the packet delivery ratios for different protocols using RWP Model. Also, traffic overhead as a percentage of goodput is much higher for AODV since high mobility leads to frequent broadcasts and route discoveries for DSR. Also, periodic message exchanges and mobility leads to worse performance of DSR in higher mobility scenarios. DSR packets have to carry considerably more routing information which leads to drop in throughput at higher traffic flows.

Choosing the right mobility model

Having discussed various mobility models and their suitability to various scenarios, it is of utmost importance to choose the right mobility model for the desired simulation scenario. RWP models and Random Walk models may provide a first step to test most ad hoc networks. More complex settings and parameters can be included in the simulation setup. However, care must be taken to maintain stationarity and randomness in the simulation.

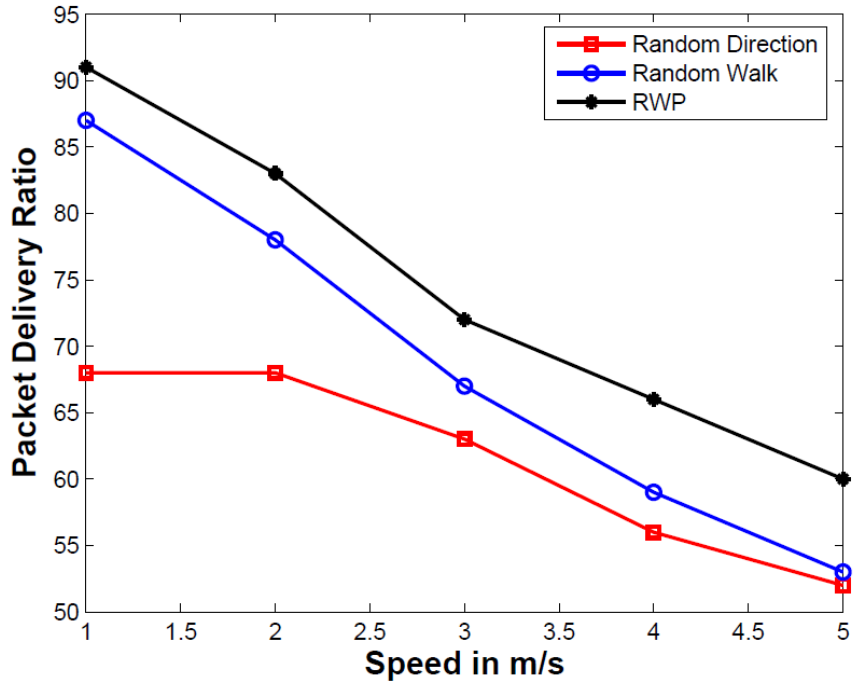


Figure 2.12: Packet delivery ratio for various mobility models using Dynamic Source Routing protocol

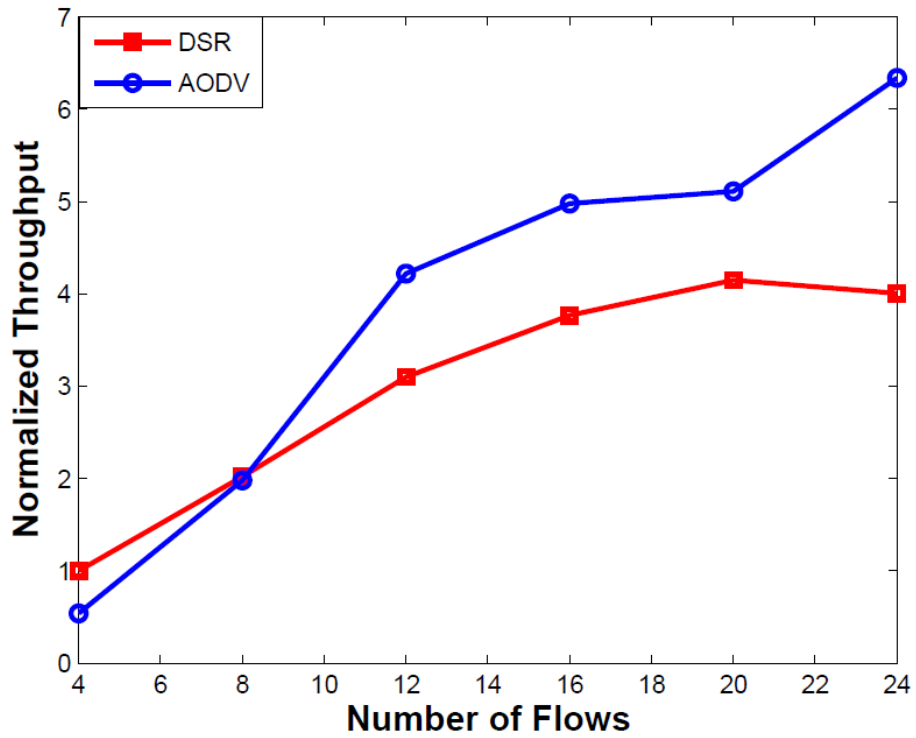


Figure 2.13: Effect of traffic flows on throughput for Random Walk mobility model

For instance, DSR is a source routing protocol. The distinguishing feature of this routing protocol is that it routes routes packets on demand. A source routing protocol is one where every packet contains the complete route information, i.e., a list of nodes in the order that the data packet should traverse through in its header. In an On Demand routing protocol, a routing path to a destination node is obtained only when there is data to be sent. We chose DSR and AODV since they perform well in many of the experimental evaluations of routing protocols.

From the results however, we find that in spite of their best features, the routing protocols can fail to provide the desired results under the wrong mobility conditions. Hence mobility models and real world mobility conditions decide which protocol should be used under various scenarios.

2.6 Mobility Models vs other methods

In spite of the specialized mobility models used in simulation studies, it may sometimes not be suited for certain applications. This may be due to the fact that certain real world scenarios cannot be replicated in a simulation setting. Also, scalability issues, unforeseen circumstances such as outages, network disruptions may not be reproducible in a controlled computer simulation.

Hence, in such cases, it may be better to choose a simulation study using data from an existing real-world system. Such data are called data traces. Data traces and their characteristics are dealt with in greater detail in the next chapter.

2.7 Discussion

We have evaluated the performances of various mobility models using a couple of routing protocols. These results provide an insight into the understanding of protocol performance under mobile conditions. Most clustering algorithms deal with static or slowly-changing topologies. Hence this study of routing protocols with mobility helps in understanding the

behavior of mobility. We have determined that DSR performs better under lower mobility while AODV performs in high mobility and higher traffic flows. In a dense network with several simultaneous flows, AODV achieves lower delay and higher throughput. Also, this study demonstrates the scalability of a routing protocol with respect to mobility.

Chapter 3

Mobility Prediction

3.1 Introduction

Predicting a mobile user's next location before the actual movement is termed as *mobility prediction*. Accurate and fast mobility prediction methods are an important topic of research due to the emergence of ubiquitous wireless networks and increasing number of users. The ability to track and predict a mobile user's location is important from the perspective of network management for today's mobile systems and applications. Mobility prediction becomes all the more important since its effect can be seen at multiple levels of the network.

At the network level, mobility can influence handoff management, buffer and flow control, adaptive resource allocation [28] and congestion control, call admission control, and quality of service (QoS) provisioning [29] [30]. In the application level, better mobility prediction techniques can greatly influence the effectiveness of location aware services [30] [31] [32] [33]. Prediction can be helpful in keeping track of the profile and location of users.

In order to ensure timely handoffs, we need to allocate resources at neighboring APs to facilitate the mobile user to join an adjacent AP without terminating the connection (i.e., minimize call dropping probability). Reserving resources at several or all neighboring APs causes a definite wastage of resources leading to under-utilization of the network. Moreover, it may not be possible to allocate resources at all neighboring APs to all current users in the present AP. Hence, prior knowledge of a mobile user's next destination is helpful in allocating resources. This process is called mobility management. Slow moving users in a wireless network offer better localization techniques, alternate handover schemes to endure

seamless handoffs, etc but offer other challenges such as disjoint WLAN networks and random mobility.

3.2 Motivation

Mobile users exhibit regularity in their movements. Human beings are habitual in many ways and there is a regularity even in the randomness of movement. For instance, a mobile user moving along a straight path is highly likely to follow the same path until he encounters some intersection. Also, users tend to move in a non-random path and follow other landmarks such as straight roads, better paths, etc. To predict the mobility of a user, we can exploit the user's movement patterns, past habits, historic mobility profiles, etc.

Mobility prediction can also help develop a snapshot of the future network topology and allow for smooth transition into topology changes. Also, in ad hoc networks, new routing paths can be formulated ahead of time and routing overhead reduced.

Mobility prediction techniques are commonly based on historical movement patterns of the user populations. Predictions can be for the next step of mobile user movement or for a whole sequence of movements. There are also separate advantages of performing mobility predictions from the client's or the AP's perspectives.

3.3 Existing Methods of Mobility Prediction

Several mobility prediction schemes have been proposed in the literature to tackle the problems of handover management in wireless management. Mobility prediction algorithms make the assumption that there is a certain regularity in the mobility patterns which allows for prediction using certain metrics such as velocity, current location, direction, etc. Almost all prediction algorithms rely on the fact that user movements are based on some pattern and are not completely random [34] [35] [36] [37]. Prediction schemes are beneficial to many applications and several such predictors that have been proposed are discussed in this section.

Predictive mobility management algorithms for supporting mobile communications [38] employs detection algorithms to decompose the complicated daily movement into two parts: regular pattern part and random movement part. The Movement Circle and the Movement Track model [38] have been proposed and used to predict the regular movement while the random parts of the movement are modeled and predicted by the Markov chain model.

Profile-based prediction [39] is a mobility prediction method to address indoor movements in places such as corridors, rooms, etc. It classifies motion into several categories such as deterministic, random, purely random, etc. Since it is an indoor prediction, it can guarantee QoS by reserving resources even in highly random scenarios.

Mobility Prediction methods modeled on historic movement profiles [1] [15] based on the compression algorithm by Lempel-Ziv [40] have also been studied. The LZ (Lempel Ziv) algorithm considers movement patterns to be generated by a finite-state Markov source. In this model, the subsequent symbol is dependent only on the current state of the system. Then a LZ tree is constructed with nodes comprised of the most recent locations visited by the user [41]. To predict a user's next location, the tree is traversed and the most frequently seen path is chosen.

Blough. et al [42] propose a class of domain independent location predictors that do not require any semantic knowledge of their locations. Only past movements are studied to perform predictions. The principal conjecture is that there exists a temporal regularity in the node movements. These movements are modeled to predict user movements.

A more simplistic form of Lempel Ziv prediction is using a K^{th} order Markov predictor [43]. In this method, the finite state Markov source is limited to a specific K . The authors here have used a Markovian prediction model on a data trace set collected at Dartmouth College. The model's performance was reported to be as good as that of the LZ predictor without the complexity of building a LZ tree. Also, the O(2) model provides an excellent accuracy compared to even higher order Markov models.

Most of the discussed methods of mobility prediction use only historic mobility data to perform prediction. Also, almost all of them are stand alone prediction models that have not been analyzed as part of a complete network management system.

Only few mobility prediction algorithms exist that address network resource issues in conjunction with mobility prediction. One such algorithm proposed for resource management assumes a cooperation architecture and mobility management functionality. In this policy based mobility management technique [44], problems such as differentiating highest and lowest priority traffic, guaranteeing delivery to priority traffic (based on QoS metrics), guaranteeing resources such as bandwidth, etc. Location determination can also be factored into the algorithm by using different positioning methods. Further, this work describes other actions executed by the implemented policy-based mobility management scheme like radio access technology association, user and flow context transfer, handover decision, and deployment priority. The framework also shows how the different definitions of the mobility management relate to each other. Also, several other prediction schemes such as those in [45] [46] try to tackle certain issues such policy based user movements. Other studies include specific scenarios such as studying the nature of campus networks and the effect of mobility on such networks [47] [48] [49].

3.3.1 Challenges in Mobility Prediction

Having studied the mobility models, we can see that there exist several key challenges that constrict fast and accurate mobility prediction. Some of the challenges are summarized below.

1. Accurate mobility prediction depends on several factors such as complete knowledge of the network topology, mobility habits of users, etc.
2. Most prediction models depend on building a mobility profile of the user. A complete profile development of a mobile user is not feasible and hence a 100% accuracy is impossible.

3. Better prediction is possible for more regular users. Also, users who show regularity in movement can be predicted with better accuracy.
4. Data collection and system learning takes time and resources. For a completely new scenario with no dataset, it takes time to build the models and train the mobility management system.
5. User movement also depends on the spatio-temporal correlations of other variables; in a campus setting, these may be the schedule of classes or the locations of users. Having complete knowledge of all these extraneous variables is usually very difficult.
6. Even with all the techniques, *regular* users can sometimes behave unpredictably.

3.4 Mathematical Preliminaries

In this section, we shall define some mathematical terms and notations we will repeatedly use in this chapter.

A *random process* is the counterpart to a deterministic process [50]. Instead of dealing with only one possible reality of how the process might evolve under time, in a stochastic or random process there is some uncertainty in its future evolution described by probability distributions. This means that even if the initial condition is known, there are many possibilities the process might lead to, but some paths may be more probable than others.

A random variable \mathbf{x} is a rule for assigning the output of a chance outcome α to a number $\mathbf{x}(\alpha)$. A stochastic process is a function of time of the random variable, i.e., $\mathbf{x}(t)$. It is a rule that assigns the chance outcome α to a function $\mathbf{x}(t, \alpha)$ [50] [51]. The domain of t is the set R of all real numbers. If R is the real axis \mathbb{R} , the stochastic process is said to be a continuous time process and is discrete if R is the set of integers.

Common examples of processes modeled as stochastic time series include stock market and exchange rate fluctuations, signals such as speech, audio and video signals, medical data

like a patient's EKG, EEG, blood pressure or temperature, and random movement such as Brownian motion or random walks.

3.4.1 Markov Chains

A Markov chain is a discrete random process with Markovian property [50]. Markov chain is a term used to denote a Markov process that has a discrete state space. In other words, it has a finite number of states. A discrete-time Markov Chain is defined for discrete times. A discrete time Markov process signifies a system in which the system is in a random state at each time slot and the state changes randomly between time slots. The Markov property states that the conditional probability distribution for the system at the next time slot given its current state depends only on the current state of the system. It does not depend on any of the previous states of the system.

The system changes from one slot to another randomly. Hence, it is not possible to predict the exact future state of the system. The statistical properties of the system help predict the future steps which is what is used in several applications.

The changes of state of the system are called state transitions. Probabilities associated with various state changes are called state transition probabilities. The set of all states and transition probabilities completely characterizes a Markov chain. A completely defined Markov Chain has all states, state transitions defined. Hence, the transition process could go on forever since there is always a current state and a next state.

A Markov chain can be defined mathematically using two components – a transition matrix and an initial state distribution. A transition matrix is defined as follows.

Assume a finite set $S = \{1, \dots, n\}$ of states in a probabilistic system.

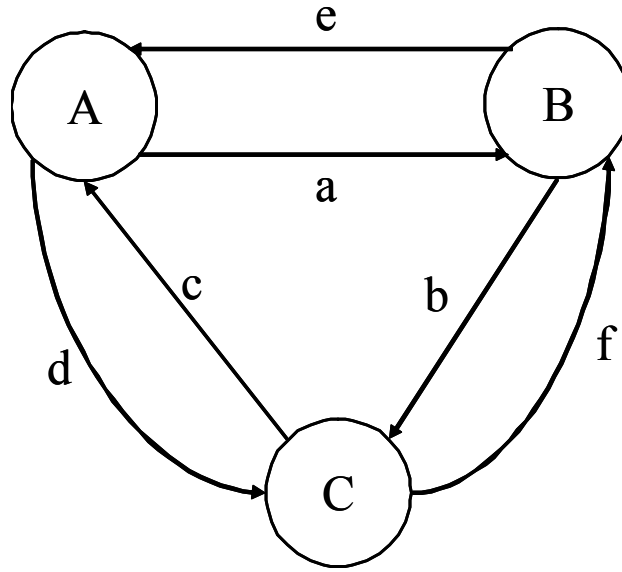


Figure 3.1: A Markov Chain showing states, state transitions and transition probabilities

p_{ij} is the probability of transition from state i to state j in the system. Assign to each pair $(i, j) \in S^2$ of states a real number p_{ij} such that the properties

$$p_{ij} \geq 0 \quad \forall (i, j) \in S^2 \quad (3.1)$$

$$\sum_{j \in S} p_{ij} = 1 \quad \forall i \in S \quad (3.2)$$

are satisfied. The Figure 3.1 shows a Markov chain with 3 states namely A, B and C and the transition probabilities between them denoted by a, b, \dots, f .

