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<th><strong>Project</strong></th>
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<td><strong>Project director</strong></td>
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<td><strong>Title</strong></td>
<td>Cellular Architectures &amp; Resource Management</td>
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<td><strong>Project date</strong></td>
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October 31, 1996

Dr. Darleen Fisher
National Science Foundation
4201 Wilson Boulevard, Rm. 1175
Arlington, Virginia 22230

Dear Dr. Fisher:

Enclosed is the yearly progress report for project NCR-9523969 Cellular Architectures and Resource Management.

Please let me know if you require any further information.

Yours Sincerely,

Gordon L. Stüber
Professor
ANNUAL NSF GRANT PROGRESS REPORT

NSF Program: CISE-NCR
NSF Award Number: NCR-9523969

Pl Name: Gordon L. Stuber
Chin-Tau Lea
Pl Institution: Georgia Tech

Pl Address: School of Electrical and Computer Engineering
Georgia Institute of Technology
Atlanta, GA 30332-0250

XXX Check if Continued Funding is Requested

Date: October 31, 1996

Please Include the Following Information:

1. Brief summary of progress to date and work to be performed during the succeeding period;
2. Statement of funds estimated to remain unobligated --if more than 20%-- at the end of the period for which NSF currently is providing support (not required for participants in the Federal Demonstration Project);
3. Proposed budget for the ensuing year in the NSF format, only if the original award letter did not indicate specific incremental amounts or if adjustments to a planned increment exceeding the greater of 10% or $10,000 are being requested;
4. Current information about other research support of senior personnel, if changed from the previous submission;
5. Any other significant information pertinent to the type of project supported by NSF or as specified by the terms and conditions of the grant;
6. A statement describing any contribution of the project to the area of education and human-resource development, if changed from any previous submission; and
7. Updated information on animal care and use, Institutional Biohazard Committee and Human Subject Certification, if changed substantially from those originally proposed and approved.

I certify that to the best of my knowledge (1) the statements herein (excluding scientific hypotheses and scientific opinions) are true and complete, and (2) the text and graphics in this report as well as any accompanying publications or other documents, unless otherwise indicated, are the original work of the signatories or individuals working under their supervision. I understand that the willful provision of false information or concealing a material fact in this report or any other communication submitted to NSF is a criminal offense (U.S. Code, Title 18, Section 1001.)

P.I. Signature:

NSF Form 1328 (1/94)
Cellular Architectures
and Resource Management

Progress Report for
NCR-9523969

Prepared for
National Science Foundation

Prepared by
Gordon L. Stüber and Chin-Tau Lea
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Darleen Fisher and Aubrey Bush
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4201 Wilson Boulevard, Rm 1175
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October 1996
1 Summary of Progress

This project addresses the following three issues i) cellular architectures, ii) link quality evaluation and handoff algorithms, and iii) distributed dynamic channel assignment. The following progress has been made to date. Publications that have been supported from this project are listed at the end of this section. Copies of these publications (manuscripts if submitted) are attached.

Hierarchical Cellular Architectures

An innovative hierarchical microcell/macrocell architecture has been developed [1]. By applying the concept of cluster planning, the proposed sectoring arrangement can provide good shielding between micro- and macro-cells. As a result, underlaid microcells can reuse the same frequencies as overlaying macrocells without decreasing the macrocell system capacity. With the proposed method, microcells not only can be gradually deployed, but they can be extensively installed to provide complete coverage and increase capacity throughout the service area. With these flexibilities, the proposed method allows existing macrocellular systems to evolve smoothly into a hierarchical microcell/macrocell architecture.

Macrodiversity Cellular Architectures

In a macrodiversity cellular system, switching radio links between base stations cannot be done instantaneously. Thus branch selection is usually based on the measurement of the slowly-varying local mean power rather than the rapidly-varying instantaneous signal power. We have developed an exact mathematical model to analyze the performance of a local-mean-based macrodiversity cellular system in a shadowed-Rician (desired) /shadowed-Rayleigh (interfering) channel [2,3]. We have
investigated the impact of both fading (Rician or Rayleigh) and shadowing in terms of co-channel interference (CCI) probability. An analytical model has also been developed to incorporate the effects of branch correlation on macrodiversity systems.

Publications


2 Objectives for Next Year

The following items will be addressed during the next year.

SIR-based handoff algorithms

A new algorithm to estimate the signal-to-(interference ratio plus noise) ratio $S/(I+N)$ will developed for TDMA cellular systems. Initial simulation results show that the $S/(I+N)$ can be estimated to within 0.5 dB in less than half a second for high speed mobiles. We believe that the $S/(I+N)$ is a better handoff criterion that $S+I+N$, since it reflects the true radio link quality. This research will differ from existing studies by combining a handoff algorithm with particular $S/(I+N)$ estimation techniques. Several SIR-based handoff algorithms will be studied and their performance evaluated through software simulation. Initial results suggest that the proposed SIR-based
handoff algorithms can achieve near perfect handoff performance for macrocell deployments.

Cellular Architectures with Smart Antennas

Smart antennas based on adaptive null steering, adaptive beam steering, or beam switching have gained enormous interest in the cellular industry. Smart antennas lead to capacity gains through the effective control of co-channel interference. The use of smart antennas in hierarchical and macrodiversity cellular architectures has not been studied before. By employing smart antennas at the base stations in our newly developed hierarchical cellular architecture (see reference [1] above), it may be possible to recover most of the macrocell performance degradation that is caused by the cell sector rotations. In fact, it may even be possible to reduce the basic reuse cluster size from a 7-cell reuse cluster to a 4-cell reuse cluster. Application of smart antennas to macrodiversity architectures is also a possibility and will lead to further capacity gains. In this part of the study, we will investigate the use of smart antennas in hierarchical and macrodiversity cellular architectures. Emphasis will be initially directed toward switched-beam smart antennas, since they are the simplest and most economical to implement and deploy.

Performance of a new macrodiversity cellular network

We will continue the investigation of the new macrodiversity network architecture described in our proposal. Our study will focus on the unique characteristic of the network: mobility and capacity are convertible. In the new architecture, a request of the network to support higher mobility is the same as request for more bandwidth; conversely, the network’s capacity will increase if the average level of subscriber mobility drops. In the coming year, we will investigate the capacity gain of the new
network created by this unique property.

Modeling Mobility in Power Control

One of the elements missing in most literature related to power control is mobility. Without it, the performance of a power control scheme and its convergence cannot be reliably predicted. We will explore the random walk model to model mobility in wireless communications. Combining the mobility model with a conventional CCI analysis, we will study power control in a more dynamic environment. The power control schemes we will focus on are linear schemes where the transmitting power adjustment is a linear function of the deviation of the received signal from the target level. We will focus on two implementations of a linear scheme: incremental and direct compensation. In the former, the adjustment is done one notch at a time; in the latter, a direct compensation is given immediately. The issues to be studied include the effect of mobility, the slope of the linear power control, and the inter-relationship between CCI and power consumption.

Modeling Voice Activity Effect

The next step is to extend the mobility model to study the effect of voice activity on power saving and outage probability. Voice activity detection has been used in GSM to save power. It can also reduce interference. The problem is the lack of a suitable model to evaluate the gain of both in a dynamic environment. The mobility model we develop above can be extended to study this problem. We intend to construct a Markov model for voice activity and another for mobility. We combine the two and evaluate the performance gain in terms of power saving and interference reduction. We then add power control and see how much further improvement to be gained by combing the two in a wireless network.
3 Education and Human Resource Development

The following Ph.D. students have been supported from this grant:

- **Li-Chun Wang** – completed his Ph.D. and is now with AT&T Research, Crawford Hill Laboratory, Holmdel NJ.

- **Kai-Wei Ki** – completed his Ph.D. and is now an Associate Professor, Dept of EE, Taipei Institute of Technology, Taipei, Taiwan.

- **Mustafa Turkboylari** – new Ph.D. student that has started his Ph.D. program in January 1996 under the supervision of Prof. Stüber.

- **Chi-Jui Ho** – new Ph.D. student that has started her Ph.D. program under the supervision of Prof. Lea.
Architecture Design, Frequency Planning, and Performance Analysis for a Microcell/Macrocell Overlaying System

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Abstract

An innovative hierarchical microcell/macrocell architecture is presented. By applying the concept of cluster planning, the proposed sectoring arrangement can provide good shielding between micro- and macro-cells. As a result, underlaid microcells can reuse the same frequencies as overlaying macrocells without decreasing the macrocell system capacity. With the proposed method, microcells not only can be gradually deployed, but they can be extensively installed to provide complete coverage and increase capacity throughout the service area. With these flexibilities, the proposed method allows existing macrocellular systems to evolve smoothly into a hierarchical microcell/macrocell architecture.

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1This research was supported by Nortel and the National Science Foundation under contract NCR-9523969. It was completed while Dr. Li-Chun Wang was a Ph.D. student at Georgia Tech.
I Introduction

Hierarchical microcell/macrocell architectures have been proposed for future personal communications systems [1]. These architectures provide capacity relief to a macrocell system and offer many advantages over a pure microcell system. Unlike the pure microcell system, which requires extensive microcell base station (BS) deployment throughout the whole service area, a hierarchical architecture allows gradual deployment of microcells as user demand increases. The hierarchical architecture also protects investment cost in the existing macrocellular system, while a pure microcell system requires replacement of the macrocell BSs. Furthermore, the fast handoff requirement in a pure microcell system can be relieved in the overlaying architecture by temporally connecting the call to a macrocell BS [2].

The method of sharing the radio spectrum is the key issue for hierarchical microcell/macrocell systems. Different kinds of frequency sharing schemes have been proposed in the literature [3, 4, 5]. Orthogonal sharing partitions the frequency channels into two disjoint sets: one for macrocells and one for microcells [3]. Channel borrowing requires that the underlaid microcells utilize the free channels of adjacent macrocells [4]. A overlaying scheme that combines dynamic channel allocation (DCA) and power control is proposed in [5]. Each of the above schemes has some problems. Orthogonal sharing [3] decreases the macrocell system capacity if the available spectrum has already been assigned to macrocells. Channel borrowing [4] can only relieve hot spot traffic, but it is ineffective if the neighboring cells also have heavy traffic. The scheme in [5] requires power control (both uplink and downlink) and DCA, both of which will increase implementation cost.

This paper introduces an innovative hierarchical microcell/macrocell architecture to circumvent the above trade-offs. Under the proposed architecture, microcells can reuse the macrocell frequencies and will not decrease the macrocell system capacity. Furthermore, unlike the channel borrowing scheme, which is effective only when the neighboring cells have free channels, the proposed architecture allows the microcells to be deployed throughout the
whole service area regardless of the traffic loading of the neighboring macrocells. Compared to the system in [5], our architecture neither requires DCA nor downlink power control.

The remainder of this paper is organized as follows. Section II describes the system architecture. Section III offers a frequency planning algorithm that identifies the low-interference macrocell frequencies can be used in the microcells. Section IV describes the propagation model and system assumptions. The co-channel interference performance of the overlaying macrocells and underlaid microcells are discussed in Section V and Section VI. The adjacent channel interference is discussed in Section VII. We conclude our discussion in Section VIII.

II System Architecture

Fig. 1 shows a traditional 3-sector \( N = 7 \) cellular system, where each cell consists of three sectors and \( N \) is the number of cells per cluster. In this system the total channels are partitioned into 21 sets. The channel sets are assigned to the sectors so as to satisfy the frequency reuse constraint, e.g., channel set \( 4_3 \) in Fig. 1. The widely distributed co-channel interference makes it difficult to reuse the channel sets outside of their designated sectors. In the following we introduce a cluster planning procedure to change the conventional sectoring scheme into a new structure.

Cluster planning procedure:

1. Assign the same channels to each cell site as in the traditional 3-sector \( N = 7 \) cellular system (Fig. 1), where seven cells form a cluster and share the entire spectrum;

2. Divide macrocell clusters into three adjacent groups (Fig. 2);

3. Let the first group be the reference group;

4. Rotate the channel sets of the sectors in the second group \( 120^\circ \) clockwise with respect to the first group;
5. Rotate the channel sets of the sectors in the third group 120° counter-clockwise with respect to the first group.

Based on the above procedure, the sector rotations create low-interference regions outside the areas of the designated macrocell sectors for each channel set. These low-interference regions are called micro-areas. Fig. 3 shows the result of rotating the sectors. We see that zones A ~ F have a very low interference for channel set 4β, since they are located in the back-lobe areas of the macrocell sectors using channel set 4β. Thus microcells can be introduced in these areas that use channel set 4β.

III Underlaid Microcell Planning Algorithm

As shown in Section II, microcells in the proposed architecture that are located in micro-areas can reuse certain macrocell channel sets. To have a greater flexibility in selecting the microcell BS locations, it is important that we identify all possible micro-areas and the channels sets they can use. In our system, macrocells use frequencies on the front-lobe area of their directional antennae, while microcells reuse the same frequencies on the back-lobe area. In the conventional 3-sector N = 7 cellular system (Fig. 1), the back-lobe area of each channel set will still encounter some first-ring interferers. To protect the back-lobe areas from the first tier interferers, we rotate the sectors through the cluster planning procedure described in Section II. Cluster planning creates low-interference micro-areas as shown in Fig. 3, that lie in the back-lobe areas of the first-tier interferers. For ease of indexing, a micro-area denotes a region of three adjacent macrocell sectors, each of which belongs to different BS. Fig. 4 shows an example of a micro-area. Each micro-area has an interference neighborhood, defined as the 18 neighboring macrocell sectors that surround the micro-area.

Let Ψ\textsuperscript{i} represent the channel set in the sector \(i = \alpha, \beta, \text{and} \gamma\) of cell site Ψ (Ψ = 1 to 7); associate the superscript \(j\) in Ψ\textsuperscript{i} \(j = 1\) to 3) with three types of cluster rotations, \(-120°, 0°,\) and \(120°\). Then the following interesting observation can be made:
**Observation:** Consider a micro-area and its interference neighborhood. A micro-area can be located in the back-lobe area of the sectors using channel sets $\Psi^i_j$ and $\Psi^i_{1-j}$ ($j = 1$ to $3$), if and only if it is surrounded by the main-lobe of three co-channel macrocell sectors using channel set $\Psi^i_0$ ($j = 1$ to $3$).

Based on the above observation, the following algorithm has been developed to determine the macrocell channel sets that can be reused in a micro-area.

**Macrocels channel selection algorithm:**

- Objective: identify low-interference macrocell channels that can be reused in the underlaid microcells.

- For any micro-area and its interference neighborhood $M$, let

  $$\Theta = \{ \Psi^i_j \in M \}$$

  denote the union of channel sets $\Psi^i_j$ that are used in $M$.

- From $\Theta$, a $3 \times 3$ indicator matrix $B_\Psi = [b_{ij}]$ is constructed for cell cites $\Psi = 1$ to $7$, where

  $$b_{ij} = \begin{cases} 1 & \text{if the channel set } \Psi^i_j \in M; \\ 0 & \text{otherwise.} \end{cases}$$

- If a certain indicator matrix $B_\Psi$ has a row of ones and two rows of zeros, then the zero-rows of $B_\Psi$ correspond to the macrocell channel sets available for the micro-area.

**Example:** We illustrate the above algorithm by the following example. According to Figs. 3 and 4, the interference neighborhood of micro-area $A$ is

$$\Theta = \left\{ 1^2_\alpha, 1^2_\beta, 1^2_\gamma, 2^2_\alpha, 2^2_\beta, 2^2_\gamma, 3^2_\alpha, 3^2_\beta, 3^2_\gamma, 3^2_\alpha, 4^2_\alpha, 4^2_\beta, 4^2_\gamma, 5^1_\alpha, 5^1_\beta, 5^1_\gamma, 6^2_\alpha, 6^2_\beta, 6^2_\gamma, 7^2_\alpha, 7^2_\beta, 7^2_\gamma \right\}.$$
The indicator matrices are

\[
B_1 = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{pmatrix} \quad B_2 = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{pmatrix} \quad B_3 = \begin{pmatrix} 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \\
B_4 = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad B_5 = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix} \quad B_6 = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix} \\
B_7 = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{pmatrix}
\]

Examination of the indicator matrices \(B_\Psi (\Psi = 1 \text{ to } 7)\), reveals that \(B_4\) is the only matrix having a row of ones and two rows of zeros; the second row and the third rows of \(B_4\) are the zero-rows. According to the above algorithm, \(4_3\) and \(4_7\) are the low-interference macrocell channel sets available for use in micro-area \(A\). To see if microcells can be established in any location, we have examined a system with more micro-areas in Fig. 5. Through the above channel selection algorithm, Table 1 shows that each micro-area in the service area can reuse two macrocell channel sets. Recall that a macrocell area represents an area of three macrocell sectors, each of which belongs to three different cell sites. Thus a macrocell area can has five channel sets – three for macrocells and two for microcells. In a macrocell area, each of three macrocell sectors reuses its channel sets only once, while a micro-area can reuse its two macrocell channel sets many times, say \(C_\mu\) times, with a suitable co-channel reuse distance. Thus it is implied that a macrocell area can use \(3 + 2 \times C_\mu\) channel sets simultaneously. Compared with three channel sets in the conventional three-sector macrocell, the system capacity of the proposed architecture increases by a factor of \(1 + 2 \times C_\mu/3\) times.
IV Propagation Model and System Assumptions

IV-A Propagation model

Our analysis considers the simple path loss model \[8\]

\[ p_r = \frac{p_t (h_b h_m)^2}{d^4}, \]  

(1)

where \(p_r\) and \(p_t\) are the received and transmitted powers, \(h_b\) and \(h_m\) are the antenna heights of the base station (BS) and the mobile station (MS), respectively, and \(d\) is the distance between the transmitter and receiver. Note that we incorporate the antenna gains in the transmitted power. Although (1) is derived from a macrocell environment, it is still characteristic of the path loss outside of the microcells \[3\].

IV-B Assumptions

Interference: In the hierarchical architecture, we consider four types of co-channel interference. In addition to the usual macrocell-to-macrocell and microcell-to-microcell co-channel interference, we must also consider macrocell-to-microcell and microcell-to-macrocell co-channel interference. Adjacent channel interference is also discussed in Section VII.

Antenna: The macrocell BSs are assumed to use 120° directional antennae, while microcell BSs use omni-directional antennae. The MS also use omni-directional antennae.

Uplink power control: In this paper, we adopt the power control scheme used in IS-54 and AMPS \[7\]. The transmitted power of Class IV IS-54 portable handsets is adjusted in six levels from -22 dBW to -2 dBW in steps of 4 dB. Downlink power control is not required in the proposed architecture. Before proceeding, we first clarify our notation. When \(M\) and \(\mu\) are used, they represent macrocells and microcells, respectively; when \(m\) and \(b\) are used, they denote the MS and BS, respectively; when \(d\) and \(u\) are used, they indicate the downlink (BS-to-MS) and uplink (MS-to-BS), respectively.
V Macrocell Performance

As shown in Section II, the new cluster planning technique with sector rotation can create some low interference regions so that microcells can reuse macrocell frequencies. Nevertheless, some macrocells will experience higher interference after rotating the sectors. To evaluate the influence of the sector rotations on the macrocell performance, we simulate both the conventional macrocellular system (Fig. 1) and the proposed hierarchical cellular system (Fig. 3) without the underlaid microcells. Fig. 6 shows the simulation results of the uplink signal-to-interference (S/I) performance for both systems, assuming that the MSs are uniformly distributed in each sector and they transmit with the maximum power. We consider the uplink case because performance is usually better in the downlink than in the uplink [3]. With respect to 90% coverage probability, one can observe that the sector rotation technique creates low interference regions at the cost of about 3.1 dB, 3.3 dB, and 3.5 dB of S/I degradation for path loss exponent $\beta = 3.6, 3.8, \text{and } 4.0$. It is noteworthy that even after sector rotations, the macrocell can maintain S/I higher than 20 dB in 90% of the coverage area. In the following, we further include the underlaid microcells to analyze the performance of the proposed hierarchical cellular system. For ease of analysis, we hereafter adopt the worst case scenario, i.e., when a MS is on the cell boundary.

V-A Downlink co-channel interference analysis

By applying (1), we express the signal-to-interference ratio (S/I) received by the MS at the macrocell boundary as

$$\frac{S_M^d}{I_M^d + J_{\mu M}^d} = \frac{p_{t,b}M(h_b^{M}h_m)^2}{R_M^4} - \sum_{i=1}^{N_M} p_{t,b}M(h_b^{M}h_m)^2 \frac{Z^\mu}{D_i^4} + \sum_{j=1}^{C^\mu} \sum_{k=1}^{p_{t,b}M(h_b^{M}h_m)^2} \frac{d_{jk}^4}{D_i^4}$$

where
\[ S_M^d = \text{MS received power from the desired macrocell BS} \]
\[ I_M^d = \text{downlink macrocell-to-macrocell interference} \]
\[ J_{\mu M}^d = \text{downlink microcell-to-macrocell interference} \]
\[ P_{t, b}^M = \text{macrocell BS transmitted power} \]
\[ P_{t, b}^\mu = \text{microcell BS transmitted power} \]
\[ N_M = \text{the number of macrocell interferers} \]
\[ Z_u = \text{the number of interfering micro-areas} \]
\[ C_\mu = \text{the number of microcell clusters in a micro-area} \]
\[ D_i = \text{MS distance to the} \ i\text{-th interfering macrocell BS} \]
\[ d_{j, k} = \text{MS distance to the} \ k\text{-th interfering microcell BS in the} \ j\text{-th micro-area} \]
\[ h_b^M = \text{macrocell BS antenna height} \]
\[ h_b^\mu = \text{microcell BS antenna height} \]
\[ h_m = \text{MS antenna height} \]
\[ R_M = \text{macrocell radius} \]

Referring to Fig. 5 and Table 1, we examine the downlink interference when a macro-cell MS using channel set \(1_\beta\) is located at the macrocell boundary near micro-area 56. One can find that the macrocell-to-macrocell downlink interference \(I_M^d\) mainly comes from two first-tier macrocell BSs near micro-areas 77 and 68 with distances \([D_1, D_2] = [4, 3.61]R_M\). However, we also consider the three second-tier interfering BSs near micro-areas 11, 17 and 62 at distances \([D_3, D_4, D_5] = [8.89, 8.89, 8.72]R_M\). For the microcell-to-macrocell downlink interference \(J_{\mu M}^d\), one can find six interfering micro-areas 35, 48, 54, 80, 86, and 99 in the first tier with distances \([\bar{d}_1, \bar{d}_2, \bar{d}_3, \bar{d}_4, \bar{d}_5, \bar{d}_6] = [3, 4.58, 3.46, 6, 5.2, 6.25]R_M\). The second-tier interfering micro-areas 3, 29, 41, and 92 have distances \([\bar{d}_7, \bar{d}_8, \bar{d}_9, \bar{d}_{10}] = [7.55, 9, 7.94, 12]R_M\). We assume that each micro-area has \(C_\mu\) microcell reuse clusters, with each cluster having \(K_\mu\) microcells. Through the channel selection algorithm in Section III, each micro-area is assigned two macrocell channel sets. We further partition these two sets of channels into
$K_{\mu}$ groups and then assign each group to the $K_{\mu}$ microcells in each cluster. In this manner, a macrocell channel set is used $C_{\mu}$ times in a micro-area. For ease of analysis, we assume that the distance $\bar{d}_j$ approximates $d_{j,k}$, where $\bar{d}_j$ is the distance from a macrocell MS to the center of the $j$-th interfering micro-area and $d_{j,k}$ is defined in (2). In our example, the microcell BS antenna height is one third of macrocell BS antenna height, i.e., $h_b^\mu/h_b^M = 1/3$.

With the above assumptions in (2),

$$\frac{S_M^d}{I_M^d + J_{\mu M}^d} = \frac{1}{1.02875 \times 10^{-2} + C_{\mu} \left(\frac{P_{t,b}^\mu}{P_{t,b}^M}\right) \times 2.79449 \times 10^{-3}}. \quad (3)$$

We show the downlink S/I performance in terms of $C_{\mu}$ and $P_{t,b}^\mu/P_{t,b}^M$ in Fig. 7 with consideration of only first-tier interfering BSs and in Table 2 with both first- and second-tier interfering BSs. Observe that S/I $\geq$ 18 dB for $C_{\mu} = 6$ and $P_{t,b}^\mu/P_{t,b}^M \leq 0.3$. In other words, the channel set $4_{\beta}$ can be reused six times in the micro-area while still keeping the macrocell downlink S/I greater than 18 dB. Furthermore, by comparing the results in Table 2 with Fig. 7, one can find that the second-tier interfering BSs only degrade the S/I by about 0.5 dB.

V-B Uplink co-channel interference analysis

By modifying (2) slightly, we can formulate the uplink S/I performance as

$$\frac{S_M^u}{I_M^u + J_{\mu M}^u} = \frac{P_{t,m}^M (h_b^M h_m)^2}{\sum_{i=1}^{N_M} P_{t,m,i}^M (h_b^M h_m)^2 + \sum_{j=1}^{\infty} \sum_{k=1}^{\infty} C_{\mu} P_{t,m,i}^\mu (h_b^M h_m)^2 / d_{jk}^4} \quad (4)$$

where

$S_M^u$ = macrocell BS received power from the desired MS

$I_M^u$ = uplink macrocell-to-macrocell interference

$J_{\mu M}^u$ = uplink microcell-to-macrocell interference

$P_{t,m}^M$ = macrocell MS transmitted power

$P_{t,m}^\mu$ = microcell MS transmitted power
with the other parameters defined following (2). With directional antennae, the macrocell BSs experience fewer interfering micro-areas in the uplink direction as compared with the downlink direction. Consider the macrocell sector that is assigned with channel set $2\gamma$ and near micro-area 37. This macrocell sector encounters two first-tier and four second-tier macrocell interfering MSs with $[D_1, D_2, D_3, D_4, D_5, D_6] = [3.61, 3.61, 8.54, 8.19, 8.19, 7.81]R_m$, and interfering micro-areas 23, 55, 61, 68, 74, 100, (i.e. $Z_\mu = 6$) with $[d_1, d_2, d_3, d_4, d_5, d_6] = [7.0, 7.0, 14.7, 5.3, 11.5, 9.53]R_m$. We ignore the effect of the three other interfering micro-areas 4, 17, 49 because they are located in the back-lobe area of the sector using channel set $2\gamma$. By substituting the above values into (4), the uplink S/I performance for this example becomes

$$\frac{S_{uM}^u}{J_{uM}^u + J_{\mu M}^u} = \frac{1}{1.2677 \times 10^{-2} + C_\mu \left( \frac{p_{\mu M}}{p_{t,m}} \right) \times 2.11 \times 10^{-3}}. \tag{5}$$

Fig. 8 shows the results. It is observed that S/I is higher than 18 dB for $C_\mu = 1 \sim 6$ if

$$\frac{p_{\mu M}}{p_{t,m}} \leq 0.2 \tag{6}.$$

Note that we obtained (6) by assuming that the interfering macrocell MSs are on the cell boundary and are transmitting with the maximum power. Thus (6) can be used to determine the maximum microcell MS's transmitted power. For the IS-54 Class IV portable handset (that adjusts its transmitted power in six levels from -22 dBW to -2 dBW), (6) implies that the maximum microcell MS transmitted power is -9 dBW, which is still in the operation range of the Class IV terminal. Thus the requirement in (6) can be fulfilled by the current uplink power control scheme in IS-54 system without changing the MS transmitted power specification.

