Generic Adaptive Handoff Algorithms Using Fuzzy Logic and Neural Networks

by

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Abstract

Efficient handoff algorithms cost-effectively enhance the capacity and Quality of Service (QoS) of cellular systems. This research presents novel approaches for the design of high performance handoff algorithms that exploit attractive features of several existing algorithms, provide adaptation to dynamic cellular environment, and allow systematic tradeoffs among different system characteristics. A comprehensive foundation of handoff and related issues of cellular communications is given. The tools of artificial intelligence utilized in this research, neural networks and fuzzy logic, are introduced. The scope of existing simulation models for macrocellular and microcellular handoff algorithms is enhanced by incorporating several important features. New simulation models suitable for performance evaluation of soft handoff algorithms and overlay handoff algorithms are developed. Four basic approaches for the development of high performance algorithms are proposed and are based on fuzzy logic, neural networks, unified handoff candidate selection, and pattern classification. The fuzzy logic based approach allows an organized tuning of the handoff parameters to provide a balanced tradeoff among different system characteristics. The neural network based approach suggests neural encoding of the fuzzy logic systems to simultaneously achieve the goals of high performance and reduced complexity. The unified candidacy based approach recommends the use of a unified handoff candidate selection criterion to select the best handoff candidate under given constraints. The pattern classification based approach exploits the capability of fuzzy logic and neural networks to obtain an efficient architecture of an adaptive handoff algorithm. New algorithms suitable for microcellular systems, overlay systems, and systems employing soft handoff are described. A basic adaptive algorithm suitable for a microcellular environment is proposed. Adaptation to traffic, interference, and mobility has been superimposed on the basic generic algorithm to develop another microcellular algorithm. An adaptive overlay handoff algorithm that allows a systematic balance among the design parameters of an overlay system is proposed. Important considerations for soft handoff are discussed, and adaptation mechanisms for new soft handoff algorithms are developed.

Dedicated to My Exceptional Parents:
Dhananjay C. Tripathi and Damini D. Tripathi

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Chapter 1

Introduction

This chapter introduces handoff, provides an outline of this dissertation, and summarizes significant contributions of the research reported here.

1.1 Motivation

Cellular communications provides communication facility to users called mobile stations (MSs). A service area (or geographical region) is divided into a number of cells. Several such cells constitute a cluster. The available frequency spectrum is used in each cluster. Each cell in a cluster uses a fraction of the available channels in the spectrum allocated according to a channel assignment strategy and is served by a base station (BS). *Handoff is a process of transferring a mobile station from one base station or channel to another.* The channel change due to handoff occurs through a change in a time slot, frequency band, codeword, or combination of these for time division multiple access (TDMA), frequency division multiple access (FDMA), code division multiple access (CDMA), or a hybrid scheme, respectively. The handoff process determines the spectral efficiency (i.e., the maximum number of calls that can be served in a given area) and the quality perceived by users. Efficient handoff algorithms cost-effectively preserve and enhance the capacity and Quality of Service (QoS) of communication systems.

Many of the existing handoff algorithms do not exploit the advantages of multi-criteria handoff, which can give better performance than single-criterion algorithms due to the flexible and complementary nature of handoff criteria. The existing algorithms do not exploit knowledge about the sensitivities of handoff parameters to different characteristics of a cellular environment. The adaptation and learning capabilities of artificial intelligence (AI) tools have not been fully utilized. The existing algorithms fail to consider the behavior of other handoff algorithms in a given cellular environment and to provide a systematic procedure for the adaptation of handoff parameters to the dynamic cellular environment. *This research presents novel approaches for the design of high performance handoff algorithms that exploit attractive features of several existing algorithms, provide adaptation to the dynamic cellular environment, and allow systematic tradeoff among different system characteristics.*

1.2 Report Outline

This report contains twelve chapters. Figure 1.1 illustrates the organization of the report. Chapter 2 provides background information and a literature survey on handoff, believed to be the most comprehensive survey of the subject to the date. Chapter 3 introduces the tools of AI used to develop adaptive intelligent handoff algorithms. The mechanisms used to analyze handoff algorithms are explained in Chapter 4. Novel generic handoff approaches are described in Chapters 5 through 8. Generic handoff algorithms for different cellular system deployment scenarios such as microcells, overlays, and systems employing soft handoff are the topics of Chapters 9 through 11. Chapter 12 is the concluding chapter. Details of the chapters are briefly described here.

- **Chapter 2: Foundation of Cellular Handoff**. This chapter investigates various aspects of handoff and includes an in-depth literature survey of handoff related research work. Desirable features of handoff and complexities of handoff are discussed. Several cellular system deployment scenarios that dictate certain handoff constraints are illustrated. Handoff and other related resource management tasks of cellular systems are described, and implementation of the handoff process is explained.

- **Chapter 3: Fuzzy Logic and Neural Networks**. This chapter gives a brief introduction to the AI related tools used in this research (artificial neural networks and fuzzy logic). In particular, concepts of fuzzy logic are explained. A popular form of a fuzzy logic system is illustrated. The basic element of neural

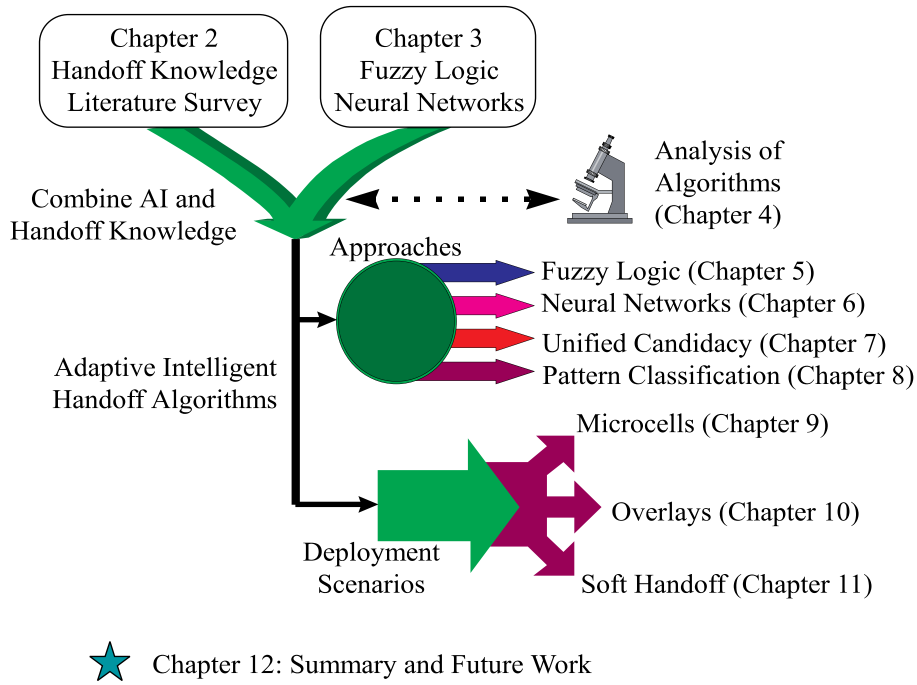

Figure 1.1: Report Organization

networks, the neuron, is introduced. Two ANN paradigms, multi-layer perceptron and radial basis function network, are briefly described. Characteristics of fuzzy logic and neural networks are highlighted. Finally, the application of fuzzy logic and neural networks to handoffs is briefly explained.

- **Chapter 4: Analysis of Handoff Algorithms**. This chapter explains mechanisms used to evaluate handoff related performance of cellular systems. Simulation is the most widely used handoff evaluation mechanism. Several simulation models used in this research are described. The scope of existing simulation models for macrocellular and microcellular handoff algorithms is enhanced by incorporating several important features. New simulation models suitable for performance evaluation of soft handoff algorithms and overlay handoff algorithms are proposed.

- **Chapter 5: A Fuzzy Logic Based Algorithm**. This chapter proposes a new class of handoff algorithms that combines the attractive features of several existing algorithms and adapts the handoff parameters using fuzzy logic. Known sensitivities of handoff parameters are used to create a fuzzy logic rule base. The design procedure for a generic fuzzy logic based algorithm is outlined.

- **Chapter 6: A Neural Encoded Fuzzy Logic Algorithm**. This chapter proposes neural encoding of a fuzzy logic system (FLS) to circumvent the large storage and computational requirements of the FLS. The neural network learns how the FLS works. The input-output mapping capability and compact data representation capability of neural networks are exploited here to derive an adaptive handoff algorithm that retains the high performance of the original fuzzy logic based algorithm and that has an efficient architecture for storage and computational requirements.

- **Chapter 7: A Unified Handoff Candidacy Algorithm**. This chapter proposes a fuzzy logic based algorithm with a unified handoff candidate selection criterion and adaptive direction biasing. The unified handoff candidate selection criterion allows simultaneous consideration of several handoff criteria to select the best handoff candidate under given constraints. Enhanced direction biasing is achieved by adapting the direction biasing parameters.

- **Chapter 8: Pattern Classification Based Algorithms**. This chapter proposes a new class of adaptive handoff algorithms that views the handoff problem as a pattern classification problem. Neural networks and fuzzy logic systems are good candidates for pattern classifiers due to their properties such as nonlinearity and to their generalization capability.

- **Chapter 9: Microcellular Algorithms**. Microcells impose distinct constraints on handoff algorithms due to the characteristics of the propagation environment. A generic adaptive algorithm suitable for a microcellular environment is proposed. Adaptation to traffic, interference, and mobility has been superimposed on the basic generic algorithm to develop another algorithm.

- **Chapter 10: Overlay Algorithms**. An overlay system is a hierarchical architecture that uses large macrocells to overlay clusters of small microcells. Different handoff scenarios exist in an overlay environment, each with distinct objectives. This chapter proposes an adaptive overlay handoff algorithm that allows a systematic balance among the design parameters of an overlay system.

- **Chapter 11: Soft Handoff Algorithms**. Soft handoff exploits spatial diversity to increase signal energy for improved performance. A good soft handoff algorithm achieves a balance between the quality of the signal and the associated cost. This chapter highlights important considerations for soft handoff and develops adaptation mechanisms for new soft handoff algorithms.

- **Chapter 12: Conclusion**. This chapter discusses the significance of the research work done as part of this dissertation and proposes several major areas of future research.

1.3 Significant Research Contributions

The following is a list of significant contributions of this dissertation research.

- *Development of A New Class of Algorithms Based on Fuzzy Logic Systems.* This class of algorithms represents the first attempt to systematically develop a truly adaptive algorithm using a comprehensive knowledge base in a unified framework. The proposed approach allows an organized tuning of the handoff parameters to provide a balanced tradeoff among different system characteristics. The overall system performance enhancement is exemplified by a 1.7 dB improvement in SIR distribution (or a 16% improvement in call drop probability), a 2.8 call improvement in traffic distribution, and a six second reduction in the handoff delay due to the interference, traffic, and mobility adaptation of the proposed algorithm.

- *Development of A New Class of Algorithms Based on Neural Encoded Fuzzy Logic Systems.* This algorithm answers the complexity concerns of the algorithms based on fuzzy logic. This approach proposes neural encoding of the fuzzy logic systems to simultaneously achieve the goals of high performance and reduced complexity. The approach shows that the storage requirements can be reduced by a factor of 7.2 and the computational requirements can be reduced by a factor of 8.8 compared to the fuzzy logic based algorithms.

- *Development of A New Class of Algorithms Based on Unified Candidacy.* This approach recommends the use of a unified handoff candidate selection criterion to simultaneous consider several handoff criteria to select the best handoff candidate under given constraints. This approach also utilizes adaptive direction biasing to obtain a fast handoff algorithm and provides additional degrees of freedom in obtaining a tradeoff among critical design considerations.

- *Development of A New Class of Algorithms Based on Pattern Classification.* This approach exploits the pattern classification capability of fuzzy logic and neural networks to obtain an efficient architecture of an adaptive handoff algorithm. The proposed algorithms can provide a 1.8 dB improvement in SIR distribution and a four call improvement in traffic distribution over a conventional algorithm.

- *Development of Adaptive Handoff Algorithms for Microcellular Systems.* Algorithms that address specific problems of microcellular systems are proposed. The proposed algorithms perform uniformly well in generic handoff scenarios in microcells. The number of handoffs is reduced by 37%. Adaptation mechanisms provide a 0.5 dB improvement in SIR distribution and a 0.25 call improvement in traffic distribution without compromising the performance of the algorithms in generic handoff scenarios.

- *Development of An Adaptive Handoff Algorithm for Macrocell-Microcell Overlay Systems.* An adaptive handoff algorithm that considers requirements of different handoff scenarios in an overlay system and attempts to achieve the system's goals is proposed. Improved SIR and traffic distributions are obtained using the proposed algorithm. For example, the call blocking probability is reduced by a factor of 1.8 and the handoff blocking probability is reduced by a factor of three.

- *Development of Adaptive Soft Handoff Algorithms.* Important considerations for soft handoff are used to develop adaptation mechanisms for new soft handoff algorithms. The adaptive algorithm provides a 1.1 dB improvement in RSS and a two call improvement in traffic distribution and reduces the network load by exploiting mobility adaptation.

- *Development of a Simulation Test-Bed for the Performance Evaluation of Handoff Algorithms.* Simulation is the most versatile tool for evaluating handoff related system performance. The existing simulation models for macrocellular and microcellular handoff algorithms do not allow evaluation of all the major design parameters of a system. The scope of such models has been enhanced by providing additional means of performance evaluation. Information on good simulation models that allow investigation of handoff algorithms in cellular overlays and soft handoff situations has not appeared in the literature. The simulation models proposed here for the analysis of overlay and soft handoff algorithms can provide a strong foundation for the handoff research.

- *Thorough Study of Handoff Related Design Issues and Creation of a Knowledge Base for the Design of Adaptive High Performance Handoff Algorithms.* A comprehensive foundation for handoff and related cellular system design issues is created. This knowledge base educates the reader on various aspects of handoff and paves the way for designing several components of a cellular system from a global perspective.

Chapter 2

Foundation of Cellular Handoff

This chapter presents various aspects of handoff and discusses handoff related features of cellular systems. Desirable features of handoff are highlighted, and complexities of handoff are described. Several system deployment scenarios that dictate specific handoff requirements are illustrated. An account of handoff related resource management tasks of cellular systems is given. Implementation of the handoff process is explained.

2.1 Introduction to Handoff

Some of the terminology used in cellular communications is explained next [5].

- **Mobile Station (MS)**. The mobile station is intended for use while in motion at an unspecified location.
- **Base Station (BS)**. The base station is a fixed station used for radio communication with MSs.
- **Mobile Switching Center (MSC)**. The mobile switching center coordinates the routing of calls in a large service area. It is also referred to as the **Mobile Telephone Switching Office (MTSO)**.
- **Forward Channel**. The forward channel is the radio channel used for the transmission of information from the base station to the mobile station. It is also known as the **downlink**.
- **Reverse Channel**. The reverse channel is the radio channel used for the transmission of information from the mobile station to the base station. It is also known as the **uplink**.

- **Handoff**. Handoff is a process of transferring a mobile station from one base station or channel to another. The channel change due to handoff occurs through a time slot for time division multiple access (TDMA), frequency band for frequency division multiple access (FDMA), and codeword for code division multiple access (CDMA) systems [1].

- **Cochannel Interference (CCI)**. The cochannel interference is caused when the desired signal and another signal in some remote cell are using the same frequency or channel.

The following phases are involved in the planning of cellular communications [3]:

- Assessment of traffic density;
- Determination of cell sizes and capacity;
- Decisions about omnidirectional or sectored cells and antenna directions;
- Selection of best BS sites to cover the required area;
- Frequency allocation;
- Choice of power control parameters; and
- Selection of handoff parameters.

This chapter carries out an in-depth investigation of the handoff aspects of cellular planning. The handoff process determines the spectral efficiency (i.e., the maximum number of calls that can be served in a given area [2]) and the quality perceived by users [3]. Efficient handoff algorithms cost-effectively preserve and enhance the capacity and Quality of Service (QoS) of communication systems [4].

Figure 2.1 shows a simple handoff scenario in which an MS travels from BS A to BS B. Initially, the MS is connected to BS A. The overlap between the two cells is the handoff region in which the mobile may be connected to either BS A or BS B. At a certain time during the travel, the mobile is handed off from BS A to BS B. When the MS is close to BS B, it remains connected to BS B.

The overall handoff procedure can be thought of as having two distinct phases [6]: the initiation phase (in which the decision about handoff is made) and the execution phase (in which either a new channel is assigned to the MS or the call is forced to terminate). Handoff algorithms normally carry out the first phase.

Handoff may be caused by factors related to *radio link*, *network management*, or *service options* [7] [8].

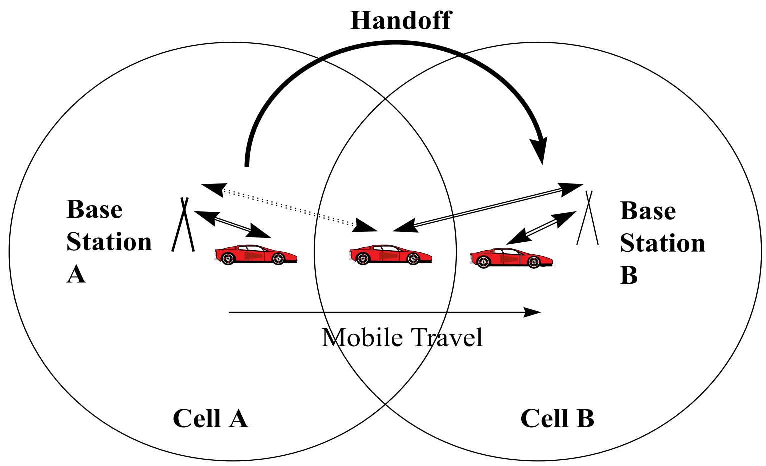

Figure 2.1: Handoff Scenario in Cellular Systems

- **Radio Link Related Causes**. Radio link related causes reflect the quality perceived by users. Some of the major variables affecting the service quality are *received signal strength (RSS), signal-to-interference ratio (SIR), and system related constraints*. Insufficient RSS and SIR reduce the service quality. Moreover, if certain system constraints are not met, service quality is adversely affected.

  Handoff is required in the following situations due to reduced *RSS* [8]: (i) when the MS approaches the cell boundary (the RSS drops below a threshold) and (ii) when the MS is inside the signal strength holes in a cell (the signal is too weak to be detected easily).

  SIR drops as CCI increases, and handoff is required. Bit error rate (BER) can be used to estimate SIR.

  An example of *a system related constraint* is the synchronization requirement in a TDMA system. In this case, when the propagation delay between the transmitter and the receiver approaches a threshold, handoff is necessary.

- **Network Management Related Causes**. The network may handoff a call to avoid congestion in a cell. For a macroscopic diversity call, the handoff of calls in progress may be required since the same channel must be obtained in a number of BSs. If the network identifies that the path used for information transfer is malfunctioning or is not the shortest one, it may handoff the call.

- **Service Options Related Causes**. When an MS asks for a service that is not provided at the current BS, the network may initiate a handoff so that the desired service can be offered [7]. A handover may also be initiated by the MS to connect to a service provider with a lower tariff.

Network management and service related handoffs are usually infrequent and easy to tackle. However, radio link related handoffs are most commonly encountered and most difficult to handle.

A handoff made within the currently serving cell (e.g., by changing the frequency) is called an *intracell handoff*. A handoff made from one cell to another is referred to as an *intercell handoff*. Handoff may be hard or soft. *Hard handoff (HHO)* is "break before make," meaning that the connection to the old BS is broken before a connection to the candidate BS is made. HHO occurs when handoff is made between disjointed radio systems, different frequency assignments, or different air interface characteristics or technologies [9]. *Soft handoff (SHO)* is "make before break," meaning that the connection to the old BS is not broken until a connection to the new BS is made. In fact, more than one BS are normally connected simultaneously to the MS. For example, in Figure 2.1, both the BSs will be connected to the MS in the handoff region. Details of SHO are given in Section 2.9.3.

This chapter includes five major topics.

- **Topic 1: Desirable Features and Complexities of Handoff**. Topic 1 consists of Section 2.2. Section 2.2.1 describes desirable features of handoff. An efficient handoff algorithm can achieve many of these features by making appropriate tradeoffs. However, several factors such as topographical features, traffic variations, propagation environments and system-specific constraints pose stiff challenges to handoff algorithms and complicate the handoff process. These complexities are discussed in Section 2.2.2.

- **Topic 2: Deployment Scenarios and Handoff**. Topic 2 describes different system deployment scenarios and their constraints on the handoff procedure and consists of Section 2.3. Handoff algorithms with a specific set of parameters cannot perform uniformly well in different communication system deployment scenarios since these scenarios are characterized by peculiar environments. Such system scenarios are the focus of Section 2.3. Examples of different system structures include macrocells, microcells, overlays, integrated cellular systems, integrated cordless and cellular systems, and integrated terrestrial and satellite systems. Note that these system structures are expected to co-exist in future wireless communication systems, and they warrant a closer study.

- **Topic 3: Handoff Algorithms**. Topic 3 consists of Sections 2.4-2.6. Handoff algorithms are distinguished from one another in two ways: the variables they use (called handoff criteria) and the strategies they use to process handoff criteria. Handoff criteria are discussed in Section 2.4. Section 2.5 describes conventional handoff algorithms, and Section 2.6 describes emerging handoff algorithms.

- **Topic 4: Resource Management in Cellular Systems**. Topic 4 views handoff and other resource management tasks and details handoff related system performance improvement and consists of Sections 2.7 and 2.8. Prioritizing handoff is one way to improve handoff related system performance. Section 2.7 discusses handoff prioritization schemes (such as guard channels and queuing). *Handoff* represents one of the radio resource management tasks carried out by cellular systems. Other resource management functions include *admission control*, *channel assignment*, and *power control*. If some of the resource management tasks are treated in an integral manner, better overall performance can be obtained in a global sense by making appropriate tradeoffs. Such integrated resource management is the topic of Section 2.8.

- **Topic 5: Implementation of Handoff**. Topic 5 describes how the handoff procedure is implemented and consists of Section 2.9. The decision making process of handoff may be centralized or decentralized. Handoff protocols characterize the approaches used by different systems to execute the process of handoff.

2.2 Desirable Features and Complexities of Handoff

2.2.1 Desirable Features of Handoff

An efficient handoff algorithm can achieve many desirable features by trading different operating characteristics. Figure 2.2 summarizes the major desirable features of handoff algorithms, and several desirable features of handoff algorithms mentioned in the literature are described below [7, 2, 4, 10, 11, 12, 13, 14].

- Handoff should be fast so that the user does not experience service degradation or interruption. Service degradation may be due to a continuous reduction in signal strength or an increase in CCI. Service interruption may be due to a "break before make" approach of HHO. Note that the delay in the execution of a handoff algorithm adds to the network delay at the Mobile Switching Center (MSC) or Mobile Telephone Switching Office (MTSO). Fast handoff also reduces CCI since it prevents the MS from going too far into the new cell.

- Handoff should be reliable. This means that the call should have good quality after handoff. SIR and RSS help determine the potential service quality of the candidate BS.

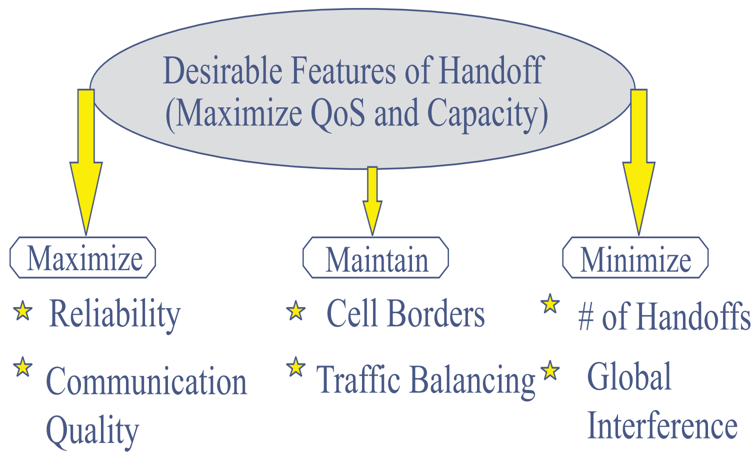

Figure 2.2: Desirable Features of Handoff Algorithms

- Handoff should be successful; a free channel should be available at the candidate BS. Efficient channel allocation algorithms and some traffic balancing can maximize the probability of a successful handoff.

- The effect of handoff on the quality of service (QoS) should be minimal. The quality of service may be poor just before handoff due to a continuous reduction in RSS, SIR, etc.

- Handoff should maintain the planned cellular borders to avoid congestion, high interference, and use of assigned channels inside the new cell. Each BS can carry only its planned traffic load. Moreover, there is a possibility of increased interference if the MS goes far into another cell site while still being connected to a distant BS because cochannel distance is reduced and the distant BS tends to use a high transmit power to serve the MS.

- The number of handoffs should be minimized. Excessive handoffs lead to heavy handoff processing loads and poor communication quality, which may be due to the following: (i) the more attempts at handoff, the more chances that a call will be denied access to a channel, resulting in a higher handoff call dropping probability, (ii) a lot of handoff attempts causes more delay in the MSC processing of handoff requests, which will cause signal strength to decrease over a longer time period to a level of unacceptable quality. Also, the call may be dropped if sufficient SIR is not achieved. Handoff requires network resources to connect the call to a new BS. Thus, minimizing the number of handoffs reduces the switching load. Unnecessary handoffs should be prevented; the current BS might be able to provide the desired service quality without interfering with other MSs and BSs.

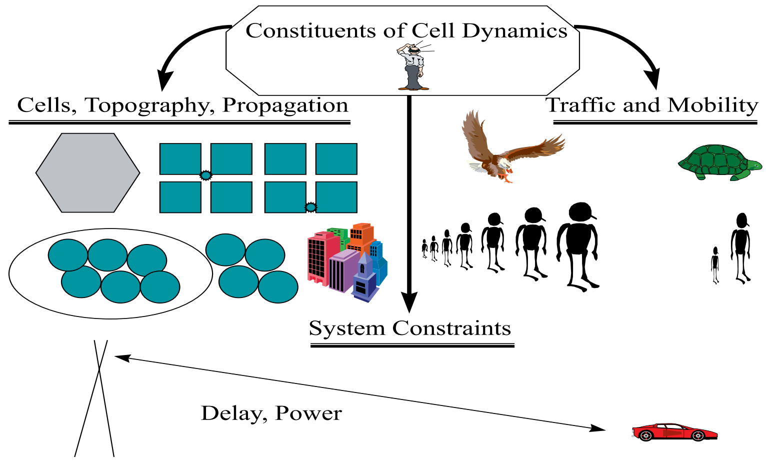

Figure 2.3: Complexities of Handoff

- The target cell should be chosen correctly since there may be more than one candidate BS for handoff. Identification of a correct cell prevents unnecessary and frequent handoffs.
- The handoff procedure should minimize the number of continuing call drop-outs by providing a desired QoS (e.g., by ensuring a certain SIR).
- Handoff should have minimal effect on new call blocking. For example, if some channels (called guard channels) are reserved exclusively for handoff, new call blocking probability will increase due to the reduction in the number of channels available for a new call.
- The handoff procedure should balance traffic in adjacent cells, eliminating the need for channel borrowing, simplifying cell planning and operation, and reducing the probability of new call blocking.
- The global interference level should be minimized by the handoff procedure. Transmission of bare minimum power and maintenance of planned cellular borders can help achieve this goal.

2.2.2 Complexities of Handoff

Existing handoff algorithms can give good performance only under certain situations due to complexities associated with handoff. There are several factors that complicate the handoff process and necessitate the design of better handoff algorithms. Figure 2.3 shows the complexities associated with handoff.

- **Cellular Structure**. Different cellular structures or layouts put different constraints on handoff algorithms. Disjoint microcells and macrocells are expected to coexist in the cellular systems [4]. In this case, microcells cover hot spots, while macrocells cover low traffic areas. Different radii cells require different handoff algorithm parameters (threshold, bias, etc.) to obtain good performance [15]. Some service areas may contain microcell-macrocell overlay in which microcells serve high traffic areas and macrocells serve high speed users and overflow traffic.

  As the cell size decreases, the number of handoffs per call increases, the variables such as RSS, SIR, and BER change faster, and the time available for processing the handoff requests decreases [16]. Moreover, the number of MSs to be handled by the infrastructure also increases.

- **Topographical Features**. A signal profile is characterized by the magnitude of the propagation path loss exponent and the breakpoint (i.e., the distance at which the magnitude of the propagation path loss exponent changes) and varies according to the terrain. The performance of a handoff algorithm depends on the signal profile in a region.

  [17].

- **Traffic**. In practice, traffic distribution is a function of time and space [18]. The system should perform well under traffic variations. Some of the approaches to cope with spatial nonuniformities of traffic are traffic balancing in adjacent cells, use of different cell sizes, nonuniform channel allocation in cells, and dynamic channel allocation.

- **Propagation Phenomena**. The radio propagation is strongly affected by surroundings. For example, due to a certain topological environment, the received signal strength can be higher at places far from a BS than at places near the BS [18]. Propagation characteristics in microcells are different from those in macrocells (e.g., the street corner effect) [19]. In fact, it is shown in [13] that environment dependent handoff parameters can give better performance than environment independent handoff parameters.

- **System Constraints**. Some cellular systems are equipped with dynamic power control algorithms that allow the MS to transmit the least possible power while maintaining a certain quality of transmission. These systems coordinate power control and handoff algorithms to achieve their individual goals [11]. It may be beneficial to do channel allocation in conjunction with handoff and/or power control (see Section 2.8).

- **Mobility**. When an MS moves away from a BS at a high speed, the quality of communication degrades quickly. In such a case, handoff should be made quickly.

More importantly, *the evolution of a network is usually an on-going process* [3]; new cells are gradually introduced, increasing the capacity to meet the demand. This network evolution necessitates adaptive resource management. The performance of growing cellular systems needs to be monitored and re-engineered frequently to maintain the QoS cost-effectively [20]. In summary, *to obtain high performance in the dynamic cellular environment, handoff algorithms should adapt to changing traffic intensities, topographical alterations, and the stochastic nature of the propagation conditions.*

2.3 Cellular System Deployment Scenarios

The radio propagation environment and related handoff challenges are different in different cellular structures. A handoff algorithm with fixed parameters cannot perform well in different system environments. Specific characteristics of the communication systems should be taken into account while designing handoff algorithms. Several basic cellular structures (such as macrocells, microcells, and overlay systems) and special architectures (such as underlays, multichannel bandwidth systems, and evolutionary architectures) are described next. Integrated cordless and cellular systems, integrated cellular systems, and integrated terrestrial and satellite systems are also described.

2.3.1 Macrocells

Macrocell radii are in several kilometers. Due to the low cell crossing rate, centralized handoff is possible despite the large number of MSs that the MSC has to manage. The signal quality in the uplink and the downlink is approximately the same. The transition region between the BSs is large; handoff schemes should allow some delay to avoid flip-flopping. However, the delay should be short enough to preserve the signal quality because the interference would increase as the MS penetrates the new cell. This cell penetration is called *cell dragging*. Macrocells have relatively gentle path loss characteristics [4]. The averaging interval (i.e., the time period used to average the signal strength variations) should be long enough to get rid of fading fluctuations. First generation and second generation cellular systems provide wide area coverage even in cities using macrocells [19]. Typically, a BS transceiver in a macrocell transmits high output power with the antenna mounted several meters high

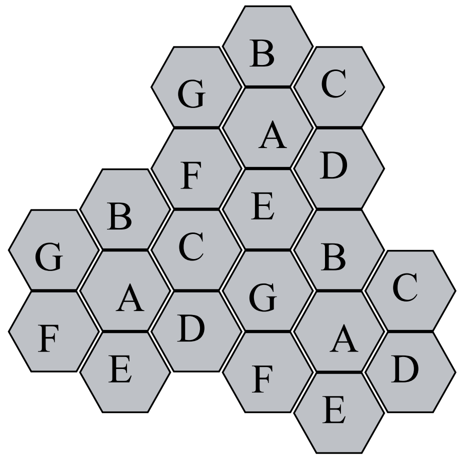

Figure 2.4: Seven-Cell Clusters in a Macrocellular System

on a tower to illuminate a large area. Figure 2.4 shows three clusters of seven cells in a macrocellular system. A cluster consists of a group of cells marked A through G.

2.3.2 Microcells

Some capacity improvement techniques (e.g., improved methods for speech coding, channel coding and modulation) will not be sufficient to satisfy the required service demand. The use of microcells is considered the single most effective means of increasing the capacity of cellular systems [19]. Microcells increase capacity, but radio resource management becomes more difficult. Microcells can be classified as one-, two-, or three-dimensional, depending on whether they are along a road or a highway, covering an area such as a number of adjacent roads, or located in multilevel buildings respectively [21]. Microcells can be classified as hot spots (service areas with a higher traffic density or areas that are covered poorly), downtown clustered microcells (contiguous areas serving pedestrians and mobiles) and in-building 3-D cells (serving office buildings and pedestrians) [22] . The overlap region between the adjacent cells helps provide a seamless handoff. The required overlap puts a constraint on the smallest achievable cell size. Thus, there is a tradeoff between the size of the overlap region (or the quality of communication during handoff) and the capacity of the system [15]. Cell boundaries expand and contract due to shadow fading [15].

Typically, a BS transceiver in a microcell transmits low output power with the antenna mounted at a lamp-post level (approximately 5m above ground) [19]. The MS also transmits low power, which leads to longer battery life and increased mobility. Since BS antennas have lower heights compared to the surrounding buildings, RF signals propagate mostly along the streets [14, 23, 24]. The antenna may cover 100-200m in each street direction, serving a few city blocks. This propagation environment has low time dispersion, which allows high data rates [15].

Microcells are more sensitive than macrocells to the traffic and interference due to short-term variations (e.g., traffic and interference variations), medium/long-term alterations (e.g., new buildings), and incremental growth of the radio network (e.g., new base stations) [25]. The number of handoffs per cell is increased by an order of magnitude, and the time available to make a handoff is decreased [26]. Using an umbrella cell is one way to reduce the handoff rate. Due to the increase in the microcell boundary crossings and expected high traffic loads, a higher degree of decentralization of the handoff process becomes necessary [1]. The microcellular environment is highly interference-limited (i.e., noise is negligible and interference is a major concern) [1].

Microcells present the following constraints not typically found with macrocells [22]: (i) the amount of cabling must be reduced to enable the installation of several BS antennas at lamp-post level, (ii) a much denser cluster of wire lines and BSs is required, increasing the cost of infrastructure, (iii) the real estate is expensive in urban areas. These constraints pose stiff technical challenges to microcell engineering, and efficient resource management is required to achieve the maximum possible spectral efficiency.

Microcells encounter a propagation phenomenon called *corner effect*. The corner effect is characterized by a sudden large drop (e.g., 20-30 dB) in the signal strength (e.g., in 10-20m distance) when a mobile turns around a corner. The corner effect is due to the loss of the line of sight (LOS) component from the serving BS to the MS. The corner effect demands a faster handoff and can change the signal quality very quickly. The rapid change in the RSS due to the corner effect affects the uplink more than the downlink in a microcellular environment. When a mobile turns a corner, the RSS at the MS becomes weaker. The uplink interference remains the same and downlink interference changes, potentially getting weaker [4]. A long measurement averaging interval is not desirable due to the corner effect. Moving obstacles can temporarily hinder the path between a BS and an MS, resembling corner effect.

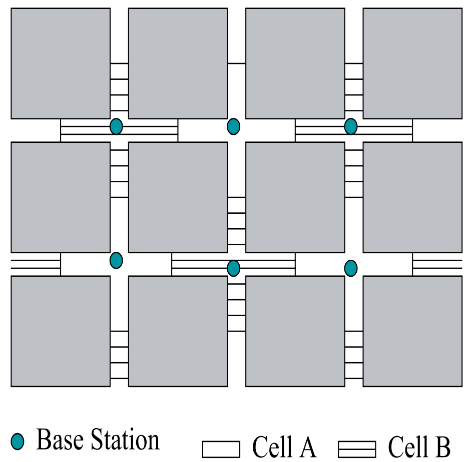

Figure 2.5: Half Square Cell Plan in a Microcellular System

In a microcellular system, there may be two types of handoff scenarios, a line-of-sight (LOS) handoff and a non-line-of-sight (NLOS) handoff. An LOS handoff is a handoff from one LOS BS to another LOS BS. An NLOS handoff is a handoff from an NLOS BS to an LOS BS. In an LOS handoff, premature handoff requests should be prevented. In an NLOS handoff, the handoff must be completed as quickly as possible as the user turns around the corner. Some of the solutions to deal with these different requirements for the LOS and NLOS handoffs in microcells are umbrella cells, macro-diversity, and switching to mobile-controlled handoff [4].

Reference [27] studies the properties of symmetrical cell plans in a Manhattan-type environment. Cell plans affect SIR performance in uplink and downlink significantly. The symmetrical cell plans have four nearest co-channel BSs located at the same distance. Such cell plans can be classified into *half square (HS)*, *full square (FS)*, and *rectangular (R)* cell plans. These cell plans are described next:

- **Half Square Cell Plan**. This cell plan places BSs with omni-directional antennas at each intersection, and each BS covers half a block in all four directions. This cell plan avoids the street corner effect and provides the highest capacity. This cell plan has only LOS handoffs. Figure 2.5 shows an example of a half square cell plan in a microcellular system.

- **Full Square Cell Plan**. A BS with an omni-directional antenna is located at every other intersection, and each BS covers a block in all four directions. It is possible for an MS to experience the street corner effect for this cell plan. The FS cell plan can have LOS or NLOS handoffs. Figure 2.6 shows an example of a full square cell plan in a microcellular system.

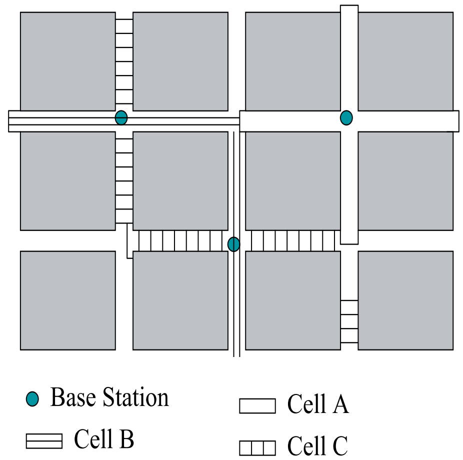

Figure 2.6: Full Square Cell Plan in a Microcellular System

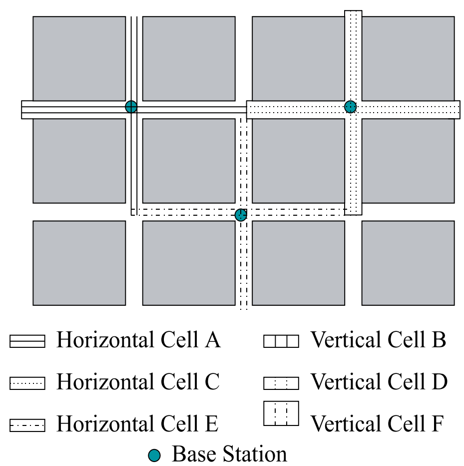

Figure 2.7: Rectangular Cell Plan in a Microcellular System

- **Rectangular Cell Plan**. Each BS, located in the middle of the cell, covers a fraction of either a horizontal or vertical street. This cell plan is scalable; fewer BSs can be used initially, and additional BSs can be added as the user density increases. Figure 2.7 shows an example of a rectangular cell plan in a microcellular system.

2.3.3 Macrocell/Microcell Overlays

The congestion of certain microcells, the lack of service of microcells in some areas, and the high speed of some users are some reasons for higher handoff rates and signaling load for microcells [7]. To alleviate some of these problems, a mixed cell

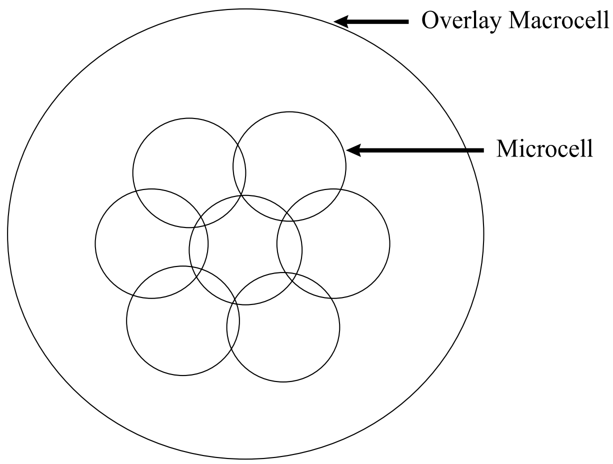

Figure 2.8: A Microcell/Macrocell Overlay System

architecture (called an overlay/underlay system) consisting of large size macrocells (called umbrella cells or overlay cells) and small size microcells (called underlay cells) can be used. Figure 2.8 illustrates an overlay system.

The macrocell/microcell overlay architecture provides a balance between maximizing the number of users per unit area and minimizing the network control load associated with handoff. Macrocells provide wide area coverage beyond microcell service areas and ensure better intercell handoff [17]. Microcells provide capacity due to greater frequency reuse and cover areas with high traffic density (called *hot spots*). Examples of hot spots include an airport, a railway station, or a parking lot. In less congested areas (e.g., areas beyond a city center or areas outside the main streets of a city), traffic demand is not very high, and macrocells can provide adequate coverage in such areas. Macrocells also serve high speed MSs and the areas not covered by microcells (e.g., due to lack of channels or inadequate transmit power). Also, after the microcellular system is used to its fullest extent, the overflow traffic can be routed to macrocells. One of the important issues for the overlay/underlay system is the determination of optimum distribution of channels in the macrocells and microcells [28]. Reference [29] evaluates four approaches to sharing the available spectrum between the two tiers: Approach 1 uses TDMA for microcell and CDMA for macrocell; Approach 2 uses CDMA for microcell and TDMA for macrocell; Approach 3 uses TDMA in both the tiers; Approach 4 uses orthogonal frequency channels in both the tiers.

The overlay/underlay system has several advantages over a pure microcell system [30]: (i) the BSs are required only in high traffic load areas, and since it is not necessary to cover the whole service area with microcells, infrastructure costs are saved; (ii) the number of handoffs in an overlay system is much less than that in a microcell system because fast moving vehicles can be connected to the overlay macrocell; (iii) both calling from an MS and location registration can be easily completed through the microcell system.

There are several classes of umbrella cells [30]. In one class, orthogonal channels are distributed between microcells and macrocells. In another class, microcells use channels that are temporarily unused by macrocells [31]. In yet another class, microcells reuse the channels already assigned to macrocells and use slightly higher transmit power levels to counteract the interference from the macrocells. Within the overlay/underlay system environment, four types of handovers need to be managed [32]: microcell to microcell, microcell to macrocell, macrocell to macrocell, and macrocell to microcell.

Reference [33] describes combined cell splitting and overlaying. Reuse of channels in the two cells is done by establishing an overlaid small cell served by the same cell site as the large cell. Small cells reuse the split cell's channels due to the large distance between the split cell and the small inner cell while the large cell cannot reuse these channels. Overlaid cells are approximately 50% more spectrally efficient than *segmenting*, the process of distributing the channels among the small- and large-size cells to avoid interference.)

A practical approach for implementation of a microcell system overlaid with an existing macrocell system is proposed in [30]. This reference introduces channel segregation (a self-organized dynamic channel assignment) and automatic transmit power control to obviate the need to design channel assignment and transmit power control for the microcell system. The available channels are reused automatically between microcells and macrocells. A slight increase of transmit power for the microcell system compensates for the macrocell to microcell interference. Simulation results indicate that the local traffic is accommodated by the microcells laid under macrocells without any significant channel management efforts.

The methodology of the GSM-based system is extended to the macrocell/microcell overlay system in [34] that recommends the use of random frequency hopping and adaptive frequency planning, and different issues related to handoff and frequency planning for an overlay system are discussed.

Four strategies are designed to determine a suitable cell for a user for an overlay system [35]. Two strategies are based on the dwell time (the time for which a call can be maintained in a cell without handoff), and the other two strategies are based on user speed estimation. A speed estimation technique based on dwell times is also proposed.

A CDMA cellular system can provide full connectivity between the microcells and the overlaying macrocells without capacity degradation. Reference [22] analyzes several factors that determine the cell size, the SHO zone, and the capacity of the cell clusters. Several techniques for overlay-underlay cell clustering are also outlined.

Reference [36] studies the feasibility of a CDMA overlay that can share the 1850-1990 MHz PCS band with existing microwave signals (transmitted by utility companies, state agencies, etc.). The results of several field tests demonstrate the application of such an overlay for the PCS band.

The issue of use of a CDMA microcell underlay for an existing analog macrocell is the focus of [37]. It is shown that high capacity can be achieved in a microcell at the expense of a slight degradation in macrocell performance. Reference [37] finds that transmit and receive notch filters should be used at the microcell BSs. It shows that key parameters for such an overlay are the powers of the CDMA BS and MS transmitters relative to the macrocell BSs and the MSs served by the macrocells.

2.3.4 Special Architectures

There are several special cellular architectures that try to improve spectral efficiency without a large increase in the infrastructure costs. Some of these structures, discussed here, include an *underlay/overlay system* (which is different from an overlay/underlay system described earlier) and a *multichannel bandwidth system*. Many cellular systems are expected to evolve from a macrocellular system to an overlay/underlay system described earlier. A study that focuses on such evolution is described in Section 2.3.4.

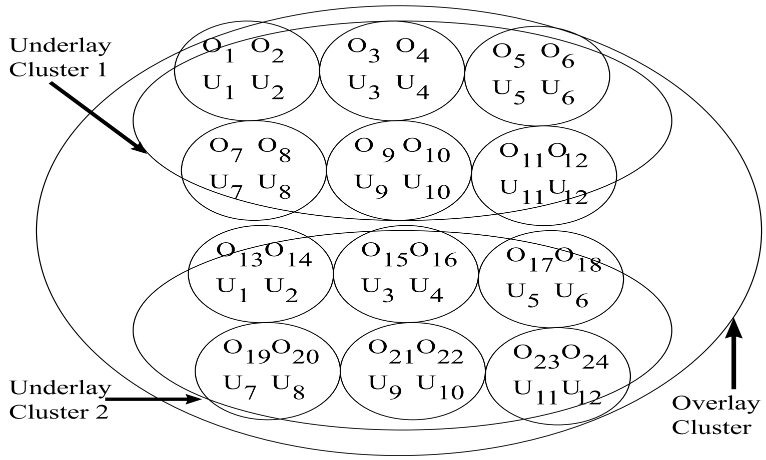

Figure 2.9: An Underlay/Overlay System

Underlay/Overlay System

An underlay/overlay system explained here is different from an overlay/underlay system described earlier in Section 2.3.3. In an overlay/underlay system, frequency spectrum is divided between the macrocells and microcells in such a way that a macrocell uses certain channels throughout the cellular system. Also, the macrocell typically has a separate BS and a transmission tower. However, in an underlay/overlay system, a tighter reuse factor is used within an overlay.

For example, assume that there are thirty six channels in a cluster of twelve cells. If there is no overlay or underlay, three channels will be available for each cell. In the conventional overlay/underlay system, two channels per cell can be used in a cluster of twelve microcells while the macrocell will use the remaining twelve channels throughout the cluster region. If uniform distribution of traffic is assumed, the effective number of channels per cell will still be three (two channels from a microcell and one channel from a macrocell). On the other hand, in one arrangement of an underlay/overlay scheme, two reuse factors, twelve and six, will be used instead of just one reuse factor, twelve, as shown in Figure 2.9. Within a cluster of twelve cells, two channels per cell will be used in an overlay system (channels O_1 through O_{24} in Figure 2.9), and the remaining twelve channels will be distributed using the reuse factor of six (channels U_1 through U_{12} in Figure 2.9). Thus, within a single overlay cluster, there will be two underlay clusters, and each underlay cluster has a

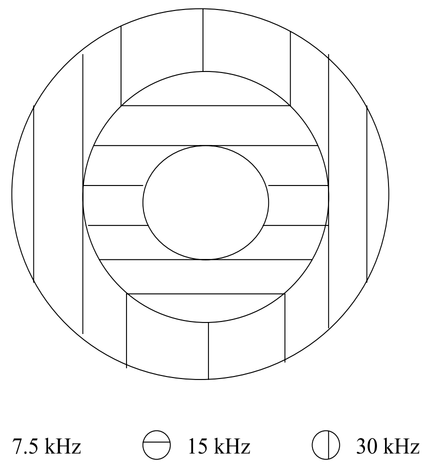

Figure 2.10: A Multiple Channel Bandwidth System

reuse factor of six. Hence, effectively there will be four channels per cell in an underlay/overlay system compared to three channels per cell for a non underlay/overlay system. Further improvement in capacity can be obtained by using an even tighter reuse factor of three in an underlay cluster. In this case, there will be four underlay clusters within an overlay cluster. The overlay cluster uses two channels per cell, and the underlay cluster uses four channels per cell. Thus, effectively six channels per cell will be available. The underlay/overlay scheme can enhance capacity of the system without the infrastructure costs because the same BSs, transmission towers, and other hardware can be shared.

Multiple Channel Bandwidth System

Multiple channel bandwidths can be used within a cell to improve spectral efficiency. In a multiple channel bandwidth system (MCBS), a cell has two or three ring-shaped regions with different bandwidth channels. Figure 2.10 shows an MCBS.

Assume that 30 kHz is the normal bandwidth for a signal. Now, for a three-ring MCBS, 30 kHz channels can be used in the outermost ring, 15 kHz channels in the middle ring, and 7.5 kHz channels in the innermost ring. The areas of these rings can be determined based on the expected traffic conditions. Thus, instead of using 30 kHz channels throughout the cell, different bandwidth channels (e.g., 15 kHz, and 7.5 kHz) can be used to increase the number of channels in a cell. The MCBS uses the fact that a wide bandwidth channel requires a lower (C/I) ratio (carrier to interference ratio) than a narrow channel bandwidth system for the same voice quality. For example, (C/I) requirements for 30kHz, 15 kHz, and 7.5 kHz channel bandwidths are 18 dB, 24 dB, and 30 dB, respectively, based on subjective voice quality tests [2]. If the transmit power at a cell cite is the same for all the bandwidths, a wide channel can serve a large cell, while a narrow channel can serve a relatively small cell. Moreover, since a wide channel can tolerate a higher level of CCI, it can afford a smaller (D/R) ratio (the ratio of co-channel distance to cell radius). Thus, in the MCBS, more channels become available due to multiple bandwidth signals, and frequency can be reused more closely in a given service region due to different (C/I) requirements.

Evolutionary Architecture

Existing cellular systems are expected to evolve from large size cells to small size cells to cope with the increasing service demand. This type of evolution is the focus of [38], which considers three cell layout scenarios: the first layout has a non-layered cell architecture with macrocells; the second layout has a layered architecture with macrocells and medium size microcells; the third layout has macrocells and small size microcells. For these layouts, the user penetration rate (the rate that the system can withstand to meet the QoS requirements) is estimated. A simulation model has also been developed to evaluate the performance of some handoff algorithms. Different types of environment (such as domestic, office, streets) and different types of services (such as circuit switched voice, packet switched voice, and packet switched data services) have been taken into account.

2.3.5 Integrated Wireless Systems

Integrated wireless systems are exemplified by integrated cordless and cellular systems, integrated cellular systems, and integrated terrestrial and satellite systems. Such integrated systems combine the features of individual wireless systems to achieve the goals of improved mobility, low cost, etc.

Integrated Terrestrial Systems

Terrestrial intersystem handoff may be between two cellular systems or between a cellular system and a cordless telephone system. Examples of systems that need intersystem handoffs include GSM-DECT, CDMA in macrocells, and TDMA in microcells.

When a call initiated in a cellular system controlled by an MSC enters a system controlled by another MSC, intersystem handoff is required to continue the call [8]. In this case, one MSC makes a handoff request to another MSC to save the call. The MSCs need to have software for intersystem handoff if intersystem handoff is to be implemented. Compatibility between the concerned MSCs should be considered, too.

There are several possible outcomes of an intersystem handoff [8]: (i) a long distance call becomes a local call when an MS becomes a roamer; (ii) a long distance call becomes a local call when a roamer becomes a home mobile unit; (ii) a local call becomes a long distance call when a home mobile unit becomes a roamer; (iv) a local call becomes a long-distance call while a roamer becomes a home mobile unit.

There is a growing trend toward service portability across dissimilar systems, such as GSM and DECT [39]. For example, it is nice to have an intersystem handoff between the cordless and cellular coverage. Cost effective handoff algorithms for such scenarios represent a significant research area. This paper outlines different approaches to achieving intersystem handoff. Simulation results are presented for handoff between GSM and DECT/WACS. It is shown that a minor adjustment to the DECT specification can greatly simplify the implementation of an MS capable of an intersystem handoff between GSM and DECT.

Integrated Terrestrial and Satellite System

In an integrated cellular/satellite system, advantages of satellites and cellular systems can be combined. Satellites can provide wide area coverage, completion of coverage, immediate service, and additional capacity (by handling overflow traffic). A cellular system can provide a high capacity economical system. Some of the issues involved in an integrated system are discussed in [40]. In particular, the procedures of the GSM are examined for their application to the integrated systems.

The future public land mobile telecommunication system (FPLMTS) will provide a personal telephone system that enables a person with a handheld terminal to reach anywhere in the world [41]. The FPLMTS will include low-earth-orbit (LEO) or geostationary-earth-orbit (GEO) satellites as well as terrestrial cellular systems. When an MS is inside the coverage area of a terrestrial cellular system, the BS will act as a relay station and provide a link between the MS and the satellite. When an MS is outside the terrestrial system coverage area, it will have a direct communication link with the satellite. Different issues such as system architecture, call handling, performance analysis of the access, and transmission protocols are discussed in [41]. The two handoff scenarios in an integrated system are described below.

Handoff from the Land Mobile Satellite System (LMSS) to the Terrestrial System. While operating, the MS monitors the satellite link and evaluates the link performance. The RSSs are averaged (e.g., over a thirty second time period) to minimize signal strength variations. If the RSS falls below a certain threshold N consecutive times (e.g., N=3), the MS begins measuring RSS from the terrestrial cellular system. If the terrestrial signals are strong enough, handoff is made to the terrestrial system, provided that the terrestrial system can serve the BS.

Handoff from the Terrestrial System to the Land Mobile Satellite System (LMSS). When an MS is getting service from the terrestrial system, the BS sends an acknowledge request at predefined intervals to ensure that the MS is still inside the coverage area. If an acknowledge request signal from the MS is not received at the BS for N consecutive times, it is handed off to LMSS.

Reference [42] focuses on personal communication systems with hierarchical overlays that incorporate terrestrial systems and satellite systems. The lowest level in the hierarchy is formed by microcells. Macrocells overlay microcells and form the middle level in the hierarchy. Satellite beams overlay macrocells and constitute the topmost hierarchy level. Two types of subscribers are considered, satellite-only subscribers and cellular/satellite dual subscribers. Call attempts from satellite-only subscribers are served by satellite systems, while call attempts from dual subscribers are first directed to the serving terrestrial systems with the satellites taking care of the overflow traffic. An analytical model for teletraffic performance is developed, and performance measures such as traffic distribution, blocking probability, and forced termination probability are evaluated for low speed and high speed users.

2.4 Handoff Criteria

Several variables have been proposed and used as inputs, or *handoff criteria*, to handoff algorithms. The handoff criteria discussed here include signal strength, SIR, distance, transmit power, traffic, call and handoff statistics, and velocity.

- **Received Signal Strength (RSS)**. This criterion is simple, direct, and widely used. Many systems are interference limited, meaning that signal strength adequately indicates the signal quality, and this is the motivation behind signal strength based decision. Moreover, there is a close relation between the RSS and the distance between the BS and the MS. The lack of consideration of CCI is a disadvantage of this criterion. CCI is more important in microcells (with a cell radius less than 1 km) than in macrocells since microcellular systems are interference limited and macrocells are noise-limited, (with cell radius exceeding 35 km in rural areas). Moreover, several factors (e.g., topographical changes, shadowing due to buildings, and multipath fading) can cause the actual coverage area to be quite different from the intended coverage area. The RSS criterion can also lead to excessive number of handoffs.

- **Signal-to-Interference Ratio (SIR)**. An advantage of using SIR or C/I as a criterion is that SIR is a parameter common to voice quality, system capacity and dropped call rate. BER is often used to estimate SIR. When actual (C/I) is lower than the designed (C/I), voice quality becomes poor, and the rate of dropped calls increases. SIR also determines the reuse distance. Unfortunately, CIR may oscillate due to propagation conditions and may cause the ping-pong effect (in which the MS repeatedly switches between the adjacent BSs). Another disadvantage is that even though BER is a good indicator of link quality, bad link quality may be experienced near the serving BS, and handoff may not be desirable in such situations [1]. In an interference-limited environment, a deterioration in BER does not necessarily imply the need for an intercell handoff; an intracell handoff may be sufficient [17].

  In [43], two methods for estimating raw channel BER over a Rayleigh fading channel are presented. The first method uses a preselected pseudo-noise (PN) sequence as a frame synchronization pattern. This sequence is transmitted over a Rayleigh fading channel. A decision variable is calculated by finding the autocorrelation of the channel-corrupted PN sequence with the original PN sequence. The autocorrelation value is related to the channel signal-to-noise ratio (SNR) to compute the raw BER estimate. The second method assumes that bounded distance decoders are used in a Reed-Solomon based system to estimate the number of errors in a received word prior to decoding. First, the channel symbol error rate (SER) is estimated by assuming that the number of errors in a received word is less than the error correction capability of the code. Then, using the channel SER, raw channel BER and post-decoder BER are derived.

Reference [41] proposes BER as a handoff criterion for an integrated system that consists of a cellular system and a terrestrial system. The level crossing rate (LCR) is an important quantity that characterizes the rate at which the envelope of Rayleigh faded signals crosses a specified signal level in the positive slope. The LCR is used to determine average signal strength. From the average signal strength, the BER is determined based on the modulation scheme used for data transmission.

- **Distance**. This criterion can help preserve planned cell boundary. The distance can be estimated based on signal strength measurements [44], delay between the signals received from different BSs [45], etc. Distance measurement can improve the handoff performance [11]. If handoff occurs at the midway between two BSs, it distributes the channel utilization evenly [26]. The distance measurement requires some special technical equipment and is possible in systems with only a common clock. Synchronization between the BSs is also required. Since future systems will require the location information of the MS, distance measurement will be available for use as a handoff criterion. The distance criterion may be useful for a macrocellular system, but it is prohibitive in a microcellular system since the precision of the distance measurement decreases with smaller cell sizes [1]. Theoretical analysis in [46] does not consider distance criterion better than others.

  The determination of cell boundaries can avoid unnecessary handoffs. In the German cellular system C, (C/I) and other data (such as signal strength, phase jitter, and the phase difference of the received digital signals) are measured and processed to detect the cell boundaries [47].

- **Transmit Power**. Transmit power can be used as a handoff criterion to reduce the power requirement, reduce interference, and increase battery life.

- **Traffic**. Traffic level as a handoff criterion can balance traffic in adjacent cells [3]. Reference [48] develops an analytical model for traffic performance analysis of a system. Statistics of dwell times are important for teletraffic performance evaluation [48].

- **Call and Handoff Statistics**. Statistics such as total time spent in the cell by a call and arrival time of a call in a cell can also be used as handoff criteria [7]. Elapsed time since last handoff is also a useful criterion since it can reduce the number of handoffs [8].

- **Velocity**. Velocity is an important handoff criterion, especially for overlay systems and velocity adaptive algorithms. Several algorithms use an estimate of velocity to modify handoff parameters. In [49], a method to adaptively change the averaging interval in a handoff algorithm for both small and large cells is presented. The method is based on the estimation of mobile velocity through maximum Doppler frequency f_D. This paper also outlines a method for estimating f_D from squared deviations of the signal envelope, both in Rayleigh fading and Rician fading environments. An adaptive scheme for optimal averaging has also been suggested. Some of the methods for estimating f_D use the following criteria: mobile velocity, level crossings, spectrum or autocorrelation analysis, and squared deviations of logarithmically compressed envelope (amplitude) measurements. Reference [49] describes the last approach. The effects of averaging interval, CCI, and additive white Gaussian noise (AWGN) on f_D estimation are analyzed. The f_D estimates can then be used to modify weighting factors of exponential averaging in a handoff algorithm.

2.5 Conventional Handoff Algorithms

Handoff algorithms are distinguished from one another in two ways, handoff criteria and processing of handoff criteria. Conventional handoff algorithms are described here while emerging handoff algorithms are described in Section 2.6. Figure 2.11 summarizes the various types of handoff algorithms.

2.5.1 Signal Strength Based Algorithms

There are several variations of signal strength based algorithms, including relative signal strength algorithms, absolute signal strength algorithms, and combined absolute and relative signal strength algorithms. These algorithms are briefly discussed next.

Relative Signal Strength Algorithms

According to the relative signal strength criterion [14], the BS that receives the strongest signal from the MS is connected to the MS. The advantage of this algorithm is its ability to connect the MS with the strongest BS. However, the disadvantage is the excessive handoffs due to shadow fading variations associated with the signal strength. In many of the existing systems, measurements for candidate BSs are not performed if field strength for the existing BS exceeds a prescribed threshold. The advantage of this approach is that the reduced processing load. However, the disadvantage is the MS's retained connection to the current BS even if it passes the

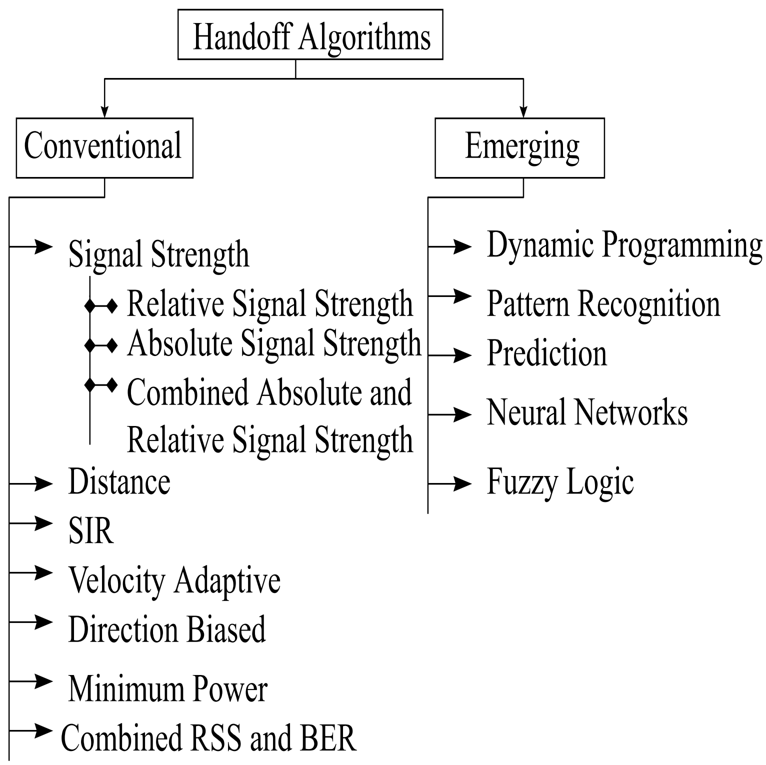

Figure 2.11: Handoff Algorithms at a Glance

planned cell boundary as long as the signal strength is above the threshold. A variation of this basic relative signal strength algorithm incorporates hysteresis. For such an algorithm, a handoff is made if the RSS from another BS exceeds the RSS from the current BS by an amount of hysteresis. The North American Personal Access Communication Systems (PACS) personal communication services (PCS) standard combines hysteresis with a dwell timer [4]. Hysteresis reduces the number of unnecessary handoffs but can increase dropouts since it can also prevent necessary handoffs by introducing a delay in handoff [13]. A necessary balance between the number of handoffs and delay in handoff needs to be achieved by appropriate hysteresis and signal strength averaging. Reference [6] describes a software simulator that allows the design of the number of samples to be averaged and of the hysteresis margin. Rectangular and exponential averaging windows are considered. The averaging should consider the MS speed and shadow fading. The shadow fading is characterized by a Gaussian distribution with zero mean and certain standard deviation (which depends on the environment). A scheme for estimating the shadow fading standard deviation based on squared deviations of the RSS at the MS is proposed in [50].

It is shown in [51] that the optimum handoff algorithm parameters are very sensitive to shadow fading standard deviation. To achieve robustness, more averaging and less hysteresis are required. However, to detect sudden changes in signal strength (e.g., due to street corner effect), less averaging and more hysteresis are required. To resolve this conflict, shadow fading deviation is estimated and used [49]. If the averaging interval is too short, fading fluctuates greatly. If it is too long, handoff is delayed. Thus, it is important to have an adaptive averaging interval. The time varying intensity of Rayleigh fading depends on the maximum Doppler frequency proportional to the mobile velocity. Similarly, shadow fading depends on the velocity due to its dependence on distance. Thus, an averaging interval can be determined based on maximum Doppler frequency. Reference [49] determines the adaptive averaging interval through estimating maximum Doppler frequency by exploiting Rayleigh fading fluctuations.

References [52] and [53] characterize the variance of signal strength of the cell propagation environment and present its effect on handoff parameters such as signal averaging time and hysteresis. The simulation results based on GSM indicate that dynamic adjustment of propagation dependent handoff parameters could enhance the handoff performance.

In a microcellular environment, a large hysteresis will avoid the ping-pong effect for LOS handoff while delaying NLOS handoff (that must be done very quickly to save the call) [4]. The use of umbrella cells, the use of microdiversity, and mobile-controlled handoff [19] are some solutions to such contradictory goals. The umbrella cell approach provides compatibility with existing systems.

Absolute Signal Strength Algorithms

For this algorithm, when the RSS drops below a threshold level, handoff is requested. Typical threshold values are -100 dBm for a noise-limited system and -95 dBm for an interference-limited system [8]. Better handoff initiation can be obtained by varying the threshold [8]. The threshold level should be varied according to the *path loss slope L of the RSS* and the *level crossing rate (LCR) of the RSS*. If the slope L is high or LCR is high, the MS is quickly moving away from the BS, and, hence, handoff should be made fast (i.e., the handoff initiation threshold should be made higher in magnitude). If the slope L or LCR is low, the MS is moving slowly. So, handoff can be slow; the handoff initiation threshold can be made comparatively smaller. Thus, the mobile velocity and path-loss slope L can be used to determine the handoff initiation threshold dynamically such that the number of unnecessary handoffs is minimized and necessary handoffs are completed successfully.

This algorithm has a serious disadvantage. When a threshold level is set based on the RSS, the following situations pose a problem [8]: (i) when RSS is high due to high interference, the handoff will not take place, although, ideally, handoff is desirable to avoid interference; (ii) when RSS is low, handoff takes place even if voice quality is good, although, ideally, such a handoff is not required, and some systems use supervisory audio tone (SAT) information with the RSS to avoid handoff.