We define the transition matrix A by

$$\begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & 0 & \dots & a_{nn} \end{pmatrix}$$

Let $(X_n)_{n \in \mathbb{N}_0}$ be a sequence of random variables whose values lie in S . Here, n indicates the time at which the system is in state X_n .

The sequence $(X_n)_{n \in N_0}$ is called a homogeneous Markov chain with discrete time, state space S , and transition matrix A ,

if and only if $\forall n \in N_0$ the condition

$$P \left[X_{n+1} = j \mid X_0 = i_0, \dots, X_n = i_n \right] = P \left[X_{n+1} = j \mid X_n = i_n \right] = p_{i_n j} \quad (3.3)$$

is satisfied for all $(i_0, \dots, i_n, j) \in S^{n+2}$, for which

$$P[X_0 = i_0, \dots, X_n = i_n] > 0 \quad (3.4)$$

Equation (3.3) defines the memory or Markov property of a Markov Chain. In the above example, the order of the Markov Chain is 1 since the transition probabilities are only dependent on the preceding state. Also, the homogeneity condition ensures that the transition probabilities are constant with time.

First order Markov chains can be extended to higher order Markov Processes. Higher order processes with finite memory s can be extended as being in the space S^s .

We also need to define the initial distribution of a Markov Chain to completely describe it. The discrete set of initial distributions on the space S is defined by

$$R_S = \{ \mathbf{P} = (P_i)_{i \in S} : P_i \geq 0, \sum_{i \in S} P_i = 1 \} \quad (3.5)$$

$$\mathbf{P}_0 = (P_{0i})_{i \in S} \in R_S \quad (3.6)$$

The relation (3.6) is known as the initial distribution of the Markov Chain $(X_n)_{n \in N_0}$ if $A[X_0 = i] = A_{0i}$ for all states $i \in S$.

The ij^{th} entry $a_{ij}^{(n)}$ of the matrix A_n gives the probability that the Markov chain, starting in state s_i will be in after n steps. The n^{th} order transition probabilities are given by

$$p(n)_{ij} = P[X_{m+n} = j | X_m = i], n \in N \quad (3.7)$$

These are obtained by summing over all possible intermediate states. Paths of length $n + 1$ with initial state i and final state j are considered. Hence,

$$p_{in}^n = \sum_{(i_1, \dots, i_{n-1}) \in S^{n-1}} P[X_{m+n} = j | X_m = i, X_{m+1} = i_1 \dots X_{m+n-1} = i_{n-1}] \quad (3.8)$$

$$= \sum_{(i_1, \dots, i_{n-1}) \in S^{n-1}} p_{ii_1} \prod_{j=1}^{n-2} p_{i_j i_{j+1}} p_{i_{n-1} j} \quad (3.9)$$

$(a_{ij}^{(n)})_{(i,j) \in S^2}$ is the same as the n 'th power A^n of the transition matrix A .

Also, $a_{ij}^{(0)} := \delta_{ij}$ which leads to A^0 equals the identity matrix I_m . Hence, given \mathbf{A}_0 of X_0 , the distribution of X_n leads to $\mathbf{A}_0 A^n$, $n \in N_0$.

For $\mathbf{A} = (A_1, \dots, A_m) \in R_S$, we can define a Markov chain with state space S , transition matrix $A = (a_{ij})_{(i,j) \in S^2}$ given by $p_{ij} = A_j$, $i \in S$.

Let us also consider a random initial distribution $\mathbf{A}_0 \in R_S$.

Also, $\forall n \in N_0$,

$$A \left[X_{n+1} = j \mid X_0 = i_0, \dots, X_n = i_n \right] = A \left[X_{n+1} = j \mid X_n = i_n \right] = A_j \quad (3.10)$$

This is called an “independent chain” with respect to the transition matrix \mathbf{A} .

We have described the basics of random processes and Markov chains in this section. In the following section, we propose some methods to model the mobility patterns as random processes.

3.4.2 First Order Markov Model

In this section, we model the mobility patterns as a First Order Markov Process.

Consider a scenario where a mobile user is connected to an AP. Here we are assuming a wireless local area network (WLAN) such as a network based on 802.11a, b, and g. The network consists of access points (APs) and mobile hosts. The APs are connected to a backbone network which may be connected to a wired data network such as the Internet. The network serves both mobile and stationary users who may be equipped with laptops, PDAs, internet-enabled phones, etc. The user may move away from this AP (say A_j) and connect to an adjacent AP (A_k) after some time. The model proposed here attempts to predict this transition from A_j to A_k ahead of the user's movement by analyzing the history and transition paths.

A Markov Chain model [50] towards this objective was studied in detail in [52] using a campus wireless trace dataset. In this case, only the user's previous movement is known. For example, if the user moved to A_j from A_i , only this information is known to the system. The system also has a knowledge of the probability of transition from A_i to A_j and A_j to A_k . Using this information, the system predicts the transition of the user from A_j to some other adjacent AP. There are several deficiencies in this model. For instance, the user's path to the current AP A_j may be from several paths but the last immediate AP could have been A_i . These path transitions may be different for various users based on user movement histories and the paths taken. Hence a more complex model is necessary to make more accurate predictions.

In this context, a k -th Order Markov model where $k > 1$ is a logical extension to this model. The system understands user movements for the past k transitions. For instance, the user's current location is modeled as a random variable Y and $Y_i Y_{i+1} \dots Y_k$ denoted by Y_{ik} be the sequence of random variables. For example, a second order model is written as

$$P = P[AP_{next} | AP_{current}, AP_{previous}]$$

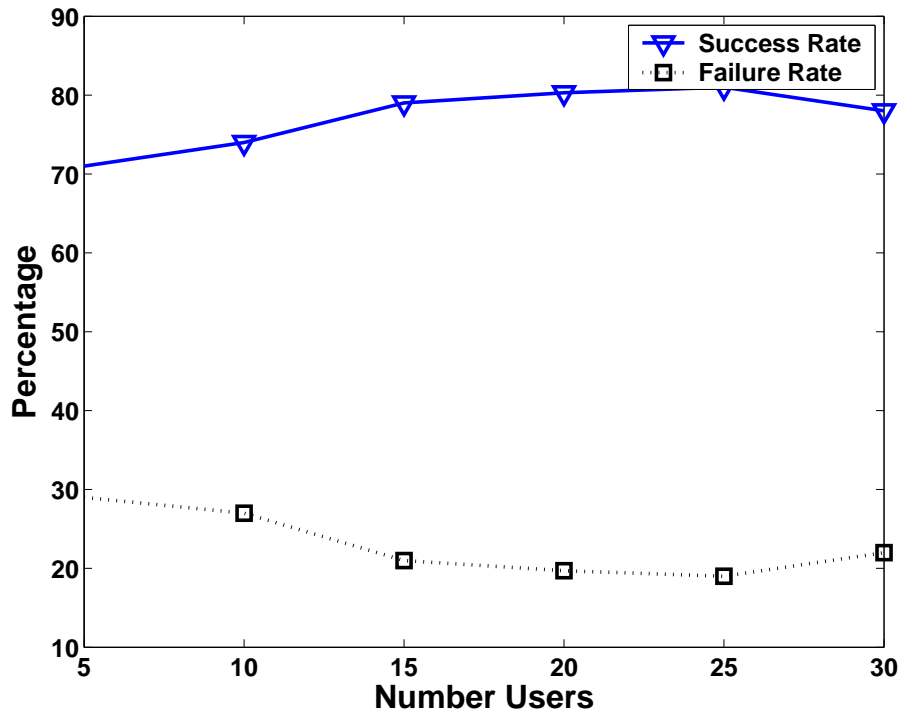


Figure 3.2: Initial Prediction success rate

Results

To validate the claims, we have mobile user-association data collected at an access point. This dataset consists of 8 APs and a set of users who frequent these APs on a regular basis. This data has been parsed to extract the AP and unique user information and the frequency of connections between the users and the APs. The transition probabilities and the matrix is built using this information. We now have the user history over a period of time and this gives the probability of transition between any adjacent APs.

A random users information is used to test the accuracy of the system. The users current AP connection is used and the system predicts the next AP connection that the user moves to. This is validated against the actual movement from the data set. Accuracy and false predictions are also noted. This experiment is repeated for various users several times. Also, every time an accurate prediction is made, the transition probabilities are updated to better reflect the user movement history. Some of the results from the experiments are

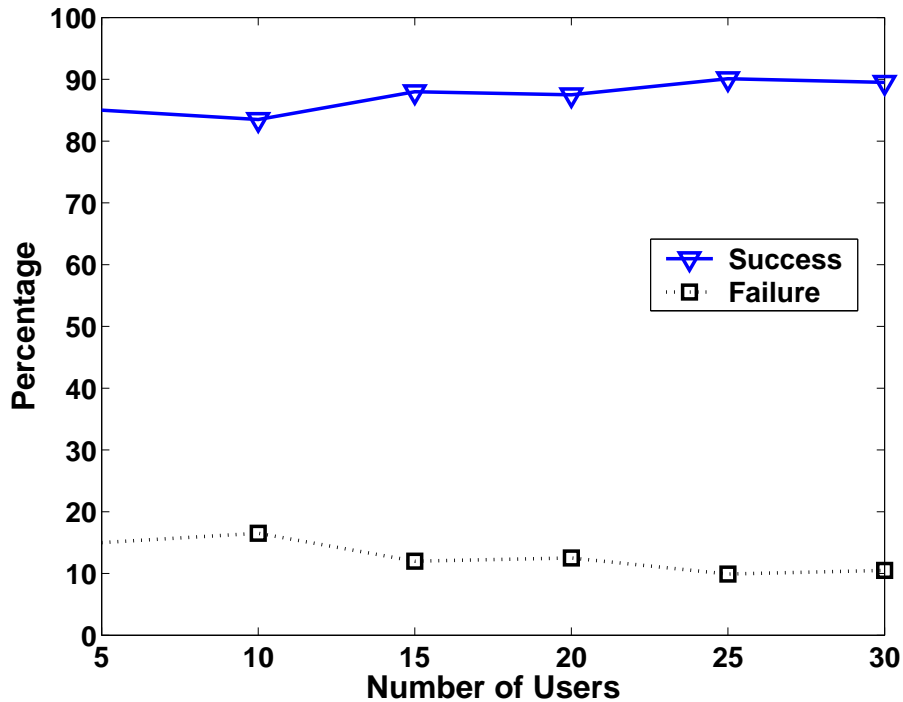


Figure 3.3: Prediction Success rate after training

discussed here. Figure 3.2 shows the prediction success of the system modeled. In Figure 3.2, we see that with a smaller number of users and under initial conditions, the system performs prediction with moderate success. By initial conditions, we mean that the users data is barely enough to build a transition matrix and use the prediction algorithm. Hence, there is a higher failure rate which indicates that the system is still learning from the users movement data.

We perform a thousand iterations and feed the data into the prediction system; the system learns from the inaccurate estimates and corrects the transition matrix accordingly. After these iterations we can see the success rate in Figure 3.3. We can clearly see that the Markov chain model is best suited to work under steady state conditions. The Figure 3.3 shows that the success rate is higher by about 15% and is consistently over 90%. Figure 3.4 shows the variation of transition probability stabilization. The three curves show the probability variation for three different users. We can see that the three states shown in the

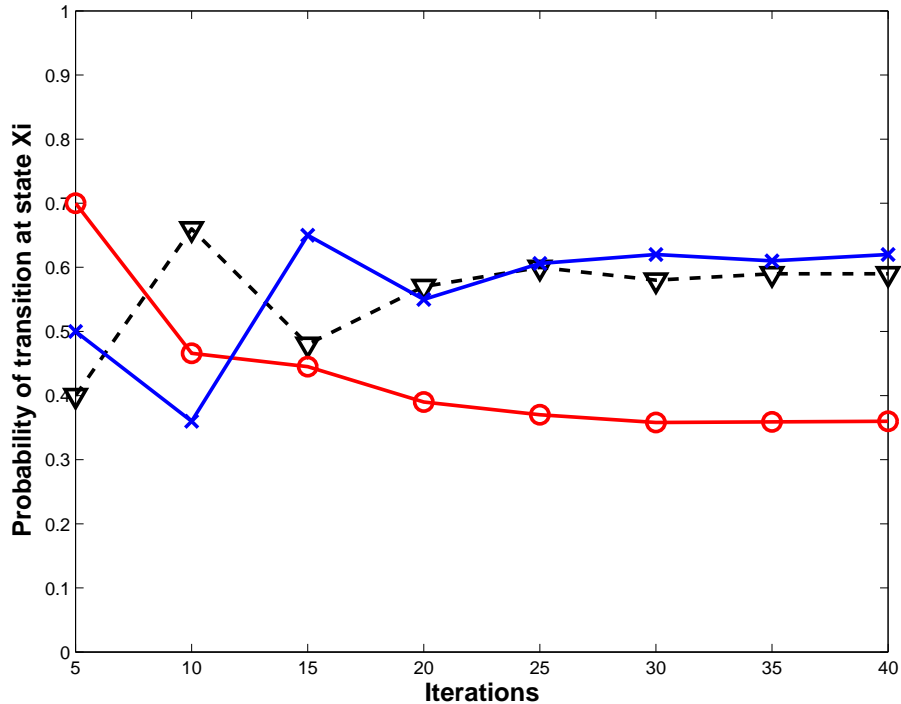


Figure 3.4: Transition probabilities of 3 states during the initial and steady states

figure reach steady state conditions after a few iterations and the system accuracy improves only after the steady state is reached.

3.5 Hidden Markov Model

Mobility patterns were modeled as a First Order Markov Model were seen in the preceding section. We propose to model the same problem using a Hidden Markov Model (HMM). A HMM is defined by a finite set of states (some hidden and some observable), a set of state transition probabilities, an alphabet of output symbols (also referred to as emissions) and a set of emission probabilities. The emission probabilities denote the distribution of output symbols that are emitted from each state. There are several advantages to modeling the solution to incorporate hidden states as opposed to a simple Markov Chain. In order to understand the necessity to model a HMM, we first demonstrate the drawbacks of the simple Markov chain model.

In the Markov Chain discussed previously, an observer (or another AP) may not be able to observe all the transitions in a network. In other words, the observer may sometimes only see the transition from AP_i to AP_j ; however, some transitions could be hidden from the observer by the system or by the user. For example, in places where a user may connect to any one of multiple APs, the observer can only see the movement of the user from one place to another but cannot determine which AP the user is connected to. In this case, the APs are the hidden states and the locations are the observable states. Hence the problem is to identify the APs corresponding to the location of the user.

In this section, the HMM and the method of using it to solve the problem of mobility prediction are explained. There are several classical papers in the area of statistical source modeling and speech recognition theory that have used the concept of HMM to model various hidden parameters [53] [54] [55]. As explained earlier, it may be noted that only the outcome and not the state is visible to an external observer. Hence the states are hidden from the observer and the name Hidden Markov Model.

