Handoff Management for Third Generation Cellular Networks

by

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Abstract

This work describes methods for controlling handoff in third generation cellular networks Third generation networks must deal with high user densities and disparities in user requirements which requires efficient and flexible handoff techniques Methods used to estimate parameters of the radio channel such as velocity estimation, distance measurement, and fading parameter estimation are described A method of analyzing the handoff performance in second generation networks giving statistics on basestation assignment, and mean received signal strength is given A new handoff algorithm for third generation networks is developed Imprecise data is managed using a fuzzy logic decision system Simulation results are presented which show that the new algorithm gives superior performance to the second generation handoff algorithm The algorithm can be easily adjusted to treat different classes of users differently in a natural and robust fashion

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1. Introduction

The first wireless networks had only one fixed radio terminal which serviced all of the mobile terminals in the network. This configuration has two limitations. First, the capacity of the network is limited by the bandwidth and power that has been allocated to it. Second, if a mobile moves out of the radio coverage area of the fixed terminal then it can't communicate with the network.

To solve these problems, the cellular network concept was developed. In a cellular network, there are several fixed radio terminals, called basestations, which connect to the mobiles. The radio coverage area of one basestation is called a cell. A simplified view of this network can be seen in Figure 1.1. Each cell is given a portion of the radio resources (i.e. bandwidth or power) allocated to the wireless network. Two cells can use the same resources if they are far enough apart that they do not interfere. The capacity of the network can, in theory, be increased to any amount. As well, the radio coverage problem can be solved by placing a basestation in any area that we wish to be covered by the wireless network.

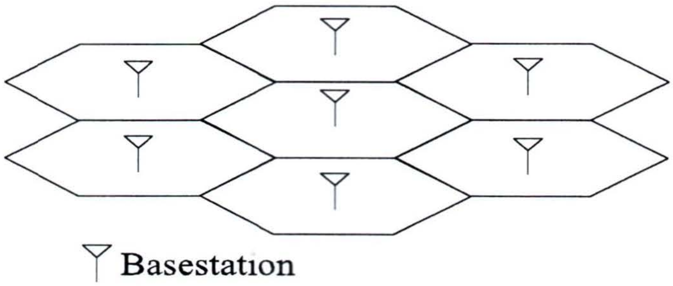


Figure 1.1: Cellular Network Configuration

1.1 Introduction to Handoff

The disadvantage of the cellular network is that user mobility management becomes more complex. The mobiles must be able to change what basestations they are connected to in order to maintain good quality links as they move. This process of changing basestations is referred to as handoff or handover. Random processes in the radio environment complicate the decision of when to perform handoff. The capacity of a wireless cellular network is reduced by the overhead created by the handoff process.

A trade-off exists between the number of handoffs performed and the quality of the links with the mobile terminals. In most current wireless networks, when a handoff is performed there is a short interruption of service and a danger that the call will be dropped or lost. As well, performing a handoff consumes a certain amount of network resources as the basestations exchange data and allocate resources for the communication links. Performing more handoffs increases the signal quality of the links with the current basestation since it increases the amount of time the mobiles are connected to the optimal basestations.

Signal quality is a function of how much information can be reliably transmitted through the radio channel. It is reduced by random noise, interference from other channels, and heavy path loss.

There are two common ideal handoff models that are used for handoff analysis. Which model is used depends on what the precise goal of the handoff algorithm is.

The first ideal handoff algorithm model connects each mobile terminal to the basestation which can provide it with the highest quality link at any given time. This algorithm assumes that the overhead and risk associated with a handoff is small or non-existent. Although this model provides the best link performance, the analysis of performance can be quite difficult since all the basestations must be considered at all locations. We will refer to this model as the ideal handoff algorithm.

The second ideal handoff algorithm model connects each mobile terminal to the basestation which provides the best mean signal at any given location. This model gives a low number of handoffs while still providing fair performance. Analysis of the cellular network is simple since only the basestation which provides the best mean performance needs to be considered for at any given location. We will refer to this model as the ideal mean handoff algorithm.

Both of these models assume that some prediction method exists for calculating the future quality of wireless links. The performance of a handoff algorithm is strongly dependent on the accuracy of its prediction algorithm[9]. Unfortunately, no perfectly accurate method exists, so neither algorithm can be used in real systems.

The development of cellular networks has been divided into three generations. Each generation is more complex, has higher capacity, and is more reliable than the preceding generation.

The first generation consists of analog networks designed to carry voice only All network management takes place at the basestation Handoffs in such systems can require around ten seconds to perform[22] This makes handoffs very dangerous as a mobile terminal can move quite a distance in that amount of time, increasing the chance the call will be accidentally terminated As well, there is a substantial link interruption during the handoff process which is audible to the user

The second generation consists of cellular networks which transmit information digitally The second generation mobiles contain more complex control circuitry which allows them to contribute more to the handoff decision process This development is called Mobile Assisted Handoff Off (MAHO), the mobiles measure channel parameter values required for the handoff decisions This makes the handoff process faster In second generation networks, handoffs take only one or two seconds[22] The link interruption is also shorter and less audible to the user

The method used to divide the common radio resources between different users can affect the handoff constraints Some second generation systems, using the multiple access technology, known as spread spectrum or CDMA have an additional advantage The mobile terminals in these systems can communicate with more than one basestation at a time[32] This process is known as soft handoff It allows mobile terminals to create a link with a new basestation before they have to disconnect the link with the old basestation Handoffs on wireless networks using this scheme are very safe and require no interruption of service. Soft handoff also can improve the average quality of links as will be shown in later chapters.

Third generation cellular networks, sometimes called Personal Communication Systems (PCS), will be purely digital. They will support several data types with varying error and data rate requirements[17]. As well, the handoff algorithm will have to support users of different mobility types and have handoff policies that treat each category differently. The handoff policy for pedestrians will have to be different than that of vehicular users in order to maximize capacity and to provide the best quality of service for all users.

1.2 Description of Work

This thesis describes methods to improve handoff performance in third generation cellular networks. The objective is to create handoff procedures which will maximize the capacity of the system while ensuring links of the proper quality.

The focus of the thesis is on the handoff triggering process at the signal level. Another body of work on handoff, in the literature, focuses on the data management associated with handoff: how the information about a mobile unit is passed between the communicating basestations. Other work is concerned with methods for ensuring that sufficient radio resources are available at the destination basestations. This thesis will assume that all basestations have the necessary resources to accept a handoff call, if one is requested.

The first part of this work covers supporting techniques for the handoff algorithm. These techniques are used to gather information about the channel that can be used to calculate the optimal parameters for the handoff algorithm.

The second part of the work covers modeling of the conventional handoff algorithm that is used in current cellular networks. This model helps us determine the shortfalls and advantages of this algorithm. It gives some insight into how deviations from one of the ideal handoff models affects the cellular network's performance.

1.3 Thesis Outline

Chapter 2 describes a model of the radio channel in a cellular network.

In Chapter 3, techniques that support the handoff decision process are described and analyzed. These include methods for estimating the velocity, position, fading parameters, and signal quality at the mobile terminal.

In Chapter 4, the conventional handoff algorithm will be described and its performance will be analyzed. An analytical analysis of the performance of the conventional algorithm will be presented and a comparison of the algorithm with the ideal cases will be done. An analysis of the capacity of the system using a realistic handoff model will be presented.

In Chapter 5, a fuzzy logic based handoff algorithm is presented. A comparison of this algorithm with the conventional algorithm is performed. The effects of this on system performance and capacity is described.

Chapter 6 contains conclusions of the work and recommendations for future work. An outline of how the techniques described in the thesis could be applied for multiple user types is given.

2. System Model

This chapter focuses on the received signal strength at the mobile of a signal transmitted from the basestation. It is assumed that the reverse channel is identical or that forward channel measurements, at least, give a good indication of reverse link performance. The mobile radio channel is subject to long term and short term fading. Since the fading is multiplicative, the envelope of the received signal can be modeled as[19]:

$$r(x,t) = p(x)f(x,t)l(x) \tag{2.1}$$

where $r(x,t)$ is the received signal strength when the mobile is at position x at time t, $p(x)$ is the deterministic path loss from the basestation to the mobile, $f(x,t)$ is the fast fading process, and l(x) is the long term fading process.

To simplify analysis, the received signal strength is analyzed in the decibel domain where (2.1) becomes

$$R(x,t) = P(x) + F(x,t) + L(x), \tag{2.2}$$

where $R(x,t)$, $P(x)$, $F(x,t)$, and $L(x)$ are the values of $r(x,t)$, $p(x)$, $f(x,t)$, and $l(x)$ converted to the logarithmic decibel domain.

In this thesis, if the variable for a signal is given an upper case letter then it is referring to a value in the decibel domain, otherwise it is referring to a signal in the linear domain.

The deterministic component of the received power, $P(x)$, is assumed to be exponential. It is defined as being:

$$P(x) = K_1 + K_2 \log_{10}\left[d(x)\right], \tag{2.3}$$

where $d(x)$ is the distance between the mobile and basestation when the mobile is at position x. K_1 and K_2 are constants, representing the fixed component of the received power and the exponent of the power loss over distance, respectively. K_2 is equal to -20 in free space, however, in actual propagation conditions in wireless networks it can vary from -30 to -50 depending on the amount of absorbing matter in the propagation environment and the amount of multipath propagation. K_2 is set to -30 for the analysis described in this thesis. This gives the lowest ratio between the path loss factor and the fading factors which is the worst case for handoff algorithms.

Long term fading is caused by large geographical objects in the propagation domain. The long term fading is modeled as having a Gaussian distribution in the decibel domain[13]. Such random variables are referred to as lognormal. The spatial autocorrelation function of the random variable L(x) has been modeled as[10]

$$R_{LL}(\Delta x) = \sigma^2 \exp\left(\frac{-|\Delta x|}{d_0}\right) \tag{2.4}$$

The quantity σ is the standard deviation of the long term fading. Typical values range from 4 dB to 5 dB in rural environments to up to as high as 8 dB in urban environments. The constant d_0 determines the spatial correlation of the long term fading. For all simulations described in this work the value of d_0 is set to be 20 metres, a typical value for suburban and urban environments.

Fast fading, a direct result of multipath propagation, can be modeled with several distributions The most common are Ricean, Rayleigh, and Nakagami distributions Rayleigh fading models the multipath fading when there is no line of sight propagation path Ricean fading models situations where there is a strong line of sight propagation path along with other propagation paths Nakagami fading can model both of these cases by changing parameters in the distribution function

Because the time scale of fast fading is too fast for handoff to be able to compensate for it directly, averaging is used to remove the effects of fast fading so that it does not effect the handoff decision Fast fading determines what signal to interference ratio is required for good communication

2.1 Averaging Filters

We assume that the mobile is moving at velocity v, so that the position of the mobile x, is given by

$$x = vt \tag{2.5}$$

This makes the Doppler frequency ,f_d, equal to

$$f_d = \frac{v}{\lambda}, \tag{2.6}$$

where λ is the wavelength of the carrier frequency of the radio transmission The bandwidth of the fast fading process is equal to twice the Doppler frequency

The purpose of averaging is to find an approximation of $P(x)+L(x)$ There are two averaging filter types that are commonly used to accomplish this

The most common type is the rectangular filter which has the impulse response of

$$h(t) = \begin{cases} \frac{\kappa_1}{T_m} & t < T_m \\ 0 & otherwise \end{cases} \tag{2.7}$$

The second kind of filter used is the exponential filter which has the impulse response

$$h(t) = \begin{cases} \kappa_2 \exp\left(\frac{-t}{T_m}\right) & t > 0 \\ 0 & otherwise \end{cases} \tag{2.8}$$

T_m is a constant equal to the averaging time of the filter. κ_1 and κ_2 are constants that make the energy of the impulse response of both filters be unity.

If the speed of the mobile is known, then the time constants can be translated into distance values. The averaging time of the filters are converted to averaging distances by the relation:

$$d_{av} = vT_m \tag{2.9}$$

With both of these filters, the value of $P(x)+L(x)$ can be estimated fairly well with a constant negative bias due to the effects of the fast fading. The value of T_m is selected so that d_{av} is close to d_0. The estimation is insensitive to small changes in the value of T_m selected for a fixed velocity[7].

In actual practice, however, analog filters can not be used. The value of T_m has to be adjusted when the mobile moves to another cell where the value of d_0 is different, or if the mobile changes velocity. Therefore, the use of digital filters is more applicable. The digital filters will be specified in terms of their z-transforms.

The z-transform of the filter which gives the impulse response in (2.7) is a N-point block averaging filter with N given by

$$N = \frac{T_m}{T_s} \tag{2.10}$$

where T_s is the sampling period. This makes its z-transform

$$H(z) = \frac{1}{N}\sum_{k=0}^{N-1} z^{-k} = \frac{z^N - 1}{Nz^{N-1}(z-1)} \tag{2.11}$$

The z-transform of (2.8) is more difficult to calculate, since it is impossible to match the full response of the analog filter with a digital filter. Noting that (2.8) is the impulse response of a single pole Butterworth filter we can find the z-transform as[14]:

$$H(z) = \frac{C_1(z+1)}{z + C_2}, \tag{2.12}$$

where C_1 and C_2 are constants calculated using T_m and T_s.

2.2 Decision Model

In an actual wireless system, there is a finite amount of time between when a handoff is triggered to when it is performed. In this thesis, instantaneous handoff will be assumed. That is, when a handoff is triggered, it is performed immediately. This is not realistic, but it simplifies analysis.

This gives an upper bound on the performance of the handoff algorithms. Since the amount of time to perform a handoff is controlled by the network configuration, not by the handoff triggering algorithm, the penalty will be equal to any handoff algorithm. This makes comparing different handoff algorithms using this assumption valid.

We create a random variable $D(k)$, which gives the handoff decision for interval k. If $D(k)=A$ then it means in interval k the mobile is connected to basestation A.

3. Supporting Technologies for Handoff

In order to make a good handoff decision, the network must determine the parameters of the prospective radio channels between the basestations and the mobile terminals. An understanding of the characteristics of these estimation procedures will assist in making a handoff algorithm which is feasible and gives good performance.

3.1 Velocity Estimation

The velocity of the mobile terminal is an important parameter for any handoff algorithm. It can be used to approximate the time the mobile will stay within its current cell. A high speed mobile is unlikely to be moving on a circular path so it is likely to be leaving the cell in a predictable time frame. Low speed mobiles can make fast direction changes so the dwell time of a mobile in a cell will have a high variance. The speed can be used to translate the sampling period, T_s, for the digital filter described in Section 2.1 to a sampling distance, d_s. This is important for tuning the averaging time of the digital filters.

Velocity estimation is based on the fact that the bandwidth of the fast fading process is proportional to the speed of the mobile from equation (2.6). Two methods proposed for velocity estimation use the level crossing rate of the envelope, and the covariance of the envelope[30]. The autocovariance function for the fast fading envelope assuming

Rayleigh fading has been shown, in the case where the phase of the propagation paths from the basestation to the mobile terminal are uniformly distributed, to be[34]

$$A_{ff}(\tau) = J_0^2(2\pi f_d \tau), \tag{3 1}$$

where J_0 is the Bessel function of order zero of the first kind It is possible to estimate what the envelope of the covariance function is by calculating

$$E\{[r(k) - r(k+1)]^2\} = 2\{E[r(k)^2] - E[r(k)r(k+1)]\}, \tag{3 2}$$

where *r(k)* is the sample of the received signal strength during interval k If we assume that during this period $l(x)$ and $p(x)$ are constant, then equation (3 2) is a function of $A_{ff}(\tau)$ only

$$E[r(k)^2] - E[r(k)r(k+1)] = A_{ff}(0) - A_{ff}(T_s) \tag{3 3}$$

Using this, it is possible to derive an estimate for f_d and, thus, the velocity

The level crossing rate method uses a result from level crossing theory that the number of times a process crosses any level is proportional to a weighted average of its frequency content[15] A level crossing rate model has been developed for the Rayleigh process which is useful for calculating the Doppler frequency[34] By counting the number of mean level crossings, an estimate of the Doppler frequency can be calculated

3 2 Distance Estimation

The distance between the mobile and basestation can give a good indicator of the possibility of a high quality link As well as the obvious mean path loss factor, there is also, in urban environments, a higher probability that there is a line-of-sight propagation path at shorter distances than at longer distances. Two direct methods of measuring the distance are to use the received signal strength or alternatively the transmission delay[6].