A variation of the basic threshold algorithm is a two-level algorithm, which provides more opportunity for a successful handoff [8]. Two handoff thresholds, L_1 and L_2, are defined with L_1 higher than L_2 as shown in Figure 2.12. When the RSS drops below L_1, a handoff request is initiated. If the MS is in a signal strength hole in the current cell or the candidate cell is busy, the possibility of handoff must be assessed. In this case, handoff is requested periodically (e.g., every five seconds). The handoff request is entertained only if the new RSS is stronger (Situation 1 in

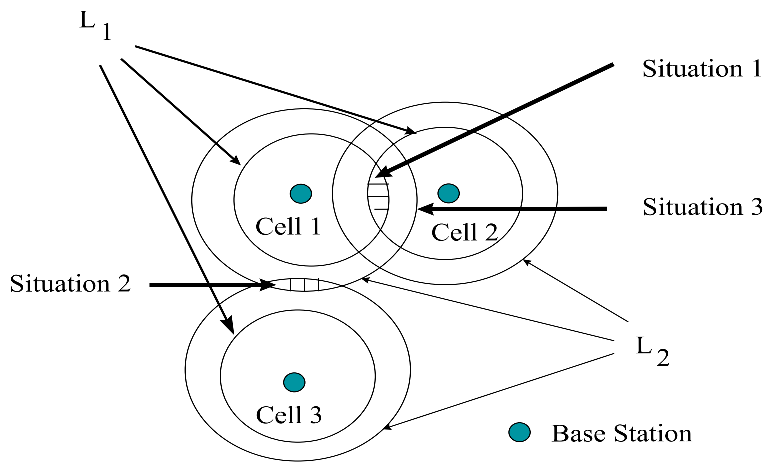

Figure 2.12: A Two-Level Handoff Algorithm

Figure 2.12). However, if the RSS reaches L_2, handoff will be made regardless of the relative signal strength of the candidate BS (Situation 2 in Figure 2.12). Due to the two-level algorithm, the MS may come out of the hole, or the candidate BS may have a free channel for handoff between L_1 and L_2. If a single threshold L_2 were used, the L_2 boundary might have been close to the candidate BS, causing interference (Situation 3 in Figure 2.12). However, in a two-level algorithm, L_1 boundaries of the BSs will have allowed handoff to be made earlier, avoiding high interference levels.

Combined Absolute and Relative Signal Strength Algorithms

According to this algorithm, handoff takes place if the following two conditions are satisfied [54]: the average signal strength of the serving BS falls below an absolute threshold T (dB), and the average signal strength of the candidate BS exceeds the average signal strength of the current BS by an amount of h (hysteresis) dB. The first condition prevents the occurrence of handoff when the current BS can provide sufficient signal quality. Reference [24] has shown that an optimum threshold (T) achieves the narrowed handoff area (and hence reduced interference) and a low expected number of handoffs. Basic variables for this handoff algorithm are the length and shape of the averaging window, the threshold level, and the hysteresis margin [4].

Some of the findings of [15] for this algorithm are: (i) the probability of not finding a handoff candidate channel decreases as the overlap region increases; (ii) the probability of not finding a handoff candidate increases as the handoff threshold increases; (iii) the probability of a late handoff decreases as handoff threshold increases; (iv) the probability of unnecessary handoffs (i.e., the ping-pong effect) increases as handoff threshold increases; (v) the probability of unnecessary handoff decreases as hysteresis increases.

2.5.2 Distance Based Algorithms

This algorithm connects the MS to the nearest BS. The relative distance measurement is obtained by comparing propagation delay times. This criterion allows handoff at the planned cell boundaries, giving better spectrum efficiency compared to the signal strength criterion [14]. German cellular system C450 uses this handoff criterion [55]. However, it is difficult to plan cell boundaries in a microcellular system due to complex propagation characteristics. Thus, the advantage of distance criterion over signal strength criterion begins to disappear for smaller cells due to inaccuracies in distance measurements. A relative signal strength based algorithm gives less interference probability compared to a relative distance based algorithm. In particular, when an LOS path exists between the current and distant BS and the MS, the current BS gives stronger signal strength compared to the nearer NLOS BS. In such cases, the relative signal strength criterion can avoid interference; relative distance criterion experiences more interference.

2.5.3 SIR Based Algorithms

For toll quality voice, SIR at the cell boundary should be relatively high (e.g., 18 dB for AMPS and 12 dB for GSM). However, a lower SIR may be used for capacity reasons since cochannel distance and cluster size (i.e., the number of cells per cluster) are small for lower SIR and channels can be reused more frequently in a given geographical region [8]. SIR is a measure of communication quality. This algorithm makes a handoff when the current BS's SIR drops below a threshold and another BS can provide sufficient SIR. Hysteresis can be incorporated in the algorithm. The lower SIR may be due to high interference or low carrier power. In either case, handoff is desirable when SIR is low. However, SIR-based handoff algorithms prevent handoffs near nominal cell boundaries and cause cell-dragging and high transmit power requirements [56]. In analog systems, measuring SIR during a call is difficult. Hence, sometimes interference power is measured before a call is connected, and combined signal and interference power is measured during the call.

Reference [57] has suggested an uplink SIR-based algorithm for a power controlled system. Each user tries to achieve a target SIR γ_t. Handoff is made when the user's SIR drops below a threshold γ_{ho}, which is normally less than γ_t.

2.5.4 Velocity Adaptive Algorithms

Handoff requests from fast moving vehicles must be processed quickly. A handoff algorithm with short temporal averaging windows can be used to tackle fast users. However, the concept of a "short" averaging window is relative to the mobile speed. Thus, optimal handoff performance will be obtained only at one speed if the length of the averaging window is kept constant. A velocity adaptive handoff algorithm provides good performance for MSs with different velocities by adjusting the effective length of the averaging window [58]. A velocity adaptive handoff algorithm can serve as an alternative to the umbrella cell approach to tackle high speed users if low network delay can be achieved, which can lead to savings in the infrastructure. One of the velocity estimation techniques uses level crossing rate (LCR) of the RSS in which the threshold level should be set as the average value of the Rayleigh distribution of the RSS [59], requiring special equipment to detect the propagation dependent average receiver power. Reference [59] proposes a method of velocity estimation in a Rayleigh fading channel based on velocity's proportionality to the Doppler frequency. The velocity estimation technique exploits diversity reception. If the MS is already using selection diversity, special equipment is not required for this method.

In [58], velocity adaptive handoff algorithms for microcellular systems are characterized. The amount of spatial averaging required for local mean estimation is discussed. Three methods for velocity estimation are analyzed: level crossing rate method, zero-crossing rate method, and covariance approximation method. Sensitivity of algorithms to Rice (a type of fading) factors, non-isotropic scattering, and additive Gaussian noise are also addressed. A method for choosing proper window length using analog averaging has been analyzed. The signal statistics (e.g., mean) are estimated, the accuracy of which depends on Rice factor K, averaging distance, and the angle of the specular component with the MS direction θ. The required spatial averaging distance for local mean estimates in microcells depends on K and θ. Discrete averaging can be used to determine the number and spacing of samples. It is found that the spatial averaging distance required to sufficiently reduce the effects of fading depends on K and θ. For sample averaging, sample spacing should be less than 0.5 λ (half the wavelength). Usually, a spatial averaging distance of 20 λ to 40 λ is sufficient for microcells. A velocity adaptive handoff algorithm can adapt the temporal averaging window (i.e., a window with a certain time length) by either keeping the sampling period constant and adjusting the number of samples per window or vice versa.

2.5.5 Direction Biased Algorithms

In an NLOS handoff, the MS experiences the corner effect as explained in Section 2.3.2. Hence, if the MS moves fast and is not handed off quickly enough to another BS, the call will be dropped. Connecting the fast moving vehicles to an umbrella cell is one solution, and using better handoff algorithms is another solution. A direction-biased handoff algorithm represents such an alternative solution [60]. Direction biasing improves *cell membership properties* and handoff performance in LOS and NLOS scenarios in a multi-cell environment. A handoff algorithm is said to possess good *cell membership properties* if the probability that the MS is assigned to the closest BS is close to one throughout the call duration [60]. Improvement in cell memberships leads to fewer handoffs and reduced interference.

The basic idea behind this algorithm is that handoffs to the BSs towards which the MS is moving are encouraged, while handoffs to the BSs from which the MS is receding are discouraged. This algorithm reduces the probability of dropped calls for hard handoffs (e.g., for TDMA systems). The algorithm also reduces the time a user needs to be connected to more than one base station for soft handoffs (e.g., for CDMA systems), allowing more potential users per cell.

A variation of the basic direction-biased algorithm is the pre-selection direction-biased algorithm [60]. If the best BS is a receding one and has a quality only slightly better than the second best BS which is being approached, the handoff should be made to the second best BS because it is more likely to improve its chances of being selected. This provides a fast handoff algorithm with good cell membership properties without the undesirable effects associated with large hysteresis. Another variation of the basic direction-biased algorithm is a fuzzy logic based direction-biased algorithm [60].

2.5.6 Minimum Power Algorithms

A minimum power handoff (MPH) algorithm that minimizes the uplink transmit power by searching for a suitable combination of a BS and a channel is suggested in [56]. This algorithm reduces call dropping but increases the number of unnecessary handoffs. To avoid a high number of handoffs, the use of a timer is suggested. First, the channel that gives minimum interference at each BS is found. Then, the BS that has a minimum power channel is determined.

Reference [11] uses a power budget criterion to ensure that the MS is always assigned to the cell with the lowest path loss, even if the thresholds for signal strength or signal quality have not been reached. This criterion results in the lowest transmit power and a reduced probability of CCI.

2.5.7 RSS and BER Based Algorithms

An algorithm based on both RSS and BER is described in [26]. For RSS, a threshold is used for the current BS, and a hysteresis window is used for the target BS. For BER, a separate threshold is defined. The target BS can be either included or excluded from the handoff decision process. The latter scheme is used in GSM in which the mobile does not know the signal quality of the target BS. In principle, it is possible to measure BER of the control channel of the target BS. Three parameters considered in the simulations in [26] are RSS threshold, BER threshold, and RSS hysteresis window size. The effects of these parameters on handoff probability are shown in this paper. In general, a low threshold value reduces the handoff request probability. The best threshold value is the average signal level at the mid-point between two BSs. However, due to the propagation environment, this threshold must be estimated for each base site. An RSS hysteresis delays handoff significantly. The higher the BER threshold, the earlier the handoff request. Moreover, if the BER threshold of target BS is used, handoff request is delayed. The handoff request probability differs significantly with location (or BS sites), showing that propagation characteristics are highly dependent on local terrain features and environment. From experimental results, it was found that the signal level and BER profiles varied significantly. RSS gives a direct indication of the received energy at the MS, while BER gives an indication of CCI and transmission quality. The effect of threshold level of RSS on handoff is opposite to that of BER since the gradient of BER level is opposite to that of RSS level. If the gradient of the signal level is steep, the handoff region is less sensitive to a small variation in the threshold. Hysteresis is useful in preventing premature handoff requests if signal profiles are fluctuating. This is very useful in small site cells. In large site cells, hysteresis should be relatively small since it may introduce a delay in handoff initiation. Actual data (i.e., measured RSS and BER) is used in a software simulator that implements handoff schemes [26].

2.6 Emerging Handoff Algorithms

2.6.1 Dynamic Programming Based Handoff Algorithms

Dynamic programming allows a systematic approach to optimization. However, it is usually model dependent (particularly the propagation model) and requires the estimation of some parameters and handoff criteria, such as signal strengths. So far, dynamic programming has been applied to very simplified handoff scenarios only.

Handoff is viewed as a reward/cost optimization problem in [61]. RSS samples at the MS are modeled as stochastic processes. The reward is a function of several characteristics (e.g., signal strength, CIR, channel fading, shadowing, propagation loss, power control strategies, traffic distribution, cell loading profiles, and channel assignment). Handoffs are modeled as switching penalties that are based on resources needed for a successful handoff. Dynamic programming is used to derive properties of optimal policies for handoff. Simulation results show this algorithm to be better than a relative signal strength based algorithm.

Reference [62] views signal strength based handoff as an optimization problem to obtain a tradeoff between the expected number of handoffs and number of service failures, events that occur when the signal strength drops below a level required for an acceptable service to the user. An optimal solution is derived based on dynamic programming and is used for comparison with other solutions. The handoff problem is defined as a finite horizon dynamic programming problem, and an optimal solution is obtained through a set of recursive equations. This optimal solution is complex and requires *a priori* knowledge of the mobile trajectory. A locally optimal (or greedy) algorithm has been derived that uses the threshold level and gives a reasonable number of handoffs. A technique for adapting the algorithm is also suggested.

In [63], the handoff problem is formulated in a stochastic control framework. A Markov decision process formulation is used, and optimum handoff strategies are derived by dynamic programming. The optimization function includes a cost for switching and a reward for improving the quality of the call. The optimum decision is the hysteresis value representing the difference in RSSs from the BSs.

2.6.2 Pattern Recognition Based Handoff Algorithms

Reference [64] formulates the handoff problem as a pattern recognition problem. Pattern recognition (PR) identifies meaningful regularities in noisy or complex environments. These techniques are based on the idea that the points that are close to each other in a mathematically defined feature space represent the same class of objects or variables. *Explicit PR techniques* use discriminant functions that define (n-1) hypersurfaces in an n-dimensional feature space. The input pattern is classified according to their location on the hypersurfaces. *Implicit PR techniques* measure the distance of the input pattern to the predefined representative patterns in each class. The sensitivity of the distance measurement to different representative patterns can be adjusted using weights. The clustering algorithms and fuzzy classifiers are examples of implicit methods. The environment in the region near cell boundaries is unstable, and many unnecessary handoffs are likely to occur. The PR techniques can help reduce this uncertainty by efficiently processing the RSS measurements.

2.6.3 Prediction-based Handoff Algorithms

Prediction-based handoff algorithms use the estimates of future values of handoff criteria, such as RSS. Reference [65] proposes this technique and shows it to be better than the relative signal strength algorithm and the combined absolute and relative signal strength algorithm via simulations. An adaptive prediction based algorithm has been proposed to obtain a tradeoff between the number of handoffs and the overall signal quality [65]. Signal strength based handoff algorithms can use path loss and shadow fading to make a handoff decision. The path loss depends on distance and is determinate. The shadow fading variations are correlated and hence can be predicted. The correlation factor is a function of the distance between the two locations and the nature of the surrounding environment [66]. The proposed prediction based algorithm exploits this correlation property to avoid unnecessary handoffs. The future RSS is estimated based on previously measured RSSs using an adaptive FIR filter. The FIR filter coefficients are continuously updated by minimizing the prediction error. Depending upon the current value of the RSS (RSS_c) and the predicted future value of the RSS (RSS_p), handoff decision is given a certain priority. Based on the combination of RSS_c and RSS_p, hysteresis may be added if it will not affect the handoff performance adversely. The final handoff decision is made based on the calculated handoff priority.

2.6.4 Neural Handoff Algorithms

Most of the proposed neural techniques have shown only preliminary simulation results or have proposed methodologies without the simulation results. These techniques have used simplified simulation models. Learning capabilities of several paradigms of neural networks have not been utilized effectively in conjunction with handoff algorithms to date.

Reference [1] presents a signal strength based handoff initiation algorithm using a binary hypothesis test implemented as a neural network. However, simulation results are not presented.

In [16], a methodology based on an ANN is proposed. Preliminary simulation results show that this methodology is suitable for multicriteria handoff algorithms.

2.6.5 Fuzzy Handoff Algorithms

In [67], a fuzzy handoff algorithm is proposed. The fuzzy handoff algorithm has been shown to possess enhanced stability (i.e., less frequent handoffs). A hysteresis value used in a conventional handoff algorithm may not be enough for heavy fadings, while fuzzy logic has inherent fuzziness that can model the overlap region between the adjacent cells, which is the motivation behind this fuzzy logic algorithm.

Reference [64] uses a fuzzy classifier to process the signal strength measurements to select a BS to serve a call. The performance of this algorithm in a microcellular environment is evaluated.

In [68], a handoff procedure using fuzzy logic is outlined. It incorporates signal strength, distance, and traffic. Preliminary simulation results are presented.

Reference [12] explains the concept of cell membership degree to handoff. The methodology proposed in this paper allows systematic inclusion of different weight criteria and reduces the number of handoffs without excessive cell coverage overlapping. It is shown that the change of RSS threshold as a means of introducing a bias is an effective way to balance traffic while allowing few or no additional handoffs. It is suggested that a combination of range and RSS modified by traffic weighting might give good performance. Different fuzzy composition methods to combine the cell membership degrees of different criteria methods are investigated. Effects of changes in the cell membership degrees on handoff performance have been evaluated.

2.7 Handoff Prioritization

One of the ways to reduce the handoff failure rate is to prioritize handoff. Handoff algorithms that try to minimize the number of handoffs give poor performance in heavy traffic situations [69]. In such situations, a significant handoff performance improvement can be obtained by prioritizing handoff.

2.7.1 Introduction to Handoff Priority

Channel assignment strategies with handoff prioritization have been proposed to reduce the probability of forced termination [70, 71]. Two basic methods of handoff prioritization, guard channels and queuing, are explained next.

- **Guard Channels**.

  Guard channels improve the probability of successful handoffs by reserving a fixed or dynamically adjustable number of channels exclusively for handoffs. For example, priority can be given to handoff by reserving N channels for handoffs among C channels in the cell [72]. The remaining (C-N) channels are shared by both new calls and handoff calls. A new call is blocked if the number of channels available is less than (C-N). Handoff fails if no channel is available in the candidate cell. However, this concept has the risk of underutilization of spectrum. An adaptive number of guard channels can help reduce this problem.

Efficient usage of guard channels requires the determination of optimum number of guard channels, knowledge of the traffic pattern of the area, and estimation of the channel occupancy time distributions.

- **Queuing of Handoff**.

  Queuing is a way of delaying handoff [8]; the MSC queues the handoff requests instead of denying access if the candidate BS is busy. Queuing new calls results in increased handoff blocking probability. The probability of a successful handoff can be improved by queuing handoff requests at the cost of increased call blocking probability and a decrease in the ratio of carried-to-admitted traffic since new calls are not assigned a channel until all the handoff requests in the queue are served. Queuing is possible due to the overlap region between the adjacent cells in which an MS can communicate with more than one BS.

  If handoff requests occur uniformly, queuing is not needed; queuing is effective only when handoff requests arrive in groups and when traffic is low. Queuing's conditional effectiveness has two causes: first, if there is a lot of traffic, it is highly unlikely that a queued handoff request will be entertained, and secondly, when there is moderate traffic and when traffic arrives in bundles, a queued handoff request is likely to be entertained due to potential availability of resources in the near future and the lower probability of new handoff requests in the same period.

  Queuing is very beneficial in macrocells since the MS can wait for handoff before signal quality drops to an unacceptable level. However, the effectiveness of queuing decreases for microcells due to stricter time requirements. The combination of queuing and channel reservation can be employed to obtain better performance [73].

Joint optimization of queuing and handoff parameters may be better due to the reasons listed below[69].

- When handoff algorithms are designed to optimize dropout probability and the number of unnecessary handoffs, excessive dropouts occur due to channel blocking during high traffic intensities. These strategies minimize the number of handoff attempts per boundary crossing, and sufficient time may not be available for entertaining the handoff requests under heavy traffic conditions.

- Different handoff algorithms introduce different delays in handoff requests. Hence, the delay associated with handoff queuing may not be acceptable for some handoff algorithms. The performance improvement achievable by handoff queuing is variable and dependent on handoff algorithms.

- Some handoff requests may demand higher priority in a queue to save the call. This can be investigated properly by noting both the traffic and transmission characteristics.

2.7.2 Handoff Priority Schemes

Reference [69] investigates the performance of different handoff priority schemes using a simulation model that incorporates transmission and traffic characteristics. The priority scheme of GSM has been evaluated. The simulation results show that the queuing and channel reservation schemes improve the dropout performance significantly, and the priority schemes provide up to 16% further improvement.

Reference [71] presents a handoff prioritization scheme to improve the service quality by minimizing handoff failures and spectrum utilization degradation. If all the channels are occupied, new calls are blocked while handoff requests are queued. The handoff queue is dynamically reordered based on the measurements. The performance of the proposed handoff priority technique has been evaluated through simulations and compared with nonprioritized call handling and the first in first out (FIFO) queuing scheme. The proposed scheme is shown to provide a lower probability of forced termination, a reduction in call blocking, a small reduction in traffic, and a small reduction in delay compared to the FIFO scheme under all traffic conditions. The new proposed scheme improves the probability of forced termination at the cost of an increase in call blocking and a decrease in the ratio of combined-to-offered traffic. The priorities are defined by the RSS at the MS from the current BS. The degradation rate in service due to queuing depends on the velocity of the MS, and the proposed method considers this degradation rate.

Reference [72] discusses two methods of giving priority to handoffs in a mobile system with *directed retry*, a feature of a cellular system, which allows the user to use a free channel in one of the neighboring cells [74]. Directed retry decreases the call blocking probability by sacrificing the handoff failure rate because there are fewer channels available for handoff in the candidate cell. This paper presents simulation results of two handoff priority methods for a cellular system with directed retry.

2.8 Handoff and Other Resource Management Tasks

2.8.1 Introduction to Resource Management

Some of the radio resource management tasks performed by cellular systems include admission control, channel assignment, power control, and handoff [57, 75]. An integrated radio resource management scheme can make necessary tradeoffs between the individual goals of these tasks to obtain better performance. The integrated radio resource management can increase system capacity within specified quality constraints. Due to the time and space varying nature of the cellular system, the radio resource management tasks need to be adaptive to factors such as interference, traffic, and propagation environment. Adaptive radio resource management tasks can reduce the initial cell planning and make replanning easier, more organized, and more automatic. Some of the important objectives of resource management are global minimization of the interference level and handoffs and adaptation to varying traffic and interference scenarios. A combination of individual radio resource management tasks is also possible. For example, handoff and channel assignment tasks can be combined [63]; a handoff request can be queued, and handoff is made when a channel becomes available. It should be noted that traditional cell planning may not be able to utilize the available spectrum efficiently due to highly environmentally dependent radio propagation, rapid and unbalanced growth of radio traffic, and other factors [75]. The radio resource management tasks are explained next.

- **Admission Control**.

  New calls and continuing calls can be treated differently. New calls may be queued. Handoffs may be prioritized. It is important to prevent the system from being overloaded. On the other hand, capacity is the revenue for service providers, and part of the perceived service quality can be attributed to the accessibility of the network.

- **Channel Allocation**.

  Reference [70] provides a tutorial on channel assignment (or allocation) strategies. Channel assignment strategies can be classified into fixed, dynamic, and flexible.

  The Fixed Channel Assignment (FCA) strategy permanently assigns a set of channels to each cell in a cluster . Some variations of the basic FCA strategy are the FCA with Borrowing (FCAB), the FCA with Hybrid Assignment (FCAHA), and the FCA with Borrowing-with-Channel-Ordering (FCABCO).

In the FCAB, a channel can be borrowed from a neighboring cell if all the channels in a cell are busy (provided that this does not result in excessive interference). In the FCAHA, a set of channels in each cell is divided into two groups, one group is reserved for the local use and the other is kept for the lending purpose. The FCABCO extends the idea of FCAHA by dynamically varying the ratio of the local-to-borrowable channels. Reference [76] compares the performance of FCA and FCABCO with two proposed channel assignment strategies. Simulations for a forty nine-cell network have been carried out under uniform and nonuniform traffic conditions.

The Dynamic Channel Assignment (DCA) strategy makes all the channels in a cluster available for use within a cluster. The actual channel assignment for a new call attempt is based on the minimization of a cost function that depends on future blocking probability, usage frequency of the candidate channel, and reuse distance of the channel. Dynamic channel allocation does not require *a priori* frequency planning but must determine whether cochannel usage is allowed or not. If adaptation to the changing propagation and interference conditions is done in a channel allocation algorithm, such an algorithm must guarantee a safe cochannel reuse distance. Hence, a measure of interference for the handoff candidate channel is required as an input to the channel allocation algorithm. Reference [77] deals with dynamic channel allocation using an ANN. In microcells, the variations in the telephone traffic load are large compared to those in macrocells. Reference [78] proposes a DCA algorithm that adapts to these variations for a one-dimensional cellular system. The proposed algorithm maximizes the number of assigned calls and is suitable for distributed implementation. DCA gives better performance than FCA at low loads since it can adapt to traffic bursts. However, at high loads, DCA does not perform as well. Hence, some hybrid schemes have been suggested.

The Flexible Channel Assignment (FLCA) strategy permanently distributes some channels among the cells in a cluster and keeps the remaining channels available for any cell's use when that cell's permanent channels are inadequate to cope with high traffic demand.

As explained in Section 2.7, the use of guard channels exclusively for handoff requests results in underutilization of the scarce channel resources. Reference [79] presents a channel allocation algorithm that follows *most critical first policy* in which a free channel is assigned to the handoff request that would be the first to be cut-off if no channel were available at that time. Simulation results indicate that this algorithm is effective in reducing handoff failures.

Reference [80] describes signal strength based distributed channel assignment schemes for a one-dimensional cellular system.

- **Power Control**.

Power control is used to increase battery life, reduce health hazards, and contain interference. One way to exercise power control is to use SIR as a criterion. In this case, MSs try to attain a target SIR through continuous power adjustments. If the minimum possible power that meets the required (C/I) constraint at the receiver is transmitted, spectrum efficiency will increase compared to uncontrolled transmit power systems. Increasing transmit power to increase (C/I) for better transmission quality does not necessarily meet the objective since other transmitters in the system may also increase their power levels to reduce their interference, thus increasing the global interference level.

- **Handoff**.

  One easy solution to BS assignment is to assign the MS to the nearest base station. However, due to the factors described in section 2.2.2, the handoff issue becomes very complex. Intercell handoff can be viewed as an adaptive method of preserving the planned cell boundaries and subsequently reducing the interference. Adaptation to the spatial distributions of radio traffic (or interference) can be done by modifying cell areas and shapes dynamically by adapting the handoff parameters. This effect is called *cell breathing*. In the directed retry method, if the best BS is not available, the second best BS is tried for handoff. However, directed retry increases the effectively used cell areas, increasing the global interference level.

2.8.2 Resource Management Integrated Handoff Algorithms

Some algorithms that combine two or more radio resource management tasks are described next.

Combined Intracell Handoff and Channel Assignment

Channel allocation algorithms that adapt to the instantaneous interference and traffic situation can lead to an easier planning process. This is a tremendous advantage since the system grows stepwise with the traffic demand in most cases [25].

Reference [25] proposes a channel allocation algorithm that is adaptive to traffic and interference. It assumes that (C/I) of the current channel is measured periodically. This algorithm consists of several steps, which are outlined below.

1. For a new call setup or intercell handoff, reassignment is performed. In other cases, reassignment is performed if $(C/I)_{old}$ for the current channel is less than a threshold, $(C/I)_{check}$.

2. Since it may not be feasible to calculate (C/I) for all the channels, channels are checked until a channel with good (C/I) is found. This channel is taken as a candidate channel.

3. If (C/I) of the candidate channel, $(C/I)_{cand}$, and $(C/I)_{old}$ are less than a threshold, $(C/I)_{block}$, the call is blocked.

4. In the absence of call setup or intercell handoff, the candidate channel is accepted only if $(C/I)_{cand}$ exceeds $(C/I)_{old}$ by some hysteresis value.

Uplink SIR-based Integrated Handoff Algorithm

Reference [57] proposes an integrated resource management based on four SIR thresholds. The resource management tasks incorporated into the algorithm are *admission control*, *power control*, *handoff*, and *channel allocation*. A call is dropped when SIR drops below γ_{drop} (e.g., 16 dB for AMPS). γ_{drop} is considered to be the minimum tolerable SIR for an acceptable speech quality. *Power control* is achieved by a target SIR threshold γ_t. Each MS tries to attain γ_t through power control. *Call admission control* is achieved by an SIR threshold γ_{new}. A new call attempt succeeds only if it can offer an SIR higher than γ_{new}. This SIR threshold ensures that the system is not packed too tightly. Otherwise, it may be difficult to find free channels for handoff. Moreover, a new call, if admitted, will not cause severe interference to existing calls. *Handoff and channel assignment* are combined in the sense that handoff is made to the minimum interference channel when SIR drops below γ_{ho}.

RSS-based Integrated Handoff Algorithm

The algorithm proposed in [75] uses RSS and transmission quality measure for the channels as handoff criteria. The BS allocation, channel assignment, and power control are treated in an integral manner. A new BS is selected in the case of new call setup and inter-cell handoff based on signal strength and possibly some network criteria. The comparison between the candidate BSs is done under equal transmit power levels. Power control is performed to increase spectral efficiency.

Integrated Power Control and Handoff Algorithm

Reference [81] treats power control and BS assignment issues in an integral manner. The objective is to find a combination of BS assignment and transmit power to provide a feasible solution to the minimum transmit power (MTP) problem. An algorithm called minimum power assignment (MPA) is proposed, which iteratively solves the MTP problem. During an iteration of the algorithm, an MS chooses a combination of BS and transmit power for which minimum power is needed to maintain an acceptable CIR (assuming that the other MSs transmit fixed powers at that time).

Reference [82] also proposes a similar combined power control and BS selection algorithm to achieve higher capacity in a spread spectrum cellular system. The proposed algorithm adapts transmit powers of users and switches users between the BSs to minimize interference. The algorithm also reduces traffic congestion in a cell by moving the users to less congested adjacent cells.

2.9 Handoff Protocols

There are four basic types of handoff protocols, network controlled handoff (NCHO), mobile assisted handoff (MAHO), soft handoff (SHO), and mobile controlled handoff (MCHO). Figure 2.13 shows the tradeoff associated with the handoff protocols. As the handoff decision making process is decentralized (i.e., moving from NCHO to MCHO), handoff delay (i.e., the time required to execute a handoff request) decreases, but the measurement information available to make a handoff decision also decreases. These protocols are described next.

2.9.1 Network Controlled Handoff

Introduction to Network Controlled Handoff

In network controlled handoff (NCHO) protocol, the network makes a handoff decision based on measurements of the RSSs of the MS at a number of BSs. The handoff command is sent on the voice channel by blanking the voice and sending data. Sometimes the network sets up a bridge connection between the old and new BS and thus minimizes the duration of handoff. In general, the handoff process (including data

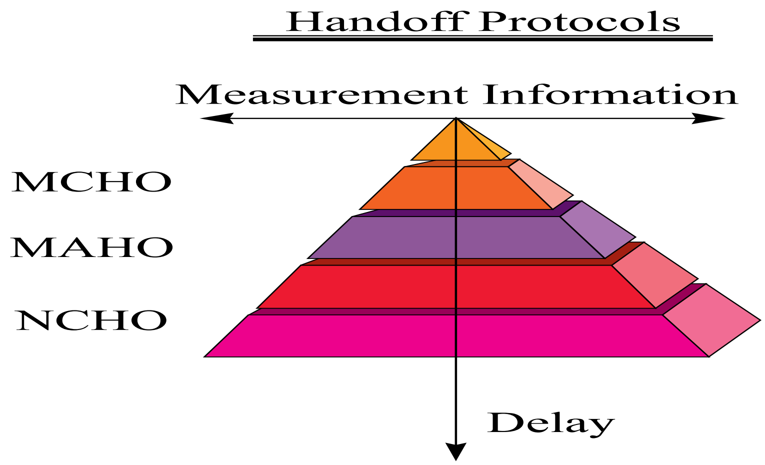

Figure 2.13: Handoff Delay and Measurement Information for Handoff Protocols

transmission, channel switching, and network switching) takes 100-200 ms and produces a noticeable click in the conversation. This click is imperceptible in a noisy voice channel; however, it is perceptible when handoff occurs at a reasonable signal quality [10]. Information about the signal quality for all users is located at a single point (the MSC). This information facilitates resource allocation. According to [83], the overall delay can be approximately five to ten seconds. This type of handoff is not suitable for a rapidly changing environment and a high density of users due to the associated delay.

Network Controlled Handoff in Practice

This type of handoff is used in first generation analog systems such as AMPS, TACS, and NMT [10]. Measurements are made only at BSs. RSSs of connected terminals are observed. SIR is measured by a supervisory audio tone (SAT). The BS transmits a tone with a frequency outside the audio range. This tone is echoed by the MS, and the BS estimates the interference from the quality of the received tone. Handoff is recognizable by the user as a clicking sound since a digital message is sent over an analog link. The measurements are made by two receivers at the BS [5]. The main receiver measures signal strengths of all its reverse voice channels. The locator receiver determines signal strengths of mobile users in neighboring cells. Based on the inputs from these receivers, the MSC decides whether handoff is necessary.

2.9.2 Mobile Assisted Handoff

Introduction to Mobile Assisted Handoff

A mobile assisted handoff (MAHO) protocol distributes the handoff decision process. The MS makes measurements, and the MSC makes decisions. According to [83], there can be a delay of one sec; this delay may be too much to counteract the corner effect.

Mobile Assisted Handoff in Practice

The TDMA/FDMA based GSM and CDMA based IS-95 standards use MAHO. Handoff related aspects of GSM are discussed here. An IS-95 based system uses SHO in conjunction with MAHO, and handoff related issues for such systems are discussed in Section 2.9.3.

In GSM, Base Station Sub-system (BSS) includes a Base Station Transceiver (BTS) and a Base Station Controller (BSC) [3]. The BTS is in contact with MSs through the radio interface and includes radio transmission and receiver devices as well as signal processing. The BSC is in contact with the network and is in charge of the radio interface management, mainly the allocation and release of radio channels and the handoff management. One BSC serves several BTSs, and several BSCs are connected to one MSC. The handoff time (the time between handoff decision and execution) in GSM is approximately one second [19]. First, handoff criteria in GSM are described. The measurement process of handoff criteria is explained. Some handoff algorithms based on GSM handoff criteria are briefly discussed. Different types of handoffs in GSM are also described.

A list of parameters used as handoff criteria in GSM is given here [3]:

- static data such as maximum transmit power of the MS, the serving BTS, and the BTSs of the neighboring cells;
- real-time measurements performed by the MS (such as the downlink transmission quality indicated by raw BER, downlink reception level on the current channel, and downlink reception levels from the neighboring cells);
- the BTS measurements (such as the uplink transmission quality quantified by raw BER, the uplink received level on the current channel, and the timing advance);
- traffic considerations, cell capacity, and load.

GSM's TDMA structure consists of traffic channels (TCHs) and a number of control channels (CCHs). Since a fixed training sequence is transmitted in a certain time slot, the receiver can estimate its BER [11]. The BTS also measures the interference level on idle traffic channels. Measurement of the BTS-MS distance is an optional feature. The values measured by the MS are averaged and transmitted once in 480 ms over the SACCH (Slow Associated Control Channel) to the BTS. The BTS algorithm processes the thirty-two most recent measurements. The operators and manufacturers have complete freedom to implement their own handoff algorithms based on available parameters. According to [53], most manufacturers have designed their handoff algorithms based on signal strength. In this case, BER and the timing advance can act as alarm condition indicators rather than handoff algorithm inputs. Handoff to a different time slot on the same frequency channel is made for interference control reasons [84].

In GSM, handoff can be internal or external. If the serving and target BTSs are located within the same BSS, the BSC for the BSS can perform handoff without the involvement of the MSC. This is referred to as *intra-BSS handoff*. In an external handoff, the MSC coordinates the handoff. This type of handoff can further be classified as *intra-MSC* (within the same MSC) and *inter-MSC* (between MSCs) [9].

GSM based handoff algorithms are evaluated in [11, 32, 52, 53]. Reference [53] is of particular interest and describes a GSM-based handoff algorithm. The MS measures the RSS of the serving BS and the neighboring BSs through Slow Associated Control CHannel (SACCH) every 480 ms. These measurements are averaged over a certain period of time. The averaged signal strength is compared with the threshold level. The MS also ranks the neighboring cells according to the magnitude of their RSSs. It compares the power budget criterion with the handover margin that helps avoid unnecessary handoffs. When the power budget criterion is met, a handoff is made to the top ranking neighboring cell if the RSS from that candidate cell is above the threshold level. The threshold value prevents handoff at low signal levels.

2.9.3 Soft Handoff

Introduction to Soft Handoff

Soft handoff (SHO) is a "make before break" connection, i.e., the connection to the old BS is not broken until a connection to the new BS is made. SHO utilizes the technique of macroscopic diversity. Macroscopic diversity is a technique in which transmissions from an MS are received at different BSs and then used to obtain a good quality communication link [85]. The same concept can be used at the MS too. Macroscopic diversity is based on the principle of diversity combining that assumes that different BSs transmit and receive the same call with uncorrelated signal paths. Macroscopic diversity can provide good performance in terms of RSS and SIR for an interference limited system. Interference limited systems can exploit spatial diversity in the form of soft handoff. Macroscopic diversity is a form of spatial diversity and uses signals from several BSs to mitigate the effect of shadow fading (signal strength variations caused by buildings, foliage, and terrain features). It is shown in [86] that a four-branch macroscopic diversity can provide a 13 dB improvement in RSS and a 15 dB improvement in SIR (for a path loss exponent of 4 and a 10 dB shadow fading standard deviation).

Some of the diversity combining techniques include *selection diversity*, *maximum ratio combining*, and *equal gain combining* [85]. In *selection diversity*, the signal with the strongest SNR is selected. *Maximum ratio combining* uses co-phased signals within each receiver, and each signal is given a weighting factor according to its SNR before summation of the signals. *Equal gain combining* gives equal weightage to all the signals before summation.

The MSs must decode the signals from all base stations, which may be using the same or different channels. Such handoffs are called single channel SHO (SCSHO) and multiple channel SHO (MCSHO), respectively [83].

- **Single Channel SHO (SCSHO)**. In this type of SHO, each participating base station transmits on the same channel. For high traffic situations, SCSHO may suffice.
- **Multichannel SHO (MCSHO)**. In this type of SHO, participating BSs use different channels. The mobile receiver decodes the signals on these orthogonal channels and achieves macroscopic diversity through diversity combining techniques. In general, signal quality will be better for MCSHO than SCSHO since

the receiver has more degrees of freedom. However, at high traffic intensities, the MCSHO handoff scheme may not be feasible due to the unavailability of channels.

Reference [83] investigates the effect of simulcasting in macrocellular and microcellular systems. Simulcasting is an example of SHO in which the MS is simultaneously connected to several BSs in the border region between the cells. The BSs participating in SHO simulcast (i.e., simultaneously transmit) replicas of the same signal to the MS.

There are several variations of SHO. The term *soft handoff* is used when old and new BSs belong to two different cells. The term *softer handoff* is used when the two signals correspond to the two different sectors of a sectorized cell [87]. When soft and softer handoffs occur simultaneously, the term *soft-softer handoff* is used. As far as the MS is concerned, there is no difference between SHO and softer handoff. For the network, additional hardware overhead is required for soft handoff. One channel element hardware and one BS-to-MSC trunk are required for each cell involved in SHO. Additional frame-by-frame selection diversity is also required at the switch. No additional hardware is required for softer handoff since the channel hardware can be configured to transmit signal to multiple sector antennas and use diversity combining techniques to process the signals from multiple sector antennas. The handoff threshold needs to be small enough to bound the overall SHO percentage but large enough to allow efficient diversity combining. The MS needs more than one demodulator to exploit diversity combining techniques.

SHO can increase the capacity if exercised carefully. SHO increases the signal energy, enhancing the robustness to combat interference. This can lead to the reduction in the channel reuse distance, thereby increasing the capacity. However, SHO increases the level of cochannel interference and forces an increase in channel reuse distance, thereby reducing the system capacity. There is a tradeoff between these two conflicting factors. SHO has an advantage of changing SIR distribution. The MSs far from the base station receive more signal energy, and this reduces outage probability. Another advantage of SHO, increased signal energy reduces the switching of the call between the BSs. This reduces the computational load. In particular, proper selection of the SHO region and its associated parameters can avoid the ping-pong effect common in hard handoff [85]. A disadvantage of SHO, the mobile undergoing SHO occupies channels between different BSs and the switch (MSC). Moreover, SHO tends to increase the traffic in the wired channels in a fixed network. The greater the number of BSs involved in SHO, the more traffic in the fixed network. Also, SHO requires an MS receiver capable of decoding multiple copies of the transmitted signal.

Soft Handoff in Practice

SHOs are common in CDMA. For IS-95, the BSs involved in SHO can transmit on the same frequency and Walsh code, and the resultant signals are handled by the receiver as additional multipaths to be incorporated into the decoded signal [9]. SHOs are imperceptible to users and require a tight synchronization between all BSs in the network to maintain data synchronization after handoff. The CDMA systems support this function by using the global positioning system (GPS) to provide a master clock. The IS-136 TDMA system does not currently support this function. Hard handoff is a normal procedure for analog cellular systems. TDMA systems typically use hard handoff unless synchronization between the BSs is available. CDMA systems forced to handoff to a different Walsh function or different frequency use hard handoff. The resultant break in connection causes speech and data to be lost; this hard handoff is perceptible to users and is a a major research issue for CDMA.

In CDMA, the MS need not switch frequencies due to handoff. The candidate BS communicates with the MS that is still connected to the old BS. The MS can switch back and forth between the two BSs. After the MS is firmly established in the new cell, the original BS disconnects the MS. Thus, CDMA based handoff provides a make-before-break switching function. After a call is initiated, the MS scans the pilots of the neighboring cells. When the MS finds the pilot signal greater than the pilot of the current cell, it initiates a handoff. The system controller assigns a modem located in the candidate cell-site to the handoff call, and the PN address of the call is given to the modem. Each modem has digital modulator and digital data receiver functions. The candidate modem finds the MS's signal and transmits the outband signal to the MS, which can switch over to the new signal after finding this signal. The system controller connects the call to the new cell and makes the old cell modem available for reassignment. This is a simple mode of handoff operation. In another mode, called diversity mode, two or more BSs demodulate the data signal from the MS. The BSs forward the demodulated signal and associated signal quality indicator to the signal controller. The system controller selects the signal with the best quality and transmits it to a proper location. It is possible for BSs to transmit undecoded or even undemodulated signals to the system controller so that a better diversity combining process can be used. The MS also performs diversity combining of the signals received from the BSs. The cell diversity mode is terminated when only one BS can provide a good quality signal. The cellular diversity mode may also be terminated if the system is overloaded and there are insufficient modems.

2.9.4 Mobile Controlled Handoff

In mobile controlled handoff (MCHO), the MS is completely in control of the handoff process. This type of handoff has a short reaction time (on the order of 0.1 sec) and is suitable for microcellular system [83]. The MS does not have information about the signal quality of other users, and yet handoff must not cause interference to other users. The MS measures the signal strengths from surrounding base stations and interference levels on all channels. A handoff can be initiated if the signal strength of the serving base station is lower than that of another base station by a certain threshold. The MS requests the target BS for a channel with the lowest interference.

The MCHO is the highest degree of handoff decentralization. Advantages of decentralization of handoff, handoff decisions can be made fast, and the MSC does not have to make handoff decisions for every mobile, which is a very difficult task for the MSC of high capacity microcellular systems [88].

The MCHO is used in the European standard for cordless telephones, Digital European Cordless Telephone (DECT) [19]. The MS and the BS monitor the current channel, and the BS reports measurements (RSS and BER) to the MS. The (C/I)s of free channels are also measured. The handoff decisions are made by the MS. Both intracell and intercell handoffs are possible. The handoff time is approximately 100 ms.

2.10 Conclusion

A high performance handoff algorithm can achieve many of the desirable features by making appropriate tradeoffs. However, several factors such as topographical features, traffic variations, propagation environments, and system-specific constraints complicate the task of handoff algorithms. Different system deployment scenarios present different constraints on handoff procedure. Handoff algorithms with a specific set of parameters cannot perform uniformly well in different communication system deployment scenarios since these scenarios impose distinct restrictions and specific environments on the handoff process. These system structures are expected to co-exist in future wireless communication systems and warrant a substantial study. The issues involved in the design and analysis of handoff algorithms were thoroughly described. In particular, different handoff criteria were analyzed. Both the conventional and emerging approaches for designing handoff algorithms were discussed. Several metrics have been proposed and used to quantify the handoff related system performance. A brief account of handoff performance measures was given. Handoff prioritization can improve handoff related system performance. Two basic handoff prioritization schemes, guard channels and queuing, were discussed. Handoff represents one of the radio resource management tasks carried out by cellular systems. Other resource management functions include admission control, channel assignment, and power control. If resource management tasks are treated in an integral manner, better overall performance can be obtained to achieve global goals by making appropriate tradeoffs.

2.11 Glossary

Acronym	Full Name
AMPS	Advanced Mobile Phone System
ANN	Artificial Neural Network
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BS	Base Station
BSC	Base Station Controller
BSS	Base Station Subsystem
BTS	Base Station Transceiver System
C/I	Carrier-to-Interference Ratio
CCH	Control Channel
CCI	Co-channel Interference
CDMA	Code Division Multiple Access
CIR	Carrier-to-Interference Ratio
DCA	Dynamic Channel Assignment
DECT	Digital European Cordless Telephone
DS-CDMA	Direct Sequence CDMA
FCA	Fixed Channel Assignment
FDMA	Frequency Division Multiple Access
FIFO	First In First Out
FLCA	Flexible Channel Assignment
GEO	Geostationary Earth Orbit
GPS	Global Positioning System
GSM	Global System for Mobile
HHO	Hard Handoff
IS-95	Interim Standard-95
LCR	Level Crossing Rate
LEO	Low Earth Orbit
LOS	Line of Sight

Acronym	**Full Name**
MAHO	Mobile Assisted Handoff
MCBS	Multichannel Bandwidth System
MCHO	Mobile Controlled Handoff
MCSHO	Multi Channel Soft Handoff
MPH	Minimum Power Handoff
MS	Mobile Station
MSC	Mobile Switching Center
MTSO	Mobile Telephone Switching Office
NCHO	Network Controlled Handoff
NLOS	Non Line of Sight
NMT	Nordic Mobile Telephone
PACS	Personal Access Communication System
PBX	Private Branch Exchange
PCS	Personal Communication Services
PN	Pseudo Noise
PR	Pattern Recognition
QoS	Quality of Service
RSS	Received Signal Strength
SACCH	Slow Associated Control Channel
SAT	Supervisory Audio Tone
SCSHO	Single Channel Soft Handoff
SIR	Signal-to-Interference Ratio
SNR	Signal to Noise Ratio
TACS	Total Access Communication System
TCH	Traffic Channel
TDMA	Time Division Multiple Access

Chapter 3

Fuzzy Logic and Neural Networks

There are several tools of AI that help utilize human knowledge about the systems to develop high performance systems. Some of the major AI tools are artificial neural networks, fuzzy logic, genetic algorithms, and expert systems. This research exploits capabilities of neural networks and fuzzy logic to develop adaptive intelligent handoff algorithms.

3.1 Introduction to Fuzzy Logic

Information can be represented by numbers or linguistic descriptions. For example, *temperature* can be represented by the number 20^oF or by the linguistic description "cold." The description "cold" is fuzzy and may represent any temperature between 10^oF and 30^oF, which can be called the *fuzzy set* (or *fuzzy region*) for the fuzzy variable *temperature*. Since humans usually think in terms of linguistic descriptions, giving these descriptions some mathematical form helps exploit human knowledge. Fuzzy logic utilizes human knowledge by giving the fuzzy or linguistic descriptions a definite structure.

A concise description of fuzzy logic theory is given next. First, basic concepts of fuzzy logic are introduced. These concepts are then utilized to explain a popular form of fuzzy logic system (FLS) that can serve as a building block in a system incorporating fuzzy logic. A comprehensive theory of fuzzy logic can be found in [89].

- **Fuzzy Set**. Let U be a collection of objects and be called the *universe of discourse*. A fuzzy set $F \in U$ is characterized by a *membership function* $\mu_F(u)$:

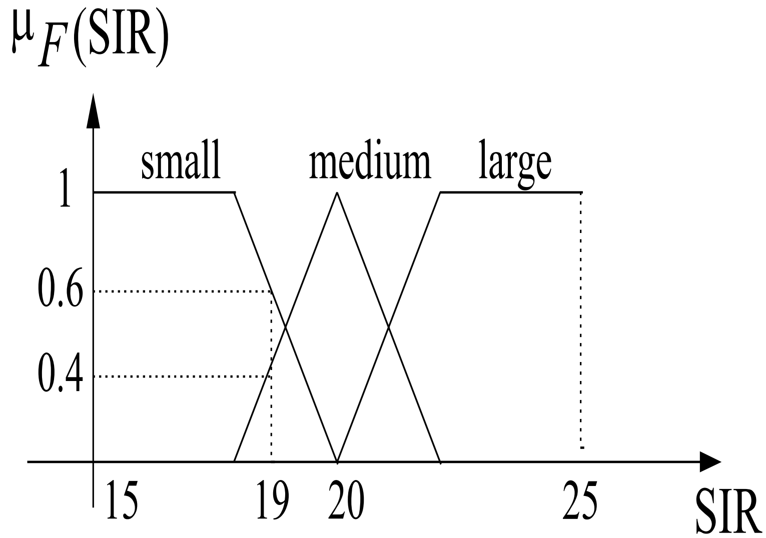

Figure 3.1: An Example of Fuzzy Logic Membership Function

$U \rightarrow [0, 1]$ where $\mu_F(u)$ represents *the degree (or grade) of membership* of $u \in U$ in the fuzzy set F.

Figure 3.1 shows the membership functions of three fuzzy sets, "small," "medium," and "large," for a fuzzy variable *SIR*. The universe of discourse is all possible values of SIRs, i.e., $U = [15, 25]$. At an SIR of 19 dB, the fuzzy set "small" has the membership value 0.6. Hence, $\mu_{small}(19) = 0.6$. Similarly, $\mu_{medium}(19) = 0.4$, and $\mu_{large}(19) = 0$.

- **Support**. The support of a fuzzy set F is the crisp set of all points $u \in U$ such that $\mu_F(u) > 0$.
- **Center**. The center of a fuzzy set F is the point (or points) $u \in U$ at which $\mu_F(u)$ achieves its maximum value.
- **T-norm**. A T-norm, denoted by *, is a two-place function from $[0, 1] \times [0, 1]$ to $[0, 1]$, which includes *fuzzy intersection*, *algebraic product*, *drastic product*, and *bounded product*, defined as

$$x * y = min(x, y)(\text{fuzzy intersection}) \tag{3.1}$$

$$x * y = xy(\text{algebraic product}) \tag{3.2}$$

$$x * y = \begin{cases} x & : \quad y = 1 \\ y & : \quad x = 1 \\ 0 & : \quad x, y < 1 \end{cases} \quad (\text{drastic product}) \tag{3.3}$$

$$x * y = max(0, x + y - 1)(\text{bounded product}) \tag{3.4}$$

where $x, y \in [0, 1]$.

- **Fuzzy Relation**. Let U and V be two universes of discourse. A fuzzy relation R is a fuzzy set in the product space $U \times V$, i.e., R has the membership function $\mu_R(u, v)$ where $u \in U$ and $v \in V$.

- **Sup-Star Composition**. Let R and S be fuzzy relations in $U \times V$ and $V \times W$, respectively. The sup-star composition of R and S is a fuzzy relation denoted by RoS and is given by

$$\mu_{RoS}(u, w) = sup_{v \in V}[\mu_R(u, v) * \mu_S(v, w)] \tag{3.5}$$

  where $u \in U$, $w \in W$, and * could be any operator in the T-norm defined earlier. It is clear that RoS is a fuzzy set in $U \times W$.

- **Fuzzy Implications**. Let A and B be fuzzy sets in U and V, respectively. A fuzzy implication, denoted by $A \to B$, is a special kind of fuzzy relation in $U \times V$ with the following membership function:

$$\mu_{A \to B}(u, v) = \mu_A(u) * \mu_B(v). \tag{3.6}$$

  This fuzzy implication is known as *fuzzy conjunction*. Other types of fuzzy implications are also available [89].

Some of the popular FLS configurations include pure FLS, Takagi and Sugeno's fuzzy system, and Mamdani's fuzzy system [89]. The components of the FLS proposed by Mamdani [90] are fuzzifier, fuzzy rule base, fuzzy inference engine, and defuzzifier as shown in Figure 3.2. This configuration of the FLS has been widely used in industrial applications and consumer products. This FLS configuration has the following advantages compared to other FLSs [89].

- This FLS has real-valued variables as its inputs and outputs, which is suitable for engineering applications where measured variables are real-valued and not fuzzy. (Pure FLSs require fuzzy variables as inputs.)

- This FLS provides a common framework, a rule base, for incorporating fuzzy IF-THEN rules to exploit human knowledge.

- This FLS allows several degrees of freedom in the selection of different components of the FLS.

- This FLS allows fusion of numerical information and linguistic information. For example, numerical information (e.g., measurements) can be used to train the FLS to derive an adaptive FLS.

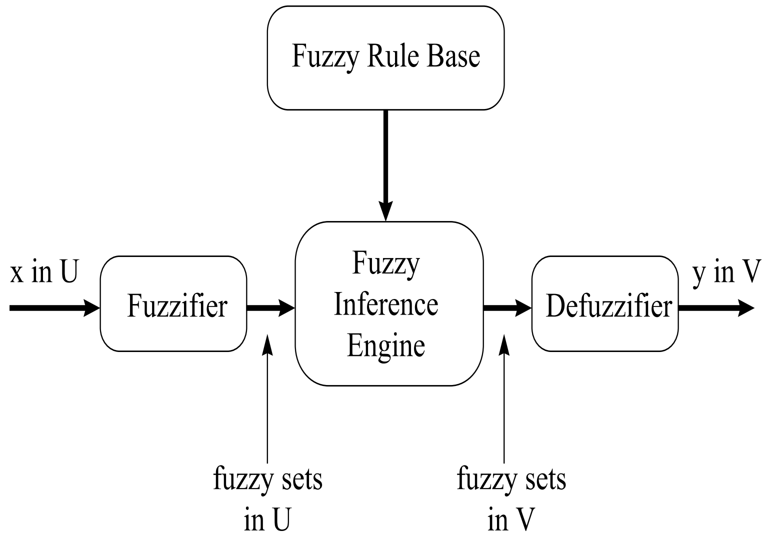

Figure 3.2: An Example of Fuzzy Logic System

The components of the Mamdani FLS are described next.

- **Fuzzifier**. The fuzzifier maps a crisp point, $\underline{x} = [x_1, x_2, ..., x_n]^T \in U$, into a fuzzy set A' in U. Two choices for the fuzzifier forms are *singleton fuzzifier* and *nonsingleton fuzzifier*.

  Singleton Fuzzifier. A' is a fuzzy singleton with support $\underline{x}$, i.e., $\mu_{A'}(\underline{x}') = 1$ for $\underline{x}' = \underline{x}$ and $\mu_{A'}(\underline{x}') = 0$ for all other $\underline{x}' \in U$ with $\underline{x}' \neq \underline{x}$.

  Nonsingleton Fuzzifier. For this fuzzifier, $\mu_{A'}(\underline{x}') = 1$, and $\mu_{A'}(\underline{x}')$ decreases from 1 as $\underline{x}'$ moves away from $\underline{x}$. For example, $\mu_{A'}(\underline{x}') = \exp(-\frac{(\underline{x}'-\underline{x})^T(\underline{x}'-\underline{x})}{\sigma^2})$ where σ is a parameter characterizing the shape of $\mu_{A'}(\underline{x}')$ and T is a transpose operation.

- **Fuzzy Rule Base**. A fuzzy rule base consists of a collection of fuzzy IF-THEN rules. A typical form is shown here:

  $$R^{(l)}: \text{ IF } x_1 \text{ is } F_1^l \text{ and ... and } x_n \text{ is } F_n^l, \text{ THEN } y \text{ is } G^l \tag{3.7}$$

  where F_i^l and G^l are fuzzy sets in $U_i \subset R$ and $V \subset R$, respectively, and where $\underline{x} = [x_1, x_2, ..., x_n]^T \in U_1 \times U_2 \times ... \times U_n$ and $y \in V$ are linguistic variables. Here, l ranges from 1 to M with M representing the total number of rules.

  Let a fuzzy rule be expressed as " IF X is A, then Y is B" where X is the input fuzzy variable, Y is the output fuzzy variable, and A and B are corresponding fuzzy (linguistic) sets. A and B can be "small" and "big" respectively. The "IF" clause of the rule is called the *antecedent*, and the "THEN" clause the *consequent*. Each antecedent and consequent in a fuzzy logic rule forms a membership function that can be of different shapes, triangular and Gaussian shapes being more popular. Each input or output fuzzy variable has a membership degree of unity at the center value of the corresponding fuzzy set. Assume that the support of the fuzzy set A is between ten and thirty, and that twenty is the center value of the membership function for the fuzzy set A. Then, the input fuzzy variable X has a membership degree of unity with set A when X is twenty.

- **Fuzzy Inference Engine**. In the fuzzy inference engine, fuzzy logic principles are used to combine the fuzzy IF-THEN rules in the fuzzy rule base, and fuzzy sets in $U = U_1 \times U_2 \times ... \times U_n$ are mapped into fuzzy sets in V. A fuzzy rule is interpreted as a fuzzy implication $F_1^l \times ... \times F_n^l \rightarrow G^l$ in $U \times V$. Let a fuzzy set $A' \in U$ be the input to the fuzzy inference engine. Then, each fuzzy IF-THEN rule determines a fuzzy set $B^l \in V$ using the sup-star composition:

$$\mu_{B^l}(u, w) = sup_{\underline{x} \in U}[\mu_{F_1^l \times ... \times F_n^l \rightarrow G^l}(\underline{x}, y) * \mu_{A'}(\underline{x})]. \tag{3.8}$$

Let $F_1^l \times ... \times F_n^l = A$ and $G^l = B$.

There are different interpretations for a fuzzy implication, and there are different T-norms as defined earlier. Hence, the above equation can be interpreted in a number of ways. One interpretation, called the *product-operation rule*, is shown here:

$$\mu_{A \rightarrow B}(u, v) = \mu_A(\underline{x}) * \mu_B(y). \tag{3.9}$$

This interpretation follows from the *fuzzy conjunction implication* by using the algebraic product for *.

Overall mapping of the fuzzy inference engine is described next. For an input A' (a fuzzy set in U), the output of the fuzzy inference engine can take two forms: (1) M fuzzy sets B^l $(l = 1, 2, ..., M)$ as in Eq. 3.8 with each one determined by one fuzzy IF-THEN rule as in Eq. 3.7, (2) one fuzzy set B', which is the union of the M fuzzy sets B^l. Thus,

$$\mu_{B'}(y) = \mu_{B^1}(y) \bigcup ... \bigcup \mu_{B^M}(y). \tag{3.10}$$

- **Defuzzifier**. The defuzzifier maps fuzzy sets in V into a crisp point, $y \in V$. One of the choices for the defuzzifier is center average defuzzifier, defined as

$$y = \frac{\sum_{l=1}^{M} \overline{y}^l(\mu_{B^l}(\overline{y}^l))}{\sum_{l=1}^{M}(\mu_{B^l}(\overline{y})^l))} \tag{3.11}$$

where $\overline{y}^l$ is the center of the fuzzy set G^l, i.e., the point in V at which $\mu_{G^l}(y)$ achieves its maximum value, and $\mu_{B^l}(\overline{y}^l)$ is given by Eq. 3.5.

3.2 Introduction to Neural Networks

Recently, artificial neural networks (ANNs) have been applied to many diverse problems. ANNs are one tool of artificial intelligence (AI) (others include fuzzy logic, genetic algorithms, and expert systems). *An ANN is a massively parallel distributed processor that stores experimental knowledge; this knowledge is acquired by a learning process and is stored in the form of parameters of the ANN* [91]. Characteristics of ANNs are massively parallel distributed architecture, ability to learn and generalize, fault tolerance, nonlinearity, and adaptivity. The learning in ANNs can be *unsupervised* or *supervised*. When an ANN undergoes learning in an *unsupervised manner*, it extracts the features from the input data based on a predetermined performance measure. When an ANN undergoes learning in a *supervised manner*, it is presented with the input patterns and the desired output patterns. The parameters of the ANN are adapted such that the application of an input pattern results in the desired pattern at the output of the ANN.

First, a fundamental component of the ANN, an artificial neuron, is explained. Using the model of the artificial neuron, two ANN architectures (or paradigms), multilayer perceptron (MLP) and radial basis function network (RBFN), are explained. A procedure for using these ANN paradigms for function approximation is outlined. *Note that the specific task of interest is to map the inputs of the FLS to the outputs of the FLS, and this mapping problem can be viewed as a function approximation problem.* The MLP and RBFN have been proven to be universal approximators [91], and hence they are used here to approximate the functional mapping between the FLS inputs and outputs.

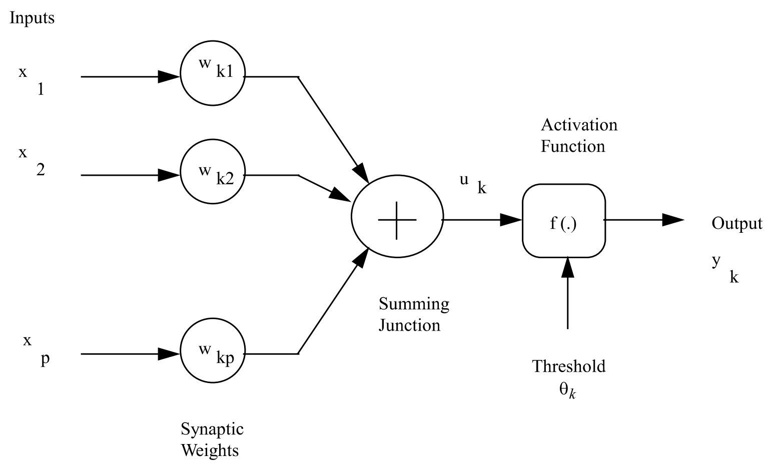

Figure 3.3: A Nonlinear Model of an Artificial Neuron

3.2.1 Fundamentals of ANNs

The ANN consists of a number of neurons arranged in a particular fashion. A nonlinear model of the artificial neuron is shown in Figure 3.3. The three basic elements of a neuron are *the synaptic weights* (or *weights*), *the summing junction*, and *the activation function* (Figure 3.3). Different activation functions include hard limit, linear, log-sig, and tan-sig. Threshold θ_k shown in Figure 3.3 can be considered as one of the weights with -1 as input. The *weights* and *threshold* (also known as *bias*) are referred to as *parameters* of the neuron. The activation functions can be used with or without the bias. Usually, the ANN consists of more than one neuron. The output of a neuron k is given by the following two equations:

$$u_k = \sum_{j=1}^{p} w_{kj} x_j \tag{3.12}$$

$$y_k = f(u_k - \theta_k) \tag{3.13}$$

where $x_j (j = 1, ..., p)$ are the inputs, $w_{kj} (j = 1, ..., p)$ are weights, θ_k is the threshold, $f(.)$ is the activation function, and y_k is the output of the neuron.

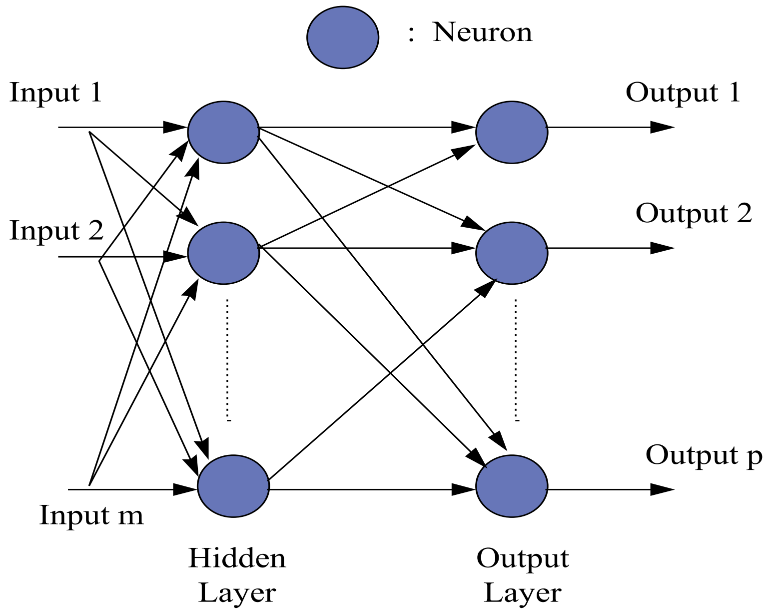

Figure 3.4: A Multilayer Perceptron

3.2.2 Paradigms of ANNs

Two paradigms of ANNs, MLP and RBFN, are briefly discussed next.

Two-layer Perceptron

Figure 3.4 shows a two-layer perceptron. Typically, the input layer is not counted as a separate layer since it does not do any processing. The first layer is called hidden layer, and it consists of several artificial neurons. The output layer consists of several neurons (equal to the number of outputs). An MLP can be trained in a supervised manner by a very popular algorithm called the *backpropagation algorithm*. The training of an ANN requires a training data set that consists of input patterns and the desired output patterns. The backpropagation algorithm can be used to change the parameters of perceptron to minimize the difference between the desired outputs (for given input patterns) and the actual outputs of the network. Details of the backpropagation algorithm can be found in [91]. The basic idea of the algorithm is explained here. The backpropagation algorithm consists of two distinct passes through the layers of the network, *a forward pass* and *a backward pass*. In the *forward pass*, an input pattern is applied to the input layer of the network, and it is processed by the parameters of the network. This produces a pattern at the output of the network. The output pattern is compared with the desired output pattern, and the error is calculated. In the *backward pass*, this error is propagated backward through the network, and the parameters of the network are modified by distributing this error among the parameters of the network. The forward and backward passes are made several times for all the training patterns. Gradually, the network begins to produce output patterns that resemble those desired. A basic backpropagation algorithm is very slow in convergence due to the requirements of small learning rates for stable learning. However, there are several techniques that can improve the speed and performance of the backpropagation algorithm, including *Nguyen-Widrow weight initialization*, *use of momentum*, and *adaptive learning rate*. It is shown in [92] that the weights generated with certain constraints result in a better function approximation. Use of Nguyen-Widrow initial conditions rather than random initial weights often reduces the training time by an order of magnitude. Momentum helps the network avoid getting stuck in shallow minima and leads to a better solution. Momentum can be included in the backpropagation algorithm by making the weight changes equal to the sum of a fraction (e.g., 0.95) of the last weight change and the new change suggested by the backpropagation learning rule. Thus, momentum allows a network to respond to both the local gradient and the recent trends in the error surface. Momentum allows the network to ignore small features in the error surface. An adaptive learning rate mechanism keeps the learning rate as high as possible while keeping the learning stable. The learning rate is adjusted based on the error performance.

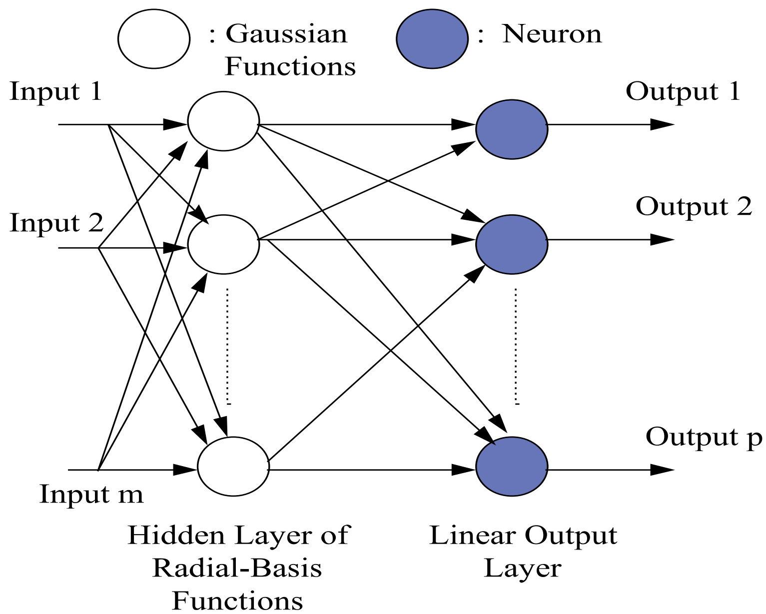

Figure 3.5: A Radial Basis Function Network

This research utilizes a two-layer perceptron with tan-sig activation functions in the hidden layer and linear activation functions in the output layer. The Neural Network Toolbox of MATLAB is used to train the two-layer perceptron.