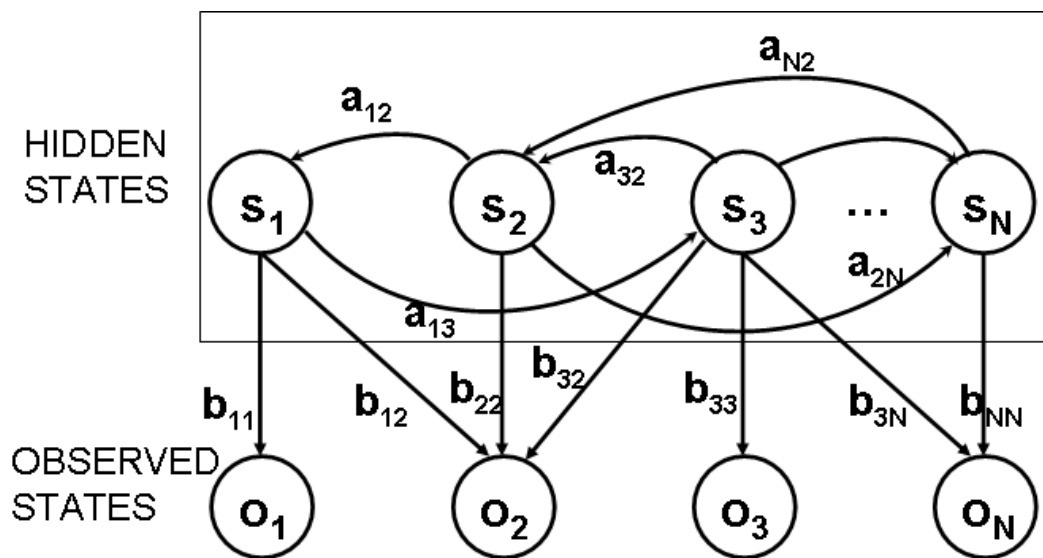


Figure 3.5: A Schematic of a Hidden Markov Model showing the hidden and observable states, state transitions and probabilities.

A HMM is defined by a finite set of states, a set of state transition probabilities, an alphabet of output symbols (also referred to as emissions) and a set of emission probabilities. The emission probabilities denote the distribution of output symbols that are emitted from each state. Figure 3.5 shows some of the probabilistic parameters of a HMM. HMM is a stochastic process of moving between states and the process of emitting an output sequence. However, the sequences of state transitions are hidden and observed only through the sequence of emitted symbols.

A HMM is formally defined as follows.

1. $S : \{s_1 s_2 \dots s_N\}$ are the N hidden states in the system. Even though the states are hidden, they have practical significance as we shall see later in our discussion.
2. $O : \{o_1 o_2 \dots o_N\}$ are the values of the observed sequences. They symbolize the discrete alphabet size and represent the physical output of the system being modeled.
3. $\Pi = \{\pi\}$ is the initial state probabilities. Here π_i indicates the probability of starting in state i .
4. $A = \{a_{ij}\}$ are the state transition probabilities where a_{ij} denotes the probability of moving from state i to j . In a system where a state can reach *any* other state in a single transition, $a_{ij} > 0 \forall i, j$.

$$a_{ij} = P(t_k = s_j | t_{k-1} = s_i)$$

5. $B = \{b_{ik}\}$ are the observation state probabilities where b_{ik} is the probability of emitting symbol k at state i .

$$b_{ik} = P(o_k | t_k = s_j)$$

6. For ease of use, this entire model as shown in Figure 3.5 is denoted as $\lambda = (\pi, A, B)$.

From the HMM, it is easily seen that there is no one-to-one correspondence between the states and the symbols.

3.5.1 Prediction Model using HMM

The HMM is applied to the problem of mobility prediction in the following way. For an external observer (such as another network or AP) to predict the movement of a user, the APs are hidden and the user locations are the only visible observations. On the other hand, suppose the network AP controller wishes to perform mobility prediction. From that perspective, it can only see the APs and their associations with the mobile users. The actual geographic locations of the users are ‘hidden’. Hence this is a generic model that aims to provide a framework for mobility prediction.

We approach this problem from the perspective of the centralized AP controller that aims to collect information about mobile users and make mobility predictions to better allocate network resources. All APs can all send user information to the controller which stores the user histories, movement behavior and is capable of computations to make the prediction.

A HMM λ as described earlier is built for each user by the AP controller. The data for state transitions and probability transition matrices is ‘learned’ from the trace data as explained in the subsequently. This HMM model can provide solutions to three problems as explained in [53].

1. Observing the movement sequences over time, the HMM λ can give the probability that a certain observed sequence $O = o_1, o_2, \dots, o_K$ came from this model.

This is given by probability that the observed sequence O was generated by the model λ

Let $s = \{s_1 s_2 \dots s_K\}$ be a state sequence. Also, let us assume that the observations are independent. Hence,

$$P(O|s, \lambda) = \prod_{i=1}^k P(o_i|s_K, \lambda) \quad (3.11)$$

$$= b_{s1}o_1.b_{s2}o_2 \dots b_{sK}o_K \quad (3.12)$$

Probability of any state sequence is

$$P(s|\lambda) = \pi_{s1}a_{s1s2}a_{s2s3} \dots a_{s(K-1)sK} \quad (3.13)$$

Hence we have

$$P(O|\lambda) = \sum_s P(O|s, \lambda) \cdot P(s|\lambda) \quad (3.14)$$

This metric is especially useful for our proposed model since such a probability would help estimating the users movement over a longer run. Hence network resource allocation can be performed throughout the user's movement in that network.

2. Suppose the observed sequence of movements is denoted by

$$o = o_1, o_2, \dots o_k$$

The most likely sequence of hidden states corresponding to these observed sequences can help in determining the part of the user.

A solution to this problem helps in locating the hidden parameter in the model. In a model with hidden user locations, the model can give the probability if a user is located in a particular geographical area. Alternately, the external observer can also determine which AP the user is most likely connected to, given that the user is within

range of certain APs. This is a maximum likelihood problem and can be solved using the Viterbi algorithm [56] [57].

3. The last exercise is to determine the value of λ to maximize $P(O|\lambda)$ i.e., to train the model given a set of observations.

This is an important phase in the model since the model should be able to learn from the user movement histories over time and make better predictions. Also, this is a hard problem with no easy solution. It can however be computed iteratively using the Baum-Welch algorithm [58] and computing new λ based on λ_0 and given O . The iteration stops when

$$\log P(O|\lambda) - \log P(O|\lambda_0) < \epsilon \quad (3.15)$$

3.6 Experiments

We have established a mathematical model for mobility prediction. To test the validity of the claims made, we perform simulation experiments. In this section, we describe the simulation settings, mobility patterns and analysis.

3.6.1 Wireless Mobility Traces

We have earlier discussed methods of simulating mobility in computer experiments. Using mathematical mobility models does provide a first method of validating results. However, using real-world wireless traces from the field offer a more realistic environment for testing protocols and mobility prediction models.

We have used a campus wireless trace dataset available online [59]. The CRAWDDAD wireless trace sets have been collecting wireless device association and disassociation messages in WLAN networks since early 2001. All connections to its wireless network have been

stored as trace files which is a valuable mine of information. The trace files contain the wireless Network Interface Card (NIC), MAC addresses and the time of connection/disconnection for each access point. Since MAC addresses are unique, we can safely assume that each connection/disconnection associated with a MAC ID belongs to a unique user and can be treated as a mobile node.

The advantage of using this trace set is that it is being used by several other researchers for experiments to study various aspects of social mobility, campus mobility, resource allocation, etc. The ubiquitous WiFi coverage on the university campus affords a great opportunity to study handoffs and contiguous user mobility.

3.6.2 Mining Wireless Traces for Information

The wireless trace dataset contains user histories for thousands of wireless users. The logged data, as described in the earlier section, consists of AP associations to multiple users, MAC addresses of users, time stamps of associations and disassociations.

We have mined information such as the number of unique wireless network users, their association with the number of APs in the networks, the probability of transitions from one AP to another, etc from this trace dataset. We have used this data to perform simulation to verify the accuracy of the model versus actual movement, study user movement, prediction benefits, etc.

3.6.3 Trace Sets as HMMs

Wireless trace sets have provided a unique opportunity to study mobility patterns across a campus. Parsing information from a trace dataset is non-trivial. However, an even harder task is to import the data into the models that we have proposed.

The proposed HMM is a doubly stochastic process that consists of hidden and observable states. The trace sets can be used to model the observable or the hidden states depending on the scenario. Suppose we visualize the network data from the perspective of the access point,

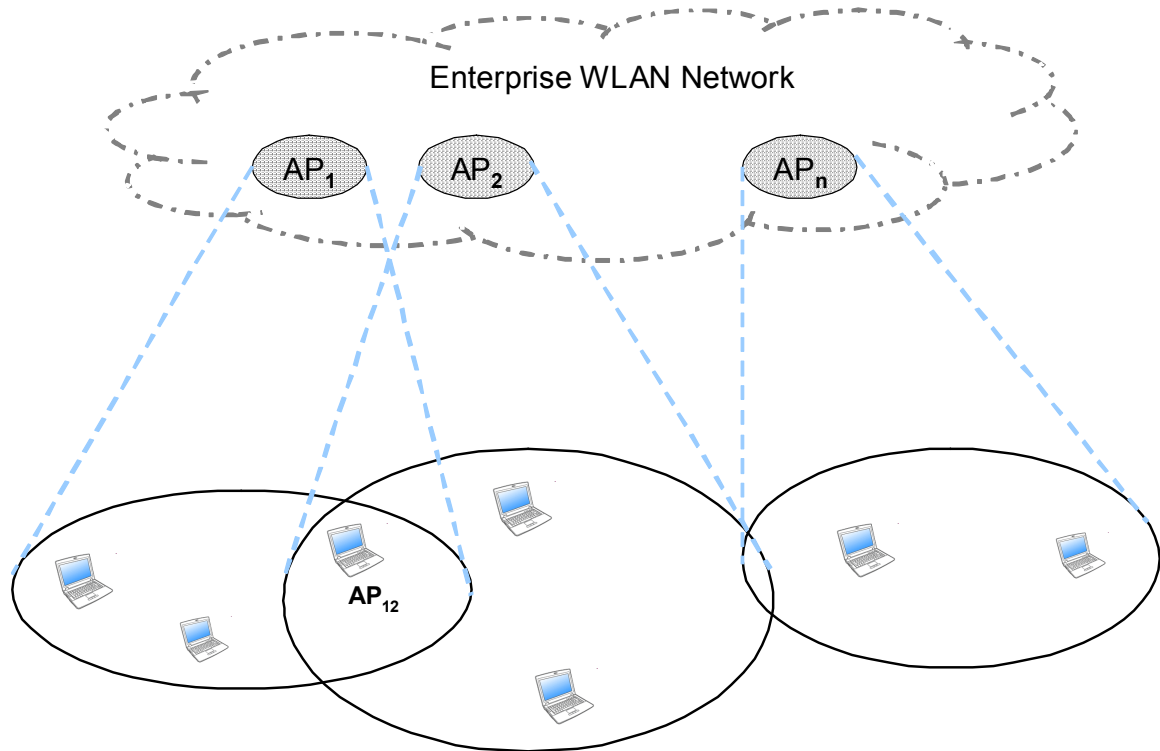


Figure 3.6: APs and the connected mobile users. User AP_{12} can be connected to either AP_1 or AP_2

we can only see the users connected to different access points. We have no way of knowing where the users are geographically located on a map. This is because several users at the exact same location may connect to one of several access points. Hence, we can conclude that all users connected to an AP are not at the same place. Here, the access points are the observable states and the location of the users are the hidden states.

On the other hand, suppose we can determine the exact location of the users, we can model the problem to be determining the most likely access point the user will connect to. Now, the users are the observable nodes and the access points are hidden.

Hence, modeling the problem as a HMM lets us conveniently redefine the problem based on the available data.

In Figure 3.6, we see the coverage of the APs and the wireless users connected to the APs. There is an overlap in the coverage areas of AP_1 and AP_2 . Hence, a user location in the overlap area such as AP_{12} could be connected to either AP_1 or AP_2 .

3.7 Results

The model proposed in the previous section has been simulated extensively to verify the claims. The data from the trace sets is imported into the model for the purpose of building the HMM. Aspects such as wireless user transitions from one access point to another are considered as mobility. Thus, the transition probabilities for the user with respect to those access points are reinforced. The developed prediction engine based on HMM is tested for accuracy in predicting the future mobility of users. Some of the results are briefly discussed below.

We have used a campus wireless trace dataset available online [59]. This dataset contains wireless user histories such as user associations with APs, duration of association, etc. From this dataset, we have mined a lot of information such as the number of unique users, their association with different APs, the probability of transitions from one AP to another, etc. Using this data, we have performed some analysis to verify the accuracy of the model versus actual movement, study user movement, prediction benefits, etc.

One main observation that we make from the dataset is shown in Figure 3.7. We see that most users always connect to only one or two APs regularly. These kind of behavioral issues influence the prediction and make it harder to predict users' next location.

The prediction accuracy is one of the most important metrics for the verification of this model. Figure 3.8 shows the prediction accuracy for several users across various APs. There is large variance across the users and APs. This is because of the 'preferred' tendency of the users to connect to a certain AP.

As mentioned earlier, Figure 3.9 shows how sequence length affects prediction accuracy. The accuracy decreases as sequence length increases due to the nature of the dataset as