VI Microcell Performance

This section studies how to determine the microcell size to achieve the required S/I performance.
VI-A Downlink microcell size

A feasible microcell size should satisfy two conditions: (1) \textit{S}-criterion: a MS will receive stronger power, \(S\), at the microcell boundary than at the macrocell boundary; (2) \textit{S/I}-criterion: the signal-to-interference ratio (S/I) at the microcell boundary is equal to or better than that at the macrocell boundary.

\textbf{S-criterion:} From path loss model in (1), the microcell radius \(R_\mu\) can be calculated as

\[
R_\mu \leq \left[ \left( \frac{p_{t,b}^\mu}{p_{t,b}^M} \right) \left( \frac{h_b^\mu}{h_b^M} \right)^2 \right]^{1/4} R_M,
\]

where \(R_M\), \(h_b^\mu\), \(h_b^M\), \(p_{t,b}^\mu\), and \(p_{t,b}^M\) are defined in (2).

\textbf{S/I-criterion:} The S/I received by the MS at the microcell boundary can be written as

\[
\frac{S_\mu^d}{I_\mu^d + J_{M_\mu}^d} = \frac{p_{t,b}^\mu (h_{\mu,b}h_m)^2}{\sum_{i=1}^{C_\mu} \frac{p_{t,b}^\mu (h_{\mu,b}h_m)^2}{D_{\mu,i}^4} + \sum_{i=1}^{N_{M,F}} \frac{p_{t,b}^M (h_{M,b}h_m)^2}{D_{M,F,i}^4} + \frac{1}{\eta} \left( \sum_{i=1}^{N_{M,B}} \frac{p_{t,b}^M (h_{M,b}h_m)^2}{D_{M,B,i}^4} \right)}
\]

where the parameters \(p_{t,b}^\mu\), \(p_{t,b}^M\), \(h_b^\mu\), \(h_b^M\), \(C_\mu\), and \(h_m\) are already defined in (2) and

- \(S_\mu^d\) = MS received power from its desired microcell BS,
- \(I_\mu^d\) = downlink microcell-to-microcell interference,
- \(J_{M_\mu}^d\) = downlink macrocell-to-microcell interference,
- \(N_{M,F}\) = the number of main-lobe macrocell interferers,
- \(N_{M,B}\) = the number of back-lobe macrocell interferers,
- \(D_{M,F,i}\) = MS distance to the \(i\)-th main-lobe interfering BS,
- \(D_{M,B,j}\) = MS distance to the \(j\)-th back-lobe interfering BS,
- \(D_{\mu,i}\) = MS distance to the \(i\)-th microcell interfering BS,
- \(R_M\) = macrocell radius,
- \(R_\mu\) = microcell radius,
- \(\eta\) = the front-to-back ratio of the directional antenna in macrocells.
Let \((S/I)_{\text{req}}\) denote the required S/I. Then (8) becomes

\[
\frac{R_{\mu}}{R_{M}} \leq \left[ \frac{(S/I)^{-1}_{\text{req}}}{C_{\mu}^{-1} \left( \sum_{i=1}^{N_{M_{i}}} \left( \frac{1}{D_{M_{i,i}}} \right)^4 \right) + \sum_{i=1}^{N_{M_{b}}} \left( \frac{1}{D_{M_{b,j}}} \right)^4 + \frac{1}{\eta} \sum_{j=1}^{N_{M_{b}}} \left( \frac{1}{D_{M_{b,j}}} \right)^4 \left( \frac{P_{t,b}}{P_{t,b}^\mu} \right) \left( \frac{h_{M,b}}{h_{\mu,b}} \right)^2} \right]^{1/4}
\]

(9)

where \(\overline{D}_{M_{i,i}} = D_{M_{i,i}}/R_{M}, \overline{D}_{M_{b,j}} = D_{M_{b,j}}/R_{M},\) and \(\overline{D}_{\mu} = D_{\mu_i}/R_{M},\) are the normalized distances of interferers with respect to macrocell radius \(R_{M}.\) Our studies assume that the microcells and macrocells have similar shapes, and that the microcell clusters are adjacent to each other in a given micro-area. Suppose the distances from a microcell MS to its interfering microcell BSs are equal and close to the microcell co-channel reuse distance \(D_{\mu}\) (i.e., \(D_{\mu_i} = D_{\mu},\) for \(i = 1, \ldots, C_{\mu}\)). Then we have [8]

\[
D_{\mu} = \sqrt{3K_{\mu}R_{\mu}},
\]

(10)

where \(K_{\mu}\) denotes the microcell cluster size. With \(C_{\mu}\) microcell clusters and \(K_{\mu}\) microcells inside each cluster, a micro-area has in total \(C_{\mu}K_{\mu}\) microcells. Suppose that taken together they are smaller than the area of a macrocell. Then

\[
R_{M} \geq \sqrt{C_{\mu}K_{\mu}R_{\mu}}.
\]

(11)

Substituting (10) (11) into (9), we get

\[
\frac{R_{\mu}}{R_{M}} \leq \left[ \frac{(S/I)^{-1}_{\text{req}}}{\frac{(C_{\mu} - 1)C_{\mu}^2}{9} + \sum_{i=1}^{N_{M_{i}}} \left( \frac{1}{D_{M_{i,i}}} \right)^4 + \frac{1}{\eta} \sum_{j=1}^{N_{M_{b}}} \left( \frac{1}{D_{M_{b,j}}} \right)^4 \left( \frac{P_{t,b}}{P_{t,b}^\mu} \right) \left( \frac{h_{M,b}}{h_{\mu,b}} \right)^2} \right]^{1/4}
\]

(12)

Notice that we consider \(N_{M_{b}}\) back-lobe macrocell interferers in (12). The back-lobe interference from the macrocell BSs can be ignored for the macrocell MS, but for the microcell MS, this kind of interference may be relatively strong compared to the received signal strength.
from the low-powered microcell BS. For the same reason, the macrocell interferers in the second ring are considered here.

**Example:** Referring to Fig. 5 and Table 1, micro-area 56 can be assigned channel sets \([4_\alpha, 4_\gamma]\). Take channel set 4_\gamma as an example. Micro-area 56 will experience three first-tier back-lobe interferers \((N_{M_b}=3)\), each of which has the following distance

\[
[D_{M_b,1}, D_{M_b,2}, D_{M_b,3}] = [2.65, 2.65, 2.65]
\]  

(13)

to the center of micro-area 56. Three main-lobe interfering macrocells in the second tier are located near micro-areas 25, 79, 64 with the distances of

\[
[D_{M_f,1}, D_{M_f,2}, D_{M_f,3}] = [5.29, 5.29, 5.29].
\]  

(14)

Additionally, three main-lobe interfering macrocell BSs in the third tier are located near micro-areas 13, 70, and 85 with distances of

\[
[D_{M_f,4}, D_{M_f,5}, D_{M_f,6}] = [7.0, 7.0, 7.0].
\]  

(15)

It is also important to determine if there exist interfering microcell BSs from neighboring micro-areas. From Fig. 5 and Table 1, one can find one feature of the proposed system architecture – the adjacent micro-areas are assigned with different macrocell channel sets. For instance, micro-area 56 in Fig.5 is assigned with the channel sets \([4_\alpha, 4_\gamma]\). The neighboring micro-areas 45, 46, 55, 57, 66, and 67 use channel sets \([6_\alpha, 6_\beta], [7_\alpha, 7_\beta], [2_\beta, 2_\gamma], [3_\alpha, 3_\gamma], [5_\alpha, 5_\gamma], [1_\alpha, 1_\gamma]\). It is obvious that when considering the interfering microcell BSs, a microcell MS will only be affected by the interfering microcell BSs in the same micro-area. Assume that each micro-area consists of \(C_\mu\) microcell clusters. Then a MS will experience the interference from the remaining \(C_\mu - 1\) microcell BSs, excluding the desired one.
Substituting (13), (14), and (15) into (12), one can obtain

\[
\frac{R_\mu}{R_M} \leq \left[ \frac{(S/I)_{\text{req}}^{-1}}{(C_\mu - 1)C_\mu^2} \times \frac{1}{9} \left( 5.0803 \times 10^{-3} + 0.0608 \times \frac{1}{\eta} \left( \frac{p_{t,b}^M}{p_{t,b}^\mu} \right) \left( \frac{h_b^M}{h_b^\mu} \right)^2 \right) \right]^{1/4}.
\] (16)

(a) \( C_\mu = 1 \): We first consider a special case where only one microcell is installed in a micro-area. In the beginning stage, this may occur when a large underlaid microcell is first installed to release traffic load of the macrocellular system. Fig. 9 shows the effect of the front-to-back ratio \( \eta \) on the microcell radius, whereby \( (S/I)_{\text{req}} = 18 \) dB and \( h_b^\mu / h_b^M = 1/3 \). If the S/I- and S-criterion result in different microcell radii, then the smaller one will be chosen. From Fig. 9, one can observe that if front-to-back ratio \( \eta \geq 10 \) dB, the microcell radius is determined by the S-criterion, but when \( \eta \leq 5 \) dB, the S/I-criterion dominates the S-criterion. For instance, in the case of \( \eta = 10 \) dB and \( p_{t,b}^\mu / p_{t,b}^M = 0.4 \), one can obtain \( R_\mu \leq 0.5R_M \) by the S/I-criterion and \( R_\mu \leq 0.46R_M \) by the S-criterion, respectively. For choosing the smaller one, the microcell radius is therefore 0.46\( R_M \). In this example, one can see that a larger front-to-back ratio \( \eta \) does not imply a larger microcell size, since the S-criterion, which is independent of \( \eta \), will dominate the S/I-criterion when \( \eta \) is large.

(b) \( C_\mu \geq 2 \): Next, we consider the case where many microcells are deployed in each micro-area. Fig. 9 shows the downlink microcell size against \( p_{t,b}^\mu / p_{t,b}^M \) for different values of \( C_\mu \), where \( p_{t,b}^\mu / p_{t,b}^M \) is the ratio of the transmitted power of the microcell BS to that of the macrocell BS, and \( C_\mu \) is the number of microcell clusters in a micro-area. It is observed that if \( C_\mu \geq 3 \), \( p_{t,b}^\mu / p_{t,b}^M \) has little effect on the downlink microcell size. This is because the interference from the microcells, \( I_{\mu}^d \), will dominate the macrocell interference, \( J_{\mu}^d \), when the number of co-channel microcells \( (C_\mu - 1) \) becomes large in a given micro-area. In other words, if a large number of microcells are installed, the S/I-criterion will become a dominating factor in determining the microcell size. In the case of \( C_\mu = 6 \), for example,
one should follow the S/I-criterion to get \( R_\mu \leq 0.165R_M \) from Fig. 9.

VI-B Uplink microcell size

Similar to the former analysis, the uplink microcell size is derived from the S/I analysis. More specifically,

\[
\frac{S^{u}_{\mu}}{I^{u}_{\mu} + J^{u}_{\mu,\mu}} = \frac{p^{u}_{t,m} (h^{u}_{b}h^{u}_{m})^2}{R^{\mu}_{\mu,up}} \cdot \sum_{i=1}^{C_{\mu}-1} \frac{p^{u}_{t,m} (h^{u}_{b}h^{u}_{m})^2}{D^{4}_{\mu,i}} + \sum_{i=1}^{N_{M,i}} \frac{p^{M}_{t,m} (h^{b}_{M}h^{M}_{m})^2}{D^{4}_{M,i}},
\]

where the parameters \( p^{u}_{t,b}, p^{M}_{t,b}, C_{\mu}, h^{M}_{b}, h^{u}_{\mu}, R_{M}, h^{u}_{b}, \) and \( h_{m} \) have been defined in (2) and (8) and

\[
\begin{align*}
S^{u}_{\mu} & = \text{microcell BS received power from the desired microcell MS}, \\
I^{u}_{\mu,\mu} & = \text{uplink microcell-to-macrocell interference}, \\
J^{u}_{\mu,\mu} & = \text{uplink macrocell-to-microcell interference}, \\
N_{M,i} & = \text{the number of macrocell interfering MSs}, \\
D_{M,i} & = \text{BS distance to the i-th interfering macrocell MS} \\
R_{\mu,up} & = \text{uplink microcell radius}.
\end{align*}
\]

Let \( D_{M,i} = \overline{D_{M,i}}R_{M} \) and \((S/I)_{req}\) denote the required S/I for a microcell BS. Using the same assumptions for getting (12), one can simplify (17) as

\[
\frac{R_{\mu,up}}{R_{M}} \leq \left[ \frac{(S/I)_{req}^{-1}}{9} + \left( \overline{C_{\mu}} - \frac{1}{9} \sum_{i=1}^{N_{M}} \left( \frac{1}{D_{M,i}} \right)^{4} \left( \frac{p^{M}_{t,m}}{p^{u}_{t,m}} \right) \right) \right]^{\frac{1}{4}}.
\]

In section VI-A we have shown that when the number of microcell clusters \( C_{\mu} \) becomes large, the downlink microcell size is insensitive to the interference from the macrocell. This is also true for determining the uplink microcell size. This will be shown by an example later. When microcell interference dominates the performance, (18) can be approximated...
as

\[
\frac{R_{\mu,up}}{R_M} \leq \left[ \frac{1}{(S/I)_{req}(C\mu - 1) C^2 \mu} \right]^\frac{1}{4}. \tag{19}
\]

By combining (10) (11) (19), we obtain the upper and lower bounds of \( K_\mu \) as

\[
\frac{1}{3} \sqrt{(S/I)_{req}(C\mu - 1)} \leq K_\mu \leq \frac{1}{C\mu} \left( \frac{R_M}{R_\mu} \right)^2. \tag{20}
\]

The relation between \( K_\mu \) and \( C\mu \) with \( R_\mu/R_M \) as a parameter is shown in Fig. 11.

**Example:** Consider again micro-area 56 in Fig. 5. Referring to Table 1, micro-area 56 can be assigned channel sets \([4_\alpha, 4_\gamma]\). Take channel set 4_\alpha for example. The worst case occurs when interfering macrocell MSs transmit maximum power, i.e., at the macrocell boundary. For the example considered, the three first-tier interfering macrocell MSs near micro-areas 45, 47, 77 are at distances \([\tilde{D}_{M,1}, \tilde{D}_{M,2}, \tilde{D}_{M,3}] = [2.0, 2.0, 2.0]\); the three second-tier interfering macrocell MSs near micro-areas 26, 53, 89 are at distances \([\tilde{D}_{M,4}, \tilde{D}_{M,5}, \tilde{D}_{M,6}] = [4.36, 4.36, 4.36]\); the three third-tier interfering macrocell MSs near micro-areas 32, 38, and 98 are at distances \([\tilde{D}_{M,7}, \tilde{D}_{M,8}, \tilde{D}_{M,9}] = [6.0, 6.0, 6.0]\). Substituting these values into (18) and letting \((S/I)_{req} = 18\) dB, we show in Fig. 12 the ratio of microcell radius to macrocell radius \( R_\mu/R_M \) against \( P_{t,m}/P_{t,m}^M \) for different values of \( C\mu \), where \( P_{t,m}^\mu/P_{t,m}^M \) is the ratio of the transmitted power of the microcell MS to that of the macrocell MS, and \( C\mu \) is the number of the microcell clusters in a micro-area. It is shown that as \( C\mu \) increases, microcell size becomes insensitive to \( P_{t,m}^\mu/P_{t,m}^M \). Suppose our objective is to implement six microcell clusters in each macro-area (i.e., \( C\mu = 6 \)) and still maintain \((S/I)_{req} = 18\) dB. We first need to know the feasible cluster size \( K_\mu \) and the microcell radius. From Fig. 11, we obtain \( K_\mu = 7 \) and \( R_\mu = 0.15 \times R_M \). Then from Fig. 12, we find the transmitted power for microcell MS should be at least 0.017 times that for macrocell MS. Consider an interfering macrocell MS which is an IS-54 Class IV portable handset transmitting at -2 dBW. Thus
the microcell MS transmitted power should be larger than -20 dBW in this case. Recall the transmitted power of an IS-54 Class IV portable handset ranges from -22 dBW to -2 dBW. Consequently, the current IS-54 Class IV portable handset can be used in both the macrocells and microcells of the proposed system architecture without changing the handset transmit power specification.

VII Adjacent Channel Interference Analysis

In this section, we will first review a frequency management plan to avoid adjacent channel interference in the conventional macrocellular system. Then we examine if this management scheme still work for the proposed hierarchical cellular system. As shown in Fig. 1, a traditional 7-cell macrocellular system has 21 sectors. If 10 MHz of spectrum is used and each channel occupies 30 KHz, then a total of 333 carriers will be assigned to the 21 sectors. A frequency plan to avoid adjacent channel interference is shown in Table 3 [8]. Each row in the table represents a frequency set that is designated to a sector. This scheme separates any two carriers assigned to adjacent sectors by seven carriers.

Applying the frequency plan in Table 3 to the proposed hierarchical cellular system (Fig. 5), we can easily see that there is no adjacent channel interference between macrocell sectors. Even with the addition of underlaid microcells, a 2-carrier separation is maintained between the carriers assigned to the the microcells and the co-site macrocells within a microarea. For example, referring to Fig. 5 and Table 1, the channel set $[4\alpha, 4\gamma]$ is assigned to micro-area 56. The co-site macrocell sectors that use channel set $1\beta, 2\alpha, \text{and } 7\gamma$ have at least a 2-carrier separation. This feature is valid for all the micro-areas with channel assignment of Table 1.
VIII Concluding Remarks

This paper has proposed a new sectoring scheme which allows underlaid microcells to reuse macrocell frequencies. For each area consisting of three macrocell sectors, the proposed architecture can reuse another two macrocell channel sets six times while retaining $S/I \geq 18$ dB. Hence, the system capacity of the proposed architecture can be five times that of a traditional 3-sector N=7 cellular system (Fig. 1). If the S/I requirement can be lowered, e.g., 9 dB in GSM, then the improvement can be even larger. The capacity improvement of the proposed architecture is achieved by deploying a large number of underlaid microcells. This feature, however, can not be easily done in other sectored cellular architectures, e.g., those in [9, 10]. The proposed architecture allows microcells to be deployed throughout the entire area, and allows them to be gradually introduced to match the increasing demand of the cellular service. With these flexibilities, the proposed architecture allows the existing macrocellular systems to smoothly evolve into a microcell/macrocell hierarchical system.

References


Figure 1: Traditional 3-sector N=7 cellular system.
Figure 2: Cluster planning for the proposed system.
Figure 3: Example of the proposed microcell/macrocell overlaying system. Microcells in micro-area A ~ F can reuse the low-interfering macrocell channel set $4g$. 

Main-lobe area of macrocell
sectors with channel set $4g$
Figure 4: Interfering neighborhood for micro-area A in Fig. 3.
Figure 5: Frequency planning for the proposed system with 100 micro-areas. Table 1 lists the available channel sets for the above 100 micro-areas.
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<td>$4_\alpha,4_\beta$</td>
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<td>$2_\beta,2_\gamma$</td>
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Table 1: Available macrocell channel sets for the 100 micro-areas in Fig. 5.
Figure 6: Comparison of the uplink S/I performance of conventional macrocells and the proposed hierarchical cellular system without the underlaid microcells for different path loss exponent $\beta$. 
Figure 7: Macrocell downlink S/I performance against $p_{t,b}^\mu / p_{t,b}^M$ for different values of $C_\mu$, where $p_{t,b}^\mu / p_{t,b}^M$ is the ratio of the transmitted power of the microcell BS to that of the macrocell BS, and $C_\mu$ is the number of microcell clusters in a micro-area.
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Table 2: Downlink S/I performance for overlaying macrocells, where $h_b^\mu/h_b^M = 1/3$. 
Figure 8: Macrocell uplink $S/I$ performance against $p_{t,m}^\mu/p_{t,m}^M$ for different values of $C\mu$, where $p_{t,m}^\mu/p_{t,m}^M$ is the ratio of the transmitted power of the microcell MS to that of the macrocell MS, and $C\mu$ is the number of microcell clusters in a micro-area.
Figure 9: Effect of front-to-back ratio $\eta$ on the microcell radius based on downlink microcell S/I performance analysis, where $R_{\mu}/R_M$ and $p_{t,\mu}/p_{t,M}$ are the cell radius ratio and transmitted power ratio of microcells over macrocells, respectively. With $(S/I)_{req} = 18$ dB and $h_b^\mu/h_b^M = 1/3$, curves (a) ~ (e) are obtained by S/I-criterion for $\eta = 0, 5, 10, 15, 20$ dB, respectively, while curve (f) is obtained by S-criterion.
Figure 10: Downlink microcell radius $R_{\mu}$ against $p_{t,\mu}^{M}/p_{t,\mu}^{M}$ for different values of $C_{\mu}$ in the case $\eta = 10$ dB, $(S/I)_{req} = 18$ dB, and $h_{b}^{M}/h_{t}^{M} = 1/3$, whereby the microcell radius is normalized with respect to the macrocell radius $R_{M}$; $p_{t,\mu}^{M}/p_{t,\mu}^{M}$ represents the ratio of the transmitted power of microcell BS to that of macrocell BS; and $C_{\mu}$ is the number of clusters in a micro-area; $\eta$ is the front-to-back ratio of the directional antenna; $h_{b}^{M}/h_{t}^{M}$ is the ratio of the microcell BS antenna to the macrocell BS antenna. Curves (a) $\sim$ (e) are obtained by S/I-criterion for $C_{\mu} = 1, 2, 4, 6, 8$, while curve (f) is obtained by S-criterion.
Figure 11: $K_\mu$ against $C_\mu$ with $R_\mu/R_M$ as a parameter, whereby $K_\mu$ is the microcell cluster size, $C_\mu$ is the number of clusters in a micro-area, and $R_\mu/R_M$ is the ratio of the microcell radius to the macrocell radius. Curve (a) represents the lower bound of $K_\mu$, while curves (b) ~ (g) represent the upper bound of $K_\mu$ for $R_\mu/R_M = 0.13, 0.15, 0.20, 0.25, 0.30, 0.35$, respectively.
Figure 12: Uplink microcell radius $R_\mu$ against $p_{t,m}^\mu/p_{t,m}^M$ for different values of $C_\mu$, where the microcell radius is normalized by the macrocell radius $R_M$, $p_{t,m}^\mu/p_{t,m}^M$ is the ratio of the transmitted power of the microcell MS to that of the macrocell MS, $C_\mu$ is the number of microcell clusters in a micro-area, and $(S/I)_{req} = 18$ dB.
Effects of Rician Fading and Branch Correlation on a Local-Mean-Based Macrodiversity Cellular System

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ABSTRACT In a macrodiversity cellular system, switching radio links between base stations cannot be done instantaneously. Thus branch selection is usually based on the measurement of the slowly-varying local mean power rather than the rapidly-varying instantaneous signal power. In this paper we offer an exact mathematical model to analyze the performance of a local-mean-based macrodiversity cellular system in a shadowed-Rician (desired) /shadowed-Rayleigh (interfering) channel. We investigate the impact of both fading (Rician or Rayleigh) and shadowing in terms of co-channel interference (CCI) probability. We also present an analytical model to incorporate the effects of branch correlation on macrodiversity systems.

I Introduction

Macrodiversity, or a large-scaled space diversity, has long been recognized as an effective tool to combat shadowing [1]. A macrodiversity system serves a mobile station (MS) simultaneously by several base stations (BSs). At any time, the BS with the best quality measure is chosen to serve the MS. The criterion for branch (or BS) selection is a key issue when designing a macrodiversity system. Usually, the branch selection is based on the local mean power rather than the instantaneous power [1, 2, 3, 4], because the branch selection algorithm cannot react to the rapidly varying instantaneous signal power. This paper focuses on local - mean - based branch selection schemes.

Previous studies on macrodiversity systems have evaluated the co-channel interference performance with shadowing only [5, 6, 7] and shadowed Rayleigh fading channels [4]. The co-channel interference performance was also discussed in [9], but it was assumed that the branch selection was based on the instantaneous signal power. The error rate performance of macrodiversity systems has been analyzed in Gaussian noise with both shadowing and Rayleigh (or Nakagami) fading [3, 8, 8]. However, these papers did not consider co-channel interference. To our knowledge, the effect of Rician fading on a local-mean-based macrodiversity system has not been studied before. Furthermore, the effect of branch correlation for macrodiversity systems has not appeared in the literature, either. This paper addresses these issues in detail.

The remainder of this paper is organized as follows. Section II briefly reviews the propagation environment. Section III presents an exact analysis for the performance gain for a local-mean-based macrodiversity system in a shadowed Rician (desired) /shadowed Rayleigh (interfering) channel. This model is extended to incorporate the effect of branch correlation in Section IV. Section V will give some numerical examples, and Section VI has some concluding remarks.

II Microcell Propagation Models

The path loss is assumed to follow the two-slope model so that the area mean received power is

$$\mu = \frac{P_i C}{d^{(1 + d/g)}}$$

(1)

where $P_i$ is the transmitted power, $C$ is a constant that incorporates the effects of antenna gain, $d$ is the distance between the transmitter and receiver, $g$ is the break point, $a$ is the basic path loss exponent, and $b$ is the additional path loss exponent.

With log-normal shadowing, the probability density function (pdf) of the local mean power, $\Omega$, has the log-normal distribution

$$f_{\Omega}(x) = \frac{1}{\sqrt{2\pi}x} \exp \left[ -\frac{(\ln x - \ln \mu)^2}{2\sigma^2} \right],$$

(2)

where $\sigma$ is the shadow standard deviation and $\mu$ is the area mean power determined by the path loss in (1).

In microcell propagation with a dominant line-of-sight (LOS) or specular component, the instantaneous signal amplitude is Rician distributed. If the power in the scattered component of the received signal is $\sigma^2$ and the amplitude of the dominant component is $A$, then the instantaneous received signal power, $p$, conditioned on the local mean power $\Omega = A^2/2 + \sigma^2$ has the non-central chi-square distribution

$$f_{p|\Omega}(x | \Omega) = \frac{K + 1}{\Omega} \exp \left[ -\frac{K}{\Omega} \right] \frac{I_0 \left( \frac{\sqrt{4K(K+1)}}{\Omega}x \right)}{\sqrt{4K(K+1)}}$$

(3)

where $I_0$ is the zero-order modified Bessel function of the first kind, and $K = A^2/2\sigma^2$ is the Rice factor.