Using the received signal strength method requires knowledge of the transmission power from one end of the link and an accurate estimate of the power loss conditions. The transmission delay calculation requires accurate time synchronization between the mobile and basestation.

The transmission delay method has the advantages that the time delay characteristics are well known and most digital transmission schemes require careful synchronization between the mobile and basestations. This makes its implementation in modern cellular systems fairly simple.

Both distance measurements schemes suffer from the problem that they measure the propagation path length from the basestation to the mobile and not the actual distance which in the case of multipath propagation can be quite different. This problem is mitigated by using direction and distance measurements from several basestations. There are also statistical methods which use hypothesis testing to reduce the error caused by non-line-of-sight propagation[33].

Mobile terminals installed in vehicles might also have access to navigation systems, such as GPS, which would give them very accurate location information which, of course, can be used to give accurate distance information.

3.3 Fading Parameter Estimation

The parameters of the fading processes are also very important to the handoff decision process, in that they can be used to determine an efficient handoff policy.

The parameters describing the slow fading process have the greatest influence on the handoff algorithm. For example, if the quantity d_0 from equation (2.4) is large, and the value of σ^2 is also large then a higher received signal strength with few handoffs can be achieved by using the link which has the higher received signal strength[26] even if its mean received signal strength is lower than that of the other basestations. If these values are small, then the optimal strategy is to attempt to link to the basestation with the highest mean received signal strength since the long term fading can change by a large amount over a relatively short distance.

The standard deviation of the long term fading can be estimated using the covariance function of the long term fading and measurements of the received signal strength. It is assumed that each sample of the received signal strength is taken at a distance of d_s metres apart. The received signal strength is then run through either of the averaging filters in equations (2.11) or (2.12). The averaged received signal strength sampled during interval k is defined as $R_{av}(k)$ and the averaged long term fading sampled during interval k is designated as $L_{av}(k)$. If exponential averaging is used and the digital filter is approximated by its continuous Butterworth filter counterpart the autocorrelation of the filtered long term fading can be given by:

$$R_{L_{Av}}(k) = \frac{d_0\sigma^2}{d_0^2 - d_{av}^2}\left[d_0 e^{-kd_s/d_0} - d_{av} e^{-kd_s/d_{av}}\right], \tag{3.4}$$

where d_{av} is a parameter for the averaging filter taken from (2.9). If the averaged path loss is assumed to be identical between two adjacent samples, and the effects of the fast fading are assumed to negligible, then the variance of the long term fading can be calculated using[26]:

$$\tilde{\sigma}^2 = \frac{V(d_0 + d_{av})}{2d_0\left(1 - \dfrac{d_0 e^{-d_s/d_0} - d_{av} e^{-d_s/d_{av}}}{d_0 - d_{av}}\right)} \tag{3.5}$$

where $\tilde{\sigma}^2$ is the estimated variance and:

$$V = E\left\{\left[R_{av}(k+1) - R_{av}(k)\right]^2\right\} \tag{3.6}$$

Because of the assumptions about the fast fading and the path loss, V can be approximated as being:

$$V = 2\left\{Var\left[L_{av}(k)\right] - Cov\left[L_{av}(k), L_{av}(k+1)\right]\right\} \tag{3.7}$$

which allows us to develop (3.5).

V can be estimated by finding the mean value of the squared difference between two adjacent values of $R_{av}(k)$ for a finite sampling window. Similar equations can be developed for the block averaging digital filter. For the block filter the estimated variance is

$$\tilde{\sigma}^2 = V\frac{N^2(1-\eta)^2}{2\left[(1-\eta)^2 + 2\eta(\eta - 1) + \eta^{N+1}(2 - \eta^{-1} - \eta)\right]}, \tag{3.8}$$

with $\eta = \exp(-d_s/d_0)$.

These equations work well if the value of σ is high (>6 dB), and the variance of the fast fading is low. Unfortunately, at low values of σ, the fast fading produces a bias on the value of V which makes the variance estimate error intolerable. This can be reduced by approximating the bias on V from the fast fading assuming that the averaged path loss remains constant. V can be calculated under the assumption that path loss remains constant between samples as

$$V = 2\left\{Var\left[L_{av}(k)\right] - Cov\left[L_{av}(k), L_{av}(k+1)\right] + E\left[F_{av}(k)^2\right] - E\left[F_{av}(k)F_{av}(k+1)\right]\right\}$$

(3.9)

where $F_{av}(k)$ is the averaged fast fading process sampled during interval k. If the sampling distance, d_s, is selected so that the fast fading can be assumed to be independent between sampling periods then it is possible to calculate the bias caused by the $F_{av}(k)$ terms. The bias for the exponential filter can be shown to be

$$2\left\{E\left[F_{av}(k)^2\right] - E\left[F_{av}(k)F_{av}(k+1)\right]\right\} = 2C_1^2 Var\left[F(k)\right] \quad (3.10)$$

where C_1 is a parameter of the averaging filter from (2.12), and F(k) is the contribution of the fast fading to the sampled power in interval k (See Appendix A). Once this bias is removed from V then (3.5) can be used to estimate the variance.

The variance of $F(k)$ is estimated from

$$W = E\left\{\left[R(k+1) - R(k)\right]^2\right\} \quad (3.11)$$

where $R(k)$ is the non-averaged received power sampled during interval k. W can be estimated by taking the mean of the squared difference between adjacent samples of received power for a finite window. If it is assumed that the long term fading and path loss is constant between adjacent samples then the value of W is twice the variance of the fast fading term.

Graphs of some simulations of this estimation technique are shown in Figure 3.1, Figure 3.2, and Figure 3.3. Values are shown for both block averaging and exponential filters. The sampling distance, d_s, is 0.25 metres. The estimated value of V is exponentially averaged over a distance of 200 metres.

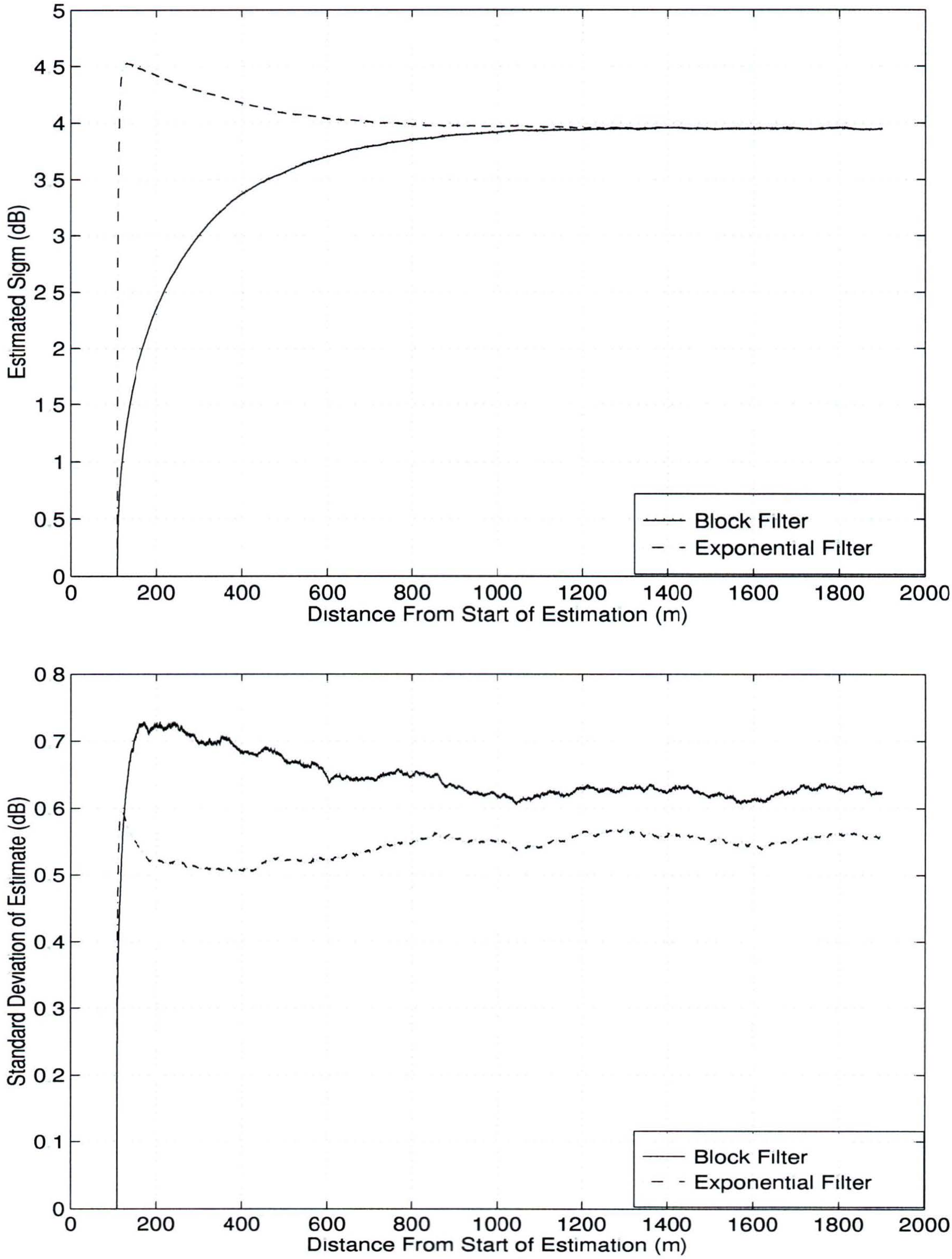


Figure 3.1: σ Estimation for σ=4 dB

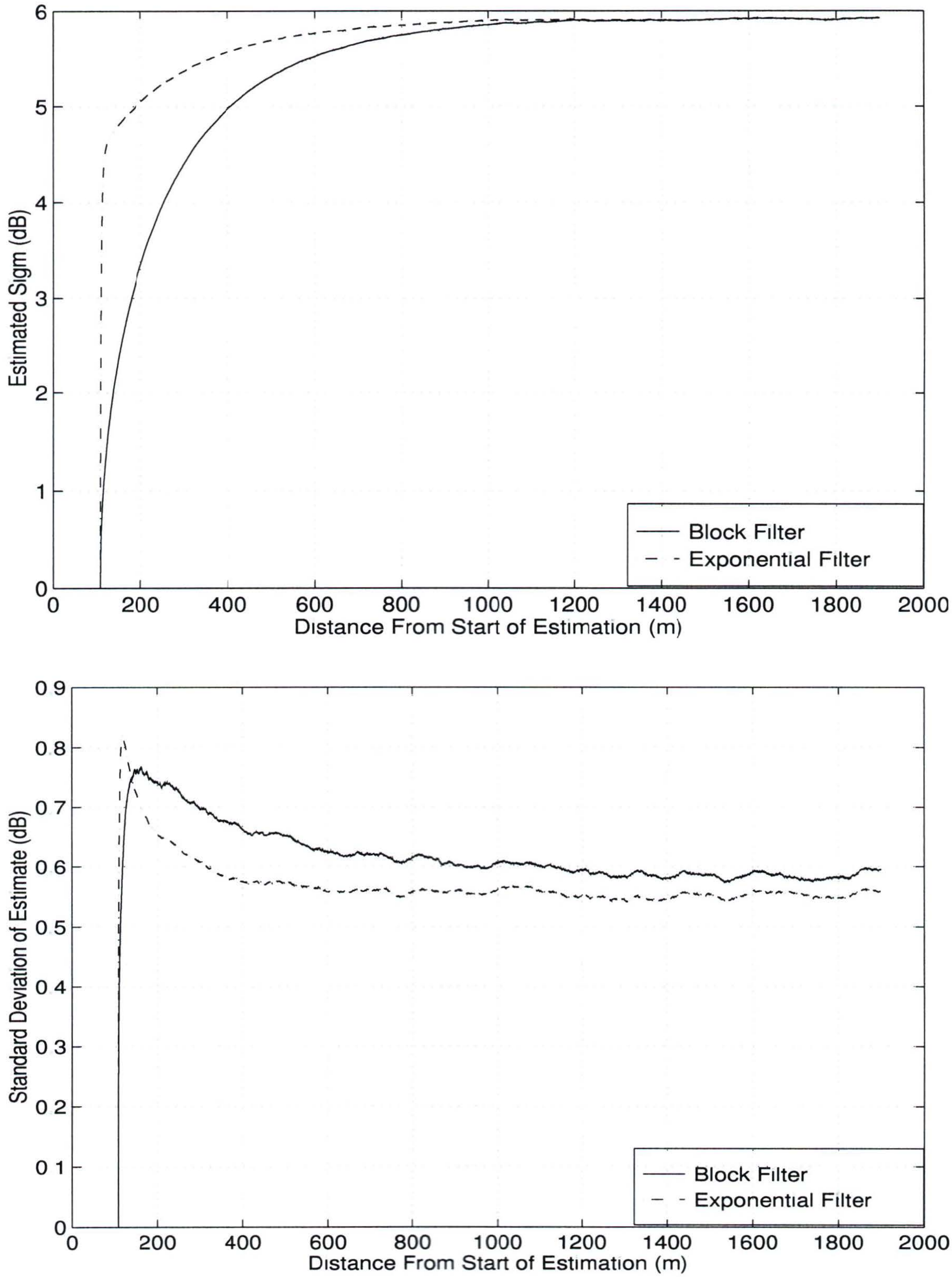


Figure 3.2: σ Estimation for σ=6 dB

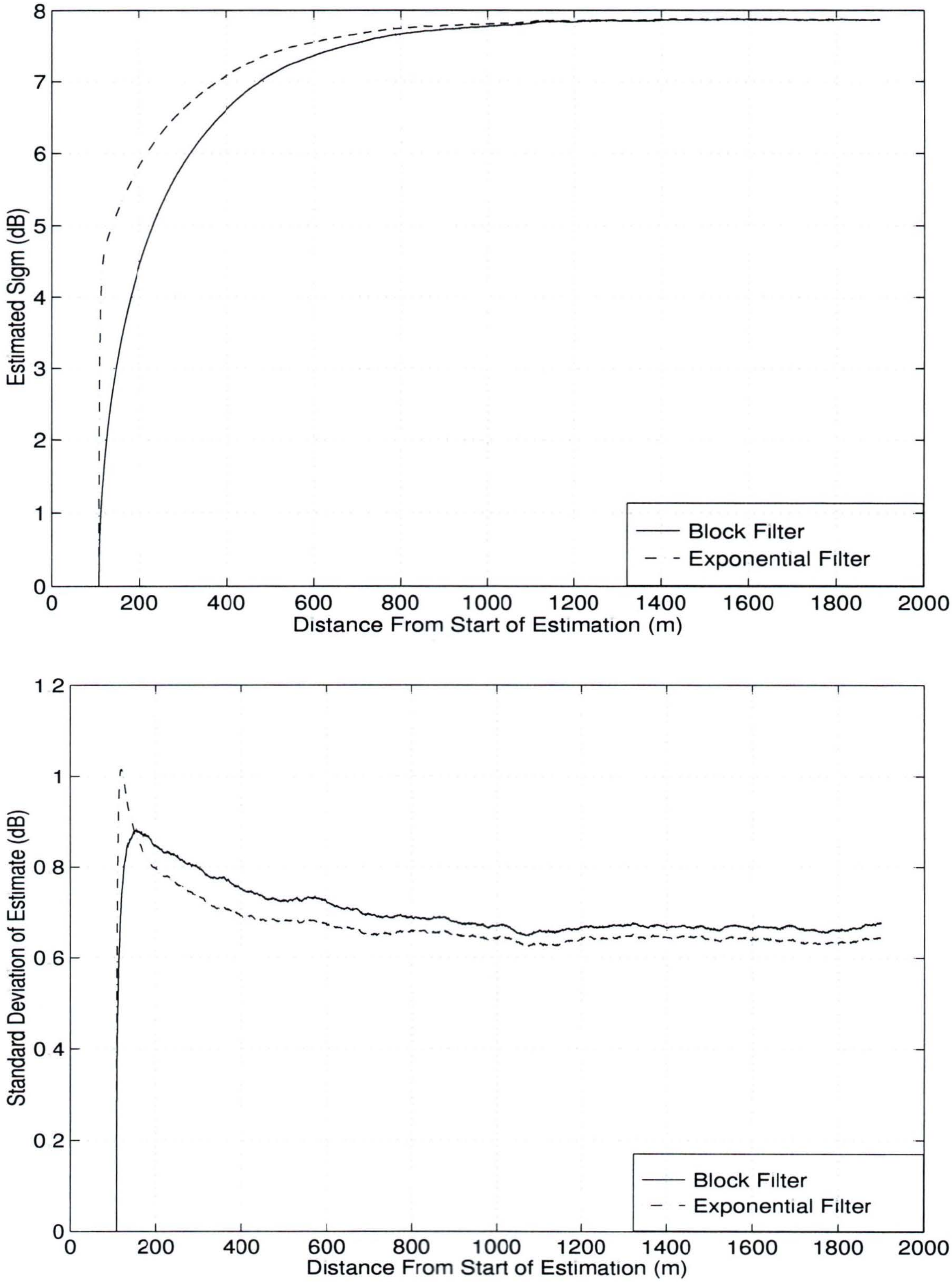


Figure 3.3: σ Estimation for σ=8 dB

The validity of the independence assumption for the fast fading is tested in Table 3.1. The table is split into parts giving the biasing for the block filter and the exponential filter. Three values are listed for each sampling distance: the assumed bias, which is the bias calculated using the assumptions above, the simulated bias which gives the bias calculated from simulations, and the bias calculated using an analytical autocovariance function for the decibel domain fast fading process[8]:

$$A_{FF}(k) = \frac{\pi^2}{6M^2}\left[0.607 J_0^2\left(2\pi f_d k T_s\right) + 0.393 J_0^4\left(2\pi f_d k T_s\right) e^{-1.283 f_d |k| T_s}\right] \tag{3.12}$$

where M is log(10)/10.