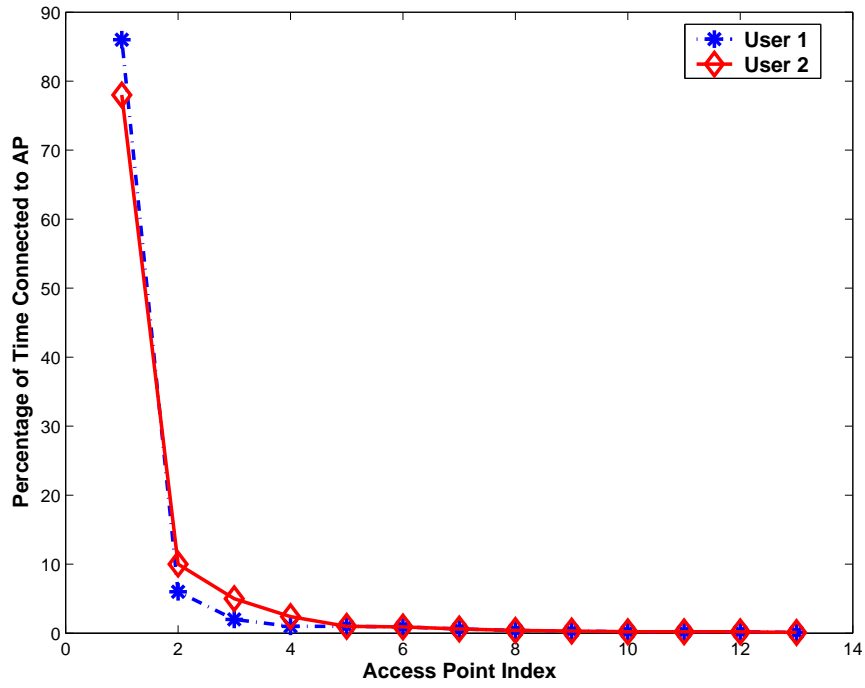


Figure 3.7: Percentage of time connected to different APs

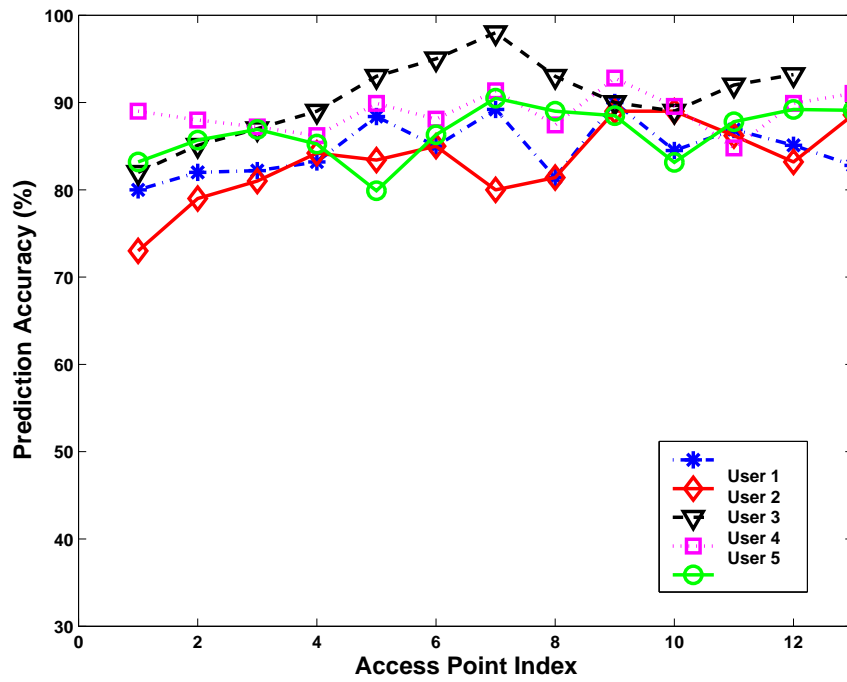


Figure 3.8: Prediction accuracy for various users using HMM

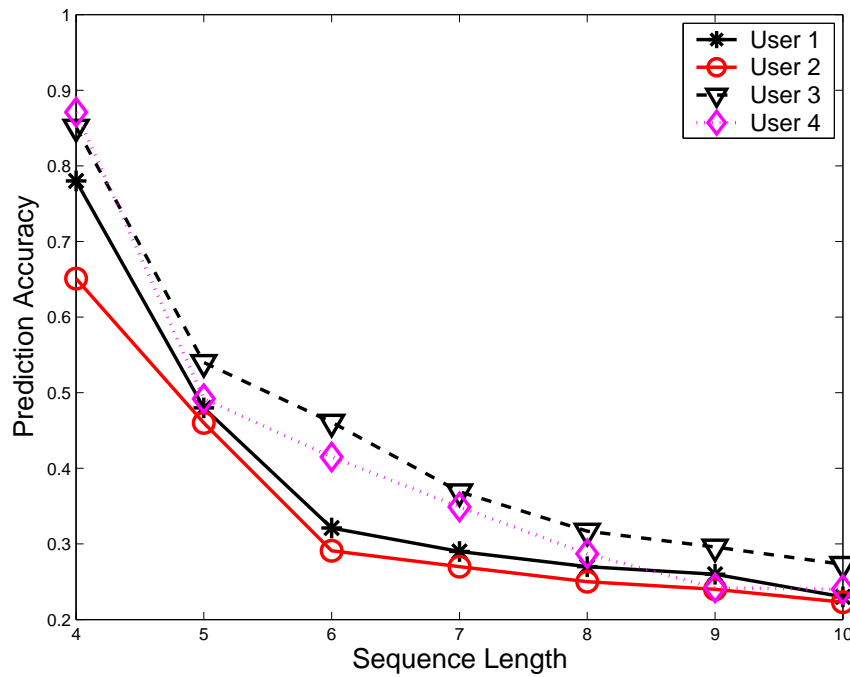


Figure 3.9: Effect of sequence length on prediction accuracy

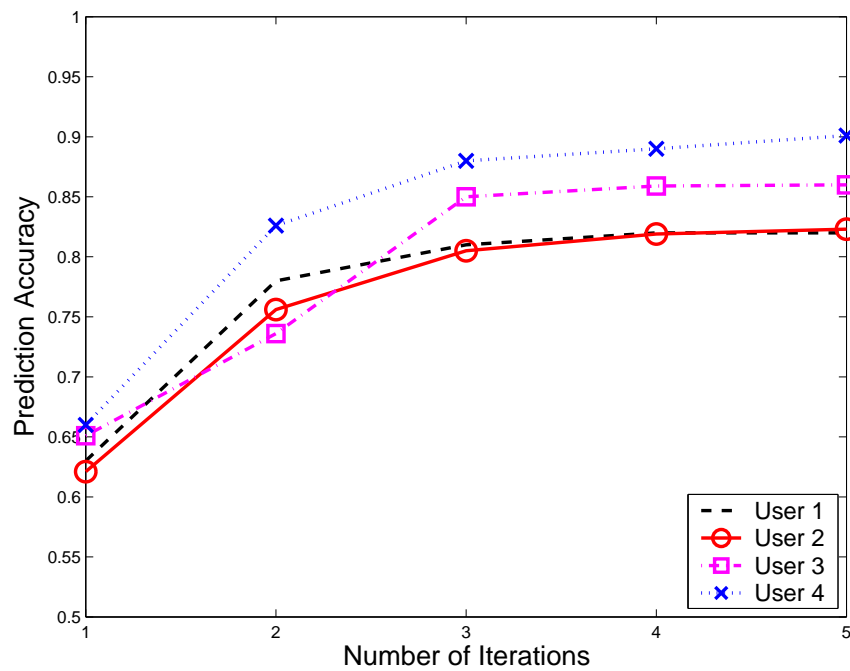


Figure 3.10: Effect of iterative improvement of HMM on prediction accuracy

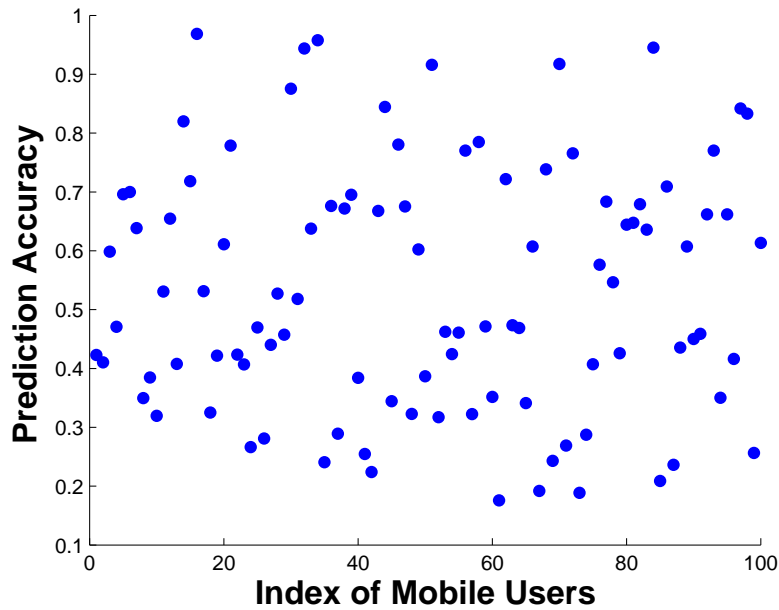


Figure 3.11: A scatter plot showing the distribution of users' average prediction accuracies

shown in figure 3.7 which biases the users towards a small percentage of APs. However, repeated training of the HMM can help in making better predictions as shown in Figure 3.10.

Figure 3.11 shows the average predictability of users in a network. There are a good percentage of users (approximately 41%) who are quite predictable since they move around a lot. Most other users in a network are random and connect only occasionally to APs other than their regular one. This is also validated by Figure 3.7.

From the simulation experiments using the HMM, we observe that highly accurate prediction of a user's mobility can be performed. The HMM model is easy to train with past data, the learning is fast and since the model is a learning model, the HMM can continue to learn with time. Also, the HMM can perform better predictions for users with regular habits.

3.8 Other prediction methods

HMM is a generic method of performing mobility prediction. In a system, depending on the scenario, different models may provide different prediction accuracies. In some cases it may be more important to generate prediction faster due to paucity of time rather than train the models for a long time. In other cases, the back end system may have the luxury of analyzing the historic movement data for a lengthy period of time to provide more accurate predictions.

Hence, we have attempted to show that the same data may be used to feed other prediction models and get comparable results.

3.8.1 Neural Networks

An artificial neural network is a mathematical model based on the operation of a neural network. It emulates the functioning of a of biological neural system. A neural network is an elegant data analysis and learning tool that can capture and represent multi variable functions. The idea for using an artificial neural system is based on the desire to model a system that can work like the human brain [60]. The artificial neural network can be characterized by the following capabilities.

1. Input variables feed into a neural network and it can acquire knowledge through learning models.
2. The knowledge gained by a neural network is represented as connection strengths known as synaptic weights.
3. A neural network needs no reprogramming and can work in parallel.

The main advantage of using a neural network lies in the fact that it can be used to model both linear and non-linear relationships in functions [61].

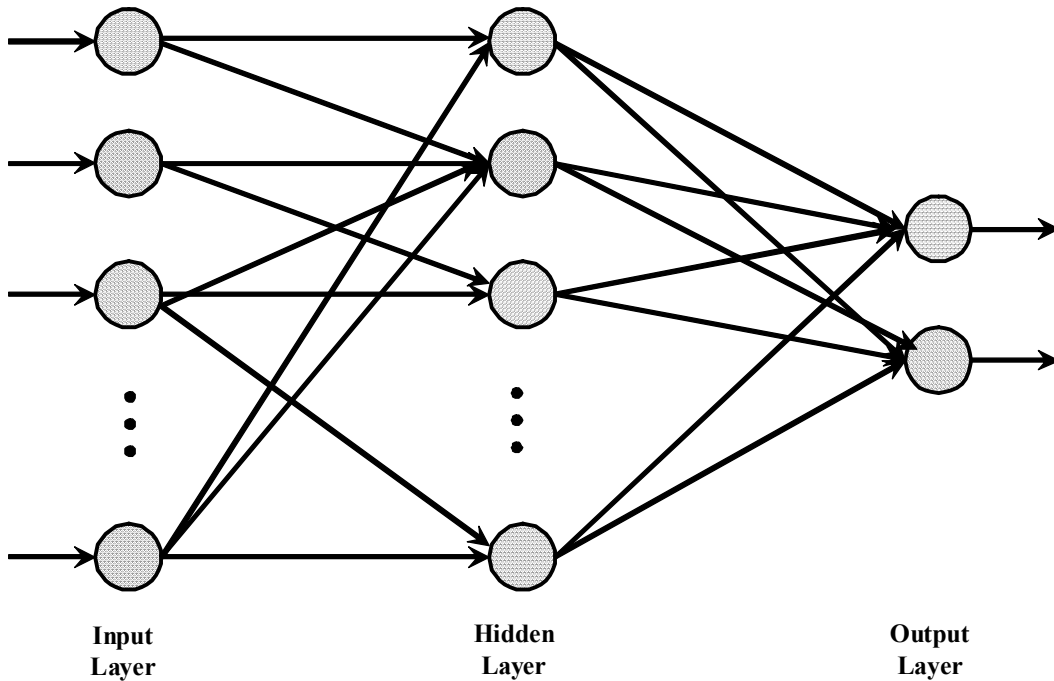


Figure 3.12: A representation of a Multi Layer Perceptron

3.8.2 MultiLayer Perceptron Neural Network Model

One of the most common and versatile neural network models is the multilayer perceptron (MLP) model [60] [62] [63]. This model belongs to a class supervised learning models since it requires a desired output to acquire knowledge and learn. This is an example of a mathematical model that can accurately map an input to an output using only historical data. Through this method, the model *acquires knowledge* and can generate the output for future inputs when the desired output is unknown. A graphical representation of an MLP is shown in Figure 3.12.

The MLP consists of an input layer, hidden layers and an output layer [64] [65] [66]. The number of hidden layers can be one or more. Every node, except the input nodes, computes a weighted sum of its inputs and applies a sigmoid function [60] to its output, which then is transmitted to the next layer.

The output of the MLP can be written as shown in Equation 3.17.

$$y = \phi \sum_{n=1}^N (w_n x_n + b) \quad (3.16)$$

$$= \phi(\mathbf{w}^{\mathbf{x}} + b) \quad (3.17)$$

where

ϕ is the activation function

\mathbf{w} denotes the vector of weights,

\mathbf{x} is a vector of inputs,

b is the system bias.

The MLP model generates a single output value taking inputs from multiple real-valued variables. The output is a linear/non-linear function of inputs and the weights and then weights. A nonlinear activation function may also be used.

The MLP uses a learning algorithm called backpropagation algorithm. Through backpropagation, the input data is repeatedly presented to the neural network and the output of the neural network is compared to the desired output known a priori. The computed error is then fed back i.e., backpropagated to make adjustments to the weights so that the error decreases with each iteration. Hence the neural network weights converge to the optimal value to produce the desired output. This phase is called the learning phase.

The learning phase consists of pairs of inputs and outputs that are obtained from historic data. In our case, we have mobility traces that show the initial access point and the actual next access point the user connects to. This information is fed to the network to train the network. The training process continues until the weights and bias functions are converged to a stable value. The criterion to be optimized is typically the squared reconstruction error $\sum_t \|\mathbf{f}(\mathbf{s}(t)) - \mathbf{x}(t)\|^2$.

The error in an output node is given by

$$e_k(n) = d_k(n) - y_k(n) \quad (3.18)$$

where we are observing the error at the k^{th} output node for the n^{th} data tuple. d is the desired output value and y is the erroneous value generated by the model.

The weights and biases are corrected accordingly to minimize the output error using

$$\mathbf{e}(n) = \sum_k \frac{e_k^2(n)}{2} \quad (3.19)$$

The change in each weight can be computed as

$$\Delta w_{kj}(n) = -\mu \frac{\partial \mathbf{e}(n)}{\partial v_k(n)} y_j(n) \quad (3.20)$$

where y_j is the output of the previous neuron and μ is the learning rate. The constant μ decides the speed of convergence of the weights in the network.

If the weights of all the nodes are expressed as a matrix, then

$$W^{ih} = \mathbf{W}^{ih} + \Delta \mathbf{W}^{ih} \quad (3.21)$$

where $\mathbf{W}_j^{ih} = \mu i e + \beta \delta \mathbf{W}_{j-1}^{ih}$

$$W^{ho} = \mathbf{W}^{ho} + \Delta \mathbf{W}^{ho} \quad (3.22)$$

where $\mathbf{W}_j^{ho} = \mu h d + \beta \delta \mathbf{W}_{j-1}^{ho}$,

\mathbf{W}_{pxn}^{ih} denotes the weight matrix for links from input layer i to hidden layer h ,

μ is the learning rate and

β is the weight change momentum factor.

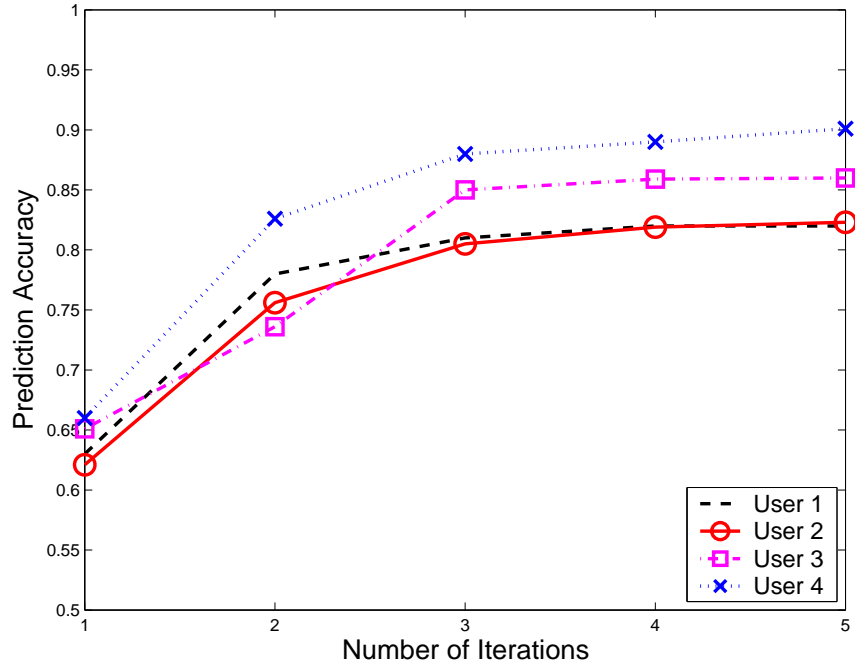


Figure 3.13: Effect of iterative improvement of Neural Networks on prediction accuracy

One hidden layer is usually enough for most models. More than one hidden layers are necessary for modeling discontinuous data with higher complexity. If two hidden layers are used, the model may be improved but it also adds the risk of the output converging to a local minima. Also, care must be taken in designing the number of neurons in the hidden layer. A lower number of neurons may produce erroneous or poor results and an excessive number of neurons will result in a very large learning phase. It may also introduce noise in the data and cause wrong outputs.