An interfering signal usually has no dominant component so that its instantaneous signal amplitude is Rayleigh distributed.
The pdf of the instantaneous interfering signal power, \( p_d \), in a Rayleigh fading channel can be obtained by letting \( K = 0 \) in (3), giving

\[
f_{p_d}(x | \Omega) = \frac{1}{\Omega} \exp \left[ -\frac{x}{\Omega} \right],
\]

where \( \Omega \) is the local mean interfering signal power.

III Co-channel Interference Probability

This section presents an analytical model for calculating the co-channel interference (CCI) probability for an \( L \)-branch local-mean-based macrodiversity system with shadowing and fading.

Our model assumes that the local mean power of the desired signal, \( \Omega_{d,k} \), is available for each branch \( k \), where \( k = 1, \ldots, L \). In practice, the desired signal power is mixed with the total interference power for each branch \( \Omega_{k} \), so that \( \Omega_{d,k} + \Omega_{i,k} \) is actually measured. However, the difference is small for large \( \Omega_{d,k}/\Omega_{i,k} \). If the branch having the largest \( \Omega_{d,k} \) is selected, then the local-mean power of the selected branch is

\[
S = \max (\Omega_{d,1}, \Omega_{d,2}, \ldots, \Omega_{d,L}).
\]

Let \( F_s(x) \) and \( f_s(x) \) denote the cumulative distribution function (cdf) and the pdf of \( \Omega_{d,k} \), respectively. If the \( \Omega_{d,k} \) are independent random variables with the pdf in (2), then \( S \) has the pdf \( f_S(y) = E[F_s(y)]^{-1} f_s(y) \). The CCI probability is

\[
P(CI) = P_r \left[ p_d / p_i < \lambda_{th} \right] = 1 - \int_0^\infty \int_{-\infty}^x f_{p_d}(y) f_{p_i}(x) dx,
\]

where \( p_d \) and \( p_i \) are the total powers of the desired and interfering signals for the selected branch with pdfs \( f_{p_d}(x) \) and \( f_{p_i}(y) \), respectively, and \( \lambda_{th} \) is the protection ratio.

III-A Pure Shadowing

The interfering signals add noncoherently so that the total interference power on the \( k \)th branch is \( \Omega_{i,k} = \sum_{j \neq k} \Omega_{i,j} \), where \( n \) is the number of interferers and \( \Omega_{i,k} \) is the power of the \( i \)th interferer on the \( k \)th branch. It is widely accepted that \( \Omega_{i,k} \) can be approximated by a log-normal random variable with area mean power \( \mu_{i,k} \) and standard deviation \( \sigma_{i,k} \). The parameters \( \sigma_{i,k} \) and \( \mu_{i,k} \) can be calculated by using a variety of methods, including Schwartz and Yeh’s method [10].

If the \( \{\Omega_{i,k}\}_{k=1}^n \) are independent and identically distributed (iid), and the \( \{\Omega_{d,k}\}_{k=1}^L \) are also iid and independent of the \( \{\Omega_{i,k}\}_{k=1}^n \), then [5, 7]

\[
P(CI) = 1 - L \int_0^\infty \left[ \int_{-\infty}^{x_{th}} \frac{1}{\sqrt{2\pi} \sigma_i} \exp \left( -\frac{(y - \ln \mu_i)^2}{2\sigma_i^2} \right) dy \right]
\times \left[ 1 - Q \left( \frac{\ln x - \ln \mu_d}{\sigma_d} \right) \right]^{L-1}
\times \frac{1}{\sqrt{2\pi} \sigma_d} \exp \left( -\frac{(\ln x - \ln \mu_d)^2}{2\sigma_d^2} \right) dx
\]

where \( Q(y) = \int_y^\infty \frac{1}{\sqrt{2\pi}} \exp(-x^2/2) dx \), and \( \sigma_d \) and \( \mu_d \) are the shadowing standard deviation and area mean power of the desired signal on the \( k \)th diversity branch, respectively.

For ease of evaluation, we let \( w = (\ln x - \ln \mu_d)/\sqrt{2}\sigma_d \) and transform (7) into a Hermite integration form. That is,

\[
P(CI) = 1 - \int_{-\infty}^\infty \left[ \frac{1 - Q \left( \frac{\sqrt{2}\sigma_d w + \ln \mu_d}{\sigma_i \lambda_{th}} \right)}{1 - Q \left( \sqrt{2}w \right)} \right]^{L-1} g(w) dw \approx 1 - \sum_{i=1}^n g(w_i) h_i,
\]

where

\[
g(w) = \frac{L}{\sqrt{\pi}} \exp \left[ -Q \left( \frac{\sqrt{2} \sigma_d w + \ln \mu_d}{\sigma_i \lambda_{th}} \right) \right]^{L-1},
\]

and \( w_i \) and \( h_i \) are the roots and weight factors of the \( n \)th-order Hermite polynomial, respectively [13].

III-B Rician Fading and Shadowing

For a local-mean-based macrodiversity system with shadowed Rician fading channels, the branch selection is still based on the best local mean power \( \Omega_{d,k} \). If \( S \) in (5) is assumed known, then by substituting (3) and (4) into (6) we obtain [7]

\[
P(CI | S, \Omega_i) = \sum_{i=1}^n \prod_{j=1, j \neq i}^n \left( \frac{\Omega_{i,j} - \Omega_{i,i}}{\Omega_{i,i} \lambda_{th}} \right)^{K-1} \frac{S}{\Omega_{i,i} \lambda_{th}} \exp \left( -\frac{S}{\lambda_{th} \Omega_{i,i}} \right)
\]

where \( \Omega_i = (\Omega_{i,1}, \ldots, \Omega_{i,n}) \) and \( K \) is the Rice factor of the desired signal. Assuming that the \( \{\Omega_{i,k}\}_{k=1}^n \) are independent, the joint pdf of \( \Omega_i \) is

\[
f_{\Omega_i}(\mathbf{x}) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi} \sigma_i \tau_i} \exp \left( -\frac{(\ln x_i - \ln \mu_{i,i})^2}{2\sigma_i^2} \right)
\]

where \( \mathbf{x} = (x_1, \ldots, x_n) \). By using (11), (10), and the pdf of \( S \), we obtain

\[
P(CI) = \int_0^\infty \cdots \int_0^\infty P(CI | S, \Omega_i) \frac{L \left[ 1 - Q \left( \frac{\ln S - \ln \mu_d}{\sigma_d} \right) \right]^{L-1}}{\sqrt{2\pi} \sigma_d S} \exp \left( -\frac{(\ln S - \ln \mu_d)^2}{2\sigma_d^2} \right) \prod_{i=1}^n \frac{1}{\sqrt{2\pi} \sigma_i} \exp \left( -\frac{(\ln \Omega_{i,i} - \ln \mu_{i,i})^2}{2\sigma_{i,i}^2} \right) dS d\Omega_i.
\]

By using the substitution \( \alpha = \ln(S/\mu_d)/\sqrt{2}\sigma_d \) and \( \beta_i = \ln(\Omega_{i,i}/\mu_{i,i})/\sqrt{2}\sigma_{i,i} \), \( i = 1, \ldots, n \), we transform (12) into a Hermite integration form, which can be evaluated with numerical ease. In particular,

\[
P(CI) = \int_{-\infty}^\infty \cdots \int_{-\infty}^\infty \frac{L \left[ 1 - Q \left( \sqrt{2}\alpha \right) \right]^{L-1}}{\sqrt{2\pi} \sigma_d} G(\alpha, \beta) \exp \left( -\alpha^2 - \sum_{i=1}^n \beta_i^2 \right) d\alpha d\beta.
\]
\[\sum_{k_0=1}^{h_0} \cdots \sum_{k_n=1}^{h_n} \frac{L}{\pi^{n+1}} \left[ 1 - Q \left( \sqrt{2\beta_{k_0}} \right) \right]^{L-1} G(x_{k_0}, x_{k_1}, \ldots, x_{k_n}) \omega_{k_0} \cdots \omega_{k_n} \]  

where \( \beta = (\beta_1, \ldots, \beta_n) \), \( x_{k_i} \) is the root of the \( h_i \)th order Hermite polynomial, and \( \omega_{k_i} \) is its corresponding weight factor. Here \( G(\alpha, \beta) \) is obtained by substituting \( S = \mu_d \exp(\sqrt{2} \sigma_d) \) and \( \Omega(\alpha) = \mu_{ij} \exp(\sqrt{2} \beta_i \sigma_{ij} - \beta_i \sigma_{ij}) \) into \( P(CI) | S, \Omega(\alpha) \) in (10). That is

\[G(\alpha, \beta) = \sum_{i=1}^{n} \prod_{j=1, j \neq i}^{n} \left( 1 - \frac{\mu_{ij} \omega_i}{\mu_{ij} \omega_i} \exp \left[ -\sqrt{2} (\beta_i \sigma_{ij} - \beta_i \sigma_{ij}) \right] \right) \frac{1}{K + 1 + \epsilon_i} \exp \left[ -\frac{K \epsilon_i}{K + 1 + \epsilon_i} \right] \]

where

\[\epsilon_i = \frac{\mu_d}{\lambda_{ih}} \frac{1}{\exp \left[ -\sqrt{2} (\sigma_d - \beta_i \sigma_{ij}) \right]} \]

IV Correlated Branches

Until now, we have assumed independent shadowing on the macrodiversity branches. This assumption may sometimes be violated because of insufficient spacing of BSs, especially in microcell systems.

For a correlated \( L \)-branch macrodiversity system, the joint pdf of \( \Omega(\alpha) \) [12]

\[f_{\Omega(\alpha)}(z) = \frac{\exp \left[ -\frac{1}{2} Y^T M^{-1} Y \right]}{(2\pi)^{L/2} \det(M) z_1 \cdots z_L} \]

where \( z = (z_1, \ldots, z_L) \), \( Y^T = [y_1, \ldots, y_L] \) denotes the transpose of column vector

\[Y = \begin{bmatrix}
\ln(z_1) - \ln(\mu_1) \\
\vdots \\
\ln(z_L) - \ln(\mu_L)
\end{bmatrix} \]

and \( \mu_1, \ldots, \mu_L \) are the area means of each diversity branch. The covariance matrix \( M \) is expressed as

\[M = \begin{bmatrix}
\sigma_1^2 & \cdots & \nu_{1L} \\
\vdots & \ddots & \vdots \\
\nu_{L1} & \cdots & \sigma_L^2
\end{bmatrix} \]

where \( \sigma_i \) is the shadowing standard deviation and \( \nu_{ij} \) is the covariance of \( \ln(\Omega_a) \) and \( \ln(\Omega_d) \)

\[\nu_{ij} = E \left[ (\ln(\Omega_a) - \ln(\mu_i)) (\ln(\Omega_d) - \ln(\mu_j)) \right] \]

It is convenient to define \( N = M^{-1} \) and express the matrix multiplication in (16) as follows.

\[Y^T MY = \sum_{i=0}^{L} N_{1i} y_i^2 + 2 \sum_{i=0}^{L-1} \sum_{j=i+1}^{L} N_{ij} y_i y_j \]

where \( N_{ij} \) is the element in the \( i \)th row and \( j \)th column.

According to (5), (16), and (20), the probability that the local mean power \( S \) at the output of the combiner being less than \( y \) is

\[\Pr(S < y) = \int_{-\infty}^{y} \cdots \int_{-\infty}^{y} \frac{1}{2\pi} \exp \left[ -\frac{1}{2} \left( \sum_{i=1}^{L} N_{1i} y_i^2 + 2 \sum_{i=1}^{L-1} \sum_{j=i+1}^{L} N_{ij} y_i y_j \right) \right] dy_1 \cdots dy_L \]

where \( N_{1i} \) and \( y_i \) are defined in (20) and (17), respectively.

The key for analyzing the CCI probability of the local-mean-based macrodiversity system is to find the pdf of the combiner output power, \( f_S(y) \). Unlike the uncorrelated case where there exists a closed-form expression for \( f_S(y) \), one can not easily get a simple closed formula for the joint distribution of more than two mutually correlated lognormal random variables. However, for \( L = 2 \),

\[f_S(y) = \frac{1}{\sqrt{2\pi} \sigma y} \exp \left[ \frac{1}{2} \left( \frac{(\ln y - \ln \mu_d)^2}{\sigma^2} \right) \right] \]

where \( y = (\ln \rho_{od} - \ln \rho_d) \) and \( d \) denotes the branch selected by the macrodiversity system. Consider the following covariance matrix \( M \)

\[M = \begin{bmatrix}
\sigma_1^2 & \mu_1 \\
\sigma_2^2 & \mu_2
\end{bmatrix} \]

and

\[N = M^{-1} = \begin{bmatrix}
\frac{1}{\sigma_1^2 - \mu_1^2} & -\mu \sigma_1 \\
-\frac{\mu}{\sigma_2^2 - \mu_2^2} & \frac{\sigma_2^2 - \mu_2^2}{\sigma_1^2 - \mu_1^2}
\end{bmatrix} \]

By substituting (24) into (22), we express the pdf of the output local-mean power of the dual macrodiversity system as

\[f_S(y) = \frac{1}{2\sigma y} \exp \left[ \frac{1}{2} \left( \frac{(\ln y - \ln \mu_d)^2}{\sigma^2} \right) \right] \]

where the correlation coefficient \( r \) is defined as \( r = \frac{\nu}{\sigma^2} \). Combining (10), (11), and (25), we obtain

\[P(CI) = \int_{-\infty}^{y} \cdots \int_{-\infty}^{y} \frac{2G(\alpha, \beta)}{\sqrt{\pi^{n+1}}} \left[ 1 - Q \left( \sqrt{2} \left( \frac{1}{\sqrt{1 - r^2}} \right) \alpha \right) \right] \]

\[\exp \left[ -\frac{1}{2} \sum_{i=1}^{n} \mu_i \sigma_i \right] d\alpha \ d\beta \]

\[\leq \sum_{k_0=1}^{h_0} \cdots \sum_{k_n=1}^{h_n} \frac{1}{\sqrt{\pi^{n+1}}} \left[ 1 - Q \left( \sqrt{2} \left( \frac{1}{\sqrt{1 - r^2}} \right) x_{k_0} \right) \right] \]

\[\times G(x_{k_0}, \ldots, x_{k_n}) \omega_{k_0} \cdots \omega_{k_n} \].
where \( \alpha \) and \( \beta \) are defined in (13), the weight factor \( w_k \), of the \( k \)-th order Hermite polynomial can be found in [13], and \( G(\alpha, \beta) \) is defined in (14).

**V Numerical Results**

We consider a cellular system with nine cells per cluster. In this case, two co-channel interferers are at 5.2 \( R \), where \( R \) is the cell radius. Assume the mobile unit is on the boundary of the cell with a distance of \( R \) to the base station. Consider a dual slope path loss model with \( a = b = 2 \) and \( g = 0.15 \) in (1). Fig. 1 (a), (b), and (c) illustrate the gain achieved by a local-mean-based \( S \)-macrodiversity system over a shadowed-Rician (desired) /shadowed-Rayleigh (interfering) channel for the Rice factors \( K = -\infty, 7, \) and 20 dB. Table I lists the threshold \( \lambda_{th} \) and diversity gain (D.G.) in terms of 5% co-channel interference (CCI) probability. Some general observations can be made: 1) a higher spreading shadow plays a higher diversity gain and a lower required threshold \( \lambda_{th} \); 2) the diversity gain per branch is decreased as the number of diversity branches is increased; 3) the diversity gain increases with the requirement of the system, e.g., the diversity gain for 5% CCI probability is higher than that for 10% CCI probability. In addition, we see that the diversity gain seems to be affected little by fading and that a shadowed Rayleigh channel has the least diversity gain.

We evaluate the effects of correlation coefficient \( \rho \) on a 2-branch macrodiversity system with \( \sigma = 6 \) dB and various \( K = -\infty \) dB (Fig. 2 (a)); \( K = 10 \) dB (Fig. 2 (b)). Observe that as \( \rho \) approaches one, the diversity gain becomes zero. Furthermore, for \( \rho = 0.7 \), the diversity gain will be reduced to about 50% of the gain when \( \rho = 0 \).

**VI Concluding Remarks**

We consider a cellular system with nine cells per cluster. This paper presented an analytical model for calculating the co-channel interference probability of a local-mean-based macrodiversity system in a shadowed Rician (desired) / shadowed Rayleigh (interfering) channel. Compared to a pure shadowing channel, Rayleigh fading degrades the S/I performance by about 4 ~ 5 dB at 10% CCI probability. However, as the Rice factor \( K \) gets large, the degradation of S/I is within 1 dB. We also observe that fading (either Rayleigh or Rician) has little effect on the diversity gain of local-mean-based macrodiversity systems. The diversity gain is the same, but Rayleigh fading is always worse than Rician fading.

In two-branch macrodiversity system, a branch correlation coefficient of \( \rho = 0.7 \) will reduce the diversity gain by 50%. We considered correlated shadowing between diversity branches, but shadowing components between the desired and interfering signals are assumed to be independent in this paper. Furthermore, it has been shown that the correlation of shadowing components between interferers does not significantly influence the CCI probability performance [11]. The results obtained in this paper will be close to the results derived for the environment with multiple correlated log-normal shadowing interferers.

**References**


**Table I:** Macrodiversity gain (D.G.) and the threshold \( \lambda_{th} \) of S/I set at the receiver in terms of 5% co-channel interference probability (CCI) over a channel with both shadowing and Rician fading in terms of \( \sigma = 6 \) dB.

<table>
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<th>( L )</th>
<th>( K = -\infty ) dB</th>
<th>( K = 7 ) dB</th>
<th>( K = 20 ) dB</th>
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Figure 1: The CCI probability, $P(CI)$, against the required threshold, $\lambda_{th}$, at the receiver for the local-mean-based macrodiversity system over the shadowed-Rician (desired) / shadowed-Rayleigh (interfering) channel with Rice factor (a) $K = -\infty$ dB, (b) $K = 7$ dB, and (c) $K = 20$ dB, where the solid lines (---) denote the case for shadowing standard deviation $\sigma = 10$ dB and the dashed lines (----) for $\sigma = 6$ dB; $a = b = 2, g = 0.15R$; two interferers are located at a distance of 5.2R.

Figure 2: Effect of branch correlation coefficient $r$ on the local-mean-based macrodiversity system with Rice factor (a) $K = -\infty$ dB and (b) $K = 10$ dB, where $\sigma = 6$ dB; $a = b = 2, g = 0.15R$; two interferers are located at a distance of 5.2R.
Effects of Rician Fading and Branch Correlation on a Local-Mean-Based Macrodiversity Cellular System

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Abstract

In a macrodiversity cellular system, switching radio links between base stations cannot be done instantaneously. Thus branch selection is usually based on the measurement of the slowly-varying local mean power rather than the rapidly-varying instantaneous signal power. In this paper we offer an exact mathematical model to analyze the performance of a local-mean-based macrodiversity cellular system in a shadowed-Rician (desired) /shadowed-Rayleigh (interfering) channel. We investigate the impact of both fading (Rician or Rayleigh) and shadowing in terms of co-channel interference (CCI) probability. We also present an analytical model to incorporate the effects of branch correlation on macrodiversity systems.

This research was supported by the National Science Foundation under grant NCR-9523969. Submitted to IEEE Transactions on Vehicular Technology.
I Introduction:

Macrodiversity, or a large-scaled space diversity, has long been recognized as an effective tool to combat shadowing [1, 2]. A macrodiversity system serves a mobile station (MS) simultaneously by several base stations (BSs). At any time, the BS with the best quality measure is chosen to serve the MS. The criterion for branch (or BS) selection is a key issue when designing a macrodiversity system. Usually, the branch selection is based on the local mean power rather than the instantaneous power [1, 3, 4, 5, 6, 7], because the branch selection algorithm cannot react to the rapidly varying instantaneous signal power. This paper focuses on local – mean – based branch selection schemes.

Previous studies on macrodiversity systems have evaluated the co-channel interference performance with shadowing only [8, 9, 10] and shadowed Rayleigh fading channels [7]. The co-channel interference performance was also discussed in [12], but it was assumed that the branch selection was based on the instantaneous signal power. The error rate performance of macrodiversity systems has been analyzed in Gaussian noise with both shadowing and Rayleigh (or Nakagami) fading [6, 5, 4, 11, 3]. However, these papers did not consider co-channel interference. To our knowledge, the effect of Rician fading on a local-mean-based macrodiversity system has not been studied before. Furthermore, the effect of branch correlation for macrodiversity systems has not appeared in the literature, either. This paper addresses these issues in detail.

The remainder of this paper is organized as follows. Section II briefly reviews the propagation environment. Section III presents an exact analysis for the performance gain for a local-mean-based macrodiversity system in a shadowed Rician (desired) / shadowed Rayleigh (interfering) channel. This model is extended to in-
corporate the effect of branch correlation in Section IV. Section V will give some numerical examples, and Section VI has some concluding remarks.

II Microcell Propagation Models

The path loss is assumed to follow the two-slope model so that the area mean received power is [18]

$$\mu = \frac{P_t C}{d^a(1 + d/g)^b},$$  \hspace{1cm} (1)

where $P_t$ is the transmitted power, $C$ is a constant that incorporates the effects of antenna gain, $d$ is the distance between the transmitter and receiver, $g$ is the break point, $a$ is the basic path loss exponent, and $b$ is the additional path loss exponent.

With log-normal shadowing, the probability density function (pdf) of the local mean power, $\Omega$, has the log-normal distribution

$$f_\Omega(x) = \frac{1}{\sqrt{2\pi}\sigma x} \exp \left[ -\frac{(\ln x - \ln \mu)^2}{2\sigma^2} \right],$$  \hspace{1cm} (2)

where $\sigma$ is the shadow standard deviation and $\mu$ is the area mean power determined by the path loss in (1).

In microcell propagation with a dominant light-of-sight (LOS) or specular component, the instantaneous signal amplitude is Rician distributed. If the power in the scattered component of the received signal is $\sigma^2$ and the amplitude of the dominant component is $A$, then the instantaneous received signal power, $p$, conditioned on the local mean power $\Omega = A^2/2 + \sigma^2$ has the non-central chi-square distribution

$$f_{p|\Omega}(x | \Omega) = \frac{K + 1}{\Omega} \exp \left[ -K - \frac{(K + 1)x}{\Omega} \right] I_0 \left( \sqrt{\frac{4K(K + 1)x}{\Omega}} \right)$$  \hspace{1cm} (3)

where $I_0$ is the zero-order modified Bessel function of the first kind, and $K = A^2/2\sigma^2$ is the Rice factor.
An interfering signal usually has no dominant component so that its instantaneous signal amplitude is Rayleigh distributed. The pdf of the instantaneous interfering signal power, \( p \), in a Rayleigh fading channel can be obtained by letting \( K = 0 \) in (3), giving

\[
f_{p|\Omega}(x \mid \Omega) = \frac{1}{\Omega} \exp\left[ -\frac{x}{\Omega} \right],
\]

where \( \Omega \) is the local mean interfering signal power.

### III  Co-channel Interference Probability

This section presents an analytical model for calculating the co-channel interference (CCI) probability for an \( L \)-branch local-mean-based macrodiversity system with shadowing and fading. Our model assumes that the local mean power of the desired signal, \( \Omega_{d,k} \), is available for each branch \( k \), where \( k = 1, \ldots, L \). In practice, the desired signal power is mixed with the total interference power for each branch \( \Omega_{I,k} \), so that \( \Omega_{d,k} + \Omega_{I,k} \) is actually measured. However, the difference is small for large \( \Omega_{d,k}/\Omega_{I,k} \).

If the branch having the largest \( \Omega_{d,k} \) is selected, then the local-mean power of the selected branch is

\[
S = \max(\Omega_{d,1}, \Omega_{d,2}, \ldots, \Omega_{d,L}) .
\]

Let \( F_k(x) \) and \( f_k(x) \) denote the cumulative distribution function (cdf) and the pdf of \( \Omega_{d,k} \), respectively. If the \( \Omega_{d,k} \) are independent random variables with the pdf in (2), then \( S \) has the pdf \( f_S(y) = L \left[ F_k(y) \right]^{L-1} f_k(y) \). The CCI probability is

\[
P(CI) = P_r[p_d/p_I < \lambda_{th}]
\]

\[
= 1 - \int_0^\infty \left[ \int_{-\infty}^{\lambda_{th}} f_{p_I}(y)dy \right] f_{p_d}(x)dx ,
\]
where $p_d$ and $p_I$ are the total powers of the desired and interfering signals for the selected branch with pdfs $f_{p_d}(x)$ and $f_{p_I}(y)$, respectively, and $\lambda_{th}$ is the protection ratio.

III-A Pure Shadowing

The interfering signals add noncoherently so that the total interference power on the $k$th branch is $\Omega_{I,k} = \sum_{i=1}^{n} \Omega_{I,k,i}$, where $n$ is the number of interferers and $\Omega_{I,k,i}$ is the power of the $i$th interferer on the $k$th branch. It is widely accepted that $\Omega_{I,k}$ can be approximated by a log-normal random variable with area mean power $\mu_{I,k}$ and standard deviation $\sigma_{I,k}$. The parameters $\sigma_{I,k}$ and $\mu_{I,k}$ can be calculated by using a variety of methods, including Schwartz and Yeh’s method [20].

If the $\{\Omega_{I,k}\}_{k=1}^{n}$ are independent and identically distributed (iid), and the $\{\Omega_{d,k}\}_{k=1}^{L}$ are also iid and independent of the $\{\Omega_{I,k}\}_{k=1}^{n}$, then [8, 10]

$$P(CI) = 1 - L \int_0^\infty \left[ \int_0^{\chi_k} \frac{1}{\sqrt{2\pi}\sigma_I y} \exp \left[ -\frac{(\ln y - \ln \mu_I)^2}{2\sigma_I^2} \right] dy \right] \times \left[ 1 - Q \left( \frac{\ln x - \ln \mu_d}{\sigma_d} \right) \right]^{L-1} \left( \frac{1}{\sqrt{2\pi}\sigma_d x} \exp \left[ -\frac{(\ln x - \ln \mu_d)^2}{2\sigma_d^2} \right] \right) dx \quad (7)$$

where $Q(y) = \int_y^\infty \frac{1}{\sqrt{2\pi}} \exp(-x^2/2)dx$, and $\sigma_d$ and $\mu_d$ are the shadowing standard deviation and area mean power of the desired signal on the $k$th diversity branch, respectively.