The simulations were all performed using Rayleigh fading generated with the method detailed in reference [37]. Note that the bias removal methods make no assumptions about the distribution of the fast fading process, only a fairly simple assumption about its autocovariance function which should be accurate given any fast fading process.

	Block Filter			Exponential Filter		
Sampling Distance (d_s)	Assumed Bias (dB^2)	Simulated Bias (dB^2)	Analytical Bias (dB^2)	Assumed Bias (dB^2)	Simulated Bias (dB^2)	Analytical Bias (dB^2)
0.10	0.000556	0.000537	0.000555	0.000137	0.000133	0.000318
0.20	0.002222	0.002205	0.002219	0.000538	0.000582	0.000581
0.30	0.005000	0.005003	0.004992	0.001190	0.001218	0.001216
0.40	0.008889	0.008859	0.008875	0.002083	0.002074	0.002075
0.50	0.013889	0.013829	0.013868	0.003204	0.003282	0.003292
0.60	0.020000	0.019966	0.019969	0.004542	0.004579	0.004582
0.70	0.031250	0.031215	0.031154	0.006089	0.006076	0.006066
0.80	0.040816	0.040611	0.040691	0.007834	0.007944	0.007957
0.90	0.055556	0.055422	0.055461	0.009769	0.009813	0.009815
1.00	0.055556	0.055418	0.055470	0.011885	0.011845	0.011842

Table 3.1. Bias Calculations for Different Sampling Distances

3.4 Signal Quality Estimation

How signal quality is estimated depends on how the channel is managed.

If no power control is being used then a good estimate of signal quality is the Bit Error Rate (BER) of the channel. This is the ratio of bits being received in error to the total number of bits transmitted. An estimate of the BER can be obtained by either taking output from the decoder or by transmitting a known sequence through the channel and finding the correlation between the received copy and a known local or 'clean' copy[4]. The BER will be affected by the fading in the channel, the amount of interference, the amount of noise, and the type of propagation.

If power control is being used then, theoretically, the BER should be constant. A more useful indicator of signal quality is, then, the amount of power required to obtain the target BER. If a low amount of power is required then the link quality can be judged to be good. If a high amount of power is required then the signal quality is poor.

4. Handoff Models for Cellular Networks

The handoff algorithms used in second generation cellular networks are based on the received signal strength (RSS) measurements of a pilot signal from the basestations at the mobile terminal. In the ideal handoff case the mobile would always be connected to the basestation giving the highest RSS at the moment. Two things prevent this algorithm from being used in practice. First, use of this simple algorithm would result in a large number of handoffs being triggered when the mobile is close to the cell boundary and the RSS from several basestations are close to the RSS from the current basestation. Second, the RSS must be averaged as described in section 2.1 to remove the effects of fast fading, otherwise the handoff algorithm will attempt to compensate for fast fading, and this will create more handoffs with very small gains in performance. This averaging adds a delay from when another basestation provides a better RSS to when a handoff is triggered.

One method to avoid these problems is to only trigger a handoff when the averaged RSS from a candidate basestation exceeds the averaged RSS from the current basestation by more than a fixed hysteresis margin. This handoff algorithm will be referred to as the conventional handoff algorithm since it is the handoff algorithm used by most modern cellular networks (e.g. GSM, and D-AMPS). This hysteresis adds another delay to the handoff algorithm.

This chapter describes a method of analyzing the RSS at the mobile when this handoff algorithm is being used.

4.1 Assignment Probabilities

Vijayan and Holtzman[31] have devised a method for calculating the assignment probabilities of a mobile for the two basestation case They make the simplifying assumption that the level crossing processes of the averaged RSSs are Poisson processes Under this assumption, Vijayan et al calculated the probability of the difference between the averaged RSSs of two basestations crossing the hysteresis level h in the positive direction as

$$p_u(k) = \frac{d_s}{\sqrt{2\pi\lambda_0}} \exp\left(\frac{-\left(h - m(kd_s)\right)^2}{2\lambda_0}\right)\left[m'(kd_s)Q\left(\frac{-m'(kd_s)}{\sqrt{\lambda_2}}\right) + \sqrt{\frac{\lambda_2}{2\pi}}\exp\left(-\frac{m'(kd_s)^2}{2\lambda_2}\right)\right] \tag{4.1}$$

and the hysteresis level $-h$ in the negative direction as

$$p_d(k) = \frac{d_s}{\sqrt{2\pi\lambda_0}} \exp\left(\frac{-\left(h + m(kd_s)\right)^2}{2\lambda_0}\right)\left[-m'(kd_s)Q\left(\frac{-m'(kd_s)}{\sqrt{\lambda_2}}\right) + \sqrt{\frac{\lambda_2}{2\pi}}\exp\left(-\frac{m'(kd_s)^2}{2\lambda_2}\right)\right] \tag{4.2}$$

The value k is the interval for which the crossing probabilities are to be calculated, d_s is the distance between samples, h is the hysteresis level, λ_0 is the variance of the difference of the averaged RSS between the two basestations, λ_2 is the variance of the first derivative of the difference of the averaged RSS between the two basestations, $m(x)$ gives the mean difference between the averaged RSS of the two basestations at position x, $m'(x)$ denotes the derivative of $m(x)$, $Q(v)$ is the Q-function defined as

$$Q(v) = \frac{1}{\sqrt{2\pi}} \int_{v}^{\infty} \exp\left(\frac{-x^2}{2}\right) dx \qquad (4\ 3)$$

We use the random variable $D(k)$ defined in section 2 2 $D(k)=A$ if the mobile is connected to basestation A in interval k and $D(k)=B$ if the mobile is connected to basestation B in interval k The value of $m(x)$ is defined to be the mean difference of the RSS from basestation A and basestation B when the mobile is at position x Therefore a mobile is assigned to basestation A if in the last sampling interval the difference of the RSSs crossed the h level in the up direction but did not cross the $-h$ level in the down direction, or the mobile was assigned to basestation A two intervals ago and no significant level crossings occurred From this, and equations (4 1) and (4 2), the probability of the mobile being assigned to the initial basestation A(i e $P(D(1)=A)=1$) at an interval k can be found to be

$$P(D(k)=A) = p_u(k-1)\left[1-p_d(k-1)\right] + \left[1-p_u(k-1)\right]\left[1-p_d(k-1)\right]P\left(D(k-1)=A\right) \qquad (4\ 4)$$

Vijayan and Holtzman use an analog first order Butterworth filter to average the RSS from each basestation In the analysis presented in this chapter an N-point block averaging digital filter is used for the reasons given in Section 2 1 The use of a digital filter makes the process of calculating the variances a little more complex All the signals are converted to their digital equivalents and then the power spectral densities of these signals are calculated to compute the variances

The long term fading can be modeled as white Gaussian noise that has been filtered by a first order Butterworth filter. The Butterworth filter used to create the proper autocorrelation function for the long term fading is digitized by matching its impulse response to give a digital filter with the power spectral density of

$$|F(\omega)|^2 = \frac{1-\exp(-2a)}{1-2\exp(-a)\cos(\omega)+\exp(-2a)} \tag{4.5}$$

with $a = d_s/d_0$. The power spectral density of the block averaging filter is

$$|G(\omega)|^2 = \frac{1}{N^2}\frac{1-\cos(N\omega)}{1-\cos(\omega)} \tag{4.6}$$

From this, the values of λ_0 and λ_2 can be calculated as

$$\lambda_0 = \frac{2\sigma^2}{\pi}\int_0^{\pi}|F(\omega)|^2|G(\omega)|^2\,d\omega\text{, and} \tag{4.7}$$

$$\lambda_2 = \frac{2\sigma^2}{\pi}\int_0^{\pi}\omega^2|F(\omega)|^2|G(\omega)|^2\,d\omega \tag{4.8}$$

The Poisson assumption has been shown to provide satisfactory results as long the value of h is larger than σ. Usually, in order to get the required number of handoffs, the value of h must be larger than σ, so this restriction does not greatly limit the applicability of the model.

4.2 Distribution of RSS

Some work has been performed on calculating the distribution of the RSS from the selected basestation[23],[39]. This work is based on a simplified handoff model which uses the value of $R(x,t)$ for each of the basestations as the decision variables. This chapter expands the above work by including the effects of RSS averaging.

The decision variable at interval k, $S(k)$ is given by

$$S(k) = \frac{1}{N} \sum_{i=k-N+1}^{k} A(i) - B(i), \tag{4.9}$$

where $A(i)$ and $B(i)$ are the RSSs from the basestations A and B sampled during interval i.

Assuming instantaneous handoff

$$\begin{aligned} S(k) > h \quad &\Rightarrow \quad D(k) = A \\ S(k) < -h \quad &\Rightarrow \quad D(k) = B \\ -h \le S(k) \le h \quad &\Rightarrow \quad D(k) = D(k-1) \end{aligned} \tag{4.10}$$

The distribution of the received signal power from the selected basestation during interval k, $y(k)$, is given by

$$P\big(y(k) \le W\big) = \int_{-\infty}^{\infty} P\left(D(k) = A, 10^{\frac{A(k)}{10}} \le W, S(k) = x\right) + P\left(D(k) = B, 10^{\frac{B(k)}{10}} \le W, S(k) = x\right) dx \tag{4.11}$$

It is possible to rewrite the probabilities in equation (4.11) in the form below:

$$P\left(D(k)=A,10^{\frac{A(k)}{10}}\leq W,S(k)=x\right)=P\big(S(k)=x\big)P\left(D(k)=A,10^{\frac{A(k)}{10}}\leq W\middle|S(k)=x\right)$$

(4 12)

For *S(k)<-h* or *S(k)>h* it is simple to show that *D(k)* and *A(k)* are independent given *S(k)*, since *S(k)* determines *D(k)* completely However, in the region *-h≤S(k)≤h*, this proof becomes more involved First, we use equation (4 9) to rewrite *S(k)* as

$$S(k)=\frac{1}{N}A(k)+\frac{1}{N}A(k-1)+U \tag{4 13}$$

where *U* is a random variable dependent on *A(k-1)* and *A(k)* This allows us to rewrite the probabilities in equation (4 12), noting that in the region of interest *D(k-1)=D(k)*, as

$$P\left(D(k)=A,10^{\frac{A(k)}{10}}\leq W,S(k)=x\right)=P\big(S(k)=x\big)$$
$$P\left(D(k-1)=A,10^{\frac{A(k)}{10}}\leq W\middle|A(k-1)=Nx-A(k)+NU\right)$$

(4 14)

Now we use the fact that *A(k)* is a Gaussian Markovian process because of the exponential autocorrelation in (2 3) This means that the distribution of *A(k)* is independent of any event in the intervals *k-1, k-2, ,2,1,0* given *A(k-1)* $D(k\text{-}1)$ is dependent on $A(k\text{-}2)$, $A(k\text{-}3)$, , $A(2)$, and $A(1)$ but $A(k)$ is independent of these values if $A(k\text{-}1)$ is given, therefore $A(k)$ is independent of $D(k\text{-}1)$ if $A(k\text{-}1)$ is known This shows that *D(k)* is independent of *A(k)* if *S(k)* is given The independence of *D(k)* and *B(k)* given *S(k)* can be proven identically This allows us to define the distribution of $y(k)$, the distribution of the sampled RSS from the selected basestation in interval k, as

$$P\left(y(k) \le W\right) = \begin{array}{l} \int_{-\infty}^{\infty} P\left(S(k)=x\right) P\left(10^{\frac{A(k)}{10}} \le W \middle| S(k)=x\right) P\left(D(k)=A \middle| S(k)=x\right) + \\ P\left(S(k)=x\right) P\left(10^{\frac{B(k)}{10}} \le W \middle| S(k)=x\right) P\left(D(k)=B \middle| S(k)=x\right) dx \end{array}$$

(4 15)

The distributions of A(k) and B(k) given S(k) are simple to calculate Details on how to obtain these distributions are given in the following section This shows that if the distribution of *D(k)* given *S(k)* is known, then the distribution of the received signal strength *y*(*k*) can also be calculated

4 3 Bounds on the Mean Value of RSS

Using the relation $E[y]=E\{E[y(k)|x]\}$, we can calculate the mean value of *y*(*k*) using

(4 16)

$$E\left[y(k)\right] = \begin{array}{l} \int_{-\infty}^{\infty} P\left(S(k)=x\right) E\left[10^{\frac{A(k)}{10}} \middle| S(k)=x\right] P\left(D(k)=A \middle| S(k)=x\right) + \\ P\left(S(k)=x\right) E\left[10^{\frac{B(k)}{10}} \middle| S(k)=x\right] P\left(D(k)=B \middle| S(k)=x\right) dx \end{array}$$

The distribution of $P(D(k)=A|S(k)=x)$ is unfortunately difficult to calculate since *S(k)* is not Markovian However, it is possible to calculate functions for $P(D(k)=A|S(k)=x)$ which will bound the mean of *y*(*k*)

These bounding function will be derived for A(k), knowing that the functions for B(k) can be derived in a similar fashion

Using well known properties of Gaussian processes we calculate the correlation coefficient between $S(k)-E[S(k)]$ and $\beta(A(k)-E[A(k)])$ where $\beta=Var(S(k))/Var(A(k))$ $(=\lambda_0/\sigma^2)$, which makes the variance of the two random variables equal. We start by using the Markov property of $A(k)$ to define $A(N)$ as

$$A(N)-E\left[A(N)\right]=\eta\left\{A(N-1)-E[A(N-1)]\right\}+\sqrt{1-\eta^2}N_{AN} \qquad (4.17)$$
$$=\eta^{N-1}N_{A1}+\sqrt{1-\eta^2}\sum_{i=2}^{N}\eta^{N-i}N_{Ai}$$

with $\eta=exp(-d_s/d_0)$, the correlation coefficient between $A(k)$ and $A(k-1)$, and N_{A1} ... N_{AN} being independent and identically distributed (i.i.d.) Gaussian random variables of zero mean and variance σ^2. Using a similar definition for $B(N)$, we can define $S(N)$ as

$$S(N)-E\left[S(N)\right]=\frac{1}{N}\left\{\left[\frac{1-\eta^N}{1-\eta}\right]\left(N_{A1}-N_{B1}\right)+\sqrt{1-\eta^2}\sum_{i=2}^{N}\left[\frac{1-\eta^{N-i+1}}{1-\eta}\right]\left(N_{Ai}-N_{Bi}\right)\right\},$$

(4.18)

where N_{B1} ... N_{BN} are i.i.d. Gaussian random variables with the same parameters as N_{A1} ... N_{AN}. The correlation coefficient can then be calculated as

$$\rho=E\left[\frac{\left\{S(N)-E\left[S(N)\right]\right\}\beta\left\{A(N)-E\left[A(N)\right]\right\}}{\sigma^2}\right]=\frac{\beta\left(1-\eta^2\right)}{N\left(1-\eta\right)} \qquad (4.19)$$