3.8.3 Results

A simulation experiment is conducted using the same wireless data traces is used to perform mobility prediction using MLP Neural Network. Simulation is performed using MATLAB software. All experimental settings from the HMM prediction experiment are maintained the same. Some of the results of the experiment are discussed in this section.

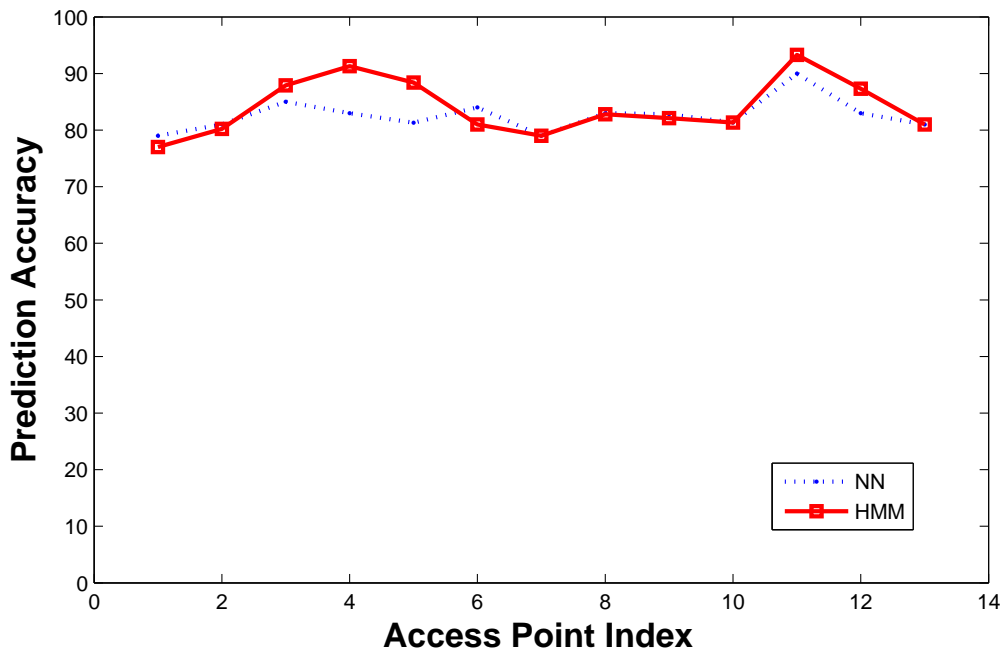


Figure 3.14: A comparison of prediction accuracies between Neural Network and Hidden Markov Model

Figure 3.14 shows a comparison of the prediction accuracies for the MLP Neural Network model to the HMM. The same users and access point settings are used for the experiment. It can be seen from Figure 3.14 that the prediction accuracies are almost the same. Hence MLP Neural Network provides an excellent model to produce highly accurate predictions.

In Figure 3.15, a comparison of prediction accuracies for the Neural Network and Hidden Markov Model can be seen. It is easily seen that the HMM outperforms the MLP model for longer sequence lengths. For movement sequences over 4 states, the Neural Network model is incapable of performing predictions

One of the obvious disadvantages of using the MLP model is the time it takes for the synaptic weights to converge. Figure 3.16 shows the number of iterations the model takes to converge to produce a stable and accurate output. While MLP model is quite accurate, it can take a very long time to get out of the ‘learning phase’. Moreover, we have simulated

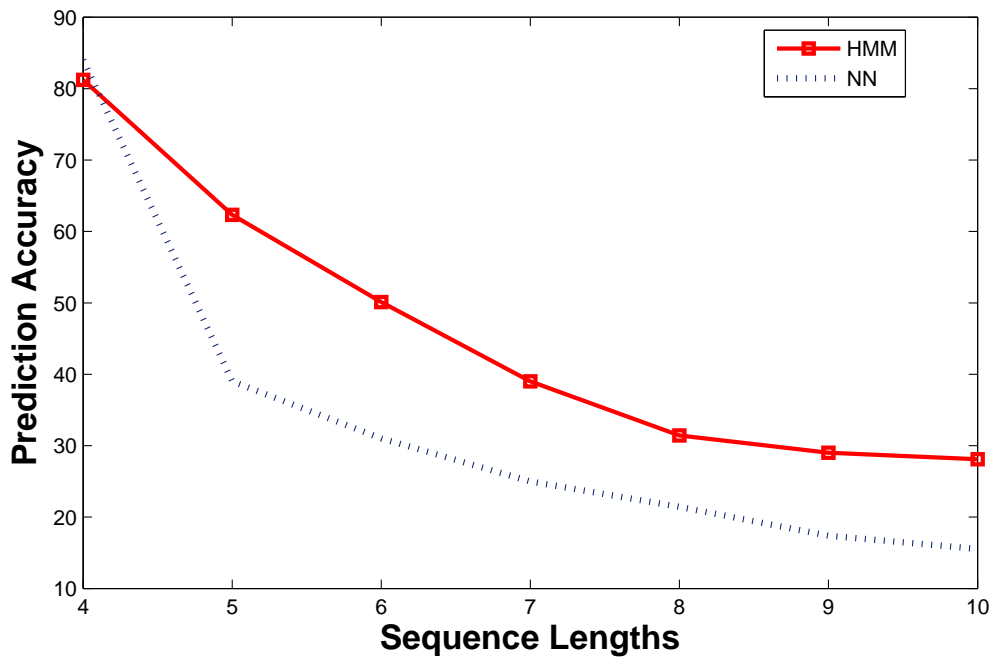


Figure 3.15: A comparison of prediction accuracy between Neural Networks and Hidden Markov Models over long movement sequences

the model using only one hidden layer. Increasing the number of hidden layers can greatly increase the convergence time.

3.9 Discussion

In this chapter, we have studied the mobility prediction schemes in literature and experimented with two prediction methods. We have proposed performing prediction using the HMM and the MLP Neural Network models. Accurate mobility prediction is essential for providing location based services and network management. It is shown that with a trace data set, we can achieve a very high accuracy in mobility prediction. Also, there are several similarities, advantages and disadvantages in using HMMs and Neural Networks as we have shown in [47] [67] [68] .

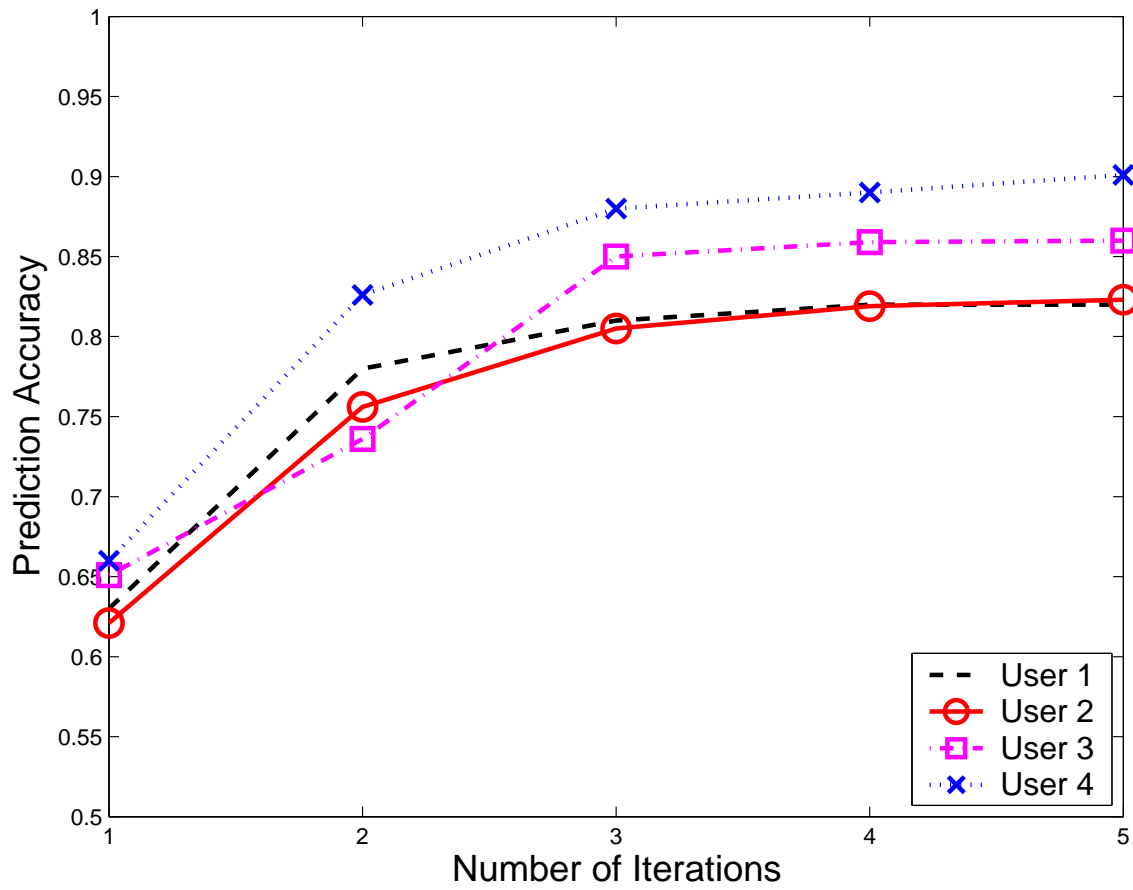


Figure 3.16: Optimal weight coefficients convergence in a MLP Neural Network model

3.9.1 Comparison of Neural Networks and HMM Models

Neural Networks and Hidden Markov Models have several advantages over each other. HMMs can be trained rapidly since their learning phase can be quite short. Also, the Markov models can be made into k th order models to capture recent path changes. On the other hand, MLPs can predict the next state of the system based only on the previous state.

Also, training HMMs required a lot less historic data before producing accurate predictions. In contrast, Neural Networks take a long time to learn, require more historic data information and can be more complex. However, Neural Networks can be used when no data is available at all; but since it is a supervised learning model, the network can start off with arbitrary synaptic weights and eventually adapt its coefficients correctly if it is fed the correct feedback. The feedback loop error can be minimized with successive iterations and the model made to converge over time.

Chapter 4

Resource Allocation in Wireless Networks

4.1 Overview

In a large network, keeping track of devices, servers and active connections is a challenge. The problem is tougher in the case of wireless networks involving hundreds or thousands of users. The process of managing all these devices, providing a constant supply of resources and administering and maintaining them is called network management.

Wireless networks pose significant management challenges in several ways. One of the main challenges in network management is to provision the available resources optimally. Resources may mean bandwidth, time slots, QoS requirements, etc. However, providing real-time services is challenging due to the binding delay/jitter requirements and also due to complex network dynamics.

Enterprise wireless networks are very complex systems with several inter-dependent components that affect their performance. These components, besides radio interference, may include various network protocols, traffic flows, dynamic network topologies, device hardware and software. Moreover, it is very difficult to characterize and analyze how these devices interact with each other.

Resources are always scarce in wireless networks with radio spectrum being the most important. With increasing number of users, over-provisioning bandwidth as done in wireline networks is not feasible. Hence, the importance of efficiently allocating bandwidth resources cannot be overemphasized.

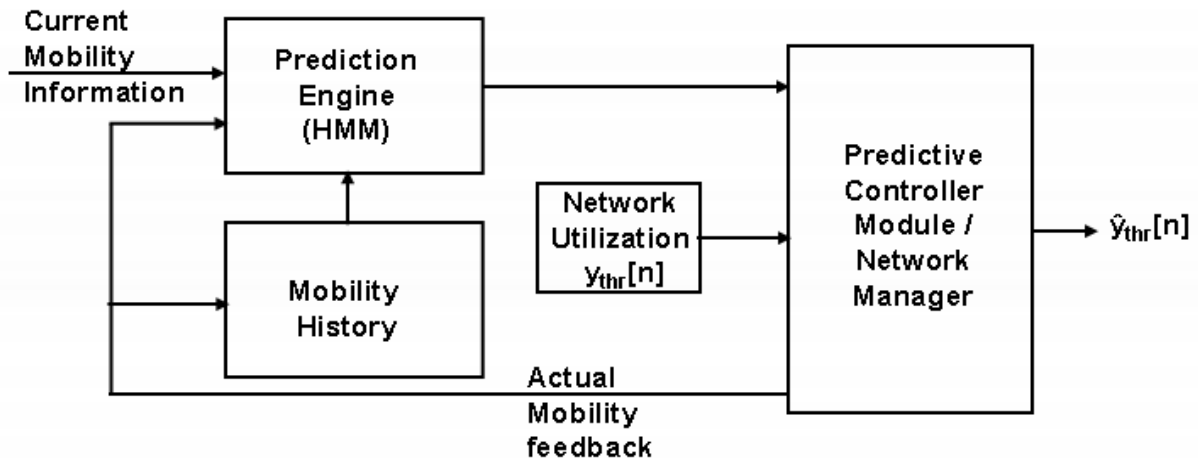


Figure 4.1: The proposed network model

4.2 Network Management using Mobility Prediction

In Chapter 3, we have performed mobility prediction using historic movement data. The objective of performing mobility prediction was to provide better localization and location aware services. It is possible to utilize the same data and results of mobility prediction for network management.

The framework consists of two parts - the prediction model shown in Figure 4.1 and the control theoretic feedback model for resource utilization in Figure 4.2.

4.3 Control Theory in Resource Allocation

Control systems [69] [70] have been applied [71] [72] to solve problems in communication networks. Several problems in the domain of computing and communication systems have been modeled using control theoretic approaches [71] [72] [73] [74]. Some of these include network flow-control problem, CPU resource allocation problems, etc. One common characteristic of such problems is that they involve time variant inputs that cannot

be characterized by closed form solutions. Hence a control system is ideal in such models since it can be made adaptive to the changing input-output parameters and resource conditions [75] [76] [77] [78] [79].

There are no models that also solve the problem of prediction and management as a single issue in mobile wireless networks. We propose to address the resource allocation issue as an integral part of the mobility prediction framework.

4.4 Proposed model and Mathematical analysis

The model in Figure 4.1 shows a block diagram of the network mobility prediction. The prediction engine is driven by a HMM or a Neural Network Model. The current mobility information and a history of the users' past movements is used to make predictions. The data for the predictions is stored in a mobility database which updates mobility of users moving to adjacent network APs.

The predictive controller module in Figure 4.1 is a control system shown in more detail in Figure 4.2. The controller consists of a network manager which decides the current resource utilization and helps makes an estimate of the network usage. This information is fed to the estimator after a delay to denote that it uses stale historic data, i.e., only events that have already transpired. This generates the estimated threshold function x_{est} or \hat{x} which is used to output function for the resource allocation. The resource allocation engine only produces a fractional value denoting the network resource usage. A value greater than 1 would mean an overloaded network.

In mobility prediction, user mobility can be random, bursty, stochastic and non-stationary. These parameters result in uncertainty in reserving resources, thereby demanding adaptive models that can regulate the traffic and allocate resources optimally.