Radial-Basis Function Network (RBFN)

The RBFN consists of three different layers, an input layer, a hidden layer, and an output layer as shown in Figure 3.5. The input layer acts as an entry point for the input vector; no processing takes place in the input layer. The hidden layer consists of several Gaussian functions that constitute arbitrary basis functions (called *radial-basis functions*); these basis functions expand the input pattern onto the hidden layer space. This transformation from the input space to the hidden layer space is nonlinear due to nonlinear radial-basis functions. The output layer linearly combines the hidden layer responses to produce an output pattern. The rationale behind the working of the

RBFN, a pattern-classification problem expressed in a high-dimensional space is more likely to be linearly separable than in a lower-dimensional space. The parameters of the RBFN are linear weights (in the output layer) and the positions and spreads of the Gaussian functions. A complete learning procedure can be found in [91]. Basically, in a supervised learning mode, these RBFN parameters are changed according to a gradient descent procedure that represents a generalization of the least-mean-squares (LMS) algorithm.

Two distinct phases of learning in the RBFN are selection of centers of the radial basis functions and determination of linear weights. Some of the methods for the selection of RBF centers are random selection (based on the training patterns), unsupervised selection, and supervised selection. Some of the methods for linear weight determination are pseudo-inverse memory and LMS algorithm. These weight determination methods find a mapping between the hidden unit space and the output layer. This research utilizes a three-layer RBFN. The Neural Network Toolbox of MATLAB is used to train the RBFN.

3.3 Conclusion

The tools of AI, such as neural networks and fuzzy logic, possess certain useful features such as nonlinearity, massive parallelism, learning capability, and human knowledge encoding capability. In particular, this research uses a full-fledged fuzzy logic system proposed by Mamdani. Two paradigms of neural networks, a multilayer perceptron and a radial basis function network, are utilized in this research.

Chapter 4

Analysis of Handoff Algorithms

The performance analysis of handoff algorithms consists of two aspects, the performance metrics (or performance measures) and performance evaluation mechanisms. The performance metrics quantify the performance of handoff algorithms. The evaluation mechanisms provide a means to collect statistics of performance metrics. Several performance metrics appearing in and proposed in the literature are defined. Three major handoff evaluation mechanisms (analytical, simulation, and emulation) are briefly discussed. Basic constituents of simulation mechanisms are explained. Simulation models used and developed for this research are described. Existing simulation models for macrocellular and microcellular algorithms are enhanced by considering several significant aspects of cellular systems. Simulation models that provide good insight into the behavior of soft handoff and overlay algorithms are proposed.

4.1 Handoff Performance Measures

Figure 4.1 depicts the handoff analysis procedure, which consists of two major components, performance evaluation mechanisms and performance metrics. Many perfor-

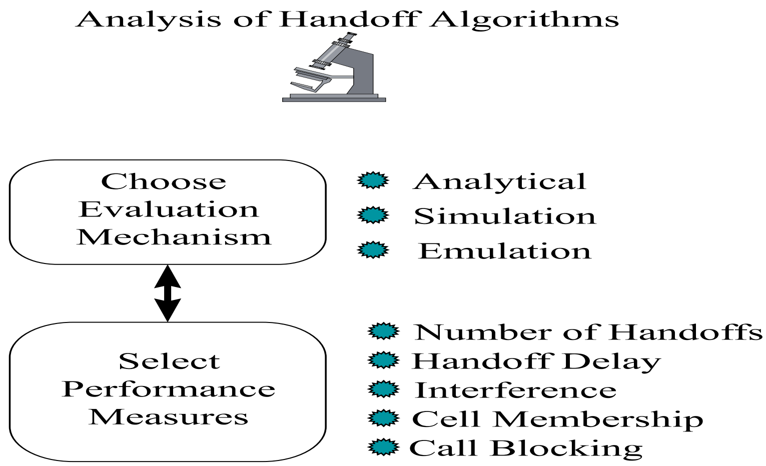

Figure 4.1: Procedure for the Analysis of Handoff Algorithms

mance measures have been proposed and used to evaluate the handoff related system performance [4] [7] [11] [60].

- **Call blocking probability** is the probability that a new call attempt is blocked. Some handoff prioritization schemes sacrifice this measure to obtain better handoff performance.

- **Handoff blocking probability** is the probability that a handoff attempt is blocked. This measure is highly dependent on the channel assignment strategy adopted in a system.

- **Handoff probability** is the probability that a handoff is made during a call. Appropriate handoffs should be made, while unnecessary handoffs should be avoided.

- **Call dropping probability** is the probability that an ongoing call is prematurely terminated. Proper handoffs can reduce the call dropping probability.

- **Probability of an unnecessary handoff** is the probability that a handoff is made despite an acceptable quality of the ongoing call. A handoff algorithm should try to minimize this measure.

- **Handoff rate** is the number of handoffs per unit of time. Higher handoff rate leads to high processing load, which can have a detrimental effect on the system performance, particularly at high traffic intensities.

- **Duration of interruption** is the time duration for which the MS is not connected to any BS [17].

- **Delay** is the time interval between the initiation of a handoff request and the execution of the handoff request.
- **Interference probability** is the probability that the carrier-to-interference ratio (C/R) is less than the protection ratio [14]. Small interference probability leads to better spectrum efficiency. The cluster size in a cellular system is primarily determined by the average interference probability.
- **Assignment probability** is the probability that the MS is connected to a particular BS [14]). This measure can give an idea about the interference caused by handoffs and the preservation of the planned cellular borders.

Some of these performance indices are dependent on channel allocation strategies and not the handoff algorithm alone (e.g., call blocking probability, handoff blocking probability). Some performance metrics may not be easily measurable in a given simulation model. In such cases, it is possible to infer a performance metric based on some other indirect measure. For example, call blocking probability and handoff blocking probability can be inferred from the CDF (cumulative distribution function) of traffic (i.e., number of calls in a cell) if a simulation model does not explicitly give these probabilities. The average number of handoffs made during a travel can give an idea about the handoff probability. CDFs of RSS and SIR can give an indication of the call dropping probability.

4.2 Handoff Evaluation Mechanisms

Three basic mechanisms used to evaluate the performance of handoff algorithms include the analytical approach, the simulation approach, and the emulation approach.

4.2.1 Analytical Approach

This approach can quickly give a preliminary idea about the performance of some handoff algorithms for simplified handoff scenarios. This approach is valid only under specified constraints (e.g., assumptions about the RSS profiles). Actual handoff procedures are quite complicated, and they are not memoryless. This makes the analytical approach less realistic. Real world situations make this approach complex and mathematically intractable. Some of the analytical approaches appearing in the literature are briefly touched upon below.

In [51], the level crossings of the difference between the RSSs from two BSs were modeled as Poisson processes for stationary signal strength measurements. In [93], this analytical work was extended to nonstationary signal strength measurements, and the level crossings were modeled as Poisson processes with time-varying rate functions. The results in [51] and [93] are useful for determining the averaging interval and hysteresis level to achieve an optimum balance between the number of unnecessary handoffs and the delay in handoff for a simplified scenario in which an MS travels along a straight line from one BS to another at a constant velocity. Reference [94] incorporates the effect of CCI in the signal strength based handoff algorithm analysis presented in [51]. Reference [54] develops an analytical model for analyzing performance of handoff algorithms based on both absolute and relative signal strength measurements and compares analytical results with simulation results.

Reference [88] derives bounds for some performance measures and gives analytical expressions for the performance measures for a particular (linear) class of algorithms. Linear handoff algorithms do not use hysteresis and use only one quality measure (i.e., signal strength).

The effect of handoff techniques on cell coverage and reverse link capacity for a spread spectrum CDMA system is investigated in [95]. The paper shows that SHO increases both the cell coverage and reverse link capacity significantly compared to conventional hard handoff and derives quantitative performance improvement measures for cell coverage and capacity of the reverse link.

In [96], prioritized handoff schemes have been analyzed. It was assumed that the probability density function (pdf) of the speeds of cell-crossing terminals is the same as the pdf of the terminal speeds in cells. Reference [97] derives a more precise pdf using biased sampling in boundaries. The resultant analysis is computationally less complex and more accurate compared to the approach in [96].

An analytical model is proposed in [98] to study the traffic performance of a microcell/macrocell overlay for a PCS architecture. If a call cannot be served by a microcell, it is connected to a macrocell. The call is blocked if no channel is available in the macrocell. The overflow traffic to the overlay macrocell is computed. The residual time distribution for a macrocell is derived based on the assumed residual time distribution for a macrocell. The call termination probability for the macrocell is computed using the overflow traffic as input.

Reference [99] presents teletraffic performance of a highway microcellular system with a macrocell overlay, assuming a TDMA scheme with 10 channels per carrier and one carrier per BS. The teletraffic analysis assumes that the mobile speeds follow truncated Gaussian distribution. The probability of new call blocking and handoff call forced termination have been evaluated for three scenarios: when no priority is given to any MS, when priority is given to handoff calls, and when a macrocell overlay makes channels available to transfer calls from the MSs that would be blocked during a microcellular handoff.

The teletraffic analysis of a hierarchical cellular network (in which umbrella cells accept handoff requests that cannot be managed by microcells) is the focus of [100].

The handoff flow from a microcell to a macrocell is modeled as a Markov modulated Poisson process, and call blocking and call dropping probabilities are calculated.

4.2.2 Simulation Approach

The simulation approach is the most commonly used handoff evaluation mechanism. Several simulation models suitable for evaluation of different types of handoff algorithms under different deployment scenarios have been proposed and used in the literature. Usually, the analytical studies of handoff algorithms consider handoff between two BSs. However, the simulation approach allows incorporation of many features of a cellular system and a cellular environment into the evaluation framework. This approach provides a common testbed for comparison of different handoff algorithms. This approach also provides insight into the behavior of the system [4]. Despite being cost-effective, measurements made at the BSs for handoff performance evaluation are not very useful since they cannot characterize small area performance. Field measurements are useful, but they are time-consuming and expensive. Software simulation provides fast, easy, and cost-effective evaluation. Simulation models usually consist of one or more of the following components: cell model, propagation model, traffic model, and mobility model. These components are described first, and specific simulation models are discussed next. Figure 4.2 shows the components of a typical simulation model.

Basic Components of Simulation Models

- **Cell Model**. Cell planning strategies differ in microcells and macrocells, which can be considered as circles while considering handoff between two BSs in a neighborhood of two, three, or four cells. A macrocellular system is sometimes simulated as a 49-cell toroidal system that has seven-cell clusters with uniformly

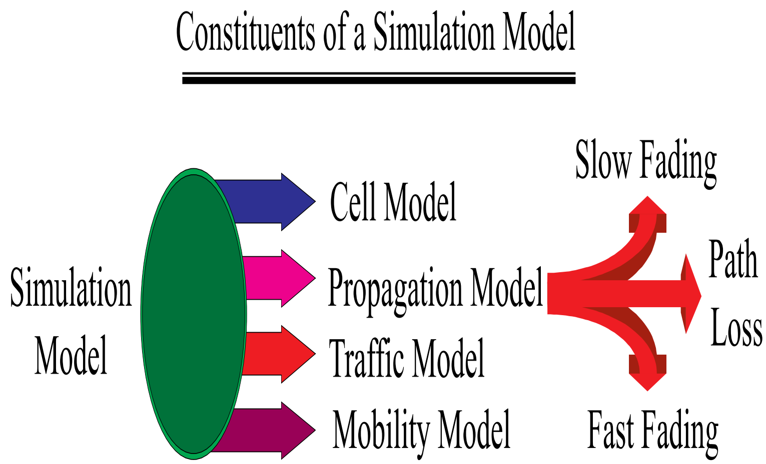

Figure 4.2: Simulation Model Components

distributed traffic. Reference [27] discusses microcell cell planning in Manhattan environment. The city is modeled as a chessboard with squares representing blocks and streets being located between the blocks. Different cell plans described in Section 2.3.2 can be used to simulate a microcellular environment.

- **Propagation Model**. The performance of wireless communication systems depends on the mobile radio channel significantly. The radio wave propagates through the mobile radio channel through different mechanisms such as reflection, diffraction, and scattering. Propagation models predict the average signal strength and its variability at a given distance from the transmitter. Different propagation models exist for outdoor and indoor propagation and for different types of environments (such as urban or rural)[5]. Macrocells and microcells have different propagation characteristics. Reference [101] presents signal attenuation measurements for microcells and shows that the conventional propagation models (e.g., Hata and Okumura models) are not valid for a microcell environment. The 900 MHz and 1.8 GHz signal attenuation measurements were carried out for BS antenna heights ranging from 5m to 20m and an MS antenna height of 1.5m in Melbourne, Australia. The main features of the models discussed here have been experimentally validated in the literature. For example, reference [102] suggests path loss, large-scale fading, and small-scale fading models for a microcellular system based on actual measurements. Reference [103] describes computer models of Rayleigh, Rician, log-normal, and land mobile satellite fading channels based on processing of a white Gaussian random process. The *propagation model* usually consists of a *path loss model*, a *large-scale fading model*, and a *small-scale fading model*.

  Path Loss Model.

In macrocells, the path loss model is used for several aspects of cell planning such as BS placement, cell sizing, and frequency reuse [15]. The path loss models of Hata and Okumura can be used for macrocells. Microcells have different models for LOS and NLOS propagation.

For an *LOS propagation*, two frequently used models are a *flat earth model* and a *two slope model*. In the *flat-earth model*, one direct ray and another reflected ray (with 180 degree phase shift) contribute to the total received E-field. In Reference [102], an empirical path loss model, a *two slope model*, is suggested. The path loss increases with a certain slope to a threshold distance (called a *breakpoint*) and then increases with a higher slope. In reality, wave propagation in microcells is complicated and consists of reflections and diffractions in addition to free space propagation. However, the main features of path loss can still be described by these empirical models. For certain parameter settings, the two slope path loss model approaches the flat-earth model.

For an *NLOS propagation*, a LOS propagation is assumed to the street corner. After the corner, propagation path loss is calculated by placing an imaginary transmitter at the corner with the transmit power equaled to the power received at the corner from the LOS BS.

Large-Scale Fading Model.

According to [102], the distribution of the large scale fading component is close to a log-normal distribution for a majority of LOS and NLOS streets with different standard deviations. The distribution is actually a truncated log-normally distributed variation. In simulations, the variation should not be greater than $\pm 3\ \sigma$. For the measurements obtained in Reference [102], the average value of σ was found to be 4 dB for LOS streets and 3.5 dB for NLOS streets.

Reference [66] proposes an exponential autocorrelation model for shadow fading in mobile radio channels. The results show that the model fit is good for moderate and large cells; the predictions are less accurate for microcells due to multipath.

Small-Scale Fading Model.

Small-scale (or short term) fading is usually modeled as a Rician distribution where parameter K (Rice factor) varies with distance. When K=0, the variation is Rayleigh fading. Reference [102] suggests a small scale fading model in terms of polynomials based on the Rician distribution. Small-scale fading is neglected since it gets averaged out due to short correlation distance relative to that of shadow fading.

- **Traffic Model**. Traffic can be assumed to be uniform for macrocells. However, road structures need to be considered for microcells, and traffic can be allowed only along the streets. The new call arrival process is modeled as an independent

Poisson process with a certain mean arrival rate. The new call durations are independent exponential random variables with a certain mean.

- **Mobility model**. The MSs have different velocities following a truncated Gaussian distribution. The MS velocity is typically assumed to be constant throughout the call.

Specific Simulation Models

A brief account of widely used simulation models is given here.

References [93, 51, 63, 88, 62, 12] use a two-BS model that is simple and widely used for evaluating signal strength based algorithms. This model is suitable for small size macrocells and LOS handoffs in microcells. In this model, an MS travels from one BS to another in a straight line at a constant velocity. The path loss is calculated using a single slope formula, and shadow fading is assumed to be log-normal with an exponential correlation function.

A model suitable for evaluating the performance of signal strength algorithms is used in [52, 53]. The model has a four-cell neighborhood, and the MS travels from one BS to another in a straight line with a constant velocity. The model assumes that there is no power control, and all BSs transmit at the same power level. The path loss is calculated using Hata's model, and shadow fading is log-normally distributed. Reference [64] has a three-cell neighborhood instead of four-cell neighborhood as in [52, 53].

Two routes of an MS in a cluster of seven cells are considered in [11]. The *first route* is from one BS to another in which the MS crosses cell borders such that it is inside the overlapping region for a minimum duration of time. This route gives insight into the behavior of the handoff algorithm in the handoff area. The *second route* is from one BS to another in which the MS is in the overlapping region most of the time. This second route is more likely to have handoff complications than the first route. The four-cell model of [52] can be easily modified to create these two MS routes by adjusting the cell radii.

Reference [56] uses an SIR-based model that can be used for integrated dynamic resource management tasks. Twenty BSs are uniformly spaced on a ring. The traffic model and the mobility models used in [56] are the same ones described earlier. The new calls are uniformly distributed throughout the ring.

A model suitable for evaluating LOS and NLOS handoffs in a microcellular environment is used in [60]. The LOS and NLOS propagation models are similar to the ones described earlier. The log-normal shadow fading with exponential correlation function for large-scale fading and Rician fading model for small-scale fading are used.

The model of [19] is suitable for a microcellular environment. Two NLOS paths are considered, which give insight into the behavior of handoff algorithms when there are multiple street crossings. The effect of (C/I) is studied in [19] for a particular cell plan. A worst case scenario (i.e., (C/I) of 12 dB) is used to account for interference. Reference [19] also studies the (C/I) distribution for the MS and the BS.

A comprehensive model for a microcellular system is presented in [75]. This reference considers a Manhattan-like structure and places a BS at every other corner. At every street crossing, an MS either goes straight or turns with a given probability. The model is formed into a torus-like structure to avoid edge effects. The LOS propagation model is taken from [101]. For the NLOS model, it is assumed that buildings are infinitely tall, and there is a fixed loss of 20 dB every diffraction street corner. Shadow fading is not considered, but small-scale fading is modeled as Rayleigh fading.

A comprehensive simulation model suitable for macrocellular and microcellular environments is described in [104, 13, 105]. The conventional macrocellular environment is modeled by a forty nine-cell toroidal structure that has seven-cell clusters with 1km radius cells [106]. The microcellular system has half-square cells with 100m block size. The simulation model for a microcell system considers both the transmission and traffic characteristics. Such combined analysis of transmission and traffic characteristics provides a more realistic scenario for performance evaluation of a cellular system. Reference [20] gives a brief account of the simulation model (called M2 simulation) developed at AT&T; this model includes the effects of propagation, traffic, and system configuration.

The model of [73] is suitable for evaluating handoff performance in a mixed cell environment. An urban Manhattan-like environment is simulated in which a cluster consists of four microcells. Four clusters cover the service area with a macrocell overlaying the microcells. User mobility has been modeled as Gaussian with the mean value varying with the distance from the starting position of the MS. A sharp linear velocity decrease is adapted before turning, and a linear increase has been considered after the corner until the previous velocity is restored. The path loss is calculated using the two-slope law. Second and fourth powers are used. The street corner is simulated by a 4 dB/m linear decrease from the street corner, lasting up to 20m. Afterward, an NLOS propagation is assumed. Large-scale fading is simulated by uncorrelated log-normal distribution. New calls follow Poisson model and are uniformly distributed along the streets.

The performance of an SHO algorithm suitable for a CDMA system is analyzed in [107]. Exploitation of diversity in the cell overlap region provides better handoff performance but requires additional resources. A compromise between diversity usage and resource utilization has been analyzed here. The handoff performance is quantified by the performance measures such as active set updates, number of BSs involved in SHO, and outage probability. An SHO algorithm is modeled on conventional handoff algorithms. When a user is in communication with both the BSs, the user is in SHO and is said to be in the active set. A balance between the number of users in the active set and the number of active set updates is required. When a user's signal crosses a threshold, the user is added to the set. The user is removed from the set when the MS is below another threshold for a certain period of time (controlled by a timer). This timer reduces the number of active set updates significantly while increasing the average size of the set slightly.

Reference [85] studies the application of SHO in wideband direct sequence CDMA (DS-CDMA) systems. Propagation aspects of SHO are also presented.

In Reference [87], simulation results on soft/softer handoff in CDMA are presented. The effects of SHO and propagation factors including log-linear path loss and log-normal shadowing are considered. The simulation model and results on soft/softer handoff statistics for different thresholds and propagation environments are presented.

4.2.3 Emulation Approach

The emulation approach uses a software simulator consisting of a handoff algorithm to process measured variables (such as RSS and BER). Actual propagation measurement based simulation has the advantage of giving better insight into the behavior of the radio channels, and it gives more accurate data. The main disadvantages to this approach are periodic measurement requirements and inadequacy for comparison of different handoff algorithms on the same platform.

Reference [26] uses measured data in handoff simulation (the measured data was obtained by conducting 1700 MHz experiments in an urban environment in southern England). The path loss was found to follow a two slope formula with different slopes for different locations. The short term fading was found to be Rician with Rice factors varying from ten to zero depending upon the distance between the MS and the BS.

It was found that the optimal handoff threshold level was different for different cites [26].

Reference [67] introduces an indoor propagation simulator. The indoor simulator models trace thirteen rays over a cross-corridor and exhibit good agreement with the experiments of 950 MHz propagation with multipath fadings.

Reference [108] describes an experimental digital cellular system that consists of a PBX-based MSC, three BSs, two MSs, and a radio channel simulator. Experimental results indicate that the handoff decision can be made within a second, and the handoff procedure works well under typical microcell propagation conditions.

4.3 A Macrocellular Simulation Model

A simulation model usually consists of some of the following components: (i) Cell Model, (ii) Propagation Model, (iii) Traffic Model, and (iv) Mobility Model. These components are described here. The simulation model used here is a modified version of the model used in [52] and [53].

- **Cell Model and Mobility Model**. The cell model consists of a neighborhood of four cells as shown in Figure 4.3. Cell radius is 10 km, and the maximum overlap between cell A and C is 2 km. The BS EIRP (Effective Isotropic Radiated Power) is 100 W. The MS travels from one BS to another (BS A to BS C) at a constant speed (e.g., 65 mph), and such a journey is repeated five hundred times. The MS velocity remains constant throughout the journey.

- **Propagation Model**. Small-scale fading is neglected since it gets averaged out due to short correlation distance relative to that of shadow fading.

  Path Loss Model.

  Hata's model is used to calculate path-loss. A set of equations used in the simulation model is taken from [5]. Path-loss is given by

  $$L_{50(urban)} = 69.55 + 26.16\log(f_c) - 13.82\log(h_{te}) - a_{h_{re}} + (44.9 - 6.55\log(h_{te}))\log(d) \tag{4.1}$$

  where f_c is the carrier frequency (in MHz), h_{te} is the effective BS (or transmitter) antenna height in m, h_{re} is the effective MS (or receiver) antenna height

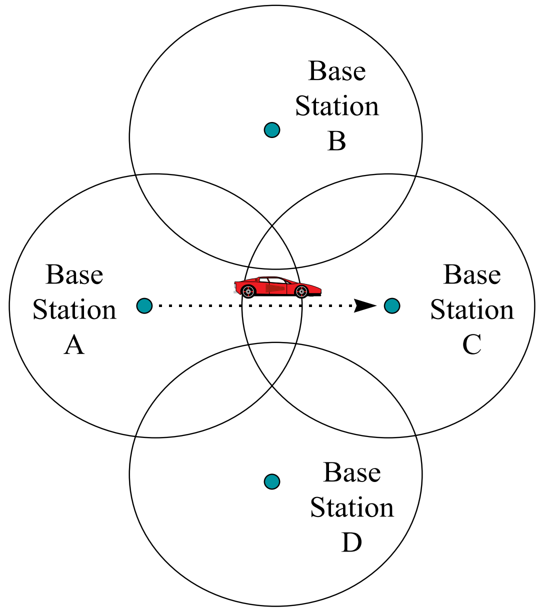

Figure 4.3: Four BS Neighborhood Cell Model

in m, d is the transmitter-receiver (T-R) separation distance in km, and $a_{h_{re}}$ is the correction factor for different sizes of the coverage area. In simulations, the following values are used: $f_c = 900MHz$, $h_{te} = 30m$, and $h_{re} = 3m$.

For a medium size city,

$$a_{h_{re}} = (1.1 \log(f_c) - 0.7)h_{re} - (1.56 \log(f_c) - 0.8). \qquad (4.2)$$

In general, the path loss models of Hata and Okumura can be used for macrocells while different models are used for line-of-sight (LOS) and non-line-of-sight (NLOS) propagation in microcells.

Large-Scale Fading Model.

According to [102], the distribution of the large-scale fading component is close to a lognormal distribution. Reference [66] proposes an exponential autocorrelation model for shadow fading for macrocells and microcells that has been experimentally validated through measurements. The correlation at 100 m was found to be 0.82 for a large cell in suburban environment. The correlation was 0.3 at 10 m in a microcell. It was found that the RSS measurements are highly correlated in macrocells and less correlated in microcells.

The generation of a correlated shadow fading process from uncorrelated Gaussian samples is described next. It is assumed that a sequence **n** is an uncorrelated process with samples that have 0 mean and σ_2 standard deviation. Assume that the sequence **n** needs to be converted into a sequence **x** with 0-mean, σ_1

standard deviation, and an exponential autocorrelation function given by

$$\rho(d) = E[x(D)x(D+d)] = \sigma_1^2 \exp(-d/d_0) \tag{4.3}$$

where d is the distance separating two samples and d_0 is a parameter that can be used to specify correlation at a particular distance. For example, for a normalized autocorrelation of 0.82 at a distance of 100m, $d_0 = 500m$. In other words, $\exp(-d/d_0) = \exp(-100/500) = 0.82$.

Let $\mathbf{x}$ be the required correlated shadow fading process and d_s be the sampling distance. Then,

$$x(D+d_s) = \alpha x(D) + n(D). \tag{4.4}$$

The parameter α needs to be determined. The autocorrelation is

$$E[x(D+d_s)x(D)] = E[x(D)(\alpha x(D) + n(D))] \tag{4.5}$$
$$E[x(D+d_s)x(D)] = \alpha E[x(D)^2] + E[n(D)x(D)] \tag{4.6}$$
$$E[x(D+d_s)x(D)] = \alpha\sigma_1^2 \tag{4.7}$$

(since n(D) and x(D) are independent and 0-mean processes).

Equating Eq. 4.3 and Eq. 4.7,

$$E[x(D+d_s)x(D)] = \rho(d) = \sigma_1^2 \exp(-d/d_0) = \alpha\sigma_1^2. \tag{4.8}$$

Hence,

$$\alpha = \exp(-d/d_0). \tag{4.9}$$

Now,

$$n(d) = x(D+d_s) - \alpha x(D) \tag{4.10}$$
$$n^2(d) = x^2(D+D_s) - 2x(D+d_s)\alpha x(d) + \alpha^2 x^2(d) \tag{4.11}$$
$$E[n^2(d)] = E[x^2(D+D_s)] - 2E[x(D+d_s)x(d)]\alpha + \alpha^2 E[x^2(d)] \tag{4.12}$$
$$\sigma_2^2 = \sigma_1^2 - 2\alpha\sigma_1^2\alpha + \alpha^2\sigma_1^2 \tag{4.13}$$
$$\sigma_2^2 = \sigma_1^2 - \alpha^2\sigma_1^2 \tag{4.14}$$
$$\sigma_2^2 = \sigma_1^2(1-\alpha^2). \tag{4.15}$$

This derivation is in conformity with the results presented in [57] and indicates that a 0-mean uncorrelated process can be used to create a 0-mean correlated process with desired variance and autocorrelation.

- **Traffic Model**. Traffic distribution is assumed to be uniform in the four cells under consideration.

The basic simulation model used in [52] was modified to model user mobility, traffic, and interference. Traffic is quantified by the number of calls in a cell. The number of calls in the four BSs is changed uniformly between zero and sixty-two (maximum number of trunked channels) every seventy-five simulation steps (15% of the total simulation runs). Interference is modeled by considering a subset of the cochannel BSs, located at a distance of $D = \sqrt{N}R$ from the center of the cell. Here, N is the cluster size (number of cells in a cluster), and R is the cell radius. The actual number of such interfering BSs is selected uniformly between zero and six every seventy-five simulation runs. Only the first tier of interferers is considered. Note that traffic and interference have been modeled this way to get a preliminary indication of the traffic and interference related performance of the handoff algorithm. The simulation model used here provides several important performance metrics (such as crossover distance and average number of handoffs during a journey) that may be obscured in other models.

Some of the features of the basic simulation model are listed below.

1. This model is simple.

2. This model includes a realistic scenario in which an MS has a four base station neighborhood and travels from one BS to another. A two base station neighborhood is a less realistic scenario.

3. This model is applicable to a macrocellular environment where BS antennas are tens of meters high and the BS transmits several Watts of power. This model can be used for a microcellular environment after making proper modifications in the propagation model.

4. This model allows a detailed study of the handoff process in a handoff region. In particular, this model allows an in-depth analysis of the behavior of a handoff algorithm in the cell overlap region, and it allows elegant evaluation of certain

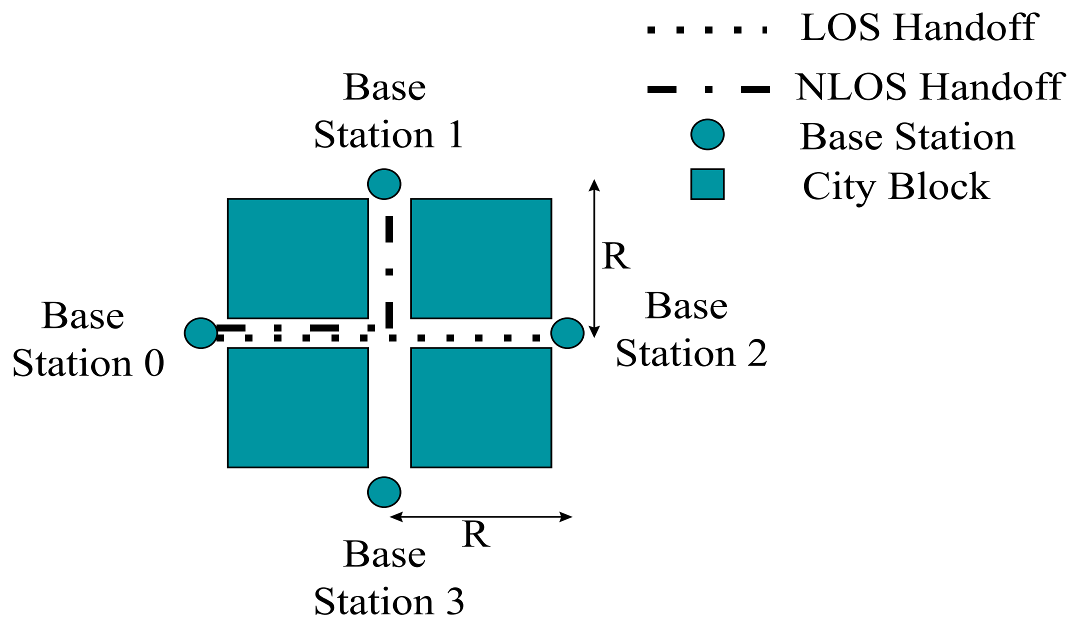

Figure 4.4: Generic Handoff Scenarios in a Microcellular System

significant handoff-related system performance metrics.

5. The effect of different cell radii and different size cell overlap regions on the performance of a handoff algorithm can be investigated using this model.

4.4 A Microcellular Simulation Model

The simulation model has the following salient features.

- **Cell Model**. A four BS neighborhood shown in Figure 4.4 is used. The BS transmit power is one Watt. The cell radius is $R = 250m$ (the same as the city block size in Figure 4.4).

- **Propagation Model**. Microcells have different models for LOS and NLOS propagation. Here, a model similar to the one proposed in [102] is used. This is an empirical path loss model called a *two slope model* in which the path loss increases with a certain slope to a threshold distance (called a *breakpoint*) and then increases with a higher slope. Mathematically, RSS at a distance d from a LOS BS is given by

$$RSS(d) = P_t - (10a \log d + 10b \log d/g) + s(d) \tag{4.16}$$

where P_t is the BS transmit power (in Watts), d is the distance of the MS from the LOS BS (in m), and $s(d)$ is correlated shadow fading sample. The parameters a, b, and g define the path loss (a=2, b=2, and g=150). The corner effect begins at 255m from BS 0. For an *NLOS propagation*, a LOS propagation is assumed up to the street corner. After the corner, propagation path loss is calculated by placing an imaginary transmitter at the corner with the transmit power equal to the power received at the corner from the LOS BS. RSS at a distance (d+R) from the NLOS BS is given by

$$RSS(d) = P_t - (10a \log d + 10b \log d/g) + s(d) \tag{4.17}$$

where P_t is the power received at the intersection from the NLOS power (in Watts), d is the distance of the MS from the intersection (in m), $(d + R)$ is the distance of the MS from the NLOS BS (in m), R is the distance of the intersection from the NLOS BS (in m), and $s(d)$ is the correlated shadow fading sample. Other parameters are the same as earlier. Note that P_t is calculated using the path loss formula for the LOS case (Equation 4.16).

Correlated log-normal shadow fading is used to model *large-scale fading*. The log-normal shadow fading deviation is 7 dB (medium intensity). A normal range for shadow fading standard deviation for microcells is from 5 to 9 dB (8 dB to 14 dB for macrocells). An exponential autocorrelation model proposed in [66] is used. The exponential autocorrelation function is given by

$$\rho(d) = E[x(D)x(D + d)] = \sigma_1^2 \exp(-d/d_0) \tag{4.18}$$

where d is the distance separating two samples and d_0 is a parameter that can be used to specify correlation at a particular distance. Here, a correlation distance of 8.5 m is used, which gives a correlation of 0.3 at a distance of 10 m. In other words, $d_0 = 8.5m$, and $\exp(-d/d_0) = \exp(-10/8.5) = 0.3$. *Small-scale fading* is neglected since it gets averaged out due to short correlation distance relative to that of shadow fading.

- **Traffic, Mobility, and Interference Model**. The MS travels at a constant speed from BS 0 to BS 2 during a LOS handoff scenario and from BS 0 to BS 1 during a NLOS handoff scenario. The maximum speed is 35 mph (or 15.64 m/sec), the average speed is 25 mph (or 11.18 m/sec), and the minimum speed is 15 mph (or 6.71 m/sec). There are a maximum of four LOS interferers. The maximum number of channels per BS is twenty. The number of ongoing calls in a cell and the number of interferers are chosen randomly every 10% of the total simulation time during the travel of the MS from one BS to another.

- **Measurement Sampling and Averaging**. The measurement sample time is 0.1 sec, and the averaging distance is 6.3 m (which is a distance of 40λ). Sample averaging is used to obtain velocity adaptive averaging.

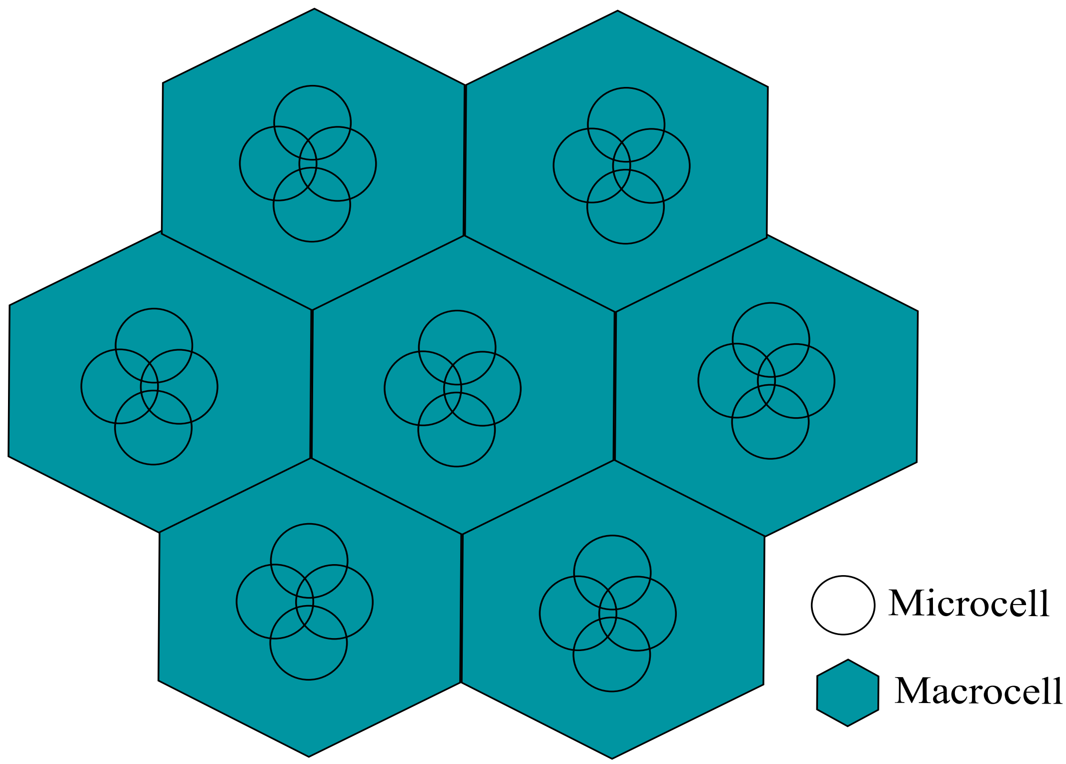

Figure 4.5: Cell Layout for an Overlay System

4.5 An Overlay Simulation Model

The simulation model proposed here allows evaluation of a handoff algorithm in generic handoff scenarios in an overlay system. This model gives details of critical performance metrics that quantify performance of significant aspects of overlay handoff. The model also gives an idea of traffic and interference related system performance. Salient features of the proposed simulation model are discussed next.

- **Cell Model**. Figure 4.5 shows the cell layout, which consists of a cluster of seven macrocells, with each macrocell overlaying a cluster of four microcells.

- **Propagation Model**. Hata's model is used to calculate path-loss for macrocells. A set of equations used in the simulation model is taken from [5]. Path-loss is given by

$$L_{50(urban)} = 69.55 + 26.16\log(f_c) - 13.82\log(h_{te}) - a_{h_{re}} + (44.9 - 6.55\log(h_{te}))\log(d) \tag{4.19}$$

where f_c is the carrier frequency (in MHz), h_{te} is the effective BS (or transmitter) antenna height in m, h_{re} is the effective MS (or receiver) antenna height in m, d is the transmitter-receiver (T-R) separation distance in km, and $a_{h_{re}}$ is the correction factor for different sizes of the coverage area. In simulations, the following values are used: $f_c = 900MHz$, $h_{te} = 30m$, and $h_{re} = 3m$.

For a medium size city,

$$a_{h_{re}} = (1.1 \log(f_c) - 0.7)h_{re} - (1.56 \log(f_c) - 0.8). \tag{4.20}$$

For a microcell, a model similar to the one proposed in [102] is used. This is an empirical path loss model called a *two slope model* in which the path loss increases with a certain slope to a threshold distance (called a *breakpoint*) and then increases with a higher slope. Mathematically, RSS at a distance d from a BS is given by

$$RSS(d) = P_t - (10a \log d + 10b \log d/g) + s(d) \tag{4.21}$$

where P_t is the BS transmit power (in Watts), d is the distance of the MS from the BS (in m), and $s(d)$ is the correlated shadow fading sample. The parameters a, b, and g define the path loss (a=2, b=2, and g=150).

Correlated log-normal shadow fading is used to model *large-scale fading*. The log-normal shadow fading deviation is 11 dB for macrocells and 7 dB for microcells. An exponential autocorrelation model proposed in [66] is used. The exponential autocorrelation function is given by

$$\rho(d) = E[x(D)x(D+d)] = \sigma_1^2 \exp(-d/d_0) \tag{4.22}$$

where d is the distance separating two samples and d_0 is a parameter that can be used to specify correlation at a particular distance. For macrocells, a correlation distance of 500 m is used, which gives a correlation of 0.82 at a distance of 100 m. In other words, $d_0 = 500m$, and $\exp(-d/d_0) = \exp(-100/500) = 0.82$. For a microcell, a correlation distance of 8.5 m is used, which gives a correlation of 0.3 at a distance of 10 m. In other words, $d_0 = 8.5m$ and $\exp(-d/d_0) = \exp(-10/8.5) = 0.3$. *Small-scale fading* is neglected since it gets averaged out due to short correlation distance relative to that of shadow fading.

- **Traffic, Mobility, and Interference Model**. The new call durations are independent exponential random variables with 120 sec mean. Traffic is assumed to be uniform. The new call arrival process is modeled as an independent Poisson process with a certain mean arrival rate. The mean call arrival rate is given by $\lambda = Tr_{load}MB\mu$ where λ is the mean call arrival rate, Tr_{load} is the normalized traffic load (0 to 1), M is the number of channels per base station, B is the number of base stations in the cell, and $\mu = 1/cd$ (cd is the call duration in sec). The MSs have different velocities following a truncated Gaussian distribution. The MS velocity is typically assumed to be constant throughout the call. The maximum speed is 70 mph, the average speed is 45 mph, and the minimum speed is 20 mph. There are a maximum of six cochannel interferers. The number of cochannel interferers is chosen randomly every 1% of the total simulation time for every user in the system.

- **Measurement Sampling and Averaging**. The measurement sample time is 0.25 sec, and the averaging distance is 260 m for macrocells and 50 m for microcells. Sample averaging is used to obtain velocity adaptive averaging.
- **Initial Cell Selection**. When a new call arrives, the call is assigned to the nearest macrocell if the user velocity is greater than the velocity threshold V_{th} or if no microcell BS can provide sufficient RSS to the MS.

4.6 A Soft Handoff Simulation Model

The simulation model proposed here allows evaluation of a handoff algorithm in generic handoff scenarios, such as the absence of soft handoff, two-way soft handoff, and three-way soft handoff. This model details critical performance metrics that quantify the performance of significant aspects of soft handoff such as diversity usage, resource utilization, and network load. The model also gives a preliminary idea of traffic and mobility related system performance. Salient features of the proposed simulation model are discussed next.

- **Cell Model**. The fourteen BS neighborhood shown in Figure 4.6 is used. The BS transmit power is one Watt. The cell radius is $R = 3km$.
- **Propagation Model**. Hata's model is used to calculate path-loss. A set of equations used in the simulation model is taken from [5]. Path-loss is given by

$$L_{50(urban)} = 69.55 + 26.16\log(f_c) - 13.82\log(h_{te}) - a_{h_{re}} + (44.9 - 6.55\log(h_{te}))\log(d) \tag{4.23}$$

where f_c is the carrier frequency (in MHz), h_{te} is the effective BS (or transmitter) antenna height in m, h_{re} is the effective MS (or receiver) antenna height in m, d is the transmitter-receiver (T-R) separation distance in km, and $a_{h_{re}}$ is the correction factor for different sizes of the coverage area. In simulations, the following values are used: $f_c = 900MHz$, $h_{te} = 30m$, and $h_{re} = 3m$.

For a medium size city,

$$a_{h_{re}} = (1.1\log(f_c) - 0.7)h_{re} - (1.56\log(f_c) - 0.8). \tag{4.24}$$

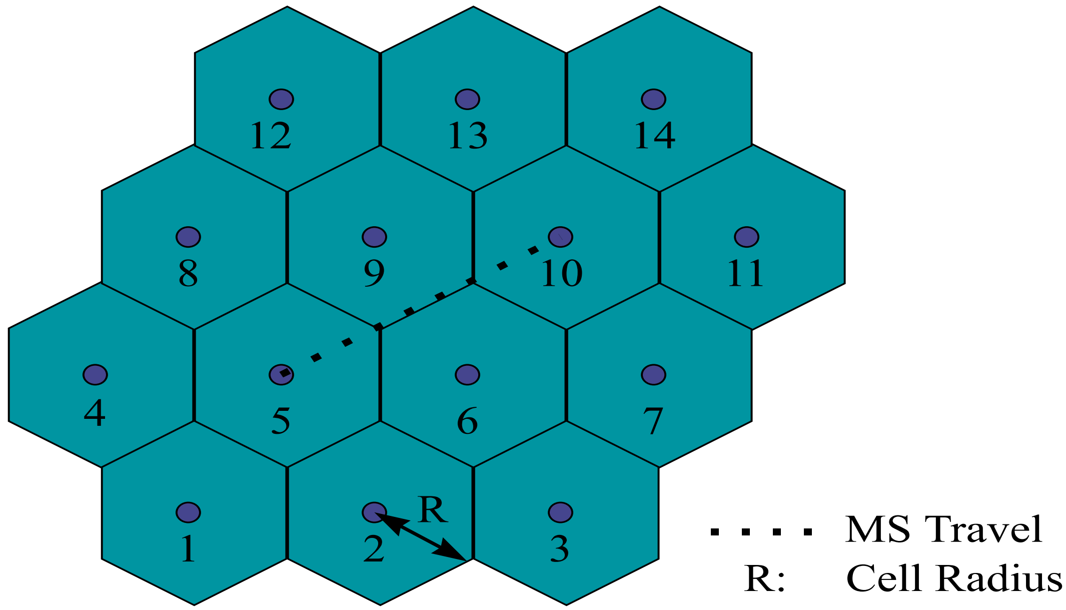

Figure 4.6: Soft Handoff Cell Layout

In general, the path loss models of Hata and Okumura can be used for macrocells.

Correlated log-normal shadow fading is used to model *large-scale fading*. The log-normal shadow fading deviation is 11 dB (medium intensity). A normal range for shadow fading standard deviation for macrocells is from 8 dB to 14 dB. An exponential autocorrelation model proposed in [66] is used. The exponential autocorrelation function is given by

$$\rho(d) = E[x(D)x(D+d)] = \sigma_1^2 \exp(-d/d_0) \tag{4.25}$$

where d is the distance separating two samples and d_0 is a parameter that can be used to specify correlation at a particular distance. Here, a correlation distance of 500 m is used, which gives a correlation of 0.82 at a distance of 100 m. In other words, $d_0 = 500m$, and $\exp(-d/d_0) = \exp(-100/500) = 0.82$. *Small-scale fading* is neglected since it gets averaged out due to short correlation distance relative to that of shadow fading.

- **Traffic, Mobility, and Interference Model**. The MS travels at a constant speed from BS 5 to BS 10. The maximum speed is 85 mph, the average speed is 65 mph, and the minimum speed is 45 mph. There is a maximum of six cochannel interferers. The maximum number of channels per BS is sixty. The number of ongoing calls in a cell and the number of interferers are chosen randomly every 10% of the total simulation time during the travel of the MS from one BS to another.

- **Measurement Sampling and Averaging**. The measurement sample time is 0.5 sec, and the averaging distance is 260 m. Sample averaging is used to obtain velocity adaptive averaging.

4.7 Conclusion

This chapter discusses the performance analysis of handoff algorithms. Different performance measures proposed in the literature are defined. Three basic evaluation mechanisms (analytical, simulation, and emulation) are briefly discussed. Basic constituents of simulation mechanism are explained. Existing simulation models for macrocellular and microcellular algorithms are enhanced by considering several significant aspects of cellular systems. Simulation models that allow thorough analysis of soft handoff and overlay algorithms are proposed.

Chapter 5

A Fuzzy Logic Based Algorithm

This chapter proposes a new class of handoff algorithms that combines the attractive features of several existing algorithms and adapts the handoff parameters using fuzzy logic. Known sensitivities of handoff parameters are used to create a fuzzy logic rule base. The design procedure for a generic fuzzy logic based algorithm is outlined. Extensive simulation results for a conventional handoff algorithm (absolute and relative signal strength based algorithm) and a fuzzy logic based algorithm are presented. This chapter shows that an adaptive multicriteria fuzzy handoff algorithm performs better than a signal strength based conventional handoff algorithm. *More importantly, the proposed class of algorithms allows a systematic tradeoff among different system characteristics in the dynamic cellular environment.*

5.1 Introduction

This chapter presents a novel unified approach for the design of a class of handoff algorithms that exploits attractive features of several existing algorithms, provides adaptation to the dynamic cellular environment, and allows systematic tradeoff among different system characteristics. The proposed class of algorithms exploits several fuzzy logic attributes (such as efficient and complete utilization of system knowledge, ability to resolve conflicting requirements, and simplicity) to adapt handoff parameters to obtain high performance in a complex cellular environment. A generalized framework for the design of fuzzy logic based handoff algorithms is proposed, and a complete design procedure is described.

Section 5.2 discusses various issues involved in the design and evaluation of generic high performance handoff algorithms. A new class of fuzzy logic based handoff algorithms is proposed and illustrated in Section 5.3. The performances of a conventional algorithm and a fuzzy logic algorithm are evaluated in Section 5.4. Finally, Section 5.5 summarizes the chapter.

5.2 Handoff Algorithms: Design and Analysis Issues

This section discusses design and analysis procedures for a handoff algorithm. Several steps involved in the handoff algorithm design are outlined. Different metrics that have been used to measure handoff related system performance are briefly touched upon here. Three basic mechanisms used to evaluate performance of handoff algorithms are discussed.

5.2.1 Design and Analysis Procedure

Figure 5.1 shows a block diagram that illustrates the design of high performance handoff algorithms. Steps involved in the handoff algorithm design and analysis are listed below.

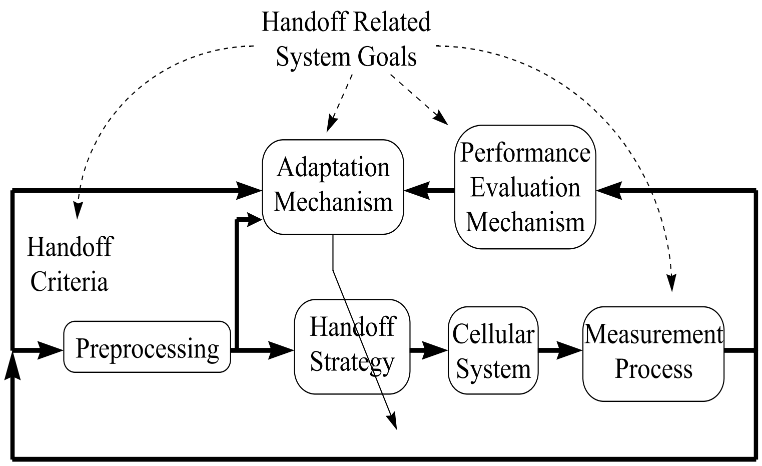

Figure 5.1: Block Diagram of a High Performance Handoff Algorithm

1. **Analysis of Handoff Related System Goals**. Study handoff related cellular system goals. Analyze desirable features of a handoff algorithm, and determine the required attributes of a handoff algorithm.

2. **Determination and Preprocessing of Handoff Criteria**. Determine handoff criteria based on desired goals, system requirements, and availability of measurements. Preprocess handoff criteria before using them in a handoff algorithm. For example, some criteria, such as RSS, may need averaging.

3. **Handoff Strategy**. Process the handoff criteria using a selected strategy. Adapt the parameters of the handoff strategy by considering the performance metrics and the desired goals.

4. **Handoff Strategy**. Evaluate the developed algorithm using a suitable simulation model.

This research uses the simulation approach for evaluating the performance of handoff algorithms. Details of the simulation model were given in Chapter 4.

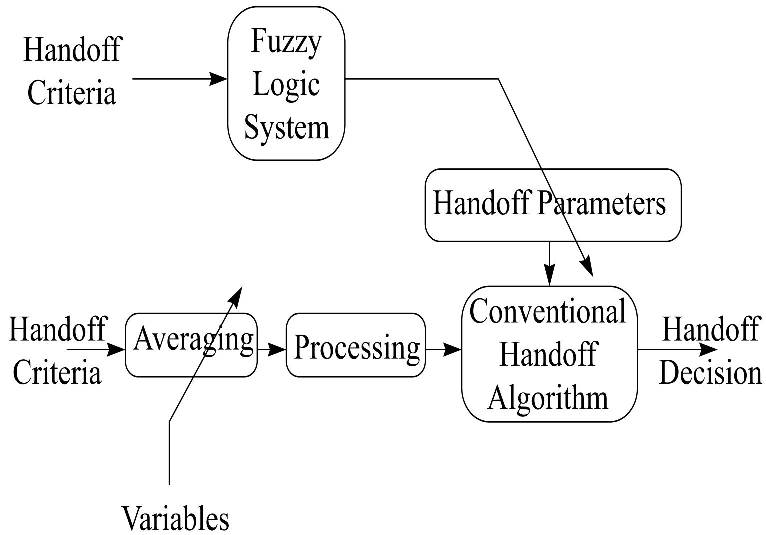

Figure 5.2: Block Diagram of Generic Fuzzy Logic Based Handoff Algorithms

5.3 A Class of Fuzzy Logic Based Adaptive Handoff Algorithms

5.3.1 Design Procedure

This chapter proposes a new class of adaptive handoff algorithms based on fuzzy logic, and Figure 5.2 shows a generic block diagram of this proposed class. *The main idea is to combine attractive features of existing algorithms to obtain an efficient algorithm and to adapt the parameters of this efficient algorithm to the dynamic cellular environment using a fuzzy logic system.* Major phases involved in the design of the proposed class of algorithms are:

1. Identification of desirable features and associated handoff algorithm attributes;

2. Selection and processing of handoff criteria;

3. Determination of the basic conventional handoff algorithm;

4. Design of a fuzzy logic system.

These phases are discussed in detail next.

Desirable Features and Associated Handoff Algorithm Attributes

Two major goals of handoff algorithms are high *spectral efficiency* and high *communication quality*. *Spectral efficiency* is quantified by performance metrics such as call blocking probability and handoff blocking probability. *Communication quality* is quantified by performance metrics such as SIR and the number of dropped calls. Several desirable features of handoff algorithms determine the extent to which these goals are achieved, and some mentioned in the literature [7, 2, 4, 14, 13, 12, 11, 10] are further explained here. An efficient handoff algorithm can achieve many of these features by possessing certain attributes and making appropriate tradeoffs among various operating characteristics. Chapter 2 describes desirable features of a handoff algorithm. The attributes of an algorithm associated with these features are discussed next.

- Handoff should be fast so the user does not experience service degradation or service interruption. Service degradation may be due to a continuous reduction in signal strength or an increase in co-channel interference (CCI).

  Required Attributes.

  1. A handoff algorithm should be simple so it can be executed quickly. However, a simple algorithm may be unable to make appropriate tradeoffs due to restricted degrees of freedom.
  2. There should be a buffer between the call drop received signal strength (RSS) threshold and the handoff RSS threshold and between the call drop signal-to-interference ratio (SIR) threshold and the handoff SIR threshold.
  3. Higher threshold and lower hysteresis values should be used for vehicles with a higher quality degradation rate. Lower threshold and higher hysteresis values should be used for vehicles with a lower quality degradation rate to prevent excessive interference due to early handoffs.

- Handoff should be reliable; the quality of the call after handoff should be good.

Required Attributes.

1. If the SIR threshold is included as part of a handoff algorithm, the search for a better BS (i.e., a BS with better SIR) can be started early.
2. Hysteresis in RSS can help increase the chances of obtaining a better BS.
3. Measurements of the SIRs of candidate BSs may not be available, and in such cases, RSS plays a more important role in ensuring the reliability of handoff.

- Handoff should be successful; a free channel should be available at the candidate BS.

  Required Attributes.

  1. Efficient channel allocation algorithms can maximize the probability of a successful handoff. Channel allocation and handoff may be combined.
  2. Traffic balancing can increase the probability of a successful handoff.

- The handoff procedure should balance traffic in adjacent cells, obviating the need for channel borrowing, simplifying cell planning and operation, and reducing the probability of new call blocking and handoff blocking (thereby increasing the number of potential users that can be accommodated in the future).

  Required Attribute. Traffic adaptation can provide traffic balancing.

- Handoff should maintain the planned cellular borders to avoid congestion, high interference, and use of the assigned channels of the previously serving cell while inside the new cell. Each BS can carry only its planned traffic load. Moreover, increased interference is possible if the MS goes deep into a new cell site while still connected to the distant but currently serving BS. This interference occurs because cochannel distance is reduced and because the BS and MS tend to use a high transmit power when far apart.

  Required Attributes.

  1. Since RSS is an indicator of the distance between the BS and the MS, an RSS based algorithm can help preserve planned cell boundaries.
  2. It should be noted that even though intrinsic traffic balancing perturbs planned cell boundaries, combined traffic and interference adaptation can achieve a systematic tradeoff between traffic balancing and resultant interference.

- The number of handoffs should be minimized. Excessive handoffs lead to heavy handoff processing loads and poor communication quality. The more handoff attempts, the more chances that a call will be denied access to a channel, which will result in a higher handoff dropping probability. If there are a lot of handoff attempts, there will be more delay in the processing of handoff requests at the MSC. This increased delay may cause the signal strength to decay to an unacceptable quality. Furthermore, the call may be dropped if the SIR deteriorates too much. Handoff requires network resources to connect the call to a new BS. Thus, minimizing the number of handoffs reduces the switching load. Unnecessary handoffs should be prevented; the current BS might be able to provide the desired service quality without interfering with other MSs and BSs.

Required Attributes.

1. The target cell should be chosen correctly since there may be more than one candidate BS for handoff. Identification of a correct cell prevents unnecessary and frequent handoffs.
2. Velocity adaptive averaging, hysteresis, and direction biasing can help reduce the number of handoffs.

- The handoff procedure should minimize the number of continuing call drop-outs.

  Required Attribute. A handoff algorithm should provide sufficient RSS and SIR to help achieve this goal.

- The global interference level should be minimized by the handoff procedure. Minimum power transmission and planned cellular border maintenance can help achieve this goal.

  Required Attributes.

  1. Better RSS and SIR distribution allow the MS to transmit low power, reducing the overall interference.
  2. Reduction in handoff delay can help maintain planned cell borders.

Based on the desirable features discussed earlier and the study of the properties and behavior of existing algorithms, a configuration of a generic handoff algorithm, shown in Figure 5.3 and Figure 5.4, was derived. This configuration uses the combination of an absolute and relative RSS based algorithm and an SIR based algorithm. The RSS based algorithm has threshold ($RSS_{threshold}$) and hysteresis ($RSS_{hysteresis}$) as parameters, while the SIR based algorithm has threshold ($SIR_{threshold}$) as a parameter. The SIR threshold parameter allows the initiation of a better handoff candidate search early. The RSS based parameters are adapted to the cellular environment.

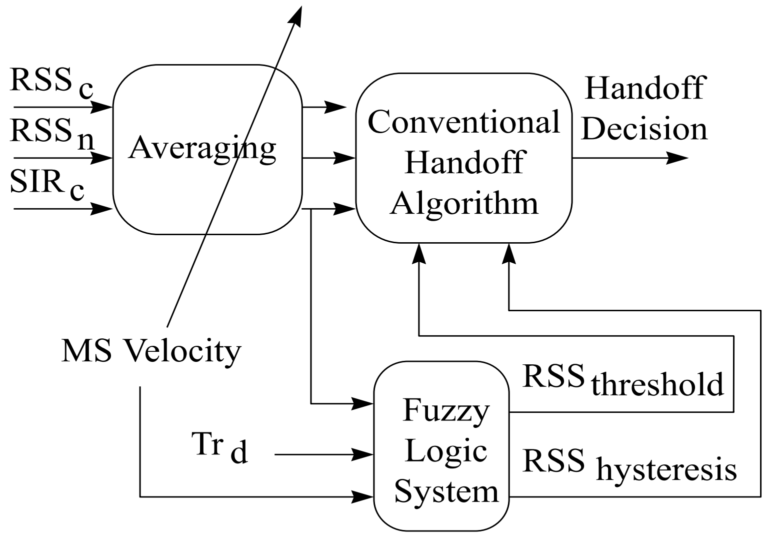

Figure 5.3: A Generic Adaptive Fuzzy Logic Based Algorithm

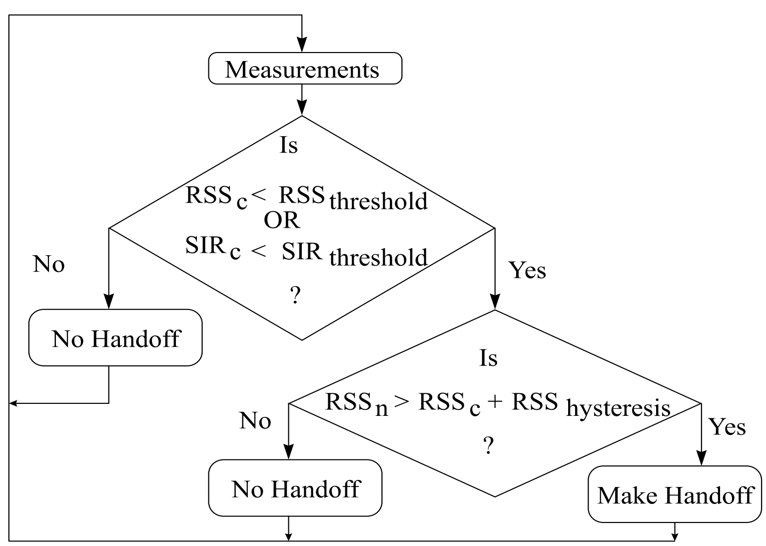

Figure 5.4: The Conventional Handoff Algorithm for the Generic Fuzzy Logic Based Algorithm

Specifically, SIR of the current BS (SIR_c), traffic difference (Tr_d (i.e., the difference in the number of calls in the current and the neighboring BS, $Tr_c - Tr_n$)), and call quality degradation rate (quantified by the MS velocity in the simulation model considered here) are used to adapt the handoff parameters. It is assumed that the MS makes necessary measurements. However, the proposed algorithm can be easily extended to include BS measurements. Note that actual systems may have specific requirements (e.g., maximum permissible round-trip delay). Such requirements can be incorporated as part of either the basic conventional algorithm or the adaptation mechanism. Handoff criteria averaged according to the velocity adaptive averaging mechanism include RSS of the current BS (RSS_c), RSS of the neighboring BS (RSS_n), and SIR of the current channel (SIR_c). The MS velocity and the traffic difference (Tr_d) are not averaged since their instantaneous values are of interest. Since the basic parameters to be adapted, $RSS_{threshold}$ and $RSS_{hysteresis}$, are related to RSS, the variables RSS_c and RSS_n are not used to adapt these parameters. An FLS is used as an adaptive mechanism. The inputs to the FLS are SIR_c, $(Tr)_d = (Tr)_c - (Tr)_n$, and MS velocity, and the outputs of the FLS are $RSS_{threshold}$ and $RSS_{hysteresis}$. The details of the FLS are given in Section 5.3.1.

Selection and Processing of Handoff Criteria

The handoff criteria and other variables need to be measured. If some measurements are not available, estimates of these variables are required. Several handoff criteria were discussed in Chapter 2. To keep the algorithm general and simple, RSS, SIR, traffic, and velocity are used as handoff criteria, and transmit power and distance are excluded. An improved SIR distribution can lead to potentially lower MS transmit power. Since distance measurement accuracy decreases with decreasing cell size, distance is not used as a criterion. However, both MS transmit power and distance measurements can be incorporated if desired.

Examples of *preprocessing* include averaging of measurements, putting different emphases on different criteria, and direction biasing. Some of these preprocessing techniques are briefly discussed next. Certain handoff criteria (e.g., RSS) need to be averaged to mitigate the effects of the propagation environment. To prevent an excessive number of dropped calls, handoff requests should be processed quickly for vehicles that are moving away from the serving BS at high velocities. A fixed time averaging interval gives best performance at only one velocity. For example, for a fixed parameter handoff algorithm with a fixed time averaging window, two situations exist: (i) for high velocities, handoff delay is long, and the number of handoffs are fewer and (ii) for low velocities, the handoff delay is short, and the number of handoffs are more. Also, there is a velocity (between the high and low extremes) that gives optimum performance for both the handoff delay and the number of handoffs. To provide similar performance (i.e., the desired tradeoff between the handoff delay and the number of handoffs) to users with different velocities, the temporal window must be adapted based on the MS velocity. Reference [58] proposes velocity adaptive averaging algorithms for a microcellular environment. These algorithms provide good performance for MSs with different velocities by adjusting the effective length of the averaging window. A velocity adaptive handoff algorithm can serve as an alternative to the umbrella cell approach to tackle high speed users if low network delay can be achieved, which can lead to savings in the infrastructure. The temporal window length can be changed by either keeping the sampling period constant and adjusting the number of samples per window, or vice versa. For microcells, the sampling distance of 0.5λ and the averaging distance of 20λ to 40λ are sufficient according to [58]. In this chapter, the measurement sampling period T_s is 0.5 sec (as in GSM), and the number of samples per window are adjusted according to the MS velocity. A spatial window of 780λ (i.e., 260 m for $f_c = 900MHz$) is used. The averaging distance of $260m$ was determined based on simulations. For a velocity of 65 mph (or 29.06 m/sec), eighteen samples are used, while for a velocity of 85 mph (or 38 m/sec), fourteen samples are used. This chapter assumes that velocity estimation is available. Several methods for estimating velocity are described in [58].

The averaged criteria can be further processed before their use in a handoff algorithm. For example, each criterion can be emphasized differently. Also, some base stations (BSs) may be favored based on the direction in which the mobile station (MS) is moving; this process is called *direction biasing*. The basic idea behind direction biasing is to encourage handoff to the BS that the MS is approaching and to discourage handoff to the BS from which the MS is receding. Reference [60] proposes direction biased handoff algorithms which have better cell membership properties, defined as a probability of close to one throughout the call duration [60]. Improved cell membership properties can help preserve cell boundaries (thereby reducing the interference) and reduce the number of handoffs.

A Basic Conventional Handoff Algorithm

A conventional algorithm based on RSS and SIR was used in conjunction with the FLS. This algorithm is shown in Figure 5.4. According to the absolute and relative RSS-based part of the algorithm, handoff takes place if the following two conditions are satisfied [54]: (i) the average signal strength of the serving BS falls below an absolute threshold ($RSS_{threshold}$) and (ii) the average signal strength of the candidate BS exceeds the average signal strength of the current BS by an amount of ($RSS_{hysteresis}$). Condition (i) prevents the occurrence of handoff when the current BS can provide sufficient signal quality, while condition (ii) reduces the ping-pong effect. Reference [24] has shown that an optimum threshold achieves a narrowed handoff area (and hence reduced interference) and a low expected number of handoffs. According to the SIR based part of the algorithm, a handoff candidate search is initiated when SIR_c drops below a threshold, $SIR_{threshold}$. An algorithm based on both RSS and BER is described in [26]. For RSS, a threshold is used for the current BS, and a hysteresis window is used for the target BS. For BER, a separate threshold is defined. The target BS can be either included or excluded from the handoff decision process. The latter scheme is used in GSM where the mobile does not know the signal quality of the target BS. In principle, it is possible to measure BER of the control channel of the target BS.