This allows us to calculate the conditional mean of $A(k)$ as

$$E\left[A(k)|S(k)\right]=\frac{\rho\left\{S(k)-E\left[S(k)\right]\right\}}{\beta}+E\left[A(k)\right], \qquad (4.20)$$

and the conditional variance as

$$Var\left[A(k)|S(k)\right]=\frac{\left(1-\rho^2\right)Var\left[S(k)\right]}{\beta^2} \quad (4\ 21)$$

The conditional expected value of $10^{A(k)/10}$, using the fact that the probability density function of a Gaussian random variable conditioned on the value of another Gaussian random variable is also Gaussian[20], is

$$E\left[10^{\frac{A(k)}{10}}\middle|S(k)=x\right]=\int_{-\infty}^{\infty}10^{\frac{y}{10}}\frac{1}{\sqrt{2\pi Var\left[A(k)|S(k)\right]}}\exp\left\{-\frac{\left[y-E\left[A(k)|S(k)=x\right]\right]^2}{2Var\left[A(k)|S(k)\right]}\right\}dy$$

$$=\exp\left[\frac{M\left(2\rho x-2\rho E\left[S(k)\right]+2\beta E\left[A(k)|S(k)=x\right]+M\beta Var\left[A(k)|S(k)\right]\right)}{2\beta}\right],$$

(4 22)

where M=log(10)/10 The derivative of this expression with respect to x is positive indicating that $E[10^{A(k)/10}\ |S(k)=x]$ increases with x This property bounds the mean value of y

A function which gives an upper bound on the mean can be shown to be (see Appendix B)

$$\tilde{P}_{UB}\left(D(k)=A|S(k)=x\right)=\begin{cases}1 & S(k)>C\\ 0 & S(k)\le C\end{cases}, \text{ and} \quad (4\ 23)$$

where

$$\int_C^{\infty}P\left(S(k)=x\right)dx=P\left(D(k)=A\right) \quad (4\ 24)$$

A function which gives a hard lower bound on the mean can be shown to be

$$\widetilde{P}_{LB}(D(k)=A|S(k)=x)=\begin{cases}1 & S(k)>h, S(k)\le E\\ 0 & otherwise\end{cases}, \tag{4 25}$$

where

$$\int_{-h}^{E} P(S(k)=x)dx = P(D(k)=A)-P(S(k)>h), \tag{4.26}$$

with the proof being similar to the proof given in Appendix B.

If it can be shown that *P(D(k)=A|S(k)=x)* increases with *x* then a tighter lower bound is given by the following function

$$\widetilde{P}_{LB2}(D(k)=A|S(k)=x)=\begin{cases}1 & S(k)>h\\ F & -h\le S(k)\le h,\\ 0 & S(k)<-h\end{cases} \tag{4 27}$$

where

$$F\int_{-h}^{h} P(S(k)=x)dx = P(D(k)=A)-P(S(k)>h) \tag{4 28}$$

A proof of this is given in Appendix C.

A full proof that *P(D(k)=A|S(k)=x)* increases with *x* has not been completed but intuitively it seems plausible since the correlation of *S(k)* with all of its past values is positive, and if *D(k)=A* then some past value of *S(k)* was greater than *h*, which increases the possibility that *S(k)* is a high value.

The corresponding functions for $P(D(k)=B|S(k)=x)$ can be shown from the law of total probability to be

$$P\big(D(k) = B|S(k) = x\big) = 1 - P\big(D(k) = A|S(k) = x\big) \tag{4.29}$$

These equations allow hard bounds to be calculated for the mean RSS if the assignment probabilities are known. In practice, these values can not be calculated exactly but the method given in Section 4.1 can approximate them very closely.

A method for calculating approximations on the bounds for the mean RSS is to estimate the assignment probabilities using (4.4) and then calculate values for the constants C, E, and F using root finding methods. Then (4.23), (4.25) and (4.27) can be inserted into (4.16) to compute bounds on the mean.

4.4 Results

To show some sample results of the method, we demonstrate a simple test case where the mobile is moving directly away from one basestation and towards another as shown in Figure 4.1.

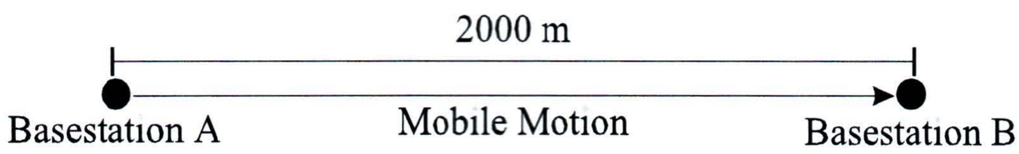


Figure 4.1: Simulation Configuration

The parameters are d_s=1 m, h=20 dB, σ=6 dB, and N=20 The three different bounds on the mean are converted to decibel values to make the results easier to compare As well, an estimate of the true mean was obtained by averaging over 10000 simulated runs of a mobile over the path The resulting mean RSS over distance are shown in Figure 4 2

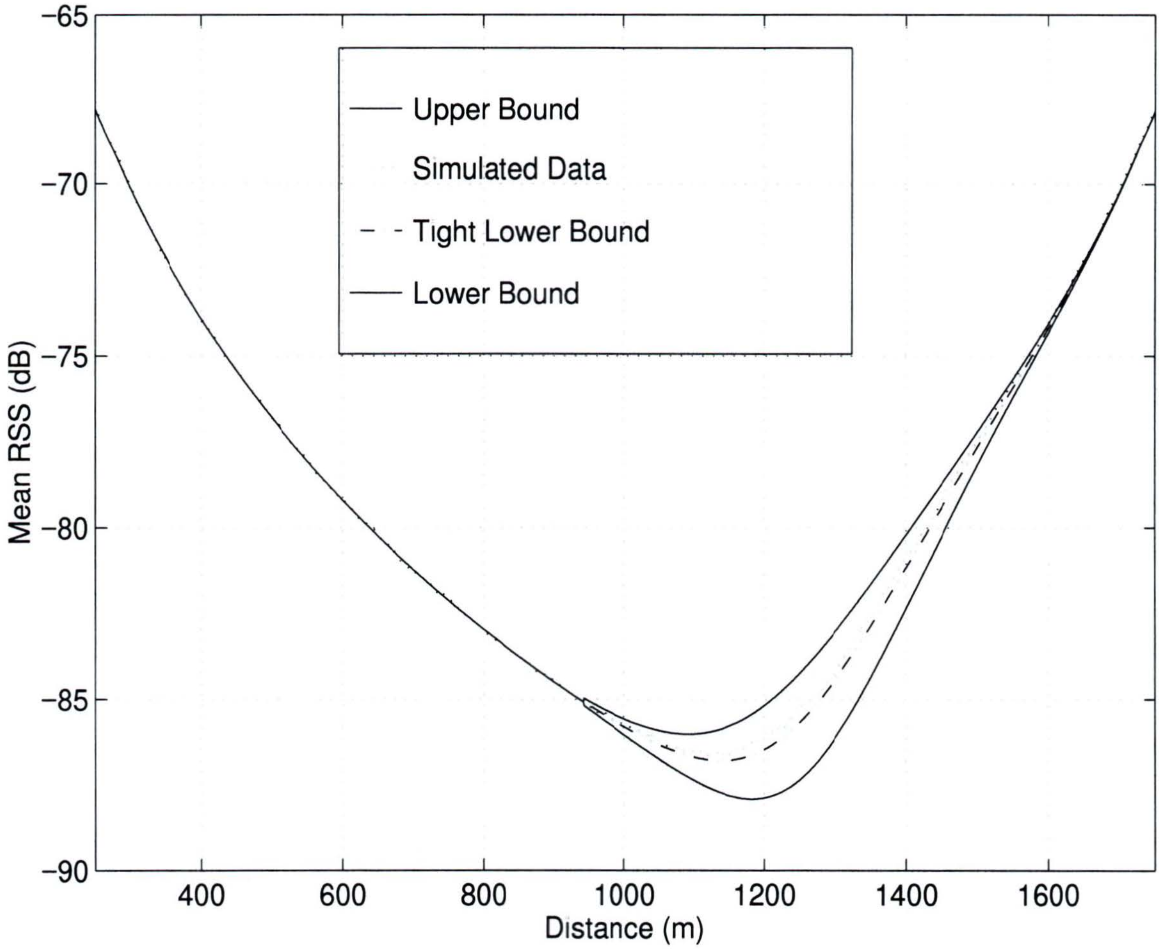


Figure 4 2: Comparison of Bounds on the Mean RSS

4.5 Analysis

This chapter has shown how bounds on the mean RSS of a hysteresis based hard handoff algorithm can be calculated These bounds have been shown to be fairly tight

Some work on the mean RSS in the literature[39] claims the lower bound of the mean RSS during hard handoff is the mean RSS from a distance based ideal mean RSS handoff algorithm, where the mobile is always connected to the nearest basestation This is not necessarily the case as is shown in Figure 4 3(using the same parameters as Figure 4 2)

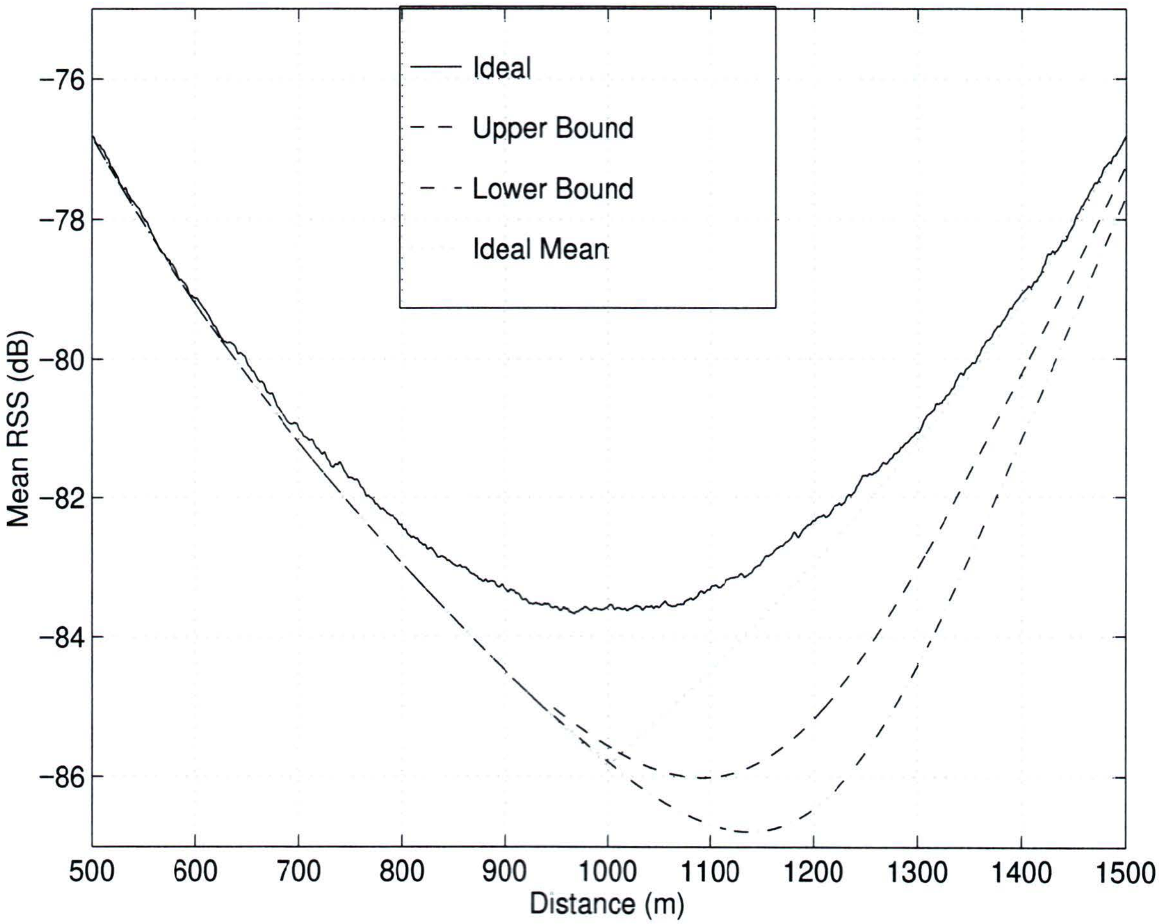


Figure 4.3: Comparison with Ideal Handoff Algorithms

The values for the ideal handoff RSS based algorithm are also shown for comparison.

A problem with the conventional handoff algorithm is the drop in the mean RSS after the mobile has crossed the cell boundary. This is caused by mobiles outside of the original cell still communicating with the original cell. This drop in the mean RSS after the cell boundary will have several effects, all which will lower the capacity of the network. A major effect is that higher transmitted power will be required for communications. To make matters worse, mobile terminals are communicating at fairly high power outside of the boundaries of the original cell which means they will cause a large amount of interference. To compensate for this, the re-use distance (the distance between cells using the same radio channel resources) must be increased which will cause another reduction of capacity. This phenomenon is called "cell-dragging"[22].

The most common solution to cell dragging is to lower the hysteresis level to reduce the lag. Unfortunately, this also increases the number of handoffs. Figure 4.4 shows a graph of the mean RSS when h is reduced to 10 dB. The drop in mean RSS is reduced to within acceptable limits but the mean number of handoffs is increased to 2.056 from 1.004, when the hysteresis is 20 dB.

Figure 4.4 shows the danger of choosing the parameters of a handoff algorithm based solely on the number of handoffs without paying attention to other parameters of system performance. Often in the literature, if the mean number of handoffs is greater than one, the extra handoffs are called "unnecessary" handoffs. As can be seen here, these extra handoffs can have a positive impact on system performance.

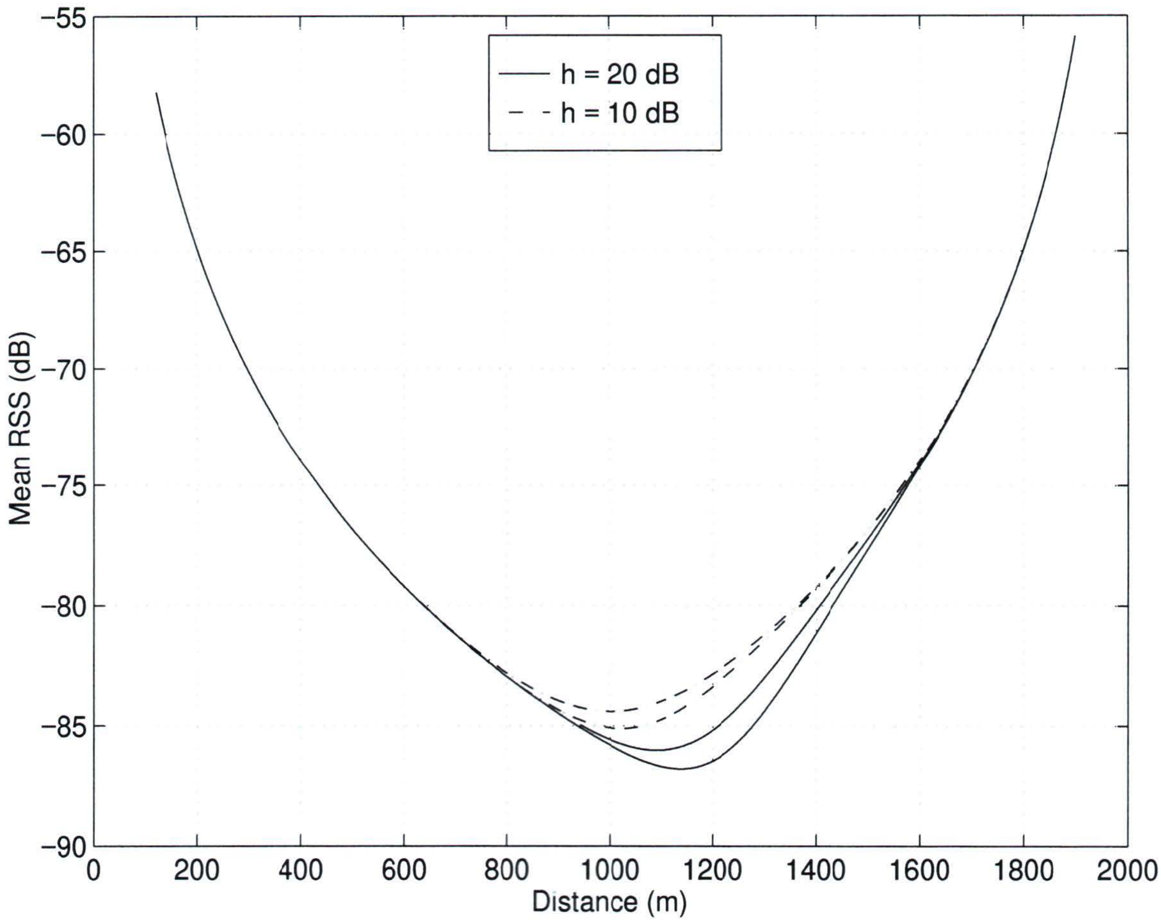


Figure 4.4: Mean RSS Drop Reduction

The second method used to reduce the handoff lag is to implement soft-handoff This is only possible for cellular networks using CDMA Soft handoff was briefly described in Section 1 1 In this case, the mobile can connect to several basestations at once In theory, this allows it to communicate with the best basestation out of the set it is connected to This makes the mean RSS equal to the ideal handoff algorithm case As can be seen in Figure 4 3, this is a substantial improvement The difficulty is that this can only be truly achieved for the link channel from the mobile to the basestation. For the channel from the basestation to the mobile, the basestation must communicate as if it was connected to the mobile alone[32]. This causes a mobile in soft-handoff to produce more interference than mobiles connected to only one basestation. To compensate for this, the number of mobiles in soft handoff must be kept low, which reduces the benefit of the soft handoffs.