The proposed predictive control model determines the threshold for input to regulate the incoming users depending on parameters such as number of users and effective resource utilization. Effective resource utilization is defined as the fraction of network resources being

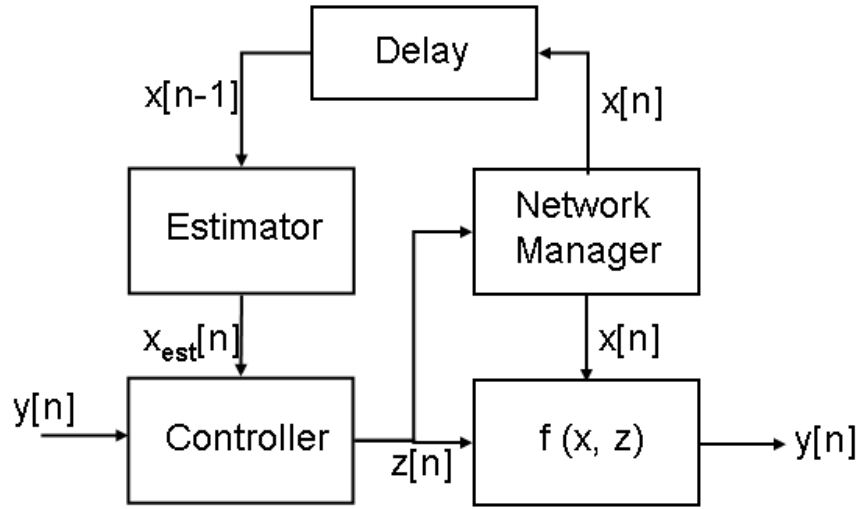


Figure 4.2: Details of the network controller

used at any given time. The solution proposed is a predictive controller that is driven by the HMM. Other proactive tasks such as capacity planning and intelligent learning can also be performed.

To describe Figure 4.2, a few terminologies and notations are needed. Let $d[n]$ be the average network demand due to all existing users at the time instant n and $z[n]$ the regulating value. The actual quantity of network resources being utilized at any moment is a function of d and z and is denoted by x . Relative utilization of the network is denoted by $y[n]$. This is defined as the ratio of the measured network resource usage to the total available network resource.

$$y[n] = f(x[n], z[n]) \quad (4.1)$$

$$y[n] = \frac{x[n]}{z[n]} \quad (4.2)$$

The controller has to maintain the effective network utilization at a specified threshold level, say y_{thr} . Hence,

$$z[n] = z[n - 1] - G_a[n] \left(y_{thr} - \frac{x[n - 1]}{z[n - 1]} \right) \quad (4.3)$$

G_a is the adaptive loop feedback gain and is negative to indicate negative feedback.

$$G_a[n] = \mu \left(\frac{x[n - 1]}{y_{thr}} \right) \quad (4.4)$$

where μ is the loop control constant that ‘regulates’ the level of control in the feedback loop.

The adaptive loop feedback gain as

$$G_a[n] = \frac{z[n - 1]}{y_{thr}} \quad (4.5)$$

Hence, $z[n]$ becomes

$$z[n] = \frac{x[n - 1]}{y_{thr}} \quad (4.6)$$

Since the predictability of $x[n]$ is straightforward as established by $f(\cdot)$, $z[n]$ is obtained by

$$z[n] = \frac{x_{est}[n]}{y_{thr}} \quad (4.7)$$

Since this is a model for a system with memory using historic data to estimate the resource utilization at any instant, the control system depends on the current and the average loads.

Hence,

$$x[n] = \min (z[n], d[n]) \quad (4.8)$$

In an ideal scenario, the network is always able to meet the demands of the users. The network demand should always be less than the total available resources. and hence, we have $d[n] \leq z[n]$. However, due to the unpredictability of mobile users, there are bursty arrivals and demand exceeds supply. The arrivals are bound by the resources available and $x[n] = z[n]$. The goal of the controller is to regulate the number of users in the network depending on the resource availability where $d[n]$ is observable.

To analyze the estimator shown in Figure 4.2, the state space model [71] is given by

$$x_n^{(i)} = \Psi^{(i)} x_{n-1}^{(i)} + \Gamma^{(i)} z_{n-1} \quad (4.9)$$

$$y_n^{(i)} = C^{(i)} x_n^{(i)} + \eta_n \quad (4.10)$$

This is a generalized model equation with the superscript (i) denoting model index. Estimating these coefficients results in errors that are also represented by η_n , the error coefficient. The output $y_n^{(i)}$ predicted by the model is also iteratively corrected using repeated estimation. A separate correction index δ_n that accounts for all other inherent model errors is also introduced.

$x_n^{(i)}$ is a state estimation performed by the model and can be expressed as a single state vector in the form

$$x_n^{(in)} = \begin{bmatrix} x_n^{(i)} \\ \delta_n^{(i)} \end{bmatrix} \quad (4.11)$$

The generalized state vector can be written as

$$x_n^{(in)} = \Psi^{(in)} x_{n-1}^{(in)} + \Gamma^{(in)} z_{n-1} + \Delta^{(in)} \delta_{n-1} \quad (4.12)$$

$$y_n^{(i)} = C^{(in)} x_n^{(in)} + \eta_n \quad (4.13)$$

However, we know that the information at the estimator above is old and is denoted by a time lag. Hence, the estimated information is denoted as

$$\hat{x}_{n|n-1}^{(in)} = \Psi^{(in)} \hat{x}_{n-1|n-1}^{(in)} + \Gamma^{(in)} z_{n-1} + \Delta^{(in)} \delta_{n-1} \quad (4.14)$$

$$\hat{y}_{n|n-1}^{(i)} = C^{(in)} \hat{x}_{n|n-1}^{(in)} + \eta_n \quad (4.15)$$

\hat{x} notation explicitly denotes the predicted value of x . The prediction is made from the state variables in the previous time slot. These equations can be solved using the standard linear algebraic methods described in [69].

The uniqueness of this solution is that at each time slot, an optimization problem formulation is solved. The design of the controller is such that the formulation of the objective function is to minimize the controller function over a horizon of m time slots.

At the beginning, only the initial control conditions are applied to the system. The state space models are updated and then the system iteratively updates the conditions from the controller. The desired effective resource utilization is 83.3% as used in most networks.

The initial mode for the estimation is defined by

$$y'_{n+j|n} = \sum_{i=1}^l a_n^{(i)} \hat{y}_{n+j|n}^{(i)} \quad (4.16)$$

where $a_n^{(i)}$ are the coefficients of the model weight vectors and $\hat{y}_{n+j|n}^{(i)}$ are the predicted individual model outputs. These have been calculated using the state estimation results explained earlier.

For the predictive control solution, we need to derive a solution from the linear model described above. The objective function is formulated as follows. The error over the prediction range of m time slots is give as

$$\Omega_{err} = (Y - Y')^T A_y (Y - Y') \quad (4.17)$$

where Y is the vector, \hat{Y} is the vector defining the predicted output values over the range $\hat{y}_{n+1|n}$ through $\hat{y}_{n+m|n}$, i.e.,

$$Y' = \begin{bmatrix} y'_{n+1|n} \\ y'_{n+2|n} \\ \vdots \\ y'_{n+m|n} \end{bmatrix} \quad (4.18)$$

The correction of the controller in the loop is given by

$$\Theta = \Delta Z^T A_z \Delta Z \quad (4.19)$$

where

$$\Delta Z = \begin{bmatrix} \Delta z_n \\ \Delta z_{n+1} \\ \vdots \\ \Delta z_{n+m-1} \end{bmatrix} \quad (4.20)$$

Z_0 is a column vector of elements z_{n-1} of size $m \times 1$

The optimization problem is formulated as follows and solved numerically.

$$\min \Psi = \Omega_{err} + \Theta \quad (4.21)$$

4.5 Simulation

The model proposed in the previous section has been simulated to verify the proposed ideas. The prediction engine based on HMM is separately tested for accuracy in predicting the future mobility of users. Also, the control system is tested for stability and integrated with the prediction model as a whole to regulate network resource utilization. Some of the results are briefly discussed in the subsequent sections.

Using mobility data, we have performed analysis using MATLAB simulations to verify the accuracy of the model versus actual movement, study user mobility, prediction benefits, etc. The control system has been simulated using the Control System toolbox and Simulink from MATLAB.

4.5.1 MATLAB Simulink Modeling

Simulation of the feedback based control system is performed in MATLAB using the Simulink toolbox. MATLAB Simulink is a specialized control system toolbox that provides advanced features of control theoretic principles. Simulink is an environment for multidomain simulation and Model-Based Design for dynamic control and embedded systems. Simulink models are hierarchical and allow for using both top-down and bottom-up approaches.

We have used MATLAB extensively to simulate some of the models described in the earlier chapters. Mobility prediction models using HMM were implemented in MATLAB since it provides extensive features for data mining and analysis. Since Simulink is an integrated component of the MATLAB environment, it is relatively easy to perform analysis of control systems and also derive full advantage of features offered in both environments.

4.5.2 Simulation Parameters

A MATLAB simulink scenario is used to perform simulation for the complete system involving the prediction engine and the controller. The threshold value for the network is decided based on the effective resource utilization rate. The resource utilization rate is defined as the ratio of the total resource being used to the total available network resource which is always less than unity.

The desired optimum effective utilization rate has been set at 0.833 and the feedback loop coefficients converge accordingly. Various model characteristics such as resource utilization, time required for stability, percentage of mobile users dropped and errors in estimation are observed via simulation. The simulation results are discussed below.

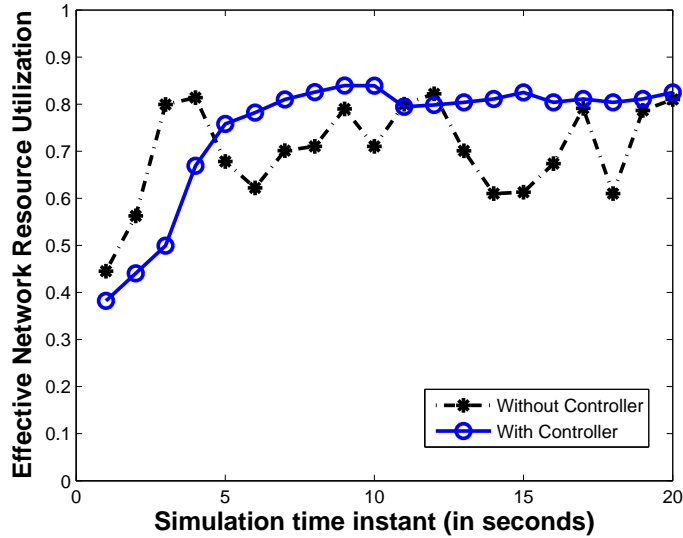


Figure 4.3: Simulated resource utilization \hat{y}_{thr} with and without controller

4.6 Results

The effectiveness of the controller is shown in Figure 4.3. With the feedback control system, the network resource is managed more effectively than when it operates without a controller. A HMM without a controller can still achieve high utilization but only at certain times; a controller helps regulate the number of users to optimize resource utilization. In the same figure, it is also seen that the effective resource utilization using a controller is approximately 83%, which was the threshold set by the network.

Figure 4.4 proves the same as a function of resource utilization with plain HMM prediction, without prediction and with prediction-based controller. Figure 4.5 shows the percentage of users ‘dropped’ (i.e., denied admission to prevent overloading of the network).

Figure 4.6 shows that the model is stable and the coefficients indeed converge in finite time. Network load is an important parameter in predicting network utilization. Network load estimation errors also decrease with time. Comparing Figures 4.6 and 4.7, we can see that the errors reduce significantly as shown in Fig 4.7 after the model coefficients converge.

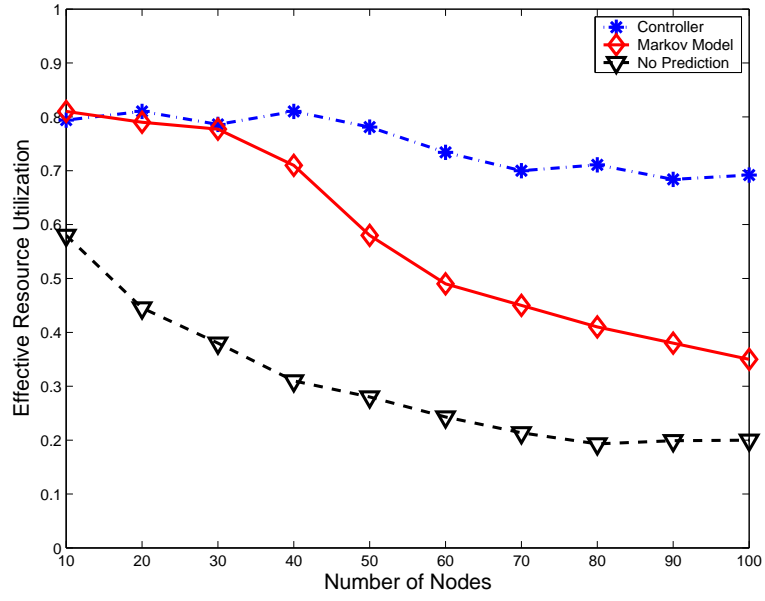


Figure 4.4: Resource utilization \hat{y}_{thr} as a function of number of users

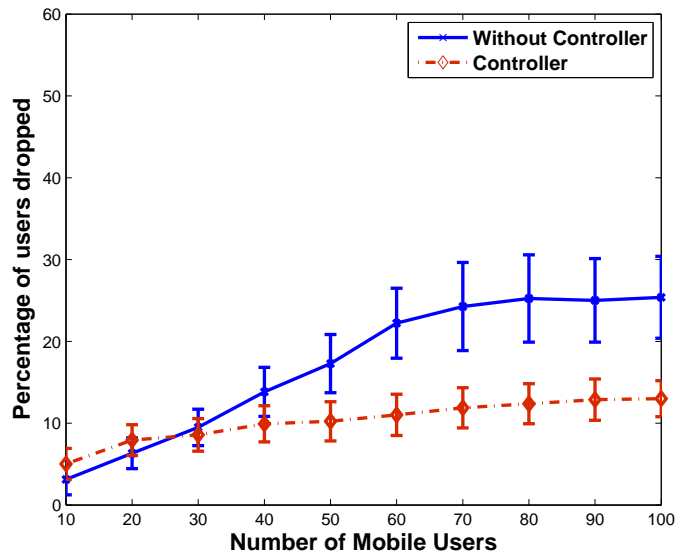


Figure 4.5: Percentage of dropped users

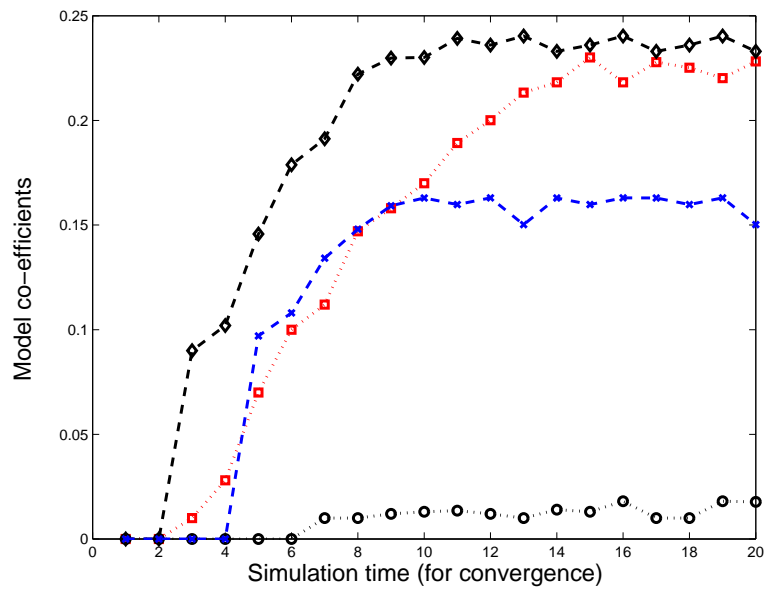


Figure 4.6: Simulation convergence time for model coefficients $a_n^{(i)}$

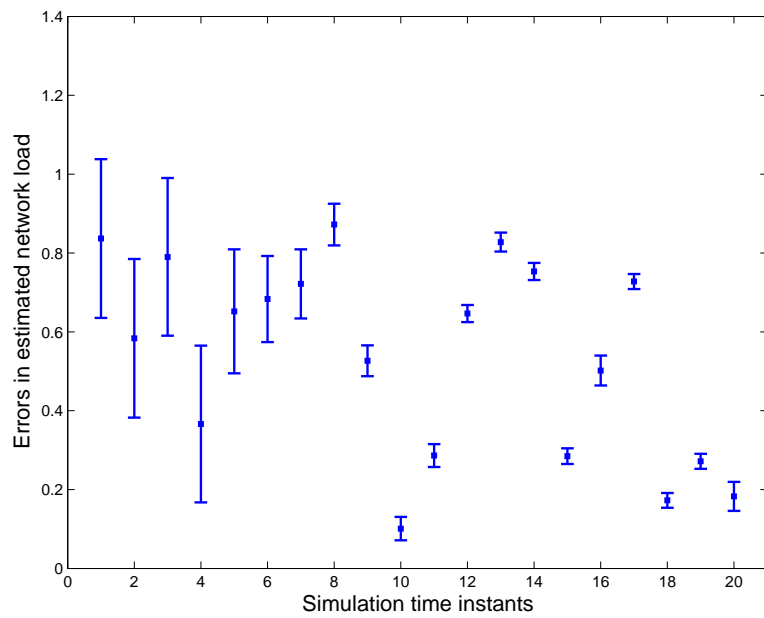


Figure 4.7: Mean errors in estimated network load at various instants

4.7 Discussion

The prediction scheme uses an HMM which delivers mobility information to a predictive control system. We have shown increased utilization, reduced blocking scalability and rapid convergence [67] [68] through extensive simulation experiments. The proposed scheme can be effectively incorporated into existing wireless network architectures. To our knowledge, this is the first time control theory is used for studying the effect of mobility on mobile network performance.