A Fuzzy Logic System

A fuzzy logic rule base is created based on the known sensitivity of handoff algorithm parameters (e.g., RSS threshold and RSS hysteresis) to interference, traffic, etc. This research utilizes the Mamdani FLS described earlier. The singleton fuzzifier, the product operation fuzzy implication for fuzzy inference, and the center average defuzzifier are used. The fuzzy rule base is discussed next and is shown in the Table 5.1. Each of the input fuzzy variables is assigned to one of the three fuzzy sets, “High”, “Normal” or “Low”. Each of the output variables is assigned one of the seven fuzzy sets, “Highest”, “Higher”, “High,” “Normal,” “Low,” “Lower,” or “Lowest.” An example of the universes of discourse for the input and output fuzzy variables is shown in Figure 5.5.

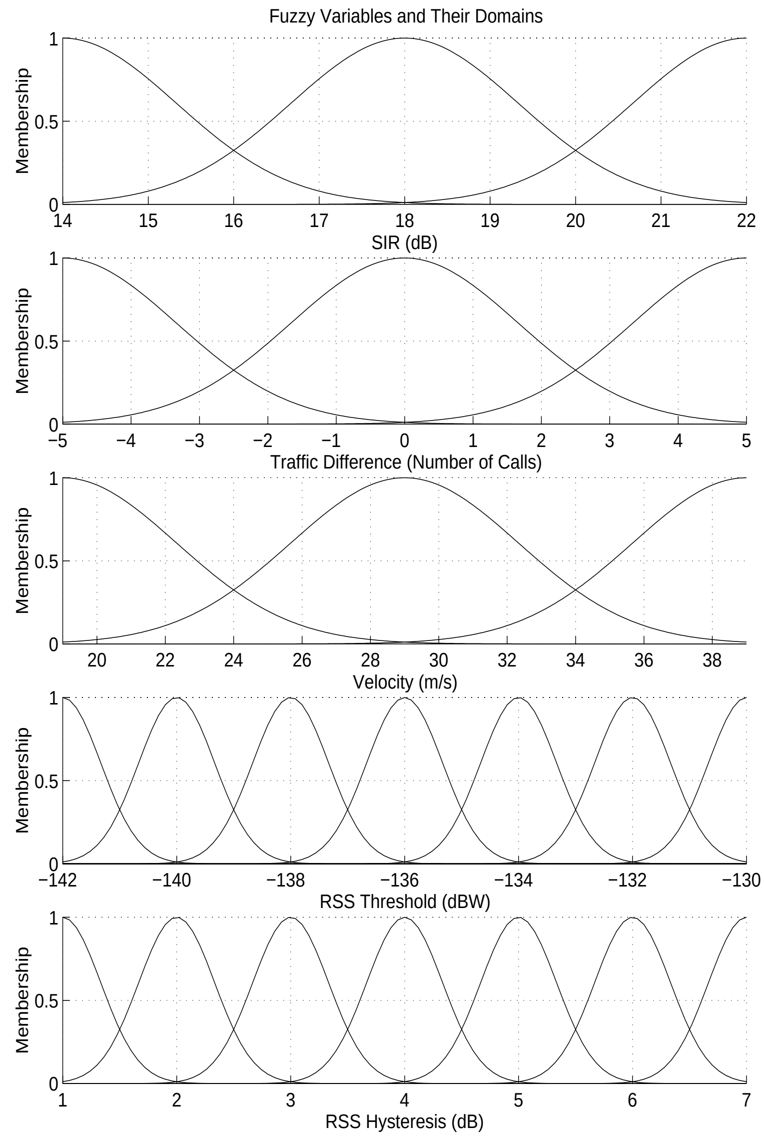

Figure 5.5: Membership Functions of Fuzzy Variables

For example, consider the fuzzy variable SIR_c. Its universe of discourse is defined from 14 dB to 22 dB. The fuzzy set "High" for the SIR_c is defined from 18 dB to 22 dB with the maximum membership at 22 dB. Similarly, the fuzzy set "Normal" for the SIR_c is defined from 14 dB to 22 dB with the maximum membership at 18 dB, and the fuzzy set "Low" for the SIR_c is defined from 14 dB to 18 dB with the maximum membership at 14 dB. *The degrees of freedom for each of the fuzzy variables are centers of the Gaussian membership functions, spreads of the membership functions, and ranges of the universes of discourse.* If equal weight is given to the input fuzzy variables, the creation of the fuzzy logic rule base is facilitated. The sensitivity of the input fuzzy variable to the output of the FLS can be controlled by changing the universe of discourse. Moreover, the addition of more fuzzy sets in a given universe of discourse can give improved resolution and better sensitivity control. To keep the complexity of the fuzzy logic rule base low, the universe of discourse for each input fuzzy variable was classified into three fuzzy sets. The universe of discourse for the output fuzzy variable was divided into seven regions so that appropriate weight can be given to the different combinations of the input fuzzy sets.

Examples. Assume that SIR_c is "Low," Tr_d is "High," and MS velocity is "High." These conditions indicate that the handoff should be *encouraged* as much as possible; this is rule number nineteen. To make the fastest handoff, $RSS_{threshold}$ is increased to the highest value, and $RSS_{hysteresis}$ is decreased to the lowest value. Now "High," Tr_d is "Low," and MS velocity is "Low," handoff is *discouraged* as much as possible. The philosophy behind the other rules states that if the majority of the input variables suggest encouraging a handoff, threshold is increased and hysteresis is decreased. On the other hand, if the majority of the input variables suggest discouraging a handoff, threshold is decreased, and hysteresis is increased. The extent to which the threshold and hysteresis are changed to encourage or discourage a handoff

Table 5.1: Fuzzy Logic Rule Base

Rule No.	$\mathbf{SIR_c}$	$\mathbf{(TR)_d}$	**MS Velocity**	$\mathbf{RSS_{threshold}}$	$\mathbf{RSS_{hysteresis}}$
1	High	High	High	High	Low
2	High	High	Normal	Normal	Normal
3	High	High	Low	Low	High
4	High	Normal	High	Normal	Normal
5	High	Normal	Normal	Low	High
6	High	Normal	Low	Lower	Higher
7	High	Low	High	Low	High
8	High	Low	Normal	Lower	Higher
9	High	Low	Low	Lowest	Highest
10	Normal	High	High	Higher	Lower
11	Normal	High	Normal	High	Low
12	Normal	High	Low	Normal	Normal
13	Normal	Normal	High	High	Low
14	Normal	Normal	Normal	Normal	Normal
15	Normal	Normal	Low	Low	High
16	Normal	Low	High	Normal	Normal
17	Normal	Low	Normal	Low	High
18	Normal	Low	Low	Lower	Higher
19	Low	High	High	Highest	Lowest
20	Low	High	Normal	Higher	Lower
21	Low	High	Low	High	Low
22	Low	Normal	High	Higher	Lower
23	Low	Normal	Normal	High	Low
24	Low	Normal	Low	Normal	Normal
25	Low	Low	High	High	Low
26	Low	Low	Normal	Normal	Normal
27	Low	Low	Low	Low	High

depends upon how many variables agree on a particular direction of the threshold and hysteresis change. Resolving conflicting criteria in accordance with the global system goals is an important advantage of fuzzy logic. For example, consider rule 2. “High” SIR_c discourages a handoff, while “High” Tr_d encourages a handoff. MS velocity is neutral. Hence, the fuzzy logic rule makes the logical decision to keep the threshold and hysteresis values nominal.

5.3.2 Analysis of Proposed Class of Algorithms

The proposed class of fuzzy algorithms has a number of advantages over existing algorithms. Some of the significant advantages are mentioned here.

- **Use of Good Features of Existing Algorithms**. The proposed algorithm utilizes several good features of existing algorithms. For example, a combined RSS and SIR based algorithm with handoff parameters, such as threshold and hysteresis, is used as a conventional algorithm in Figure 5.2. This algorithm leads to fewer handoffs, reduced ping-pong effect, and fewer unnecessary handoffs. The proposed class of algorithms does not *replace* the existing algorithms; it *complements* the existing algorithms. The proposed technique enhances the performance of conventional algorithms by providing a robust adaptation mechanism to make appropriate tradeoffs.

- **Use of Multiple Handoff Criteria**. Multicriteria algorithms provide better performance than single criterion algorithms due to the additional flexibility and complementary nature of the criteria. For example, consider a situation in which (i) the traffic in the handoff candidate cell is low and (ii) SIR for the current cell is very high. If an adaptive single criterion handoff algorithm based on traffic is used, it would increase the handoff threshold, encouraging a handoff. An adaptive single criterion handoff algorithm based on SIR would lower the handoff threshold, discouraging a handoff. However, a multicriteria handoff algorithm can consider both measurements (traffic and SIR) and make a decision that is consistent with the global system goals.

- **Adaptation**. The proposed algorithm is adaptive to interference, traffic, and velocity. Adaptation to *interference* gives better RSS and SIR distribution, resulting in fewer dropped calls, better communication quality, potentially lower MS transmit power requirements, and better cell memberships. Adaptation to *traffic* provides traffic balancing, reducing the blocking probability of new calls and handoff calls. Adaptation to *velocity* (or *quality degradation rate*) gives good performance at different MS speeds.

- **Fuzzy Logic Attributes**. One of the advantages of fuzzy logic is simplicity. Also, the knowledge about the system can be better exploited with fuzzy logic algorithms than with conventional algorithms [89]. Moreover, conflicting criteria can be resolved using fuzzy logic.

- **Systematic Balance**. The proposed algorithm allows a systematic compromise among various characteristics by properly tuning the parameters of the fuzzy logic rule base.

Increased complexity is a disadvantage of the proposed algorithms compared to conventional algorithms. Nevertheless, inherent parallelism in an FLS partially offsets this increase in complexity. Moreover, there are several ways of reducing this complexity. For example, an FLS can be represented compactly using some neural network paradigms, leading to the savings in the storage and computational requirements.

5.4 Performance Analysis of Proposed and Conventional Algorithms

The performances of the proposed and conventional handoff algorithms have been evaluated using several performance metrics, covering major aspects of handoff related system performance. These performance metrics include *cumulative distribution function (CDF) of RSS*, *CDF of SIR*, *CDF of traffic*, *average number of handoffs*, and *cross-over distance*. When an MS is connected to a BS, the RSS from the BS, the downlink SIR, and the number of calls in the BS are stored, and these stored values are used to derive CDFs of RSS, SIR, and traffic, respectively. The average number of handoffs and the average 50% cross-over distance for an MS journey (i.e., the distance of the MS from the BS where the probability that the MS is connected to the BS is 0.5) are also stored. The CDFs of RSS and SIR can imply the call drop probability, call quality, and potential uplink transmit power requirements. For example, high values of RSS and SIR indicate that the call drop probability will be low, the call quality will be good, and the MS can transmit comparatively less power. The traffic CDF can give an idea of traffic balancing (or new call or handoff blocking probability). For example, a lower number of calls in a cell implies a high probability of successful network access since more new calls or handoff requests can be entertained by the network. A lower number of handoffs indicates a lower switching load and a shorter delay in the processing of a handoff request. The cross-over distance indicates the interference level, handoff delay, and MS power requirements.

5.4.1 Interference Adaptation

Figure 5.6 shows the CDF of SIR for a conventional algorithm and the fuzzy algorithm, illustrating that the CDF of the SIR for a fuzzy algorithm is to the right of the CDF of SIR for the conventional algorithm with an improvement of approximately 1.0 dB. Note that the traffic and velocity adaptation were not in effect when this simulation result was obtained, isolating the performance improvement due to interference adaptation and showing the function of the interference adaptation part of the fuzzy logic rule base. Also note that the improvement of SIR can be changed by tuning the fuzzy logic parameters. For example, Figure 5.7 shows the CDF of SIR when there was less improvement (0.6 dB) compared to Figure 5.6 tuning. On the other hand, Figure 5.8 shows the CDF of SIR when there was more improvement (1.5 dB) compared to the Figure 5.6 tuning. The FLS parameters can be tuned in a number of ways, and here, the definitions of the fuzzy sets "High" and "Low" for the fuzzy variables $RSS_{threshold}$ and $RSS_{hysteresis}$ were changed. The centers of the membership functions for the fuzzy set "High" of the fuzzy variable $RSS_{threshold}$ were -130dBm, -132 dBm, and -134 dBm

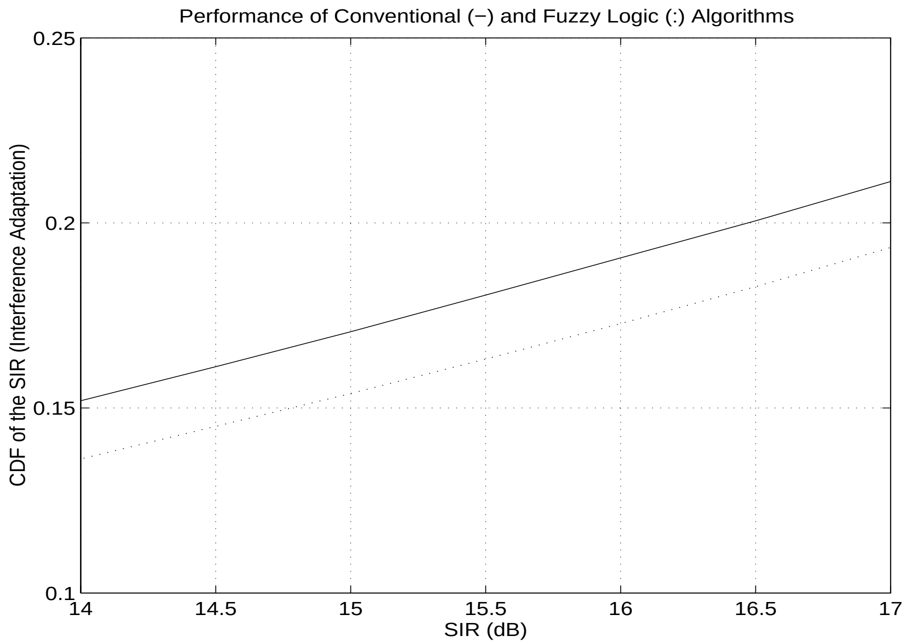

Figure 5.6: CDF of SIR ("Normal" Degree of Interference Adaptation)

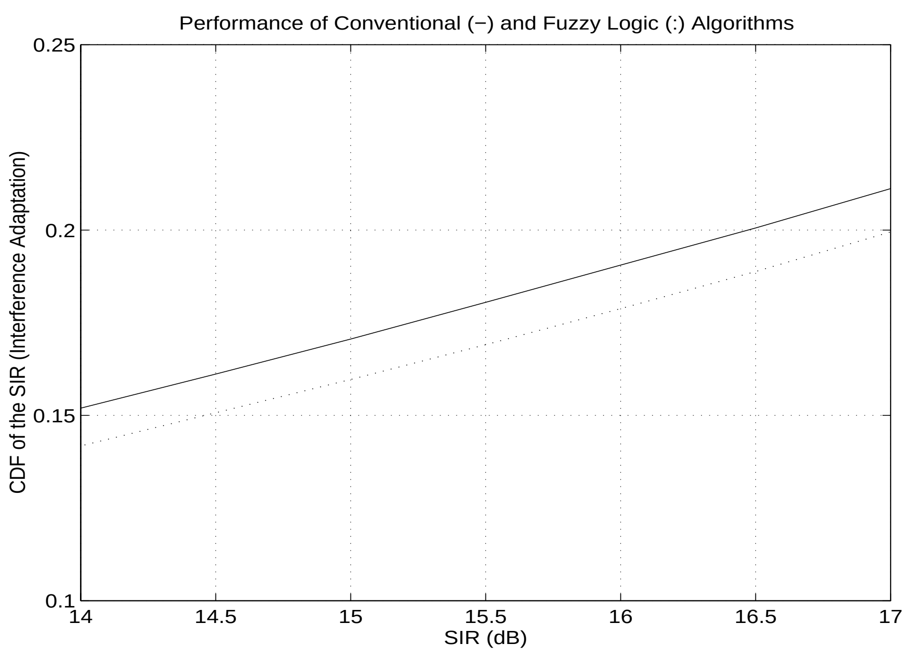

Figure 5.7: CDF of SIR ("Lower" Degree of Interference Adaptation)

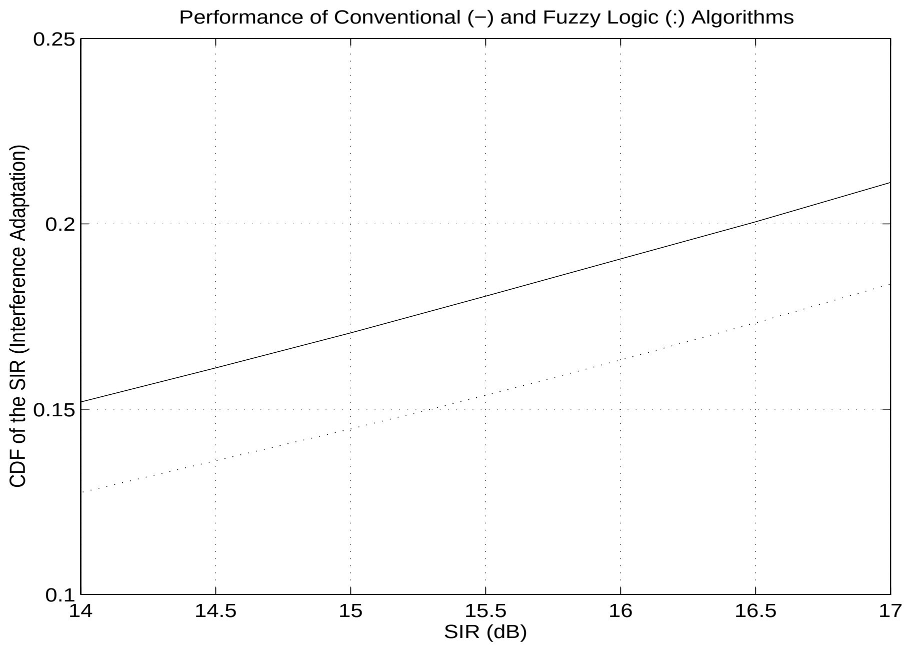

Figure 5.8: CDF of SIR ("Higher" Degree of Interference Adaptation)

for Figure 5.8, Figure 5.6, and Figure 5.7, respectively. The centers of the membership functions for the fuzzy set "Low" of the fuzzy variable $RSS_{threshold}$ were -142dBm, -140 dBm, and -138 dBm for Figure 5.8, Figure 5.6, and Figure 5.7, respectively. The centers of the membership functions for the fuzzy set "High" of the fuzzy variable $RSS_{hysteresis}$ were 20.0 dB, 18.5 dB, and 17.0 dB for Figure 5.8, Figure 5.6, and Figure 5.7, respectively. The centers of the membership functions for the fuzzy set "Low" of the fuzzy variable $RSS_{hysteresis}$ were 12.0 dB, 13.5 dB, and 15.0 dB for Figure 5.8, Figure 5.6, and Figure 5.7, respectively. The same definitions of the "High" and "Low" fuzzy sets for the fuzzy variables $RSS_{threshold}$ and $RSS_{hysteresis}$ were used to obtain "Higher," "Normal," and "Lower" degrees of adaptation for different test cases (such as interference adaptation and traffic adaptation). The centers of the membership functions for the fuzzy sets "Normal" of the fuzzy variables $RSS_{threshold}$ and $RSS_{hysteresis}$ were chosen to be -136 dBm and 16.0 dB, respectively, in all the test cases. Assume that the call is dropped at SIR of 14.0 dB. An approximate idea about the call drop probability can be obtained by comparing the probabilities of SIR distribution at this value of SIR for the conventional and fuzzy algorithms. The probability that SIR is less than 14 dB is 0.1519 for the conventional algorithm and 0.1367 for the fuzzy algorithm with "Normal" degree of interference adaptation. Thus, there is an improvement of $((0.1519 - 0.1362)/0.1519)100\% = 10\%$. For a "Low" degree of interference adaptation, there is an improvement of $((0.1519-0.1418)/0.1519)100\% = 7\%$, and for a "High" degree of interference adaptation, there is an improvement of $((0.1519 - 0.1275)/0.1519)100\% = 16\%$. Thus, there can be a 7% to 16% improvement in call drop probability depending upon the tuning of the fuzzy logic parameters. The maximum possible improvement depends on system related constraints (e.g., the maximum permissible MS transmit power and the maximum permissible distance between an MS and a BS).

5.4.2 Traffic Adaptation

The traffic adaptation capability of the fuzzy logic system is demonstrated next for traffic distribution. The interference and velocity adaptation were switched off during this simulation to clearly show the effect of traffic adaptation. Figure 5.9 shows that the CDF of traffic for the fuzzy algorithm is to the left of the CDF of traffic for the conventional algorithm, giving an improvement of 1.8 calls in the traffic distribution. Also note that the improvement of traffic can be changed by tuning the fuzzy logic parameters. For example, Figure 5.10 shows the CDF of traffic when there was less improvement (1.0 call) compared to the Figure 5.9 tuning, and Figure 5.11 shows the CDF of traffic when there was more improvement (2.8 calls), compared to the Figure 5.9 tuning.

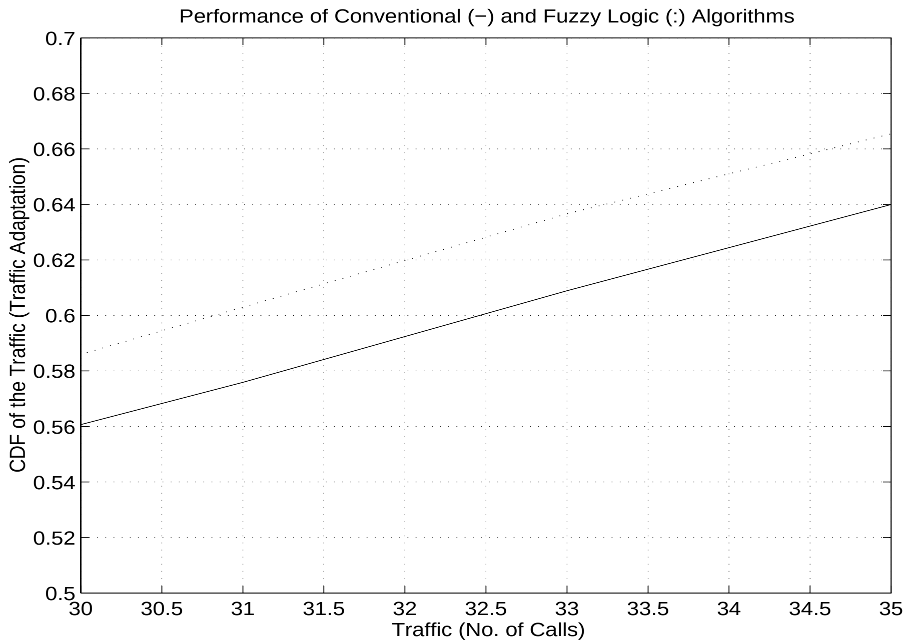

Figure 5.9: CDF of Traffic ("Normal" Degree of Adaptation)

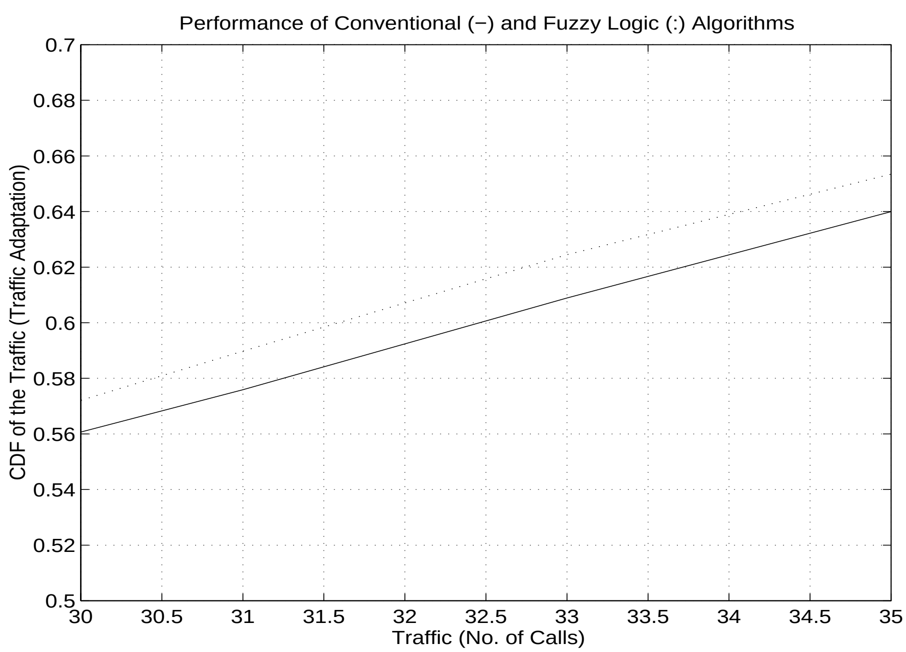

Figure 5.10: CDF of Traffic ("Lower" Degree of Adaptation)

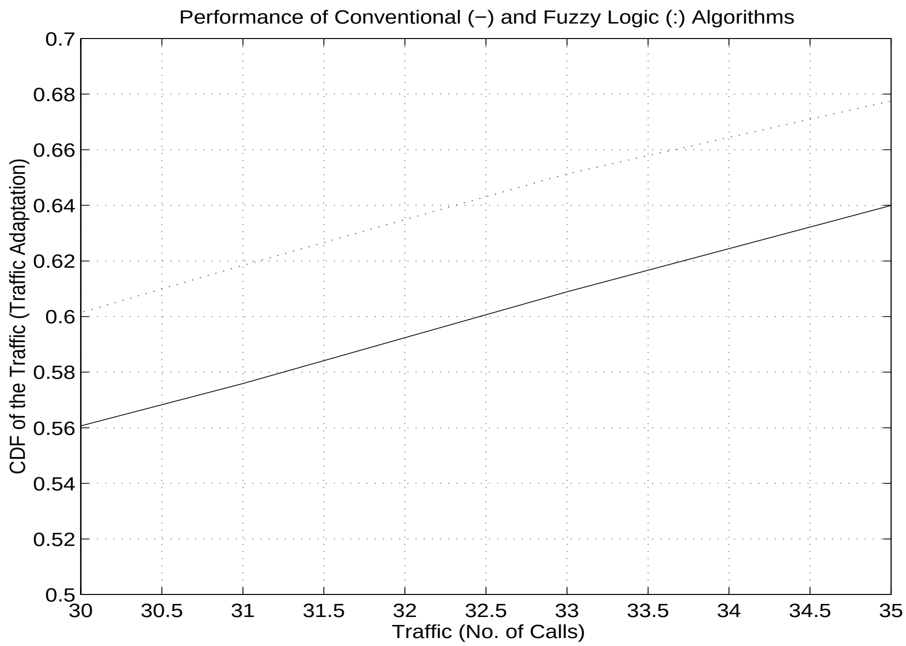

Figure 5.11: CDF of Traffic ("Higher" Degree of Adaptation)

5.4.3 Velocity Adaptation

The velocity adaptation capability of the fuzzy logic system is demonstrated next for the cross-over distance. The interference and traffic adaptation were switched off during this simulation result to show the effect of velocity adaptation. Figure 5.12 shows the 50% cross-over distance and the average number of handoffs during the MS's travel at different velocities. The minimum velocity is 45 mph (or 20 m/s), the average velocity is 65 mph (or 29 m/s), and the maximum velocity is 85 mph (or 38 m/s). The results corresponding to the fuzzy algorithm are shown by the symbols "*," "+," and "x" without the circles, while the results corresponding to the conventional algorithm are shown by encircled symbols. The symbols "*," "+," and "x" are associated with minimum, average, and maximum velocities, respectively. The operating point for the fuzzy algorithm is to the left of the operating point of

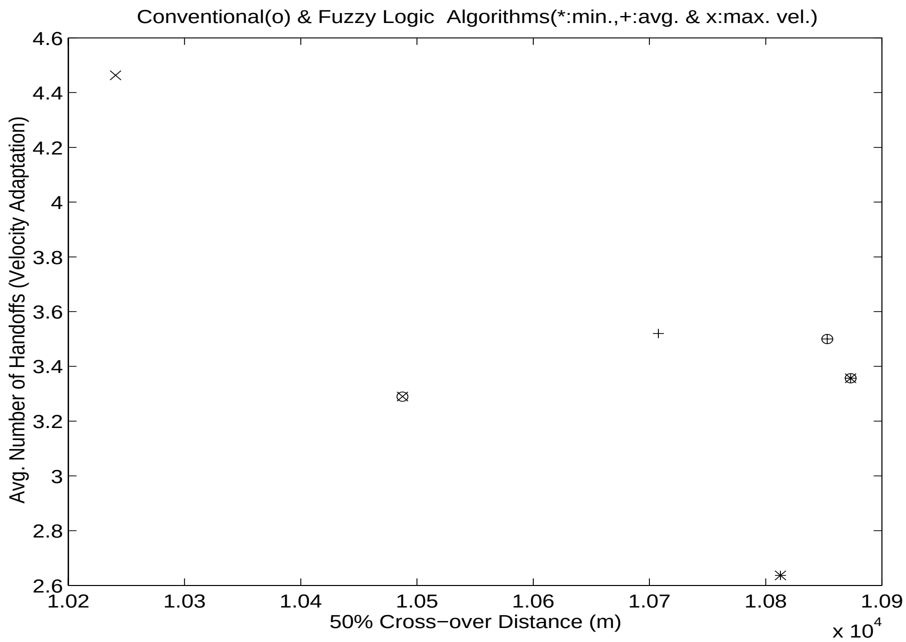

Figure 5.12: Effect of Velocity Adaptation

the conventional algorithm because the fuzzy algorithm tends to reduce cross-over distance, giving less interference. The improvement in the handoff delay can be determined by comparing the reduction in cross-over distance for different velocities. For the low velocity (20 m/s), there is a reduction of 60m in cross-over distance, an improvement of $60/20 = 3.0$ sec in handoff delay. For the average velocity (29 m/s), there is a reduction of 150m in cross-over distance – an improvement of $150/29 = 5.1$ sec in handoff delay. For the high velocity (38 m/s), there is a reduction of 230m in cross-over distance, an improvement of $2350/38 = 6.1$ sec in handoff delay. Thus, the improvement in handoff delay conforms with the desired goal (i.e., handoff should be faster for high velocities).

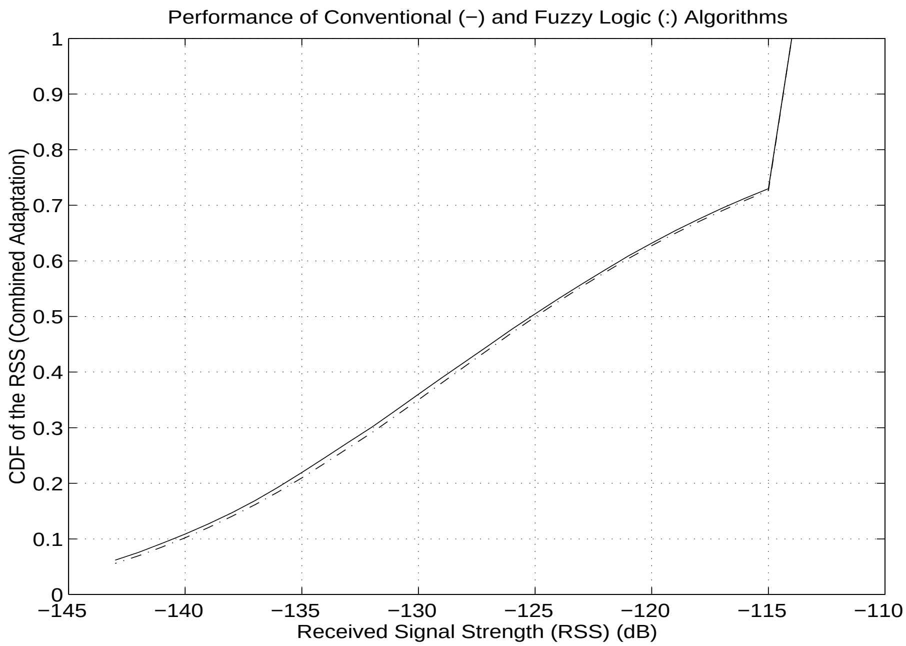

Figure 5.13: Effect of Combined Adaptation on RSS Performance

5.4.4 Combined Interference, Traffic, and Velocity Adaptation

Figure 5.13 shows the RSS distribution when all the components of adaptation are in effect simultaneously. There is not much difference between the CDFs of the RSS for conventional and fuzzy algorithms, but there is a marginal improvement (a fraction of a dB) with the fuzzy algorithm.

Figure 5.14 shows the SIR distribution when all the components of adaptation are in effect simultaneously. The fuzzy algorithm shows an improvement of 0.8 dB over the conventional algorithm. Note that the SIR improvement depends on which rules contribute to the overall fuzzy logic outputs. In practice, certain situations will give higher improvement than that shown here. For example, there may have been numerous occasions where conflicting requirements would have forced the FLS to keep

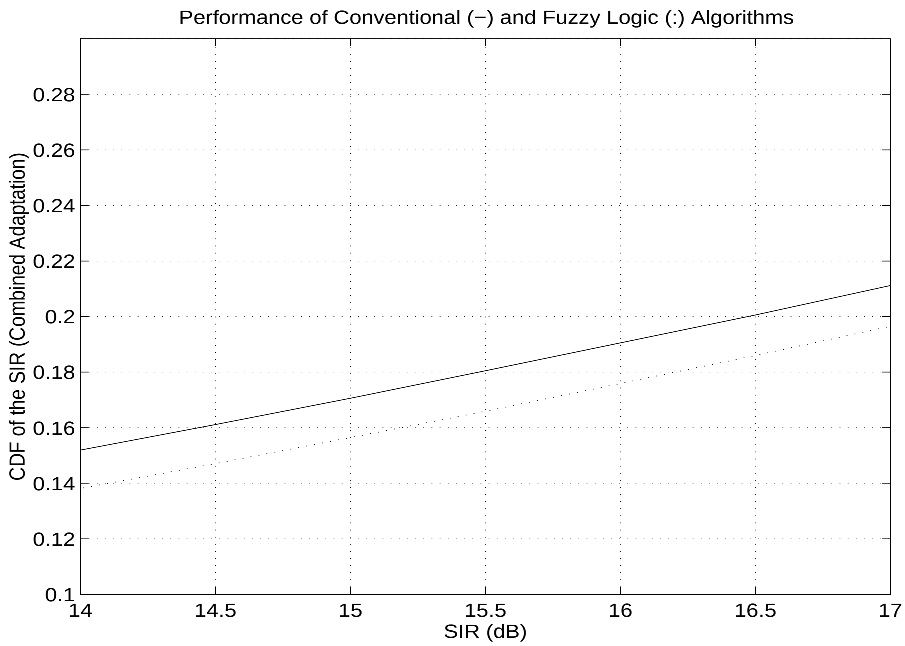

Figure 5.14: Effect of Combined Adaptation on SIR Performance

the handoff parameters as nominal values, limiting the perceived SIR improvement. If several events indicate that the handoff parameter changes to a higher degree, more improvement in SIR would be visible. Figure 5.15 shows traffic distribution when all the components of adaptation were in effect simultaneously, and the fuzzy algorithm shows an improvement of 1.8 calls over the conventional algorithm. As discussed earlier for SIR, certain situations in practice will give higher improvement than that shown here. For example, if there is a non-uniform traffic distribution, more improvement would be feasible. Figure 5.16 shows velocity adaptation when all the components of adaptation work together and shows results for an average velocity of 65 mph (29 m/s). This figure shows that the handoff delay is reduced by 160m or $160/29 = 5.5$ sec with the fuzzy algorithm.

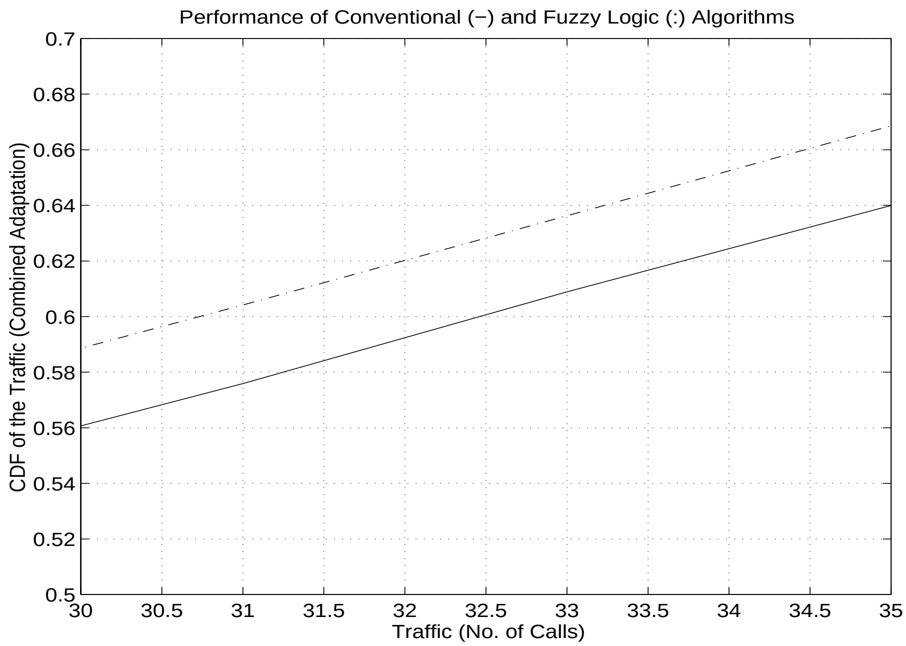

Figure 5.15: Effect of Combined Adaptation on Traffic Performance

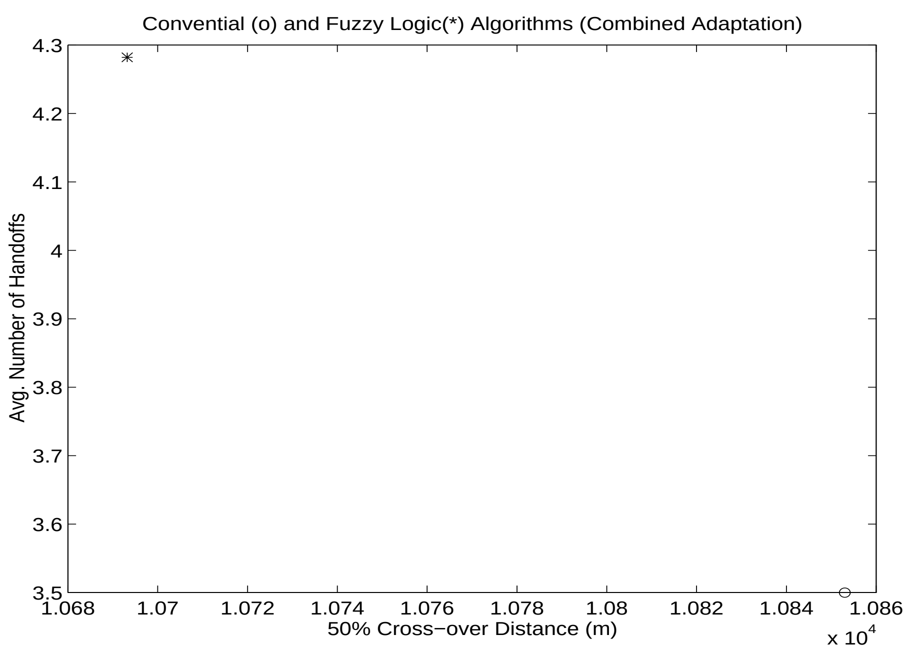

Figure 5.16: Effect of Combined Adaptation on Velocity Performance

5.5 Conclusion

This chapter introduces a new class of handoff algorithms that exploits the knowledge of the working of several existing algorithms and uses fuzzy logic to adapt the parameters of handoff algorithms. A fuzzy logic rule base is created using the known sensitivities of handoff parameters. The design procedure for a generic fuzzy logic based algorithm is outlined. Simulation results for both a conventional and fuzzy logic based algorithm are analyzed in detail. It is shown that a multicriteria fuzzy handoff algorithm gives better performance than a signal strength based conventional handoff algorithm. Furthermore, the proposed approach allows tuning of the FLS parameters to achieve a balanced tradeoff among different system characteristics in the dynamic cellular environment. Simulation results indicate that SIR distribution is improved by 0.5 dB to 1.7 dB due to interference adaptation (giving 7% to 16% improvement in call drop probability), traffic distribution is improved by 1.0 to 2.8 calls due to traffic adaptation, and handoff delay is reduced by three seconds to six seconds due to velocity adaptation.

Chapter 6

A Neural Encoded Fuzzy Logic Algorithm

This chapter proposes a new class of handoff algorithms that combines attractive features of several existing algorithms and adapts the parameters of a handoff algorithm using a neural encoded fuzzy logic system. Known sensitivities of handoff parameters can be used to design a fuzzy logic system (FLS), which can then be used to adapt the handoff parameters to obtain improved performance in a dynamic cellular environment. However, the FLS has large storage requirements and high computational complexity. This chapter proposes neural encoding of the FLS to circumvent these demands; a neural network learns how the FLS works. Several neural network paradigms such as a multilayer perceptron (MLP) and a radial basis function network (RBFN) can be universal approximators. The input-output mapping capability and compact data representation capability of neural networks are exploited here to derive an adaptive handoff algorithm that retains the high performance of the original fuzzy logic based algorithm and that has an efficient architecture for storage and computational requirements. Extensive simulation results for a conventional handoff algorithm (absolute and relative signal strength based algorithm) and a neural algorithm are presented. It is shown in this chapter that an adaptive multicriteria neural handoff algorithm performs better than a conventional signal strength based handoff algorithm.

6.1 Introduction

An adaptive handoff algorithm based on neural networks is proposed in this chapter. Known sensitivities of handoff parameters can be used to create a fuzzy logic system (FLS). Since neural networks can represent information compactly, good savings in storage and computational requirements can be obtained if the fuzzy logic rule base is replaced by a neural network. This chapter discusses the utilization of two neural networks, a multilayer perceptron (MLP) and radial basis function network (RBFN), to mimic the working of the FLS. These network paradigms are trained to learn the relationship among the inputs and the outputs of the fuzzy logic rule base. The trained neural networks are used to adapt the parameters of a handoff algorithm. The performance of this adaptive neural handoff algorithm is compared with the conventional handoff algorithm. The simulation results show that the proposed neural algorithm possesses a very low complexity architecture while retaining the high performance of the original fuzzy logic based handoff algorithm.

The configuration of a generic handoff algorithm, shown in Figure 6.1 and Figure 6.2, was proposed in [109]. This configuration uses the combination of an absolute and relative received signal strength (RSS) based algorithm and a signal-to-interference ratio (SIR) based algorithm. The RSS based algorithm has threshold ($RSS_{threshold}$) and hysteresis ($RSS_{hysteresis}$) as parameters, while the SIR based algorithm has threshold ($SIR_{threshold}$) as a parameter. The SIR threshold parameter

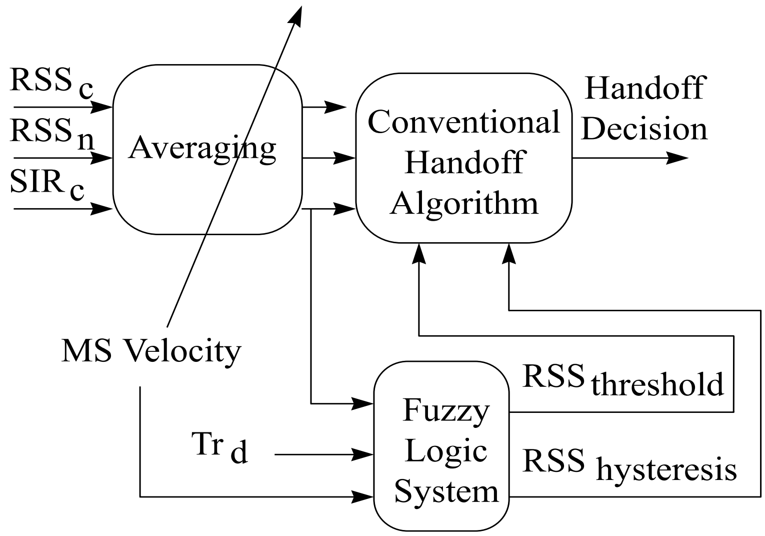

Figure 6.1: An Adaptive Fuzzy Logic Based Algorithm

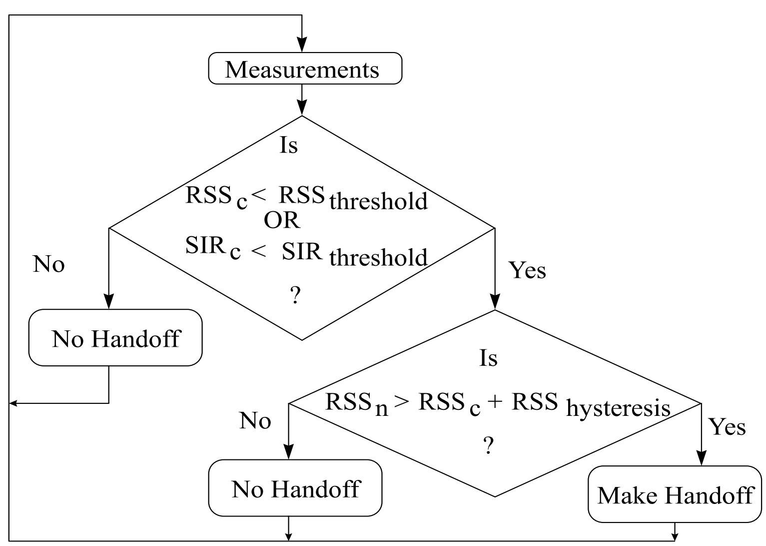

Figure 6.2: A Conventional Algorithm for a Generic Fuzzy Logic Based Handoff Algorithm

allows the initiation of the search for a better handoff candidate early on. The RSS based parameters are adapted using the FLS. It is assumed that the MS makes necessary measurements. However, the proposed algorithm can be easily extended to include BS measurements. Note that in actual systems, there may be specific requirements (e.g., maximum permissible round-trip delay). Such requirements can be incorporated as part of either the basic conventional algorithm or the adaptation mechanism. Handoff criteria that are averaged according to the velocity adaptive averaging mechanism include RSS of the current BS (RSS_c), RSS of the neighboring BS (RSS_n), and SIR of the current channel (SIR_c). The MS velocity and the traffic difference Tr_d (i.e., the difference in the number of calls in the current BS and the neighboring BS) are not averaged since their instantaneous values are of interest. Since the basic parameters to be adapted, $RSS_{threshold}$ and $RSS_{hysteresis}$, are related to RSS, the variables RSS_c and RSS_n are not used to adapt these parameters. An FLS is used as the adaptation mechanism. The inputs to the FLS are SIR_c, $(Tr)_d = (Tr)_c - (Tr)_n$ ($(Tr)_c$ is the number of calls in the current BS, and $(Tr)_n$ is the number of calls in the neighboring BS), and MS velocity. The outputs of the FLS are $RSS_{threshold}$ and $RSS_{hysteresis}$.

The inherent parallelism in FLSs allows an efficient implementation of the fuzzy logic based algorithm. However, the algorithm is still much more complex than conventional algorithms that consist of only a few binary IF-THEN rules. Moreover, as the number of inputs to the FLS increases or as the universes of discourse for the fuzzy variables are divided into more fuzzy sets, the complexity of the FLS increases even further. The complexity is two-fold, storage requirements and the number of computations to be performed every measurement sample time. A simple handoff algorithm with fewer computations and less storage requirements is desirable since it can be executed quickly and does not consume a lot of the available resources. The simplicity of a handoff algorithm is becoming more and more important as the user demand in cellular systems is expected to increase in the coming several years. The simplicity can reduce the handoff delay, the number of dropped calls, and the number of blocked calls. Moreover, the savings in computation time gives the processing unit (e.g., an MSC or a BS) an opportunity to devote time to other aspects (such as collection of measurements or intelligent resource allocation) to improve the overall system performance. Hence, it is advantageous to reduce the complexity to achieve a relatively simple algorithm with faster execution time. *In this chapter, neural encoding of the FLS is proposed to simultaneously achieve the goals of high performance and reduced complexity.* The storage requirements and computational savings are analyzed. The neural encoded FLS based algorithm is evaluated comprehensively, and its performance is compared with a conventional absolute and relative RSS based algorithm and the original fuzzy logic based algorithm. The chapter shows that the neural encoded FLS algorithm (NEFLSA) performs as well as the basic fuzzy logic algorithm (FLA) and that the NEFLSA is less complex than the FLA. The parameters of neural networks allow a tradeoff between the complexity and the approximation accuracy. As long as the neural networks perform better than the conventional algorithm and are of low complexity, the desired goals of good performance and low complexity would be achieved. The simulation results shown in this chapter are not intended to be the optimum results obtainable using fuzzy logic or neural networks. A particular configuration of fuzzy logic system designed in [109] was chosen as a basic FLS, and two paradigms of neural networks (MLP and RBFN) were trained to mimic the operation of this FLS.

Section 6.2 describes a procedure for using a neural network as an adaptation mechanism in place of the FLS. The performances of a conventional algorithm and the proposed neural algorithm are evaluated in Section 6.3. Finally, Section 6.4

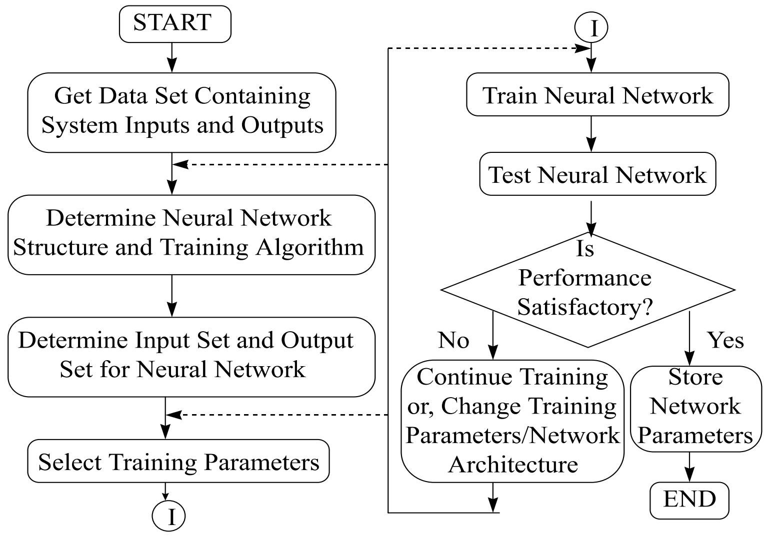

Figure 6.3: Design Procedure for an ANN Application

summarizes the chapter.

6.2 Application of Neural Networks to Handoff

An ANN can be trained to learn complex relationships among the inputs and the outputs of a system. After the ANN is trained, the parameters of the ANN can be used to estimate the outputs for given inputs. Figure 6.3 shows the flowchart illustrating the training mechanism of the ANN in a supervised learning mode. A generic training procedure with its application to the FLS mapping is explained next.

1. *Get the data set that contains the system inputs and desired outputs.* Different possible combinations of the inputs are applied to the FLSs, and the corresponding outputs of the FLS are calculated. The FLS inputs and outputs constitute the data set.

2. *Determine the structure of the neural network and the associated learning algorithm.* Since the problem of function approximation is a generalization problem, two suitable paradigms, backpropagation network and radial-basis function network, are considered here.

3. *Determine the input set and the target output set for the neural network.* Since the mapping between the FLS inputs and outputs is static, input and output data sets collected in Step 1 can serve as the input set and the target output set with proper scaling. It is important to scale the training data set so that the network parameters do not saturate. In general, the input data set obtained in Step 1 may need to be preprocessed for use with the ANN when the system outputs depend not only on the current inputs but also on the history of inputs and outputs.

4. *Select the training parameters (such as the learning rate and number of neurons) and train the neural network using an appropriate algorithm.* If the network does not perform satisfactorily, several possible options are an increase in the training time, preprocessing of inputs, use of a different ANN paradigm, or use of different training parameters. Once the network has been trained, the mapping between the FLS inputs and the corresponding outputs is stored in the parameters of the ANN.

The complexity of a handoff algorithm can be analyzed in terms of storage requirements and computational requirements. At every sampling instant, the outputs of the adaptive mechanisms (FLS, MLP and RBFN) need to be calculated.

The output of an FLS, y, is given by

$$y = \frac{\sum_{l=1}^{R} \overline{y}^l(\mu_{B^l}(\overline{y}^l))}{\sum_{l=1}^{R}(\mu_{B^l}(\overline{y}^l))} \tag{6.1}$$

where R is the number of rules, $\overline{y}^l$ is the center of the output fuzzy set, and $\mu_{B^l}(\overline{y}^l)$ is calculated as

$$\mu_{B^l}(\overline{y}^l) = \prod_{i=1}^{m} \exp(-(\frac{x_i - \overline{x_i}^l}{\sigma_i^l})^2) \tag{6.2}$$

where m is the number of inputs to the FLS, $\overline{x_i}^l$ is the center of the fuzzy set for input i for rule l, and σ_i^l is the spread of the fuzzy set for input i for rule l. Since the FLS considered here is a single-output system, two FLSs are required to calculate two outputs. However, all the computations need not be carried out separately for these two FLSs since the membership values (i.e., $\mu_{B^l}(\overline{y}^l)$) are the same for a given input vector. Only $\overline{y}^l$ related calculations need to be carried out for individual outputs.

The output of an MLP is given by

$$Y = W_2 \tanh(W_1 X + B_1) + B_2 \tag{6.3}$$

where W_1 is a hidden layer weight matrix of size $N \times m$, B_1 is a hidden layer bias matrix of size $N \times 1$, W_2 is an output layer weight matrix of size $p \times N$, B_2 is an output layer bias matrix of size $p \times 1$, X is an $m \times 1$ input vector, Y is a $p \times 1$ output vector, and "tanh" is the hyperbolic tangent function.

The output of an RBFN is given by

$$Y = W_2 A_1 + B_2 \tag{6.4}$$

with

$$A_1 = radbas(dist(W_1, X) \times B_1). \tag{6.5}$$

Here, W_1 consists of centers of Gaussian functions and is of size $N \times m$, B_1 consists of spreads associated with Gaussian functions and is of size $N \times 1$, W_2 is an output layer weight matrix of size $p \times N$, B_2 is an output layer bias matrix of size $p \times 1$, X is an $m \times 1$ input vector, Y is a $p \times 1$ output vector, and "dist" is the distance between X and each row of W_1. In other words,

$$dist(w, X) = \sqrt{\sum_{j=1}^{p} (w_j - X_j)^2}. \tag{6.6}$$

Here, w represents one row of W_1.

"Radbas" is the radial-basis function given by

$$radbas(x) = \exp(-x^2). \tag{6.7}$$

The storage requirements of the FLS, MLP, and RBFN are derived next.

- **FLS Storage Requirements**.

  For an FLS rule, m centers ($\overline{x_i}^l$) and m spreads (σ_i^l)for the antecedent part of the rule and p centers ($\overline{y}^l$) for the consequent part of the rule are required. Thus, for each rule, a total of $(2m+p)$ elements are required (Eq. 6.1 and 6.2). Since there are R rules in an FLS, a total of $(2m+p)R$ elements need to be stored for the FLS.

- **MLP Storage Requirements**.

  For an MLP, W_1, B_1, W_2, and B_2 are required. Since W_1 is of size $N \times m$ and B_1 is of size $N \times 1$, the number of elements for the first layer is $Nm + N$. Since W_2 is of size $p \times N$ and B_2 is of size $p \times 1$, the number of elements for the second layer is $pN + p$. The total number of elements are $Nm + N + pN + p = m(N+1) + p(N+1) = (m+p)(N+1)$.

- **RBFN Storage Requirements**.

  For an RBFN, the parameters W_1, B_1, W_2, and B_2 have the same dimensions as in the case of an MLP. Hence, a total of $(m+p)(N+1)$ elements are needed for RBFN.

Table 6.1 summarizes the storage requirements for an FLS, MLP, and RBFN.

In this chapter, R=27, m=3, p=2, N=5 for BPNN, and N=8 for RBFN. Table 6.2 gives the improvement in storage requirements for the neural techniques. The

Table 6.1: Storage Complexity of Adaptation Mechanisms

System	**Elements**
FLS	$(2m+p)R$
MLP	$(m+p)(N+1)$
RBFN	$(m+p)(N+1)$

Table 6.2: Specific Examples of Storage Complexity

System	**Elements**
FLS	216
MLP (N=5)	30
RBFN (N=8)	45

MLP and RBFN give an improvement of the factor 7.2 (i.e., 216/30) and 4.8 (i.e., 216/45) over the FLS for storage requirements.

The computational complexities of the FLS, MLP, and RBFN are derived next. The operations of addition and subtraction are grouped together and referred to as adds. Also, the operations of multiplication and division are grouped together and referred to as multiplies. Evaluations of functions (such as exponential, square-root) are referred to as functions.

- **FLS Computations**. For each rule, the input vector is processed by Eq. 6.2. There are one subtraction, one division, one multiplication (squaring operation), and one function (exponential) evaluation for each element of the input vector Xb that has m elements. Thus, there are one add, two multiplies, and one function. For each rule, there are m adds, $2m$ multiplies, and m functions due to m inputs. The m exponential terms and $\overline{y}^l$ are multiplied, requiring m more multiplies. Hence, there are mR adds, $3mR$ multiplies, and mR functions for R rules. There are $(R-1)$ additions (of $\overline{y}^l$ and μ_{B^l}) in the numerator of Eq. 6.1 and one division of the numerator and denominator in Eq. 6.1. Thus, there are $Rm+(R-1)=(m+1)R-1$ adds, $3mR+1$ multiplies, and mR functions for one output calculation. For each additional output, there are R multiplies (of $\overline{y}^l$ and μ_{B^l}) and $(R-1)$ adds (of the terms $\overline{y}^l\mu_{B^l}$ and one numerator-denominator division). Hence, there are additional $(R+1)$ multiplies and $(R-1)$ adds for each additional output. If there are p outputs, $(R+1)(p-1)$ additional multiplies and $(R-1)(p-1)$ additional adds are required. Thus, the total number of adds is $(m+1)R-1+(R-1)(p-1) = mR+R-1+Rp-R-p+1 = mR+Rp-p$, the total number of multiplies is $3mR+1+(R+1)(p-1) = 3mR+1+Rp-R+p-1 = (3m+p-1)R+p$, and the total number of functions is mR.

- **MLP Computations**. Each row of W_1X multiplication requires m multiplies and $(m-1)$ adds. Since there are N rows in W_1, a total of mN multiplies and $(m-1)N$ adds are required. W_1X and B_1 addition requires N more adds. Thus, $(m-1)N+N = mN$ adds are required. Hence, mN multiplies, mN adds, and N functions (tanh calculations) are required to carry out $\tanh(W_1X+B_1)$ operation. The multiplication of W_2 and tanh terms is between the $p \times N$ and $N \times 1$ matrices, requiring pN multiplies and $(p-1)N$ adds. The result of this multiplication is added to the $p \times 1$ matrix B_2, requiring additional p adds. Hence, the total number of adds are $mN + pN = (m+p)N$, and the total number of multiplies are $mN + pN = (m+p)N$.

- **RBFN Computations**. There are m subtractions, m multiplies (squaring operation), $(m-1)$ adds, and one function (square-root) for each row of W_1 in Eq. 6.6. Hence, there are $(2m-1)$ adds, m multiplies, and one function for Eq. 6.6. For N rows of W_1, there are $(2m-1)N$ adds, mN multiplies, and N functions. The distance function is $N \times 1$, and it is added to B_1 of size $N \times 1$. This requires N additions. Hence, there are $N(2m-1)+N = 2mN$ adds, Nm multiplies, and N functions for the argument of "radbas" in Eq. 6.5. The $N \times 1$ matrix is processed by radial basis functions. In each radial function, there is one multiplication (squaring) and one function evaluation (exponential) operation. Thus, there are N more multiplies and N more function evaluations. Hence, there are $2mN$ adds, $Nm+N$ multiplies, and $2N$ functions for the calculation of A_1. The evaluation of Eq. 6.4 requires pN multiplies and pN adds. Hence, there are a total of $2mN+pN = N(2m+p)$ adds, $Nm+N+pN = (m+p+1)N$ multiplies, and $2N$ functions.

Table 6.3 summarizes the computational requirements of the FLS, MLP, and RBFN.

Table 6.4 shows the improvement in computational requirements for the neural methods. There is an improvement of 8.8 ($486/55 = 8.8$) and 3.8 ($486/128 = 3.8$) for MLP and RBFN, respectively, over the FLS.

Table 6.3: Computational Complexity of Adaptation Mechanisms

System	Multiplies	Adds	Function Evaluations
FLS	$3m + R + p$	$m + 2R + (p-1)R$	mR
MLP	$N(m+p)$	$N(m-1) + p(N-1) + N + p$	N
RBFN	$N(p+m+1)$	$N(p+2m)$	$2N$

Table 6.4: Specific Examples of Computational Complexity

System	Multiplies	Adds	Function Evaluations	Total Operations
FLS	272	133	81	486
MLP (N=5)	25	25	5	55
RBFN (N=8)	48	64	16	128

6.3 Performance Evaluation

Figure 6.4 shows the input data of the training data set. These different combinations of inputs are applied to the FLS, and the corresponding FLS outputs are calculated. The FLS outputs constitute the output data of the training data set. This output data serves as the target or desired output when a neural network is trained. The ranges of SIR, traffic difference, and velocity are from 15 dB to 21 dB, -2 to 2 calls, and 20 m/s to 38 m/s, respectively. Figure 6.5 shows the input test data used for testing the generalization property of the trained ANNs. The test inputs were generated randomly within the specified ranges of the variables. The corresponding FLS outputs are the desired outputs. Hence, if an ANN has learned the input-output mapping of the FLS well, the presentation of the test inputs shown here produces the outputs that are similar to the desired test outputs.

Table 6.5 summarizes some of the results for MLP. E_{train} is the Frobenius norm

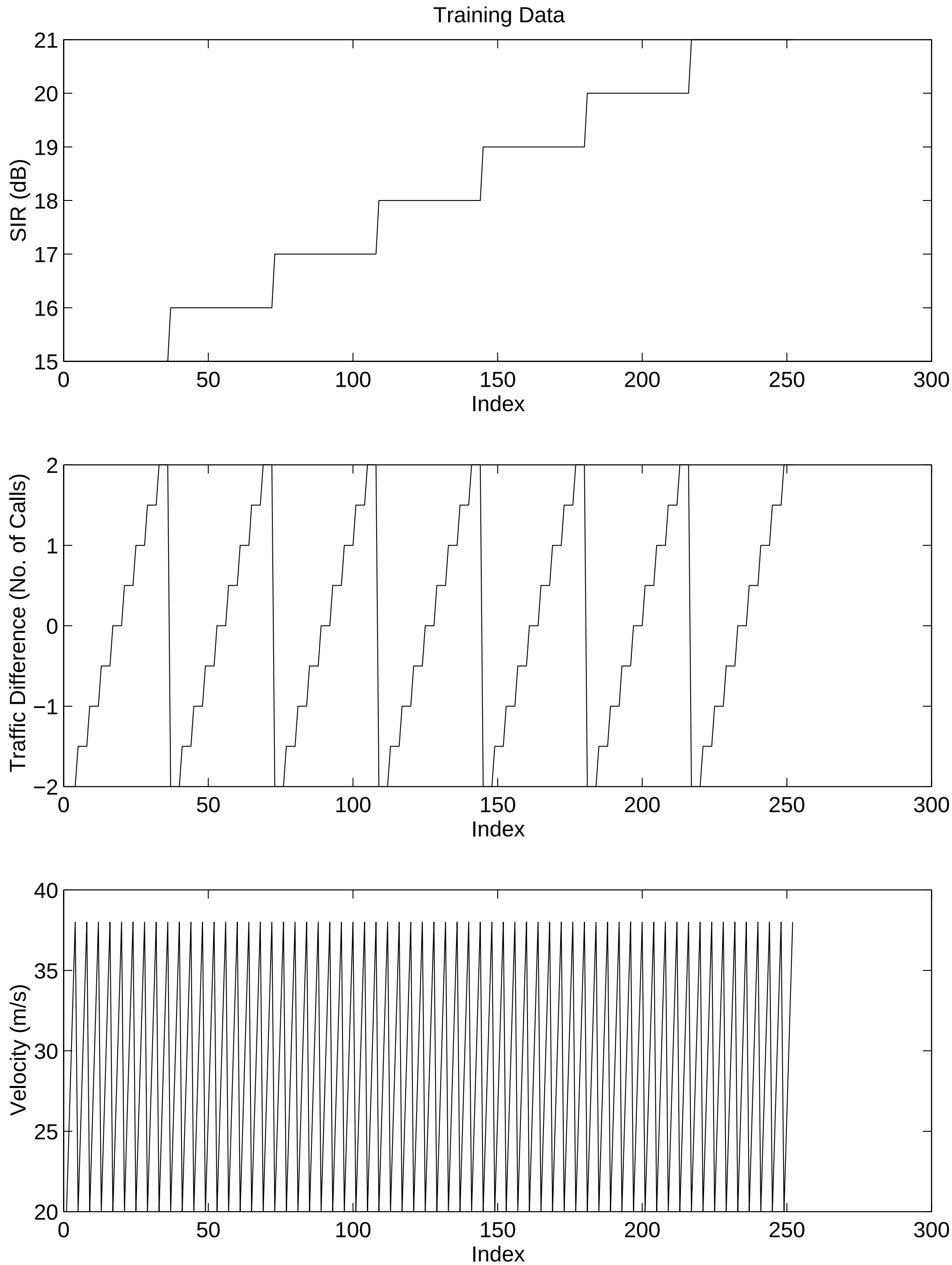

Figure 6.4: Training Data for Neural Networks

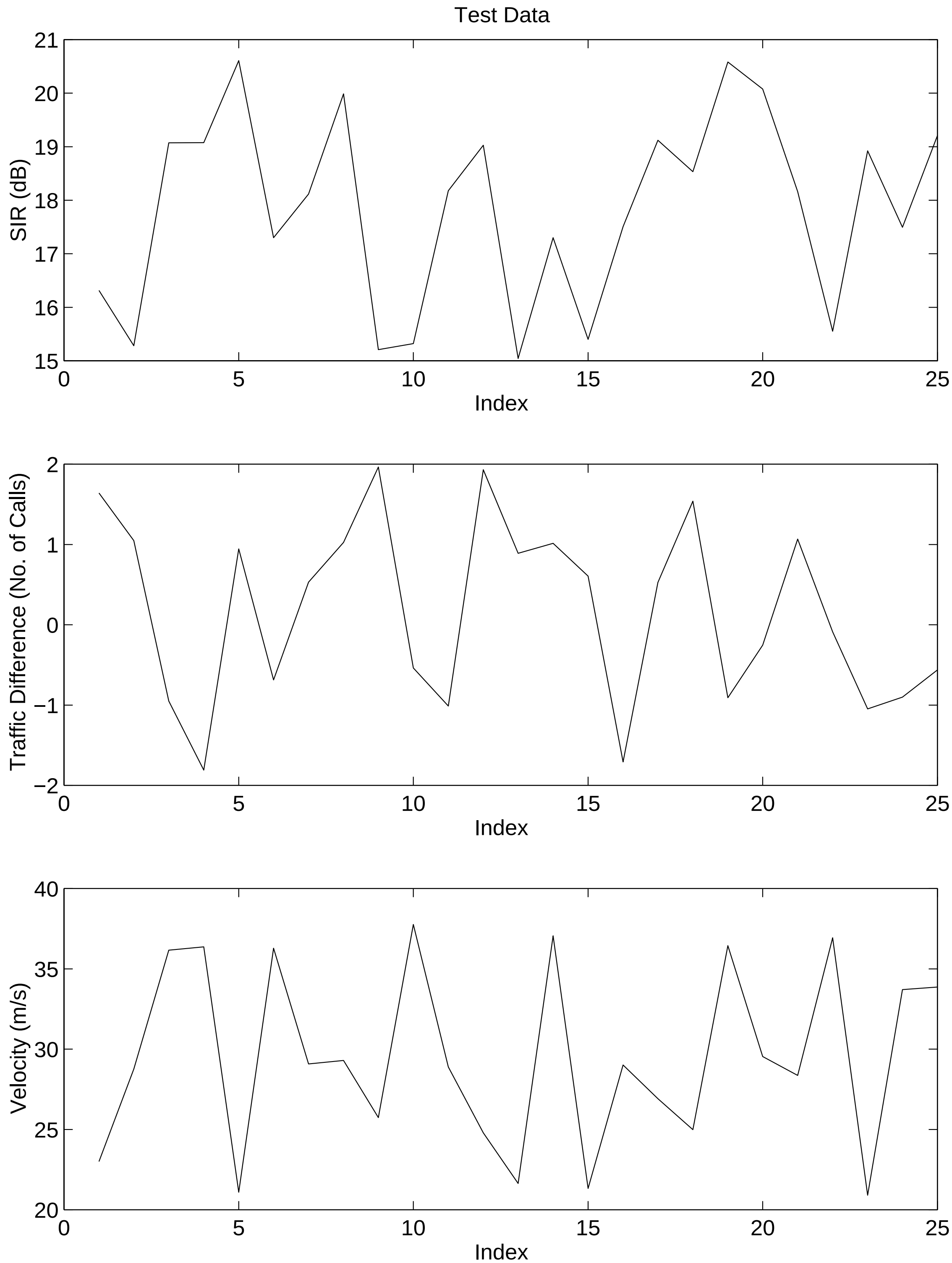

Figure 6.5: Test Data for Neural Networks

Table 6.5: Training and Test Results for MLP

Number	**No. of Hidden Layer Neurons**	E_{train}	E_{test}
1	5	24.58	8.17
2	8	16.32	8.33
3	12	16.01	8.09
4	17	16.47	8.07
5	21	16.22	8.06

of the difference between the desired outputs and the outputs of the MLP for the training data. E_{test} is the Frobenius norm of the difference between the desired outputs and the outputs of the MLP for the test data. A different number of hidden layer neurons were trained for different training times (5000 to 15000 epochs). One epoch is one pass through the training set. In general, more neurons can lead to an improved mapping. However, complexity increases as the number of neurons increases. The number of neurons is chosen to be eight as a compromise between the accuracy of generalization and complexity. Since the main interest is to represent the FLS with as few neurons as possible, a tradeoff between the number of neurons and the mapping accuracy must be achieved. For the application under consideration, the error performance of the MLP is quite acceptable.