For ease of evaluation, we let $w = (\ln x - \ln \mu_d)/\sqrt{2\sigma_d}$ and transform (7) into a Hermite integration form. That is,

$$P(CI) = 1 - \int_{-\infty}^{\infty} g(w) \exp(-w^2)dw \simeq 1 - \sum_{i=1}^{n} g(w_i)h_i \quad , \quad (8)$$
\begin{equation}
    g(w) = \frac{L}{\sqrt{\pi}} \left[ 1 - Q \left( \frac{\sqrt{2} \sigma_d w + \ln \frac{\mu_d}{\sigma_d \mu_{th,l}}}{\sigma_d} \right) \right] [1 - Q (\sqrt{2} w)]^{L-1},
\end{equation}
and \( w_i \) and \( h_i \) are the roots and weight factors of the \( n \)-th order Hermite polynomial, respectively [23].

**III-B Rician Fading and Shadowing**

For a local-mean-based macrodiversity system with shadowed Rician fading channels, the branch selection is still based on the best local mean power \( \Omega_{d,k} \). If \( S \) in (5) is assumed known, then by substituting (3) and (4) into (6) we obtain [10]

\begin{equation}
    P(CI \mid S, \Omega_I) = \sum_{i=1}^{\infty} \frac{\Omega_{I,i}^{n-1}}{\prod_{j=1,j \neq i}^{n} (\Omega_{I,i} - \Omega_{I,j})} \frac{K + 1}{K + 1 + \frac{S}{\Omega_{I,i} \lambda_{th}}} \exp \left[ -K \frac{S}{\lambda_{th} \Omega_{I,i}} \right] \frac{S}{K + 1 + \frac{S}{\Omega_{I,i} \lambda_{th}}}
\end{equation}

where \( \Omega_I = (\Omega_{I,1}, \cdots, \Omega_{I,n}) \) and \( K \) is the Rice factor of the desired signal. Assuming that the \( \{\Omega_{I,k}\}_{k=1}^{n} \) are independent, the joint pdf of \( \Omega_I \) is

\begin{equation}
    f_{\Omega_I}(\varepsilon) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi} \sigma_{\Omega_{I,i}}} \exp \left[ -\frac{(\ln \varepsilon_i - \ln \mu_{I,i})^2}{2\sigma^2_{\Omega_{I,i}}} \right]
\end{equation}

where \( \varepsilon = (x_1, \cdots, x_n) \). By using (11), (10), and the pdf of \( S \), we obtain

\begin{equation}
    P(CI) = \int_{0}^{\infty} \cdots \int_{0}^{\infty} P(CI \mid S, \Omega_I) \frac{L }{\sqrt{2\pi} \sigma_d} \left[ 1 - Q \left( \frac{\ln S - \ln \mu_d}{\sigma_d} \right) \right]^{L-1} \exp \left[ -\frac{(\ln S - \ln \mu_d)^2}{2\sigma^2_d} \right] \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi} \sigma_{\Omega_{I,i}}} \Omega_{I,i} \exp \left[ -\frac{(\ln \Omega_{I,i} - \ln \mu_{I,i})^2}{2\sigma^2_{\Omega_{I,i}}} \right] dS d\Omega_I.
\end{equation}
By using the substitution \( \alpha = \ln(S/\mu_d)/\sqrt{2\sigma_d} \) and \( \beta_i = \ln(\Omega_{I,i}/\mu_{I,i})/\sqrt{2\sigma_{I,i}} \), \( i = 1, \ldots, n \), we transform (12) into a Hermite integration form, which can be evaluated with numerical ease. In particular,

\[
P(CI) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \frac{L \left[ 1 - Q\left(\sqrt{2\alpha}\right)\right]^{L-1} G(\alpha, \beta)}{\sqrt{\pi}^{n+1}} \exp \left[ -\alpha^2 - \sum_{i=1}^{n} \beta_i^2 \right] d\alpha \ d\beta
\]

\[
\simeq \sum_{k_1=1}^{h_1} \cdots \sum_{k_n=1}^{h_n} \frac{L \left[ 1 - Q\left(\sqrt{2x_{k_0}}\right)\right]^{L-1} G(x_{k_0}, x_{k_1}, \ldots, x_{k_n})}{\sqrt{\pi}^{n+1} w_{k_0} \cdots w_{k_n}}
\]

(13)

where \( \beta = (\beta_1, \ldots, \beta_n) \), \( x_{k_i} \) is the root of the \( h_i \)th order Hermite polynomial, and \( w_{k_i} \) is its corresponding weight factor. Here \( G(\alpha, \beta) \) is obtained by substituting \( S = \mu_d \exp(\sqrt{2\alpha\sigma_d}) \) and \( \Omega_{I,i} = \mu_{I,i} \exp(\sqrt{2\beta_i\sigma_{I,i}}) \), \( i = 1, \ldots, n \), into \( P\left(CI \mid S, \Omega_I\right) \) in (10). That is

\[
G(\alpha, \beta) = \sum_{i=1}^{n} \frac{1}{\prod_{j=1}^{n} \left(1 - \frac{\mu_{I,i}}{\mu_{I,i}} \exp\left[\sqrt{2}(\beta_j\sigma_{I,j} - \beta_i\sigma_{I,i})\right]\right)} \frac{K+1}{K+1+\epsilon_i} \exp \left[ -\frac{K\epsilon_i}{K+1+\epsilon_i} \right]
\]

(14)

where

\[
\epsilon_i = \frac{\mu_d}{\lambda_{th}\mu_{I,i}} \exp\left[\sqrt{2}(\alpha\sigma_d - \beta_i\sigma_{I,i})\right].
\]

(15)

### IV Correlated Branches

Until now, we have assumed independent shadowing on the macrodiversity branches. This assumption may sometimes be violated because of insufficient spacing of BSs, especially in microcell systems.

For a correlated \( L \)-branch macrodiversity system, the joint pdf of \( \Omega_d \) \cite{22}

\[
f_{\Omega_d}(z) = \frac{\exp\left[ -\frac{1}{2}YT^TM^{-1}Y \right]}{\sqrt{(2\pi)^L \det(M)}} z_1 \cdots z_L
\]

(16)
where \( z = (z_1, \ldots, z_L) \), \( Y^T = [y_1, \ldots, y_L] \) denotes the transpose of column vector

\[
Y = \begin{bmatrix}
\ln(z_1) - \ln(\mu_1) \\
\vdots \\
\ln(z_L) - \ln(\mu_L)
\end{bmatrix}
\] (17)

and \( \mu_1, \ldots, \mu_L \) are the area means of each diversity branch. The covariance matrix \( M \) is expressed as

\[
M = \begin{bmatrix}
\sigma_1^2 & \cdots & \nu_{1L} \\
\vdots & \ddots & \vdots \\
\nu_{L1} & \cdots & \sigma_L^2
\end{bmatrix}
\] (18)

where \( \sigma_i \) is the shadowing standard deviation and \( \nu_{i,j} \) is the covariance of \( \ln(\Omega_{ai}) \) and \( \ln(\Omega_{di}) \)

\[
\nu_{ij} = E \left[ (\ln(\Omega_{di}) - \ln(\mu_i)) (\ln(\Omega_{di}) - \ln(\mu_j)) \right] .
\] (19)

It is convenient to define \( N = M^{-1} \) and express the matrix multiplication in (16) as follows.

\[
Y^TNY = \sum_{i=0}^L N_{ii}y_i^2 + 2 \sum_{i=0}^{L-1} \sum_{j=i+1}^L N_{ij}y_iy_j
\] (20)

where \( N_{ij} \) is the element in the \( i \)th row and \( j \)th column.

According to (5), (16), and (20), the probability that the local mean power \( S \) at the output of the combiner being less than \( y \) is

\[
\Pr(S < y) = \int_{-\infty}^{y} \cdots \int_{-\infty}^{y} \frac{1}{\sqrt{(2\pi)^L \det(M)z_1 \cdots z_L}} 
\exp \left[-\frac{1}{2} \left( \sum_{i=1}^L N_{ii}y_i^2 + 2 \sum_{i=1}^{L-1} \sum_{j=i+1}^L N_{ij}y_iy_j \right) \right] d\bar{z}
\] (21)

where \( N_{ij} \) and \( y_i \) are defined in (20) and (17), respectively.

The key for analyzing the CCI probability of the local-mean-based macrodiversity system is to find the pdf of the combiner output power, \( f_S(y) \). Unlike the
uncorrelated case where there exists a closed-form expression for \( f_S(y) \), one can not easily get a simple closed formula for the joint distribution of more than two mutually correlated lognormal random variables. However, for \( L = 2 \),

\[
f_S(y) = \frac{1}{\sqrt{2\pi \det(M)}} \left\{ \frac{1}{\sqrt{N_{22}}} \exp \left[ -\frac{y^2}{2} \left( \frac{N_{11}}{N_{22}} - \frac{N_{12}}{N_{22}} \right) \right] [1 - Q \left( \left( \frac{N_{11}}{\sqrt{N_{11}}} + \frac{N_{12}}{\sqrt{N_{11}}} \right) y \right)] \right. \\
\left. + \frac{1}{\sqrt{N_{11}}} \exp \left[ -\frac{y^2}{2} \left( \frac{N_{22}}{N_{11}} - \frac{N_{12}}{N_{11}} \right) \right] [1 - Q \left( \left( \frac{N_{22}}{\sqrt{N_{22}}} + \frac{N_{12}}{\sqrt{N_{22}}} \right) y \right)] \right\} \tag{22}
\]

where \( y = (\ln p_d - \ln \Upsilon_d) \) and \( d \) denotes the branch selected by the macrodiversity system. Consider the following covariance matrix \( M \)

\[
M = \begin{bmatrix} \sigma^2 & \mu \\ \mu & \sigma^2 \end{bmatrix}, \tag{23}
\]

and

\[
N = M^{-1} = \frac{1}{\sigma^4 - \mu^2} \begin{bmatrix} \sigma^2 & -\mu \\ -\mu & \sigma^2 \end{bmatrix}. \tag{24}
\]

By substituting (24) into (22), we express the pdf of the output local-mean power of the dual macrodiversity system as

\[
f_S(y) = \frac{\sqrt{2}}{\sqrt{\pi} \sigma y} \left\{ 1 - Q \left[ \left( \frac{1 - r}{\sqrt{1 - r^2}} \right) \left( \frac{\ln y - \ln \mu_d}{\sigma} \right) \right] \exp \left[ -\frac{(\ln y - \ln \mu_d)^2}{2\sigma^2} \right] \right\} \tag{25}
\]

where the correlation coefficient \( r \) is defined as \( r = \frac{\nu}{\sigma^2} \). Combining (10), (11), and (25), we obtain

\[
P(CI) = \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} \frac{2G(\alpha, \beta)}{\sqrt{\pi}^{n+1}} \left[ 1 - Q \left( \sqrt{2} \left( \frac{1 - r}{\sqrt{1 - r^2}} \right) \alpha \right) \right] \exp \left[ -\alpha^2 - \sum_{i=1}^{n} \beta_i^2 \right] d\alpha \ d\beta
\]

\[
= 12 \sum_{k_n=1}^{h_n} \ldots \sum_{k_0=1}^{h_0} 2 \frac{1 - Q \left( \sqrt{2} \left( \frac{1 - r}{\sqrt{1 - r^2}} \right) x_{k_0} \right)}{\sqrt{\pi}^{n+1}} G(x_{k_0}, \ldots, x_{k_n}) \frac{w_{k_0} \ldots w_{k_n}}{P(CI)}. \tag{26}
\]
where $\alpha$ and $\beta$ are defined in (13), the weight factor $w_k$ of the $h$th order Hermite polynomial can be found in [23], and $G(\alpha, \beta)$ is defined in (14).

V Numerical Results

We consider a cellular system with nine cells per cluster. In this case, two co-channel interferers are at 5.2 $R$, where $R$ is the cell radius. Assume the mobile unit is on the boundary of the cell with a distance of $R$ to the base station. Consider a dual slope path loss model with $a = b = 2$ and $g = 0.15$ in (1). By letting $L = 1$ in (13) and (8), we show the results of shadowing, Rician fading, and Rayleigh fading in Fig. 1 for the case of no macrodiversity. For 10\% CCI, the performance of a shadowed Rayleigh fading channel is about 4 dB worse than a pure shadowing channel. On the other hand, the degradation with Rician fading is less than 1 dB for $K = 7$ dB to 20 dB. Surprisingly, Rician fading can sometimes improve the performance when the threshold in receiver is high.

Figs. 3 (a) and (b) illustrate the gain achieved by a local-mean-based S-macrodiversity system over a shadowed-Rician (desired) /shadowed-Rayleigh (interfering) channel for the Rice factors $K = 7$ and 20 dB. For comparison, Figs. 2 (a) and (b) shows the CCI probability performance in pure shadowing channels and shadowed Rayleigh channels, respectively. Table 1 – 4 list the threshold $\lambda_{th}$ and diversity gain (D.G.) in terms of 5 and 10\% co-channel interference (CCIP) probability. Diversity gain here is defined as the additional S/I (in dB) that is required by a system without diversity to produce the same CCI probability. Some general observations can be made: 1) a higher shadowing spread leads to a higher diversity gain and a lower required threshold $\lambda_{th}$; 2) the diversity gain per branch is decreased as the number of diversity branches is increased; 3) the diversity gain increases with the requirement
of the system, e.g., the diversity gain for 5% CCI probability is higher than that for 10% CCI probability. In addition, we see that the diversity gain seems to be affected little by fading and that a shadowed Rayleigh channel has the least diversity gain.

We evaluate the effects of correlation coefficient $r$ on a 2-branch macrodiversity system with various $K$ and $\sigma$, $K = -\infty$ dB and $\sigma = 6$ dB (Fig. 4 (a)); $K = 10$ dB and $\sigma = 6$ dB (Fig. 4 (b)); $K = -\infty$ dB and $\sigma = 10$ dB (Fig. 5 (a)); $K = 10$ dB and $\sigma = 10$ dB (Fig. 5 (b)). With respect to 10% CCI probability, Table 5 lists $\lambda_{th}$ with different $r$. Observe that as $r$ approaches one, the diversity gain becomes zero. Furthermore, for $r = 0.7$, the diversity gain will be reduced to about 50% of the gain when $r = 0$.

VI Concluding Remarks

This paper presented an analytical model for calculating the co-channel interference probability of a local-mean-based macrodiversity system in a shadowed Rician (desired) / shadowed Rayleigh (interfering) channel. Compared to a pure shadowing channel, Rayleigh fading degrades the S/I performance by about 4 ~ 5 dB at 10% CCI probability. However, as the Rice factor $K$ gets large, the degradation of S/I is within 1 dB. We also observe that fading (either Rayleigh or Rician) has little effect on the diversity gain of local-mean-based macrodiversity systems. The diversity gain is the same, but Rayleigh fading is always worse than Rician fading.

In two-branch macrodiversity system, a branch correlation coefficient of $r = 0.7$ will reduce the diversity gain by 50%. We considered correlated shadowing between diversity branches, but shadowing components between the desired and interfering signals are assumed to be independent in this paper. Furthermore, it has been shown that the correlation of shadowing components between interferers does not signifi-
cantly influence the CCI probability performance [21]. The results obtained in this paper will be close to the results derived for the environment with multiple correlated log-normal shadowing interferers.

References


Table 1. Macrodiversity gain (D. G.) and the threshold $\lambda_{th}$ of S/I set at the receiver in terms of 5 % and 10 % co-channel interference probability (CCIP) over a pure shadowing channel.

<table>
<thead>
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<th>$\sigma = 10$ dB</th>
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<td></td>
<td>5 % CCIP</td>
<td>10 % CCIP</td>
<td>5 % CCIP</td>
<td>10 % CCIP</td>
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<td>20.46</td>
<td>11.78</td>
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</table>

Table 2. Macrodiversity gain (D. G.) and the threshold $\lambda_{th}$ of S/I set at the receiver in terms of 5 % and 10 % co-channel interference probability (CCIP) over a channel with both shadowing and Rayleigh fading.

<table>
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<th>$\sigma = 10$ dB</th>
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<td>-</td>
<td>9.55</td>
<td>-</td>
</tr>
<tr>
<td>4</td>
<td>11.78</td>
<td>6.29</td>
<td>15.51</td>
<td>5.96</td>
</tr>
<tr>
<td>5</td>
<td>13.13</td>
<td>7.64</td>
<td>16.80</td>
<td>7.25</td>
</tr>
</tbody>
</table>
Table 3. Macrodiversity gain (D. G.) and the threshold $\lambda_{th}$ of S/I set at the receiver in terms of 5 % and 10 % co-channel interference probability (CCIP) over a channel with both shadowing and Rician fading $K_d = 7$ dB.

<table>
<thead>
<tr>
<th>$L$</th>
<th>$\sigma = 6$ dB</th>
<th>$\sigma = 10$ dB</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5 % CCIP</td>
<td>10 % CCIP</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{th}$</td>
<td>D. G.</td>
</tr>
<tr>
<td>1</td>
<td>9.34</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>13.81</td>
<td>4.47</td>
</tr>
<tr>
<td>3</td>
<td>16.11</td>
<td>6.77</td>
</tr>
<tr>
<td>4</td>
<td>17.47</td>
<td>8.13</td>
</tr>
</tbody>
</table>

Table 4. Macrodiversity gain (D. G.) and the threshold $\lambda_{th}$ of S/I set at the receiver in terms of 5 % and 10 % co-channel interference probability (CCIP) over a channel with both shadowing and Rician fading $K_d = 20$ dB.

<table>
<thead>
<tr>
<th>$L$</th>
<th>$\sigma = 6$ dB</th>
<th>$\sigma = 10$ dB</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5 % CCIP</td>
<td>10 % CCIP</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{th}$</td>
<td>D. G.</td>
</tr>
<tr>
<td>1</td>
<td>10.86</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>15.56</td>
<td>4.70</td>
</tr>
<tr>
<td>3</td>
<td>17.51</td>
<td>6.65</td>
</tr>
</tbody>
</table>
Table 5. Effects of branch correlation on a 2-branch macrodiversity.

<table>
<thead>
<tr>
<th>$r$</th>
<th>$\sigma = 6$ dB (K = -\infty) dB</th>
<th>$\sigma = 6$ dB (K = 10) dB</th>
<th>$\sigma = 10$ dB (K = -\infty) dB</th>
<th>$\sigma = 10$ dB (K = 10) dB</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\lambda_{th}$</td>
<td>D. G.</td>
<td>$\lambda_{th}$</td>
<td>D. G.</td>
</tr>
<tr>
<td>0</td>
<td>13.54</td>
<td>3.99</td>
<td>17.75</td>
<td>4.33</td>
</tr>
<tr>
<td>0.1</td>
<td>13.39</td>
<td>3.84</td>
<td>17.45</td>
<td>4.03</td>
</tr>
<tr>
<td>0.3</td>
<td>12.78</td>
<td>3.23</td>
<td>16.90</td>
<td>3.48</td>
</tr>
<tr>
<td>0.5</td>
<td>12.23</td>
<td>2.68</td>
<td>16.26</td>
<td>2.84</td>
</tr>
<tr>
<td>0.7</td>
<td>11.46</td>
<td>1.91</td>
<td>15.53</td>
<td>2.11</td>
</tr>
<tr>
<td>0.9</td>
<td>10.51</td>
<td>1.02</td>
<td>14.46</td>
<td>1.04</td>
</tr>
<tr>
<td>1.0</td>
<td>9.55</td>
<td>-</td>
<td>13.42</td>
<td>-</td>
</tr>
</tbody>
</table>

Fig. 1. Comparison of CCI probability, $P(CI)$, for no macrodiversity over pure shadowing channels, shadowed Rayleigh channels, and shadowed Rician channels, where $\sigma = 6$ dB, $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of 5.2R.
Fig. 2. The CCI probability, $P(CI)$, against the required threshold, $\lambda_{th}$, at the receiver for the local-mean-based macrodiversity system over (a) pure shadowing channels and (b) shadowed Rayleigh channels, where the solid lines (——) denote the case for shadowing standard deviation $\sigma = 10$ dB and the dashed lines (---) for $\sigma = 6$ dB; $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of 5.2R.
Fig. 3. The CCI probability, $P(CI)$, against the required threshold, $\lambda_{th}$, at the receiver for the local-mean-based macrodiversity system over the shadowed-Rician (desired) / shadowed-Rayleigh (interfering) channel with Rice factor (a) $K = 7$ dB and (b) $K = 20$ dB, where the solid lines (—) denote the case for shadowing standard deviation $\sigma = 10$ dB and the dashed lines (— — —) for $\sigma = 6$ dB; $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of $5.2R$. 
Fig. 4. Effect of branch correlation coefficient $r$ on the local-mean-based macrodiversity system with Rice factor (a) $K = -\infty$ dB and (b) $K = 10$ dB, where $\sigma = 6$ dB; $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of $5.2R$. 

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Fig. 5. Effect of branch correlation coefficient $r$ on the local-mean-based macrodiversity system with Rice factor (a) $K = -\infty \text{ dB}$ and (b) $K = 10 \text{ dB}$, where $\sigma = 10 \text{ dB}$, $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of $5.2R$. 
ANNUAL NSF GRANT PROGRESS REPORT

NSF Program: CISE-NCR

NSF Award Number: NCR-9523969

Period Covered By This Report: 97/02/01 - 98/01/31

Date: October 31, 1997

Pl Name: Gordon L. Stüber

Chin-Tau Lea

Pl Institution: Georgia Tech

Pl Address: School of ECE

Georgia Tech

Atlanta, GA 30332-0250

☑ Check if Continued Funding is Requested

Please include the following information:

1. Brief summary of progress to date and work to be performed during the succeeding period;

2. Statement of funds estimated to remain unobligated --if more than 20%-- at the end of the period for which NSF currently is providing support (not required for participants in the Federal Demonstration Project);

3. Proposed budget for the ensuing year in the NSF format, only if the original award letter did not indicate specific incremental amounts or if adjustments to a planned increment exceeding the greater of 10% or $10,000 are being requested;

4. Current information about other research support of senior personnel, if changed from the previous submission;

5. Any other significant information pertinent to the type of project supported by NSF or as specified by the terms and conditions of the grant;

6. A statement describing any contribution of the project to the area of education and human-resource development, if changed from any previous submission; and

7. Updated information on animal care and use, Institutional Biohazard Committee and Human Subject Certification, if changed substantially from those originally proposed and approved.

I certify that to the best of my knowledge (1) the statements herein (excluding scientific hypotheses and scientific opinions) are true and complete, and (2) the text and graphics in this report as well as any accompanying publications or other documents, unless otherwise indicated, are the original work of the signatories or individuals working under their supervision. I understand that the willful provision of false information or concealing a material fact in this report or any other communication submitted to NSF is a criminal offense (U.S. Code, Title 18, Section 1001.)

P.I. Signature: [Signature]

NSF Form 1328 (1/94)
Cellular Architectures
and Resource Management

Progress Report for
NCR-9523969

Prepared for
National Science Foundation

Prepared by

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Sponsor Technical Contact

Thomas Fuja

National Science Foundation
Network and Communications Research Program
4201 Wilson Boulevard, Rm 1175
Arlington, VA 22230

October 1997
1 Summary of Progress

This project addresses the following three issues i) cellular architectures, ii) link quality evaluation and handoff algorithms, and iii) distributed dynamic channel assignment. The following progress has been made to date. Publications that have been supported from this project are listed at the end of this section. Copies of these publications (manuscripts if submitted) are attached.

Hierarchical Cellular Architectures

An innovative hierarchical microcell/macrocell architecture has been developed [1]. By applying the concept of cluster planning, the proposed sectoring arrangement can provide good shielding between micro- and macro-cells. As a result, underlaid microcells can reuse the same frequencies as overlaying macrocells without decreasing the macrocell system capacity. With the proposed method, microcells not only can be gradually deployed, but they can be extensively installed to provide complete coverage and increase capacity throughout the service area. With these flexibilities, the proposed method allows existing macrocellular systems to evolve smoothly into a hierarchical microcell/macrocell architecture.

Macrodiversity Cellular Architectures

In a macrodiversity cellular system, switching radio links between base stations cannot be done instantaneously. Thus branch selection is usually based on the measurement of the slowly-varying local mean power rather than the rapidly-varying instantaneous signal power. We have developed an exact mathematical model to analyze the performance of a local-mean-based macrodiversity cellular system in a shadowed-Rician (desired) /shadowed-Rayleigh (interfering) channel [2,3]. We have investigated the impact of both fading (Rician or Rayleigh) and shadowing in terms of co-channel interference (CCI) probability. An analytical model has also been developed to incorporate the effects of branch correlation on macrodiversity systems.

MAWCC: A New Network Architecture

Current cellular systems are based on the concept of cell. Although cell allows channel reuse, it has also become a metaphor for channel confinement and leads to the thorny problem of handoff and call-dropping. The problem will get much worse as cellular services move toward high-speed and multirate.

In [4], we extend the idea originally described in our earlier research [8] and present a new wireless network architecture: called MAWCC for its main characteristic—
MAcrodiversity Without Channel Confinement. In MAWCC, mobility equals capacity. The convertibility between the two (capacity and mobility) makes MAWCC a total departure from a conventional wireless network. If offers more options for tackling the issues of mobility, handoff, and call dropping.

SIR Estimation in TDMA Cellular Systems

A new algorithm to estimate the signal-to-(interference ratio plus noise) ratio $S/(I+N)$ was developed for TDMA cellular systems [5,6]. Simulation results show that the $S/(I+N)$ can be estimated to within 0.5 dB in about 0.5 s for the IS-54/136 system and to within 0.5 dB in about 0.1 s for the GSM system. The estimator is computationally simple and outperforms all other $S/(I+N)$ estimators that have been reported previously in the literature.

Modeling Mobility in Power Control

One of the elements missing in most literature related to power control is mobility. Without it, the performance of a power control scheme and its convergence cannot be reliably predicted. In [7] we use random walk to model mobility. Combining the mobility model with a conventional CCI analysis, we study power control in a more dynamic environment. The power control schemes we focus on in the paper are linear schemes where the power adjustment is a linear function of the deviation of the received signal from the target level. We study two implementations of a linear scheme: incremental and direct compensation. In the former, the adjustment is done one notch at a time; in the latter, a direct compensation is given immediately. The issues studied include the effect of mobility, the slope of the linear power control, effect of power quantization levels, and the inter-relationship between CCI and power consumption.

Publications


3. Wang, L.-C., Stüber, G.L., and Lea, C.-T., "Effects of Rician Fading and Branch Correlation on a Local-Mean-Based Macrodiversity Cellular System," accepted for publication in *IEEE Transactions on Vehicular Technology*.


## 2 Objectives for Next Year

The following items will be addressed during the next year.