As well, there are situations where a CDMA cellular network is forced to make hard handoffs. Current CDMA standards are designed to work with older standards which are divided in the frequency domain (FDMA). To facilitate this, the CDMA systems divide the allocated frequency band into several separate CDMA systems. Sometimes a mobile must handoff between these regions. In this case, soft-handoff can not be used.

4.6 Multiple Basestation Analysis

Considering more than two basestations makes the analysis much more difficult. The analysis in the literature makes the simplifying assumption that the RSS difference between two basestations is independent of any other RSS difference including ones which share one basestation[1],[25]. The analysis is good for cases when the difference of the mean RSS from different basestations is large.

When the mean of the RSS from different basestations becomes close, the accuracy of these methods suffer. This, however, is the case where multiple basestation analysis is most useful. It is also a case that occurs quite frequently in microcells where basestations are placed quite close together.

5. A Fuzzy Logic Based Handoff Algorithm

The conventional handoff algorithm has several limitations that make improvements on it attractive First, the received signal strength is not a perfect indicator of link quality It is possible for there to be two basestations that give the same received signal strength but to have different signal link qualities This could be caused by multipath propagation If one basestation provides only one propagation path with all the signal energy, it will give a better quality link than another basestation with its energy spread over several different paths since the different paths can destructively interfere with each other

Also, as noted in the previous chapter, the conventional algorithm suffers from a lag in assigning the mobile to a more favourable basestation This is caused by the hysteresis in the handoff algorithm

A way to reduce these problems is to use other information as well as the received signal strength to make the handoff decision Chapter 3 describes how several parameters can be obtained by a mobile terminal The most useful of these for handoff is the signal quality of the current link, the distance to each of the basestations, and the parameters of the long term fading Velocity estimation is used to maintain a constant sampling distance

There are other papers on the use of multiple data sources in making the handoff decison There has been some work on the use of absolute RSS as well as relative RSS[38], velocity information[2], and direction information[3] Most of this work uses hard boundaries to deal with the other information sources. If the information sources have significant error or imprecision the performance of these handoff algorithms suffer.

A difficulty is there is a large imprecision in the measuring techniques. This means that while there is no (or a very small) bias in the measured values, there can be a large random error in the measured values. The use of fuzzy logic is proposed to allow these imprecise values to still be used constructively in the decision process.

5.1 Brief Introduction to Fuzzy Logic

Conventional logic can be shown to be based on set theory. The truth of a proposition is generally proved by showing that some object or objects belong to some set. For any given set, a function can be developed which can determine whether any object in the universe of discourse belongs to the set. We call this function the membership function for that set.

$$\mu_A(x) = \begin{cases} 1 & x \in A \\ 0 & x \notin A \end{cases}, \tag{5.1}$$

where A is the set and x is an object in the universe of discourse. From these membership functions, the standard Boolean logical operations of AND, and OR can be derived.

There are unfortunately some decision processes that conventional logic can not be used to solve easily. For example, there is the problem of Socrates' beard. The problem statement is:

"Socrates has a large and bushy beard If you pluck out his beard, one hair at a time, at what point does he cease to have a beard?"

The difficulty that conventional logic has with this problem is in order to resolve the two sets of bearded people, and non-bearded people some dividing line must be selected This dividing line will appear to be artificial to the observer

However, fuzzy logic can develop a solution Fuzzy logic is based on the concept that objects can be partial members of a set That is, the membership function can take any value in the interval [0,1]

$$0 \le \mu_A(x) \le 1 \qquad (5\ 2)$$

Fuzzy logic can be used to solve or reformulate the problem of Socrates beard quite nicely A membership function for the fuzzy set of bearded people can be formed based on the number of hairs that a person has on his face As the number of hairs on his chin decreases so does Socrates membership in the fuzzy set of bearded people So the question of when Socrates ceases to have a beard is answered by a matter of degrees instead of with a yes or no answer This is a more natural approach

Fuzzy sets can be defined with less precise definitions and still allow membership in these sets to be used in decision making processes This allows fuzzy logic to be used in what is called Linguistic Computing[36] An algorithm is stated in natural language and then this algorithm is converted to operations on fuzzy sets For example, for a decision process, a control algorithm can be specified as

If x is C_1 and y is C_2 then z is R_1
If x is C_3 and y is C_4 then z is R_2

C_1, C_2, C_3, and C_4 are conditions, and R_1 and R_2 are reactions. The variables x, y represent state variables or inputs to the system, z represents some controllable variable in the system. If this is translated into fuzzy set operations (where $\in$ denotes fuzzy membership in a set) then the control algorithm becomes:

If $x \in C_1$ and $y \in C_2$ then $z \in R_1$
If $x \in C_3$ and $y \in C_4$ then $z \in R_2$

Using logical operations defined for fuzzy sets then the two rules can be written as:

$$\begin{aligned} \mu_{R_1}(z) &= \mu_{C_1}(x) \wedge \mu_{C_2}(y) \\ \mu_{R_2}(z) &= \mu_{C_3}(x) \wedge \mu_{C_4}(y)\text{'} \end{aligned} \quad (5.3)$$

where '$\wedge$' is the logical operator AND defined for Fuzzy logic.

The definition of the AND operator depends on how the different condition factors are to be considered for the control process. There are two popular methods for doing this. The first method is to use a fixed weight for each different control factor. In this case, the control system in (5.3) becomes[24]:

$$\begin{aligned} \mu_{R_1}(z) &= w_x \mu_{C_1}(x) + w_y \mu_{C_2}(x) \\ \mu_{R_2}(z) &= w_x \mu_{C_3}(x) + w_y \mu_{C_4}(x)\text{'} \end{aligned} \quad (5.4)$$

with w_x and w_y being the weights for inputs x and y respectively. This controls the amount of influence that each factor has on the output membership values.

The ordered weighting approach offers another level of flexibility to the decision process. Here weights are assigned to the different input factors based on their ranking. This is referred to as Ordered Weighted Aggregates (OWA) and it allows more flexibility in the decision process[35]. The control process using this technique becomes:

$$\begin{aligned}\mu_{R_1}(z) &= w_1 \max(\mu_{C_1}(x), \mu_{C_2}(y)) + w_2 \min(\mu_{C_1}(x), \mu_{C_2}(y)) \\ \mu_{R_2}(z) &= w_1 \max(\mu_{C_3}(x), \mu_{C_4}(y)) + w_2 \min(\mu_{C_3}(x), \mu_{C_4}(y))\end{aligned} \quad (5.5)$$

with w_1 and w_2 being weights for the different ranked factors. This tunes the control algorithm to give high weights to indicators indicating a strong tendency towards a control response, or towards indicators which give low value towards a possible control response. Another way of stating this is the control rules can be tuned to be OR-like (where only one condition needs to be satisfied), or it can be tuned to be AND-like (where all conditions need to be satisfied). The weight of one specific condition can be adjusted by changing its membership function. The advantage of this control scheme is that the decision making mechanism is separated from the weighting of each condition.

Once the membership of the response in several fuzzy sets is obtained some method must be used to change these membership values into a crisp value which can actually be used in a real system. This process is called defuzzification. Fortunately for the fuzzy handoff algorithm, the control response consists of choosing between several options. The defuzzification is simply choosing the option with the highest membership value.

5.2 The Fuzzy Handoff Algorithm

The use of fuzzy logic to handle handoff decision problems is relatively new. There has been some work in the area[5],[16],[28] but a full evaluation of the technique over several sets of fading parameters has not been done.

The fuzzy handoff algorithm is implemented in the following steps which are repeated every sampling interval. First, the parameters of the different channels between the mobile and different basestations are sampled. For the current basestation, the RSS, the signal quality, and the distance are sampled. For candidate basestations, only the RSS and distance are sampled. For each parameter, its value in the fuzzy set of acceptable values for that parameter is calculated. Then the membership values are used in a fuzzy decision process to calculate which basestation the mobile should be connected to in the next interval.

The RSS is sampled because it is easy to obtain. Its measurement does not require any extra hardware in the mobile and its behaviour is well understood.

Distance is used as a decision criteria because it is also fairly easy to obtain. The use of the distance can also help reduce the "cell dragging" problem, it can keep mobiles using specified channels only in the regions that were chosen to use them.

The signal quality is useful because it gives a sample of the true performance of the radio link. This allows the handoff algorithm to respond reasonably to situations where the signal quality is different from what a straight RSS analysis would show. For example, if the mobile moves into a location where the RSS is high but a lot of power is required for good communication with the current basestation, then the algorithm can handoff to another basestation. Alternatively, the algorithm can avoid handoffs in situations where the RSS is weak but a low amount of power is required for good communication.

5.2.1 Fuzzy Set Membership Functions

An acceptable value for a parameter is a value that, if the values of no other parameters of the channel are known, the probability that the channel would give a good signal quality for the near future is high.

For distance, acceptable values are low values. The membership function for the fuzzy set of acceptable distances is defined as

$$\mu_{AcceptableDistance}(d) = \begin{cases} 1 & d < \frac{R}{2} \\ 1 - \frac{2d - R}{3R} & \frac{R}{2} \le d \le 2R \\ 0 & d \ge 2R \end{cases} \tag{5.6}$$

where R is the cell radius.

Acceptable RSS from any given basestations are values where the RSS from the basestation that are high compared to the RSS from the currently connected basestation. The RSS membership in the fuzzy set of acceptable RSSs for a basestation is calculated by taking the average of the last N readings of the RSS from that basestation and subtracting the average of the last N readings of the RSS from the currently connected basestation This averaging is performed to remove the effects of fast fading This value, AVG, can be used to obtain the membership value from the definition

$$\mu_{AcceptableRSS}(AVG)=\begin{cases} erf\left(\dfrac{AVG}{a\sigma}\right) & AVG>0 \\ 0 & AVG\leq 0 \end{cases} \tag{5.7}$$

where σ is the standard deviation of the long term fading from (2 4) and a is a constant used to control the weight of RSS in the decision process

The signal quality is a more complicated variable In this chapter, we will assume that power control is not being used and therefore the BER can be used as a indicator of signal quality If power control is being used then the signal quality can be calculated from a non-linear function of how much power is being used over how much power the mobile has available A low amount of used power means the membership in the fuzzy set of acceptable quality is near unity The BER is averaged over N readings just like the RSS readings above This is to remove the effects of burst errors The membership of the averaged BER in the fuzzy set of acceptable BER is

$$\mu_{AcceptableBER}(BER)=\begin{cases} 1-b(BER) & BER<\dfrac{1}{b} \\ 0 & BER\geq\dfrac{1}{b} \end{cases} \tag{5.8}$$

where b is a constant which can be changed to vary the weight of the BER in the handoff decision

5.2.2 The Fuzzy Handoff Decision Process

The objective of the handoff algorithm is to select, at the end of each sampling interval, which basestation the mobile will communicate with during the next sampling interval. The evaluation of each link is done with the following control rules, expressed in natural language:

<u>For Candidate Basestations:</u>

If RSS is acceptable and the distance is acceptable then handoff to this basestation.

<u>For Current Basestation:</u>

If signal quality is acceptable and distance is acceptable then don't handoff to any other basestation.

When translated to fuzzy set operations the control rules become:

<u>For Candidate Basestations:</u>

$$\mu_{Handoff}(BS_n) = w_1\, max(\mu_{AcceptableRSS}(RSS_n), \mu_{AcceptableDistance}(d_n)) + (1-w_1)\, min\left(\mu_{AcceptableRSS}(RSS_n), \mu_{AcceptableDistance}(d_n)\right) \quad (5.9)$$

<u>For the Current Basestation:</u>

$$\mu_{Handoff}(BS_n) = w_1\, max(\mu_{AcceptableBER}(BER), \mu_{AcceptableDistance}(d_n)) + (1-w_1)\, min\left(\mu_{AcceptableBER}(BER), \mu_{AcceptableDistance}(d_n)\right) \quad (5.10)$$

BS_n refers to the basestation n, RSS_n refers to the RSS from the nth basestation, and d_n is the distance between the mobile and basestation n. w_1 is a weighting factor to control the decision process The basestation with the highest value for $\mu_{Handoff}(BS_n)$ is selected If it is different from the current basestation then a handoff is performed

Attention needs to be paid to the selection of the values for the constants a, b, and w_1 These values determine the sensitivity of the algorithm to the different measured parameters

For a and b, the precision of the measurements techniques for the RSS and BER need to be considered as well as the usefulness of these values for determining the future quality of the link If the correlation distance of the fading, d_0, is high and the propagation type (line-of-sight/ non-line-of-sight) remains identical most of the time then low values of a and b will work well If the type of propagation environment can change quickly, and the correlation distance is very short, then RSS and BER do not give very good indicators of future link quality so only large changes in their values should trigger handoffs In this case, the value of a should be large and the value of b should be small

A danger when combining several types of information from different sources into one decision process is that bad information sources can create a decision process that is less effective than when only accurate information sources are used[11] Thus, a careful analysis is required before implementation

The handoff algorithm will perform best when the data source which gives the most accurate and precise information about the future quality of the radio links causes the greatest variation in the values of $\mu_{Handoff}(BS_n)$

Since these distributions can change depending on the exact configuration of the cellular network and what multiple access technique is being used, this work will use parameters based on the assumption that the reliability of all the estimated parameters for predicting link quality are equal. The value of w_1 is selected to be 0.5. This causes an even weighting of all factors. The values of the other parameters will be described for each case analyzed.

5.3 Analysis of Handoff Algorithms

The handoff algorithm's performance will be evaluated by considering two basestation and four basestation situations. Performance will be measured with respect to the conventional handoff algorithm for several values of σ commonly found in urban cellular networks.

The two basestation case is identical to the situation used to analyze the conventional algorithm's performance in Chapter 4. The two basestations are 2000 metres apart and the mobile moves from one directly towards the other. Both algorithms will make a handoff decision every sampling period which is chosen so the sampling distance, d_s, is 1 metre.

The fast fading is assumed to be constant during one symbol period. This allows the mean BER for a sampling period to be approximated by[21]:

$$BER(k) = \frac{1}{2}\left(1 - \sqrt{\frac{\gamma(k)}{1+\gamma(k)}}\right), \tag{5.11}$$

where $\gamma(k)$ is the mean value of the signal to noise ratio during sampling interval k, and coherent BPSK modulation is assumed. The quantity $\gamma(x)$ is calculated using

$$\gamma(k) = 10^{\frac{r(k)-Floor}{10}} \tag{5.12}$$

where $r(k)$ is the mean RSS during interval k, and *Floor* is a constant.