Chapter 5

Effect of Mobility on Interference

5.1 Overview

We have studied various aspects of mobility. We have characterized the general movement of users, studied the effects of mobility on wireless network parameters such as throughput, data rates, etc and we have proposed solutions to deal with some of its detrimental effects.

With increasing number of users, cells are being split into nano and femtocells; wireless networks are being made smaller to prevent interference amongst various networks. However, the cells and networks cannot be split indefinitely. Mobility and interference together have been extensively studied for cellular networks for a long time [80] [81] [82]. Interference effects arising out of mobility have also been studied in the context of routing, network modeling, etc [83] [84].

One other important aspect is the effect of mobility on interference dynamics and outage perceived by users. Outage can be defined as the probability that the quality of service (e.g., measured by Signal to Interference Ratio (SIR)) is less than a predefined threshold. Due to movement of mobile users, the location of interfering nodes change by time. As a result, the statistics of interference dynamics needs to be considered in our analysis. In this chapter, we aim to obtain analytical models for outage which consider mobility as a parameter.

There are few studies which take into account the effect of mobility on quality of service and outage. One study [85] uses a fluid model for mobility and defines f as the ratio of outer cell received power to the inner cell received power. Using this factor, analytical results are found for outage probability. However, the considered mobility model is not very practical and is limited in scope.

Another research study [80] focuses on the impact of mobility of low-speed users. It aims to model how interference evolves with respect to the mobility of users who move in a random fashion. WienerLévy process is used as a stochastic tool for characterizing the impact of mobility on the future behavior of interference. The considered is simplified and only distance-based path loss model is considered while neglecting the effect of fading in analysis.

In this chapter, we consider a power-controlled cellular system and obtain cell cross-over probability for different edges of a cell and for different mobility models using simulation. First, assuming that users are uniformly distributed at the beginning, we obtain time dependent equations for the number of users in a cell considering different models. Second, we obtain analytical results for distances between an arbitrary node and a particular victim BS. These distances are then used to find the amount of interference to the victim BS using distance-dependent as well as log-normal shadowing. The aggregate interference is then modeled as a Gaussian random variable assuming central limit theorem holds. We obtain analytical results for mean variance of aggregate interference which are enough to characterize the Gaussian random process. The outage probability therefore can be easily found using this statistical model.

5.2 System Model

The cellular system is modeled as a tessellation of hexagonal cells. The nodes inside each cell employ power control so that the received power of each node at its associated base station (BS) is a constant P_f . The channel model is a combination of distance-dependent path loss as well as shadow fading.

Now let us consider Figure 5.1. Focusing on a single cell in the cellular system, the received power, P_r , from the m^{th} nearest node in the cell to the BS is given by [86]:

$$P_r = \zeta_m P_{t,m} r_m^{-\alpha} \quad (5.1)$$

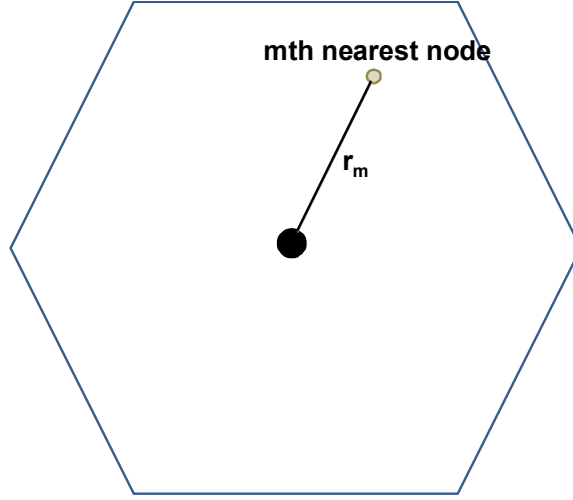


Figure 5.1: Representation of the m^{th} nearest node from the BS in a cell

where ζ_m is the shadow fading factor, α is the path loss exponent, r_m is the distance between BS and m^{th} nearest node and $P_{t,m}$ is the transmit power level of m^{th} nearest node. We assume that perfect power control is employed by the nodes and $P_{t,m}$ is

$$P_{t,m} = \frac{1}{\zeta_m} P_f r_m^\alpha, \quad (5.2)$$

so that the received power is fixed (i.e., P_f).

5.2.1 Proposed Approach

In Figure 5.2, the tessellation of cells is shown. The cells are numbered starting from the bottom outer perimeter cell as shown. The numbering is continued in an counter-clockwise manner and the perimeter hierarchy is determined as illustrated in the figure. The number of nodes in a cell (i, j) at time t is defined by $n_{i,j}^t$. Given that nodes are distributed uniformly with density λ at time $t = 0$, several mobility models are used to determine $n_{i,j}^t$.

For this purpose, we find the probabilities $p_i (i = 1, 2, \dots, 6)$ of nodes crossing the edges of a cell in a time interval Δt as seen in Figure 5.3. These probabilities depend on the mobility model, cell size, Δt and speed among other factors.

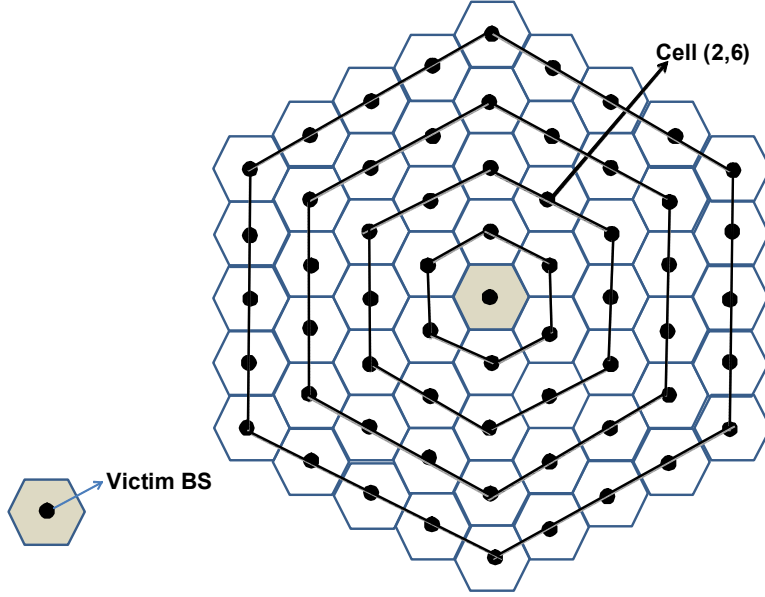


Figure 5.2: Cellular geometry and cell numbering

Using these probabilities, we can find the evolution of $n_{i,j}^t$. For example, for cell (2,6), it can be seen that

$$\begin{aligned}
 n_{2,6}^t &= n_{2,6}^{t-1} (1 - q) + n_{2,5}^{t-1} (p_5) + n_{2,7}^{t-1} (p_2) + n_{1,3}^{t-1} (p_4) \\
 &\quad + n_{1,4}^{t-1} (p_3) + n_{3,8}^{t-1} (p_6) + n_{3,9}^{t-1} (p_1)
 \end{aligned} \tag{5.3}$$

where

$$q = \sum_{i=1}^6 p_i$$

5.3 Interference Analysis

Consider Figure 5.4 in which the distance between m th nearest node to the BS in cell (i, j) and the BS in the victim cell, denoted by $d_{i,j,m}$ is found using the law of cosines.

$$\begin{aligned}
 d_{i,j,m}^2 &= H_{ij}^2 + r_m^2 - 2H_{ij}r_m \cos\left(\frac{3\pi}{2} - \alpha_m\right) \\
 &= H_{ij}^2 + r_m^2 + 2H_{ij}r_m \sin \alpha_m
 \end{aligned} \tag{5.4}$$

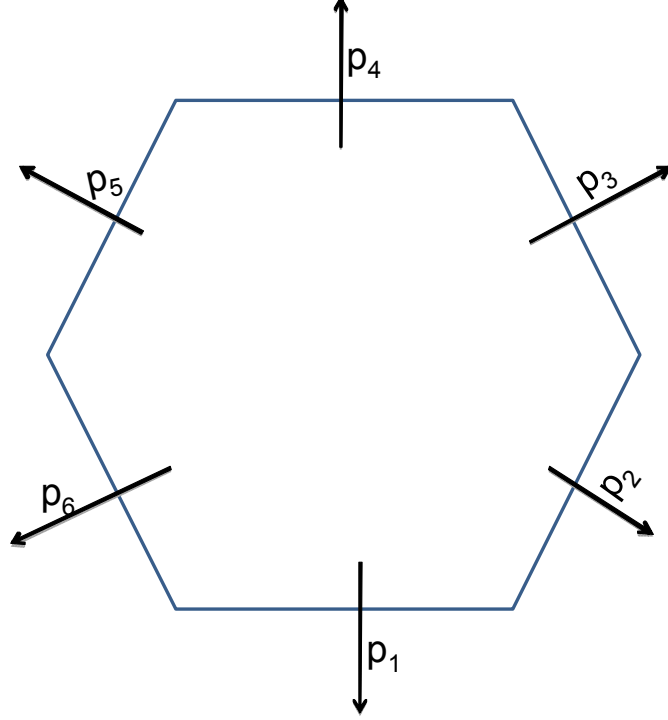


Figure 5.3: Cell cross-over probability from different edges of a cell

Lemma 1 By assigning $k = (j - 1) \bmod i$, H_{ij} can be found as:

$$H_{ij} = \sqrt{3R^2(i^2 + k^2 - ik)} \quad (5.5)$$

Proof: By assigning $k = (j - 1) \bmod i$, we can see from Figure 5.4 that H_{ij} equals x_k in Figure 5.5. By using the law of cosines sequentially, equation ?? can be obtained.

Interference originated from nodes in cell(i,j) on the victim BS at time t will be

$$\begin{aligned} I_{ij}^t &= \sum_{m=1}^{n_{i,j}^t} \eta_m P_{t,m} d_{i,j,m}^{-\alpha} \\ &= \sum_{m=1}^{n_{i,j}^t} \frac{\eta_m}{\zeta_m} P_f \left(\frac{r_m}{d_{i,j,m}} \right)^\alpha = \sum_{m=1}^{n_{i,j}^t} \rho_m P_f \left(\frac{r_m}{d_{i,j,m}} \right)^\alpha \end{aligned} \quad (5.6)$$

where η_m is the shadow fading component for the link between m^{th} nearest node in cell(i,j) to its BS and the victim BS and the relation for $P_{t,m}$ is obtained from Equation 5.2. We

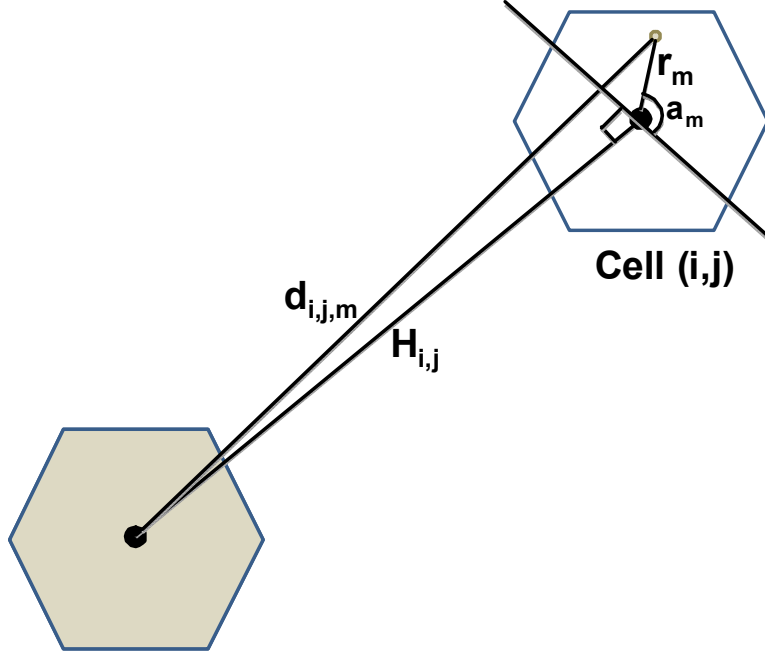


Figure 5.4: Distances between the interfering nodes and the victim BS

also have $\rho_m = \frac{\eta_m}{\zeta_m}$. It is easily seen that if η_m and ζ_m both correspond to σ dB Log-normal shadowing, ρ_m corresponds to $\sqrt{2}\sigma$ dB Log-normal shadowing.