SIR-based handoff algorithms

S/(I+N) is a better handoff criterion than the total received signal power, S+I+N, since it reflects the true radio link quality. In this part of the research we will incorporate the S/(I+N) estimation algorithm that we have developed into S/(I+N)-based handoff algorithms. Such algorithms will be essential for microcellular systems with their characteristically erratic radio propagation environments. Several S/(I+N)-based handoff algorithms will be studied and their performance evaluated through software simulation. The objective is to maintain consistent and near optimal handoff performance. That is, we would like to make the handoff regions small and keep them small under a variety of radio propagation conditions, e.g., different mobile station velocities, scattering environments, etc.
Capacity of MAWCC in High-, Low-, and Mixed-Mobility Environment

Compared to that of a conventional cellular network, the capacity gain of MAWCC can be significant. This gain comes from three factors: (1) macrodiversity, (2) higher trunking efficiency of DCA, and (c) the convertibility between mobility capacity and handoff (as shown in the example above). Items (1) and (2) have been widely studied for different environments. Item (3) is mostly unknown and will be investigated in this research.

We intend to built a simulator to study the capacity gain of MAWCC in detail. We also intend to design an analytical model in our study. This study involves both handoff modeling and link quality modeling. In [8], it was shown that handoffs in MAWCC can be likened to collisions of particles in a chamber. We will extend the concept and evaluate MAWCC’s capacity in a high-, low-, and mixed-mobility environment. We will also compare MAWCC’s capacity with that of the macrocell-overlaying-microcell architecture.

Handoff Reduction in MAWCC

In a traditional cellular system, a mobile unit immediately requires a handoff as it crosses a cell boundary. But a mobile unit in MAWCC can travel a much longer distance before a handoff is needed. One is that macrodiversity can lead to a shorter channel reuse distance. If we keep the distance the same, it means that a mobile user can travel a longer distance without violating the co-channel interference requirement. The other reason, given below, is more surprising.

The inherent imperfect packing of DCA allows a mobile unit to travel a greater distance. For example, suppose a cellular system imposes a reuse distance of 4 during call setup. Due to imperfect packing, the real average reuse distance is increased to 5. (The maximum packing efficiency depends on the complexity of the algorithm.) In a conventional DCA system, imperfect packing is just bandwidth waste. But MAWCC converts that bandwidth waste into handoff reduction.

In this study we will show by analysis and simulation the convertibility between mobility and capacity in MAWCC and how it can reduce the number of handoffs. Reducing handoffs means reducing the forced termination probability.

SDMA and MAWCC Architecture

When two users sharing a channel in a cell under SDMA become too close to be resolved a contention will occur and a handover must be performed within the cell. This causes a reduction in capacity under SDMA and also the possibility of outage. Under MAWCC with SDMA, however, the inherent macrodiversity will allow the user under contention to simply access resources from the adjacent cell. The directionality
of the smart antennas utilized in SDMA allows the contention to be overcome because the beam from the adjacent cell will be angle/spatially separated thereby allowing SDMA to be utilized in the adjacent cell. In effect the inherent directionality of the smart antennas in SDMA combined with MAWCC give the system an extra degree of freedom resulting in less contentions and an increase in capacity.

In this part of the study we will evaluate the capacity of the system with MAWCC and SDMA and compare it to the capacity of a system with SDMA alone. An important consideration of the study will be the analysis of the contentions. Analytical results will initially be invoked to perform this study.

3 Education and Human Resource Development

The following Ph.D. students have been supported from this grant:

- **Li-Chun Wang** – completed his Ph.D. and is now with AT&T Research, Crawford Hill Laboratory, Holmdel NJ.

- **Kai-Wei Ki** – completed his Ph.D. and is now an Associate Professor, Dept of EE, Taipei Institute of Technology, Taipei, Taiwan.

- **Mustafa Turkboylari** – a Ph.D. student under the supervision of Prof. Stüber. The student has passed the Ph.D. Qualifying Exam.

- **Chi-Jui Ho** – a Ph.D. student under the supervision of Prof. Lea. The student has passed the Ph.D. Qualifying Exam.
Architecture Design, Frequency Planning, and Performance Analysis for a Microcell/Macrocell Overlaying System

Li-Chun Wang, Student Member, IEEE, Gordon L. Stüber, Senior Member, IEEE, and Chin-Tau Lea, Senior Member

Abstract—An innovative hierarchical microcell/macrocell architecture is presented. By applying the concept of cluster planning, the proposed sectoring arrangement can provide good shielding between microcells and macrocells. As a result, underlaid microcells can reuse the same frequencies as overlaying macrocells without decreasing the macrocell system capacity. With the proposed method, microcells not only can be gradually deployed, but they can be extensively installed to provide complete coverage and increase capacity throughout the service area. With these flexibilities, the proposed method allows existing macrocellular systems to evolve smoothly into a hierarchical microcell/macrocell architecture.

Index Terms—AUTHOR: PLEASE PROVIDE KEY WORDS. FOR MORE INFORMATION, EMAIL: keywords@ieee.org Hierarchical cellular architecture, microcell/macrocell overlaying system, cluster planning.

INTRODUCTION

Hierarchical microcell/macrocell architectures have been proposed for future personal communications systems [1]. These architectures provide capacity relief to a macrocell system and offer many advantages over a pure microcell system. Unlike the pure microcell system, which requires extensive microcell base-station (BS) deployment throughout the whole service area, a hierarchical architecture allows gradual deployment of microcells as user demand increases. The hierarchical architecture also protects investment cost in the existing macrocellular system, while a pure microcell system requires replacement of the macrocell BS's. Furthermore, the fast handoff requirement in a pure microcell system can be relieved in the overlaying architecture by temporarily connecting the call to a macrocell BS [2].

The method of sharing the radio spectrum is the key issue for hierarchical microcell/macrocell systems. Different kinds of frequency sharing schemes have been proposed in the literature [3]-[5]. Orthogonal sharing partitions the frequency channels into two disjoint sets: one for macrocells and one for microcells [3]. Channel borrowing requires that the underlaid microcells utilize the free channels of adjacent macrocells [4]. A overlaying scheme that combines dynamic channel allocation (DCA) and power control is proposed in [5]. Each of the above schemes has some problems. Orthogonal sharing [3] decreases the macrocell system capacity if the available spectrum has already been assigned to macrocells. Channel borrowing [4] can only relieve hot-spot traffic, but it is ineffective if the neighboring cells also have heavy traffic. The scheme in [5] requires power control (both uplink and downlink) and DCA, both of which will increase implementation cost.

This paper introduces an innovative hierarchical microcell/macrocell architecture to circumvent the above trade-offs. Under the proposed architecture, microcells can reuse the macrocell frequencies and will not decrease the macrocell system capacity. Furthermore, unlike the channel-borrowing scheme, which is effective only when the neighboring cells have free channels, the proposed architecture allows the microcells to be deployed throughout the whole service area regardless of the traffic load of the neighboring macrocells. Compared to the system in [5], our architecture neither requires DCA nor downlink power control.

The remainder of this paper is organized as follows. Section II describes the system architecture. Section III offers a frequency planning algorithm that identifies the low-interference macrocell frequencies that can be used in the microcells. Section IV describes the propagation model and system assumptions. The cochannel interference performance of the overlaying macrocells and underlaid microcells are discussed in Sections V and VI. The adjacent channel interference is discussed in Section VII. We conclude our discussion in Section VIII.

Figure

II. SYSTEM ARCHITECTURE

Fig. 1 shows a traditional three-sector N = 7 cellular system, where each cell consists of three sectors and N is the number of cells per cluster. In this system, the total channels are partitioned into 21 sets. The channel sets are assigned to the sectors so as to satisfy the frequency reuse constraint, e.g., channel set s in Fig. 1. The widely distributed cochannel interference makes it difficult to reuse the channel sets outside of their designated sectors. In the following, we introduce a cluster planning procedure to change the conventional sectoring scheme into a new structure.

A. Cluster Planning Procedure

1) Assign the same channels to each cell site as in the traditional three-sector N = 7 cellular system (Fig. 1),
where seven cells form a cluster and share the entire spectrum.

2) Divide macrocell clusters into three adjacent groups (Fig. 2).

3) Let the first group be the reference group.

4) Rotate the channel sets of the sectors in the second group 120° clockwise with respect to the first group.

5) Rotate the channel sets of the sectors in the third group 120° counterclockwise with respect to the first group.

Based on the above procedure, the sector rotations create low-interference regions outside the areas of the designated macrocell sectors for each channel set. These low-interference regions are called microareas. Fig. 3 shows the result of rotating the sectors. We see that zones A ~ F have a very low interference for channel set $4_β$ since they are located in the back-lobe areas of the macrocell sectors using channel set $4_β$. Thus microcells can be introduced in these areas that use channel set $4_β$.

III. UNDERLAI D MICROCELL PLANNING ALGORITHM

As shown in Section II, microcells in the proposed architecture that are located in microareas can reuse certain macrocell channel sets. To have a greater flexibility in selecting the microcell BS locations, it is important that we identify all possible microareas and the channels sets they can use.

In our system, macrocells use frequencies on the front-lobe area of their directional antennas, while microcells reuse the same frequencies on the back-lobe area. In the conventional three-sector $N = 7$ cellular system (Fig. 1), the back-lobe area of each channel set will still encounter some first-ring interferers. To protect the back-lobe areas from the first-tier interferers, we rotate the sectors through the cluster planning procedure described in Section II. Cluster planning creates low-interference microareas, as shown in Fig. 3, which lie in the back-lobe areas of the first-tier interferers. For ease of indexing, a microarea denotes a region of three adjacent macrocell sectors, each of which belongs to a different BS.

Fig. 4 shows an example of a microarea. Each microarea has an interference neighborhood, defined as the 18 neighboring macrocell sectors that surround the microarea.

Let $Ψ_i^j$ represent the channel set in the sector $i$ ($i = α, β,$ and $γ$) of cell site $Ψ (Ψ = 1/7)$; associate the superscript $j$ in $Ψ_i^j (j = 1/β)$ with three types of cluster rotations: $-120°, 0°,$ and $120°$. Then, the following interesting observation can be made.

A. Observation

Consider a microarea and its interference neighborhood. A
microarea can be located in the back-lobe area of the sectors 
using channel sets \( \Psi^j \) and \( \Psi^j \) (\( j = 1,2,3 \)) if and only if it is surrounded by the main-lobe of three cochannel macrocell 
sectors using channel set \( \Psi^j \) (\( j = 1,2,3 \)).

Based on the above observation, the following algorithm has been developed to determine the macrocell channel sets that can be reused in a microarea.

B. Macrocell Channel-Selection Algorithm

1) Objective: identify low-interference macrocell channels that can be reused in the underlaid microcells.

2) For any microarea and its interference neighborhood \( M \), let

\[ \Theta = \{ \Psi^j \in M \} \]

denote the union of channel sets \( \Psi^j \) that are used in \( M \).

3) From \( \Theta \), a \( 3 \times 3 \) indicator matrix \( B_\Psi = [b_{ij}] \) is constructed for cell cities \( \Psi = 1/3 \), where

\[ b_{ij} = \begin{cases} 1, & \text{if the channel set } \Psi^j \in M \\ 0, & \text{otherwise.} \end{cases} \]

4) If a certain indicator matrix \( B_\Psi \) has a row of ones and two rows of zeros, then the zero rows of \( B_\Psi \) correspond to the macrocell channel sets available for the microarea.

1) Example: We illustrate the above algorithm by the following example. According to Figs. 3 and 4, the interference neighborhood of microarea \( A \) is

\[ \Theta = \{1^2, 2^2, 3^2, 4^2, 5^2, 6^2, 7^2, 8^2, 9^2, 10^2, 11^2, 12^2, 13^2, 14^2, 15^2, 16^2, 17^2, 18^2, 19^2, 20^2, 21^2, 22^2, 23^2, 24^2, 25^2, 26^2, 27^2, 28^2, 29^2, 30^2, 31^2, 32^2, 33^2, 34^2, 35^2, 36^2, 37^2, 38^2, 39^2, 40^2, 41^2, 42^2, 43^2 \} \]

The indicator matrices are

\[
B_1 = \begin{pmatrix}
0 & 1 & 0 \\
0 & 1 & 0 \\
0 & 1 & 0 \\
\end{pmatrix},
B_2 = \begin{pmatrix}
0 & 1 & 0 \\
0 & 1 & 0 \\
0 & 1 & 0 \\
\end{pmatrix},
B_3 = \begin{pmatrix}
0 & 1 & 1 \\
0 & 0 & 0 \\
0 & 1 & 0 \\
\end{pmatrix},
B_4 = \begin{pmatrix}
0 & 1 & 1 \\
0 & 0 & 0 \\
0 & 1 & 0 \\
\end{pmatrix},
B_5 = \begin{pmatrix}
1 & 1 & 0 \\
0 & 0 & 0 \\
1 & 0 & 0 \\
\end{pmatrix},
B_6 = \begin{pmatrix}
0 & 1 & 1 \\
0 & 0 & 0 \\
1 & 0 & 0 \\
\end{pmatrix},
B_7 = \begin{pmatrix}
0 & 1 & 0 \\
0 & 1 & 0 \\
0 & 1 & 0 \\
\end{pmatrix}.
\]

Examination of the indicator matrices \( B_\Psi (\Psi = 1/3) \) reveals that \( B_4 \) is the only matrix having a row of ones and two rows of zeros; the second row and the third rows of \( B_4 \) are the zero rows. According to the above algorithm, \( 4, 5, 6, 7 \) are the low-interference macrocell channel sets available for use in microarea \( A \). To see if microcells can be established in any location, we have examined a system with more microareas in Fig. 5. Through the above channel-selection algorithm, Table I shows that each microcell in the service area can reuse two macrocell channel sets. Recall that a microarea
represents an area of three macrocell sectors, each of which belongs to three different cell sites. Thus, a macrocell area can has five channel sets—one for macrocells and two for microcells. In a macrocell area, each of three macrocell sectors reuses its channel set only once, while a microarea can reuse its two macrocell channel sets many times, say \( C_\mu \) times, with a suitable cochannel reuse distance. Thus, it is implied that a macrocell area can use \( 3 + 2 \times C_\mu \) channel sets simultaneously. Compared with three channel sets in the conventional three-sector macrocell, the system capacity of the proposed architecture increases by a factor of \( 1 + 2 \times C_\mu / 3 \) times.

IV. PROPAGATION MODEL AND SYSTEM ASSUMPTIONS

A. Propagation Model

Our analysis considers the simple path-loss model [7]

\[
p_r = \frac{p_t(h_b h_m)^2}{d^4}
\]

where \( p_r \) and \( p_t \) are the received and transmitted powers, \( h_b \) and \( h_m \) are the antenna heights of the BS and the mobile station (MS), respectively, and \( d \) is the distance between the transmitter and receiver. Note that we incorporate the antenna gains in the transmitted power. Although (1) is derived from a macrocell environment, it is still applicable to characterize the path loss outside the microcells [3].

B. Assumptions

1) Interference: In the hierarchical architecture, we consider four types of cochannel interference. In addition to the usual macrocell-to-macrocell and microcell-to-microcell cochannel interference, we must also consider macrocell-to-microcell and microcell-to-macrocell cochannel interference. Adjacent channel interference is also discussed in Section VII.

2) Antenna: The macrocell BS's are assumed to use 120° directional antennas, while microcell BS's use omnidirectional antennas. The MSs also use omnidirectional antennas.

3) Uplink Power Control: In this paper, we adopt the power control scheme used in IS-54 and AMPS [6]. The transmitted power of Class-IV IS-54 portable handsets is adjusted in six levels from -22 to -2 dBW in steps of 4 dB. Downlink power control is not required in the proposed architecture. Before proceeding, we first clarify our notation.
Fig. 5. Frequency planning for the proposed system with 100 microareas. Table I lists the available channel sets for the above 100 microareas.

When $M$ and $\mu$ are used, they represent macrocells and microcells, respectively; when $m$ and $b$ are used, they denote the MS and BS, respectively; when $d$ and $u$ are used, they indicate the downlink (BS-to-MS) and uplink (MS-to-BS), respectively.

V. MACROCELL PERFORMANCE

As shown in Section II, the new cluster planning technique with sector rotation can create some low-interference regions so that microcells can reuse macrocell frequencies. Nevertheless, some macrocells will experience higher interference after rotating the sectors. To evaluate the influence of the sector rotations on the macrocell performance, we simulate
both the conventional macrocellular system (Fig. 1) and the proposed hierarchical cellular system (Fig. 3) without the underlaid microcells. Fig. 6 shows the simulation results of the uplink signal-to-interference (S/I) performance for both systems, assuming that the MSs are uniformly distributed in each sector and they transmit with the maximum power. We consider the uplink case because performance is usually better in the downlink than in the uplink [3]. With respect to 90% coverage probability, one can observe that the sector rotation technique creates low interference regions at the cost of about 3.1, 3.3, and 3.5 dB S/I degradation for path-loss exponent $\beta = 3.6$, 3.8, and 4.0. It is noteworthy that even after sector rotations, the macrocell can maintain S/I higher than 20 dB in 90% of the coverage area. In the following, we further include the underlaid microcells to analyze the performance of the proposed hierarchical cellular system. For ease of analysis, we hereafter adopt the worst case scenario, i.e., when an MS is on the cell boundary.

### A. Downlink Cochannel Interference Analysis

By applying (1), we express the signal-to-interference ratio (S/I) received by the MS at the macrocell boundary as

$$
S_M \frac{\sum_{i=1}^{N_M} P_{t,b}(h_i^M h_m)^2}{R_{M}^d + \sum_{y=1}^{J_y} C_y \sum_{k=1}^{R_{b,y}} P_{t,b}(h_y^b h_m)^2}
$$

Fig. 4. Interfering neighborhood for microarea A in Fig. 3.
where

\[ S_M^d \] MS received power from the desired macrocell BS;
\[ I_M^d \] downlink macrocell-to-macrocell interference;
\[ J_M^d \] downlink microcell-to-macrocell interference;
\[ P_{\mu}^{t,b} \] macrocell BS/transmitted power;
\[ P_{\mu}^{t,b} \] microcell BS/transmitted power;
\[ N_M \] number of macrocell interferers;
\[ Z_M \] number of interfering microareas;
\[ C_\mu \] number of microcell clusters in a microarea;
\[ D_i \] MS distance to the \( i \)th interfering macrocell BS;
\[ d_{j,k} \] MS distance to the \( k \)th interfering microcell BS in the \( j \)th microarea;
\[ h_M^b \] macrocell BS antenna height;
\[ h_k^b \] microcell BS antenna height;
\[ h_M^n \] MS antenna height;
\[ R_M \] macrocell radius.

Referring to Fig. 5 and Table I, we examine the downlink interference when a macrocell MS using channel set \( 4_\beta \) is located at the macrocell boundary near microarea 56. One can find that the macrocell-to-macrocell downlink interference \( I_M^d \) mainly comes from the first-tier macrocell BS's near microareas 77 and 68 with distances \( [D_1, D_2] = [4, 3.61]R_M \). However, we also consider the second-tier interfering BS's near microareas 11, 17, and 62 at distances \( [D_3, D_4, D_5] = [8.89, 8.89, 8.72]R_M \). For the microcell-to-macrocell downlink interference \( J_M^d \), one can find six interfering microareas 35, 48, 54, 80, 86, and 99 in the first tier with distances \( [d_1, d_2, d_3, d_4, d_5, d_6] = [3, 4.58, 3.46, 6, 5.2, 6.25]R_M \). The second-tier interfering microareas 3, 29, 41, and 92 have distances \( [d_7, d_8, d_9, d_{10}] = [7.55, 9, 7.94, 12]R_M \). We assume that each microarea has \( C_\mu \) microcell reuse clusters, with each cluster having \( K_\mu \) microcells. Through the channel-selection algorithm in Section III, each microarea is assigned two macrocell channel sets. We further partition these two sets of channels into \( K_\mu \) groups and then assign each group to the \( K_\mu \) microcells in each cluster. In this manner, a macrocell channel set is used \( C_\mu \) times in a microarea. For ease of analysis, we assume that the distance \( d_j \) approximates \( d_{j,k} \), where \( d_j \) is the distance from a macrocell MS to the center of the \( j \)th interfering microarea and \( d_{j,k} \) is defined in (2). In our example, the microcell BS antenna height is one third of macrocell BS antenna height, i.e., \( h_M^b/\frac{h_k^b}{h_M^n} = 1/3 \). With the above assumptions in (2)

\[
\frac{S_M^d}{I_M^d + J_M^d} = \frac{1}{1.02875 \times 10^{-2} + C_\mu \left( \frac{P_{\mu}^{t,b}}{P_{t,b}^{\mu}} \right) \times 2.79449 \times 10^{-3}}
\]

We show the downlink S/I performance in terms of \( C_\mu \) and \( P_{t,b}^{\mu}/P_{t,b}^{\mu} \) in Fig. 7 with consideration of only first-tier interfering BS's and, in Table II, with both first- and second-tier interfering BS's. Observe that S/I \( \geq 18 \) dB for \( C_\mu = 6 \) and \( P_{t,b}^{\mu}/P_{t,b}^{\mu} \leq 0.3 \). In other words, the channel set \( 4_\beta \) can be reused six times in the microarea while still keeping the macrocell downlink S/I greater than 18 dB. Furthermore, by comparing the results in Table II with Fig. 7, one can find that the second-tier interfering BS's only degrade the S/I by about 0.5 dB.
TABLE II

<table>
<thead>
<tr>
<th>( \frac{S_M^U}{I_M^U + J_{\mu M}^U} ) (dB)</th>
<th>( C_\mu = 1 )</th>
<th>( C_\mu = 2 )</th>
<th>( C_\mu = 4 )</th>
<th>( C_\mu = 6 )</th>
</tr>
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<tbody>
<tr>
<td>0</td>
<td>19.88</td>
<td>19.88</td>
<td>19.88</td>
<td>19.84</td>
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<tr>
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<td>19.22</td>
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<tr>
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<td>19.42</td>
<td>19.02</td>
<td>18.65</td>
</tr>
<tr>
<td>0.3</td>
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<td>19.22</td>
<td>18.65</td>
<td>18.15</td>
</tr>
<tr>
<td>0.4</td>
<td>19.43</td>
<td>19.02</td>
<td>18.31</td>
<td>17.70</td>
</tr>
<tr>
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<td>19.32</td>
<td>18.83</td>
<td>17.99</td>
<td>17.29</td>
</tr>
<tr>
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<td>18.65</td>
<td>17.69</td>
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<tr>
<td>0.7</td>
<td>19.12</td>
<td>18.48</td>
<td>17.42</td>
<td>16.57</td>
</tr>
<tr>
<td>0.8</td>
<td>19.02</td>
<td>18.30</td>
<td>17.16</td>
<td>16.25</td>
</tr>
<tr>
<td>0.9</td>
<td>18.93</td>
<td>18.14</td>
<td>16.91</td>
<td>15.95</td>
</tr>
<tr>
<td>1.0</td>
<td>18.83</td>
<td>17.99</td>
<td>16.68</td>
<td>15.68</td>
</tr>
</tbody>
</table>

B. Uplink Cochannel Interference Analysis

By modifying (2) slightly, we can formulate the uplink S/I performance as

\[
\frac{S_M^U}{I_M^U + J_{\mu M}^U} = \frac{\sum_{i=1}^{N_M} \frac{P_{T,m}^M (h_k^M h_m^M)^2}{D_i^2} + \sum_{j=1}^{k} \sum_{k=1}^{\infty} \frac{P_{T,m}^M (h_k^M h_m^M)^2}{d_j^2}}{P_t^M}
\]

(4)

where

- \( S_M^U \) is the macrocell BS received power from the desired MS;
- \( I_M^U \) is the uplink macrocell-to-macrocell interference;
- \( J_{\mu M}^U \) is the uplink microcell-to-macrocell interference;
- \( P_{T,m}^M \) is the transmitted power of the macrocell MS;
- \( P_{\mu M}^U \) is the transmitted power of the microcell MS.

The other parameters are defined following (2). With directional antennas, the macrocell BS’s experience fewer interfering microareas in the uplink direction as compared with the downlink direction. Consider the macrocell sector that is assigned with channel set 2γ and near microarea 37. This macrocell sector encounters two first-tier and four second-tier macrocell interfering MS’s with \([D_1, D_2, D_3, D_4, D_5, D_6] = [3.61, 3.61, 8.54, 8.19, 8.19, 7.81] R_m\) and interfering microareas \([23, 55, 61, 68, 74]\) and \(100\) (i.e., \( Z_\mu = 6 \)) with \([d_1, d_2, d_3, d_4, d_5, d_6] = [7.0, 7.0, 14.7, 5.3, 11.5, 9.53] R_m\). We ignore the effect of the three other interfering microareas \(4, 17, \) and \(49\) because they are located in the back-lobe area of the sector using channel set 2γ. By substituting the above values into (4), the uplink S/I performance for this example becomes

\[
\frac{S_M^U}{I_M^U + J_{\mu M}^U} = \frac{1}{1.2677 \times 10^{-2} + C_\mu \left( \frac{P_{T,m}^M}{P_t^M} \right) \times 2.11 \times 10^{-3}}
\]

(5)

Note that we obtained (6) by assuming that the interfering macrocell MS’s are on the cell boundary and are transmitting with the maximum power. Thus, (6) can be used to determine the maximum microcell MS’s transmitted power. For the IS-54 Class-IV portable handset (that adjusts its transmitted power in six levels from \(-22 \) to \(-2 \) dBW), (6) implies that the maximum microcell MS transmitted power is \(9 \) dBW, which is still in the operation range of the Class-IV terminal. Thus, the requirement in (6) can be fulfilled by the current uplink power control scheme in IS-54 system without changing the MS transmitted power specification.

VI. MICROCELL PERFORMANCE

This section studies how to determine the microcell size to achieve the required S/I performance.

A. Downlink Microcell Size

A feasible microcell size should satisfy two conditions:

1. \( S \)-criterion: \( S \) MS will receive stronger power than the macrocell boundary.
2. \( S/I \)-criterion: the signal-to-interference ratio \( (S/I) \) at the microcell boundary is equal to or better than that at the macrocell boundary.
1) S-criterion: From the path-loss model in (1), the microcell radius \( R_\mu \) can be calculated as

\[
R_\mu \leq \left[ \left( \frac{p_{t,b}^\mu}{p_{t,b}^M} \right) \left( \frac{h_{b}^\mu}{h_{b}^M} \right)^2 \right]^{1/4} R_M
\]

(7)

where \( R_M \), \( h_{b}^\mu \), \( h_{b}^M \), \( p_{t,b}^\mu \), and \( p_{t,b}^M \) are defined in (2).