Figure 6.6 shows the desired (or actual) test data and the MLP output data. The desired data and MLP predicted data are close to each other; however, they are not identical. This means that the ANN has learned most of the FLS mapping features, but it has not learned a perfect mapping. Hence, when the performances of the fuzzy logic based algorithm and neural algorithm are compared, similar, but not identical, performances should be expected. The FLS mapping can be learned well by an ANN provided that appropriate processing is done and that a sufficient number of neurons are used. Since the goal here is to use fewer neurons, no attempt

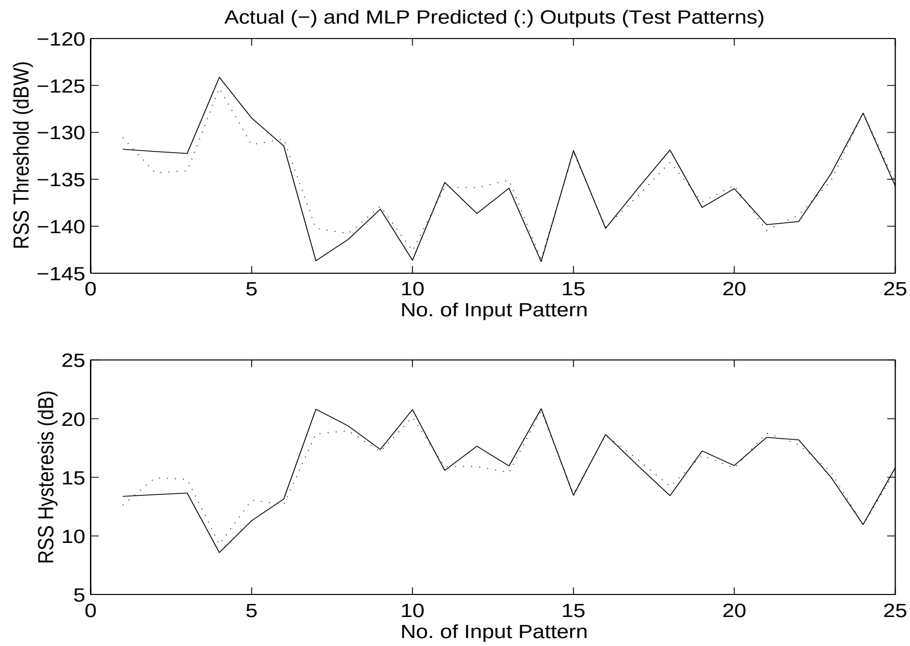

Figure 6.6: MLP Test Data Performance

is made to obtain perfect FLS mapping.

Figure 6.7 shows the RBFN mapping performance. The RBFN has learned the mapping well, but the mapping is not exact. Table 6.6 summarizes some of the results for RBFN. Different spreads for radial basis functions and different numbers of radial basis functions were tried. In general, higher numbers of radial basis functions give an improved performance with the associated increase in complexity. The number of radial basis functions is chosen to be ten as a compromise between accuracy of generalization and complexity.

As in the case of MLP, the performances of the fuzzy logic based algorithm and neural algorithm can be expected to be similar but not identical.

Figure 6.8 shows the cumulative distribution function (CDF) of RSS for conventional, fuzzy logic (FL), and MLP algorithms. As expected, FL and MLP performances are similar.

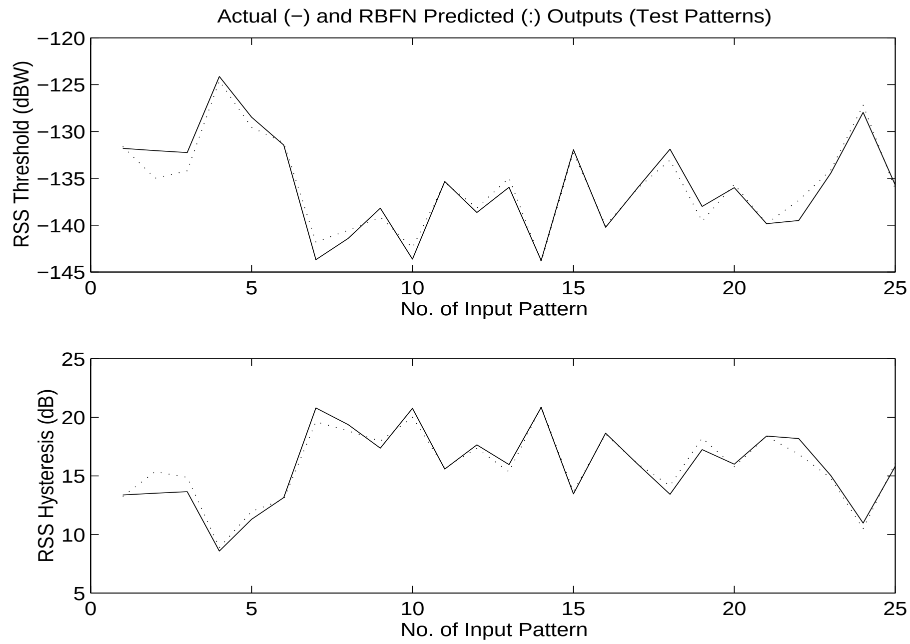

Figure 6.7: RBFN Test Data Performance

Table 6.6: Training and Test Results for RBFN

Number	**No. of Radial Basis Functions**	E_{train}	E_{test}
1	5	34.50	8.28
2	10	24.42	6.82
3	14	20.25	5.47
4	19	17.80	5.29
5	24	15.73	5.16

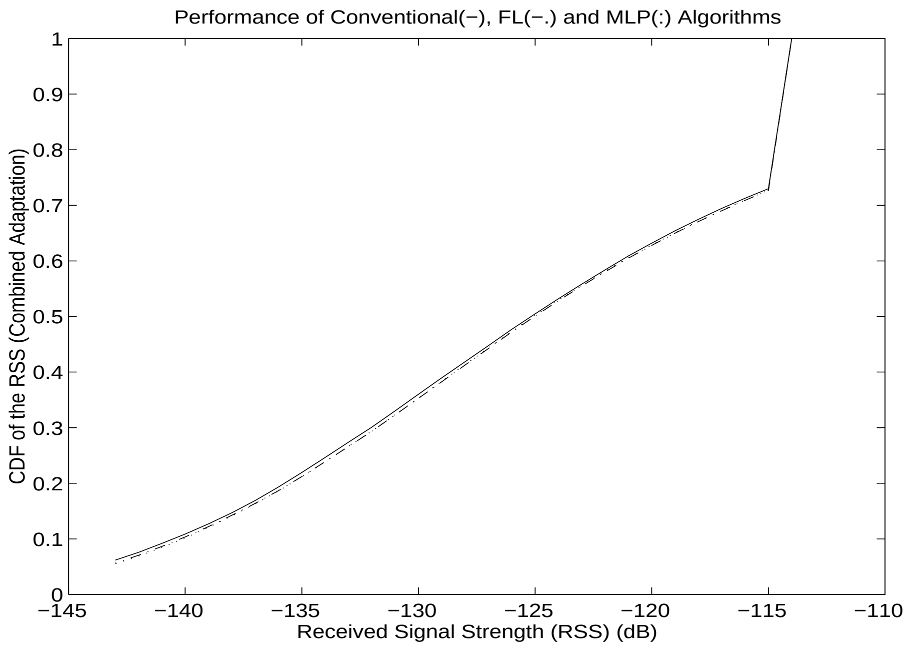

Figure 6.8: Distribution of RSS for Conventional, Fuzzy, and MLP Algorithms

Figure 6.9 shows the distribution of SIR for all the algorithms. Again, there is a close match between FL and MLP performance. The small discrepancy can be attributed to the stochastic nature of simulations and the approximate modeling of the FLS by the MLP.

Figure 6.10 shows the traffic distribution for different algorithms. The FL and MLP give similar traffic performances. Both the FL and MLP provide a two call improvement over the conventional algorithm.

Figure 6.11 illustrates the operating point for the FL and MLP algorithms. The symbols "*," "+," and "x" represent minimum (45 mph), average (65 mph), and maximum (85 mph) velocities, respectively. These symbols represent the FL operating points, while the encircled symbols represent the MLP operating points. Both FL and MLP algorithms give similar performance.

Similar simulation tests were performed for an RBFN based algorithm. The

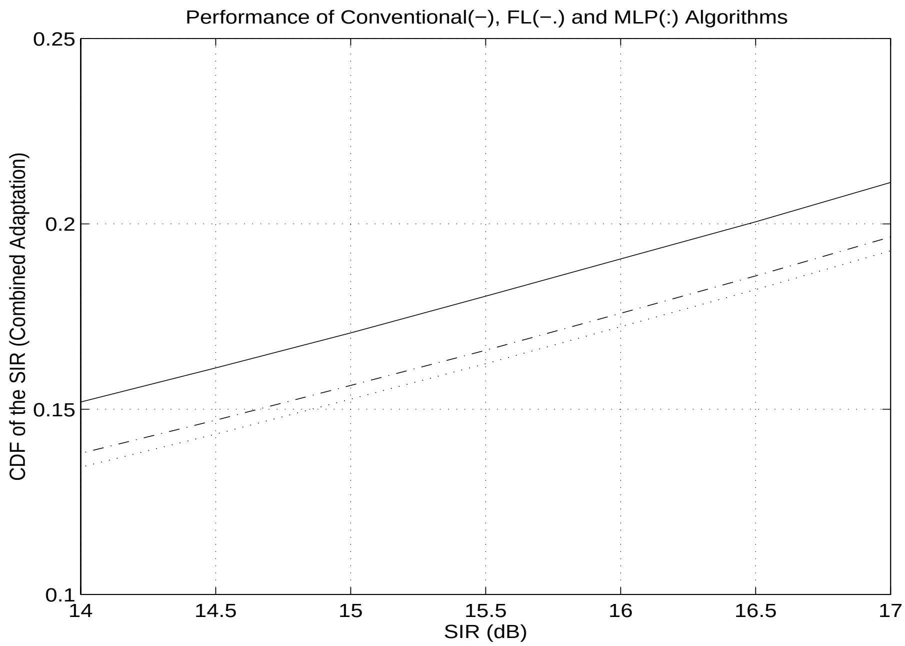

Figure 6.9: Distribution of SIR for Conventional, Fuzzy, and MLP Algorithms

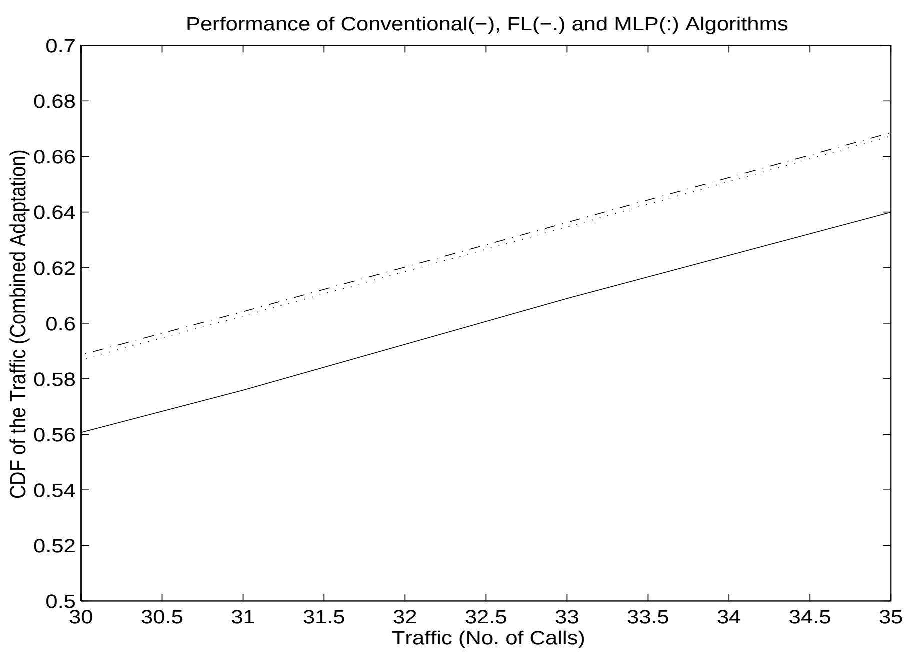

Figure 6.10: Distribution of Traffic for Conventional, Fuzzy, and MLP Algorithms

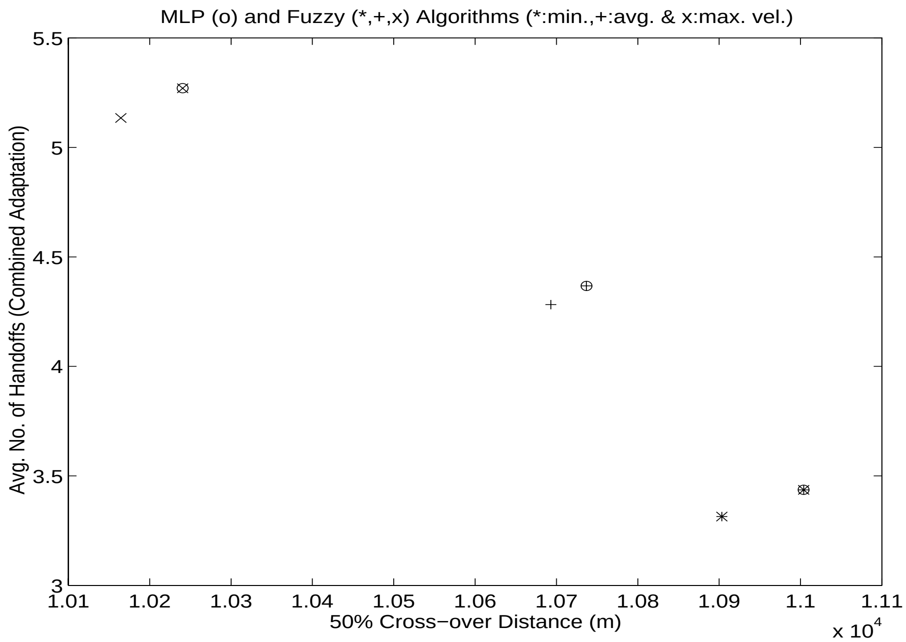

Figure 6.11: Operating Points for Conventional, Fuzzy, and MLP Algorithms

results of two representative simulations are shown here.

Figure 6.12 shows the SIR distribution for FL and RBFN algorithms. The performances of these algorithms are similar.

Figure 6.13 shows that the traffic distribution for the FL and RBFN algorithms is similar.

6.4 Conclusion

An adaptive algorithm that encodes the working of an FLS is proposed. An FLS can be designed using known sensitivities of handoff parameters, but the FLS requires the storage of many parameters and needs a lot of computations. Several neural network paradigms such as an MLP and an RBFN are universal approximators. The input-output mapping capability and compact data representation capability of these neural

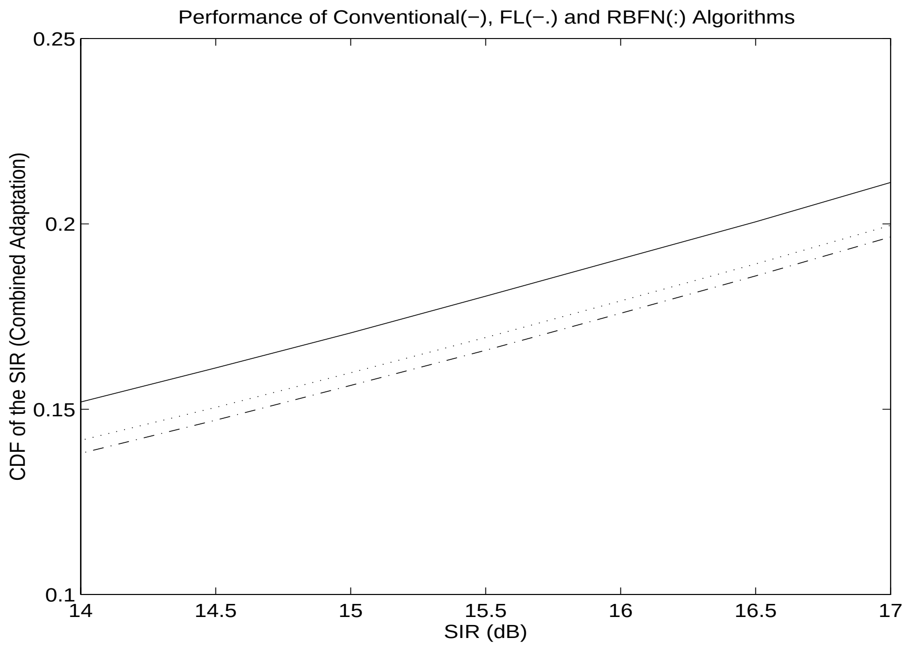

Figure 6.12: Distribution of SIR for Conventional, Fuzzy, and RBFN Algorithms

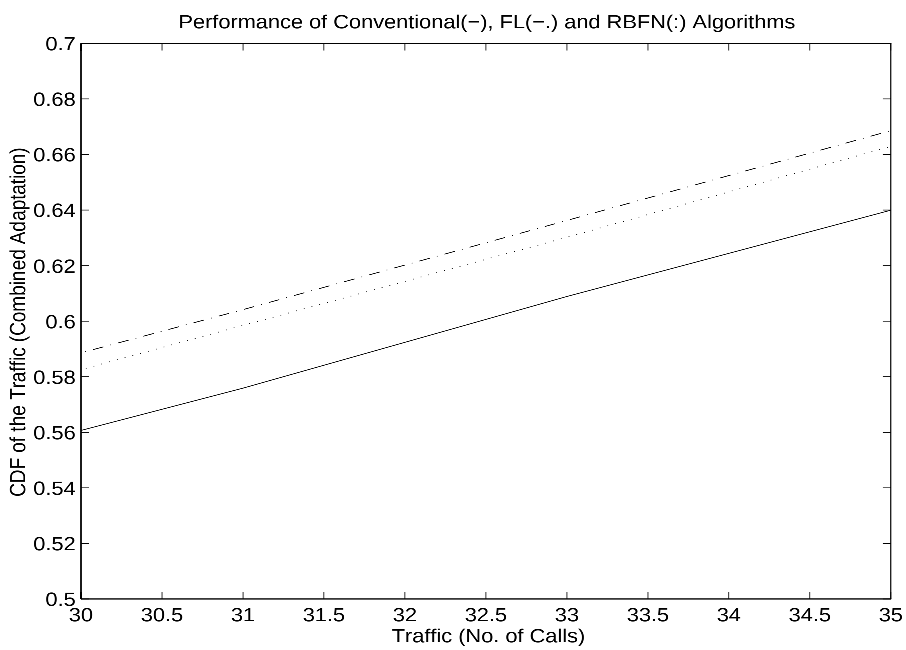

Figure 6.13: Distribution of Traffic for Conventional, Fuzzy, and RBFN Algorithms

network paradigms are exploited to represent the FLS. The neural representation of the FLS provides an adaptive handoff algorithm that retains the high performance of the original fuzzy logic based algorithm and that has an efficient architecture for meeting storage and computational requirements. The analysis of the simulation results indicates that an adaptive multicriteria neural handoff algorithm performs better than a signal strength based conventional handoff algorithm and that the fuzzy logic based algorithm and neural network based algorithm perform similarly.

Chapter 7

A Unified Handoff Candidacy Algorithm

This chapter proposes a new fuzzy logic based algorithm with a unified handoff candidate selection criterion and adaptive direction biasing. The unified handoff candidate selection criterion allows the simultaneous consideration of several handoff criteria to select the best handoff candidate under given constraints. Direction biasing has been proposed in the literature to obtain a fast handoff algorithm with certain useful characteristics. This chapter proposes a fuzzy logic based handoff algorithm with enhanced direction biasing by adapting the direction biasing parameters. Extensive simulation results for the fuzzy algorithm and the proposed algorithm are presented. This chapter shows that adaptive direction biasing improves the performance of the basic fuzzy handoff algorithm and allows additional degrees of freedom in achieving the desired balance among various system characteristics of interest.

7.1 An Adaptive Fuzzy Handoff Algorithm with Adaptive Direction Biasing

The algorithm proposed in this chapter incorporates adaptive direction biasing into the fuzzy logic algorithm proposed in [109]. Direction biasing facilitates fast handoff. Reference [60] proposed a direction biased handoff algorithm for a microcellular environment. Since microcells frequently encounter corner effect, fast moving vehicles must be connected to an umbrella cell or better handoff algorithms must be used. A direction-biased handoff algorithm represents such an alternative solution [60] and has several nice features. Direction biasing improves *cell membership properties* and handoff performance in LOS and NLOS scenarios in a multi-cell environment. The direction biased algorithm reduces the probability of dropped calls for hard handoffs (e.g., for TDMA systems) and reduces the time a user needs to be connected to more than one base station for soft handoffs (e.g., for CDMA systems), allowing more potential users per cell.

The basic idea of the direction biased algorithm, handoffs to the BSs toward which the MS is moving are encouraged, while handoffs to the BSs from which the MS is receding are discouraged. Figure 7.1 shows the flowchart of a direction biased algorithm. First, the direction biased algorithm selects the best handoff candidate BS based on the link measurements. For example, if a BS (BSn, where n is the BS identification) gives maximum RSS, it is selected as the best handoff candidate BS. The currently serving BS (BSc) and BSn are classified into one of the sets, set "Approach" (or set A) or set "Recede" (or set R). If the MS is moving toward a BS, this BS is classified into set A. If the MS is moving away from a BS, this BS is classified into set R. If both BSc and BSn are in set A or set R, the effective hysteresis (eff_h) is kept the same as the normal hysteresis value (rss_h). If BSc is in set A and BSn is in set R, the effective hysteresis is increased by the amount dir_h (which represents the amount of direction biasing). On the other hand, if BSc is in set R and BSn is in set A, the effective hysteresis is reduced by the amount dir_h.

A variation of the basic direction biased algorithm is the preselection direction biased algorithm [60]. If the best BS is a receding one and has a quality only slightly better than the second best BS, which is being approached, the handoff should be made to the second best BS because it is more likely to improve its chances of being selected in future. This rule provides a fast handoff algorithm with good cell membership properties without the undesirable effects associated with large hysteresis. Figure 7.2 shows the flowchart of the preprocessing for the preselection direction biased algorithm. This algorithm processes the link measurements to bias the best handoff candidate selection process. A BS is classified into set A or set R based on the direction of the MS travel relative to the BS. If the BS is in set A, the link quality measurement is enhanced by a preselection hysteresis (Hp) to improve the chances of the selection of the BSs in set A as handoff candidates. However, if the BS is in set R, the link quality measurement is reduced by a preselection hysteresis (Hp) to deny the chances of the selection of the BSs in set R as handoff candidates. Once the link measurements of all the BSs are preprocessed, a BS with the best preselection biased link measurement is selected as the best handoff candidate. Then, the normal direction biased algorithm is executed.

7.1.1 Proposed Algorithm

A pure direction biased handoff algorithm has four disadvantages.

1. This algorithm does not consider the effect of direction biasing on several significant aspects of handoff.

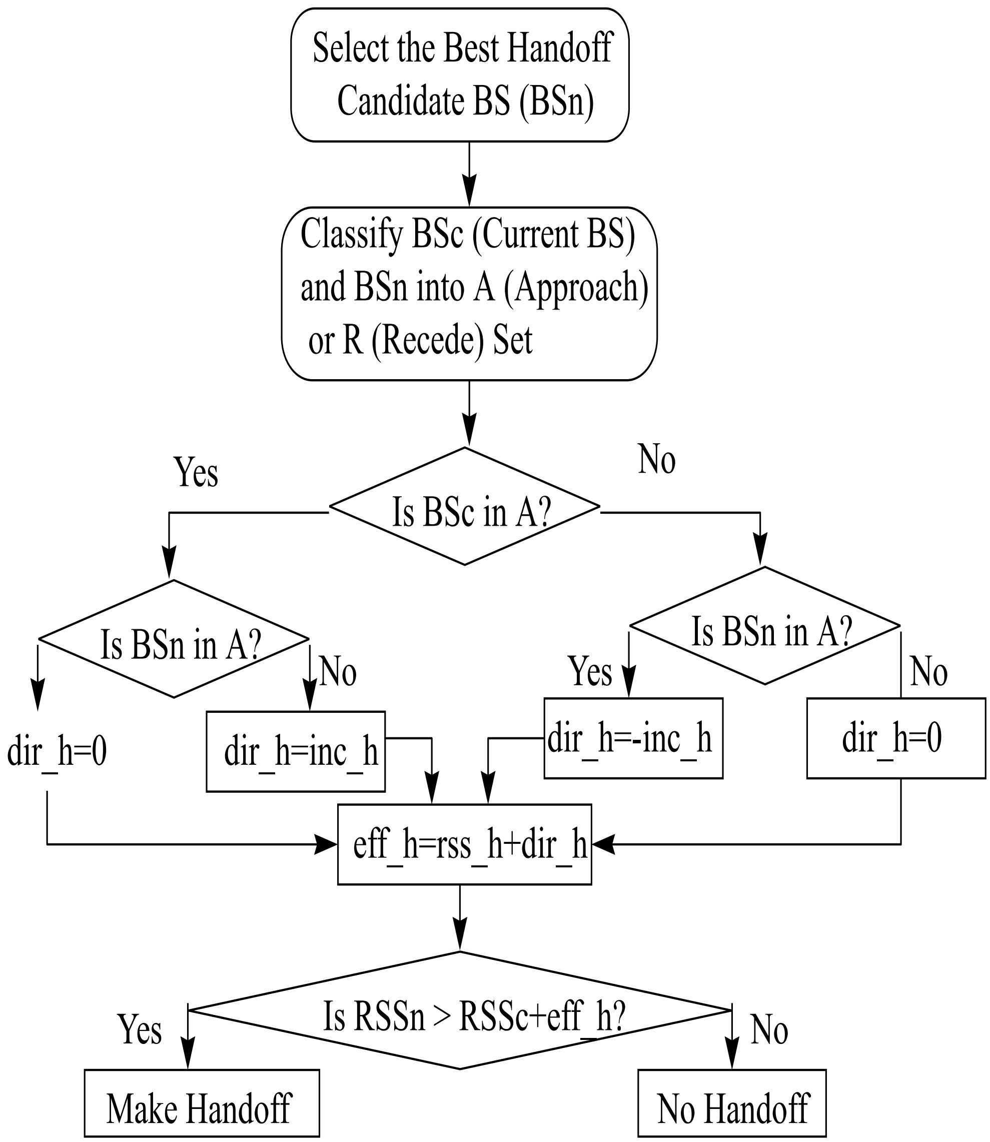

Figure 7.1: A Direction Biased Algorithm

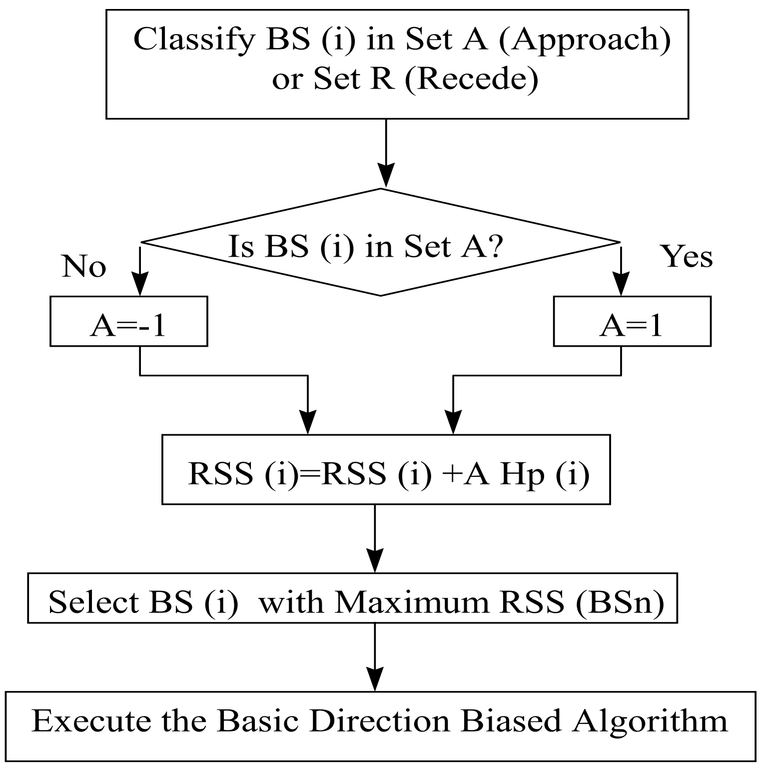

Figure 7.2: Preprocessing for Preselection Direction Biased Algorithm

2. This algorithm does not adapt handoff parameters.

3. This algorithm can lead to unnecessary handoffs (i.e., this algorithm may make a handoff even if the current BS provides good quality).

4. The direction biasing influences handoff decisions even if the mobile station (MS) is relatively close to a base station (BS); there is a constant direction bias throughout the journey of the MS. The constant direction biasing may cause this algorithm to make premature handoffs, potentially increasing the MS transmit power and causing high uplink interference.

An adaptive fuzzy logic algorithm proposed in [109] can take care of issues (1) through (3). Since direction biasing has certain nice features, an adaptive version of direction biasing has been incorporated into the basic fuzzy algorithm of [109]. This adaptive direction biasing overcomes the inherent drawback of the basic direction biasing algorithm (issue (4)) and provides improved performance. Moreover, a unified preselection performance index (UPPI) has been formulated to simultaneously consider several handoff criteria. Figure 7.3 shows the block diagram of the proposed fuzzy algorithm with UPPI and adaptive direction biasing. First, the best handoff candidate is selected using the UPPI. Several measurements (such as RSS_c, RSS_n, and SIR_c) are averaged using the velocity adaptive averaging mechanism and processed by the direction biased algorithm. This direction biased algorithm uses two parameters ($RSS_{threshold}$ and $RSS_{hysteresis}$) that are adaptive to the dynamic cellular environment. An FLS provides such adaptive parameters based on certain measurements. The value of $RSS_{hystersis}$ is modified based on adaptive direction biased hysteresis value (dir_{hyst}). The mechanism of generating dir_{hyst} is explained later. The proposed handoff algorithm with adaptive direction biasing and unified

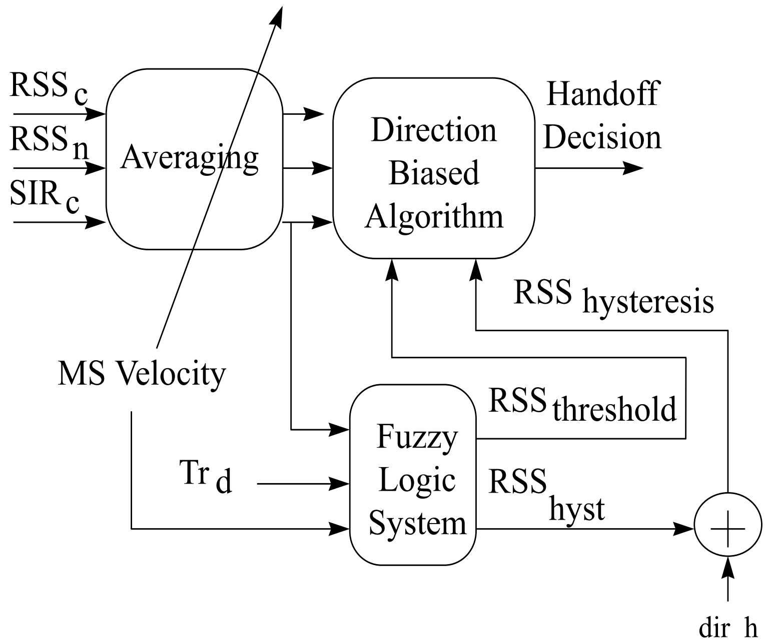

Figure 7.3: Proposed Fuzzy Algorithm with UPPI and Adaptive Direction Biasing

preselection index has two distinct features that give the algorithm an edge over the pure direction biased algorithm. These features are described below.

1. **Unified Preselection Performance Index (UPPI)**. A unified preselection performance index (UPPI) is proposed to select the best neighboring candidate for handoff. A general structure of the UPPI is

$$UPPI(j) = \sum_{i=1}^{N} C_i L_i^2 \tag{7.1}$$

where L_i is the ith *preprocessed* link measurement, N is the total number of link measurements (available from each potential handoff candidate BS), C_i is the weightage given to the associated link measurement, and j is the BS index. A BS that gives the maximum UPPI is selected as the best handoff candidate. *Preprocessing* is necessary to normalize the measurements and to ensure that maximizing the link measurement related component of the UPPI indeed leads to the maximization of the UPPI. For example, it is desirable to minimize Tr_n (the number of ongoing calls in a cell) so that handoff blocking and call blocking probabilities are reduced. Since the goal is to maximize UPPI, Tr_n must be preprocessed so that the Tr_n related component of the UPPI increases when Tr_n decreases. The UPPI considers available link measurements simultaneously so a decision consistent with the global system goals can be made. The coefficients $C_i (i = 1, 2, ..., N)$ can be adapted to reflect the change in the constituents of the dynamic cellular environment. For example, when traffic intensity in a given service region is low, traffic balancing does not pay off. In such cases, it is desirable to reduce the weight of traffic in the overall UPPI evaluation and avoid perturbing planned cell boundaries. On the other hand, when traffic intensity is high, traffic balancing reduces the handoff and call drop probability. The weight of traffic can be increased in such cases to achieve a higher degree of traffic balancing. In this chapter, two link measurements of the neighboring cells, traffic in the cell and RSS from the BS, are assumed to be available. Hence, these measurements are used as two link measurements (L_i), and the weight of these L_i can be changed via coefficients (C_i) if desired. In other words,

$$UPPI(j) = C_1 L_1^2 + C_2 L_2^2 \tag{7.2}$$

where L_1 is the *preprocessed* RSS from BS 1 and L_2 is the *preprocessed* traffic. When C_1 is zero, the selection of the best handoff candidate cell is based solely on traffic. When C_2 is zero, the selection of the best handoff candidate cell is based solely on RSS. The UPPI allows additional degrees of freedom in obtaining balance between certain system characteristics. For example, different weight can be given to RSS and traffic to obtain improved traffic balancing and adaptation. Since the basic fuzzy algorithm takes into account two neighboring cell measurements (RSS_n and Tr_n) for a handoff decision, this UPPI ensures that the best BS is chosen (under the given constraints of available measurements), providing the best handoff candidate in case handoff is necessary.

2. **Adaptive Direction Biasing Parameters**. Reference [60] uses fixed direction biasing parameters. As explained earlier, the biasing influences handoff decisions even in the vicinity of the BS, which is the drawback of this algorithm. However, a handoff should be discouraged even if the MS is receding from such a BS. Moreover, the handoff region is located (approximately) midway between the BSs, and a higher degree of direction biasing in the handoff region can prevent the ping-pong effect, reducing the number of handoffs. Based on these observations, direction biasing parameters are adapted using fuzzy logic. The input to the fuzzy logic system (FLS) is the difference between the distances of the MS from the serving BS and the candidate BS, and the output of the FLS is the incremental hysteresis value (dir_{hyst}). When the distance difference is high (i.e., when an MS is very close to one BS compared to another BS), there is a low degree of direction biasing. When the distance difference is low (i.e., when an MS is almost equidistant from both neighboring BSs), there is a high degree of direction biasing.

Rule No.	**DistanceDifference**	**dir$_{\mathbf{h}}$yst**
1	High	Low
2	Normal	Normal
3	Low	High

7.2 Performance Analysis of Proposed Algorithms

The performances of the basic fuzzy logic (FL), direction biased fuzzy logic (DBFL), and adaptive direction biased fuzzy logic (ADBFL) algorithms are evaluated next. A direction biased algorithm that considers only RSS as a UPPI component is a DBFL algorithm, and a direction biased algorithm that includes both RSS and traffic as UPPI components is a traffic direction biased fuzzy logic algorithm (TDBFL). For FL and DBFL algorithms, $C_1 = 1$ and $C_2 = 0$. For TDBFL algorithm, $C_1 = 0.7$ and $C_2 = 0.3$. Thus, in the case of the TDBFL algorithm, traffic is important in determining the best handoff candidate cell.

7.2.1 Performance Evaluation of FL, DBFL, and TDBFL Algorithms

Figure 7.4 shows the cumulative distribution function (CDF) of the received signal strength (RSS) for FL, DBFL, and TDBFL algorithms. The RSS distribution is identical for FL and DBFL algorithms, but there is a slight degradation in RSS distribution for the TDBFL algorithm. This RSS degradation occurs because the selection of the handoff candidate cell is based on both the RSS and the traffic in the neighboring cells. Hence, a slight degradation in RSS is expected. Figure 7.5 shows the SIR distribution for FL, DBFL, and TDBFL algorithms. The FL and DBFL algorithms perform similarly, but there is a 0.5 dB degradation in SIR performance of TDBFL compared to FL and DBFL algorithms. The slight degradation in RSS contributes to more degradation in SIR distribution for the TDBFL algorithm. Figure 7.6 shows the traffic distribution for FL, DBFL, and TDBFL algorithms. Again, the performance of the FL and DBFL is similar, but there is a one call improvement for TDBFL compared to FL and DBFL algorithms. This result indicates that SIR performance

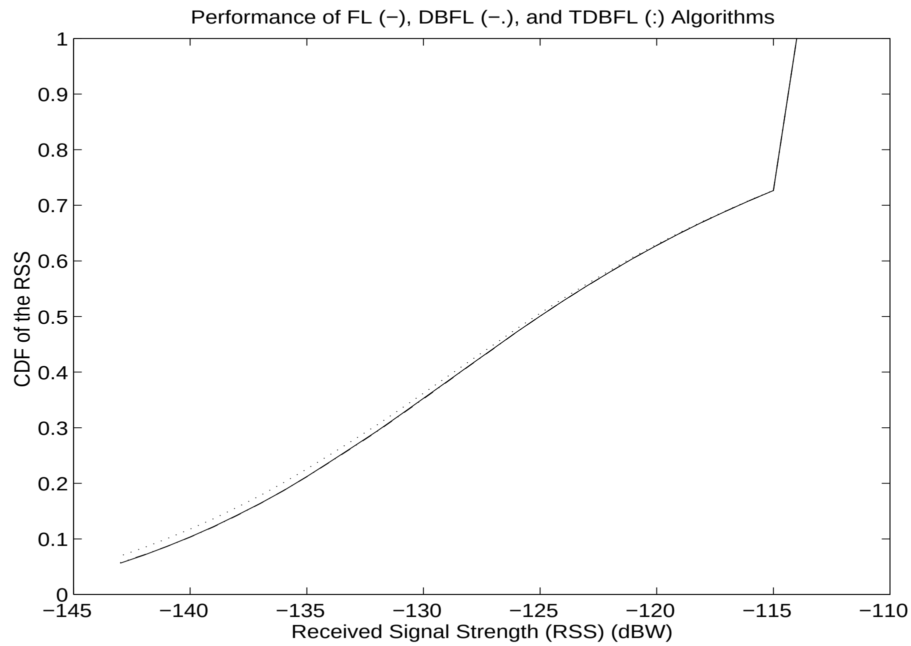

Figure 7.4: Distribution of RSS for FL, DBFL, and TDBFL Algorithms

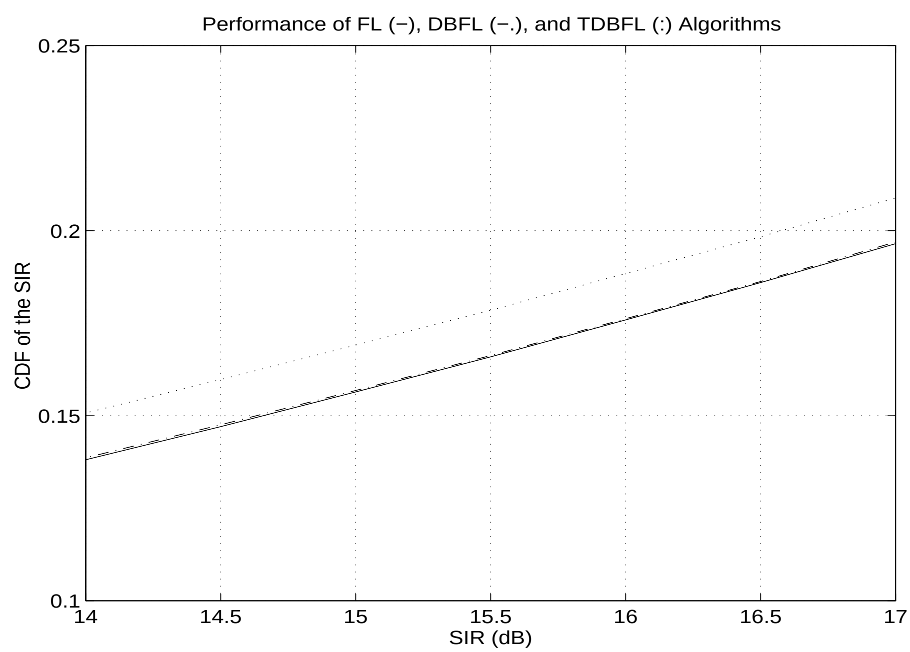

Figure 7.5: Distribution of SIR for FL, DBFL, and TDBFL Algorithms

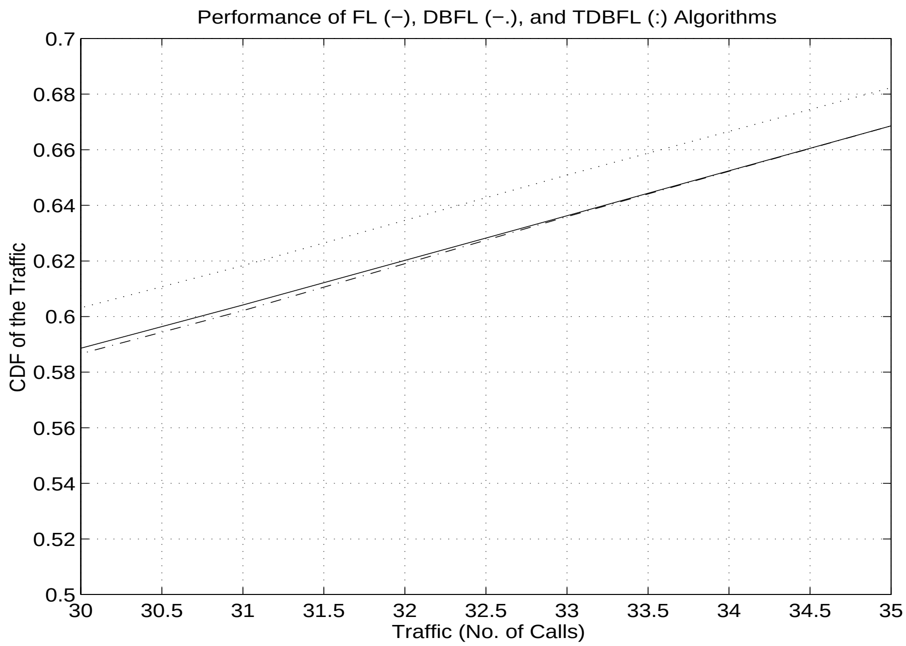

Figure 7.6: Distribution of Traffic for FL, DBFL, and TDBFL Algorithms

can be traded for better traffic performance. More importantly, this result has even more significant implications. *Since the traffic performance is not critical under low traffic intensities, a UPPI that is receptive to RSS can be used to provide improved quality of service (quantified by voice quality, MS transmit power, etc.). When the traffic intensity is high, UPPI should give more weight to traffic, and potentially, more users can be served by trading voice quality. Thus, an appropriate structure of UPPI can help achieve high performance in the dynamic cellular environment.* Figure 7.7 shows the cell membership properties for FL, DBFL, and TDBFL algorithms. $Pr(i)(i = 0, 1, 2, 3)$ is the probability that the MS is connected to BS i. The MS travels from BS 0 to BS 2 at a constant velocity (65 mph). $Pr(0)$ decreases from one to zero as the MS recedes from BS 0. $Pr(1)$ increases from zero to one as the MS approaches BS 2. Both $Pr(1)$ and $Pr(3)$ increase until the midpoint of the MS's journey since the MS is moving toward these BSs. However, after the midpoint of the

MS's journey, $Pr(1)$ and $Pr(3)$ decrease since the MS is now moving away from these BSs. As expected, the DBFL algorithm improves the cell membership properties of the basic FL algorithm. Corroborating this statement, $Pr(0)$ and $Pr(2)$ for the DBFL algorithm are lower and higher respectively than those for the FL algorithm. Moreover, $Pr(1)$ and $Pr(3)$ are higher than those for the FL algorithm until the mid-point of the MS's journey. Also, $Pr(1)$ and $Pr(3)$ are lower than those for the FL algorithm after the midpoint of the MS's journey. There is not much difference between the DBFL and TDBFL algorithm performance. Figure 7.8 shows the operating points for FL, DBFL, and TDBFL algorithms for different velocities. The DBFL algorithm gives fewer handoffs and less cross-over distance than the FL algorithm. The TDBFL gives even fewer handoffs than DBFL algorithm because traffic is important in the handoff candidate selection process for the TDBFL and because these traffic variations are less intense than RSS variations in the simulation environment. The mid-point of the MS's journey is $9km$. An operating point is defined by the average number of handoffs and the 50% cross-over distance.

7.2.2 Performance Evaluation of FL, DBFL, and ADBFL Algorithms

Figure 7.9 shows the RSS distribution for FL, DBFL, and ADBFL algorithms. The RSS distribution is identical for FL, DBFL, and ADBFL algorithms. Figure 7.10 shows the SIR distribution for FL, DBFL, and ADBFL algorithms. There is a slight degradation (0.1 dB) in SIR performance of ADBFL compared to FL and DBFL algorithms since, in the handoff region, a slightly better RSS cell may be available but will not be selected due to increased direction biasing. Since the aim is to reduce the number of handoffs due to fading in the handoff region, RSS and SIR are

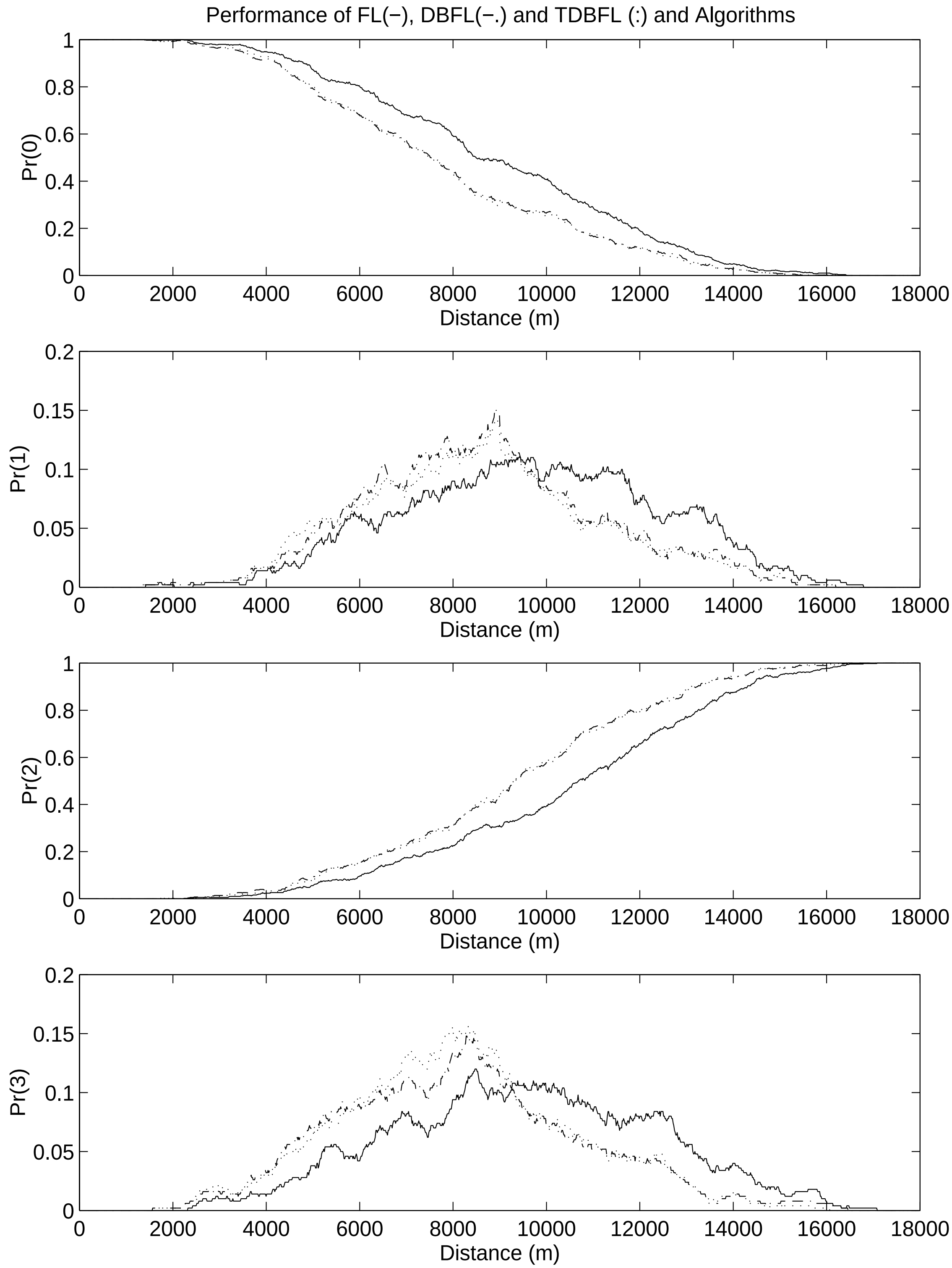

Figure 7.7: Cell Memberships for FL, DBFL, and TDBFL Algorithms

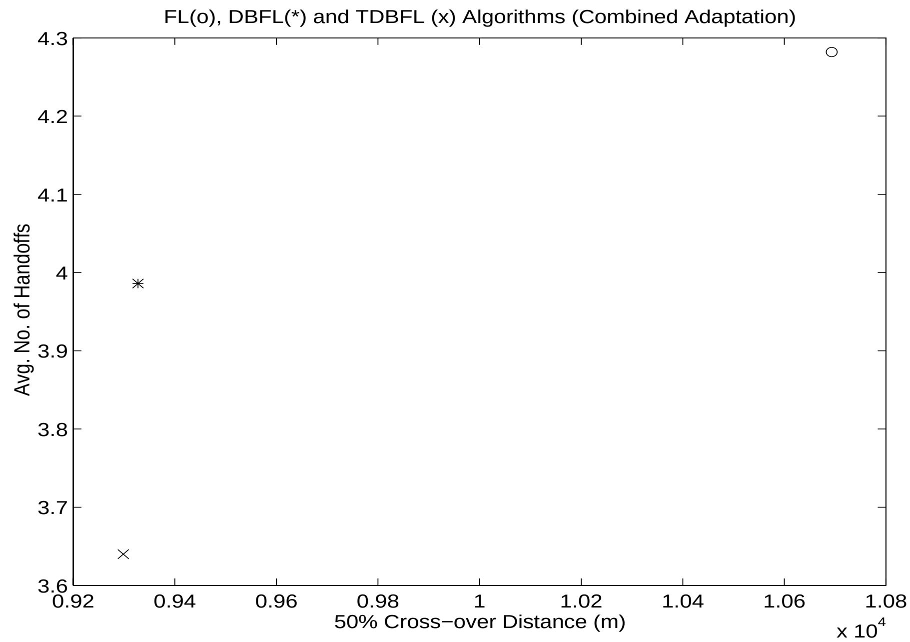

Figure 7.8: Operating Points for FL, DBFL, and TDBFL Algorithms

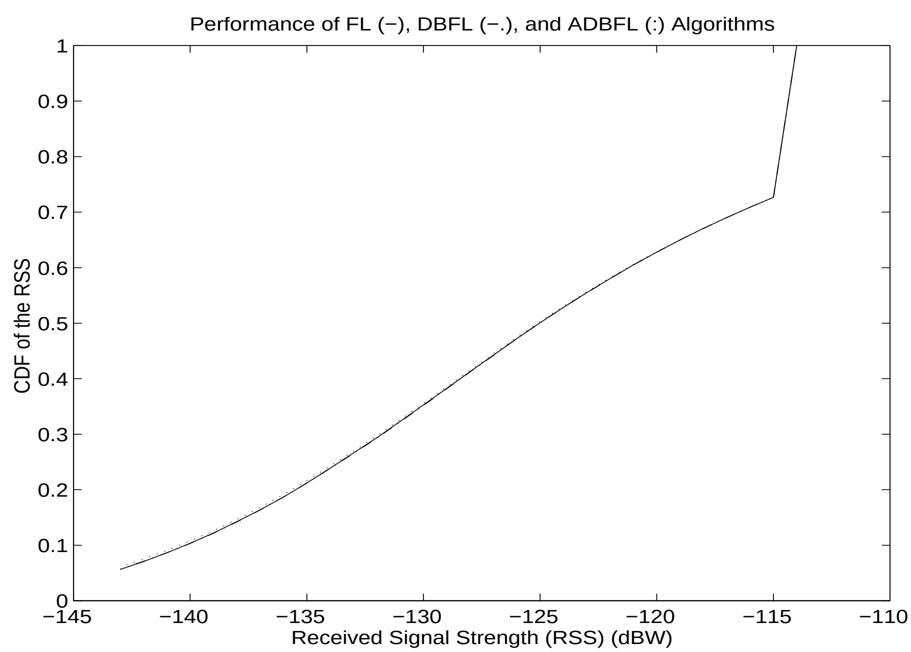

Figure 7.9: Distribution of RSS for FL, DBFL, and ADBFL Algorithms

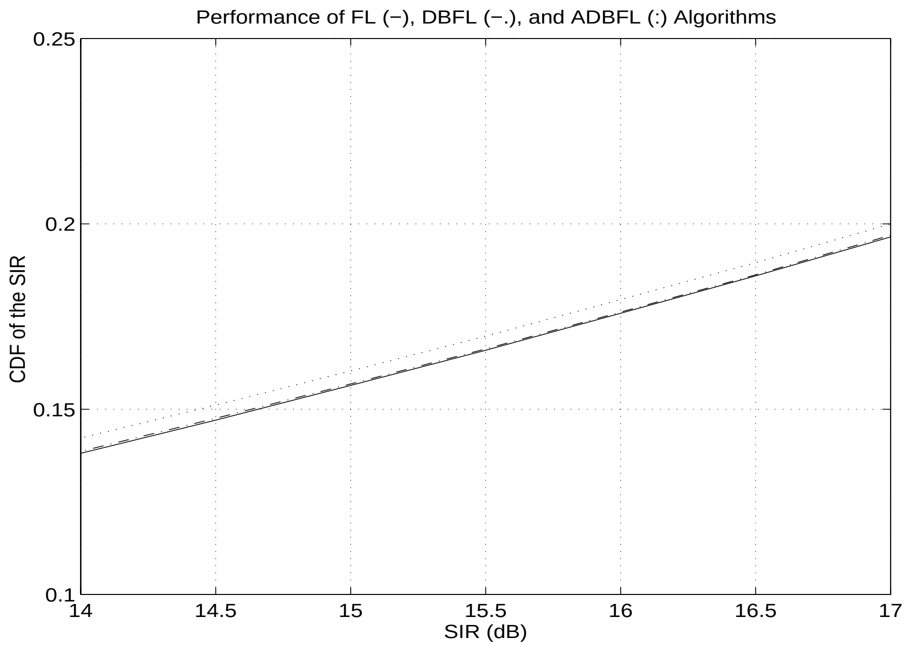

Figure 7.10: Distribution of SIR for FL, DBFL, and ADBFL Algorithms

traded off to obtain fewer handoffs. Figure 7.11 shows the traffic distribution for FL, DBFL, and ADBFL algorithms. The distribution is identical for DBFL and ADBFL algorithms and shows an improvement over the FL algorithm. Figure 7.12 shows cell memberships for FL, DBFL, and ADBFL algorithms. This figure shows the distinct advantage of ADBFL over FL and DBFL algorithms; ADBFL improves cell membership properties. This improvement is reflected in fewer handoffs and reduced cross-over distance. $Pr(0)$, $Pr(2)$, and $Pr(3)$ reduce quickly and $Pr(4)$ increases quickly after the midpoint of the MS journey. Figure 7.13 shows operating points for FL, DBFL, and ADBFL algorithms. DBFL and ADBFL provide much better performance than the FL algorithm. Also, the ADBFL algorithm gives fewer handoffs and reduced crossover distance compared to the DBFL algorithm. Thus, the ADBFL algorithm can help achieve an optimum operating point in a given environment.

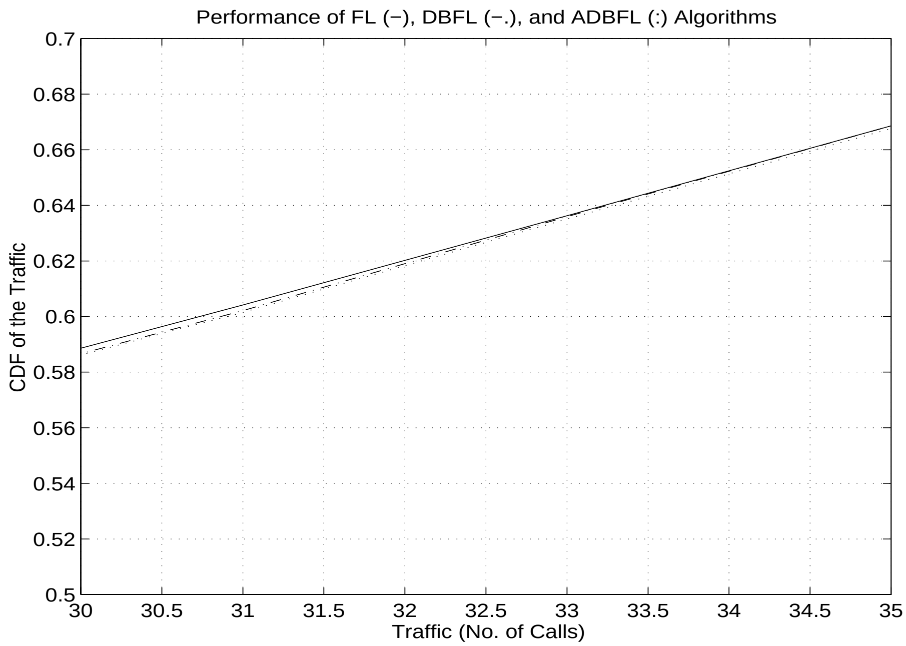

Figure 7.11: Distribution of Traffic for FL, DBFL, and ADBFL Algorithms

7.3 Conclusion

A new fuzzy logic based algorithm that uses a unified handoff candidate selection criterion and adaptive direction biasing is proposed. The unified preselection criterion allows additional degrees of freedom in obtaining desired tradeoff among the system characteristics. This criterion also simultaneously considers several handoff criteria so the best handoff candidate can be selected under specified constraints. Adaptive direction biasing helps reduce both the number of handoffs and the handoff delay. Simulation results show that the proposed algorithm enhances the performance of the basic fuzzy logic and direction biased algorithms.

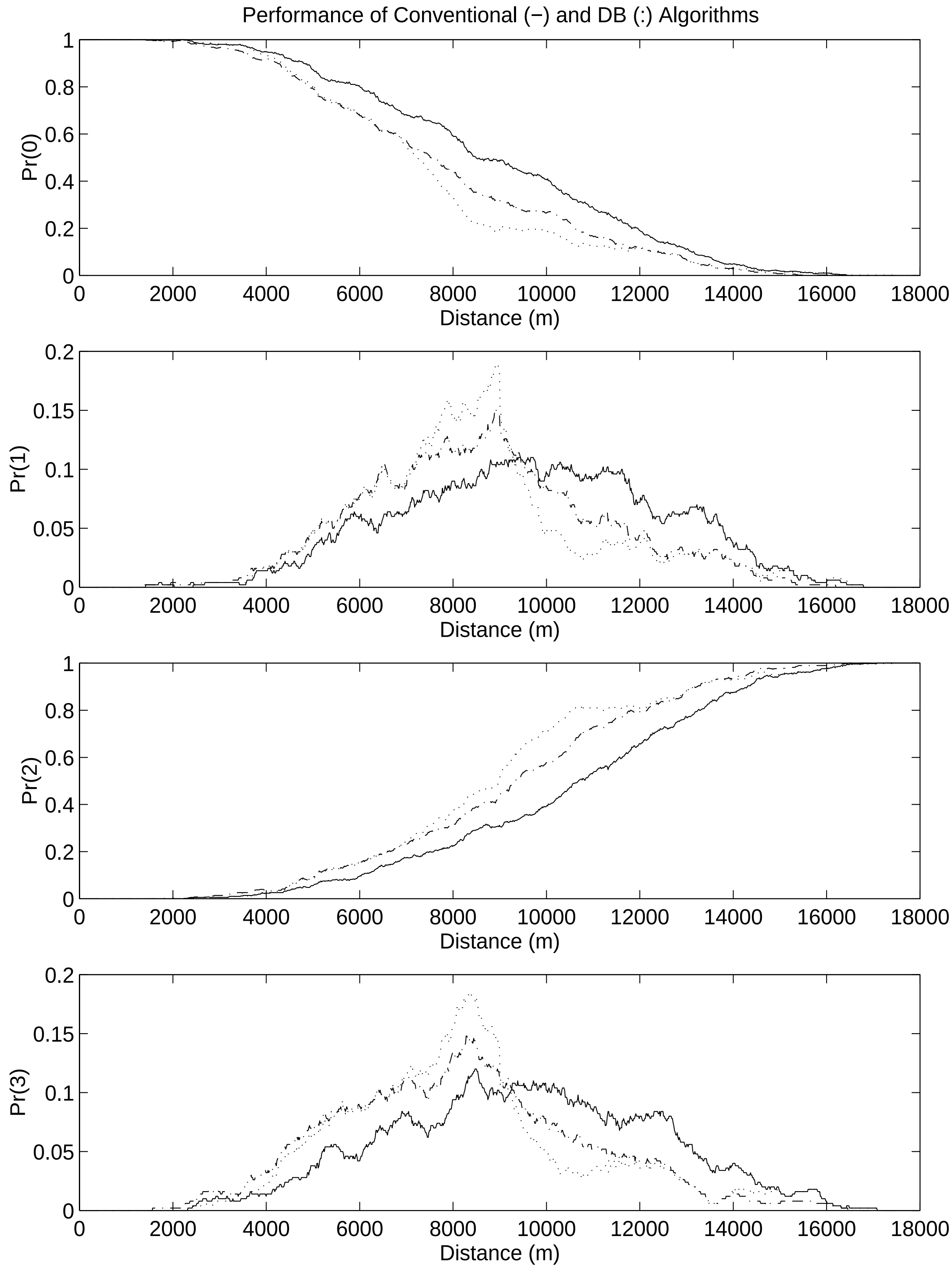

Figure 7.12: Cell Memberships for FL, DBFL, and ADBFL Algorithms

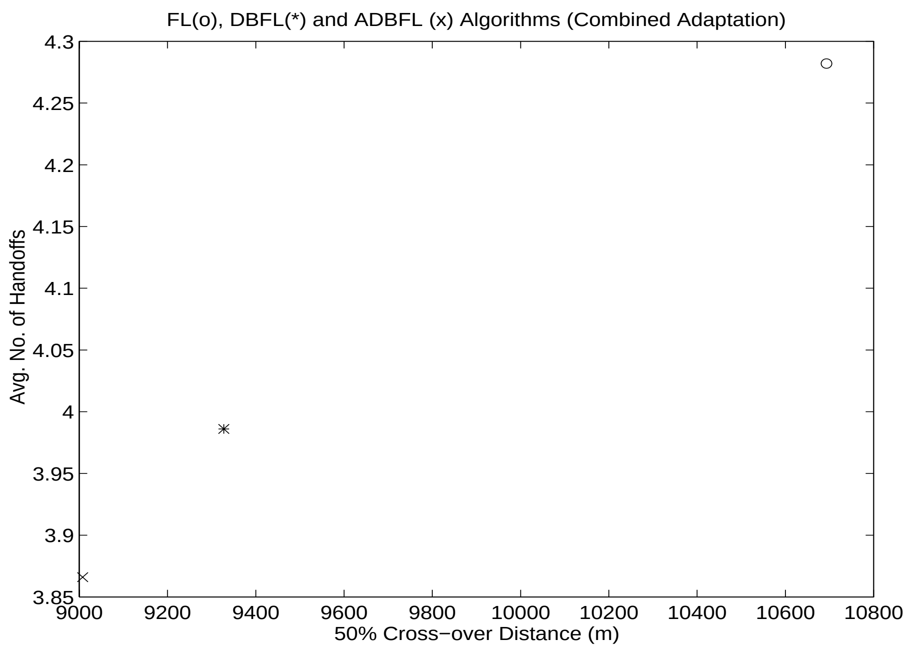

Figure 7.13: Operating Points for FL, DBFL, and ADBFL Algorithms

Chapter 8

Pattern Classification Based Algorithms

A new class of adaptive handoff algorithms that views the handoff problem as a pattern classification problem is proposed. Neural networks and fuzzy logic systems are good candidates for pattern classifiers due to their nonlinearity and generalization capability. The proposed pattern classification based algorithms are designed by considering several attractive features of existing algorithms and providing handoff parameter adaptation in a dynamic cellular environment. Extensive simulation results for a conventional handoff algorithm (absolute and relative signal strength based algorithm) and for pattern classification based algorithms are presented. It is shown that the proposed algorithms improve the distributions of SIR and traffic compared to the conventional algorithm, increasing the spectral efficiency and quality of service of the cellular system. Adaptive direction biasing is proposed to reduce the processing load and improve the cell membership properties. It is also shown that the desired balance among the system characteristics can be achieved by making appropriate design tradeoffs in a pattern classification based handoff framework.