In the two basestation case, the algorithms are compared based on their percentile crossover points. For a given percentile, the crossover point is the smallest distance where the probability of the mobile being assigned to the destination basestation is greater than the given percentage. For the cases presented here, the 10%, 50%, and 90% crossover points are shown. The algorithms are compared for the cases where the standard deviation of the long term data, σ, is 4 dB, 6 dB, and 8 dB. The results are presented in Figure 5.1, Figure 5.2, and Figure 5.3. The 90% crossover points are shown on the highest set of lines on each graph. The 50% crossover points are the middle set of lines. The 10% crossover points are the lowest set of lines.

For the analysis, the algorithms were configured for different numbers of handoffs and the performance measured. The conventional algorithm was tuned by modifying the hysteresis level. The fuzzy algorithm was tuned by changing the value of b, in the acceptable BER fuzzy set membership function. The value of a is set to be the square root of 2. The averaging length, N, is 20 points. The value of *Floor* was -110 dB.

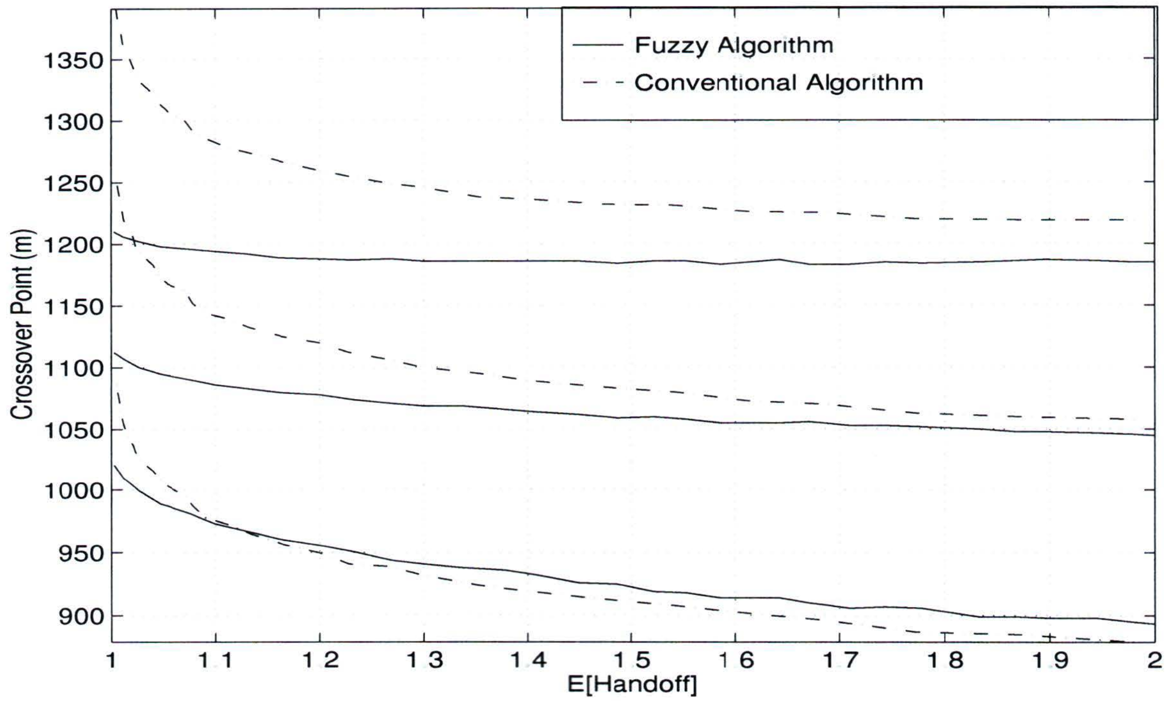


Figure 5.1: Crossover Points for σ=4 dB

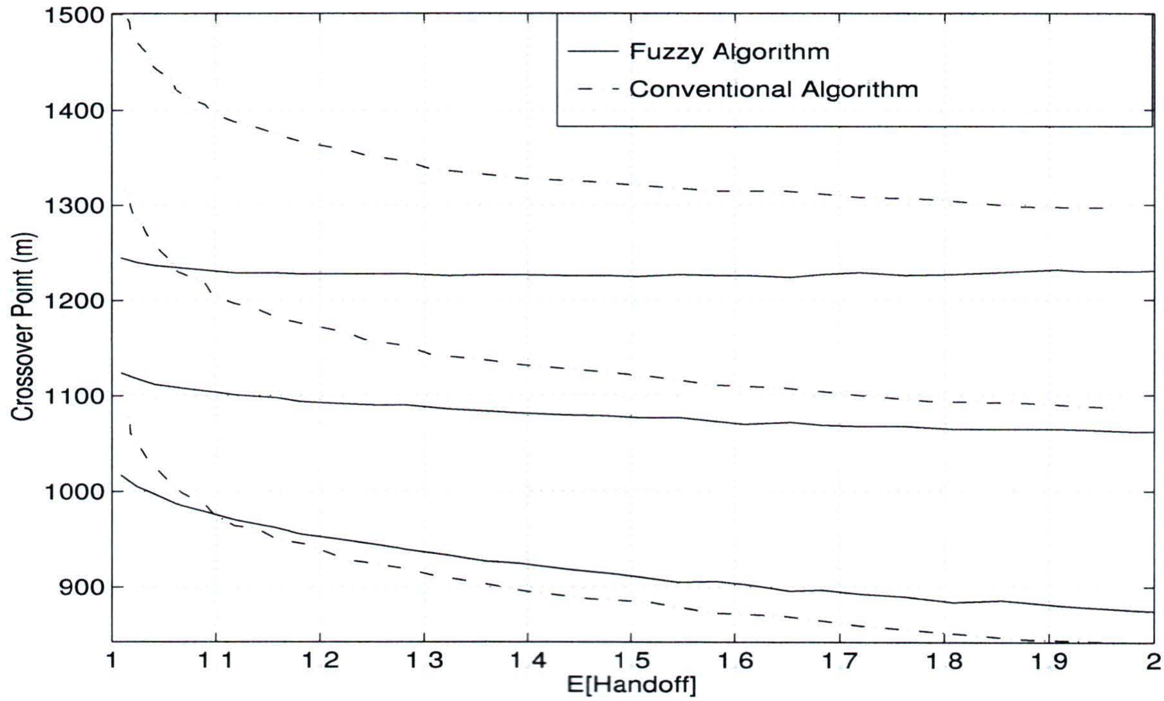


Figure 5.2: Crossover Points for σ=6 dB

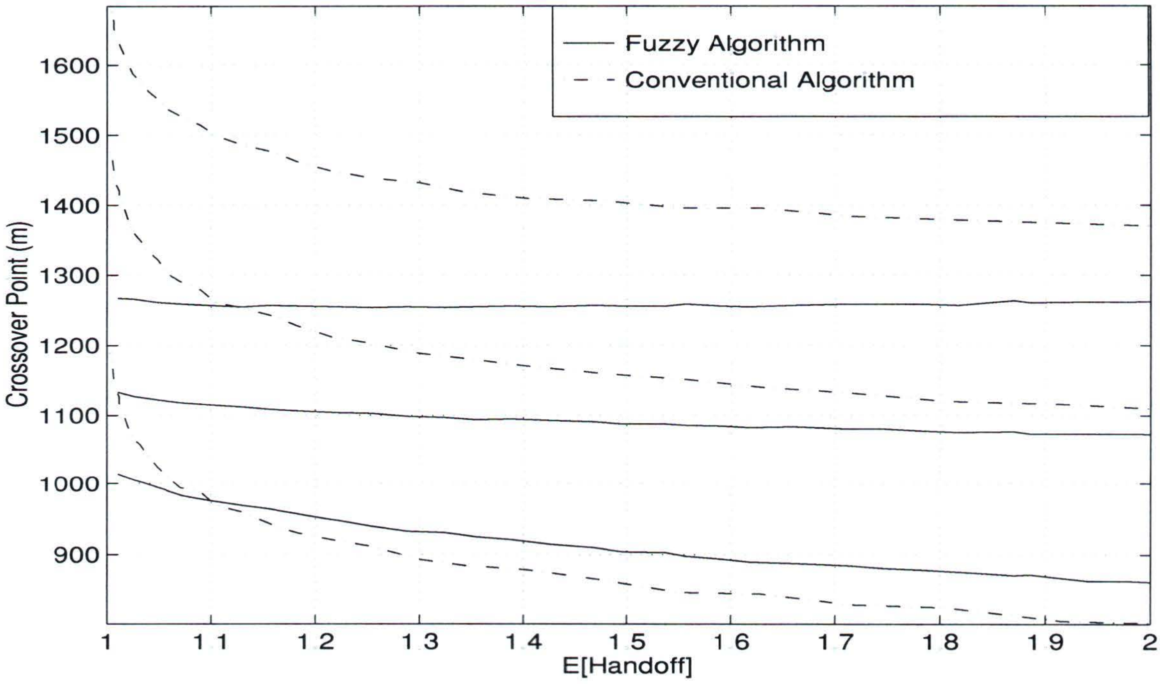


Figure 5.3. Crossover Points for σ=8 dB

This analysis shows that the fuzzy algorithm gives two improvements over the conventional handoff algorithm. First, the 50% crossover point is closer to the 1000 metre point which means the handoff region is more centred between the basestations. Second, the handoff region is narrower. The handoff region is the region where most of the handoffs take place, this is characterized by the probability of the mobile being assigned to any one basestation is not close to unity. The distance between the 10% and 90% crossover points for the fuzzy algorithm is smaller than for the conventional algorithm. The improvement of the fuzzy algorithm over the conventional algorithm becomes larger with increasing values of σ.

These improvements mean the fuzzy algorithm keeps the handoff region close to the designed cell boundary As well, the mobile does not travel far into another cell while being connected to the original cell These improvements allow the co-channel interference from the mobile to other cells to be controlled

This improvement can be attributed to the inclusion of a distance factor into the handoff algorithm However, the inclusion of the BER, or signal quality, factor means that this improvement is made without sacrificing the performance of the mobile channel Figure 5 4, Figure 5 5, and Figure 5 6 show the outage curves for each of the test cases The outage curve gives the mean number of sampling points the RSS from the selected basestation is below -100 dB during a sample run between the two basestations for a given mean number of handoffs

The figures show that the fuzzy algorithm gives fewer outages at all numbers of handoffs

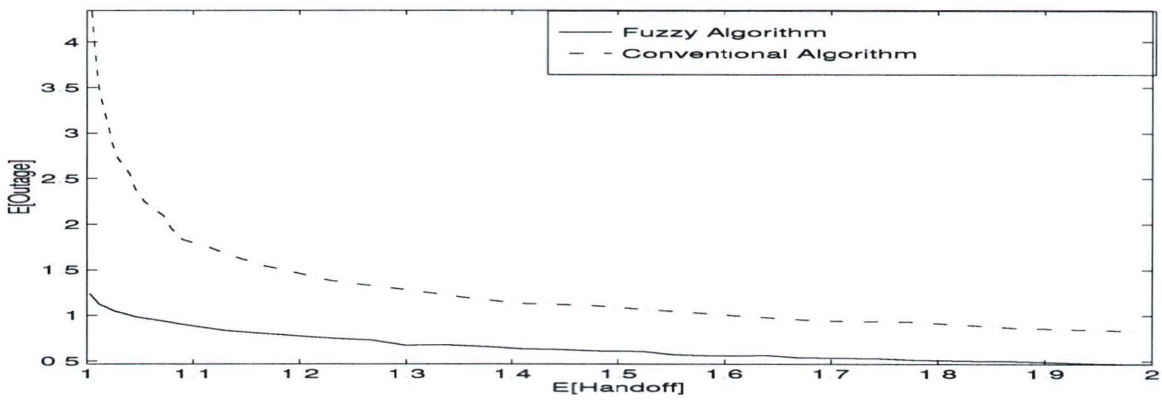


Figure 5.4: Outages for σ=4 dB

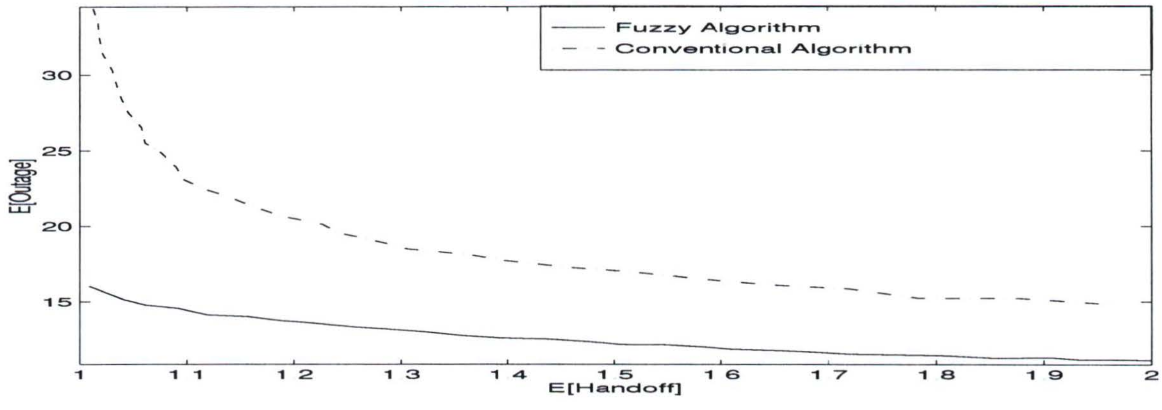


Figure 5 5 Outages for σ=6 dB

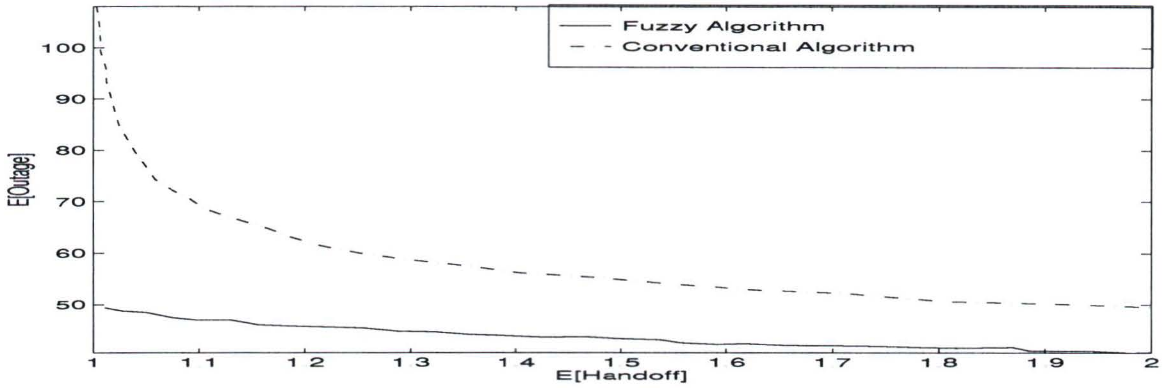


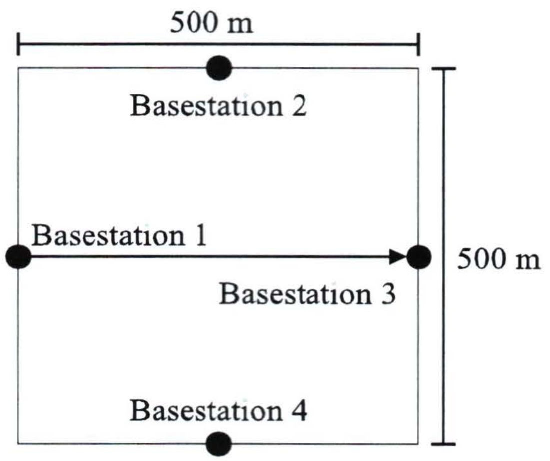
Figure 5 6: Outages for σ=8 dB

The fuzzy algorithm is also evaluated for a four basestation scenario This scenario is used to see how the fuzzy algorithm responds when there are several basestations The simulation configuration is shown in Figure 5 7 The basestation configuration resembles what could be found in an urban cellular network where the basestations need to be close together for capacity reasons At the centre point, there are four basestation that are at the same distance from the mobile This makes the handoff decision very difficult since the measured values of all basestations are very close

The parameters used for both algorithms are shown in Table 5.1. These parameters were selected so that the expected number of handoffs for both algorithms was 1.50.