2) S/1-criterion: The S/I received by the MS at the microcell boundary can be written as (8), given at the bottom of the page, where the parameters \( p_{t,b}^\mu \), \( p_{t,b}^M \), \( h_{b}^\mu \), \( h_{b}^M \), \( C_\mu \), and \( h_m \) are already defined in (2) and

\[
S^d_\mu \quad \text{MS received power from its desired microcell BS;}
\]

\[
I^d_\mu \quad \text{downlink microcell-to-microcell interference;}
\]

\[
J^d_{M,\mu} \quad \text{downlink macrocell-to-microcell interference;}
\]

\[
N_{M,\mu} \quad \text{number of main-lobe macrocell interferers;}
\]

\[
N_{M,b} \quad \text{number of back-lobe macrocell interferers;}
\]

\[
D_{M,i} \quad \text{MS distance to the } i\text{th main-lobe interfering BS;}
\]

\[
D_{M,b,j} \quad \text{MS distance to the } j\text{th back-lobe interfering BS;}
\]

\[
D_{\mu} \quad \text{microcell radius;}
\]

\[
R_\mu \quad \text{microcell radius;}
\]

\[
\eta \quad \text{front-to-back ratio of the directional antenna in macrocells.}
\]

Let \((S/I)_{req}\) denote the required S/I. Then, (8) becomes (9), given at the bottom of the page, where

\[
\bar{D}_{M,i} = D_{M,i} / R_M \quad \text{and} \quad \bar{D}_{\mu} = D_\mu / R_M
\]

are the normalized distances of interferers with respect to macrocell radius \( R_M \). Our studies assume that the microcells and macrocells have similar shapes and that the microcell clusters are adjacent to each other in a given microarea. Suppose the distances from a microcell MS to its interfering microcell BS’s are equal and close to the microcell cochannel reuse distance \( D_\mu \) (i.e., \( D_{\mu,i} = D_\mu \) for \( i = 1, \cdots, C_\mu \)). Then, we have [7]

\[
D_\mu = \sqrt{3K_\mu R_\mu}
\]

(10)

Substituting (10) and (11) into (9), we get (12), given at the bottom of the next page. Notice that we consider \( N_{M,b} \) backlobe macrocell interferers in (12). The back-lobe interference from the macrocell BS’s can be ignored for the macrocell MS, but for the microcell MS this kind of interference may be relatively strong compared to the received signal strength from the low-powered microcell BS. For the same reason, the macrocell interferers in the second ring are considered here.

\[\text{Example: Referring to Fig. 5 and Table I, microarea 56 can be assigned channel sets [4a,4b]. Take channel set 4a as an example. Microarea 56 will experience three first-tier back-lobe interferers (} N_{M,b} = 3\), each of which has the following distance:

\[
[D_{M,b,1}, D_{M,b,2}, D_{M,b,3}] = [2.65, 2.65, 2.65]
\]

(13)

to the center of microarea 56. Three main-lobe interfering macrocells in the second tier are located near microareas 25, 79, and 64 with the distances of

\[
[D_{M,1,2}, D_{M,2,3}] = [5.29, 5.29, 5.29]
\]

(14)

Additionally, three main-lobe interfering macrocell BS’s in the third tier are located near microareas 13, 70, and 85 with distances of

\[
[D_{M,1,4}, D_{M,2,5}, D_{M,3,6}] = [7.0, 7.0, 7.0]
\]

(15)

It is also important to determine if there exists interfering microcell BS’s from neighboring microareas. From Fig. 5 and Table I, one can find one feature of the proposed system architecture—the adjacent microareas are assigned with different macrocell channel sets. For instance, microarea 56 in Fig. 5 is assigned with the channel sets [4a,4b]. The neighboring microareas 45, 46, 55, 57, 66, and 67 use channel sets
[6, 8], [7, 8], [2, 2, 2], [3, 3, 3], [5, 5, 5], and [1, 1, 1]. It is obvious that when considering the interfering microcell BS's, a microcell MS will only be affected by the interfering microcell BS's in the same microarea. Assume that each microarea consists of \(C_\mu\) microcell clusters. Then, an MS will experience the interference from the remaining \(C_\mu - 1\) microcell BS's, excluding the desired one. Substituting (15), (14), and (15) into (12), one can obtain (16), given at the bottom of the page.

1) \(C_\mu = 1\): We first consider a special case, where only one microcell is installed in a microarea. In the beginning stage, this may occur when a large underlay microcell is first installed to release traffic load of the macrocellular system. Fig. 9 shows the effect of the front-to-back ratio \(\eta\) on the microcell radius, whereby \((S/I)_{req} = 18\) dB and \(h_\theta^M/h_\delta^M = 1/3\). If the \(S/I\) and \(S\)-criterion result in different microcell radii, then the smaller one will be chosen. From Fig. 9, one can observe that if front-to-back ratio \(\eta \geq 10\) dB, the microcell radius is determined by the \(S\)-criterion, but when \(\eta \leq 5\) dB, the \(S/I\)-criterion dominates the \(S\)-criterion. For instance, in the case of \(\eta = 10\) dB and \(p_{\mu}^M/p_{t,b}^M = 0.4\), one can obtain \(R_\mu \leq 0.5R_M\) by the \(S/I\)-criterion and \(R_\mu \leq 0.46R_M\) by the \(S\)-criterion, respectively. For choosing the smaller one, the microcell radius is therefore 0.46\(R_M\). In this example, one can see that a larger front-to-back ratio \(\eta\) does not imply a larger microcell size since the \(S\)-criterion, which is independent of \(\eta\), will dominate the \(S/I\)-criterion when \(\eta\) is large.

2) \(C_\mu \geq 2\): Next, we consider the case, where many microcells are deployed in each microarea. Fig. 9 shows the downlink microcell size against \(p_{\mu}^M/p_{t,b}^M\) for different values of \(C_\mu\), where \(p_{\mu}^M/p_{t,b}^M\) is the ratio of the transmitted power of the microcell BS to that of the macrocell BS and \(C_\mu\) is the number of microcell clusters in a microarea. It is observed that if \(C_\mu \geq 3\), \(p_{\mu}^M/p_{t,b}^M\) has little effect on the downlink microcell size. This is because the interference from the microcells \(I_\mu^d\) will dominate the macrocell interference \(J_\mu^d\) when the number of cochannel microcells \((C_\mu - 1)\) becomes large in a given microarea. In other words, if a large number of microcells are installed, the \(S/I\)-criterion will become a dominating factor in determining the microcell size. In the case \(C_\mu = 6\), for example, one should follow the \(S/I\)-criterion to get \(R_\mu \leq 0.165R_M\) from Fig. 10.

\[
\frac{S_\mu^u}{I_\mu^u + J_{M_\mu}^u} 
\]

\[
\text{Fig. 9. Effect of front-to-back ratio } \eta \text{ on the microcell radius based on downlink microcell } S/I \text{ performance analysis, where } R_\mu/R_M \text{ and } p_{\mu}^M/p_{t,b}^M \\
\text{are the cell radius ratio and transmitted power ratio of microcells over macrocells, respectively. With } (S/I)_{req} = 18 \text{ dB and } h_\theta^M/h_\delta^M = 1/3, \text{curves (a) } \sim \text{ (e) are obtained by } S/I\text{-criterion for } \eta = 6, 5, 10, 15, \text{ and } 20 \text{ dB, respectively, while curve (f) is obtained by } S\text{-criterion}. \]

\[
B. \text{ Uplink Microcell Size} 
\]

Similar to the former analysis, the uplink microcell size is derived from the \(S/I\) analysis. More specifically,

\[
\frac{S_\mu^u}{I_\mu^u + J_{M_\mu}^u} 
\]

\[
\text{ed: please move to next page, LHS of Eq. (17).} 
\]
Fig. 10. Downlink microcell radius $R_\mu$ against $p^\mu_{t,m}/R^M_{p_m}$ for different values of $C_\mu$ in the case $\eta = 10$ dB, $S/I_{req} = 10$ dB, and $h^\mu_b/h^M_b = 1/3$, whereby the microcell radius is normalized with respect to the macrocell radius $R^M$: $p^\mu_{t,m}/R^M_{p_m}$ represents the ratio of the transmitted power of microcell BS to that of macrocell BS; and $C_\mu$ is the number of clusters in a microarea; $\eta$ is the front-to-back ratio of the directional antenna; $h^\mu_b/h^M_b$ is the ratio of the microcell BS antenna to the macrocell BS antenna. Curves (a) $\sim$ (e) are obtained by $S/I$-criterion for $C_\mu = 1, 2, 4, 6,$ and 8, while curve (f) is obtained by $S$-criterion.

$$R_\mu = \frac{p^\mu_{t,m} \left( h^\mu_b h^\mu_m \right)^2}{R^M_{p_m}} \left( \sum_{i=1}^{C_\mu-1} \frac{p^M_{t,m} \left( h^\mu_b h^M_m \right)^2}{D^M_i} + \sum_{i=1}^{N_{M,i}} \frac{p^M_{t,m} \left( h^\mu_b h^M_m \right)^2}{D^M_{i,t}} \right)$$

where the parameters $p^\mu_{t,b}$, $p^M_{t,b}$, $C_\mu$, $h^\mu_b$, $h^M_b$, $R^M$, and $h^\mu_m$ have been defined in (2) and (8) and

$S^a_\mu$ microcell BS received power from the desired microcell MS;

$J^\mu_{M,i}$ uplink microcell-to-macrocell interference;

$J^M_{M,i}$ uplink macrocell-to-macrocell interference;

$N_{M,i}$ number of macrocell interfering MS's;

$D^M_{i,t}$ BS distance to the $i$th interfering macrocell MS;

$R^M_{\mu,up}$ uplink microcell radius.

Let $D^M_{i,t} = D^M_{i,t} R^M_\mu$ and ($S/I)_{req}$ denote the required $S/I$ for a microcell BS. Using the same assumptions for getting (12), one can simplify (17) as

$$\frac{R^M_{\mu,up}}{R^M} \leq \left[ \frac{1}{(S/I)_{req}} \right]^{1/4} \left( \frac{C_\mu - 1}{C_\mu} \right)^{1/2}$$

(18)

In Section VI-A, we have shown that when the number of microcell clusters $C_\mu$ becomes large, the downlink microcell size is insensitive to the interference from the macrocell. This is also true for determining the uplink microcell size. This will be shown by an example later. When microcell interference dominates the performance, (18) can be approximated as

$$\frac{R^M_{\mu,up}}{R^M} \leq \left[ \frac{1}{(S/I)_{req}} \right]^{1/4} \left( \frac{C_\mu - 1}{C_\mu} \right)^{1/2}$$

(19)

By combining (10), (11), and (19), we obtain the upper and lower bounds of $K_\mu$ as

$$\frac{1}{3} (S/I)_{req} (C_\mu - 1) \leq K_\mu \leq \frac{1}{C_\mu} \left( \frac{R^M_\mu}{R^M} \right)^2$$

(20)

The relation between $K_\mu$ and $C_\mu$ with $R^M_\mu/R^M$ as a parameter is shown in Fig. 11.

1) Example: Consider again microarea 56 in Fig. 5. Referring to Table I, microarea 56 can be assigned channel sets $\{a_4, a_4\}$. Take channel set $\{a_4\}$, for example. The worst case occurs when interfering macrocell MS's transmit maximum power, i.e., at the macrocell boundary. For the example considered, the three first-tier interfering macrocell MS's near microareas 45, 47, and 77 are at distances $[D^M_{i,t}, D^M_{i,t}, D^M_{i,t}] = [2.0, 2.0, 2.0]$; the three second-tier interfering macrocell MS's near microareas 26, 53, and 89 are at distances $[D^M_{i,t}, D^M_{i,t}, D^M_{i,t}] = [4.36, 4.36, 4.36]$; the three third-tier interfering macrocell MS's near microareas 32, 38, and 98 are at distances $[D^M_{i,t}, D^M_{i,t}, D^M_{i,t}] = [6.0, 6.0, 6.0]$. Substituting these values into (18) and letting $(S/I)_{req} = 18$ dB, we show in Fig. 12 the ratio of microcell radius to macrocell radius $R^\mu/R^M$ against $p^\mu_{t,m}/p^M_{t,m}$ for different $\lambda c$. 
TABLE III

<table>
<thead>
<tr>
<th>Sector</th>
<th>Frequency Plan for Avoiding Adjacent Channel Interference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1a</td>
<td>22 43 64 85 106 127 148 169 190 211 232 253 274 295 316</td>
</tr>
<tr>
<td>2a</td>
<td>23 44 65 86 107 128 149 170 191 212 233 254 275 296 317</td>
</tr>
<tr>
<td>3a</td>
<td>24 45 66 87 108 129 150 171 192 213 234 255 276 297 318</td>
</tr>
<tr>
<td>4a</td>
<td>25 46 67 88 109 130 151 172 193 214 235 256 277 298 319</td>
</tr>
<tr>
<td>5a</td>
<td>26 47 68 89 110 131 152 173 194 215 236 257 278 299 320</td>
</tr>
<tr>
<td>6a</td>
<td>27 48 69 90 111 132 153 174 195 216 237 258 279 300 321</td>
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<tr>
<td>7a</td>
<td>28 49 70 91 112 133 154 175 196 217 238 259 280 301 322</td>
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</tr>
<tr>
<td>2β</td>
<td>30 51 72 93 114 135 156 177 198 219 240 261 282 303 324</td>
</tr>
<tr>
<td>3β</td>
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<td>32 53 74 95 116 137 158 179 200 221 251 263 284 305 326</td>
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<tr>
<td>6γ</td>
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</tr>
<tr>
<td>7γ</td>
<td>42 63 84 105 126 147 168 189 210 231 262 273 294 315 336</td>
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</tbody>
</table>

Fig. 12. Uplink microcell radius $R_u$ against $p_{t,m}^{M}/p_{t,m}^{M}$, for different values of $C_u$, where the microcell radius is normalized by the macrocell radius $R_M$. $p_{t,m}^{M}/p_{t,m}^{M}$ is the ratio of the transmitted power of the microcell MS to that of the macrocell MS. $C_u$ is the number of microcell clusters in a microarea, and $(S/I)_{req} = 18$ dB.

Let $C_u$, where $p_{t,m}^{M}/p_{t,m}^{M}$ is the ratio of the transmitted power of the microcell MS to that of the macrocell MS and $C_u$ is the number of the microcell clusters in a microarea. It is shown that as $C_u$ increases, microcell size becomes insensitive to $p_{t,m}^{M}/p_{t,m}^{M}$. Suppose our objective is to implement six microcell clusters in each macroarea (i.e., $C_u = 6$) and still maintain $(S/I)_{req} = 18$ dB. We first need to know the feasible cluster size $K_u$ and the microcell radius. From Fig. 11, we obtain $K_u = 7$ and $R_u = 0.15 	imes R_M$. Then, from Fig. 12, we find the transmitted power for microcell MS should be at least 0.017 times that for macrocell MS. Consider an interfacing macrocell MS, which is an IS-54 Class-IV portable handset transmitting at $-2$ dBW. Thus, the microcell MS transmitted power should be larger than $-20$ dBW in this case. Recall the transmitted power of an IS-54 Class-IV portable handset ranges from $-22$ to $-2$ dBW. Consequently, the current IS-54 Class-IV portable handset can be used in both the macrocells and microcells of the proposed system architecture without changing the handset transmit power specification.

VIII. CONCLUDING REMARKS

This paper has proposed a new sectoring scheme, which allows underlaid microcells to reuse macrocell frequencies. For each area consisting of three macrocell sectors, the proposed architecture can reuse another two macrocell channels sets six times while retaining $S/I \geq 18$ dB. Hence, the system capacity of the proposed architecture can be five times that of a traditional three-sector $N = 7$ cellular system (Fig. 1). If the $S/I$ requirement can be lowered, e.g., $9$ dB in GSM, please define the improvement can be even larger. The capacity improvement of the proposed architecture is achieved by deploying a large number of underlaid microcells. This feature, however, cannot be easily done in other sectored cellular architectures, e.g., those in [8] and [9]. The proposed architecture allows microcells to be deployed throughout the entire area, and allows them to be gradually introduced to match the increasing demand of the global system for mobile communications (GSM).

the Global System for Mobile Communications (GSM)
cellular service. With these flexibilities, the proposed architecture allows the existing macrocellular systems to smoothly evolve into a microcell/macrocell hierarchical system.

REFERENCES


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Effects of Rician Fading and Branch Correlation on a Local-Mean-Based Macrodiversity Cellular System

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ABSTRACT In a macrodiversity cellular system, switching radio links between base stations cannot be done instantaneously. Thus branch selection is usually based on the measurement of the slowly-varying local mean power rather than the rapidly-varying instantaneous signal power. In this paper we offer an exact mathematical model to analyze the performance of a local-mean-based macrodiversity cellular system in a shadowed-Rician (desired) /shadowed-Rayleigh (interfering) channel. We investigate the impact of both fading (Rician or Rayleigh) and shadowing in terms of co-channel interference (CCI) probability. We also present an analytical model to incorporate the effects of branch correlation on macrodiversity systems.

1 Introduction

Macrodiversity, or a large-scaled space diversity, has long been recognized as an effective tool to combat shadowing [1]. A macrodiversity system serves a mobile station (MS) simultaneously by several base stations (BSs). At any time, the BS with the best quality measure is chosen to serve the MS. The criterion for branch (or BS) selection is a key issue when designing a macrodiversity system. Usually, the branch selection is based on the local mean power rather than the instantaneous power [1, 2, 3, 4], because the branch selection algorithm cannot react to the rapidly varying instantaneous signal power. This paper focuses on local — mean — based branch selection schemes.

Previous studies on macrodiversity systems have evaluated the co-channel interference performance with shadowing only [5, 6, 7] and shadowed Rayleigh fading channels [4]. The co-channel interference performance was also discussed in [9], but it was assumed that the branch selection was based on the instantaneous signal power. The error rate performance of macrodiversity systems has been analyzed in Gaussian noise with both shadowing and Rayleigh (or Nakagami) fading [2, 3, 8]. However, these papers did not consider co-channel interference. To our knowledge, the effect of Rician fading on a local-mean-based macrodiversity system has not been studied before. Furthermore, the effect of branch correlation for macrodiversity systems has not appeared in the literature, either. This paper addresses these issues in detail.

The remainder of this paper is organized as follows. Section II briefly reviews the propagation environment. Section III presents an exact analysis for the performance gain for a local-mean-based macrodiversity system in a shadowed Rician (desired) /shadowed-Rayleigh (interfering) channel. This model is extended to incorporate the effect of branch correlation in Section IV. Section V will give some numerical examples, and Section VI has some concluding remarks.

II Microcell Propagation Models

The path loss is assumed to follow the two-slope model so that the area mean received power is

\[ \mu = \frac{P_t C}{d^a(1 + d/g)^b} \]

where \( P_t \) is the transmitted power, \( C \) is a constant that incorporates the effects of antenna gain, \( d \) is the distance between the transmitter and receiver, \( g \) is the break point, \( a \) is the basic path loss exponent, and \( b \) is the additional path loss exponent.

With log-normal shadowing, the probability density function (pdf) of the local mean power, \( \Omega \), has the log-normal distribution

\[ f_{\Omega}(z) = \frac{1}{\sqrt{2\pi} \sigma z} \exp \left[ -\frac{(\ln z - \ln \mu)^2}{2\sigma^2} \right] \]

where \( \sigma \) is the shadow standard deviation and \( \mu \) is the area mean power determined by the path loss in (1).

In microcell propagation with a dominant light-of-sight (LOS) or specular component, the instantaneous signal amplitude is Rician distributed. If the power in the scattered component of the received signal is \( \sigma^2 \) and the amplitude of the dominant component is \( A \), then the instantaneous received signal power, \( p \), conditioned on the local mean power \( \Omega = A^2/2 + \sigma^2 \) has the non-central chi-square distribution

\[ f_{p\mid\Omega}(x \mid \Omega) = \frac{K + 1}{\Omega} \exp \left[ -K - (K + 1)\frac{x}{\Omega} \right] I_0 \left( \frac{4K(K + 1)x}{\Omega} \right) \]

where \( I_0 \) is the zero-order modified Bessel function of the first kind, and \( K = A^2/2\sigma^2 \) is the Rice factor.

An interfering signal usually has no dominant component so that its instantaneous signal amplitude is Rayleigh distributed.
The pdf of the instantaneous interfering signal power, \( p \), in a Raleigh fading channel can be obtained by letting \( K = 0 \) in (1), giving
\[
f_{P|\Omega}(x | \Omega) = \frac{1}{\Omega} \exp \left( -\frac{x}{\Omega} \right),
\]
where \( \Omega \) is the local mean interfering signal power.

### III Co-channel Interference Probability

This section presents an analytical model for calculating the co-channel interference (CCI) probability for an \( L \)-branch local-mean-based macrodiversity system with shadowing and fading. Our model assumes that the local mean power of the desired signal, \( \Omega_{d,k} \), is available for each branch \( k \), where \( k = 1, \ldots, L \). In practice, the desired signal power is mixed with the total interference power for each branch \( \Omega_{i,k} \), so that \( \Omega_{d,k} + \Omega_{i,k} \) is actually measured. However, the difference is small for large \( \Omega_{d,k}/\Omega_{i,k} \). If the branch having the largest \( \Omega_{d,k} \) is selected, then the local-mean power of the selected branch is
\[
S = \max(\Omega_{d,1}, \Omega_{d,2}, \ldots, \Omega_{d,L}).
\]

Let \( F_k(x) \) and \( f_k(x) \) denote the cumulative distribution function (cdf) and the pdf of \( \Omega_{d,k} \), respectively. If the \( \Omega_{d,k} \) are independent random variables with the pdf in (2), then \( S \) has the pdf \( f_S(y) = L \int \frac{L}{2\pi \sigma_d^2} f_{P_k}(y)dy \).

The CCI probability is
\[
P(CI) = P_1 \left[ p_d/p_1 < \lambda_{th} \right] = 1 - \int_{-\infty}^{\infty} \left( \int_{-\infty}^{x_{th}} f_{P_1}(y)dy \right) f_{P_1}(x)dx,
\]
where \( p_d \) and \( p_1 \) are the total powers of the desired and interfering signals for the selected branch with pdfs \( f_{P_k}(x) \) and \( f_{P_1}(x) \), respectively, and \( \lambda_{th} \) is the protection ratio.

#### III-A Pure Shadowing

The interfering signals add noncoherently so that the total interference power on the \( k \)th branch is \( \Omega_{i,k} = \sum_{i=1}^{n} \Omega_{i,k,i} \), where \( n \) is the number of interferers and \( \Omega_{i,k,i} \) is the power of the \( i \)th interferer on the \( k \)th branch. It is widely accepted that \( \Omega_{i,k} \) can be approximated by a log-normal random variable with area mean power \( \mu_{i,k} \) and standard deviation \( \sigma_{i,k} \). The parameters \( \sigma_{i,k} \) and \( \mu_{i,k} \) can be calculated by using a variety of methods, including Schwartz and Yeh’s method [10].

If the \( \{ \Omega_{i,k,i} \}^{n}_{i=1} \) are independent and identically distributed (iid), and the \( \{ \Omega_{d,k} \}^{L}_{k=1} \) are also iid and independent of the \( \{ \Omega_{i,k,i} \}^{n}_{i=1} \), then [5, 7]
\[
P(CI) = 1 - \int_{0}^{\lambda_{th}} \left[ 1 - Q \left( \frac{\ln x - \ln \mu_d}{\sigma_d} \right) \right] dx
\]
where \( Q(y) = \frac{1}{\sqrt{2\pi}} \exp \left( -y^2/2 \right)dy \), and \( \sigma_d \) and \( \mu_d \) are the shadowing standard deviation and area mean power of the desired signal on the \( k \)th diversity branch, respectively.

For ease of evaluation, we let \( w = (\ln x - \ln \mu_d)/\sqrt{2} \sigma_d \) and transform (7) into a Hermite integration form. That is,
\[
P(CI) = 1 - \int_{-\infty}^{\infty} g(w) \exp(-w^2)dw \approx 1 - \sum_{i=1}^{n} g(w_i)h_i,
\]
where
\[
g(w) = \frac{L}{\sqrt{\pi}} \left[ 1 - Q \left( \frac{\sqrt{2}\sigma_d w + \ln \frac{\mu_d}{\sigma_d \lambda_{th}}}{\lambda_{th}} \right) \right] \left[ 1 - Q \left( \sqrt{2}w \right) \right]^{L-1},
\]
and \( w_i \) and \( h_i \) are the roots and weight factors of the \( n \)-th order Hermite polynomial, respectively [13].