8.1 Handoff as a Pattern Classification Problem

A multiple criteria handoff algorithm can provide better performance than a single criterion handoff algorithm due to additional degrees of freedom and to a greater potential for achieving the desired balance among different system characteristics. Pattern classification (PC) (or pattern recognition (PR)) is a convenient and compact way of implementing a multicriteria handoff algorithm. PC identifies meaningful regularities in noisy or complex environments. These techniques are based on the idea that the points that are close to each other in a mathematically defined feature space represent the same class of objects or variables. There are two basic categories of PC techniques, *explicit techniques* and *implicit techniques.* The *explicit PC techniques* use discriminant functions that define (n-1) hypersurfaces in an n-dimensional feature space. The input pattern is classified according to their location on the hypersurfaces. The *implicit PC techniques* measure the distance of the input pattern to the predefined representative patterns in each class. The sensitivity of the distance measurement to different representative patterns can be adjusted using weights. The clustering algorithms and neural and fuzzy classifiers are examples of implicit methods.

Fuzzy logic is a good candidate for PC for several reasons. An FLS can act as a universal approximator and, hence, can mimic the working of an ideal PC by learning the relationships among the variables of a training data set. There is an inherent fuzziness in the actual cell boundaries due to the dynamics of the cellular environment, and, by nature, an FLS can model this fuzziness. The concept of the degree of membership in fuzzy logic is very similar to the PC concept of the degree to which a pattern belongs to a class.

Neural networks are also good candidates for PC. Several paradigms of neural networks can act as a universal approximator and, hence, can mimic the working of

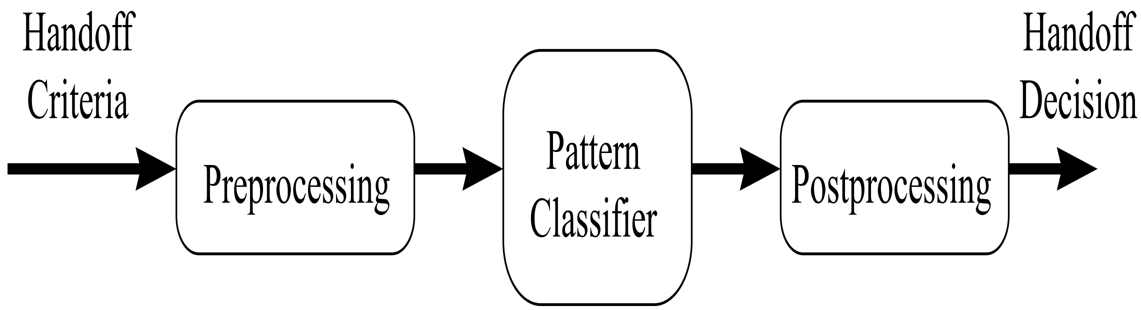

Figure 8.1: Pattern Classification Based Handoff Algorithm

an ideal pattern classifier through supervised learning on the training data set. The dynamics of the cellular environment are very complex, and nonlinearity of neural networks can model such enormous complexity. The PC concept of the degree to which a pattern belongs to a class can be learned by a neural network.

Figure 8.1 shows the block diagram of a pattern classifier. A set of handoff criteria is processed to create a pattern vector. This vector is classified into one of the classes. The class may represent base station (BS) identification, or it may represent the degree to which the mobile station (MS) belongs to a particular BS. The output of this PC can be postprocessed to decide if handoff is required. The PC approach to handoff has the following advantages:

1. The multicriteria nature of PC allows for the simultaneous consideration of several significant aspects of the handoff procedure to enhance the system performance in accordance with the defined global system goals;

2. PC is a direct approach for handoff in which testing of a sequence of binary IF-THEN rules of a conventional algorithm is replaced by a single operation of classification;

3. PC has a high potential for parallel implementation, which facilitates implementation of a fast handoff algorithm;

4. PC is inherently a single output system, and hence it is relatively less complex than the multiple output mechanisms used as part of adaptive multicriteria handoff algorithms, which can lead to an improvement in both computational and storage requirements;

5. Adaptation capability can be easily built into the PC by appropriately designing the PC (e.g., by choosing appropriate decision rules for the PC);

6. Useful features of existing handoff algorithms can be easily incorporated into the PC design by properly preprocessing the handoff criteria.

Reference [64] applies *clustering algorithms* and *PC algorithms* to RSS measurements for determining the service area of BSs. *Clustering algorithms* utilize clusters, geometrical regions where data points are concentrated according to distance measures, to assign membership values to the input pattern. A clustering algorithm undergoes unsupervised learning. Reference [64] uses a clustering algorithm called ISODATA (Iterative Self-Organizing Data Analysis Techniques A), which minimizes the sum of squared error function. The clustering algorithm works on a finite data set, and clusters evolve based on this data set. A *PC or PR* algorithm assigns the input pattern to a class based on the explicit or implicit decision rules that define boundaries between the classification regions. The PC is based on supervised learning, and it can assign membership values to new patterns after it is trained. The PC algorithm proposed in [64] requires the knowledge of the measurement statistics. A PC algorithm that overcomes this drawback and exploits several features of fuzzy logic and neural networks to provide a high performance handoff algorithm is proposed. The

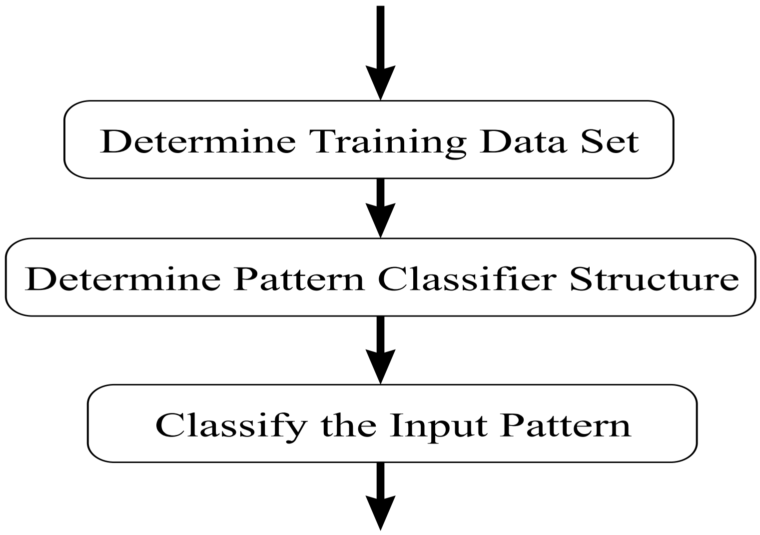

Figure 8.2: Phases of Pattern Classifier Design

proposed algorithm exploits the strengths of a full-fledged fuzzy logic system (FLS) rather than relying only on the concept of the degree of membership in a fuzzy logic theory. Moreover, the proposed algorithm facilitates the design of a handoff algorithm that performs in accordance with the defined global system goals.

A generic procedure for implementing an adaptive multicriteria handoff algorithm in a PC framework is described in Section 8.2. The performances of a conventional algorithm and the proposed neural algorithm are evaluated in Section 8.3. Finally, Section 8.4 summarizes the chapter.

8.2 Design of a Pattern Classifier for Handoff

Figure 8.2 shows three distinct phases involved in the design of a PC: determination of the training data set, determination of a PC structure, and actual operation of classification. These phases and the specific PC based handoff algorithms are discussed next.

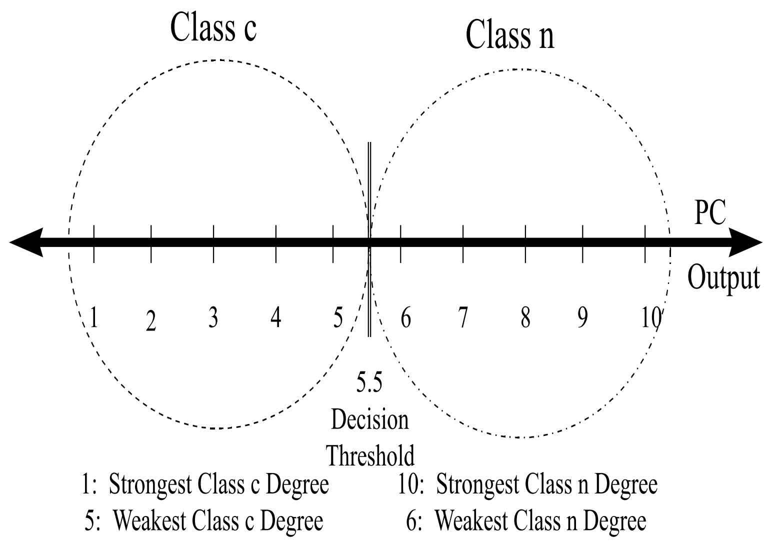

Figure 8.3: The Concept of a Degree for the PC

8.2.1 Determination of the Training Data Set

The first step is to create a training data set that consists of representative patterns and the corresponding class association degrees (i.e., the degree to which a given pattern belongs to a class). The following handoff criteria are used to form a pattern vector: $RSS_c - RSS_{threshold}$, $RSS_n - (RSS_c + RSS_{hysteresis})$, $SIR_c - SIR_{threshold}$, $Tr_d = Tr_c - Tr_n$, and *MS velocity.* RSS_c is the received signal strength (RSS) from the current BS, $RSS_{threshold}$ is the RSS threshold, RSS_n is the received signal strength (RSS) from the neighboring (or candidate) BS, $RSS_{hysteresis}$ is the RSS hysteresis, SIR_c is the SIR of the current channel, $SIR_{threshold}$ is the SIR threshold, Tr_d is the traffic difference (i.e., the difference between the number of calls in the current cell (Tr_c) and the number of calls in the neighboring cell (Tr_n)).

Figure 8.3 illustrates the concept of the association degree for the PC. Class c denotes the class of the current BS, and class n denotes the class of the neighboring BS. This figure is used with the following pieces of information to illustrate the creation of an appropriate training data set.

1. If all the elements of the pattern vector suggest that handoff should not be made, the output of the PC is one. If all the elements of the pattern vector suggest that handoff should be made, the output of the PC is ten. If an element does not encourage or discourage handoff, its position is considered neutral.

2. If the majority of the pattern elements favor a "No Handoff" decision, the output of the PC is in the range of one to five. Similarly, if the majority of the pattern elements favor a "Handoff" decision, the output of the PC is in the range of six to ten. The output value "1" indicates that the degree to which an MS belongs to class c is strongest, and the output value "5" indicates that the degree to which an MS belongs to class c is weakest. The output value "10" indicates that the degree to which an MS belongs to class n is strongest, and the output value "6" indicates that the degree to which an MS belongs to class n is weakest.

3. The output value of the PC depends on the net agreements between the elements of the pattern for a particular decision, "Handoff" or "No Handoff."

4. The training data set should cover the entire range of interest for all the variables. To minimize the number of patterns in the training data set, representative examples should be chosen carefully.

- **Examples for a "No Handoff" Decision**. If there are three agreements for "No Handoff" and two neutral positions, the net number of agreements is three and the PC output is three. If there are one agreement and four neutral positions, the net agreement is one and the output value is five. If there are four agreements and one disagreement, the net number of agreements is three and the output is three. Table 8.1 summarizes the PC outputs for the "No Handoff" decision scenario.

Table 8.1: PC Outputs for No Handoff Decision

Number	**Net Agreements**	**PC Output**
1	5	1
2	4	2
3	3	3
4	2	4
5	1	5

Table 8.2: PC Outputs for Handoff Decision

Number	**Net Agreements**	**PC Output**
1	5	10
2	4	9
3	3	8
4	2	7
5	1	6

- **Examples for a "Handoff" Decision**. If there are three agreements for "Handoff" and two neutral positions, the net number of agreements is three and the output is eight. If there are one agreement and four neutral positions, the net agreement is one and the output value is six. If there are four agreements and one disagreement, the net number of agreements is three and the output is eight. Table 8.2 summarizes the PC outputs for the "Handoff" decision scenario.

Several concepts of fuzzy logic were used to create a training data set. Each fuzzy variable (each element of the input pattern vector called $ip_j, j \in [1, 5]$) is divided into three fuzzy sets ("High" (H), "Medium" (M), and "Low" (L)). Two basic rules are used to derive a complete set of the rules, covering the entire region of interest:

- **Rule 1**. If ip_1 is H, ip_2 is L, ip_3 is H, ip_4 is L, and ip_5 is L, the output is one;
- **Rule 2**. If ip_1 is L, ip_2 is H, ip_3 is L, ip_4 is H, and ip_5 is H, the output is ten.

Since there are five fuzzy variables and three fuzzy sets, there are a total of $3^5 = 243$ rules.

8.2.2 Determination of a PC structure

The input to the PC is a pattern vector, and the output of the PC is a value that indicates the degree to which the input pattern belongs to the class c (i.e., the current BS) and class n (i.e., the neighboring BS). A technique can be used to learn the training data relationships. Two architectures of neural networks, MLP and RBFN, and the Mamdani FLS are used as PC structures. The details of neural network paradigms can be found in [91], and the details of the Mamdani FLS can be found in [89].

8.2.3 Actual Operation of Classification

If a pattern vector similar to one of the representative vectors is presented to the PC, the PC classifies it into the class associated with the closest stored pattern vector. The closeness can be quantified by the Euclidean distance between the stored patterns and the input pattern vector. The output of the PC indicates the degree to which a given pattern vector belongs to a class (or a BS).

8.2.4 Details of the PC Based Handoff Algorithms

Figure 8.4 shows the block diagram of a fuzzy logic PC (FLPC) based handoff algorithm. The link measurements, RSS_c, RSS_n, and SIR_c, are averaged using a velocity adaptive averaging mechanism [60]. MS velocity and traffic difference Tr_d are not averaged since their instantaneous values are of interest. The averaged RSS_c, RSS_n, and SIR_c are biased before forming a pattern to account for the thresholds. The FLPC assigns a class association degree to the input pattern. If this degree is greater than 5.5, handoff is made.

Figure 8.5 shows the block diagram of a neural network PC based handoff

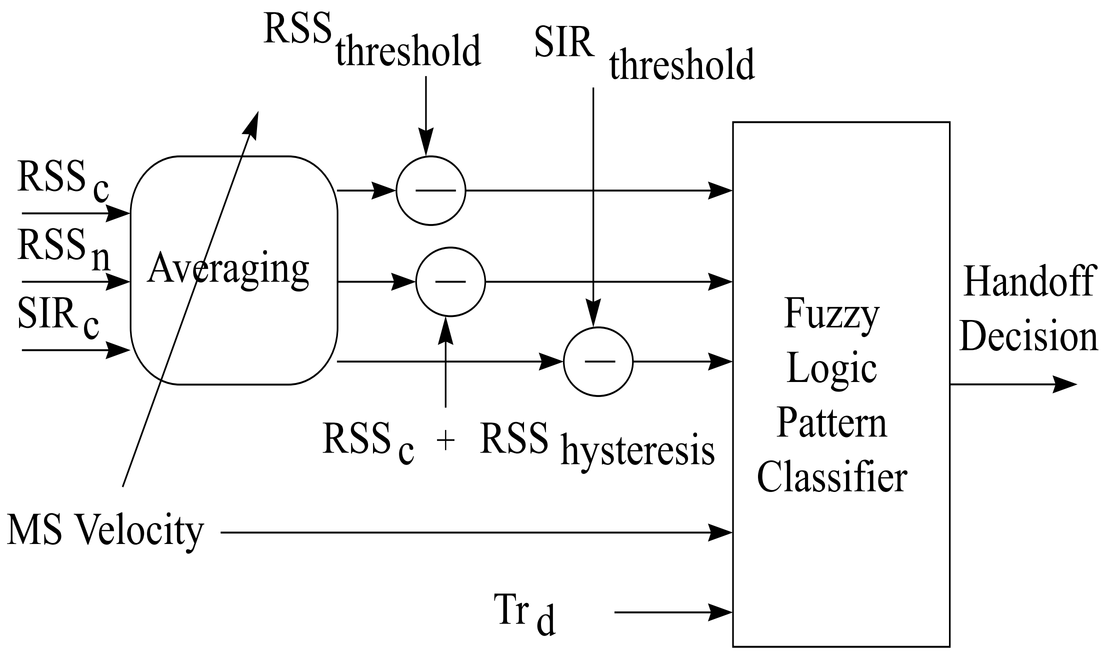

Figure 8.4: Block Diagram of a Fuzzy Logic Pattern Classifier Based Handoff Algorithm

algorithm. This algorithm is similar to the FLPC algorithm except a neural network is used as a PC instead of an FLS.

Figure 8.6 shows how adaptive direction biasing is incorporated into the basic PC based handoff algorithm. An adaptive direction biasing mechanism provides adaptive $RSS_{hysteresis}$, which is used to form an input pattern for the PC. In other respects, this algorithm is similar to the FLPC algorithm. Either an FLS or a neural network can be used as a PC.

8.3 Performance Evaluation

This section compares the performances of the conventional and proposed algorithms using several performance metrics. The conventional algorithm is a combined absolute and relative signal strength based algorithm. The macrocelluar simulation model

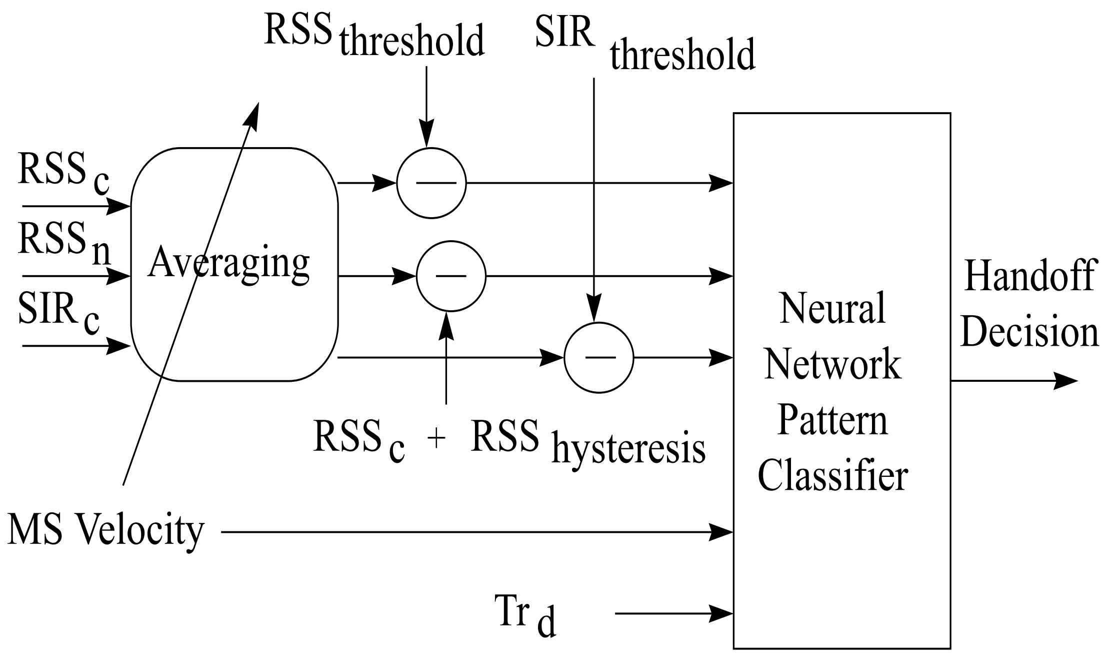

Figure 8.5: Block Diagram of a Neural Network Pattern Classifier Based Handoff Algorithm

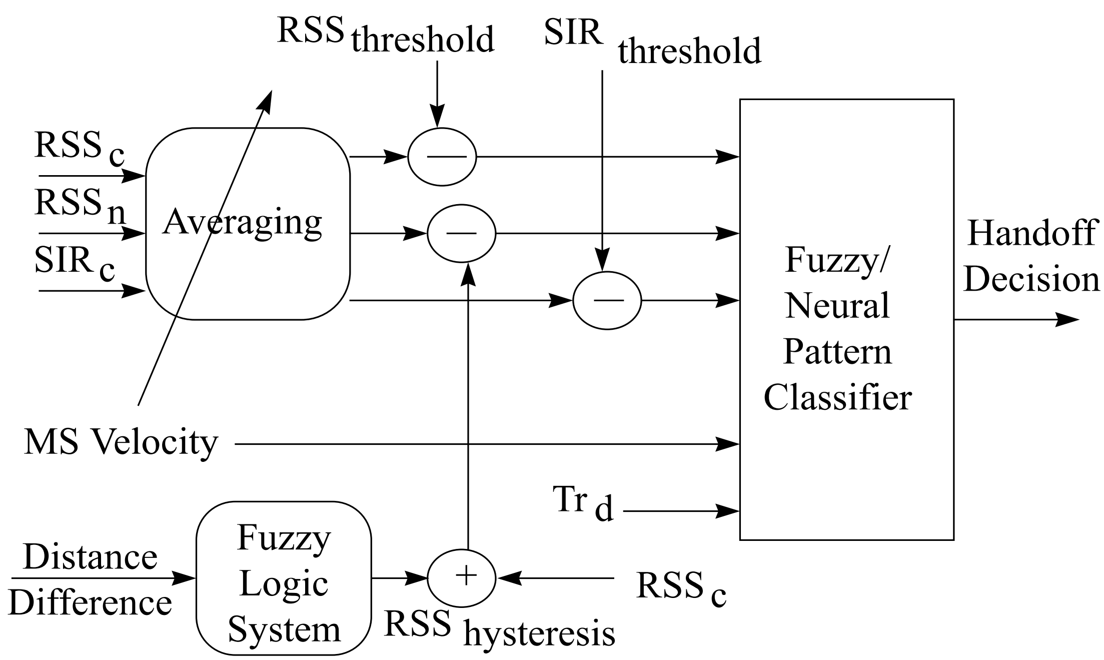

Figure 8.6: Block Diagram of a Direction Biased Pattern Classifier Based Handoff Algorithm

described in Chapter 4 is used here to analyze the algorithms.

The conventional algorithm has $RSS_{threshold}$, $RSS_{hysteresis}$, and $SIR_{threshold}$ as handoff parameters. $RSS_{threshold} = -136$ dBW, $RSS_{hysteresis} = 16$ dB, and $SIR_{threshold} = 28$ dB. The center of the input membership function for the set "Medium" of the variable ip_1 is $ip_{1_{nom}} = 0$ dB, and the centers of the input membership functions for the sets "Low" and "High" of the variable ip_1 are located at the distance of $\Delta ip_{1_{nom}} = 15$ dB from $ip_{1_{nom}}$. The center of the input membership function for the set "Medium" of the variable ip_2 is $ip_{2_{nom}} = 0$ dB, and the centers of the input membership functions for the sets "Low" and "High" of the variable ip_2 are located at the distance of $\Delta ip_{2_{nom}} = 7$ dB from $ip_{2_{nom}}$. The center of the input membership function for the set "Medium" of the variable ip_3 is $ip_{3_{nom}} = -10$ dB, and the centers of the input membership functions for the sets "Low" and "High" of the variable ip_3 are located at the distance of $\Delta ip_{3_{nom}} = 5$ dB from $ip_{3_{nom}}$. The center of the input membership function for the set "Medium" of the variable ip_4 is $ip_{4_{nom}} = 0$, and the centers of the input membership functions for the sets "Low" and "High" of the variable ip_4 are located at the distance of $\Delta ip_{4_{nom}} = 2$ from $ip_{4_{nom}}$. The center of the input membership function for the set "Medium" of the variable ip_5 is $ip_{5_{nom}} = 29$ m/sec, and the centers of the input membership functions for the sets "Low" and "High" of the variable ip_5 are located at the distance of $\Delta ip_{5_{nom}} = 9$ m/sec from $ip_{5_{nom}}$. The maximum output is ten, and the minimum output is one. The spreads of the membership functions are chosen in such a way that the membership value drops to zero at the center of the membership function of the nearest set.

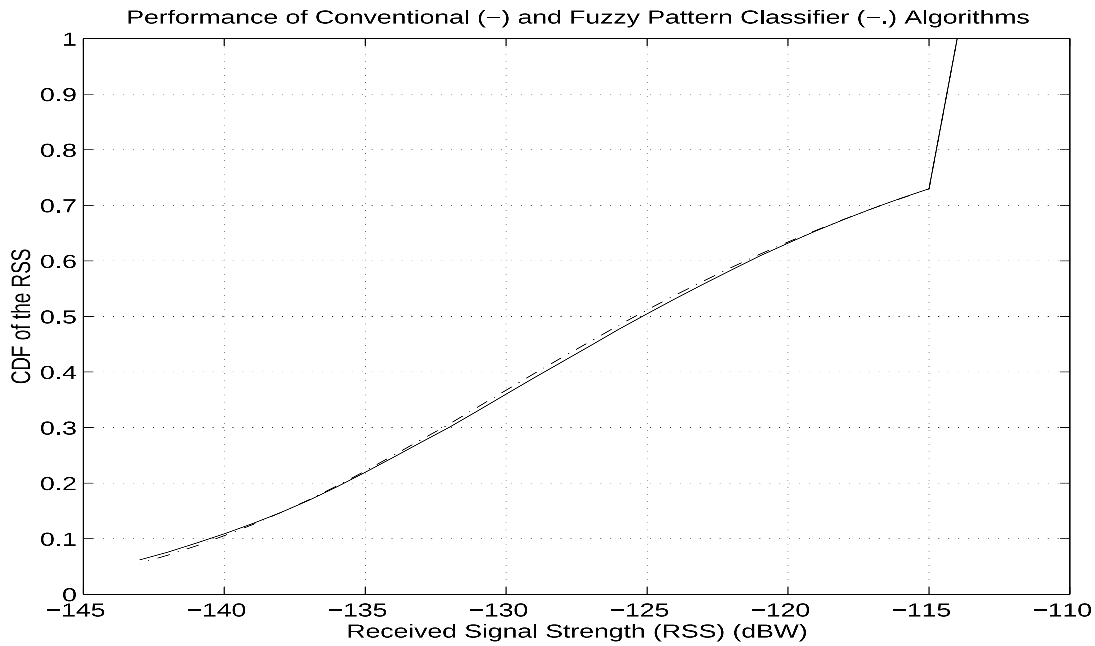

Figure 8.7: Distribution of RSS for Conventional and Fuzzy Logic PC Algorithms

8.3.1 Evaluation of a Fuzzy Logic Pattern Classifier Hand-off Algorithm

Figure 8.7 shows the cumulative distribution function (CDF) of RSS for the conventional and fuzzy logic PC (FLPC) based algorithms. Both the algorithms have similar performances.

Figure 8.8 shows the distribution of SIR for both the algorithms. The SIR distribution for the FLPC is improved by 1.3 dB compared to the conventional algorithm. This SIR improvement leads to better voice quality, fewer dropped calls, lower transmit power, and lower overall global interference level. This improvement in SIR is due to the interference adaptation of the proposed algorithm.

Figure 8.9 shows the traffic distribution for the algorithms. The FLPC gives a

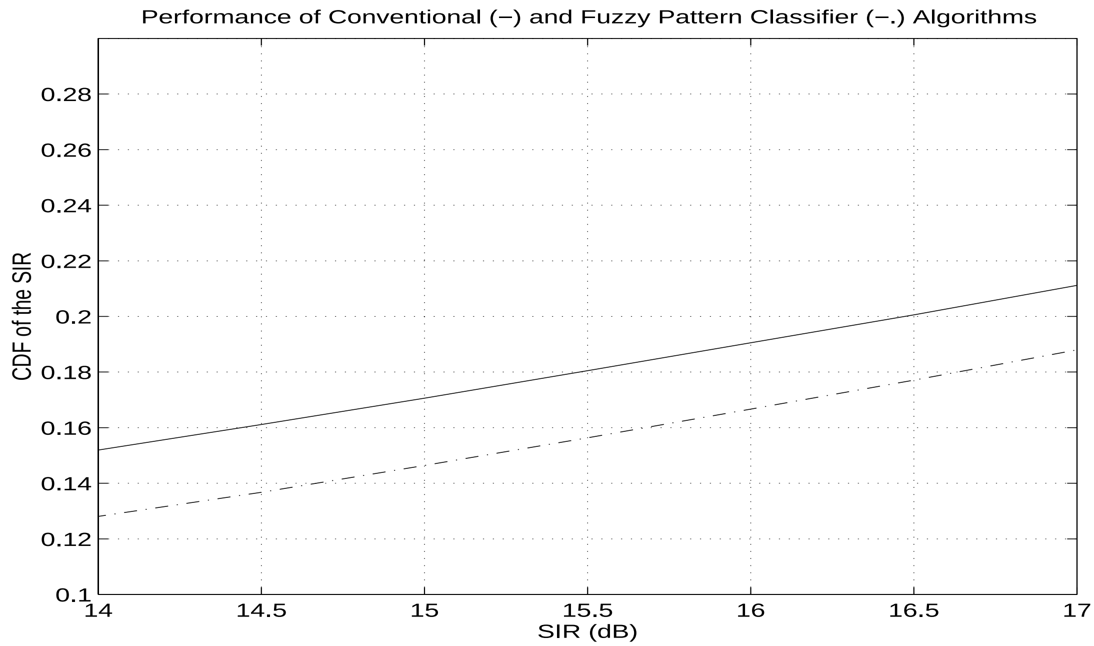

Figure 8.8: Distribution of SIR for Conventional and Fuzzy Logic PC Algorithms

4.3 call improvement in the traffic distribution. In other words, the FLPC can accommodate 4.3 more users than the conventional algorithm, reducing call and handoff blocking probabilities and enhancing spectral efficiency of the cellular system. Traffic adaptation of the proposed algorithm provides this improvement in traffic distribution.

The conventional algorithm gives an average of 3.5 handoffs and a 50% cross-over distance of 10.85km, while the FLPC gives an average of 6.2 handoffs and a 50% cross-over distance of 11.03km. Thus, the FLPC tends to give a relatively higher number of handoffs. Adaptation to the cellular environment (traffic and interference) leads to more frequent handoffs since better handoff candidates are available that can improve SIR and traffic related system performance.

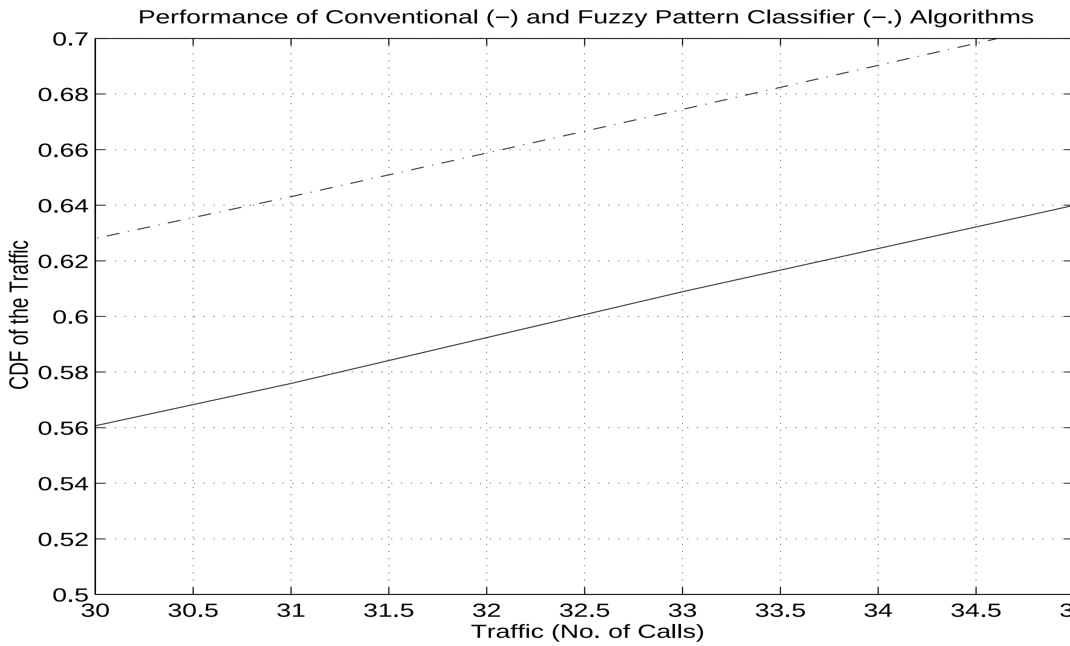

Figure 8.9: Distribution of Traffic for Conventional and Fuzzy Logic PC Algorithms

8.3.2 Evaluation of an MLP Pattern Classifier Handoff Algorithm

This section analyzes the simulation results for a neural network based PC when an MLP is used as a PC. Figure 8.10 shows the CDF of RSS for the conventional and MLP PC algorithms. The MLP PC gives slightly better RSS distribution, which can lead to better voice quality and improved cell membership properties.

Figure 8.11 shows the distribution of SIR for both the algorithms. The MLP PC algorithm gives a 1.9 dB improvement in SIR over the conventional algorithm, improving QoS related system performance.

Figure 8.12 shows the traffic distribution for different algorithms. The MLP PC gives a 3.5 call better traffic distribution than the conventional algorithm, increasing the potential number of new users.

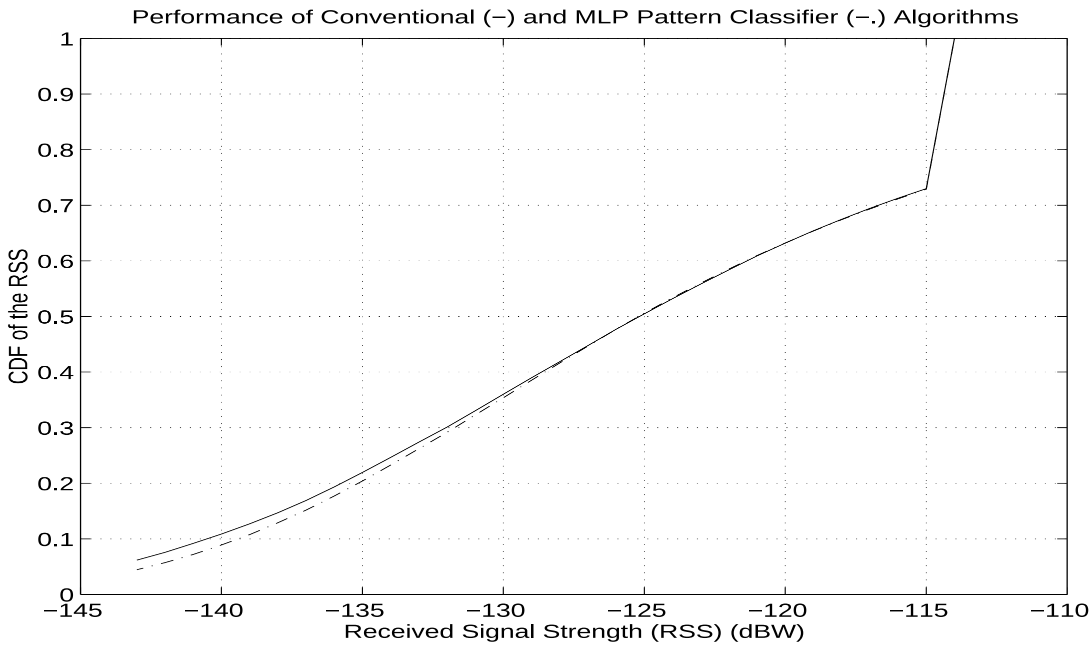

Figure 8.10: Distribution of RSS for Conventional and MLP PC Algorithms

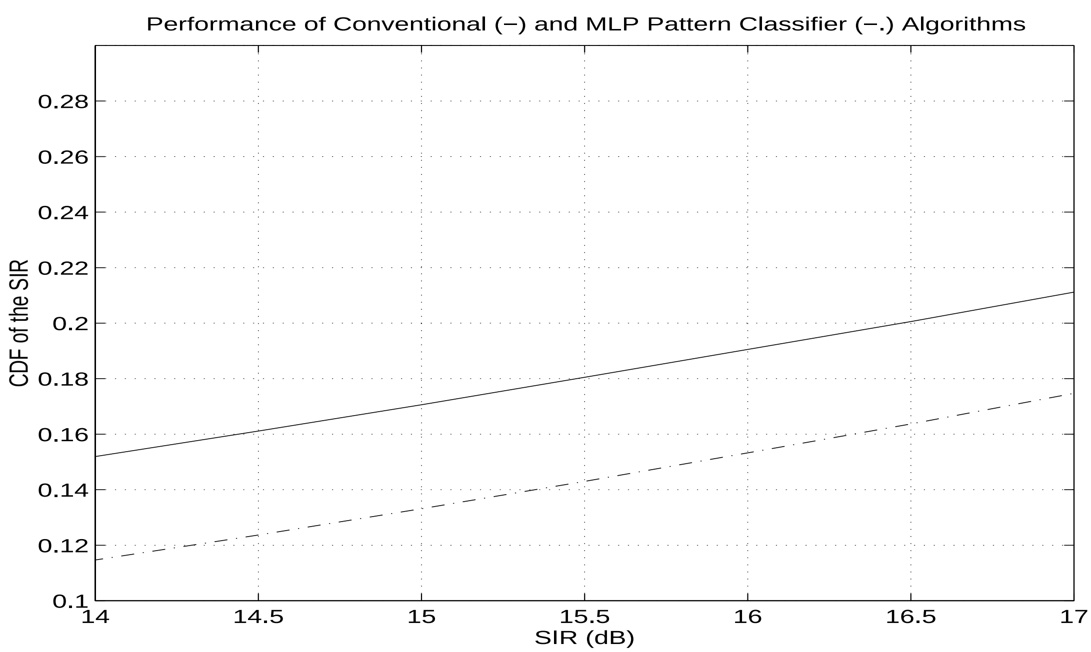

Figure 8.11: Distribution of SIR for Conventional and MLP PC Algorithms

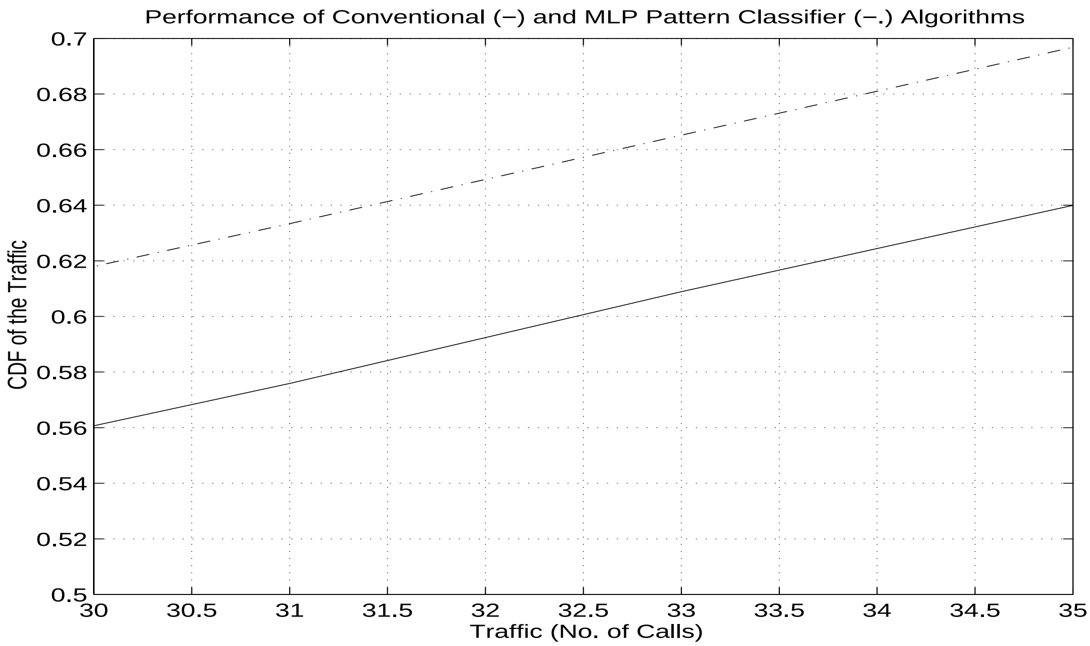

Figure 8.12: Distribution of Traffic for Conventional and MLP PC Algorithms

The conventional algorithm gives an average of 3.5 handoffs and a 50% cross-over distance of 10.85km, while the MLP PC gives an average of 7.3 handoffs and a 50% cross-over distance of 10.80km. Thus, the MLP PC increases the network load but reduces interference.

8.3.3 Evaluation of an RBFN Pattern Classifier Handoff Algorithm

This section illustrates the simulation results for a neural network based PC when an RBFN is used as a PC. Figure 8.13 shows the CDF of RSS for the conventional and RBFN PC algorithms. The RBFN PC classifier has a slightly better RSS distribution.

Figure 8.14 shows the distribution of SIR for the algorithms. There is a 1.9 dB

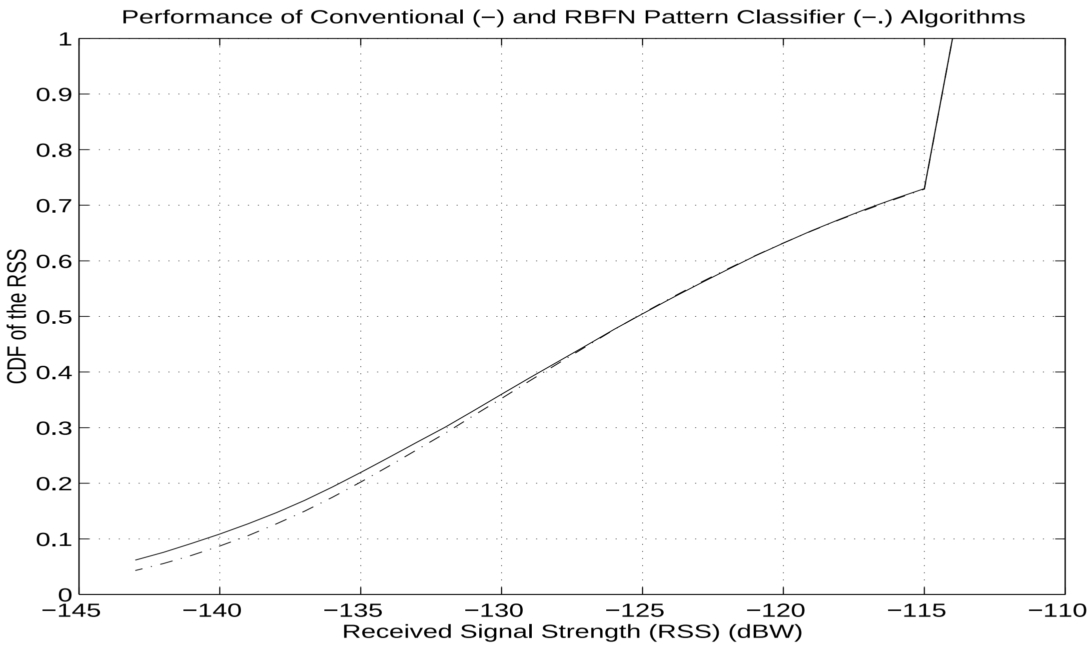

Figure 8.13: Distribution of RSS for Conventional and RBFN PC Algorithms

improvement for the RBFN PC algorithm.

Figure 8.15 shows the traffic distribution for the algorithms. The RBFN PC classifier algorithm provides a 3.5 call improvement in traffic distribution. The conventional algorithm gives an average of 3.5 handoffs and a 50% cross-over distance of 10.85km, while the RBFNPC algorithm gives an average of 7.5 handoffs and a 50% cross-over distance of 11.00km.

8.3.4 Evaluation of a Direction Biased MLP Pattern Classifier Handoff Algorithm

Figure 8.16 shows the cumulative distribution function (CDF) of RSS for the conventional and direction biased MLP PC algorithms. The direction biased MLP PC has a slightly better RSS distribution.

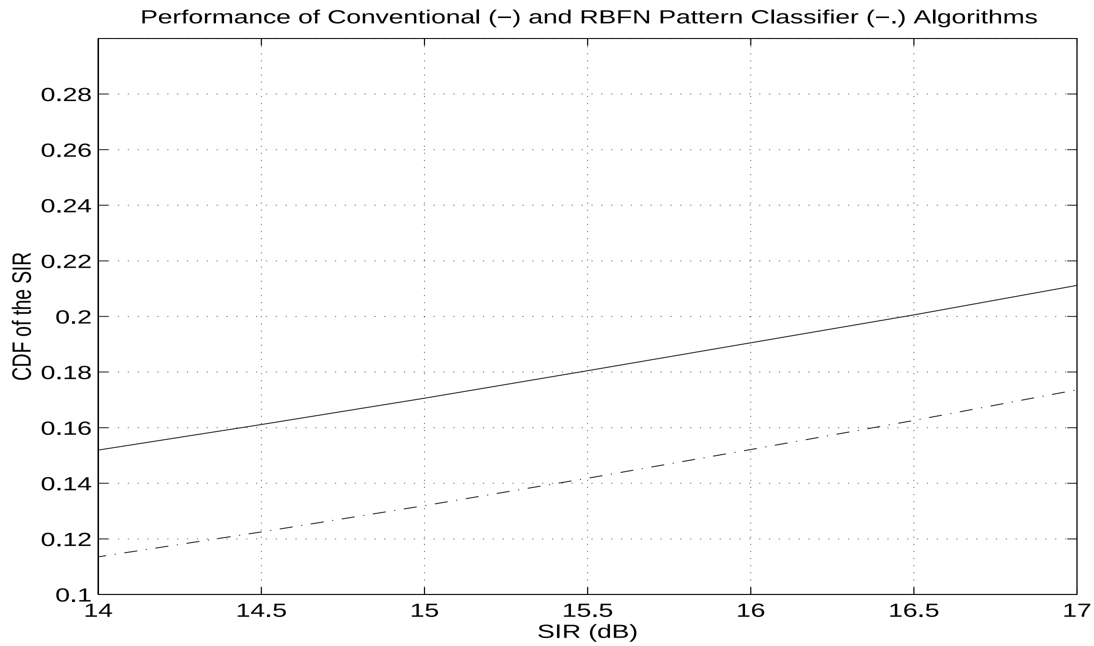

Figure 8.14: Distribution of SIR for Conventional and RBFN PC Algorithms

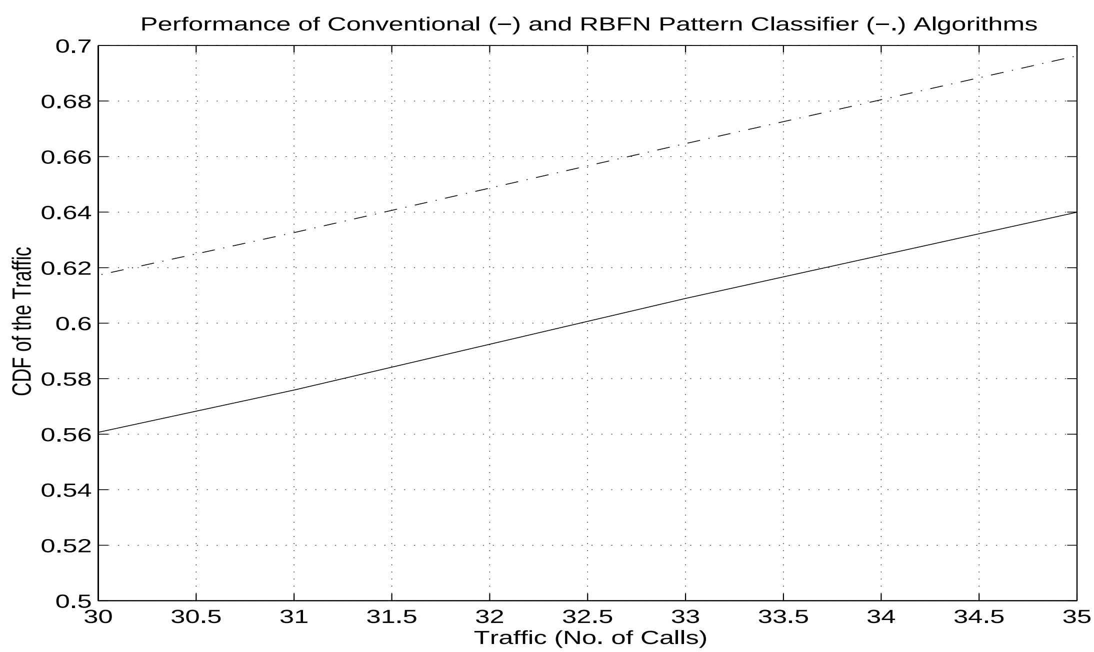

Figure 8.15: Distribution of Traffic for Conventional and RBFN PC Algorithms

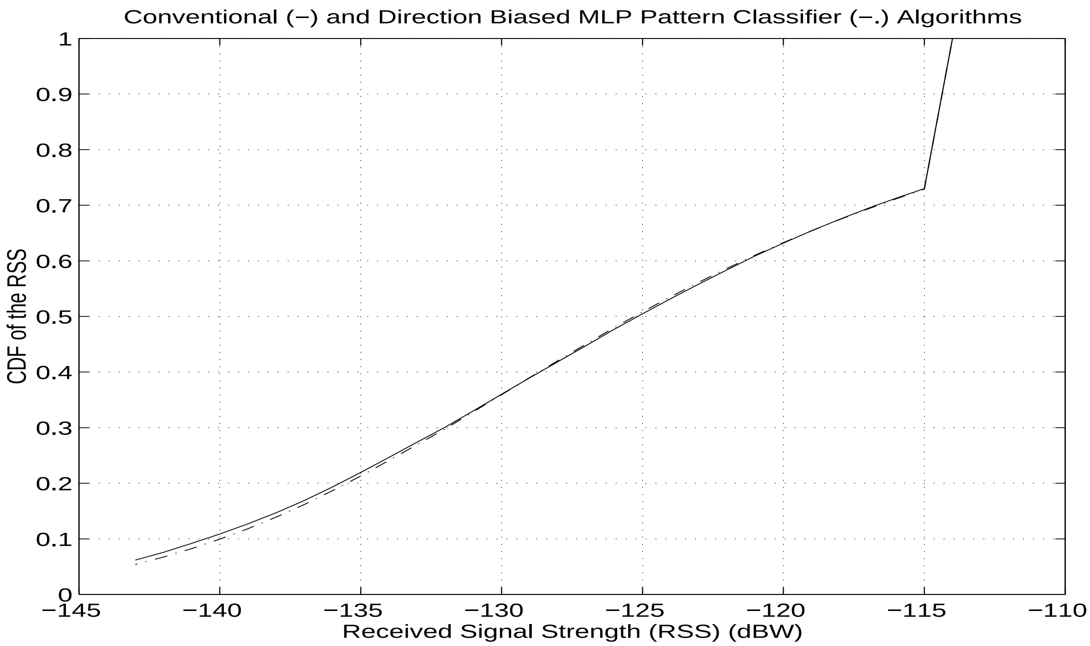

Figure 8.16: Distribution of RSS for Conventional and Direction Biased MLP PC Algorithms

Figure 8.17 shows the distribution of SIR for the algorithms. The direction biased MLP PC is 1.5 dB better than the conventional algorithm. Note the reduction in SIR improvement for the direction biased MLP PC compared to the non-direction biased MLP PC algorithm. As discussed earlier, adaptive direction biasing can trade-off SIR performance for a reduced number of handoffs and improved cell membership properties. Figure 8.18 shows the traffic distribution for two different algorithms. The direction biased MLP PC gives a 3.5 call improvement in the traffic performance.

The conventional algorithm gives an average of 3.5 handoffs and a 50% cross-over distance of 10.85km, the non direction biased MLP PC gives an average of 7.3 handoffs and a 50% cross-over distance of 10.80km, and the direction biased MLP PC gives an average of 6.5 handoffs and a 50% cross-over distance of 9.40km. The distance of 9km is midway between the cells.

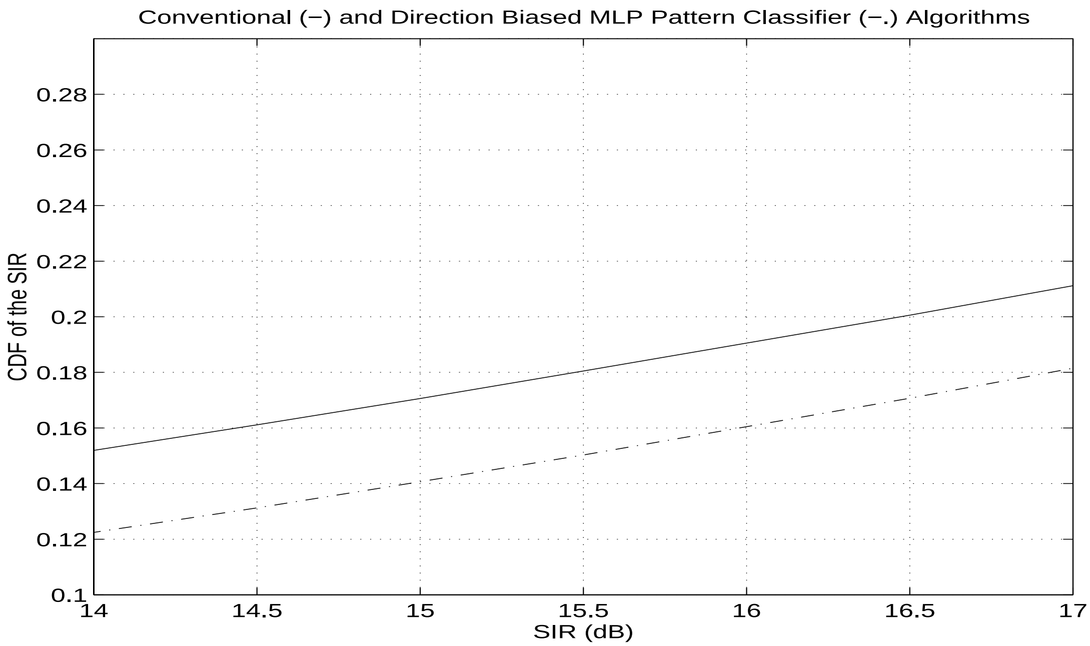

Figure 8.17: Distribution of SIR for Conventional and Direction Biased MLP PC Algorithms

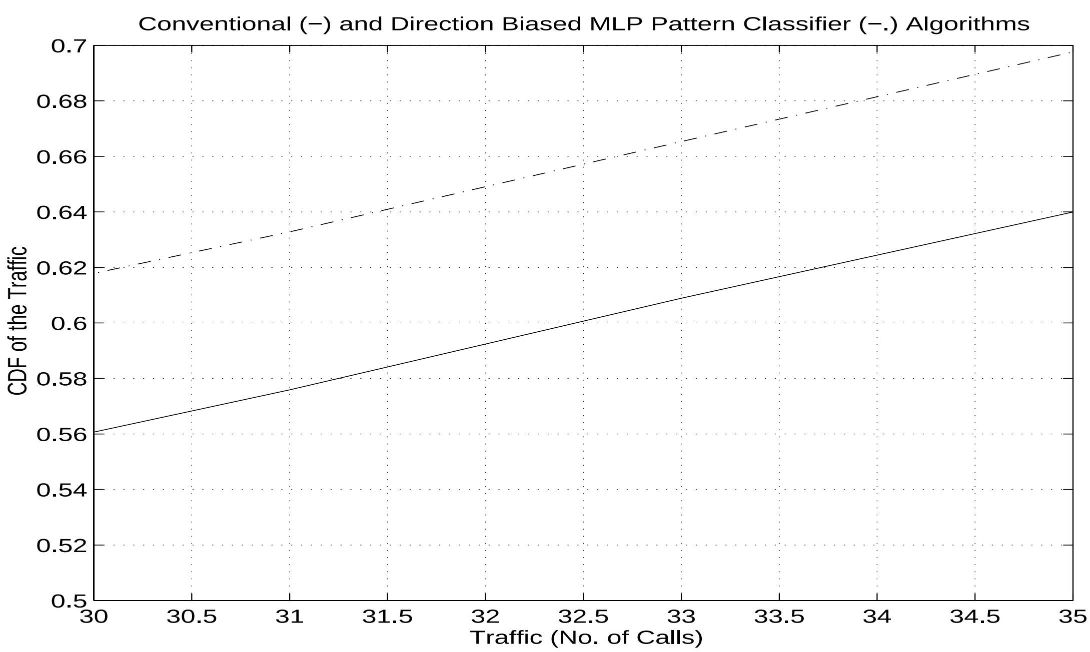

Figure 8.18: Distribution of Traffic for Conventional and Direction Biased MLP PC Algorithms

8.4 Conclusion

This chapter proposes a new class of adaptive handoff algorithms that formulates the handoff problem as a pattern classification problem. Pattern classification facilitates the efficient and convenient implementation of a multicriteria handoff algorithm. The proposed pattern classification based algorithms are designed by incorporating several attractive features of existing algorithms and providing adaptation capability in a dynamic cellular environment through neural networks and fuzzy logic systems. Extensive simulation results for a conventional handoff algorithm (absolute and relative signal strength based algorithm) and pattern classification based algorithms are presented. Adaptive direction biasing has been incorporated into the pattern classifier algorithms to reduce the processing load and improve the cell membership properties.

Chapter 9

Microcellular Algorithms

Microcells increase system capacity but make resource management difficult. They impose distinct constraints on handoff algorithms due to the characteristics of the propagation environment. A fixed parameter handoff algorithm cannot perform uniformly well in various handoff scenarios encountered by a mobile station in a microcellular environment. Adaptive handoff algorithms for microcells are proposed. The proposed non-direction biased algorithm utilizes adaptive parameters supplied by a fuzzy logic system that exploits characteristics of propagation environment. Direction biasing has been incorporated into the basic non-direction biased algorithm to obtain a good basic adaptive algorithm suitable for a microcellular environment. Adaptation to traffic, interference, and mobility has been superimposed on the basic direction biased algorithm. It is shown that the proposed algorithms provide high performance in generic handoff scenarios in a microcellular system.

9.1 Introduction to Handoffs in Microcells

Microcells increase system capacity at the cost of an increase in the complexity of resource management. In particular, the number of handoffs per call increases, and fast handoff algorithms are required to maintain an acceptable level of dropped call rate. Microcells impose distinct constraints on handoff algorithms due to the characteristics of their propagation environment. For example, a mobile station (MS) encounters a propagation phenomenon called *corner effect*, which demands a faster handoff. Figure 9.1 shows two generic handoff scenarios in microcells, a *line of sight (LOS) handoff* and a *non-line of sight (NLOS) handoff*.

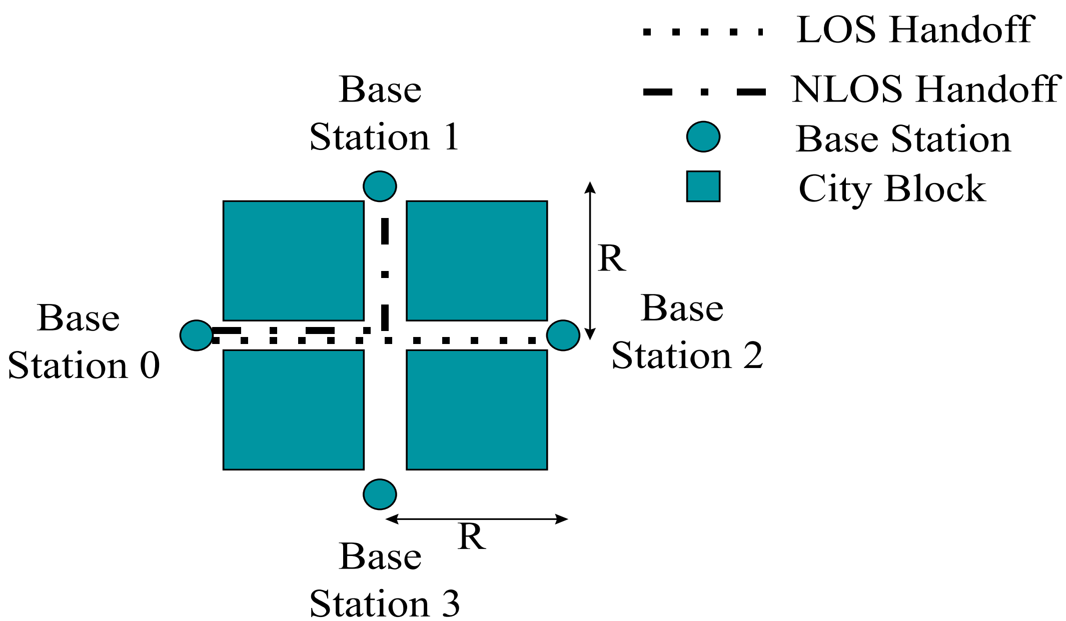

Figure 9.1: Generic Handoff Scenarios in a Microcellular System

A LOS handoff occurs when the base stations (BSs) that serve an MS are LOS BSs before and after the handoff. When the MS travels from BS 0 to BS 2, it experiences a LOS handoff. A NLOS handoff occurs when one BS is a NLOS BS before the handoff, and the other BS becomes a NLOS BS after the handoff. When the MS travels from BS 0 to BS 1, it experiences a NLOS handoff. A good handoff algorithm performs uniformly well in both generic handoff scenarios. Important considerations for designing handoff algorithms for a microcellular system are briefly described next.

- **Mobility and Traffic Characteristics**. The MS speeds are lower, and the speed range is narrower compared to a macrocellular scenario. Traffic is normally allowed only along the streets.

- **Propagation Features**. The MS experiences the corner effect as discussed earlier. Field measurements have shown that the shadow fading intensity is lower in microcells than in macrocells.

- **Measurement Averaging**. The averaging interval (or averaging distance) is shorter in microcells to respond to fast varying signal strength profiles. To provide sufficient averaging to counteract shadow fading effects, a sufficient number of samples are required, which may necessitate higher measurement sampling frequency.

- **Primary Handoff Requirements**. A handoff algorithm should be fast and should minimize the number of handoffs. A fixed parameter handoff algorithm is suboptimal in a microcellular environment. For example, if hysteresis is large, it will cause a delay in NLOS handoff, increasing the probability of a dropped call. On the other hand, if hysteresis is small, it will increase the likelihood of the ping-pong effect. Since the situation of LOS or NLOS handoff cannot be known *a priori*, a proper tradeoff must be achieved between the LOS and NLOS handoff performance. In general, a large hysteresis gives good LOS handoff performance and poor NLOS handoff performance. A small hysteresis gives good NLOS handoff performance and poor LOS handoff performance.

- **Secondary Handoff Requirements**. The algorithm should respond relatively faster to fast moving vehicles, should attempt to balance traffic, and should be adaptive to interference.

The requirement of a fast handoff for a NLOS handoff case can be met by deploying a macrocellular overlay system over an existing microcellular system. However, this is an expensive solution, and it complicates even further the resource management of the already complex microcellular system. A better solution is to design a good handoff algorithm that can perform well in both LOS and NLOS handoff cases. Some research efforts have been made to cope with the problems associated with microcellular handoffs. Reference [19] evaluates an RSS based algorithm with hysteresis for

LOS and NLOS handoffs and indicates that fast handoffs can be made in a NLOS case at the cost of a higher number of handoffs in a LOS case. A handoff algorithm that consists of an OR circuit between two separate decision making mechanisms for LOS and NLOS handoff cases is proposed in [110]. The LOS handoff decision making mechanism uses longer averaging time and smaller hysteresis, while the NLOS handoff mechanism uses shorter averaging time and large hysteresis. The performance of this algorithm is velocity sensitive; the best handoff performance is obtained only at one velocity. Reference [58] overcomes this drawback by proposing velocity adaptive handoff algorithms. Reference [60] develops direction biased handoff algorithms to improve handoff performance in LOS and NLOS cases. These algorithms are evaluated in a multi-cell environment (a four BS neighborhood model).

New adaptive handoff algorithms that perform well in both LOS and NLOS handoff situations are proposed. These new algorithms are described in Section 9.2, and Section 9.3 analyzes the performance of the algorithms from different significant aspects. Finally, Section 9.4 summarizes the chapter.

9.2 Adaptive Handoff Algorithms

This section describes the development of a generic microcellular algorithm that attempts to achieve a balance between LOS and NLOS handoff performance. The objective of this generic algorithm is to provide a good basic algorithm that meets the primary handoff requirements discussed earlier. An adaptive algorithm that attempts to meet secondary handoff requirements after making sure that the primary handoff requirements are satisfied is also described.

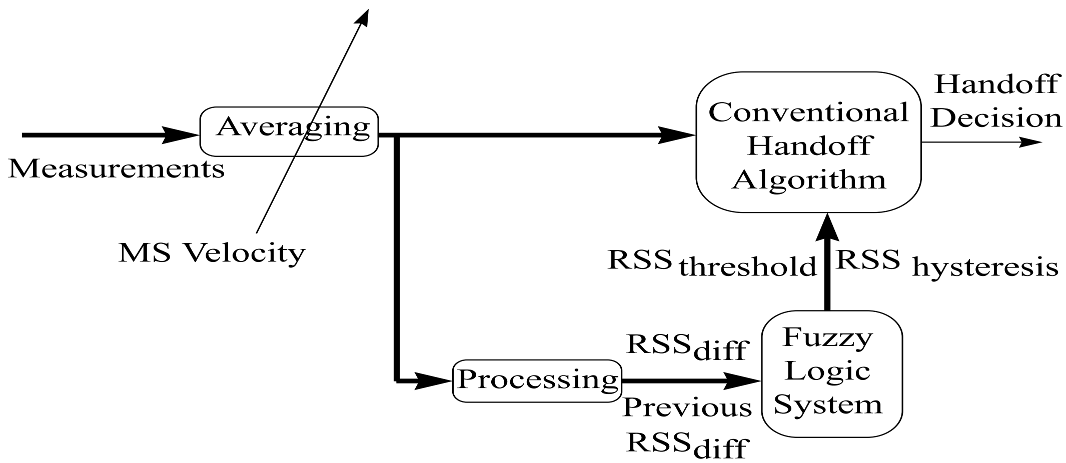

Figure 9.2: Block Diagram of an Adaptive Microcellular Handoff Algorithm

9.2.1 A Generic Microcellular Algorithm

This section describes the development of a generic microcellular algorithm in two stages. First, a non-direction biased algorithm is described, and then, direction biasing is incorporated into the algorithm to provide a basic adaptive algorithm that can perform well in a typical microcellular environment.