	Values of Parameters		
σ	4 dB	6 dB	8 dB
a	$20\sqrt{2}$	$20\sqrt{2}$	$20\sqrt{2}$
b	7.15	4.375	2.95
R	250 m	250 m	250 m
h	8.0 dB	13.0 dB	17.5 dB
Floor	-80.0 dB	-80.0 dB	-80.0 dB

Table 5.1: Values of Parameters for Four Basestation Simulation



Mobile moves through centre of square.
Arrow shows mobile motion during simulation.

Figure 5.7: Simulation Configuration for Four Basestations

The handoff performance is measured by the assignment probabilities and the mean RSS from the selected basestations.

The assignment probabilities are shown in Figure 5.8, Figure 5.9, and Figure 5.10. Note that the handoff region for the four basestation case is more centred for the fuzzy algorithm than for the conventional algorithm just as in the two basestation tests. The handoff region is also narrower. The assignment probabilities for basestation two and basestation four overlap.

As can be seen in Figure 5.11, Figure 5.12, and Figure 5.13 the improvements in the handoff region's location and width are achieved without causing a decrease in the mean received signal strength. The results show that for the cases tested the fuzzy algorithm gave superior performance for the same number of handoffs.

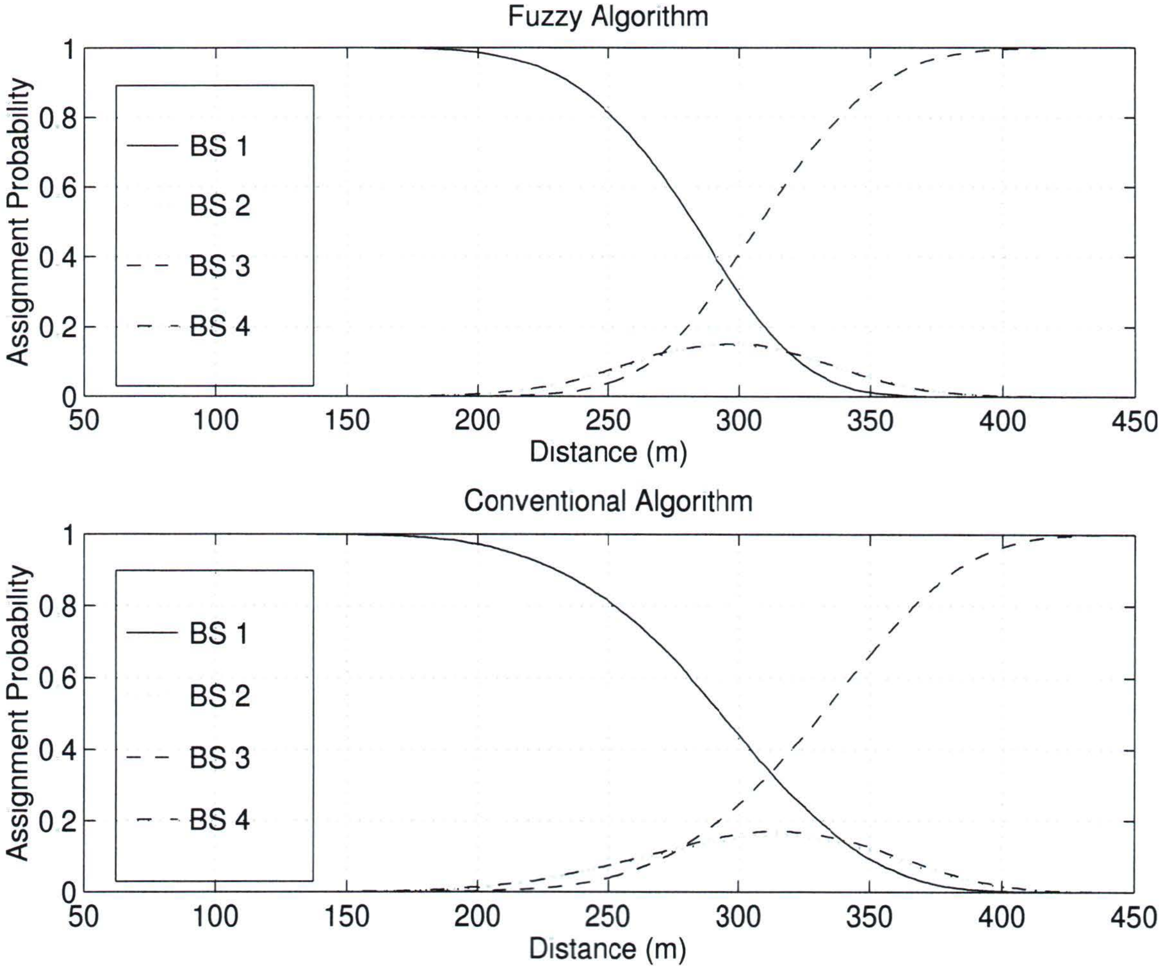


Figure 5.8: Assignment Probabilities for σ=4 dB

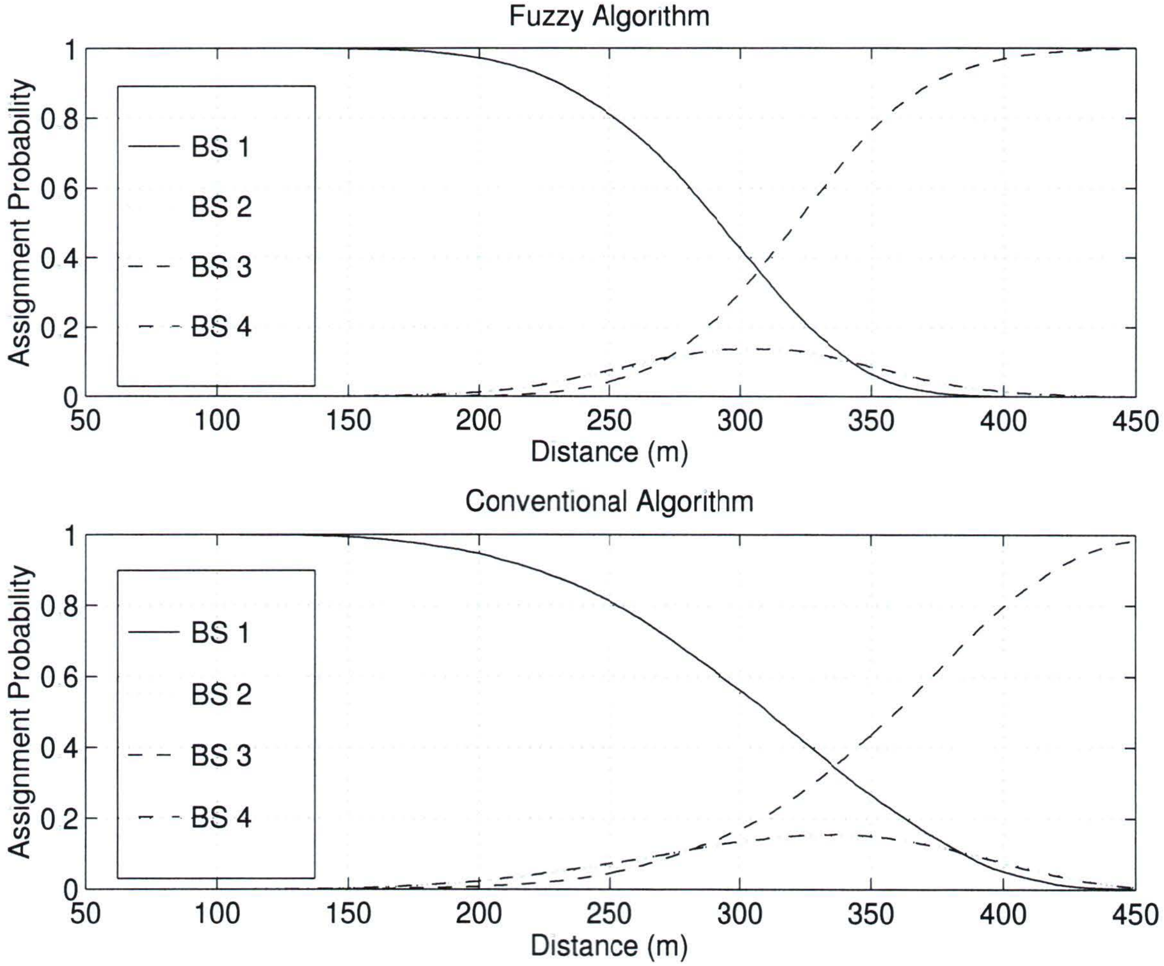


Figure 5.9: Assignment Probabilities for σ=6 dB

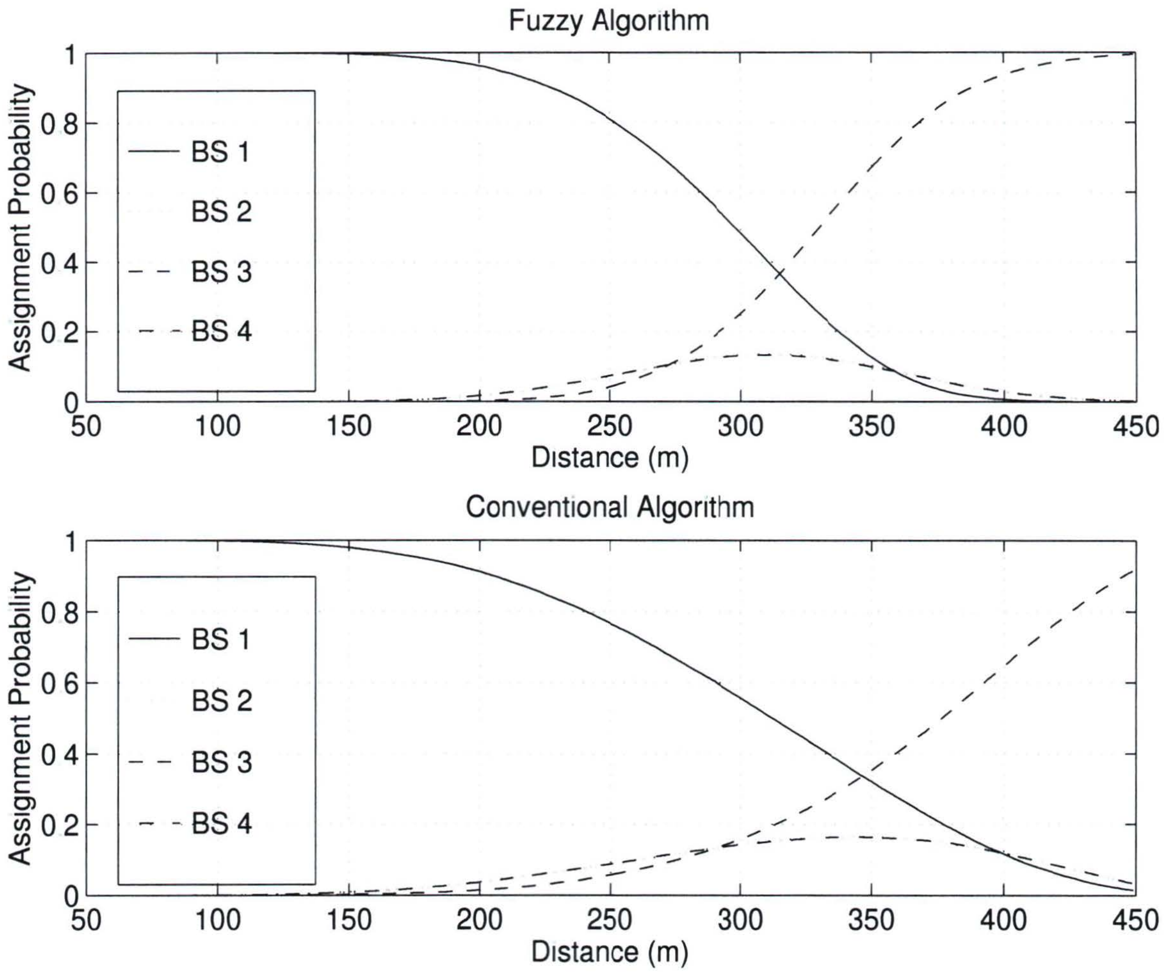


Figure 5.10 Assignment Probabilities for σ=8 dB

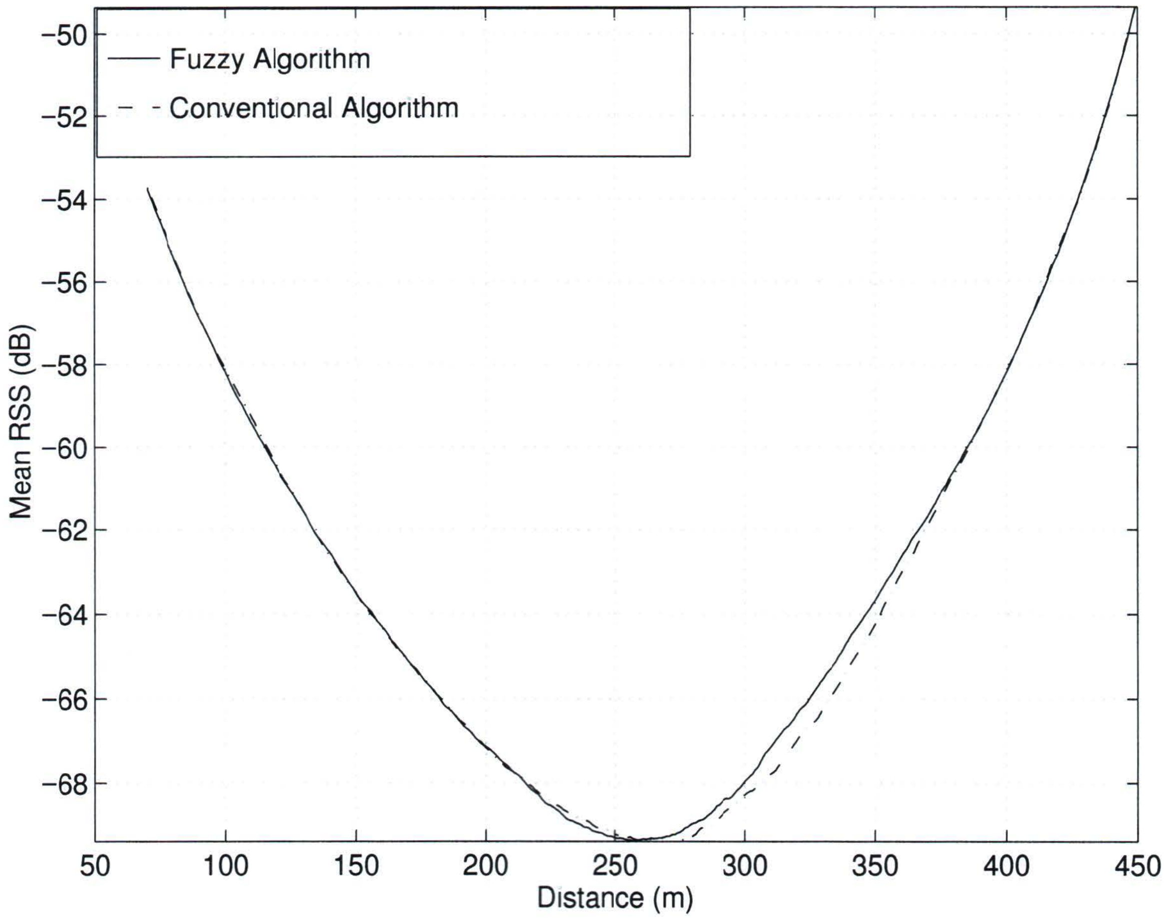


Figure 5.11 Mean RSS when σ=4 dB for Four Basestations

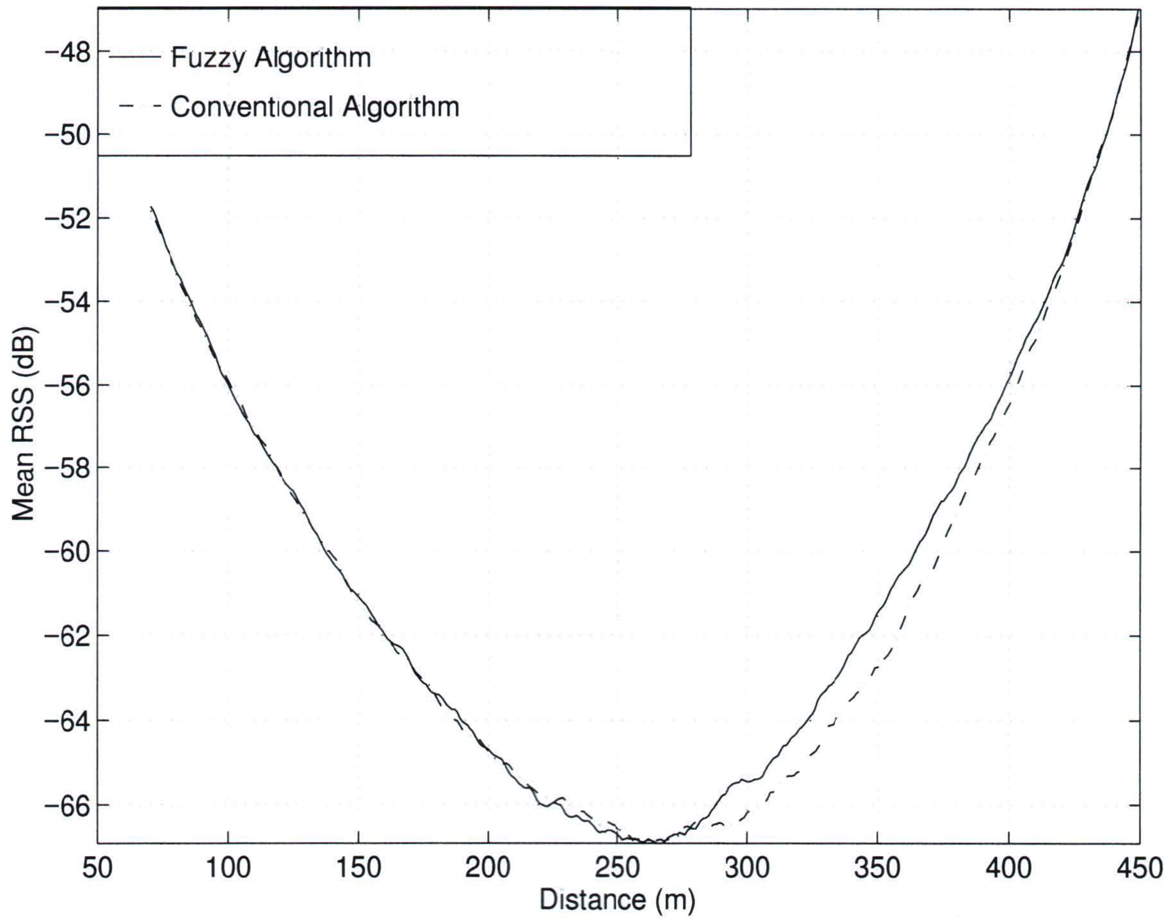


Figure 5.12. Mean RSS when σ=6 dB for Four Basestations

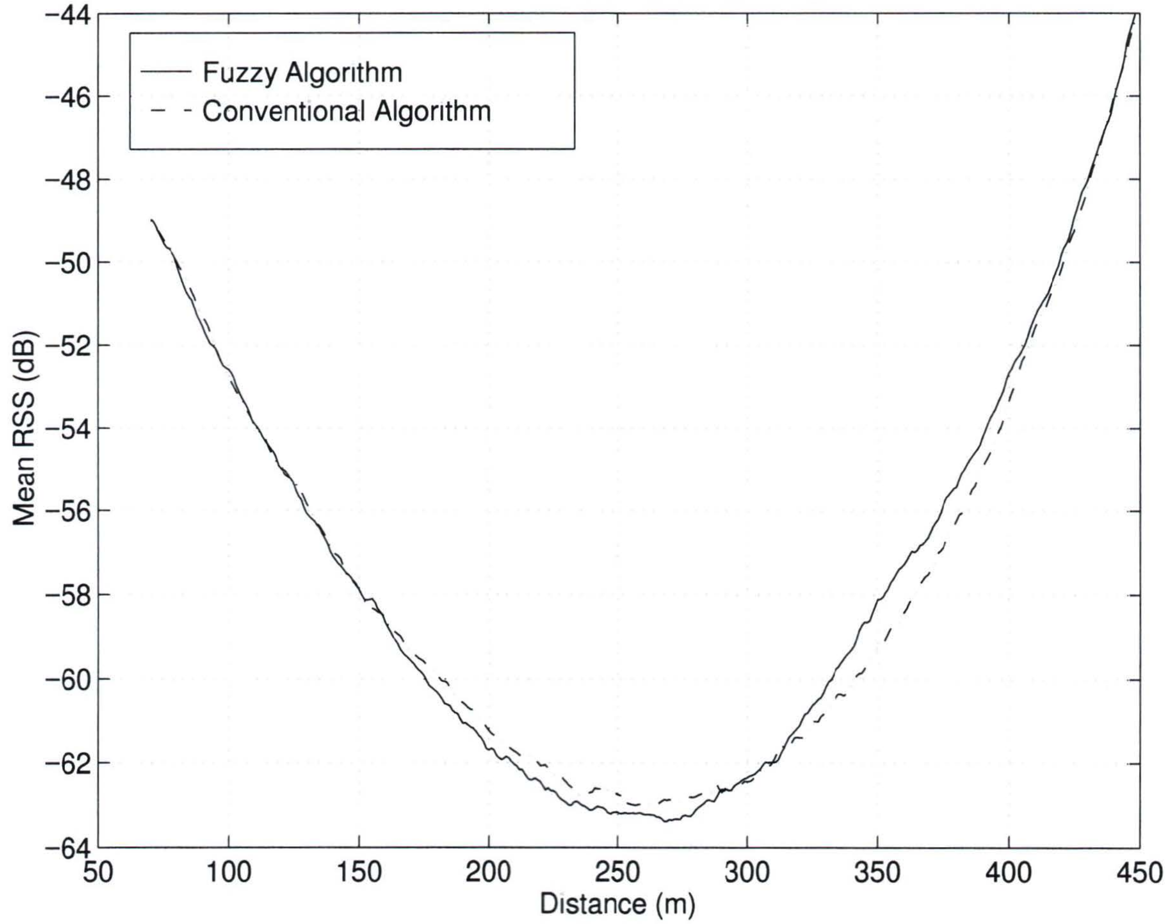


Figure 5.13 Mean RSS when σ=8 dB for Four Basestations

6. Conclusions

The extra intelligence in the mobiles for third generation cellular networks makes the estimation of signal parameters at the mobile terminal possible. This makes the use of a handoff algorithm that requires the adaptation of parameters for different signal conditions feasible.

The conventional handoff algorithm must be tuned carefully for the value of the standard deviation of the shadowing distribution. When the hysteresis level is set to be high, the algorithm will have a low number of handoffs but the mobiles will move far into the surrounding cells before they will be handed off. They will also be transmitting at quite high power while in these other cells. This will cause them to create a large amount of interference to cells assigned the same radio resources, and will thus lower the capacity of the network.

One way to avoid this problem is to adjust the hysteresis level to increase the number of handoffs and reduce the distance mobiles will travel out of the cell before being handed off. This also has the effect of reducing the amount of power required to communicate with the mobiles. A difficulty with this solution is that, for high speed mobiles, that can entail a large number of handoffs, creating a lot of overhead for the network.

Another way to deal with this problem is to use a handoff algorithm which uses information other than the received signal strength to make the handoff decision. Some of this data will have a large amount of imprecision. Fuzzy logic techniques can be used to deal with the imprecision in this data.

This fuzzy logic based handoff algorithm gives better performance than the conventional algorithm. The improvements are increased for low numbers of handoffs.

As well, the fuzzy handoff algorithm triggers handoffs closer to the cell boundary, with the region where most handoffs occur being narrower. This reduces the amount of co-channel interference and increases the capacity of the network.

6.1 Multiple User Types

A problem that third generation cellular networks must face is how to deal with various user types of different mobility classes communicating with different data requirements.

For first and second generation networks, the system was designed for the most stringent data constraints and the highest mobility user. Unfortunately, this results in wasted capacity of the network for users with less restrictive constraints and lower velocities. A third generation network should be able to take advantage of the different user types parameters to increase capacity while satisfying the data constraints.

The fuzzy logic algorithm is very useful for satisfying this property. The algorithm gives good performance even for low numbers of handoffs which makes it useful for high speed users where the number of handoffs must be reduced to avoid excessive overhead.

For the different constraints of different data types the separate parameters of the handoff algorithm for received signal strength and signal quality are very useful. By adjusting the parameters of the membership functions for the fuzzy sets of acceptable signal qualities, the tolerance of the handoff algorithm for different signal conditions can be adjusted. For example, if a certain user's data requires higher quality signal conditions, the handoff algorithm can be tuned to be more aggressive. For users that can tolerate lower signal quality, the handoff algorithm can be tuned to be less aggressive, thus relieving the network of unneeded overhead.

A useful way to think about tuning the handoff algorithm is to consider it as selecting a mean handoff rate for a certain type of user. By increasing the handoff rate, the users get better signal quality but also require more overhead. By reducing the handoff rate, the users get worse signal quality but also require less overhead. The target handoff rate is selected by looking at the user's data requirements and velocity.