#### III-B Rician Fading and Shadowing

For a local-mean-based macrodiversity system with shadowed Rician fading channels, the branch selection is still based on the best local mean power \( \Omega_{d,k} \). If \( S \) in (5) is assumed known, then by substituting (3) and (4) into (6) we obtain [7]
\[
P(CI | S, \Omega_i) = \sum_{i=1}^{n} \frac{\Omega_{i,k}^{n-1}}{\prod_{j=1, j \neq i}^{n} (\Omega_{i,k} - \Omega_{j,k})} \frac{K + 1}{\Omega_{i,k} + \Omega_{i,k} \lambda_{th}} \exp \left( -\frac{K \Omega_{i,k}}{\lambda_{th} \Omega_{i,k} + \Omega_{i,k} \lambda_{th}} \right) \frac{S}{K + 1 + \frac{S}{\Omega_{i,k} \lambda_{th}}}.
\]

where \( \Omega_i = (\Omega_{i,1}, \ldots, \Omega_{i,n}) \) and \( K \) is the Rice factor of the desired signal. Assuming that the \( \{ \Omega_{i,k} \}^{n}_{k=1} \) are independent, the joint pdf of \( \Omega_i \) is
\[
f_{\Omega_i}(\Omega_i) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi \sigma_{i,k,i}^2}} \exp \left( -\frac{(\ln x_i - \ln \mu_{i,k,i})^2}{2\sigma_{i,k,i}^2} \right),
\]
where \( x = (x_1, \ldots, x_n) \). By using (11), (10), and the pdf of \( S \), we obtain
\[
P(CI) = \int_{0}^{\infty} \int_{0}^{\infty} P(CI | S, \Omega_i) \left[ 1 - Q \left( \frac{\ln S - \ln \mu_d}{\sigma_d} \right) \right]^{L-1} \exp \left( -\frac{(\ln S - \ln \mu_d)^2}{2\sigma_d^2} \right) \frac{1}{\sqrt{2\pi \sigma_{d,i}^2}} \exp \left( -\frac{(\ln \Omega_{i,k} - \ln \mu_{i,k})^2}{2\sigma_{i,k,i}^2} \right) dS d\Omega_i.
\]

By using the substitution \( \alpha = \ln(S/\mu_d)/\sqrt{2} \sigma_d \) and \( \beta_i = \ln(\Omega_{i,k}/\mu_{i,k})/\sqrt{2} \sigma_{i,k,i} \), \( i = 1, \ldots, n \), we transform (12) into a Hermite integration form, which can be evaluated with numerical ease. In particular,
\[
P(CI) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} L \left[ 1 - Q \left( \sqrt{2} \alpha \right) \right]^{L-1} \frac{\exp \left[ -\alpha^2 - \sum_{i=1}^{n} \beta_i^2 \right]}{\sqrt{\pi} \alpha} d\alpha d\beta.
\]
\begin{equation}
\approx \sum_{k=1}^{n} \frac{L}{\sqrt{\pi}^{n+1}} \left[ 1 - Q\left( \sqrt{2}x_{kn}\right) \right]^{L-1} G(x_{kn}, x_{k1}, \ldots, x_{kn}) \omega_{kn} \ldots \omega_{k1} \tag{13}
\end{equation}

where $\bar{\beta} = (\beta_1, \ldots, \beta_n)$, $x_k$, is the root of the $k$th order Hermite polynomial, and $\omega_{kn}$ is its corresponding weight factor. Here $G(\alpha, \beta)$ is obtained by substituting $S = \mu_2 \exp(\sqrt{2} \sigma_d)$ and $\Omega_{i,i} = \mu_{i,i} \exp(\sqrt{2} \beta_i \sigma_{i,i})$, $i = 1, \ldots, n$, into $P(CI \mid S, \Omega_i)$ in (10). That is

\begin{equation}
G(\alpha, \beta) = \sum_{i=1}^{n} \prod_{j=1}^{n} \left( 1 - \frac{\mu_{i,j}}{\mu_{i,i}} \exp \left[ \sqrt{2}(\beta_i \sigma_{i,j} - \beta_i \sigma_{i,i}) \right] \right) \frac{K + 1}{K + 1 + \epsilon_i} \exp \left[ -K \epsilon_i \right] \frac{K + 1}{K + 1 + \epsilon_i}, \tag{14}
\end{equation}

where

\begin{equation}
\epsilon_i = \frac{\mu_d}{\lambda_{i,h} \mu_{i,i}} \exp \left[ \sqrt{2}(\alpha \sigma_d - \beta_i \sigma_{i,i}) \right]. \tag{15}
\end{equation}

### IV Correlated Branches

Until now, we have assumed independent shadowing on the macrodiversity branches. This assumption may sometimes be violated because of insufficient spacing of BSs, especially in microcell systems.

For a correlated $L$-branch macrodiversity system, the joint pdf of $\Omega_d$ [12]

\begin{equation}
f_{\Omega_d}(x) = \frac{\exp \left[ -\frac{1}{2} Y^T M^{-1} Y \right]}{\sqrt{(2\pi)^L \det(M)}} \tag{16}
\end{equation}

where $x = (z_1, \ldots, z_L)$, $Y^T = [y_1, \ldots, y_L]$ denotes the transpose of column vector

\begin{equation}
Y = \begin{bmatrix}
\ln(z_1) - \ln(\mu_1) \\
\vdots \\
\ln(z_L) - \ln(\mu_L)
\end{bmatrix} \tag{17}
\end{equation}

and $\mu_1, \ldots, \mu_L$ are the area means of each diversity branch. The covariance matrix $M$ is expressed as

\begin{equation}
M = \begin{bmatrix}
\sigma_1^2 & \cdots & \nu_{1L} \\
\vdots & \ddots & \vdots \\
\nu_{L1} & \cdots & \sigma_L^2
\end{bmatrix} \tag{18}
\end{equation}

where $\sigma_i$ is the shadowing standard deviation and $\nu_{i,j}$ is the covariance of $\ln(\Omega_{di})$ and $\ln(\Omega_{dj})$

\begin{equation}
\nu_{i,j} = \mathbb{E} \left[ (\ln(\Omega_{di}) - \ln(\mu_i))(\ln(\Omega_{dj}) - \ln(\mu_j)) \right]. \tag{19}
\end{equation}

It is convenient to define $N = M^{-1}$ and express the matrix multiplication in (16) as follows.

\begin{equation}
Y^T N Y = \sum_{i=0}^{L} N_{ii} y_i^2 + 2 \sum_{i=0}^{L-1} \sum_{j=i+1}^{L} N_{ij} y_i y_j \tag{20}
\end{equation}

where $N_{ij}$ is the element in the $i$th row and $j$th column.

According to (5), (16), and (20), the probability that the local mean power $S$ at the output of the combiner being less than $y$ is

\begin{equation}
\Pr(S < y) = \int_{-\infty}^{y} \ldots \int_{-\infty}^{y} \sqrt{(2\pi)^L \det(M)} x_1 \ldots x_L \exp \left[ -\frac{1}{2} \sum_{i=1}^{L} N_{ii} y_i^2 + 2 \sum_{i=1}^{L-1} \sum_{j=i+1}^{L} N_{ij} y_i y_j \right] \, dz \tag{21}
\end{equation}

where $N_{ij}$ and $y_i$ are defined in (20) and (17), respectively.

The key for analyzing the CCI probability of the local-mean-based macrodiversity system is to find the pdf of the combiner output power, $f_S(y)$. Unlike the uncorrelated case where there exists a closed-form expression for $f_S(y)$, one can not easily get a simple closed formula for the joint distribution of more than two mutually correlated lognormal random variables. However, for $L = 2$,

\begin{equation}
f_S(y) = \frac{1}{\sqrt{2\pi \det(M)}} \exp \left[ -\frac{y^2}{2} \left( \frac{N_{11} - N_{12}}{N_{22}} \right) \right] \left( 1 - Q \left( \sqrt{\frac{N_{22}}{N_{11}}} \right) y \right) \tag{22}
\end{equation}

where $y = (\ln \rho - \ln T_d)$ and $d$ denotes the branch selected by the macrodiversity system. Consider the following covariance matrix $M$

\begin{equation}
M = \begin{bmatrix}
\sigma_1^2 & \mu \\
\mu & \sigma^2
\end{bmatrix} \tag{23}
\end{equation}

and

\begin{equation}
N = M^{-1} = \frac{1}{\sigma^4 - \mu^2} \begin{bmatrix}
\sigma^2 & -\mu \\
-\mu & \sigma^2
\end{bmatrix}. \tag{24}
\end{equation}

By substituting (24) into (22), we express the pdf of the output local-mean power of the dual macrodiversity system as

\begin{equation}
f_S(y) = \frac{\sqrt{2}}{\sqrt{\pi \sigma}} \left( 1 - Q \left( \frac{1 - r}{\sqrt{1 - r^2}} \right) \frac{\ln \frac{y - \ln \mu}{\sigma}}{\sigma} \right) \exp \left[ -\frac{\ln \frac{y - \ln \mu}{\sigma}^2}{2\sigma^2} \right] \tag{25}
\end{equation}

where the correlation coefficient $r$ is defined as $r = \frac{\nu}{\sigma^2}$. Combining (10), (11), and (25), we obtain

\begin{equation}
P(CI) = \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} \frac{2G(\alpha, \beta)}{\sqrt{\pi}^{n+1}} \left[ 1 - Q \left( \sqrt{2} \left( \frac{1 - r}{\sqrt{1 - r^2}} \right) \alpha \right) \right] \exp \left[ -\alpha^2 - \sum_{i=1}^{n} \beta_i^2 \right] d\alpha \ d\beta \tag{26}
\end{equation}

\begin{equation}
\approx \sum_{k_{n1} = 1}^{k_n} \cdots \sum_{k_{n1} = 1}^{k_n} \frac{2}{\sqrt{\pi}^{n+1}} \left[ 1 - Q \left( \sqrt{2} \left( \frac{1 - r}{\sqrt{1 - r^2}} \right) x_{k_0} \right) \right] \times G(x_{k_0}, \ldots, x_{k_n}) \omega_{k_0} \ldots \omega_{k_n}, \tag{26}
\end{equation}
where $a$ and $\beta$ are defined in (13), the weight factor $w_k$ of the $k$th order Hermite polynomial can be found in [13], and $G(\alpha, \beta)$ is defined in (14).

V Numerical Results

We consider a cellular system with nine cells per cluster. In this case, two co-channel interferers are at 5.2 $R$, where $R$ is the cell radius. Assume the mobile unit is on the boundary of the cell with a distance of $R$ to the base station. Consider a dual slope path loss model with $a = b = 2$ and $g = 0.15$ in (1). Fig. 1 (a), (b), and (c) illustrate the gain achieved by a local-mean-based $S-$ macrodiversity system over a shadowed-Rician (desired) / shadowed-Rayleigh (interfering) channel for the Rice factors $K = -\infty, 7, \text{and } 20 \text{dB}$. Table I lists the threshold $\lambda_{th}$ and diversity gain (D.G.) in terms of 5% co-channel interference (CCIP) probability. Some general observations can be made: 1) a higher shadowing spread leads to a higher diversity gain and a lower required threshold $\lambda_{th}$; 2) the diversity gain per branch is decreased as the number of diversity branches is increased; 3) the diversity gain increases with the requirement of the system, e.g., the diversity gain for $5\%$ CCPI probability is higher than that for $10\%$ CCPI probability. In addition, we see that the diversity gain seems to be affected little by fading and that a shadowed Rayleigh channel has the least diversity gain. We evaluate the effects of correlation coefficient $r$ on a 2-branch macrodiversity system with $\sigma = 6 \text{ dB}$ and various $K$, $K = -\infty \text{ dB (Fig. 2 (a)); } K = 10 \text{ dB (Fig. 2 (b)).}$ Observe that as $r$ approaches one, the diversity gain becomes zero. Furthermore, for $r = 0.7$, the diversity gain will be reduced to about $50\%$ of the gain when $r = 0$

VI Concluding Remarks

We consider a cellular system with nine cells per cluster. This paper presented an analytical model for calculating the co-channel interference probability of a local-mean-based macrodiversity system in a shadowed Rician (desired) / shadowed Rayleigh (interfering) channel. Compared to a pure shadowing channel, Rayleigh fading degrades the S/I performance by about 4 – 5 dB at 10% CCPI probability. However, as the Rice factor $K$ gets large, the degradation of S/I is within 1 dB. We also observe that fading (either Rayleigh or Rician) has little effect on the diversity gain of local-mean-based macrodiversity systems. The diversity gain is the same, but Rayleigh fading is always worse than Rician fading.

In two-branch macrodiversity system, a branch correlation coefficient of $r = 0.7$ will reduce the diversity gain by 50%. We considered correlated shadowing between diversity branches, but shadowing components between the desired and interfering signals are assumed to be independent in this paper. Furthermore, it has been shown that the correlation of shadowing components between interferers does not significantly influence the CCPI probability performance [11]. The results obtained in this paper will be close to the results derived for the environment with multiple correlated log-normal shadowing interferers.

References


Table I: Macrodiversity gain (D. G.) and the threshold $\lambda_{th}$ of S/I set at the receiver in terms of 5% co-channel interference probability (CCIP) over a channel with both shadowing and Rician fading $K = -\infty, 7, 20 \text{ dB}$.

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Figure 1: The CCI probability, $P(CI)$, against the required threshold, $\lambda_{th}$, at the receiver for the local-mean-based macrodiversity system over the shadowed-Rician (desired) / shadowed-Rayleigh (interfering) channel with Rice factor (a) $K = -\infty$ dB, (b) $K = 7$ dB, and (c) $K = 20$ dB, where the solid lines (---) denote the case for shadowing standard deviation $\sigma = 10$ dB and the dashed lines (------) for $\sigma = 6$ dB; $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of 5.2R.

Figure 2: Effect of branch correlation coefficient $r$ on the local-mean-based macrodiversity system with Rice factor (a) $K = -\infty$ dB and (b) $K = 10$ dB, where $\sigma = 6$ dB; $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of 5.2R.
Effects of Rician Fading and Branch Correlation on a Local-Mean-Based Macrodiversity Cellular System

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Abstract

In a macrodiversity cellular system, switching radio links between base stations cannot be done instantaneously. Thus branch selection is usually based on the measurement of the slowly-varying local mean power rather than the rapidly-varying instantaneous signal power. In this paper we offer an exact mathematical model to analyze the performance of a local-mean-based macrodiversity cellular system in a shadowed-Rician (desired) /shadowed-Rayleigh (interfering) channel. We investigate the impact of both fading (Rician or Rayleigh) and shadowing in terms of co-channel interference (CCI) probability. We also present an analytical model to incorporate the effects of branch correlation on macrodiversity systems.
I Introduction:

Macrodiversity, or a large-scaled space diversity, has long been recognized as an effective tool to combat shadowing [1, 2]. A macrodiversity system serves a mobile station (MS) simultaneously by several base stations (BSs). At any time, the BS with the best quality measure is chosen to serve the MS. The criterion for branch (or BS) selection is a key issue when designing a macrodiversity system. Usually, the branch selection is based on the local mean power rather than the instantaneous power [1, 3, 4, 5, 6, 7], because the branch selection algorithm cannot react to the rapidly varying instantaneous signal power. This paper focuses on local – mean – based branch selection schemes.

Previous studies on macrodiversity systems have evaluated the co-channel interference performance with shadowing only [8, 9, 10] and shadowed Rayleigh fading channels [7]. The co-channel interference performance was also discussed in [12], but it was assumed that the branch selection was based on the instantaneous signal power. The error rate performance of macrodiversity systems has been analyzed in Gaussian noise with both shadowing and Rayleigh (or Nakagami) fading [6, 5, 4, 11, 3]. However, these papers did not consider co-channel interference. To our knowledge, the effect of Ricean fading on a local-mean-based macrodiversity system has not been studied before. Furthermore, the correlation effect of the wanted signal at different branches of a macrodiversity system has not appeared in the literature, either. This paper addresses these issues in detail.

The remainder of this paper is organized as follows. Section II briefly reviews the propagation environment. Section III presents an exact analysis for the performance gain for a local-mean-based macrodiversity system in a shadowed Ricean (desired) / shadowed Rayleigh (interfering) channel. This model is extended to in-
corporate the effect of branch correlation in Section IV. Section V will give some numerical examples, and Section VI has some concluding remarks.

II Microcell Propagation Models

The path loss is assumed to follow the two-slope model so that the area mean received power is [18]

\[ \mu = \frac{P_t C}{d^a (1 + d/g)^b}, \]  

(1)

where \( P_t \) is the transmitted power, \( C \) is a constant that incorporates the effects of antenna gain, \( d \) is the distance between the transmitter and receiver, \( g \) is the break point, \( a \) is the basic path loss exponent, and \( b \) is the additional path loss exponent.

With log-normal shadowing, the probability density function (pdf) of the local mean power, \( \Omega \), has the log-normal distribution

\[ f_{\Omega}(x) = \frac{1}{\sqrt{2\pi} \sigma x} \exp \left[ -\frac{(\ln x - \ln \mu)^2}{2\sigma^2} \right], \]

(2)

where \( \sigma \) is the shadow standard deviation and \( \mu \) is the area mean power determined by the path loss in (1).

In microcell propagation with a dominant light-of-sight (LOS) or specular component, the instantaneous signal amplitude is Rician distributed. If the power in the scattered component of the received signal is \( \sigma^2 \) and the amplitude of the dominant component is \( A \), then the instantaneous received signal power, \( p \), conditioned on the local mean power \( \Omega = A^2/2 + \sigma^2 \) has the non-central chi-square distribution

\[ f_{p|\Omega}(x \mid \Omega) = \frac{K + 1}{\Omega} \exp \left[ -K - \frac{(K+1)x}{\Omega} \right] I_0 \left( \sqrt{\frac{4K(K+1)x}{\Omega}} \right) \]

(3)

where \( I_0 \) is the zero-order modified Bessel function of the first kind, and \( K = A^2/2\sigma^2 \) is the Rice factor.
An interfering signal usually has no dominant component so that its instantaneous signal amplitude is Rayleigh distributed. The pdf of the instantaneous interfering signal power, \( p \), in a Rayleigh fading channel can be obtained by letting \( K = 0 \) in (3), giving

\[
f_{p|\Omega}(x | \Omega) = \frac{1}{\Omega} \exp \left[ -\frac{x}{\Omega} \right],
\]

where \( \Omega \) is the local mean interfering signal power.

### III Co-channel Interference Probability

This section presents an analytical model for calculating the co-channel interference (CCI) probability for an \( L \)-branch local-mean-based macrodiversity system with shadowing and fading. Our model assumes that the local mean power of the desired signal, \( \Omega_{d,k} \), is available for each branch \( k \), where \( k = 1, \ldots, L \). In practice, the desired signal power is mixed with the total interference power for each branch \( \Omega_{I,k} \), so that \( \Omega_{d,k} + \Omega_{I,k} \) is actually measured. However, the difference is small for large \( \Omega_{d,k}/\Omega_{I,k} \). If the branch having the largest \( \Omega_{d,k} \) is selected, then the local-mean power of the selected branch is

\[
S = \max (\Omega_{d,1}, \Omega_{d,2}, \ldots, \Omega_{d,L}) .
\]

Let \( F_k(x) \) and \( f_k(x) \) denote the cumulative distribution function (cdf) and the pdf of \( \Omega_{d,k} \), respectively. If the \( \Omega_{d,k} \) are independent random variables with the pdf in (2), then \( S \) has the pdf \( f_S(y) = L [F_k(y)]^{L-1} f_k(y) \). The CCI probability is

\[
P(CI) = P_r [p_d/p_I < \lambda_{th}]
= 1 - \int_0^\infty \left[ \int_{-\infty}^{x_{th}} f_{p_I}(y)dy \right] f_{p_d}(x)dx ,
\]

4
where $p_d$ and $p_I$ are the total powers of the desired and interfering signals for the selected branch with pdfs $f_{p_d}(x)$ and $f_{p_I}(y)$, respectively, and $\lambda_{th}$ is the protection ratio.

### III-A Pure Shadowing

The interfering signals add noncoherently so that the total interference power on the $k$th branch is $\Omega_{I,k} = \sum_{i=1}^{n} \Omega_{I,k,i}$, where $n$ is the number of interferers and $\Omega_{I,k,i}$ is the power of the $i$th interferer on the $k$th branch. It is widely accepted that $\Omega_{I,k}$ can be approximated by a log-normal random variable with area mean power $\mu_{I,k}$ and standard deviation $\sigma_{I,k}$. The parameters $\sigma_{I,k}$ and $\mu_{I,k}$ can be calculated by using a variety of methods, including Schwartz and Yeh's method [20].

If the $\{\Omega_{I,k}\}_{k=1}^{n}$ are independent and identically distributed (iid), and the $\{\Omega_{d,k}\}_{k=1}^{L}$ are also iid and independent of the $\{\Omega_{I,k}\}_{k=1}^{n}$, then [8, 10]

$$P(CI) = 1 - L \int_{0}^{\infty} \left[ \int_{-\infty}^{\chi_{th}} \frac{1}{\sqrt{2\pi} \sigma_I y} \exp \left[ -\frac{(\ln y - \ln \mu_I)^2}{2\sigma_I^2} \right] dy \right]$$

$$\times \left[ 1 - Q \left( \frac{\ln x - \ln \mu_d}{\sigma_d} \right) \right]^{L-1} \frac{1}{\sqrt{2\pi} \sigma_d x} \exp \left[ -\frac{(\ln x - \ln \mu_d)^2}{2\sigma_d^2} \right] dx$$  \hspace{1cm} (7)

where $Q(y) = \int_{y}^{\infty} \frac{1}{\sqrt{2\pi}} \exp(-x^2/2)dx$, and $\sigma_d$ and $\mu_d$ are the shadowing standard deviation and area mean power of the desired signal on the $k$th diversity branch, respectively.

For ease of evaluation, we let $w = (\ln x - \ln \mu_d)/\sqrt{2\sigma_d}$ and transform (7) into a Hermite integration form. That is,

$$P(CI) = 1 - \int_{-\infty}^{\infty} g(w) \exp(-w^2)dw \approx 1 - \sum_{i=1}^{n} g(w_i) h_i ,$$  \hspace{1cm} (8)
where
\[ g(w) = \frac{L}{\sqrt{\pi}} \left[ 1 - Q \left( \frac{\sqrt{2} \sigma_d w + \ln \frac{\mu_d}{\mu_{1,th}}}{\sigma_f} \right) \right] \left[ 1 - Q \left( \sqrt{w} \right) \right]^{L-1}, \] (9)

and \( w_i \) and \( h_i \) are the roots and weight factors of the \( n \)th-order Hermite polynomial, respectively [23].

### III-B Rician Fading and Shadowing

For a local-mean-based macrodiversity system with shadowed Rician fading channels, the branch selection is still based on the best local mean power \( \Omega_{d,k} \). If \( S \) in (5) is assumed known, then by substituting (3) and (4) into (6) we obtain [10]

\[ P(CI \mid S, \Omega_f) = \sum_{i=1}^{n} \frac{\Omega_{l,i}^{n-1}}{\prod_{j=1,j \neq i}^{n} (\Omega_{l,i} - \Omega_{l,j})} \frac{K + 1}{K + 1 + \frac{S}{\Omega_{l,i} \lambda_{th}}} \exp \left[ \frac{-K}{\lambda_{th} \Omega_{l,i}} \right] \left[ \frac{S}{\Omega_{l,i} \lambda_{th}} \right] \] (10)

where \( \Omega_l = (\Omega_{l,1}, \ldots, \Omega_{l,n}) \) and \( K \) is the Rice factor of the desired signal. Assuming that the \( \{\Omega_{l,k}\}_{k=1}^{n} \) are independent, the joint pdf of \( \Omega_l \) is

\[ f_{\Omega_l}(x) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi \sigma_{f,i}^2}} \exp \left[ \frac{-(\ln x_i - \ln \mu_{l,i})^2}{2\sigma_{f,i}^2} \right] \] (11)

where \( x = (x_1, \ldots, x_n) \). By using (11), (10), and the pdf of \( S \), we obtain

\[ P(CI) = \int_0^{\infty} \cdots \int_0^{\infty} P(CI \mid S, \Omega_f) \frac{L}{\sqrt{2\pi \sigma_d S}} \left[ 1 - Q \left( \frac{\ln S - \ln \mu_d}{\sigma_d} \right) \right] \left[ 1 - Q \left( \sqrt{w} \right) \right]^{L-1} \exp \left[ \frac{-(\ln S - \ln \mu_d)^2}{2\sigma_d^2} \right] \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi \sigma_{f,i}^2 \Omega_{l,i}}} \exp \left[ \frac{-(\ln \Omega_{l,i} - \ln \mu_{l,i})^2}{2\sigma_{f,i}^2} \right] dS d\Omega_l. \] (12)
By using the substitution \( \alpha = \ln(S/\mu_d)/(\sqrt{2}\sigma_d) \) and \( \beta_i = \ln(\Omega_{l,i}/\mu_{l,i})/(\sqrt{2}\sigma_{l,i}) \), \( i = 1, \ldots, n \), we transform (12) into a Hermite integration form, which can be evaluated with numerical ease. In particular,

\[
P(CI) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} L \frac{[1 - Q(\sqrt{2}\alpha)]^{L-1} G(\alpha, \beta)}{\sqrt{\pi}^{n+1}} \exp \left[ -\alpha^2 - \sum_{i=1}^{n} \beta_i^2 \right] d\alpha \ d\beta
\]

\[
\approx \sum_{k_n=1}^{h_n} \cdots \sum_{k_0=1}^{h_0} \frac{L \frac{[1 - Q(\sqrt{2}x_{k_0})]}{\sqrt{\pi}^{n+1}} G(x_{k_0}, x_{k_1}, \ldots, x_{k_n})}{w_{k_0} \cdots w_{k_n}}
\]

(13)

where \( \beta = (\beta_1, \ldots, \beta_n) \), \( x_k \) is the root of the \( h \)th order Hermite polynomial, and \( w_k \) is its corresponding weight factor. Here \( G(\alpha, \beta) \) is obtained by substituting \( S = \mu_d \exp(\sqrt{2}\alpha\sigma_d) \) and \( \Omega_{l,i} = \mu_{l,i} \exp(\sqrt{2}\beta_i\sigma_{l,i}) \), \( i = 1, \ldots, n \), into \( P(CI \mid S, \Omega_l) \) in (10). That is

\[
G(\alpha, \beta) = \sum_{i=1}^{n} \prod_{j=1, j \neq i}^{n} \frac{1}{\left(1 - \frac{\mu_{l,j}}{\mu_{l,i}} \exp \left[ \sqrt{2}(\beta_j\sigma_{l,j} - \beta_i\sigma_{l,i}) \right] \right)} \frac{K + 1}{K + 1 + \epsilon_i} \exp \left[ \frac{-K\epsilon_i}{K + 1 + \epsilon_i} \right]
\]

(14)

where

\[
\epsilon_i = \frac{\mu_d}{\lambda_{l,i} \mu_{l,i}} \exp \left[ \sqrt{2}(\alpha\sigma_d - \beta_i\sigma_{l,i}) \right].
\]

(15)

## IV Correlated Branches

Until now, we have assumed independent shadowing on the macrodiversity branches. This assumption may sometimes be violated because of insufficient spacing of BSs, especially in microcell systems.

For a correlated \( L \)-branch macrodiversity system, the joint pdf of \( \Omega_d \) [22]

\[
f_{\Omega_d}(\mathbf{z}) = \frac{\exp \left[ -\frac{1}{2} Y^T M^{-1} Y \right]}{\sqrt{(2\pi)^L \det(M)} z_1 \cdots z_L}
\]

(16)
where \( z = (z_1, \cdots, z_L) \), \( Y^T = [y_1, \cdots, y_L] \) denotes the transpose of column vector

\[
Y = \begin{bmatrix}
\ln(z_1) - \ln(\mu_1) \\
\vdots \\
\ln(z_L) - \ln(\mu_L)
\end{bmatrix}
\]  \hspace{1cm} (17)

and \( \mu_1, \cdots, \mu_L \) are the area means of each diversity branch. The covariance matrix \( \mathbf{M} \) is expressed as

\[
\mathbf{M} = \begin{bmatrix}
\sigma_1^2 & \cdots & \nu_{1L} \\
\vdots & \ddots & \vdots \\
\nu_{L1} & \cdots & \sigma_L^2
\end{bmatrix}
\]  \hspace{1cm} (18)

where \( \sigma_i \) is the shadowing standard deviation and \( \nu_{ij} \) is the covariance of \( \ln(\Omega_{di}) \) and \( \ln(\Omega_{dj}) \)

\[
\nu_{ij} = \mathbb{E} [(\ln(\Omega_{di}) - \ln(\mu_i)) (\ln(\Omega_{dj}) - \ln(\mu_j))] .
\]  \hspace{1cm} (19)

It is convenient to define \( \mathbf{N} = \mathbf{M}^{-1} \) and express the matrix multiplication in (16) as follows.

\[
Y^T N Y = \sum_{i=0}^{L} N_{ii} y_i^2 + 2 \sum_{i=0}^{L-1} \sum_{j=i+1}^{L} N_{ij} y_i y_j
\]  \hspace{1cm} (20)

where \( N_{ij} \) is the element in the \( i \)th row and \( j \)th column.