Non-Direction Biased Algorithm

Figure 9.2 shows the block diagram of an adaptive handoff algorithm suitable for a microcellular system. Handoff criteria are averaged according to the velocity adaptive averaging mechanism. The conventional algorithm is a combination of an absolute and relative received signal strength (RSS) based algorithm and an SIR based algorithm. The RSS based algorithm has threshold ($RSS_{threshold}$) and hysteresis ($RSS_{hysteresis}$) as parameters while the SIR based algorithm has threshold ($SIR_{threshold}$) as a parameter. If RSS drops below $RSS_{threshold}$ or SIR drops below $SIR_{threshold}$, a handoff process is initiated. If another BS can provide RSS that exceeds the RSS of the current

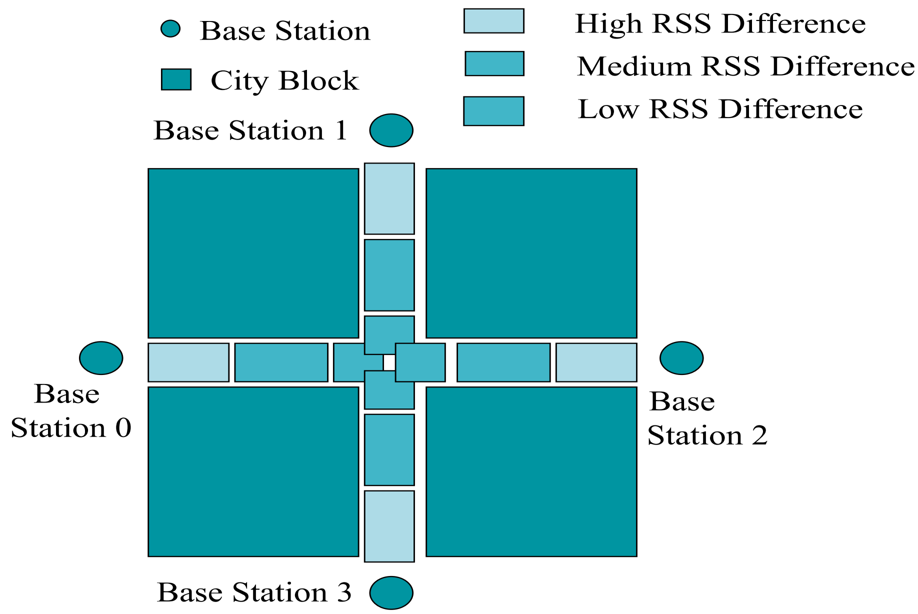

Figure 9.3: Handoff Situations in a Microcellular System

BS by an amount $RSS_{hysteresis}$, a handoff is made to the new BS. The SIR threshold parameter allows the early initiation of a better handoff candidate search. The RSS based parameters are adapted using an FLS. The input to the FLS is the difference in RSS between two best BSs (i.e., BSs from which the MS receives maximum RSSs). Generally, these BSs are LOS BSs since an MS has lower RSS from NLOS BSs. The outputs of the FLS are adaptive handoff parameters, $RSS_{threshold}$, and $RSS_{hysteresis}$. The geometry that underlines the philosophy behind the design of the FLS is illustrated in Figure 9.3. When an MS is relatively far from the intersection and close to a BS, the difference in RSS at the MS from the LOS BSs is high since the MS receives very high RSS from the closer BS and very low RSS from the far LOS BS. This situation is similar to a LOS handoff situation since the good handoff candidates are LOS BSs. Under these circumstances, it is advantageous to use high $RSS_{hysteresis}$ and low $RSS_{threshold}$ values to reduce the ping-pong effect. However, as an MS reaches the intersection, there is a likelihood of a NLOS handoff, and it is beneficial to use low $RSS_{hysteresis}$ and high $RSS_{threshold}$ to make a fast handoff in case a NLOS handoff is necessary. The intersection region is characterized by small (ideally, near zero) RSS differences. After an MS crosses an intersection, the RSS difference keeps increasing, and this situation is similar to a LOS handoff scenario. Again, it is important to use high $RSS_{hysteresis}$ and low $RSS_{threshold}$ to reduce the ping-pong effect. Based on the knowledge of such propagation characteristics of a microcellular environment, a fuzzy logic rule base is created as shown in Table 9.1. *Current RSS Difference* and *Previous RSS Difference* are inputs to the rule base, and $RSS_{threshold}$ and $RSS_{hysteresis}$ are the outputs of the rule base. *Current RSS Difference* is the difference in RSS from two best BS at the current sample time, and *Previous RSS Difference* is the difference in RSS from two best BS at the previous sample time. Consider Rule 1. When *Current RSS Difference* and *Previous RSS Difference* are high, the MS is close to a BS, and, hence, $RSS_{threshold}$ is made lowest and $RSS_{hysteresis}$ is made highest to prevent the ping-pong effect. On the other hand, when *Current RSS Difference* and *Previous RSS Difference* are low, the MS is equally far from the BSs, and, hence, $RSS_{threshold}$ is made highest and $RSS_{hysteresis}$ is made lowest to make a fast handoff in potential NLOS handoff situations. The idea of using high hysteresis for LOS handoff situations and low hysteresis for NLOS handoff situations conforms with the primary handoff objectives.

Direction Biased Algorithm

Direction biasing has been proposed in [60] to improve handoff performance. Reference [60] also shows that it is extremely difficult to estimate the direction of the MS with respect to the BSs at an intersection. Hence, direction biasing can be utilized in an algorithm when there is sufficient confidence regarding direction estimates, and

Table 9.1: Fuzzy Logic Rule Base

Rule No.	**Cur. RSS Diff.**	**Prev. RSS Diff.**	$\mathbf{RSS_{hysteresis}}$	$\mathbf{RSS_{threshold}}$
1	High	High	Lowest	Highest
2	High	Medium	Lower	Higher
3	High	Low	Low	High
4	Medium	High	Low	High
5	Medium	Medium	Medium	Medium
6	Medium	Low	High	Low
7	Low	High	Higher	Lower
8	Low	Medium	Higher	Lower
9	Low	Low	Highest	Lowest

direction biasing can be switched off when direction estimates are deemed unreliable. However, it is possible to exploit direction biasing even when direction estimates are unreliable.

Figure 9.4 denotes the regions where direction estimates are unreliable by continuous lines and labels such regions as "No Direction Estimates" in the legend. Assume that the algorithm keeps track of reliable direction estimates and stores them as *previous direction estimates*. Consider the LOS handoff case when the MS travels from BS 0 to BS 2. The reliable direction estimates are available before the MS enters the intersection. According to these estimates, the MS is moving away from BS 0 and is approaching BSs 1, 2, and 3. Assume that the direction biasing algorithm continues to use these estimates until new reliable direction estimates become available (after the MS traverses some distance beyond the intersection). After crossing the intersection, the MS is approaching BS 2, while moving away from BSs 0, 1, and 3. Thus, the direction estimates are wrong for BS 1 and BS 3 and correct for BSs 0 and 2. However, note that after the MS clears the intersection, the handoff candidates are LOS BSs, which are BS 0 and BS 2 in the case under consideration. Also note that the direction estimates being used by the algorithm are correct for both the good handoff candidate BSs (BS 0 and BS 2). Thus, there is a very small region where the use of previous direction estimates can have an adverse impact on handoff performance. On the contrary, there is a relatively larger area where the use of previously reliable direction estimates may have no significant adverse impact on handoff performance. A similar situation exists for the NLOS handoff case. In the NLOS handoff case, the MS travels from BS 0 to BS 1. Again, the reliable direction estimates are available before the MS enters the intersection. According to these reliable estimates, the MS is receding from BS 0 and moving toward BSs 1, 2, and 3. Assume that the direction biasing algorithm continues to use these estimates until new reliable direction estimates become available (after the MS clears the intersection). After crossing the intersection, the MS is approaching BS 1, while moving away from BSs 0, 2, and 3. Thus, the direction estimates are wrong for BS 2 and BS 3 and correct for BS 0 and 1. However, note that after the MS clears the intersection, the handoff candidates are LOS BSs, which are BS 1 and BS 3. Also note that the direction estimates being used by the algorithm are correct for the BS being approached by the MS (BS 1). Moreover, the direction estimate for BS 0 (away from which the MS is moving) is also correct. There is a small region where the use of previously reliable direction estimates can adversely affect handoff performance, but there is a relatively large area where handoff performance does not suffer due to the use of previously reliable direction estimate. Thus, *it is more advantageous to use previous direction estimates than to switch off direction biasing completely when the direction estimates are unreliable.* Note that the benefit of using previous direction estimates will be more pronounced for the LOS case than the NLOS case. In the LOS case, previous direction estimates are the same as true direction estimates for both good handoff candidates (LOS BSs).

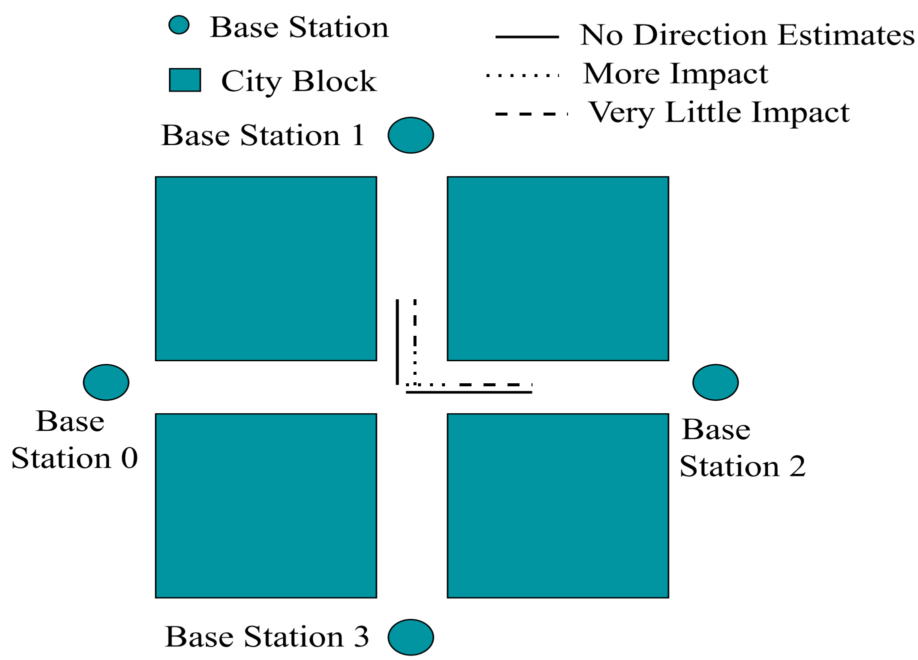

Figure 9.4: Direction Biasing and Handoff Situations in a Microcellular System

In the NLOS case, the previous direction estimates are the same as true direction estimates only for one of the good LOS handoff candidates and for the BS away from which the MS is moving.

Figure 9.5 shows the block diagram of a direction biased adaptive handoff algorithm suitable for a microcellular system. The diagram is similar to the block diagram for the earlier algorithm, and the conventional handoff algorithm is replaced by a preselection direction biased handoff algorithm [60] that accepts the adaptive handoff parameters from an FLS. Basically, the preselection direction biased algorithm encourages handoffs to the BSs toward which the MS is moving and discourages handoffs to the BSs away from which the MS is moving. The RSS measurements from the BSs are biased through a preselection procedure that selects a handoff candidate by biasing the RSS measurements. Assume that there are two best handoff candidate BSs. The best BS has a slightly better RSS than the second best BS, and the MS is moving

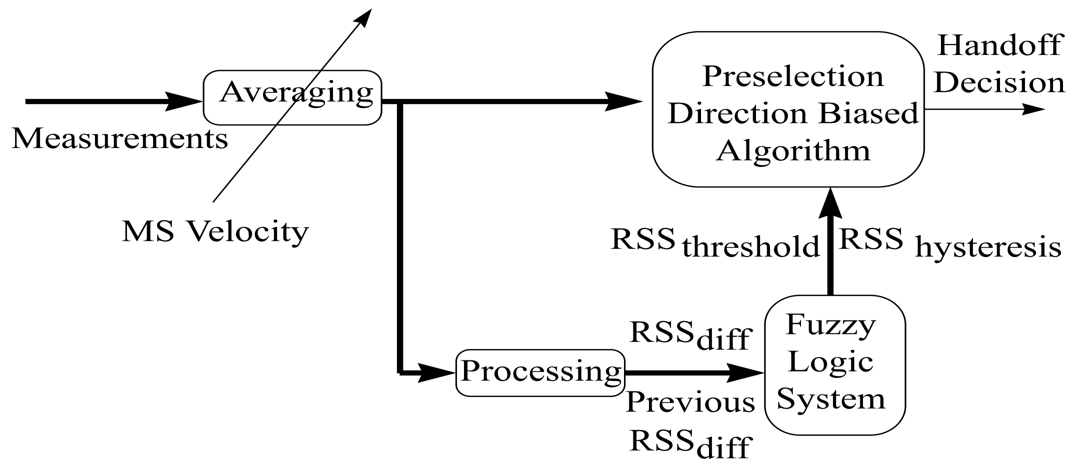

Figure 9.5: Block Diagram of a Direction Biased Adaptive Microcellular Handoff Algorithm

away from it. The MS is moving toward the second best BS. The preselection procedure ensures that the second best BS is preferred to the best BS since the second BS is more likely to be selected in the future than the currently best BS.

9.2.2 A Microcellular Algorithm with Interference, Traffic, and Mobility Adaptation

Figure 9.6 shows the block diagram of a handoff algorithm that uses a secondary FLS to provide interference, traffic, and mobility adaptation. This algorithm considers secondary handoff requirements whenever primary microcellular handoff objectives are not compromised. When an MS is near an intersection, there is a possibility of NLOS handoff, and any handoff parameter adaptation to obtain better performance in meeting secondary handoff objectives can adversely affect performance in meeting primary handoff objectives. Hence, the proposed algorithm switches on the secondary adaptation mechanism only under LOS handoff type situations (i.e., when an MS is relatively far from an intersection). The vicinity of an MS to an intersection can be

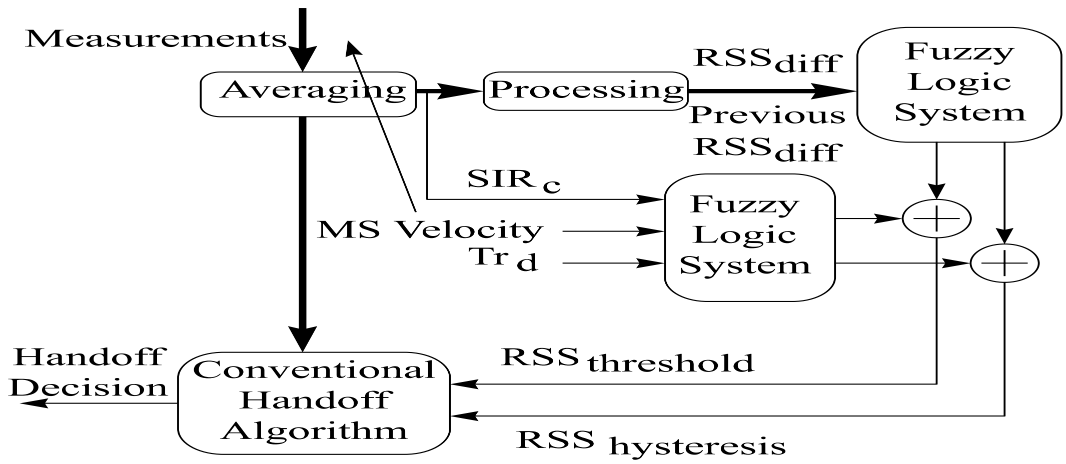

Figure 9.6: Block Diagram of a Microcellular Handoff Algorithm With Traffic and Mobility Adaptation

predicted based on the RSS difference between best BSs or the reliability of direction estimates. The primary FLS provides base values of the handoff parameters, while the secondary FLS provides incremental variations in $RSS_{threshold}$ and $RSS_{hysteresis}$ to reflect the dynamics of traffic, interference, and mobility. The inputs to the secondary FLS are SIR_c, $(Tr)_d = (Tr)_c - (Tr)_n$, and MS velocity, and the outputs of the secondary FLS are incremental $RSS_{threshold}$ ($\Delta RSS_{threshold}$) and incremental $RSS_{hysteresis}$ ($\Delta RSS_{hysteresis}$). SIR_c is SIR of the current BS, and Tr_d is traffic difference (i.e., the difference in the number of calls in the current and the neighboring BS, $Tr_c - Tr_n$).

MS velocity as an input to the FLS is the component of the MS velocity toward the serving BS. If the MS is moving toward the serving BS, the velocity is considered positive, and if the MS is moving away from the serving BS, the velocity is considered negative. A complete fuzzy logic rule base for the secondary FLS is shown in Table 9.2. The philosophy behind the design of this rule base is explained next. When all the inputs suggest a change in the handoff parameters in the same direction (i.e., either increase or decrease), the parameters are changed to the maximum extent. For example, consider Rule 9. “High” SIR_c indicates that the quality of the current link is very good. “Low” $(Tr)_d$ indicates that there are very few users in the current cell. “High” MS velocity indicates that the MS is moving toward the current BS at a high speed. All these secondary FLS inputs suggest that handoff from the current BS be discouraged. Hence, the FLS makes $\Delta RSS_{threshold}$ “Lowest” (making overall $RSS_{threshold}$ smaller) and $\Delta RSS_{hysteresis}$ “Highest” (making overall $RSS_{hysteresis}$ large).

9.3 Simulation Results

9.3.1 Parameters of the Microcellular Algorithms

The simulation model used for the evaluation of microcellular algorithms is described in Chapter 4. The conventional algorithm has $RSS_{threshold}$, $RSS_{hysteresis}$, and $SIR_{threshold}$ as handoff parameters. $RSS_{threshold}$ is set as the RSS at the intersection from a BS. Setting $RSS_{hysteresis}$ as 7.5 dB gives a good compromise between the LOS and NLOS handoff performance with good cross-over distance for the NLOS case and a reasonable number of handoffs for the LOS case. $SIR_{threshold}$ is chosen to be 28 dB. For the non-direction biased algorithm, the center of the input membership function for the set “Medium” is $RSS_{diff_{nom}} = 3.5dB$, and the centers of the input membership functions for the sets “Low” and “High” are located at the distance of $\Delta RSS_{diff} = 3.5$ dB from $RSS_{diff_{nom}}$. The center of the output membership function “Medium” for the fuzzy variable $RSS_{hysteresis}$ is located at $RSS_{hysteresis_{nom}} = 7.5$ dB, and the centers of the output membership functions for the extreme sets (e.g., “Highest” and “Lowest”) are located at the distance of $\Delta RSS_{hysteresis} = 1.8$ dB

Table 9.2: Secondary Fuzzy Logic Rule Base

Rule No.	$\mathbf{SIR_c}$	$\mathbf{(TR)_d}$	**MS Velocity**	$\mathbf{\Delta RSS_{threshold}}$	$\mathbf{\Delta RSS_{hysteresis}}$
1	High	High	Low	High	Low
2	High	High	Normal	Normal	Normal
3	High	High	High	Low	High
4	High	Normal	Low	Normal	Normal
5	High	Normal	Normal	Low	High
6	High	Normal	High	Lower	Higher
7	High	Low	Low	Low	High
8	High	Low	Normal	Lower	Higher
9	High	Low	High	Lowest	Highest
10	Normal	High	Low	Higher	Lower
11	Normal	High	Normal	High	Low
12	Normal	High	High	Normal	Normal
13	Normal	Normal	Low	High	Low
14	Normal	Normal	Normal	Normal	Normal
15	Normal	Normal	High	Low	High
16	Normal	Low	Low	Normal	Normal
17	Normal	Low	Normal	Low	High
18	Normal	Low	High	Lower	Higher
19	Low	High	Low	Highest	Lowest
20	Low	High	Normal	Higher	Lower
21	Low	High	High	High	Low
22	Low	Normal	Low	Higher	Lower
23	Low	Normal	Normal	High	Low
24	Low	Normal	High	Normal	Normal
25	Low	Low	Low	High	Low
26	Low	Low	Normal	Normal	Normal
27	Low	Low	High	Low	High

from $RSS_{hysteresis_{nom}}$. The spreads of the membership functions are chosen in such a way that the membership value drops to zero at the center of the membership function of the nearest set. For the direction biased algorithms, the hysteresis bias is $dir_{hysteresis} = 1$ dB and the preselection direction bias for RSS is $hp_{rss} = 1.5$ dB. A direction biased algorithm that switches off direction biasing when the direction estimates are unreliable is referred to as a restricted direction biased algorithm. A direction biased algorithm that uses previous direction estimates when the direction estimates are unreliable is referred to as a modified direction biased algorithm.

The performance of the algorithms is compared using an *operating point* as a performance metric. An *operating point* is defined by the (x,y) pair where x is the 50% cross-over distance and y is the average number of handoffs during a travel. Ideally, it is desired that the number of handoffs be minimum and the cross-over distance be as close as possible to the intersection (255m for the simulation model). It is assumed that the conventional algorithm gives a good cross-over distance for the NLOS case, and, hence, the proposed algorithms should try to reduce the number of handoffs as much as possible while keeping the cross-over distance the same (or closer to the intersection).

9.3.2 LOS Performance Evaluation of the Microcellular Algorithms

Figure 9.7 shows the LOS operating points for the conventional and proposed non-direction biased microcellular algorithms. The conventional algorithm has the operating point (268.20, 2.74) for the LOS case. The proposed adaptive microcellular algorithm has the operating point at (284.90, 1.66). As expected, the proposed algorithm reduces the number of handoffs since higher hysteresis values are used except

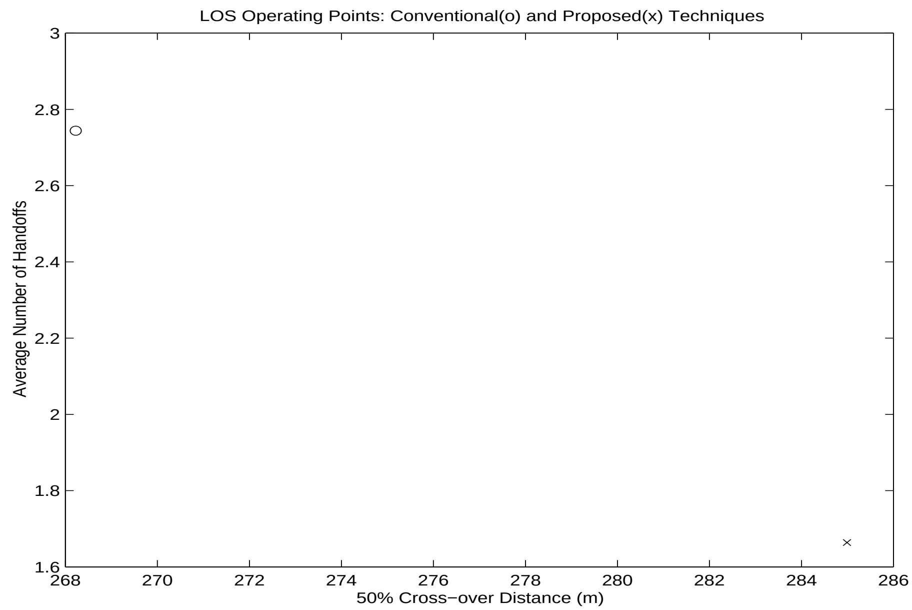

Figure 9.7: LOS Operating Points for Conventional and Proposed Adaptive Non-Direction Biased Algorithms

near the intersection. Figure 9.8 shows the LOS operating points for the conventional and proposed restricted direction biased algorithms. The restricted direction biased algorithm has the operating point at (279.40, 1.67). The direction biasing helps reduce the cross-over distance from 284.90 m to 279.40 m, an improvement of 5.50 m over the non-direction biased basic algorithm. The number of handoffs are almost the same as for non-direction biased and restricted direction biased algorithms. Figure 9.9 shows the LOS operating points for the conventional and proposed modified direction biased microcellular algorithms. The modified direction biased algorithm has the operating point at (268.22, 1.72). The modified direction biasing helps reduce the cross-over distance from 279.40 m to 268.22 m, an improvement of 11.18 m over the restricted direction biased basic algorithm.

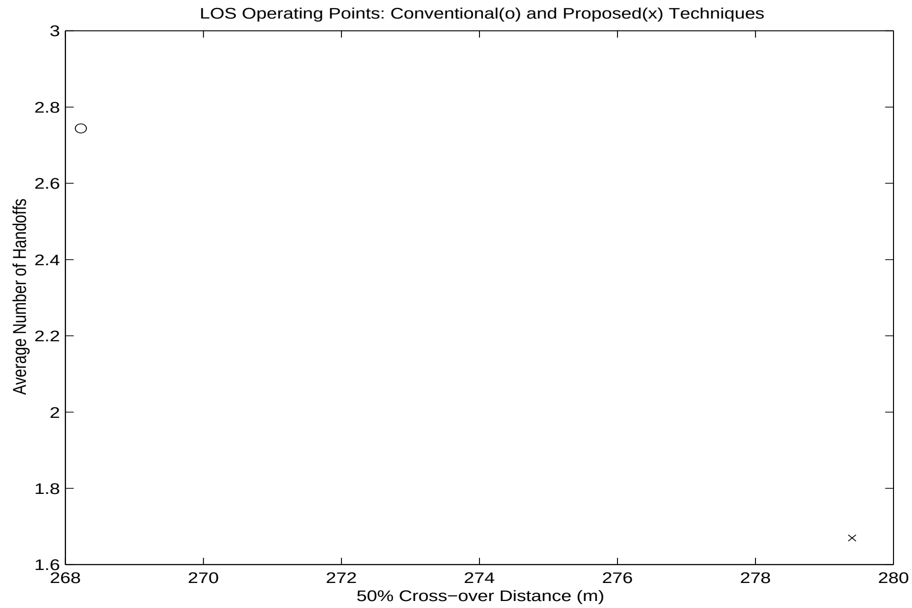

Figure 9.8: LOS Operating Points for Conventional and Proposed Restricted Direction Biased Algorithms

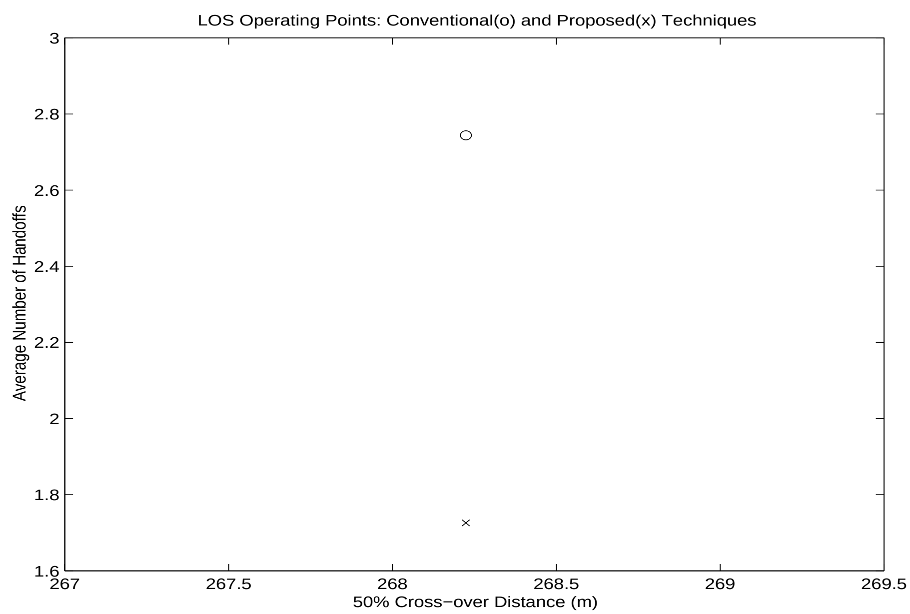

Figure 9.9: LOS Operating Points for Conventional and Proposed Modified Direction Biased Algorithms

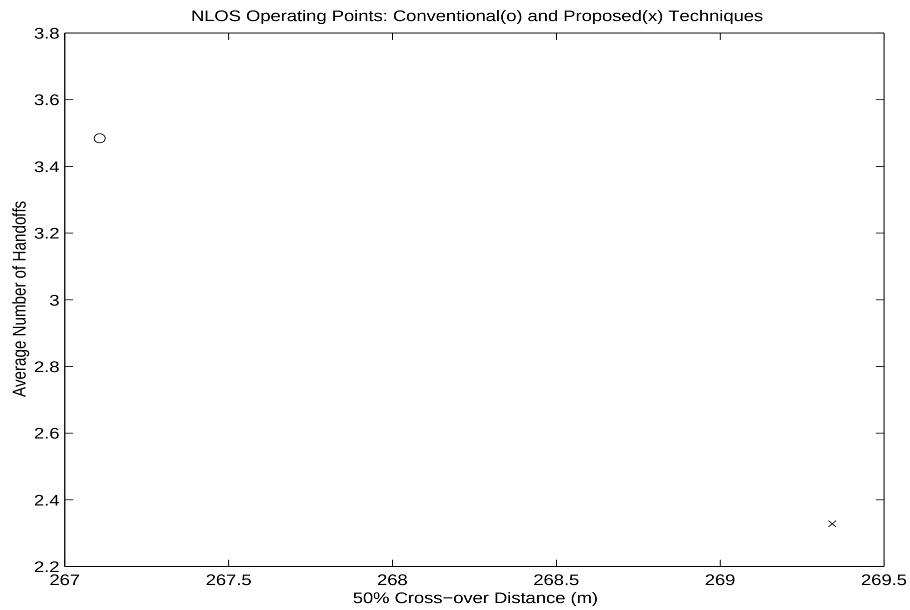

Figure 9.10: NLOS Operating Points for Conventional and Proposed Adaptive Non-Direction Biased Algorithms

9.3.3 NLOS Performance Evaluation of the Microcellular Algorithms

Figure 9.10 shows the NLOS operating points for the conventional and proposed non-direction biased microcellular algorithms. The conventional algorithm has the operating point (267.1, 3.45) for the NLOS case. The proposed adaptive microcellular algorithm has the operating point (269.34, 2.32). As expected, the proposed algorithm reduces the number of handoffs. It should be noted that the tendency of the proposed algorithm to use relatively higher hysteresis values leads to an increase in the cross-over distance. However, direction biasing will help reduce the cross-over distance, and, therefore, the non-direction biased algorithm focuses on reducing the number of handoffs. Figure 9.11 shows the NLOS operating points for the conventional and proposed restricted direction biased algorithms. The proposed restricted direction

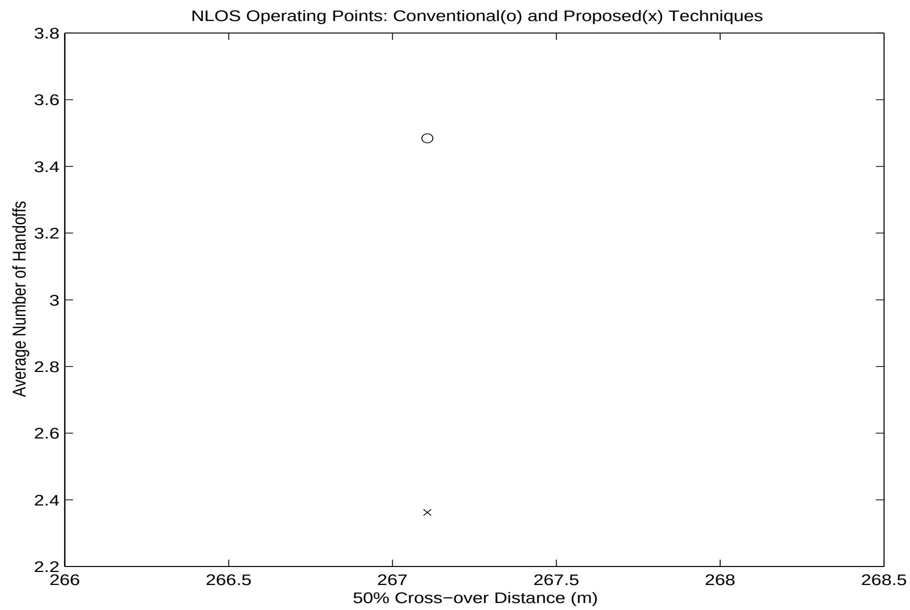

Figure 9.11: NLOS Operating Points for Conventional and Proposed Restricted Direction Biased Algorithms

biased algorithm has the operating point (267.11, 2.36). The direction biasing helps reduce the cross-over distance from 269.34 m to 267.11 m, an improvement of 2.23 m over the adaptive non-direction biased algorithm.

Figure 9.12 shows the NLOS operating points for the conventional and proposed modified direction biased algorithms. The modified direction biased algorithm has the operating point (267.11, 2.38). The modified direction biasing gives almost the same performance as the restricted direction biasing for the NLOS case.

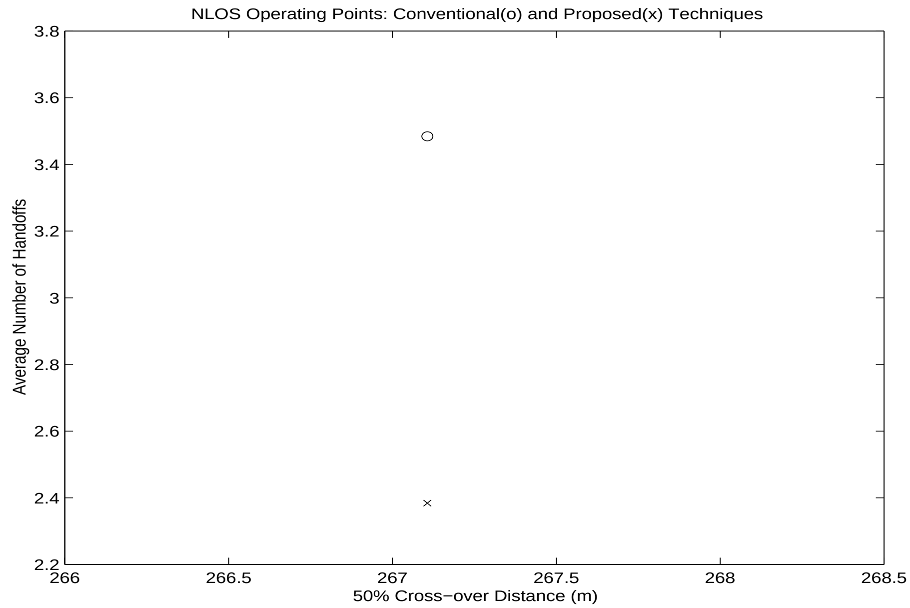

Figure 9.12: NLOS Operating Points for Conventional and Proposed Modified Direction Biased Algorithms

Table 9.3: Operating Points for Microcellular Algorithms

Scenario/Algorithm	**Conventional**	**Adaptive Modified Direction Biased**
LOS	(268.20,2.74)	(268.20,1.72)
NLOS	(267.11, 3.45)	(267.11, 2.38)

9.3.4 Performance Evaluation of the Microcellular Algorithm with Interference, Traffic, and Mobility Adaptation

Table 9.3 summarizes the operating points for the LOS and the NLOS cases for the proposed modified direction biasing algorithm and the conventional algorithm. The number of handoffs is reduced by 1.02 (or 37%) for the LOS case and 1.07 (or 31%) for the NLOS case, while the cross-over distances are preserved for both LOS and

NLOS cases. Note that if the same number of handoffs were to be obtained for the conventional algorithm for LOS and NLOS cases, it would have required larger hysteresis, leading to higher cross-over distance, increasing the interference in the LOS case and increasing the call drop probability (due to insufficient RSS) for the NLOS case. Thus, the proposed algorithm is a good generic algorithm suitable for a microcellular environment. This section uses the modified direction biased algorithm as a basic algorithm and uses a secondary mechanism (an FLS) to obtain adaptation to interference, traffic, and mobility. Adaptation to interference and traffic can be judged based on the distribution of SIR and the number of active users in a cell, respectively. The mobility adaptation can be analyzed using cross-over distance as a performance metric. This section shows the advantages of incorporating interference, traffic, and mobility adaptation into the modified direction biased algorithm.

Figure 9.13 shows the RSS distribution for the conventional and proposed adaptive algorithms for a LOS handoff scenario. As expected, there is a degradation in the cumulative distribution function (CDF) of the RSS (maximum of 0.4 dB) for the proposed algorithm since the direction biasing tends to use the BSs which have the potential of being selected in the future and not the strongest RSS BSs at the present time.

Figure 9.14 shows the SIR distribution for the conventional and proposed adaptive algorithms for a LOS handoff scenario. There is an improvement of 0.5 dB in the SIR distribution for the proposed algorithm. This indicates that the proposed algorithm is adaptive to interference, and BSs with potentially better quality (quantified by higher SIR) are preferred.

Figure 9.15 shows the traffic distribution for the conventional and proposed adaptive algorithms for a LOS handoff scenario. The traffic adaptation improves the traffic distribution by 0.25 calls compared to the conventional algorithm. The

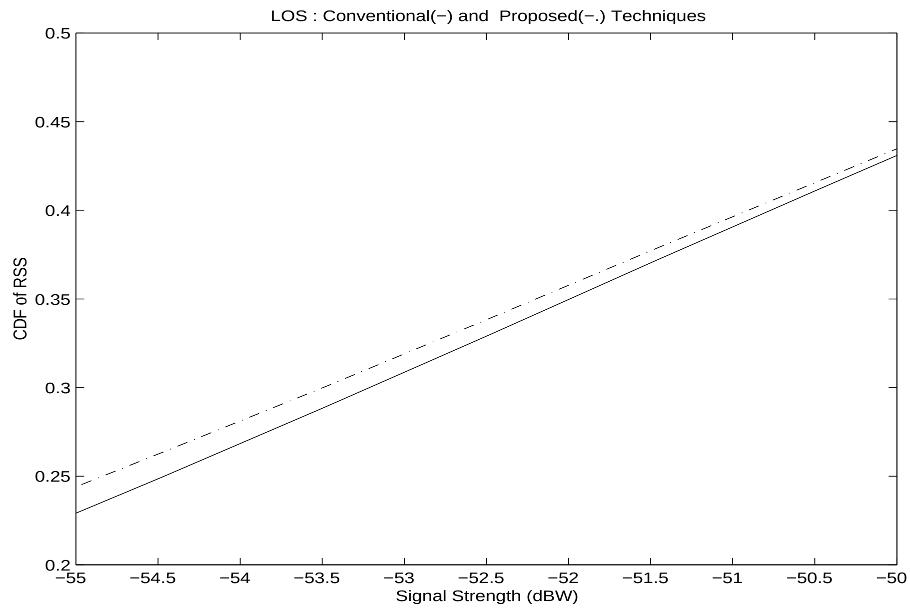

Figure 9.13: RSS Distribution for Conventional and Proposed Algorithms (LOS Handoff)

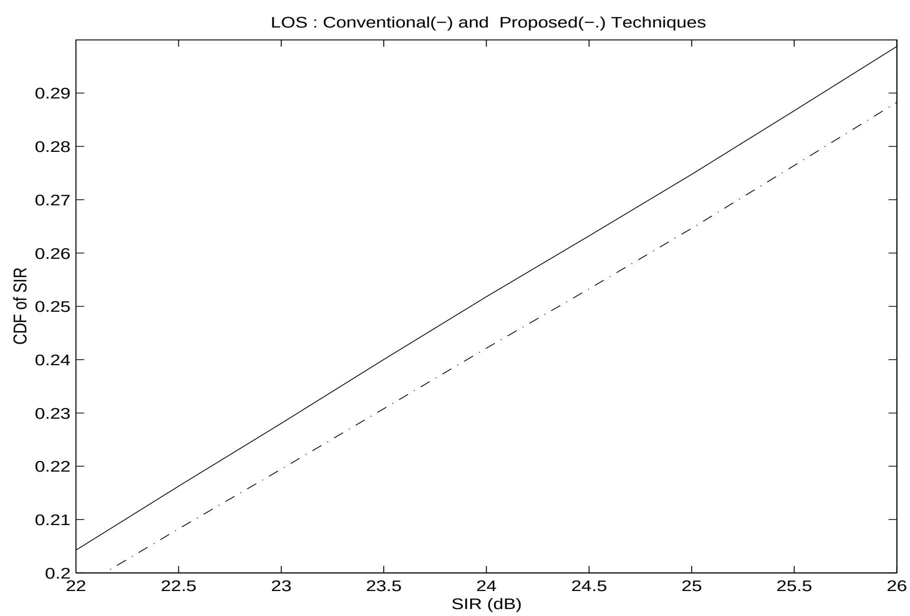

Figure 9.14: SIR Distribution for Conventional and Proposed Algorithms (LOS Handoff)

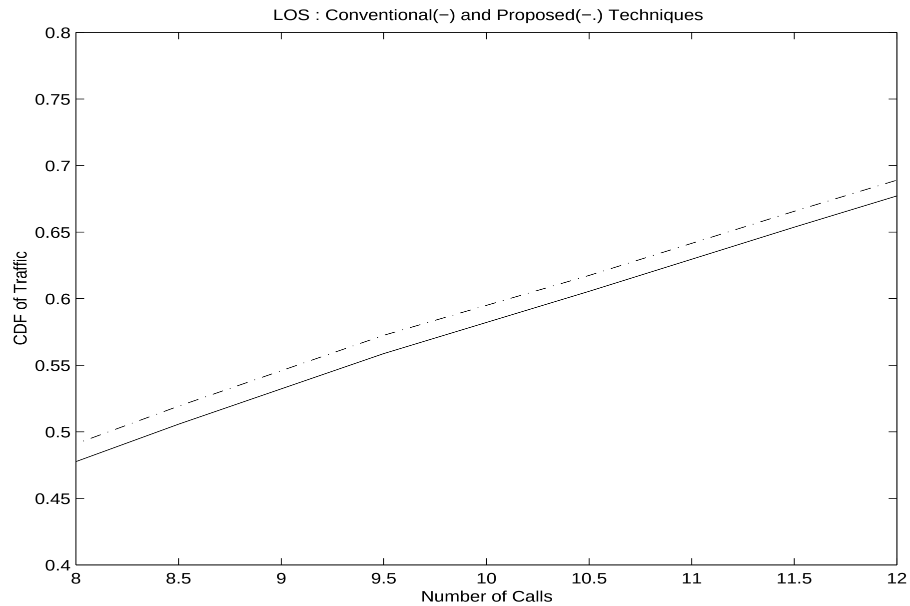

Figure 9.15: Traffic Distribution for Conventional and Proposed Algorithms (LOS Handoff)

proposed algorithm allows relatively more users to be served by the system due to this traffic balancing.

Figure 9.16 shows the RSS distribution for the conventional and proposed adaptive algorithms for a NLOS handoff scenario. There is a maximum degradation of about 0.3 dB in the RSS distribution for the proposed algorithm due to direction biasing.

Figure 9.17 shows the SIR distribution for the conventional and proposed adaptive algorithms for a NLOS handoff scenario. There is an improvement of 0.5 dB in the SIR performance of the proposed algorithm.

Figure 9.18 shows the traffic distribution for the conventional and proposed adaptive algorithms for a NLOS handoff scenario. The traffic adaptation improves the traffic distribution by 0.25 calls compared to the conventional algorithm.

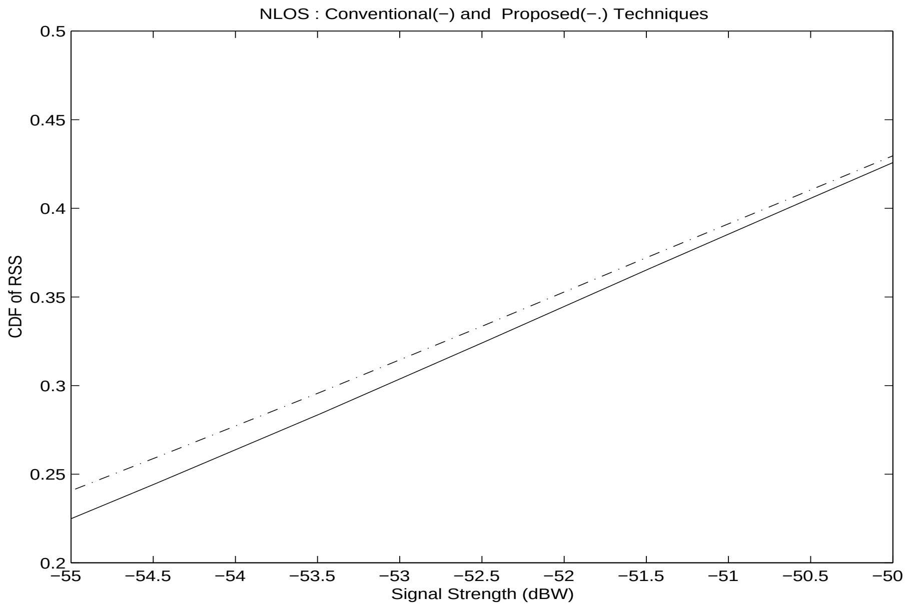

Figure 9.16: RSS Distribution for Conventional and Proposed Algorithms (NLOS Handoff)

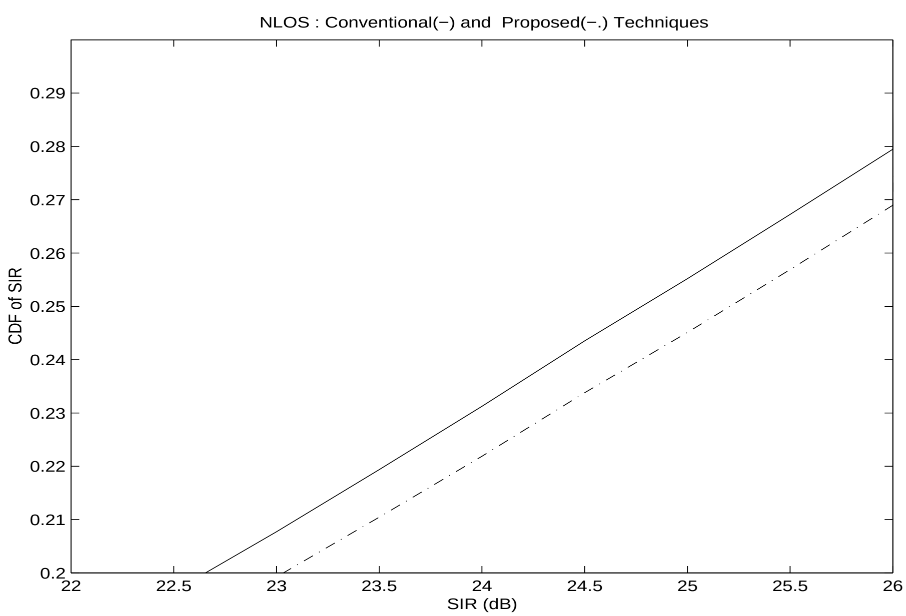

Figure 9.17: SIR Distribution for Conventional and Proposed Algorithms (NLOS Handoff)

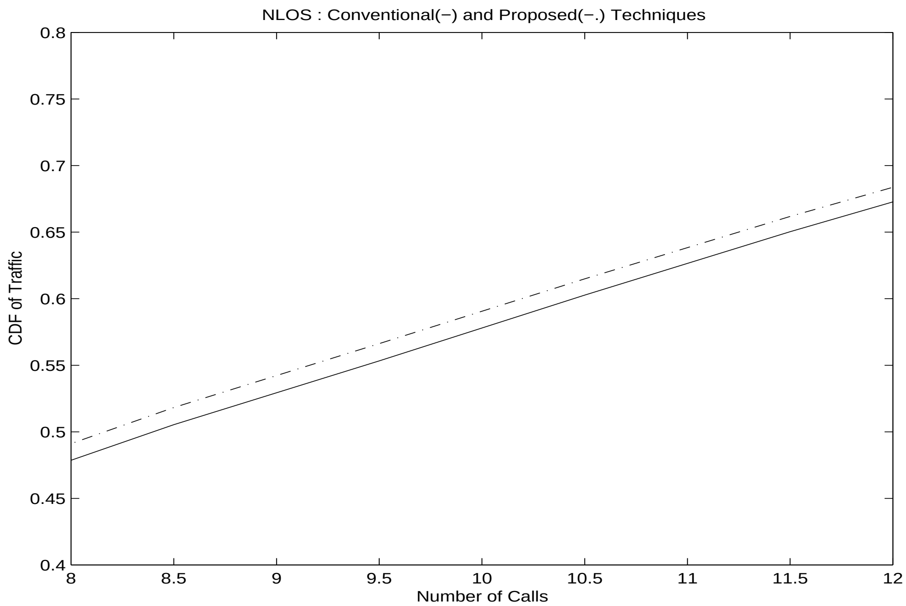

Figure 9.18: Traffic Distribution for Conventional and Proposed Algorithms (NLOS Handoff)

Note that the proposed algorithm improves the performance of the handoff algorithm with respect to interference, traffic, and mobility without compromising the primary handoff objectives since the secondary adaptation mechanism is switched on only during the LOS handoff situations. Hence, there is not a significant improvement due to adaptation. Nevertheless, the proposed algorithm tends to obtain as much improvement as possible under the given constraints.

9.4 Conclusions

The deployment of microcells increases system capacity but complicates resource management. A good handoff algorithm is a cost-effective and elegant solution to the problems associated with a microcellular environment. Microcells impose distinct constraints on handoff algorithms due to the characteristics of the propagation environment. This chapter proposes handoff algorithms that perform uniformly well in different handoff scenarios. Knowledge of the microcellular environment is utilized to design fuzzy logic systems that render the algorithms adaptation capability. The proposed modified direction biased algorithm exploits characteristics of the propagation environment and direction biasing to design an adaptive microcellular algorithm. A microcellular handoff algorithm adaptive to traffic, interference, and mobility has been superimposed over the modified direction biased algorithm to meet both the primary and secondary handoff objectives. The simulation results show that the proposed algorithms provide high performance in generic handoff scenarios of a microcellular system.

Chapter 10

Overlay Algorithms

An overlay system is a hierarchical architecture that uses large macrocells to overlay clusters of small microcells. The overlay system attempts to balance maximizing system capacity and minimizing cost. Resource management in the overlay system is much more complex than in pure macrocell and microcell systems. Different handoff scenarios exist in an overlay environment, each with distinct requirements. A fixed parameter handoff algorithm cannot perform well in a complex and dynamic overlay environment. This chapter proposes an adaptive overlay handoff algorithm that allows a systematic tradeoff among the system design parameters and improves the overall system performance in conformity with the desired goals.

10.1 Introduction to Handoffs in Cellular Overlays

An overlay system consists of large macrocells and small microcells. The macrocells are also referred to as *overlay cells* and overlay a cluster of microcells. Figure 10.1 shows a macrocell-microcell overlay system and four generic handoff scenarios. Cell

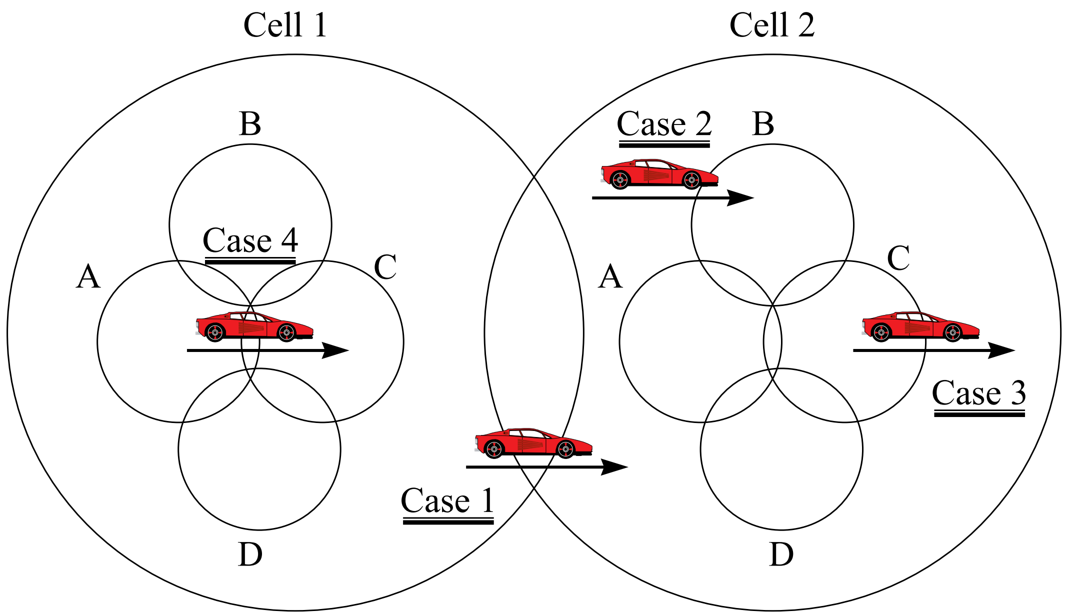

Figure 10.1: Generic Handoff Scenarios in a Macrocell-Microcell Overlay System

1 and Cell 2 are macrocells that overlay clusters of microcells. A cluster of microcells consists of cells A, B, C, and D. Four generic types of handoffs are *macrocell to macrocell*, *macrocell to microcell*, *microcell to microcell*, and *microcell to macrocell*. When an MS travels from one macrocell to another (Case 1), a *macrocell to macrocell handoff* occurs. This type of handoff typically occurs near the macrocell borders. When an MS enters a microcell from a macrocell (Case 2), a *macrocell to microcell handoff* occurs. Even though the signal strength from the macrocell is usually greater than the signal strength from the microcell (due to relatively higher macrocell BS transmit power), this type of handoff is made to utilize the microcell connection that is economical, power efficient, and spectrally efficient and that generates less interference. When an MS leaves a microcell (Case 3) and enters a macrocell, a *microcell to macrocell handoff* is made to save the call since the microcell can no longer provide a good quality communication link to the MS. When an MS travels from one

microcell to another (Case 4), a *microcell to microcell handoff* is made to reduce power requirements and get a better quality signal. An overlay system achieves a balance between maximizing the system capacity and minimizing the cost. Microcells cover areas with high traffic intensities while macrocells provide wide area coverage. Small size cells can provide very high capacity but lead to an expensive system due to infrastructure costs. An overlay system is more complex than a pure macrocell or microcell system. Important considerations for designing efficient handoff algorithms for overlay systems are outlined below.

- **Service**. An attempt should be made to maximize the microcell usage since the microcell connection has a low cost due to the better frequency reuse factor and low transmit power requirements. However, far regions should be served by macrocells for a better quality communication link. Microcell overflow traffic should be handled by macrocells.

- **Mobility**. High speed vehicles should be connected to macrocells to reduce the handoff rate and the associated network load. This will also enable a handoff algorithm to perform uniformly well for line of sight (LOS) and non line of sight (NLOS) handoffs in microcells. The handoff parameters can now be optimized for LOS handoff situations since the requirement of a very fast handoff for a typical NLOS situation can be easily avoided by connecting high speed users to macrocells.

- **Propagation Environment**. In an overlay system, a user experiences both macrocell and microcell environments as the user travels across macrocells and microcells. Different fading intensities (e.g., low and high) exist in macrocells and microcells.

- **Resource Management**. Resource management in an overlay system is a difficult task. One of the crucial issues is an optimum distribution of channels between macrocells and microcells.

- **Specific Handoff Requirements**. A handoff algorithm should perform uniformly well in the four generic handoff situations described earlier. The algorithm should attempt to achieve the goal of an overlay system (i.e., the balance between the microcell usage and network load). The algorithm should balance traffic in the cells.

Reference [73] considers an urban cellular system that has a single macrocell overlaying four clusters of microcell with each cluster having four microcells. A tradeoff between the network capacity and the probability of handoff failure has been examined. The roles of queuing of handoff requests at the microcell level and channel reservation at the macrocell level are investigated. Reference [98] proposes an analytical model to study the performance of a PCS overlay system. An iterative algorithm computes the overflow traffic from a microcell to macrocell and uses this traffic measure to compute the call completion probability. The study shows that the variance of the microcell residual time distribution and the number of microcells covered by a macrocell significantly affect the call completion probability. Reference [100] proposes call admission and handoff strategies for an overlay system. Macrocells accept handoff requests that cannot be entertained by microcells. The performance metrics evaluated include call blocking probability and call dropping probability. A mobile speed sensitive handoff criterion is proposed in [32] to differentiate between slow and fast users in an overlay system. Handoffs from macrocells to microcells are avoided for fast moving vehicles while slow users are dropped from macrocells and connected to microcells. The proposed handoff algorithm is compared with a received signal strength (RSS) based algorithm using an emulation mechanism. The paper shows that handoff rate can be reduced significantly using the speed sensitive handoff criterion. A simple approach for implementing a microcell system within an existing macrocell system is presented in [30]. The paper exploits a self-organized dynamic channel assignment and automatic transmit power control to obviate the need for their redesigning. The available channels are reused between macrocells and microcells. A slight increase in transmit power for the microcells compensates for the interference from macrocell to microcell.

A new adaptive handoff algorithm suitable for overlay systems is proposed and is described in Section 10.2. Section 10.3 analyzes the performance of the algorithms from various significant aspects. Finally, Section 10.4 summarizes the chapter.

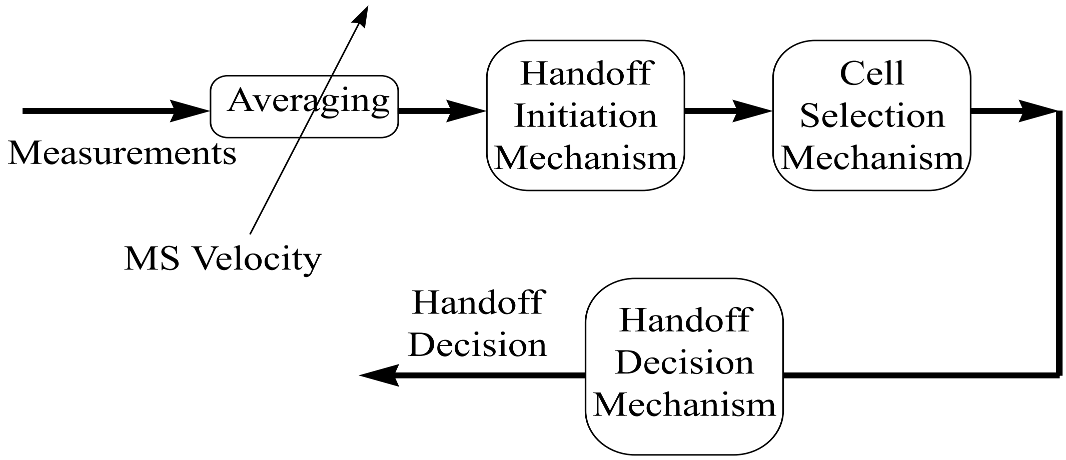

Figure 10.2: Block Diagram of a Conventional Overlay Handoff Algorithm

10.2 Overlay Handoff Algorithms

This section describes a conventional overlay algorithm and a proposed adaptive algorithm. The objective of this adaptive algorithm is to meet the handoff objectives of an overlay system by adapting handoff parameters. Figure 10.2 shows the block diagram of a conventional algorithm for an overlay system. Handoff criteria are averaged according to a velocity adaptive averaging mechanism. The *Handoff Initiation Mechanism* compares the RSS of the current BS (RSS_c) with a fixed threshold (RSS_{th}). If the current BS cannot provide sufficient RSS, the handoff process is initiated. The *Cell Selection Mechanism* determines the best macrocell "x" and the best microcell "y" as potential handoff candidates. The *Handoff Decision Mechanism* is explained next. If the currently serving cell is a macrocell, the sequence of Figure 10.3 is followed, and if the currently serving cell is a microcell, the sequence of Figure 10.4 is followed.

- If the current BS is a macrocell, the speed of the MS may be high or low. Hence, based on the speed, there is a different sequence for a handoff decision. If the MS speed is greater than the velocity threshold V_{th}, RSS_c is compared with RSS_x and a handoff is made to the macrocell "x" if RSS_x exceeds RSS_c by

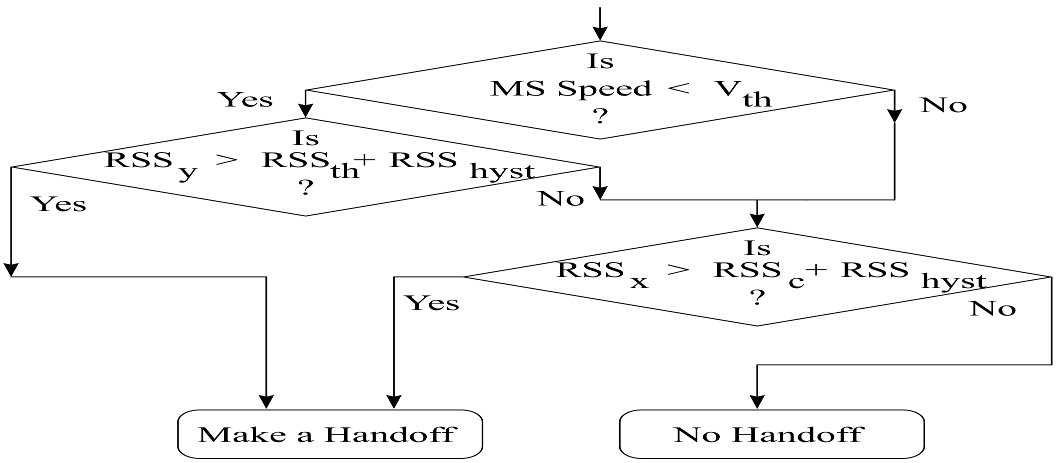

Figure 10.3: The Sequence of Steps for a Current Macrocell Connection

an amount RSS_{hyst} (hysteresis value). If the MS speed is less than V_{th}, the first attempt is made to connect the user to the microcell "y." If RSS_y exceeds the absolute threshold RSS_{th} by an amount RSS_{hyst}, a handoff is made to the microcell "y." However, if the microcell BS cannot satisfy this condition, an attempt is made for a potentially better macrocell connection. If RSS_x exceeds RSS_c by an amount RSS_{hyst}, a handoff is made to the macrocell "x."

- If the current BS is a microcell, the MS speed is low and the speed does not dictate a specific sequence of steps. If RSS_y exceeds the threshold $RSS_{threshold}$ by an amount RSS_{hyst}, handoff is made to the microcell "y." However, if the microcell BS cannot meet this requirement, an attempt is made for the macrocell BS. If RSS_x exceeds RSS_{th} by an amount RSS_{hyst}, handoff is made to the macrocell "x."

Figure 10.5 shows the block diagram of the proposed generic algorithm for an overlay system. Handoff criteria are averaged according to a velocity adaptive averaging mechanism. The *Handoff Initiation Mechanism* compares the RSS of the current BS (RSS_c) to a fixed threshold (RSS_{th}). If the current BS cannot provide sufficient RSS, the handoff process is initiated. A fuzzy logic system (FLS) serves as a *Cell Selection Mechanism* to determine the best macrocell "x" and the best microcell "y" as potential handoff candidates. The inputs of the FLS are RSS_{micro} (RSS from the microcell BS), Tr_d (traffic difference or the difference in the number of calls in the microcell and in the macrocell), and MS Velocity. The output of the FLS is the

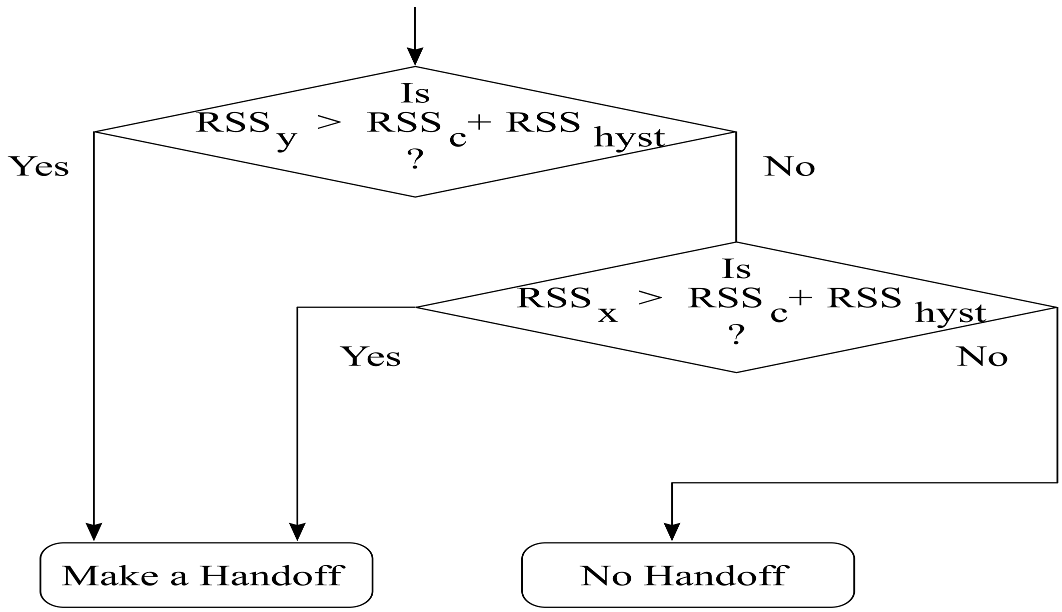

Figure 10.4: The Sequence of Steps for a Current Microcell Connection

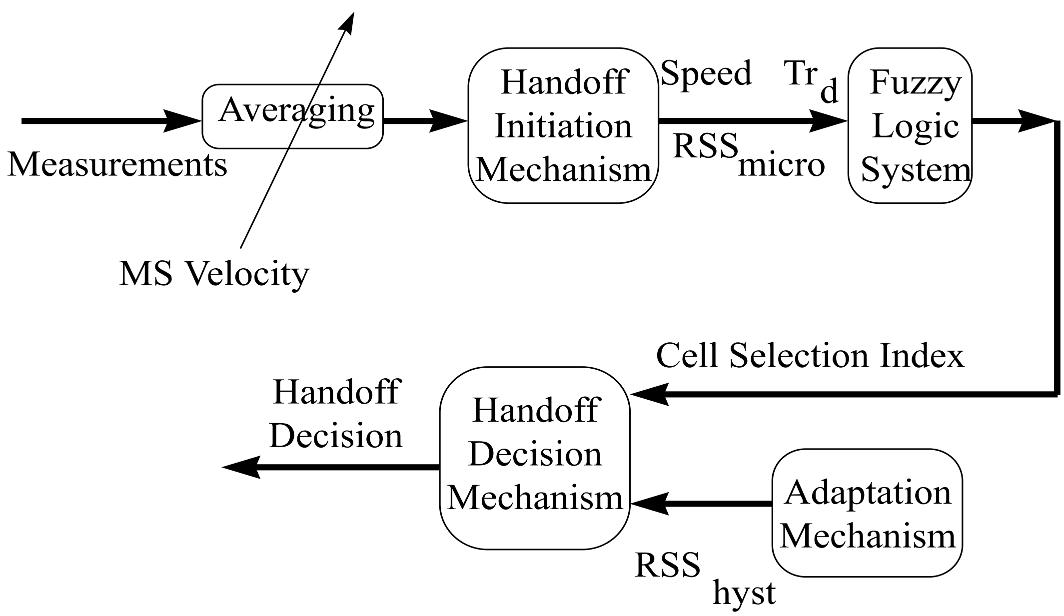

Figure 10.5: Block Diagram of a Generic Overlay Handoff Algorithm

Cell Selection Index, which indicates the degree to which a given user belongs to a microcell or a macrocell. A high value of the Call Selection Index indicates that the MS should be connected to a microcell, and a low value of the Call Selection Index indicates that the MS should be connected to a macrocell. Table 10.1 shows the entire rule base. Assume that RSS_{micro} is "Low," Tr_d is "High," and MS velocity is "High." These conditions indicate that the call should be encouraged to connect to a macrocell as much as possible; this is rule number nineteen. To indicate the highest degree of confidence for a macrocell connection, cell selection index is made lowest. Now consider rule nine. Since RSS_{micro} is "High," Tr_d is "Low," and MS velocity is "Low," the call should be encouraged to connect to a microcell as much as possible. This is done by making the cell selection index highest. If the output of the FLS is greater than zero, a microcell is selected for the communication with the MS; otherwise, a macrocell is selected.