By defining $\sigma' \triangleq \sqrt{2}\sigma \frac{\ln 10}{10}$, the first two moments of ρ_m can be found as

$$E\{\rho\} = e^{\sigma'^2/2} \quad (5.7)$$

$$E\{\rho^2\} = e^{2\sigma'^2} \quad (5.8)$$

While it is possible to obtain the statistics of r_m with certain assumptions (see next section) and α_m can be assumed uniformly distributed in $[0, 2\pi]$ and independent from r_m , the statistics of $d_{i,j,m}$ is not easy to obtain. Now,

$$\begin{aligned} E\{d_{ijm}^2\} &= H_{ij}^2 + E\{r_m^2\} + 2H_{ij}E\{r_m\}E\{\sin \alpha_m\} \\ &= H_{ij}^2 + E\{r_m^2\} \end{aligned} \quad (5.9)$$

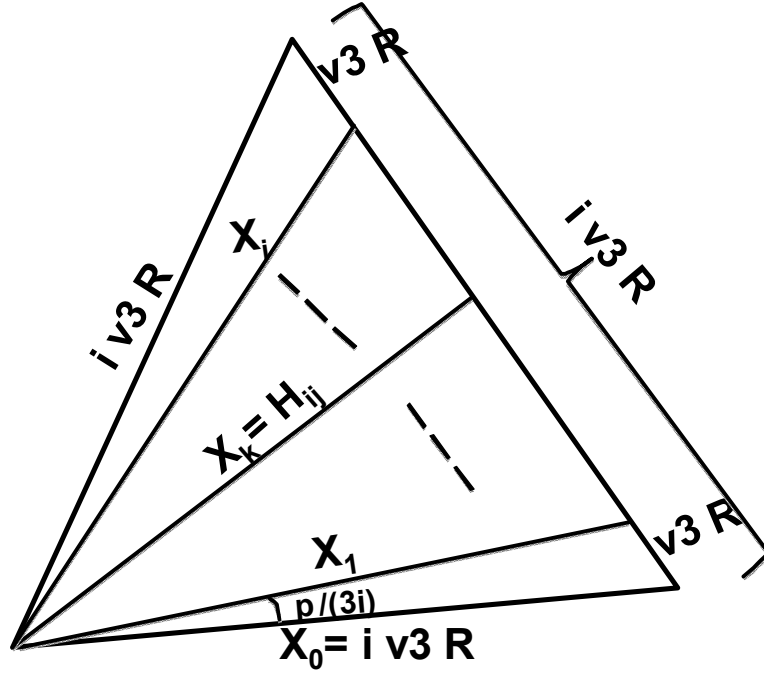


Figure 5.5: The geometry used to find H_{ij}

We estimate I_{ij}^t by \tilde{I}_{ij}^t as

$$\tilde{I}_{ij}^t = \sum_{m=1}^{n_{i,j}^t} \rho_m P_f \frac{r_m^\alpha}{[H_{ij}^2 + E\{r_m^2\}]^{\alpha/2}}$$

Total interference at the victim BS at time t can therefore be estimated as

$$\tilde{I}^t = \sum_{i,j} \tilde{I}_{ij}^t \quad (5.10)$$

Statistics of \tilde{I}^t

\tilde{I}^t is the sum of a large number of random variables and we assume that Central Limit Theorem (CLT) holds and it follows a Gaussian distribution. Therefore, mean and variance

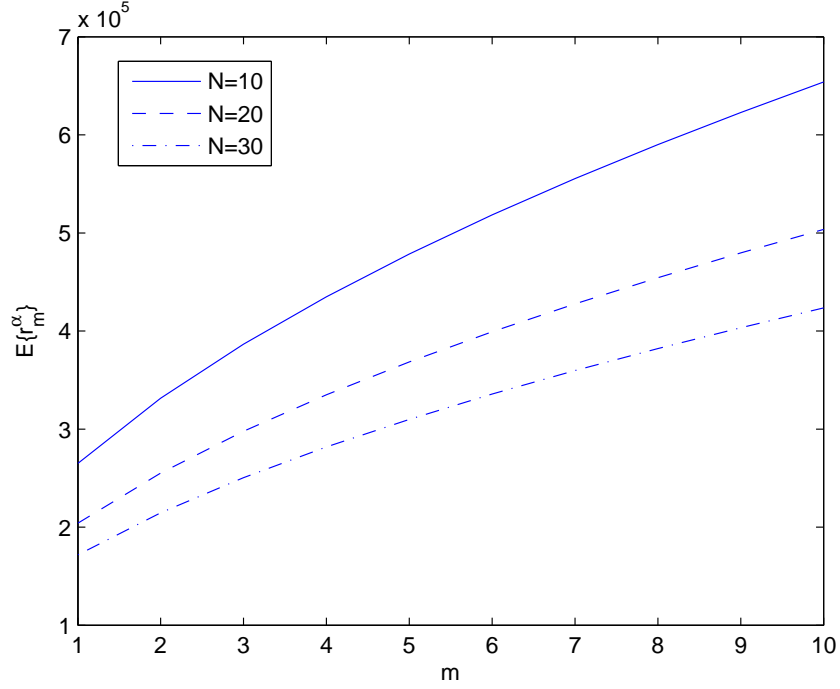


Figure 5.6: $E\{r_m^\alpha\}$ versus m for $\alpha = 3$, $R = 100$ and $N = 10, 20, 30$

of \tilde{I}^t are required to completely characterize it. They can be found as follows:

$$E\{\tilde{I}^t\} = E\{\rho\}P_f \sum_{i,j} \sum_{m=1}^{n_{i,j}^t} \frac{E\{r_m^\alpha\}}{[H_{ij}^2 + E\{r_m^2\}]^{\alpha/2}} \quad (5.11)$$

$$\text{var}\{\tilde{I}^t\} = \sum_{i,j} \sum_{m=1}^{n_{i,j}^t} \frac{P_f^2 \text{var}\{\rho_m r_m^\alpha\}}{[H_{ij}^2 + E\{r_m^2\}]^\alpha} \quad (5.12)$$

From Equation 5.11 and Equation 5.12, $E\{\rho\} = e^{\sigma^2/2}$ and $\text{var}\{\rho_m r_m^\alpha\} = e^{2\sigma^2} E\{r_m^{2\alpha}\} - e^{\sigma^2} E^2\{r_m^\alpha\}$.

Statistics of r_m

We make the assumption that at time t , the $n_{i,j}^t$ nodes inside cell (i, j) are uniformly distributed. Once we have $n_{i,j}^t = N$, we can approximate the hexagonal cell of radius R to a circular cell of radius R_0 for more clarity in analysis.

$$\begin{aligned}\pi R_0^2 &= \frac{3\sqrt{3}}{2}R^2 \\ R_0 &= \sqrt{\frac{3\sqrt{3}}{2\pi}}R\end{aligned}$$

The pdf of r_m is shown in [87] to be

$$f_{r_m} = N \binom{N}{m} F_r(r)^{m-1} (1 - F_r(r))^{N-m} f_r(r) \quad (5.13)$$

where

$$\begin{aligned}F_r(r) &= \left(\frac{r}{R_0}\right)^2 \\ f_r(r) &= \frac{2r}{R_0^2}\end{aligned}$$

Using the pdf of r_m , we can find

$$E\{r_m^\alpha\} = \int_0^{R_0} r^\alpha f_{r_m}(r) dr. \quad (5.14)$$

After simplification, and using Equation 5.13 in Equation 5.14, we find

$$E\{r_m^\alpha\} = R_0^\alpha N \binom{N}{m} \frac{{}_2F_1(\alpha/2 + m, m - N; \alpha/2 + m + 1; 1)}{\alpha/2 + m} \quad (5.15)$$

where ${}_2F_1$ is the hypergeometric function [88]. In Figure 5.6, $E\{r_m^\alpha\}$ is plotted for $\alpha = 3$, $R = 100$ and for three values of $N = 10, 20$ and 30 . As the number of nodes increases, the nodes will be more densely distributed and $E\{r_m^\alpha\}$ decreases for a given m .

5.4 Relations for $n_{i,j}^t$

Generally, one can find the following equation for $n_{i,j}^t$.

$$\begin{aligned}
n_{i,j}^t &= n_{i,j}^{t-1} (1 - q) + n_{i,j-1}^{t-1} (p_3) + n_{i,j+1}^{t-1} (p_6) + n_{i-1,j-1}^{t-1} (p_2) \\
&\quad + n_{i-1,j}^{t-1} (p_1) + n_{i+1,j}^{t-1} (p_4) + n_{i+1,j+1}^{t-1} (p_5) & 2 \leq j \leq i \\
n_{i,j}^t &= n_{i,j}^{t-1} (1 - q) + n_{i,j-1}^{t-1} (p_4) + n_{i,j+1}^{t-1} (p_1) + n_{i-1,j-2}^{t-1} (p_3) \\
&\quad + n_{i-1,j-1}^{t-1} (p_2) + n_{i+1,j+1}^{t-1} (p_5) + n_{i+1,j+2}^{t-1} (p_6) & i + 2 \leq j \leq 2i \\
n_{i,j}^t &= n_{i,j}^{t-1} (1 - q) + n_{i,j-1}^{t-1} (p_5) + n_{i,j+1}^{t-1} (p_2) + n_{i-1,j-3}^{t-1} (p_4) \\
&\quad + n_{i-1,j-2}^{t-1} (p_3) + n_{i+1,j+2}^{t-1} (p_6) + n_{i+1,j+3}^{t-1} (p_1) & 2i + 2 \leq j \leq 3i \\
n_{i,j}^t &= n_{i,j}^{t-1} (1 - q) + n_{i,j-1}^{t-1} (p_6) + n_{i,j+1}^{t-1} (p_3) + n_{i-1,j-4}^{t-1} (p_5) \\
&\quad + n_{i-1,j-3}^{t-1} (p_4) + n_{i+1,j+3}^{t-1} (p_1) + n_{i+1,j+4}^{t-1} (p_2) & 3i + 2 \leq j \leq 4i \\
n_{i,j}^t &= n_{i,j}^{t-1} (1 - q) + n_{i,j-1}^{t-1} (p_1) + n_{i,j+1}^{t-1} (p_4) + n_{i-1,j-5}^{t-1} (p_6) \\
&\quad + n_{i-1,j-4}^{t-1} (p_5) + n_{i+1,j+4}^{t-1} (p_2) + n_{i+1,j+5}^{t-1} (p_3) & 4i + 2 \leq j \leq 5i \\
n_{i,j}^t &= n_{i,j}^{t-1} (1 - q) + n_{i,j-1}^{t-1} (p_2) + n_{i,j+1}^{t-1} (p_5) + n_{i-1,j-6}^{t-1} (p_1) \\
&\quad + n_{i-1,j-5}^{t-1} (p_6) + n_{i+1,j+5}^{t-1} (p_3) + n_{i+1,j+6}^{t-1} (p_4) & 5i + 2 \leq j \leq 6i
\end{aligned}$$

$$\begin{aligned}
n_{i,1}^t &= n_{i,1}^{t-1} (1 - q) + n_{i,2}^{t-1} (p_6) + n_{i,6i}^{t-1} (p_2) + n_{i-1,1}^{t-1} (p_1) \\
&\quad + n_{i+1,6(i+1)}^{t-1} (p_3) + n_{i+1,1}^{t-1} (p_4) + n_{i+1,2}^{t-1} (p_5) & j = 1 \\
n_{i,i+1}^t &= n_{i,i+1}^{t-1} (1 - q) + n_{i,i}^{t-1} (p_3) + n_{i,i+2}^{t-1} (p_1) + n_{i-1,i}^{t-1} (p_2) \\
&\quad + n_{i+1,i+1}^{t-1} (p_4) + n_{i+1,i+2}^{t-1} (p_5) + n_{i+1,i+3}^{t-1} (p_6) & j = i + 1 \\
n_{i,2i+1}^t &= n_{i,2i+1}^{t-1} (1 - q) + n_{i,2i}^{t-1} (p_4) + n_{i,2i+2}^{t-1} (p_2) + n_{i-1,2i-1}^{t-1} (p_3) \\
&\quad + n_{i+1,2i+3}^{t-1} (p_6) + n_{i+1,2i+2}^{t-1} (p_5) + n_{i+1,2i+4}^{t-1} (p_1) & j = 2i + 1 \\
n_{i,3i+1}^t &= n_{i,3i+1}^{t-1} (1 - q) + n_{i,3i}^{t-1} (p_5) + n_{i,3i+2}^{t-1} (p_3) + n_{i-1,3i-2}^{t-1} (p_4) \\
&\quad + n_{i+1,3i+3}^{t-1} (p_6) + n_{i+1,3i+4}^{t-1} (p_1) + n_{i+1,3i+5}^{t-1} (p_2) & j = 3i + 1 \\
n_{i,4i+1}^t &= n_{i,4i+1}^{t-1} (1 - q) + n_{i,4i}^{t-1} (p_6) + n_{i,4i+2}^{t-1} (p_4) + n_{i-1,4i-3}^{t-1} (p_5) \\
&\quad + n_{i+1,4i+4}^{t-1} (p_1) + n_{i+1,4i+5}^{t-1} (p_2) + n_{i+1,4i+6}^{t-1} (p_3) & j = 4i + 1 \\
n_{i,5i+1}^t &= n_{i,5i+1}^{t-1} (1 - q) + n_{i,5i}^{t-1} (p_1) + n_{i,5i+2}^{t-1} (p_5) + n_{i-1,5i-4}^{t-1} (p_6) \\
&\quad + n_{i+1,5i+5}^{t-1} (p_2) + n_{i+1,5i+6}^{t-1} (p_3) + n_{i+1,5i+7}^{t-1} (p_4) & j = 5i + 1
\end{aligned}$$

For $n_{1,j}^t$, the above relations are valid if we substitute for $n_{0,k}^t$, the average number of nodes in the victim cell at time t for any k .

5.5 Discussion

In this chapter, we have studied the effect of mobility on interference dynamics. Cross-over probabilities of different edges of a cell are characterized by the mobility model. Aggregate interference and its statistics are stochastic in nature due to the random movement of mobile users. The aggregate interference is considered to be Gaussian in nature. However,

the Gaussian approximation holds only for larger distances. We have also analyzed the average instantaneous number of mobile users in a cell and the outage perceived by users in the cellular system.

Chapter 6

Conclusion

In this dissertation, we have studied mobility models, mobility prediction, control theoretic resource allocation and addressing interference problems related to mobility.

In Chapter 2, we discussed mobility models, problems of existing mobility models and a thorough performance analysis of mobility models under different routing protocols. It was noted that while mobility models are an easy way to validate network protocols and algorithms, they sometimes lack the necessary features to perfectly emulate real-world scenarios.

Chapter 3 proposed novel methods of mobility prediction. Firstly, instead of using mobility models, we used real-world wireless trace data in our simulations. We have analyzed the performance of Markovian methods with regard to mobility prediction. A first order Markov model was studied and observed some shortcomings. A Hidden Markov model was proposed to perform mobility prediction. The HMM provided desired abstraction models to suit the data and the scenarios. A high degree of accuracy in predicting user movement was achieved using the HMM prediction model.

We have proposed a generic frame work for modeling and predicting user movement in wireless networks. We used a HMM for mobility prediction in a wireless network in conjunction with a closed loop feedback control system. The proposed scheme is computationally simple and can be incorporated into existing wireless network architectures as seen in Chapter 4. The mobility prediction is based on a resource management method using control theoretic framework. The prediction scheme uses an HMM which delivers mobility information to a predictive control system. The model is verified by simulations and the results show increased network utilization for WLAN networks with low-speed mobility, reduced call blocking and rapid convergence of the prediction model coefficients. The model is also shown

to be scalable in the number of users. The proposed scheme can be effectively incorporated into existing wireless network architectures. To our knowledge, this is the first time control theory is used for studying the effect of mobility on mobile network performance.

Chapter 5 provided a discussion on the effect of interference on wireless users due to mobility. Interference to a wireless user from adjacent base stations was also analyzed. Due to the mobility of interfering nodes, the aggregate interference and its statistics are time-varying. Analytical results are obtained for interference statistics by using a Gaussian model and considering the effect of different mobility models.

Mobility is a key challenge in today's wireless and mobile networks. Hence, it is necessary to consider the effects of mobility on network architectures and protocols. The main contribution of this dissertation is a generic framework for mobility prediction and resource management. The flexible framework for prediction and resource allocation allows for use of other techniques such as ARMA, Neural Networks and machine learning in place of HMM. The same model can be used in various network applications such as QoS, seamless handover and jitter-free streaming applications.

Chapter 7

Future Work and Extensions

In this dissertation, we have dealt with mobility models, mobility prediction and resource allocation. These solutions are proposed to solve problems in network management. However, there is still a lot of scope for solving problems such as . This chapter discusses some of the proposed work in future as possible extensions of our existing work.

In future, we propose to investigate performance issues of time-series prediction models and compare with neural networks and ARMA models. Time series forecasting has been used for predicting data with high temporal correlation (e.g., stock market data). Exploiting the spatio-temporal characteristics of the data hold a vast potential for future research work. For instance, the campus WiFi data has a high correlation to the schedule of classes. Knowledge of student class schedules can improve the accuracies of user predictions by a high degree. We also propose to extend the probabilistic models to include user behavior such as clustering, group modeling, etc.

Mobile network management can be performed better if more of the variables involved are understood better. Hence, it is necessary to study issues such as mobile traffic-aware channel assignments and intelligent power control in WLANs, integrated wired-wireless infrastructure management, security issues involved in user mobility, etc. Problems in radio resource management can be investigated by harnessing multi-radio systems to collect network and channel statistics while the device is transmitting/receiving. Other possible solutions also include automatically shifting mobile clients to different channels to provide better service and reduce co-channel interference among access points.

Also, most large scale WLAN installations are not planned extensively before deployment. One of the biggest problems caused by mobility on users is mutual interference. This

has not been studied extensively in the context of mobile WLAN networks. Users moving around in a WLAN hotspot can reduce the data rates of all the other users connected to the same access point. Hence, a more rigorous study of interference is necessary to understand the underlying issues. Also, the expressions obtained for interference using Gaussian distribution is true only for interferers at larger distances. Hence a better fit can be investigated to cover all interferers.

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