This was not done in first generation networks because the handoff delay was quite large and handoff caused undesirable breaks in service. In the second generation networks, only hard boundary checking is done. For example in GSM, if the distance is high and the BER high, then a handoff algorithm is started to find a better basestation[29]. The objective of handoff algorithms in these networks is to reduce the number of handoffs as much as possible. For third generation networks, both these factors are reduced.

6.2 Future Work

There is still a need for considerable work in the area of handoffs for cellular networks. The model of handoffs for the conventional case could be expanded. A proof of the lower bound on the mean should be completed and then the bounds should be tightened if possible.

In this work, it was assumed that there were always available resources in the target cells for handoff calls if one is triggered. The fuzzy handoff algorithm could be modified so that the number of free channels in each cell is considered as a decision criterion.

In this work the topic of soft handoff was only covered briefly. A model of the soft handoff algorithm and how the fuzzy handoff algorithm could be modified to govern soft handoff could be most useful for third generation CDMA cellular networks.

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Appendix A: The Bias from Fast Fading on the Variance Estimator

The variance is estimated from the value given in (3.6), reproduced here for convenience

$$V = E\left\{\left[R(k+1) - R(k)\right]^2\right\} \quad \text{(A.1)}$$

From (3.9), we find the bias from fast fading on V to be

$$Bias = 2\left\{E\left[F_{av}(k)^2\right] - E\left[F_{av}(k)F_{av}(k+1)\right]\right\} \quad \text{(A.2)}$$

With some manipulation, the bias from (A.2) is found to be

$$Bias = 2\left[\sum_{k=0}^{\infty} h(k)^2 - \sum_{k=0}^{\infty} h(k)h(k+1)\right] Var\left[F(k)\right] \quad \text{(A.3)}$$

where $h(k)$ is the impulse response of the averaging filter and $F(k)$ is the contribution of the fast fading to the sampled signal power in interval k. If the digital exponential averaging filter from (2.12) is used, the bias is

$$Bias = 2C_1^2 Var\left[F(k)\right], \quad \text{(A.4)}$$

and if the digital block averaging filter from (2.11) is used the bias is

$$Bias = \frac{2Var\left[F(k)\right]}{N^2} \quad \text{(A.5)}$$

Appendix B: Proof of Upper Bound

First we denote $P(D(k)=A|S(k)=x)$ as a weighting function, $w(x)$. We wish to prove that

$$w(x) = \begin{cases} 0 & x \leq C \\ 1 & x > C \end{cases}, \tag{B.1}$$

gives the highest value for

$$E\left[10^{\frac{A(k)}{10}}\right] = \int_{-\infty}^{\infty} w(x) E\left[10^{\frac{A(k)}{10}} \middle| S(k) = x\right] P\big(S(k) = x\big) dx. \tag{B.2}$$

All, the weighting functions must satisfy the property

$$\int_{-\infty}^{\infty} w(x) P\big(S(k) = x\big) dx = P\big(D(k) = A\big). \tag{B.3}$$

Suppose a better weighting function, $u(x)$, exists. This function can be defined as

$$u(x) = \begin{cases} g(x) & x \leq C \\ w(x) - h(x) & x > C \end{cases}, \tag{B.4}$$

where $g(x)$ and $h(x)$ are positive valued functions. In order for $u(x)$ to give a higher value for $E[10^{A(k)/10}]$, the following relations must be true

$$\int_{-\infty}^{C} g(x) E\left[10^{\frac{A(k)}{10}} | S(k) = x\right] P\big(S(k) = x\big) dx \geq \int_{C}^{\infty} h(x) E\left[10^{\frac{A(k)}{10}} | S(k) = x\right] P\big(S(k) = x\big) dx, \tag{B.5}$$

and

$$\int_{-\infty}^{C} g(x)P(S(k)=x)dx = \int_{C}^{\infty} h(x)P(S(k)=x)dx \tag{B.6}$$

Since $E[10^{A(k)/10}|S(k)=x]$ is monotonically increasing with x, then

$$\int_{-\infty}^{C} g(x)E\left[10^{\frac{A(k)}{10}}\middle|S(k)=x\right]P(S(k)=x)dx \le E\left[10^{\frac{A(k)}{10}}\middle|S(k)=C\right]\int_{-\infty}^{C} g(x)P(S(k)=x)dx\,, \tag{B.7}$$

and

$$\int_{C}^{\infty} h(x)E\left[10^{\frac{A(k)}{10}}\middle|S(k)=x\right]P(S(k)=x)dx \ge E\left[10^{\frac{A(k)}{10}}\middle|S(k)=C\right]\int_{C}^{\infty} h(x)P(S(k)=x)dx \tag{B.8}$$

Combining relation (B.6) with relations (B.7) and (B.8), it can be shown that, at best, relation (B.5) can be met with equality. Therefore, there is no weighting function that can give a higher expected value than (B.1).

Appendix C: Proof of Lower Bound

We will use the notation in Appendix B We want to prove of all weighting functions with the property

$$\forall \Delta x \geq 0, \forall x \quad w(x+\Delta x) \geq w(x)\,, \tag{C 1}$$

that the weighting function

$$w(x) = \begin{cases} 0 & x < -h \\ F & -h \leq x \leq h \\ 1 & x > h \end{cases} \tag{C 2}$$

gives the lowest $E[y(k)]$ All weighting functions must also satisfy the property given in (B 3)

Now we propose that there is another weighting function, $u(x)$, which has the property in (C 1) and gives a lower value This weighting function is defined as

$$u(x) = w(x) + v(x)\,, \tag{C 3}$$

where $v(x)$ is a function with the property given in(C 1)

Now in order for $u(x)$ to satisfy the equation (B 3), $v(x)$ must have a zero at some point We designate this point P It can also be shown that to satisfy (B 3), the following must be true

$$\int_{-h}^{P} v(x)P(S(k)=x)dx = -\int_{P}^{h} v(x)P(S(k)=x)dx \qquad \text{(C 4)}$$

For $u(x)$ to give a lower value of $E[y(k)]$, the following relation must also be true

$$\int_{-h}^{P} E\left[10^{\frac{A(k)}{10}} \middle| S(k)=x\right] v(x)P(S(k)=x)dx < -\int_{P}^{h} E\left[10^{\frac{A(k)}{10}} \middle| S(k)=x\right] v(x)P(S(k)=x)dx \qquad \text{(C 5)}$$

Now, using the fact that the expected values in (C 5) will increase with x, we can write the following

$$\int_{-h}^{P} E\left[10^{\frac{A(k)}{10}} \middle| S(k)=x\right] v(x)P(S(k)=x)dx \geq E\left[10^{\frac{A(k)}{10}} \middle| S(k)=P\right] \int_{-h}^{P} v(x)P(S(k)=x)dx, \qquad \text{(C 6)}$$

and

$$\int_{P}^{h} E\left[10^{\frac{A(k)}{10}} \middle| S(k)=x\right] v(x)P(S(k)=x)dx \geq E\left[10^{\frac{A(k)}{10}} \middle| S(k)=P\right] \int_{P}^{h} v(x)P(S(k)=x)dx \qquad \text{(C 7)}$$

If we use the relations in (C 6) and (C 7) and equation (C 4), we can show that the inequality in (C 5) can not be satisfied. Therefore, the weighting function in (C 2) gives the lowest value for E[$y(k)$]

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