The parameter adaptation for the proposed generic overlay algorithm is explained next.

- If the currently serving cell is a macrocell and the candidate cell is also a macrocell, an incremental hysteresis $\Delta hyst_{macro}$ is found as shown in Figure 10.6. If the MS is moving toward both the current and the candidate BSs or moving away from the BSs, a fixed hysteresis h_{macro} is used. If the MS is moving toward the current BS and moving away from the candidate BS, a handoff is discouraged by increasing the hysteresis value by an amount Δh_{macro}. However, if the MS is moving toward the candidate BS and away from the current BS, handoff is encouraged by decreasing the hysteresis value by an amount Δh_{macro}. The overall adaptive hysteresis is $RSS_{effective} = RSS_{hyst} + \Delta hyst_{macro}$ where RSS_{hyst} is the nominal value of the RSS hysteresis. This adaptation of hysteresis is based on direction biasing and helps reduce the ping-pong effect between two macrocells. A handoff is made to the macrocell "x" if RSS_x exceeds RSS_c by an amount $RSS_{effective}$.

- If the currently serving cell is a macrocell and the candidate cell is a microcell, an incremental hysteresis is taken as Δh_{micro}. The overall adaptive hysteresis is $RSS_{effective} = RSS_{hyst} - \Delta h_{micro}$. This adaptation of hysteresis is based on the idea of encouraging handoffs to the microcells to increase microcell usage.

Table 10.1: Fuzzy Logic Rule Base for Cell Selection

Rule No.	$\mathbf{RSS_{micro}}$	$\mathbf{Tr_d}$	**MS Velocity**	**Cell Selection Index**
1	High	High	High	Low
2	High	High	Normal	Normal
3	High	High	Low	High
4	High	Normal	High	Normal
5	High	Normal	Normal	High
6	High	Normal	Low	Higher
7	High	Low	High	High
8	High	Low	Normal	Higher
9	High	Low	Low	Highest
10	Normal	High	High	Lower
11	Normal	High	Normal	Low
12	Normal	High	Low	Normal
13	Normal	Normal	High	Low
14	Normal	Normal	Normal	Normal
15	Normal	Normal	Low	High
16	Normal	Low	High	Normal
17	Normal	Low	Normal	High
18	Normal	Low	Low	Higher
19	Low	High	High	Lowest
20	Low	High	Normal	Lower
21	Low	High	Low	Low
22	Low	Normal	High	Lower
23	Low	Normal	Normal	Low
24	Low	Normal	Low	Normal
25	Low	Low	High	Low
26	Low	Low	Normal	Normal
27	Low	Low	Low	High

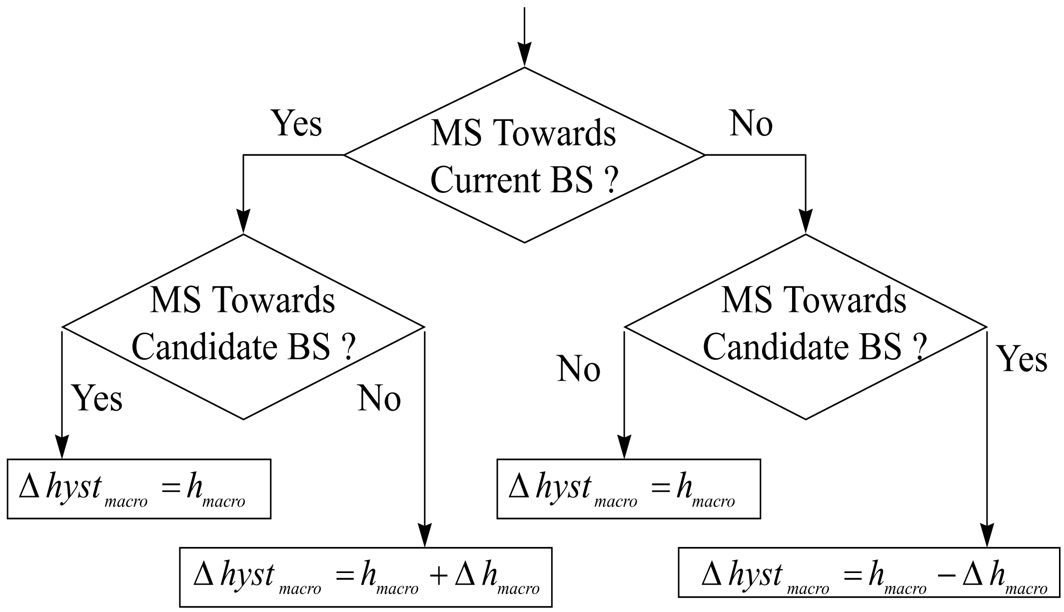

Figure 10.6: Adaptive Handoff Parameters for a Current Macrocell Connection

A handoff is made to the microcell "y" if RSS_y exceeds RSS_{th} by an amount $RSS_{effective}$.

- If the currently serving cell is a microcell and the candidate cell is also a microcell, an incremental hysteresis $\Delta hyst_{micro}$ is found as shown in Figure 10.7. If the MS is moving toward the current BS and away from the candidate BS, a handoff is discouraged by increasing the hysteresis value by an amount Δh_{micro}. However, if the MS is moving toward the candidate BS and away from the current BS, a handoff is encouraged by decreasing the hysteresis value by an amount Δh_{micro}. The overall adaptive hysteresis is $RSS_{effective} = RSS_{hyst} + \Delta hyst_{micro}$. This adaptation of hysteresis is based on direction biasing and helps reduce the ping-pong effect between two microcells. A handoff is made to the microcell "y" if RSS_y exceeds RSS_c by an amount $RSS_{effective}$.

- If the currently serving cell is a microcell and the candidate cell is a macrocell, an incremental hysteresis is taken as Δh_{macro}. The overall hysteresis is $RSS_{effective} = RSS_{hyst} - \Delta h_{macro}$. This adaptation of hysteresis is based on the idea of encouraging handoffs to the macrocells from microcells to save the call since the microcell coverage area is limited and since the call may be dropped if handoff is not made early enough. A handoff is made to the macrocell "x" if RSS_x exceeds RSS_{th} by an amount $RSS_{effective}$.

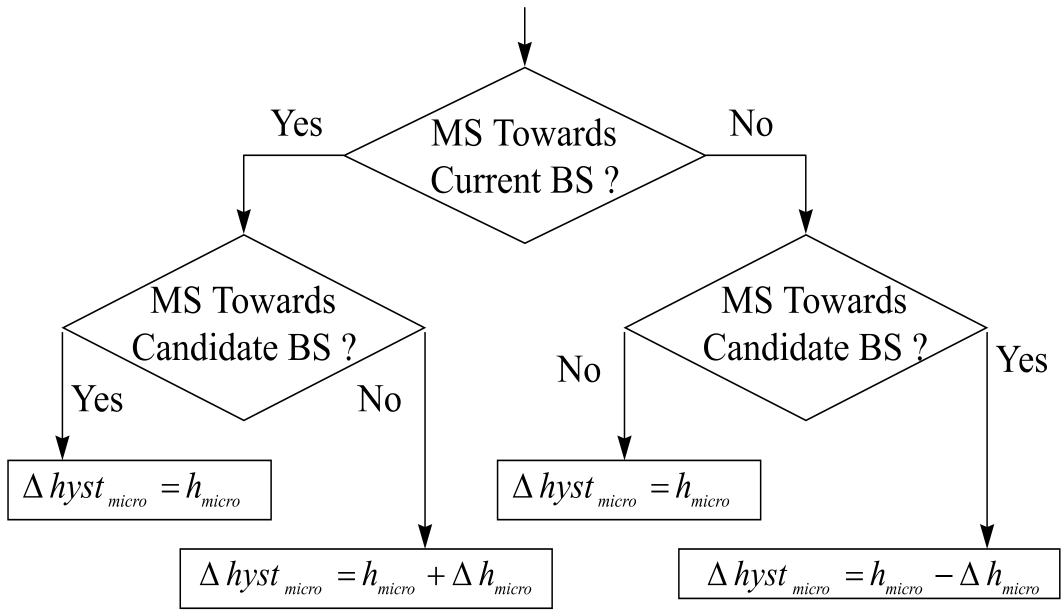

Figure 10.7: Adaptive Handoff Parameters for a Current Microcell Connection

10.3 Simulation Results

The simulation model used to evaluate overlay handoff algorithms is described in Chapter 4. Table 10.2 lists the parameters of the algorithms and simulation parameters. The center of the input membership function for the set "Normal" of the fuzzy variable RSS_{micro} is $RSS_{nom} = RSS_{mid} - 7dB$ (RSS_{mid} is the power received at the boundary of a microcell in the absence of fading), and the centers of the input membership functions for the sets "Low" and "High" are located at the distance of $\Delta RSS = 7dB$ from RSS_{nom}. The center of the input membership function for the set "Normal" of the fuzzy variable Tr_d is $Tr_{d_{nom}} = 0$, and the centers of the input membership functions for the sets "Low" and "High" are located at the distance of two from $Tr_{d_{nom}}$.The center of the input membership function for the set "Normal" of the fuzzy variable MS Velocity is $V_{nom} = 45mph$, and the centers of the input membership functions for the sets "Low" and "High" are located at the distance of $\Delta V = 25$ from V_{nom}. The center of the output membership function "Normal" for

Table 10.2: Simulation and Algorithm Parameters

Parameter	Value
Macrocell Radius	2.5 km
Microcell Radius	700m
Macrocell BS Transmit Power	290 W
Microcell BS Transmit Power	0.1 mW
No. of Channels/BS	16
Mean Call Duration	120 sec
Normalized Traffic Load	0.7
h_{macro}	4dB
Δh_{macro}	4 dB
h_{micro}	2dB
Δh_{micro}	1 dB
Velocity Threshold V_{th}	45 mph

the fuzzy variable Cell Selection Index is located at $Index_{nom} = 0$, and the centers of the output membership functions for the extreme sets (e.g., "Highest" and "Lowest") are located at the distance of $\Delta Index = 3$ from $Index_{nom}$. The spreads of the membership functions are chosen in such a way that the membership value drops to zero at the center of the membership function of the nearest set.

Figure 10.8 shows the CDF of RSS for the conventional and proposed algorithm. The proposed algorithm improves the RSS distribution that can be attributed to the better cell selection mechanism. Figure 10.9 shows the CDF of SIR for the conventional and proposed algorithm. The proposed algorithm improves the SIR distribution, leading to better quality communication links.

Figure 10.10 shows the traffic distribution for the conventional and proposed adaptive algorithms. The proposed algorithm improves the traffic distribution, balancing the traffic in the adjacent cells.

Figure 10.11 shows the microcell usage for the conventional and proposed adaptive algorithms as a function of time. A snapshot of the simulation for a time window

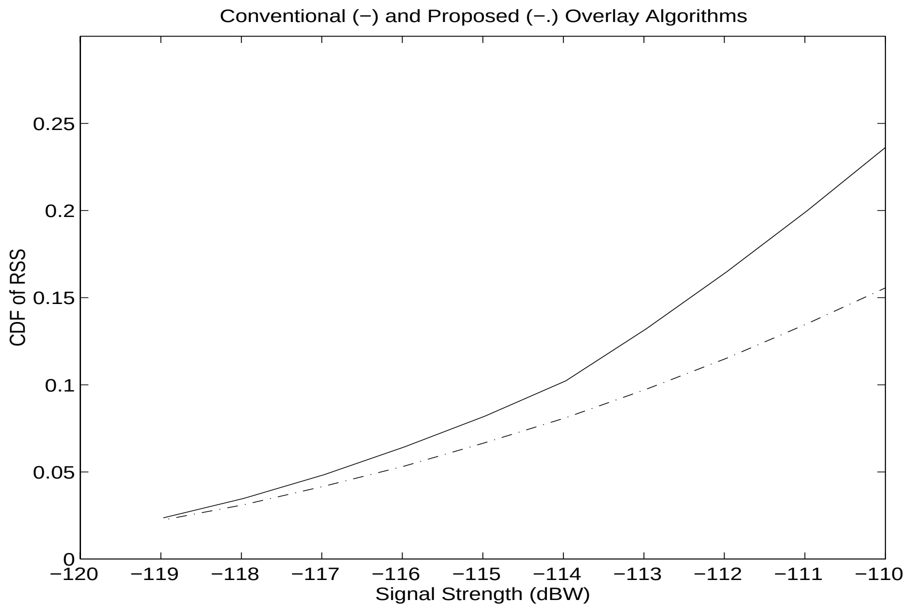

Figure 10.8: Distribution of RSS for the Conventional and Proposed Algorithms

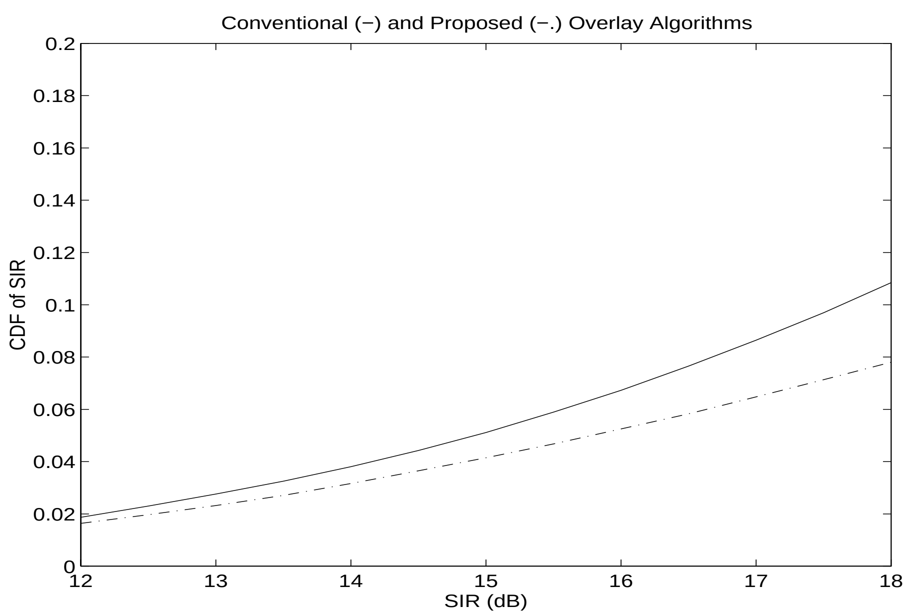

Figure 10.9: Distribution of SIR for the Conventional and Proposed Algorithms

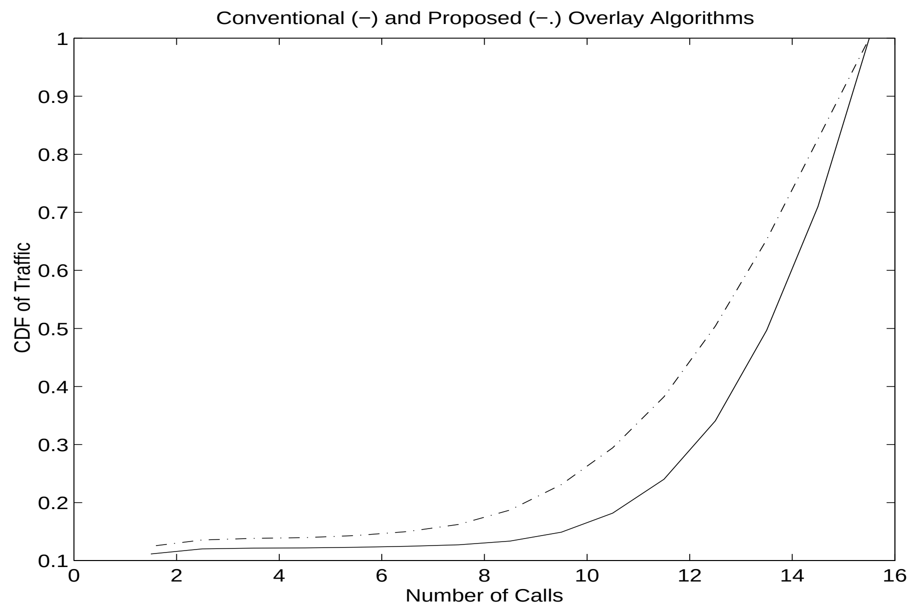

Figure 10.10: Traffic Distribution for the Conventional and Proposed Algorithms

from 300 sec to 500 sec is shown. The microcell usage factor is defined as the fraction of the total number of calls connected to microcells at a given instant. For example, if all the users are connected to microcells at a given instant, the microcell usage factor is one. If all the users are connected to macrocells at a given instant, the microcell usage factor is zero.

Figure 10.12 shows the operating points for the conventional and proposed adaptive algorithms. An operating point is defined as the (x,y) pair with "x" denoting the average number of handoffs per call and "y" denoting the macrocell usage factor (which equals (1-microcell usage factor)). The proposed algorithm tends to increase microcell usage as desired. This shows the importance of adaptive parameters since the fixed parameter algorithm restricts the microcell usage by the limitation of fixed parameters. The number of handoffs per call increases due to increased microcell usage. Note that the RSS performance is not compromised by the microcell connections

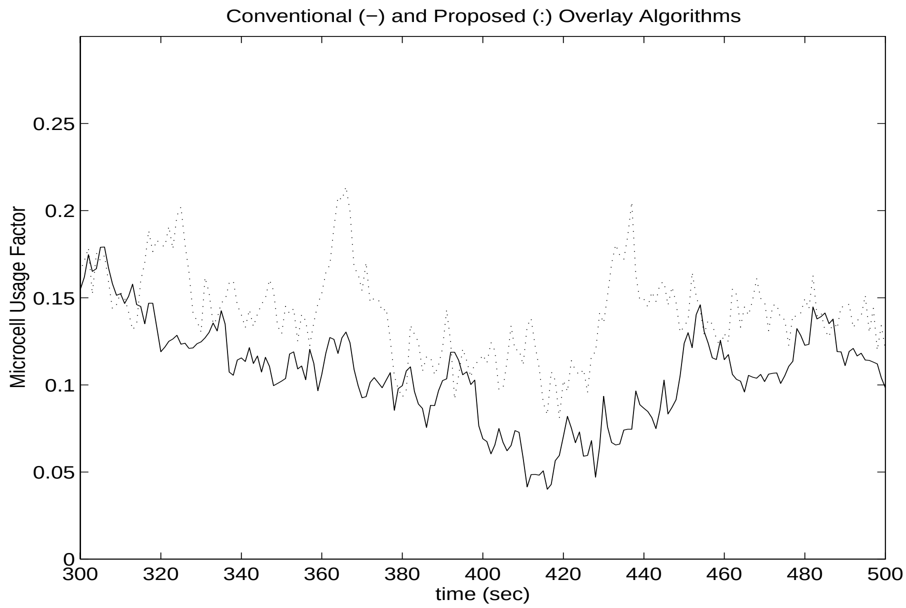

Figure 10.11: Microcell Usage for Conventional and Proposed Algorithms

Table 10.3: Summary of Performance Metrics

Parameter	**Conventional Algorithm**	**Proposed Algorithm**
Average No. of Handoffs/Call	1.03	1.94
Microcell Usage Factor	0.12	0.14
New Call Blocking Probability	0.24	0.13
Handoff Blocking Probability	0.15	0.05

(evident from the improvement in RSS performance).

Table 10.3 summarizes some of the performance metrics for the algorithms.

Traffic balancing reduces the call blocking probability by a factor of 1.8 and handoff blocking probability by a factor of 3.

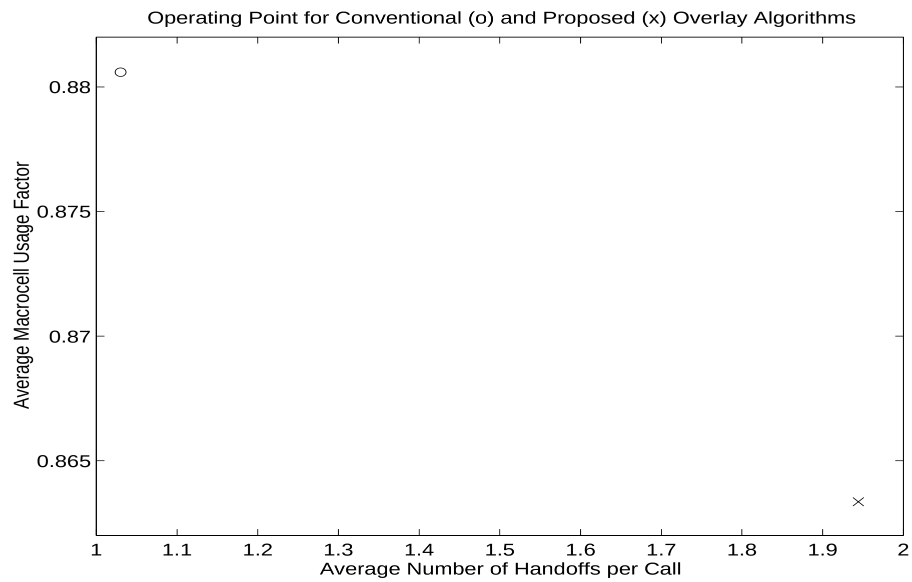

Figure 10.12: Operating Points for Conventional and Proposed Algorithms

10.4 Conclusions

Resource management tasks in the overlay system are complicated by the overlay system environment. A good overlay handoff algorithm must consider several generic handoff scenarios of an overlay system. A fixed parameter handoff algorithm cannot perform well in the complex and dynamic overlay environment. This chapter describes an adaptive overlay handoff algorithm that enhances the system performance by providing a balanced tradeoff among the system characteristics.

Chapter 11

Soft Handoff Algorithms

Soft handoff exploits spatial diversity to increase signal energy for improved performance. A good soft handoff algorithm achieves a balance between the quality of the signal and the associated cost. This chapter highlights important considerations for soft handoff and develops adaptation mechanisms for new soft handoff algorithms. Specifically, two new soft handoff algorithms that provide high performance by adapting to the dynamic cellular environment are proposed. It is shown that the proposed algorithms can help obtain an appropriate design tradeoff among different system characteristics of interest.

11.1 Introduction to Soft Handoffs

A mobile station (MS) in soft handoff communicates with more than one base station (BS) simultaneously. Soft handoff exploits spatial diversity to increase overall signal energy for better performance. A multiple access scheme called code division multiple access (CDMA) implements soft handoff.

Figure 11.1 shows generic soft handoff scenarios in a cellular system. When an

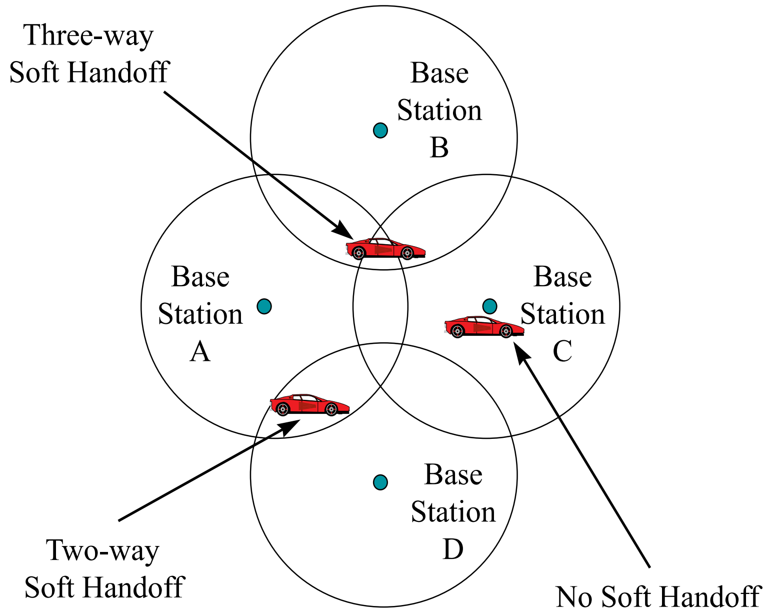

Figure 11.1: Generic Soft Handoff Scenarios in a Cellular System

MS is close to a BS (e.g., near BS C), it communicates with only that BS (BS C). However, near cell borders, it is relatively far from all adjacent BSs, and the RSS from a single BS may not be sufficient to provide a good quality communication link. In such a case, the MS combines RSSs from different BSs to obtain a good quality signal using one of the diversity combining techniques such as equal gain combining, selection combining, and maximal ratio combining. For example, in the overlap region between Cell A and Cell D, the MS is connected to both BS A and BS D, leading to a *two-way soft handoff* scenario. There may also be a *three-way soft handoff* in which the MS communicates with three BSs (e.g., BSs A, B, and C in Figure 11.1).

Research work on soft handoff is briefly discussed next. Reference [21] discusses system design aspects of CDMA including signal and waveform design, power control, soft handoff, and variable data rates. Reference [85] explains the concepts of macroscopic diversity and soft handoff. Results are reported for propagation studies that evaluate soft handoff performance using a wideband correlation type channel sounding system. The advantages of soft handoff are also highlighted. Reference [87] presents simulation results on the effects of soft handoff, frequency reuse, and non-ideal antenna sectorization on CDMA system capacity. The simulation results provide statistics of soft and softer handoffs for different values of handoff parameters. The simulation model consists of a cell layout of nineteen hexagonal cells with either omni-directional or three sectored antennas. The mobiles are uniformly distributed in the service region. The propagation model consists of log-linear path loss with uncorrelated log-normal shadowing. The pilot powers received at the MS from the BSs are ranked according to the signal strengths and compared with a handoff threshold. The number of pilots, K, with power greater than a handoff threshold is counted, and the distribution of K is found as a function of handoff threshold. It is recommended that the MS have at least three demodulators to efficiently combine the signals from the BSs. Reference [107] analyzes the tradeoff between diversity exploitation and effective resource utilization in soft handoff. The analysis quantifies the handoff performance by the number of active set updates, the number of BSs involved in soft handoff, and the outage probability of the received signal. The analysis results are validated with a simulation model that consists of a cell layout with two BSs and the MS traveling from one BS to another at a constant velocity. The propagation environment is characterized by log-linear path loss with correlated shadow fading.

High performance soft handoff algorithms need to consider several aspects specific to soft handoff situations. A good soft handoff algorithm attempts to achieve a balance between the quality of the signal and the associated cost. In general, the greater the number of BSs involved in soft handoff, the better the quality of the signal due to increased diversity gain and the higher the degree to which the network resources are consumed. Important considerations for designing soft handoff algorithms are described next.

- **Cellular System Layouts**. Soft handoff may be implemented in a macrocellular, microcellular, or overlay system. Traffic, mobility, and propagation environment in these distinct system deployment scenarios should be considered.
- **Primary Soft Handoff Requirements**. The handoff algorithm should try to maximize signal quality and minimize the number of BSs involved in soft handoff. The number of Active Set (i.e., the set that contains the list of BSs in soft handoff) updates should be minimized to reduce the network load.
- **Secondary Soft Handoff Requirements**. The algorithm should correspond to vehicle speed. The algorithm should attempt to balance traffic.

This chapter proposes adaptive soft handoff algorithms that meet primary and secondary soft handoff requirements (or objectives). These new algorithms are listed below.

11.2 Adaptive Soft Handoff Algorithms

Two new algorithms are described here. The first algorithm attempts to satisfy primary handoff requirements. The second algorithm uses the first algorithm to meet primary handoff objectives and implements an adaptation mechanism to achieve the secondary handoff goals.

11.2.1 A Generic Soft Handoff Algorithm

Figure 11.2 shows the block diagram of a generic adaptive soft handoff algorithm. A velocity adaptive averaging mechanism is used to average handoff criteria. The conventional soft handoff algorithm is illustrated in Figure 11.3. The conventional algorithm has threshold ($RSS_{threshold}$) and hysteresis ($RSS_{hysteresis}$) as handoff parameters. To qualify as a member of the Active Set, the BS must pass two tests: Test 1 evaluates an absolute strength of the BS, and Test 2 compares the relative strength

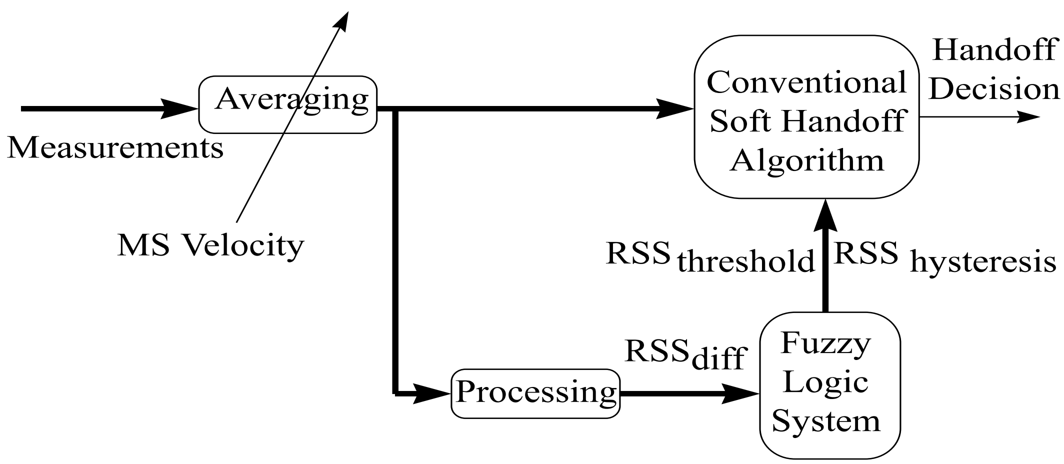

Figure 11.2: Block Diagram of an Adaptive Microcellular Handoff Algorithm

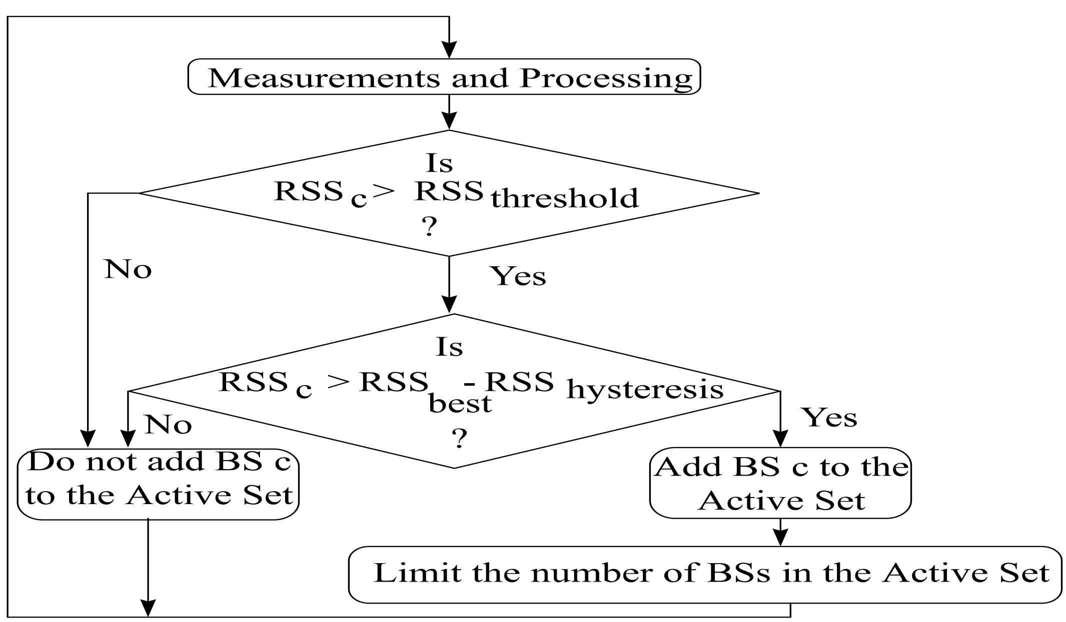

Figure 11.3: A Conventional Soft Handoff Algorithm

of the BS with respect to the best BS in the Active Set. Test 1 ensures that the BS, if admitted to the Active Set, can contribute significantly to the improvement in overall signal quality. Test 2 keeps only the best available BSs in the Active Set and tries to minimize resource utilization. According to Test 1, if RSS of a BS c (RSS_c) exceeds $RSS_{threshold}$, BS c is considered one of the potential soft handoff participants. According to Test 2, BS c actually becomes a member of the active set if RSS_c is greater than the RSS of the best BS in the active set (RSS_{best}) minus $RSS_{hysteresis}$. The RSS of each BS is evaluated using this comparison procedure, and a set of the BSs that pass these tests is determined. The number of BSs in the Active Set is limited to the number of demodulators, N, available at the MS. The Active Set consists of best N BSs if all of these N BSs have passed the tests explained earlier. The handoff parameters are adapted using a fuzzy logic system (FLS). The input to the FLS is the RSS at the MS at the previous sample time. The outputs of the FLS are adaptive handoff parameters, $RSS_{threshold}$ and $RSS_{hysteresis}$. The design philosophy for the FLS is explained next. When an MS is relatively close to a BS, the RSS at the MS is very high, and there is no need to initiate soft handoff since the current communication link already has sufficiently high RSS. To discourage any BS from becoming a member of the current Active Set (that consists of only the current BS), $RSS_{threshold}$ is set very high and $RSS_{hysteresis}$ is set very low. When the MS is far from the neighboring BSs and the MS is connected to only one BS, RSS is very low, and, hence, soft handoff should be initiated to increase overall signal strength. Soft handoff can now be encouraged by setting $RSS_{threshold}$ very low and $RSS_{hysteresis}$ very high. When the MS is far from the neighboring BSs but the MS is connected to more than one BS, RSS may be high or low depending upon the number of BSs and the quality of existing MS-BS connections. If RSS is low, the number of BSs involved in soft handoff can be kept the same by using nominal values of $RSS_{threshold}$

Table 11.1: Primary Fuzzy Logic Rule Base

Rule No.	**RSS**	$\mathbf{RSS_{threshold}}$	$\mathbf{RSS_{hysteresis}}$
1	Very High	Very High	Very Low
2	High	High	Low
3	Medium	Medium	Medium
4	Low	Low	High
5	Very Low	Very Low	Very High

and $RSS_{hysteresis}$, or it can be increased by setting $RSS_{threshold}$ low and $RSS_{hysteresis}$ high depending upon the overall quality of the existing links. If RSS is high, the number of BSs involved in soft handoff can be kept the same by using nominal values of $RSS_{threshold}$ and $RSS_{hysteresis}$ or, it can be decreased by setting $RSS_{threshold}$ low and $RSS_{hysteresis}$ high. Based on such knowledge, a fuzzy logic rule base is created. Table 11.1 shows the entire rule base.

11.2.2 A Soft Handoff Algorithm with Traffic and Mobility Adaptation

Figure 11.4 shows the block diagram of a handoff algorithm with traffic and mobility adaptation. This algorithm uses the primary FLS to provide adaptive handoff parameters to the conventional soft handoff algorithm and a secondary FLS to meet the secondary handoff goals. As discussed earlier, the input to the primary FLS is the RSS at the MS at the previous sample time. The outputs of the primary FLS are adaptive handoff parameters, $RSS_{threshold}$ and $RSS_{hysteresis}$. Inputs to the secondary FLS are Tr (traffic or number of users in a cell) and MS velocity (component of the velocity toward the BS). If the MS is moving toward a BS, the velocity is considered positive, and if the MS is moving away from the BS, the velocity is considered negative. The output of the secondary FLS is a preselection index that indicates the

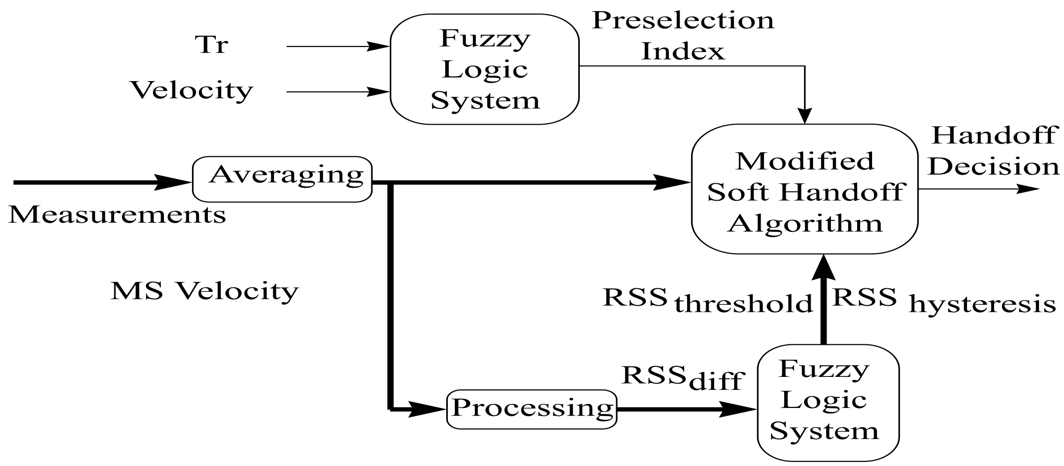

Figure 11.4: Block Diagram of a Soft Handoff Algorithm with Traffic and Mobility Adaptation

degree to which the BS is a good candidate for the Active Set if traffic and mobility were the only considerations. A complete fuzzy logic rule base is shown in Table 11.2. Consider Rule 7. The traffic in the cell is "Low" (meaning that there are very few users in the cell), and the velocity is "High" (meaning that the MS is moving at a high velocity toward the BS). This situation suggests that the BS under consideration should be encouraged to the maximum extent to become a member of the Active Set. This would help achieve traffic balancing and reduce the number of Active Set updates. Now consider Rule 3. The traffic in the cell is "High" (meaning that there are many users in the cell), and the velocity is "Low" (meaning that the MS is moving at a high velocity away from the BS). This situation suggests that the BS under consideration should be discouraged to the maximum extent from becoming a member of the Active Set. This would again help achieve traffic balancing and reduce the number of Active Set updates. The modified soft handoff algorithm is similar to the conventional soft handoff algorithm, but it selects the BSs according to the priority suggested by the preselection index. Note that the primary objectives have not been

Table 11.2: Secondary Fuzzy Logic Rule Base

Rule No.	**Traffic (Tr)**	**Velocity**	**Preselection Index**
1	High	High	Medium
2	High	Medium	Low
3	High	Low	Very Low
4	Medium	High	High
5	Medium	Medium	Medium
6	Medium	Low	Low
7	Low	High	Very High
8	Low	Medium	High
9	Low	Low	Medium

compromised since the adaptive handoff parameters are supplied by the primary FLS.

11.3 Simulation Results

11.3.1 Performance Evaluation of the Generic Soft Handoff Algorithm

The simulation model used to evaluate soft handoff algorithms is described in Chapter 4. The conventional algorithm has $RSS_{threshold}$ and $RSS_{hysteresis}$ as handoff parameters. $RSS_{threshold}$ is the RSS at the distance of cell radius (excluding the fading variations), and $RSS_{hysteresis} = 8$ dB.

For the primary FLS, the center of the input membership function for the set "Medium" is RSS_{nom} the same as $RSS_{threshold}$ for the conventional algorithm. The centers of the input membership functions for the sets "Low" and "High" are located at the distance of ΔRSS_{nom} dB from RSS_{nom} where ΔRSS_{nom} is the difference in the RSS at the distance of R and $0.8R$ from a BS. R is the cell radius. The centers of the input membership functions for the sets "Very Low" and "Very High" are located at the distance of $2\Delta RSS_{nom}$ dB from RSS_{nom}. The center of the membership function for the fuzzy set "Medium" of the output fuzzy variable $RSS_{threshold}$, $RSS_{threshold_{nom}}$, is the RSS at the distance of $1.2R$ from a BS. The centers of the membership functions for the sets "Low" and "High" of the output fuzzy variable $RSS_{threshold}$ are located at the distance of $\Delta RSS_{threshold_{nom}}$ dB from $RSS_{threshold_{nom}}$ where $\Delta RSS_{threshold_{nom}}$ is half the difference in RSS at the distance of $1.3R$ and $1.2R$ from a BS. The centers of the membership functions for the sets "Very Low" and "Very High" of the output fuzzy variable $RSS_{threshold}$ are located at the distance of $2\Delta RSS_{threshold_{nom}}$ dB from $RSS_{threshold_{nom}}$. The center of the membership function for the fuzzy set "Medium" of the output fuzzy variable $RSS_{hysteresis}$, $RSS_{hysteresis_{nom}} = 8$ dB. The centers of the membership functions for the sets "Low" and "High" of the output fuzzy variable $RSS_{hysteresis}$ are located at the distance of $\Delta RSS_{hysteresis_{nom}} = 2$ dB from $RSS_{hysteresis_{nom}}$. The centers of the membership functions for the sets "Very Low" and "Very High" of the output fuzzy variable $RSS_{hysteresis}$ are located at the distance of $2\Delta RSS_{hysteresis_{nom}}$ dB from $RSS_{hysteresis_{nom}}$. The spreads of the membership functions are chosen in such a way that the membership value drops to zero at the center of the membership function of the nearest set.

For the secondary FLS, the center of the input membership function for the set "Medium" of the input fuzzy variable $Traffic$ is $Traffic_{nom} = 30$. The centers of the input membership functions for the sets "Low" and "High" of the fuzzy variable $Traffic$ are located at the distance of $\Delta Traffic_{nom} = 28$ from $Traffic_{nom}$. The center of the input membership function for the set "Medium" of the input fuzzy variable $Velocity$ is $Velocity_{nom} = 0$ m/sec. The centers of the input membership functions for the sets "Low" and "High" of the fuzzy variable $Velocity$ are located at the distance of $\Delta Velocity_{nom} = 29$ m/sec from $Velocity_{nom}$. The centers of the output membership functions of the fuzzy sets are located equidistant from the centers

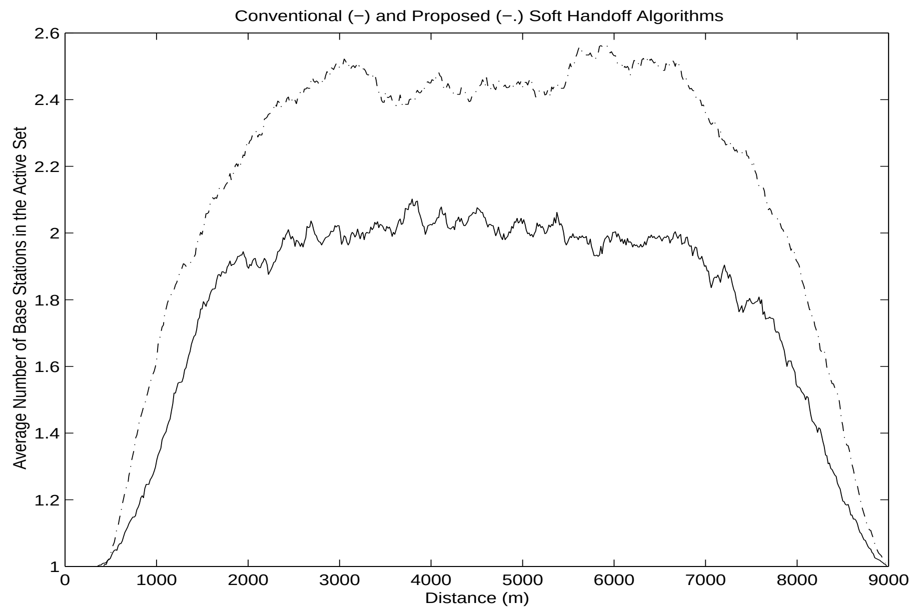

Figure 11.5: Base Stations in the Active Set as a Function of Distance

of the adjacent fuzzy sets. The spreads of the membership functions are chosen in such a way that the membership value drops to zero at the center of the membership function of the nearest set.

Figure 11.5 shows the number of base stations in the active set as a function of distance. The distance is measured from BS 5. As expected, both the conventional and proposed algorithms use more BSs near the cell borders to exploit diversity. The proposed soft handoff algorithm tends to use more BSs in the cell border region, which indicates that a fixed parameter conventional algorithm cannot fully exploit the diversity advantage of soft handoff if not properly tuned. Such tuning uncertainties can be partially compensated by using an adaptive algorithm such as the proposed generic algorithm.

Figure 11.6 shows the cumulative distribution function (CDF) of RSS for the

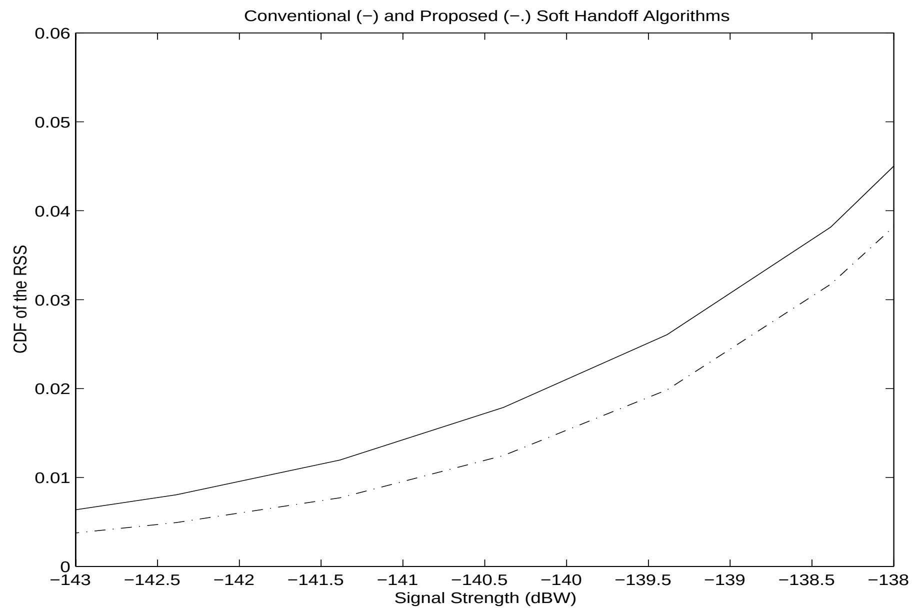

Figure 11.6: Distribution of RSS for the Conventional and Proposed Algorithms

conventional and proposed algorithm. The proposed algorithm provides a 1.2 dB improvement in the RSS distribution, which can be attributed to the increased diversity usage.

Figure 11.7 shows the RSS outage probability and the average number of base stations in the active set for the conventional and proposed algorithms. As expected, the increased diversity usage by the proposed algorithm reduces the RSS outage probability from 1.76×10^{-3} to 0.85×10^{-3} (a reduction by a factor of two) and increases the number of BSs in the Active Set from 1.75 to 2.12.

Figure 11.8 shows the SIR outage probability and the average number of base stations in the active set for the conventional and proposed algorithms. The increased diversity usage by the proposed algorithm reduces the SIR outage probability from 1.45×10^{-3} to 0.43×10^{-3}, a reduction by a factor of 3.4.

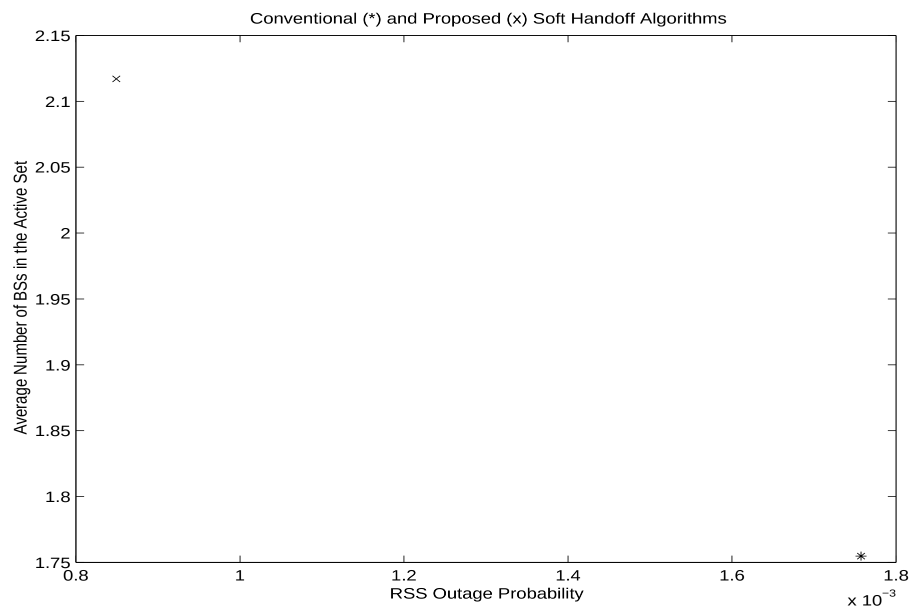

Figure 11.7: RSS Outage Probability and Average Number of BSs in the Set

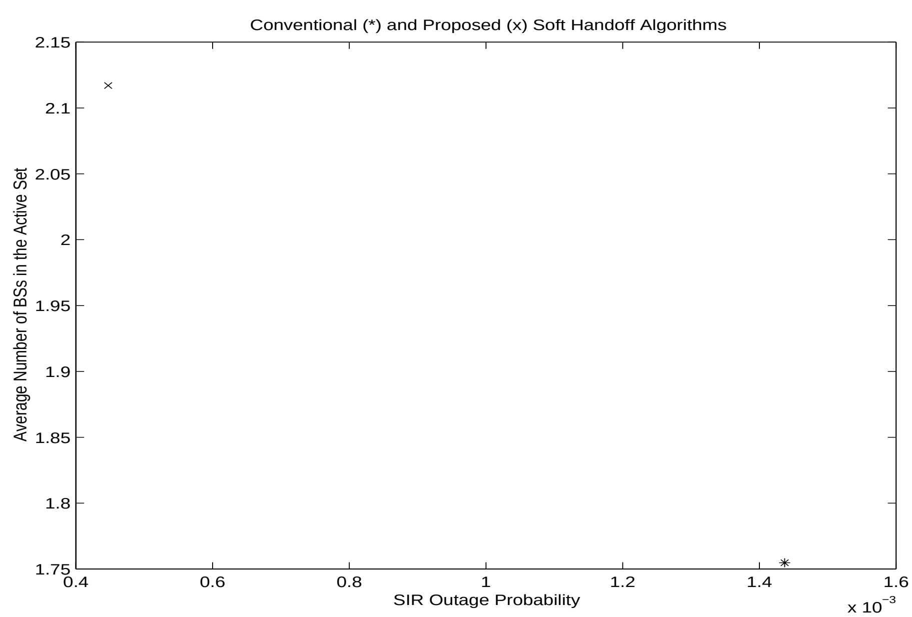

Figure 11.8: SIR Outage Probability and Average Number of BSs in the Set

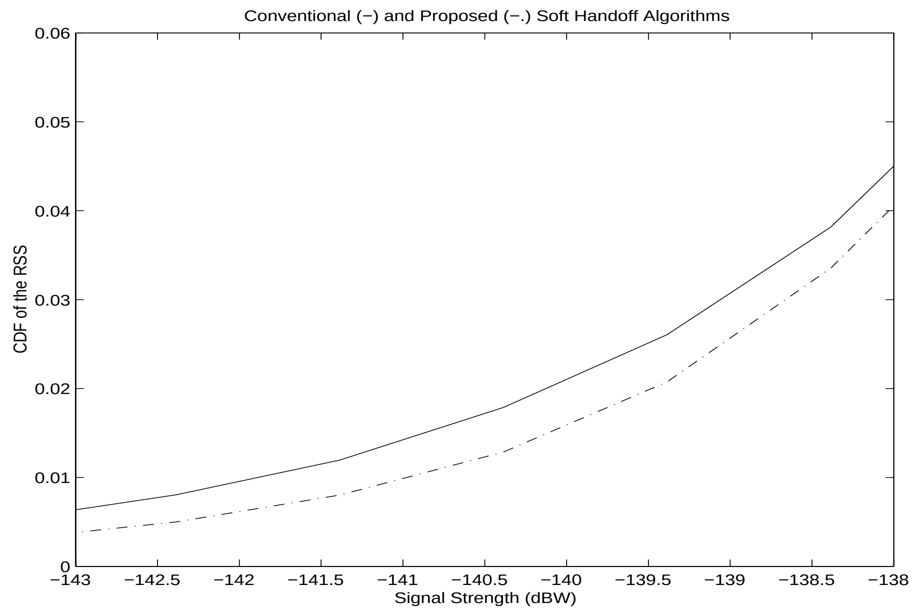

Figure 11.9: RSS Distribution for the Conventional and Proposed Algorithms

11.3.2 Traffic and Mobility Performance of Soft Handoff Algorithms

This section evaluates the traffic and mobility performance of the conventional and the proposed algorithm with traffic and mobility adaptation.

Figure 11.9 shows the RSS distribution for the conventional and proposed adaptive algorithms. The adaptive algorithm provides a 1.1 dB improvement in RSS, which is comparable with the improvement provided by the generic soft handoff algorithm. This shows that the adaptation to traffic and mobility does not affect the diversity gain of the generic algorithm significantly since the BSs that meet traffic and mobility requirements still must pass the tests of the conventional soft handoff algorithm with the adaptive handoff parameters supplied by the primary FLS.

Figure 11.10 shows the traffic distribution for the conventional and proposed adaptive algorithms. The proposed algorithm improves the traffic distribution by

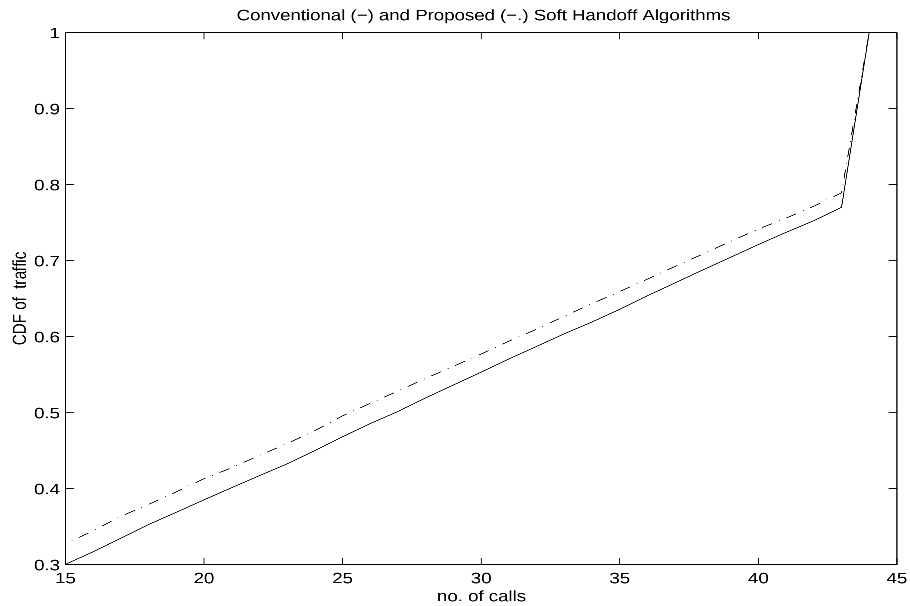

Figure 11.10: Traffic Distribution for the Conventional and Proposed Algorithms

two calls, balancing the traffic in the adjacent cells.

Figure 11.11 shows the RSS outage probability and the average number of base stations in the Active Set for the proposed algorithms. As expected, the increased diversity usage by the proposed algorithm reduces the RSS outage probability from 1.76×10^{-3} to 0.8×10^{-3} (a reduction by a factor of two) and increases the number of BSs in the Active Set from 1.75 to 2.12.

Figure 11.12 shows the SIR outage probability and the average number of base stations in the active set. The increased diversity usage by the proposed algorithm reduces the SIR outage probability from 1.45×10^{-3} to 1.28×10^{-3}, a reduction by a factor of 1.13. The SIR improvement is not significant for the adaptive algorithm since no explicit interference adaptation is built into the secondary adaptation mechanism. The slight degradation in RSS distribution of the adaptive algorithm (compared to the generic algorithm) is reflected in less improvement in SIR distribution for the

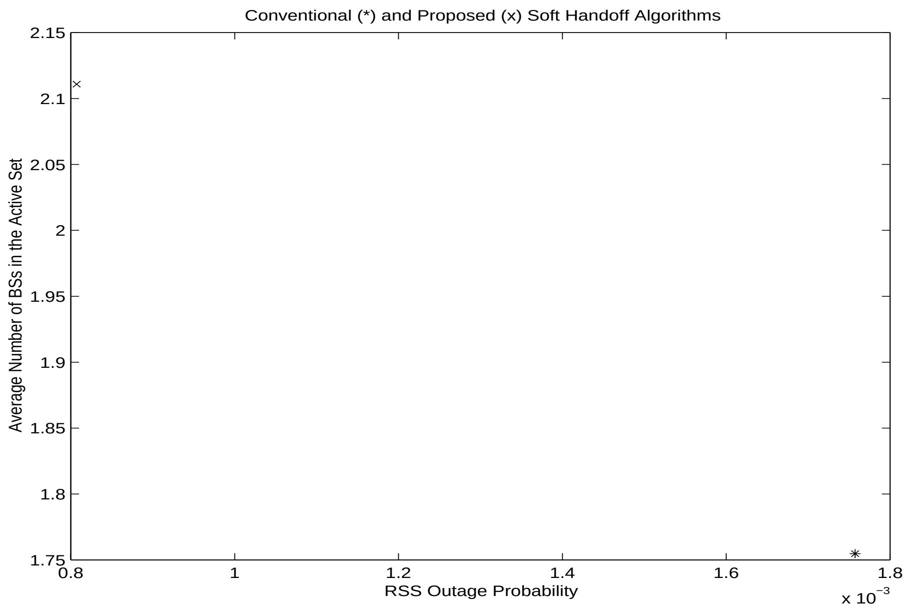

Figure 11.11: RSS Outage Probability and Average Number of BSs in the Set

proposed adaptive algorithm.

When the MS speed is low (20 m/sec), the average number of Active Set updates during a travel is 38.83. When the MS speed is average (29 m/sec), the average number of Active Set updates is 37.74. When the MS speed is high (38 m/sec), the average number of Active Set updates is 35.74. This is in line with the goal of velocity adaptation since a BS is selected based on the relative magnitude and direction of the velocity with respect to the BS. When the speed is high, an appropriate BS is selected relatively earlier (compared to a low speed scenario), reducing the frequency of Active Set updates.

11.4 Conclusions

A good soft handoff algorithm helps achieve a desired tradeoff between the quality of the signal and the associated cost. This chapter considers several aspects of soft

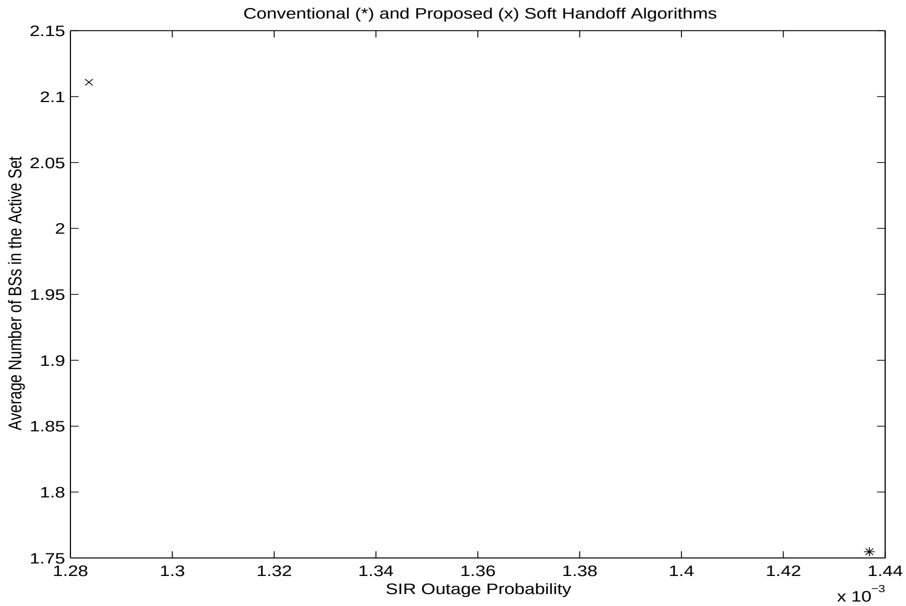

Figure 11.12: SIR Outage Probability and Average Number of BSs in the Set

handoff and proposes mechanisms to adapt the handoff parameters of soft handoff algorithms. Specifically, two new soft handoff algorithms are proposed to provide high performance by adapting to the dynamic cellular environment. The chapter shows that the proposed algorithms address critical system design issues related to soft handoff. In particular, the proposed algorithm enhances the degree of diversity exploitation if the associated cost (e.g., traffic in a cell) is not high.

Chapter 12

Conclusion

This chapter summarizes the dissertation research and discusses potential directions for future research in the area.

12.1 Summary

Handoff is an integral component of cellular communications. The handoff process determines the spectral efficiency and the quality perceived by users. The existing algorithms do not exploit knowledge about the sensitivities of handoff parameters to different characteristics of the cellular environment. Efficient handoff algorithms help preserve and enhance the capacity and QoS of communication systems. Many of the existing handoff algorithms do not exploit advantages of multi-criteria handoff. The adaptation and learning capabilities of AI tools have not been fully utilized. The existing algorithms fail to provide a systematic procedure for the adaptation of handoff parameters to the dynamic cellular environment. This research creates a knowledge base for handoff algorithms and proposes novel approaches for designing high performance handoff algorithms.

Chapter 2 discusses different aspects of handoff and provides a literature survey of handoff related research work. The contents of this chapter are extremely valuable since the full potential of any new approaches for an efficient handoff process cannot be realized without the essential knowledge about the cellular system and the response of the cellular system to different handoff parameters. *This chapter can also be useful for optimization of different system design parameters to meet global system goals.*

Chapter 3 introduces two major tools of AI that are utilized in this research. Background information on fuzzy logic and neural networks is given. These tools provide an efficient and convenient architecture to represent the designer's knowledge about the system and its environment.

Chapter 4 describes different mechanisms used to evaluate handoff related performance of cellular systems. Several simulation models used in this research are explained. Existing simulation models for evaluating macrocellular and microcellular handoff algorithms do not allow evaluation of important design considerations. Hence, the scope of such simulation models is enhanced by incorporating several important features. Information on simulation models suitable for comprehensive performance evaluation of soft handoff algorithms and overlay handoff algorithms has not appeared in the literature. The proposed simulation models fill this gap and will facilitate handoff research in these areas.

Chapter 5 outlines a design procedure for a generic fuzzy logic based algorithm. The fuzzy logic rule encodes known sensitivities of handoff parameters and adapts the handoff parameters.

Chapter 6 exploits the input-output mapping capability and compact data representation capability of neural networks to circumvent large storage and computational requirements of the FLS. Using neural networks, an adaptive handoff algorithm that retains the high performance of the original fuzzy logic based algorithm and that has an efficient architecture for storage and computational requirements is developed.

Chapter 7 introduces an algorithm with two distinct features, a unified handoff candidate selection criterion and adaptive direction biasing. Several handoff criteria can be considered in a unified framework so the best handoff candidate can be chosen under given constraints. Adaptation of direction biasing parameters leads to an enhanced form of direction biasing.

Chapter 8 views the handoff problem as a pattern classification problem and utilizes neural networks and fuzzy logic systems as pattern classifiers. The pattern classification framework can be massively parallel, providing an architecture that is efficient from the computational and storage points of view.

Chapter 9 considers distinct constraints posed by microcells on handoff algorithms due to the characteristics of the propagation environment. A generic adaptive algorithm suitable for a microcellular environment is proposed. Adaptation to traffic, interference, and mobility has also been incorporated to develop a full-fledged adaptive algorithm.

Chapter 10 addresses handoff related issues in an overlay system and proposes an adaptive handoff algorithm that allows a systematic balance among the critical system design parameters.

Chapter 11 investigates different aspects of soft handoff. This chapter highlights important considerations for soft handoff and develops adaptation mechanisms for new soft handoff algorithms. The proposed algorithm allows tuning of the handoff parameters to achieve a balance between the quality of the signal and the associated cost.

This work can be extended in several directions as described next.

12.2 Major Areas of Future Work

Some of the major future directions in handoff related research are listed and briefly discussed here.

- **Other Classes of Handoff Algorithms**. This dissertation research focuses on AI assisted algorithms and pattern recognition based algorithms. Some of the other potential new classes of algorithms capable of providing high performance may include *prediction based algorithms* and *self-tuning algorithms*. Several system characteristics can be predicted using AI tools to create fast and robust handoff algorithms. The handoff parameters can be tuned on-line by observing the behavior of the handoff algorithms on a larger time-scale by minimizing a predetermined performance index.

- **Application of the Developed Algorithms to the Cellular Standards**. This dissertation has proposed generic handoff algorithms. The algorithms can be tailored to specific cellular standards such as GSM and IS-95. A cellular standard may have provisions for several measurements (e.g., both uplink and downlink measurements). These measurements can be incorporated into the handoff criteria vector used in the proposed algorithms. Specific system constraints (e.g., maximum round-trip delay) can also be taken into account as part of the adaptation mechanisms.

- **Handoff Algorithms for Integrated Systems**. Integration of cellular and other services (such as cordless telephone) complicates the process of handoff. Integration of terrestrial and satellite systems is emerging as the next generation of wireless communication systems aims at providing global communications. Such hybrid systems require highly complex, and high performance handoff algorithms. The proposed algorithms can serve as a basis to obtain high performance algorithms for the next generation of wireless systems.

- **Integrated Resource Management**. The proposed algorithms can be integrated with other resource management tasks such as call admission control, channel assignment, and power control. A joint optimization of these tasks can enhance overall system performance. For example, one of the handoff priority schemes called guard channel reserves some channels exclusively for handoff calls. The number of such channels can be adaptively changed in conjunction with a handoff algorithm.

This dissertation develops high performance handoff algorithms and addresses the critical design issues of generic cellular systems. This research will facilitate the evolution of the next generation communication systems through the comprehensive system knowledge base and the organized tradeoff procedures discussed in this work.

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