According to (5), (16), and (20), the probability that the local mean power \( S \) at the output of the combiner being less than \( y \) is

\[
\Pr(S < y) = \int_{-\infty}^{y} \cdots \int_{-\infty}^{y} \frac{1}{\sqrt{(2\pi)^L \det(\mathbf{M}) z_1 \cdots z_L}} \exp \left[ -\frac{1}{2} \left( \sum_{i=1}^{L} N_{ii} y_i^2 + 2 \sum_{i=1}^{L-1} \sum_{j=i+1}^{L} N_{ij} y_i y_j \right) \right] d\mathbf{z}
\]  \hspace{1cm} (21)

where \( N_{ij} \) and \( y_i \) are defined in (20) and (17), respectively.

The key for analyzing the CCI probability of the local-mean-based macrodiversity system is to find the pdf of the combiner output power, \( f_S(y) \). Unlike the
uncorrelated case where there exists a closed-form expression for \( f_S(y) \), one can not easily get a simple closed formula for the joint distribution of more than two mutually correlated lognormal random variables. However, for \( L = 2 \),

\[
f_S(y) = \frac{1}{\sqrt{2\pi \det(M)}} \left\{ \frac{1}{\sqrt{N_{22}}} \exp \left[ -\frac{y^2}{2} \left( N_{11} - \frac{N_{12}}{N_{22}} \right) \right] \left[ 1 - Q \left( \left( \sqrt{N_{22}} + \frac{N_{12}}{\sqrt{N_{22}}} \right) y \right) \right] + \frac{1}{\sqrt{N_{11}}} \exp \left[ -\frac{y^2}{2} \left( N_{22} - \frac{N_{12}}{N_{11}} \right) \right] \left[ 1 - Q \left( \left( \sqrt{N_{11}} + \frac{N_{12}}{\sqrt{N_{11}}} \right) y \right) \right] \right\}
\]

(22)

where \( y = (\ln p_{od} - \ln \bar{\gamma}_d) \) and \( d \) denotes the branch selected by the macrodiversity system. Consider the following covariance matrix \( M \)

\[
M = \begin{bmatrix} \sigma^2 & \mu \\ \mu & \sigma^2 \end{bmatrix},
\]

(23)

and

\[
N = M^{-1} = \frac{1}{\sigma^4 - \mu^2} \begin{bmatrix} \sigma^2 & -\mu \\ -\mu & \sigma^2 \end{bmatrix}.
\]

(24)

By substituting (24) into (22), we express the pdf of the output local-mean power of the dual macrodiversity system as

\[
f_S(y) = \frac{\sqrt{2}}{\sqrt{\pi} \sigma y} \left\{ 1 - Q \left( \left( \frac{1 - r}{\sqrt{1 - r^2}} \right) \left( \frac{\ln y - \ln \mu_d}{\sigma} \right) \right) \exp \left[ -\frac{(\ln y - \ln \mu_d)^2}{2\sigma^2} \right] \right\}
\]

(25)

where the correlation coefficient \( r \) is defined as \( r = \frac{\nu}{\sigma^2} \). Combining (10), (11), and (25), we obtain

\[
P(CI) = \int_{-\infty}^{\infty} \cdot \int_{-\infty}^{\infty} \frac{2G(\alpha, \beta)}{\sqrt{\pi} n+1} \left\{ 1 - Q \left( \sqrt{2} \left( \frac{1 - r}{\sqrt{1 - r^2}} \right) a \right) \right\} \exp \left[ -\alpha^2 - \sum_{i=1}^{n} \beta_i^2 \right] d\alpha d\beta
\]

\[
\approx \sum_{\kappa_n = 1}^{h_n} \cdots \sum_{k_0 = 1}^{k_0} \frac{2 \left\{ 1 - Q \left( \sqrt{2} \left( \frac{1 - r}{\sqrt{1 - r^2}} \right) x_{k_0} \right) \right\} G(x_{k_0}, \cdots, x_{k_n})}{\sqrt{\pi}^{n+1} w_{k_0} \cdots w_{k_n}},
\]

(26)
where \( \alpha \) and \( \beta \) are defined in (13), the weight factor \( w_k \) of the \( h \)th order Hermite polynomial can be found in [23], and \( G(\alpha, \beta) \) is defined in (14).

V Numerical Results

We consider a cellular system with nine cells per cluster. In this case, two co-channel interferers are at 5.2 \( R \), where \( R \) is the cell radius. Assume the mobile unit is on the boundary of the cell with a distance of \( R \) to the base station. Consider a dual slope path loss model with \( a = b = 2 \) and \( g = 0.15 \) in (1). By letting \( L = 1 \) in (13) and (8), we show the results of shadowing, Rician fading, and Rayleigh fading in Fig. 1 for the case of no macrodiversity. For 10 \% CCI, the performance of a shadowed Rayleigh fading channel is about 4 dB worse than a pure shadowing channel. On the other hand, the degradation with Rician fading is less than 1 dB for \( K = 7 \) dB to 20 dB. Surprisingly, Rician fading can sometimes improve the performance when the threshold in receiver is high.

Figs. 3 (a) and (b) illustrate the gain achieved by a local-mean-based \( S \)-macrodiversity system over a shadowed-Rician (desired) /shadowed-Rayleigh (interfering) channel for the Rice factors \( K = 7 \) and 20 dB. For comparison, Figs. 2 (a) and (b) shows the CCI probability performance in pure shadowing channels and shadowed Rayleigh channels, respectively. Table 1 - 4 list the threshold \( \lambda_{th} \) and diversity gain (D.G.) in terms of 5 and 10 \% co-channel interference (CCIP) probability. Diversity gain here is defined as the additional S/I (in dB) that is required by a system without diversity to produce the same CCI probability. Some general observations can be made: 1) a higher shadowing spread leads to a higher diversity gain and a lower required threshold \( \lambda_{th} \); 2) the diversity gain per branch is decreased as the number of diversity branches is increased; 3) the diversity gain increases with the requirement
of the system, e.g., the diversity gain for 5% CCI probability is higher than that for 10% CCI probability. In addition, we see that the diversity gain seems to be affected little by fading and that a shadowed Rayleigh channel has the least diversity gain.

We evaluate the effects of correlation coefficient $r$ on a 2-branch macrodiversity system with various $K$ and $\sigma$, $K = -\infty$ dB and $\sigma = 6$ dB (Fig. 4 (a)); $K = 10$ dB and $\sigma = 6$ dB (Fig. 4 (b)); $K = -\infty$ dB and $\sigma = 10$ dB (Fig. 5 (a)); $K = 10$ dB and $\sigma = 10$ dB (Fig. 5 (b)). With respect to 10% CCI probability, Table 5 lists $\lambda_{th}$ with different $r$. Observe that as $r$ approaches one, the diversity gain becomes zero. Furthermore, for $r = 0.7$, the diversity gain will be reduced to about 50% of the gain when $r = 0$.

VI Concluding Remarks

We have presented an analytical model for calculating the co-channel interference probability of a local-mean-based macrodiversity system in a shadowed Rician (desired) / shadowed Rayleigh (interfering) channel. The local-mean-based macrodiversity system is easily implemented in the sense that it reacts to the slowly varying local-mean power. Based on the proposed analytical model, we analyzed the effect of fading, and branch-correlated shadowing of the desired signals, on the system performance.

Compared to a pure shadowing channel, Rayleigh fading degrades the S/I performance by about 4 ~ 5 dB at 10% CCI probability. However, as the Rice factor $K$ gets large, the degradation of S/I is within 1 dB. We also observe that fading (either Rayleigh or Rician) has little effect on the diversity gain of local-mean-based macrodiversity systems. The diversity gain is the same, but Rayleigh fading is always worse than Rician fading. Finally, for a two-branch macrodiversity system,
we show a desired signal shadow branch-correlation coefficient of \( r = 0.7 \) will reduce the macrodiversity gain by 50%.

There are some other interesting issues that are worthy of further study. For example, the system performance with mutually correlated multiple interferers is not addressed in this paper. Fortunately, it has been shown that the correlation of shadowing components between interferers does not significantly influence the CCI probability performance [21]. Thus, the results obtained in this paper will be close to the results derived for the environment with multiple correlated log-normally shadowed interferers. On the other hand, better techniques to study the effects of correlated shadowing between the desired signal and the interfering signals are needed.

Finally, this paper assumes that the desired signal power dominates the total received power. Implicitly, each diversity branch operates under the condition that the received desired signal power is stronger than the interference power. This assumption is generally valid for FDMA/TDMA systems, since the purpose of the frequency planning strategy used in FDMA/TDMA systems is to ensure the radio path lengths for the co-channel interferers are significantly longer than those for the desired signals. Consequently, the FDMA/TDMA systems are largely capable of avoiding the situation where the co-channel interference power received at a base station is stronger than that of the desired signal. However, this assumption is not true for a CDMA system. Thus, further research on the performance of CDMA-based macrodiversity systems are needed.

References


Table 1. Macrodiversity gain (D. G.) and the threshold $\lambda_{th}$ of S/I set at the receiver in terms of 5 % and 10 % co-channel interference probability (CCIP) over a pure shadowing channel.

<table>
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<th>$\sigma = 6$ dB</th>
<th>$\sigma = 10$ dB</th>
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<tr>
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<td>$\sigma = 10$ dB</td>
</tr>
<tr>
<td>$\lambda_{th}$ D. G.</td>
<td>$\lambda_{th}$ D. G.</td>
</tr>
<tr>
<td>$L=1$</td>
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</tr>
<tr>
<td>$L=2$</td>
<td>15.78</td>
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<tr>
<td>$L=3$</td>
<td>17.97</td>
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Table 2. Macrodiversity gain (D. G.) and the threshold $\lambda_{th}$ of S/I set at the receiver in terms of 5% and 10% co-channel interference probability (CCIP) over a channel with both shadowing and Rayleigh fading.

<table>
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<th>$\sigma = 10$ dB</th>
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<tr>
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<td>10% CCIP</td>
<td>5% CCIP</td>
<td>10% CCIP</td>
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<td>$\lambda_{th}$</td>
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<td>16.80</td>
<td>7.25</td>
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</table>

Table 3. Macrodiversity gain (D. G.) and the threshold $\lambda_{th}$ of S/I set at the receiver in terms of 5% and 10% co-channel interference probability (CCIP) over a channel with both shadowing and Rician fading $K_d = 7$ dB.

<table>
<thead>
<tr>
<th>$L$</th>
<th>$\sigma = 6$ dB</th>
<th></th>
<th>$\sigma = 10$ dB</th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>5% CCIP</td>
<td>10% CCIP</td>
<td>5% CCIP</td>
<td>10% CCIP</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{th}$</td>
<td>D. G.</td>
<td>$\lambda_{th}$</td>
<td>D. G.</td>
</tr>
<tr>
<td>1</td>
<td>9.34</td>
<td>-</td>
<td>12.89</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>13.81</td>
<td>4.47</td>
<td>16.99</td>
<td>4.10</td>
</tr>
<tr>
<td>3</td>
<td>16.11</td>
<td>6.77</td>
<td>19.06</td>
<td>6.17</td>
</tr>
<tr>
<td>4</td>
<td>17.47</td>
<td>8.13</td>
<td>20.33</td>
<td>7.44</td>
</tr>
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</table>
Table 4. Macrodiversity gain (D. G.) and the threshold $\lambda_{th}$ of S/I set at the receiver in terms of 5% and 10% co-channel interference probability (CCIP) over a channel with both shadowing and Rician fading $K_d = 20$ dB.

<table>
<thead>
<tr>
<th>L</th>
<th>$\sigma = 6$ dB</th>
<th></th>
<th>$\sigma = 10$ dB</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5% CCIP</td>
<td>10% CCIP</td>
<td>5% CCIP</td>
<td>10% CCIP</td>
</tr>
<tr>
<td>$\lambda_{th}$</td>
<td>D. G.</td>
<td>$\lambda_{th}$</td>
<td>D. G.</td>
<td>$\lambda_{th}$</td>
</tr>
<tr>
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<td>13.16</td>
<td>-</td>
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<tr>
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<td>15.56</td>
<td>4.70</td>
<td>18.42</td>
<td>4.26</td>
</tr>
<tr>
<td>3</td>
<td>17.51</td>
<td>6.65</td>
<td>20.53</td>
<td>6.37</td>
</tr>
</tbody>
</table>

Table 5. Effects of branch correlation on a 2-branch macrodiversity.

<table>
<thead>
<tr>
<th>$r$</th>
<th>$\sigma = 6$ dB</th>
<th></th>
<th>$\sigma = 10$ dB</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>$K = -\infty$ dB</td>
<td>$K = 10$ dB</td>
<td>$K = -\infty$ dB</td>
<td>$K = 10$ dB</td>
</tr>
<tr>
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<td>D. G.</td>
<td>$\lambda_{th}$</td>
<td>D. G.</td>
<td>$\lambda_{th}$</td>
</tr>
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<td>17.75</td>
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<td>1.0</td>
<td>9.55</td>
<td>-</td>
<td>13.42</td>
<td>-</td>
</tr>
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</table>
Fig. 1. Comparison of CCI probability, $P(CI)$, for no macrodiversity over pure shadowing channels, shadowed Rayleigh channels, and shadowed Rician channels, where $\sigma = 6 \text{ dB}, a = b = 2, g = 0.15R$; two interferers are located at a distance of 5.2R.
Fig. 2. The CCI probability, $P(CI)$, against the required threshold, $\lambda_{th}$, at the receiver for the local-mean-based macrodiversity system over (a) pure shadowing channels and (b) shadowed Rayleigh channels, where the solid lines (-----) denote the case for shadowing standard deviation $\sigma = 10$ dB and the dashed lines (-----) for $\sigma = 6$ dB; $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of 5.2R.
Fig. 3. The CCI probability, $P(CI)$, against the required threshold, $\lambda_{th}$, at the receiver for the local-mean-based macrodiversity system over the shadowed-Rician (desired) / shadowed-Rayleigh (interfering) channel with Rice factor (a) $K = 7$ dB and (b) $K = 20$ dB, where the solid lines (---) denote the case for shadowing standard deviation $\sigma = 10$ dB and the dashed lines (-----) for $\sigma = 6$ dB; $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of $5.2R$. 
Fig. 4. Effect of branch correlation coefficient $r$ on the local-mean-based macrodiversity system with Rice factor (a) $K = -\infty$ dB and (b) $K = 10$ dB, where $\sigma = 6$ dB; $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of 5.2R.
Fig. 5. Effect of branch correlation coefficient $r$ on the local-mean-based macrodiversity system with Rice factor (a) $K = -\infty$ dB and (b) $K = 10$ dB, where $\sigma = 10$ dB, $a = b = 2$, $g = 0.15R$; two interferers are located at a distance of $5.2R$. 
A NEW NETWORK ARCHITECTURE FOR
WIRELESS COMMUNICATIONS

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Abstract

Current cellular systems are based on the concept of cell. Although cell allows channel reuse, it has also become a metaphor for channel confinement and leads to the thorny problem of handoff and call-dropping. The problem will get much worse as cellular services move toward high-speed and multirate.

The paper presents a new wireless network architecture: called MAWCC for its main characteristic—MAcrodiversity Without Channel Confinement. In MAWCC, mobility equals capacity. The convertibility between the two (capacity and mobility) makes MAWCC a total departure from a conventional wireless network. If offers more options for tackling the issues of mobility, handoff, and call dropping.

1. Introduction

Current cellular systems are based on the concept of cell. We divide the entire region into cells and use the same channel repetitively in different cells so long as the interference requirement is not violated. Although "cell" offers channel reuse, it also leads to the vexing handoff and call-dropping problem: A call might be handed over and over during its lifetime and could be dropped in each handoff step. The problem will get much worse as the network moves toward smaller cells and multirate services. Studies have shown that high-bandwidth connections have high blocking probabilities [4]. If handing over one voice connection is problematic, imagine the chance of success of handing over a call ten times that rate. Call dropping has

1 Research is supported by a grant from NSF. Dr. Lea is on currently leave from Georgia Tech and now with Hong Kong UST.
A new network architecture for wireless communications is proposed in this paper. The new architecture—called MAWCC for its main characteristic: MAcrodiversity Without Channel Confinement—can freely convert its capacity gain from macrodiversity into handoff reduction. In MAWCC, requesting the network to support a higher mobility is the same as requesting more bandwidth; conversely, the network’s capacity will rise if the mobilities of its customers are reduced. The convertibility between the two offers more options to tackle the mobility issue than possible in a conventional wireless network.

2. MAWCC Architecture

In a cellular system, the effects of the surrounding buildings, terrain, trees, cause a large variation in the mean square envelope of the received signal power. The variation degrades the system’s performance and the resulting degradation is called the shadowing effect. To mitigate the shadowing effect we can use two (or even three) cites to serve a connection, since the probability that two paths are shadowed is much smaller than one being shadowed. This technique, called macrodiversity, can achieve a more homogeneous coverage and has long been recognized as an effective tool for combating shadowing [2,3].

One example of macrodiversity implementation is given in Figure 1 [3]. Each cell is divided into three zones and each zone is covered by a separate antenna. The selector chooses the best zone and its antenna to send and receive signal from and to the base station. Although this macrodiversity architecture improves the performance of the system, it does not address the coverage between cells and the old Ping-Pong problem during handoff remains. An entirely different concept to implement macrodiversity is described below [4]. It achieves a goal way beyond the conventional advantages of macrodiversity.

Figure 1 The zone concept described in [1].
2.1 Macrodiversity In MAWCC

Instead of using three antennas, we can use sectoring—already commonly deployed in the field—to implement macrodiversity. Figure 2 shows a three-sectored hexagonal cellular system and at the center of each cell are three directional antennas. Figure 3 shows the same topology with dashed lines added. As can be seen, the areas surrounded by the dashed lines are also hexagons. The difference between the two is just a coordinate shift. Conventionally we call the area surrounded by the solid lines a cell. We are equally correct to call the area surrounded by the dashed lines a cell. Since nothing is changed, how we define a cell is only a matter of convenience. But the two views offer drastically different interpretations about the network's structure. According to the first view, each cell has three directional antennas located at the center. According to the second view, however, each cell has three antennas sitting at the corners—same as in a macrodiversity cell (Figure 1). Sectoring, as can be seen, already has the makings of macrodiversity.
The second key element in MAWCC's implementation is dynamic channel allocation (DCA). Unlike a fixed-channel-assignment (FCA) network where each base station is assigned a fixed number of channels, a DCA network allows its base stations to access any channel in the network. Many DCA schemes have been proposed. They differ in degree of network planning and the required communication amongst base stations. For example, the DCA schemes in [14,15,16] require no network planning or communication amongst base stations. Other types of DCA schemes, like [17], require limited communication amongst base stations. Although studies have demonstrated DCA's advantage of higher trunking efficiency over FCA, DCA is not without its problems: it requires more circuits in each cell and a more complicated channel assignment scheme than a FCA scheme. Tradeoffs can be made among these factors (efficiency, complexity of channel assignment, and the number of circuits required) and as a result, various variations have been proposed. Their pros and cons can be found in [18-21].

To simplify our discussion, we assume a general DCA scheme for MAWCC in which every channel can be accessed by every cell. Besides higher trunking efficiency [5,6], DCA in MAWCC serves another major purpose: it breaks the conventional cell boundary so that adjacent cells can simultaneously serve the connection with the same channel (Figure 4). When the mobile unit moves into other cells, it carries the same channel with it and no immediate handoff is required. This continues until the co-channel interference requirement is violated. More discussion on handoff is provided in the following section.

2.2 Call Setup and Handoff in MAWCC

In call setup, the mobile unit will identify the best and the second best stations and their sectors to serve the connection. We call one active and the other stand-by. Identifying the two can be done with one power scanning. For the up link, the signal from the mobile unit is received by both serving base stations and the selection can be done at either the base station or the switch. For the down link, only the active station—the stronger of the two—transmits the signal to the mobile unit. Periodically, the two stations measure their signal strengths and report that information to the switch. Based on that information, the switch decides which station should be active or stand-by.

When the mobile unit enters another cell, it carries the same channel into the new cell as if nothing had happened (Fig. 4). This is possible because there is no boundary for a particular channel in MAWCC due to its use of DCA. In contrast, a handoff is immediately required in a conventional cellular network when the mobile unit entering a new cell. If the signal strength of the stand-by station drops below a pre-determined value, the switch will identify a new stand-by
station. For TDMA, it is preferable to have the mobile unit assist the process to alleviate the processing demand for the base stations and the switch.

It is important to note that the change of the stand-by station is not the same as a conventional handoff. A conventional handoff has two elements that lead to call dropping: (1) no channels available in the new cell, and (2) no enough time to process the handoff. These two elements do not apply to the case of changing the stand-by station because in the latter the channel is guaranteed (the same channel) and the task needs not be done immediately—the stand-by station is only standing by. Certainly there are times when two mobile units using the same channel get close enough to violate the co-channel interference requirement. Then one of them must switch its channel and a traditional handoff is required. Such activities, as shown later, are significantly less frequent than in a conventional cellular architecture.

Figure 4 The mobile unit will carry the same channel as it moves into a new cell.

Although the WCC (without-channel-confinement) feature can still be implemented without macrodiversity, it will not work well. First, without macrodiversity the connection must be handed over immediately to the neighboring cell as the mobile unit crossing the cell boundary (although the channel is still the same). The time critical characteristic of a conventional handoff remains. Second, without macrodiversity the system will be plagued by the Ping-Pong problem as a mobile unit zigzagging on the cell boundary. More important, the capacity gain created by macrodiversity can be traded for further handoff reduction (section 3)

The MAWCC concept also differs from that of soft-handoff in a CDMA system. Although macrodiversity is also used in soft handoff of a CDMA system, the WCC characteristic sets them apart. WCC allows a mobile user moving into a new cell without requesting new network resources. This feature, not possible for CDMA, is the key element of MAWCC's mobility management strategy.
3. Macrodiversity Gain and Handoff Reduction

This section offers a comprehensive study of the performance gain from macrodiversity. We then study how that gain can be converted into handoff reduction.

3.1 Capacity Gain from Macrodiversity

In a traditional macrodiversity system, the number of diversity branches is almost fixed in order to have a homogeneous coverage, and is determined by the topology of the network—for example, three branches for hexagons, four branches grids, and two branches liner arrays. But the proposed architecture does not have this restriction. For example, we have described a two-branch diversity for the hexagonal topology. With a higher cost, we can use three branches to achieve a better performance. To better understand the design tradeoff, we offer an analysis in the following. The performance improvement of macrodiversity is represented as a reduction in co-channel interference (CCI) probability, defined as the probability that the desired signal level is less than the required receiver threshold due to excessive interference.

![Figure 5](image_url) Under the worst case scenario, the locations of the interferers, where D is the minimum reuse distance and R is the radius of the cell.

3.1.1 Analytical Model

Suppose a conservative DCA policy is adopted in which a minimum reuse distance is imposed for every channel. Under the worst case scenario, the locations of the first tier interferers are similar to that in a fixed channel assignment (Figure 5). In the following we analyze the performance gain as a function of number of macrodiversity branches for the case shown in Figure 5. The performance gain of macrodiversity is strongly affected by the link-quality evaluation scheme. Various schemes have been proposed and each has a different implementation complexity. In the following we study the performance gain of macrodiversity under three link-quality measurement schemes:

1) SIR-diversity: The signal-to-interference ratio (SIR) is constantly computed and the branch with the largest SIR is selected;
2) **S-diversity**: The signal power (S) is constantly measured and the branch with the largest S is selected;

3) **(S+I)-diversity**: The signal mixed with interference, i.e. S+I, is constantly measured. The branch with the largest S+I is selected.

As implementation goes, (S+I)-diversity is the easiest to implement and only the received signal, (S+I), is monitored. S-diversity requires interference be separated from the received signal, which obviously is a difficult task. Because $S >> I$, S-macrodiversity can be considered as an approximation for the $S+I$ case. Among the three, the most desirable one is SIR-diversity. But it is also the most difficult to implement.

There are some results in the literature related to the (S+I)-microdiversity [7,8]. As for macrodiversity, the S type has been discussed in [9]. We are going to compute and compare the co-channel interference of all three forms of macrodiversity mentioned previously. As in [9], we ignore fading and only consider shadowing in the analysis. We assume that the up-link and down-link channels are symmetric and have the same statistics. For the ease of presentation, we discuss S-macrodiversity [9] and SIR-macrodiversity first. We then present the analysis for S+I-macrodiversity.

**S-macrodiversity**

For S macrodiversity, the branch with the largest desired signal power is selected to the receiver. The desired signal power at the receiver is expressed as

$$S = \max(S_1, \ldots, S_L)$$  \hspace{1cm} (1)

where $S_k$ is the signal power from the k-th branch and $L$ is the number of the diversity branches. Let $F_k(x)$ and $f_k(x)$ be the cdf and pdf of $S_k$. Assume the signal powers from each branch are i.i.d. random variables. Then the pdf of $S$ is

$$f_S(x) = L[F_k(x)]^{L-1} f_k(x)$$  \hspace{1cm} (2)

Furthermore, the total interference power of each branch has a identical distribution as that of another branch. The total interference power of a branch is also independent of the desired signal power $S$. Let $f_I$ be the pdf of the total interference power $I$ of some branch. The CCI probability of S-diversity is then equal to
\[
F_S(\lambda_{ab}) = \text{Prob}(\max_{l \in I_k} \frac{x_{l_k - f_{l_k}}}{f_{l_k}} \leq \lambda_{ab}) = 1 - \int_0^{\infty} \left[1 - F_k(x)\right]^{L-1} f_k(x) dx
\]  
(3)

Under the effect of shadowing, \( f_k(x) \) is log-normal distributed, which is written as

\[
f_k(x) = \frac{1}{\sqrt{2\pi} \sigma_x} \exp\left(-\frac{(\ln x - \bar{Y}_k)^2}{2\sigma^2}\right)
\]  
(4)

where \( \sigma_x \) is the shadowing spread and \( \bar{Y}_k \) is the area mean power. Ref [10] offered an approach to determine the composite pdf of the sum of the independent log-normal random variables, which is approximated by another log-normal random variable. We apply this approach to represent the total interference power by an approximate log-normal random variable. Let \( \sigma_f \) represent logarithmic variance and \( \bar{Y}_f \) area mean of the approximate log-normal pdf. Then substituting Eq. (4) into Eq. (3), we obtain the CCI probability with S-macrodiversity as

\[
F_S(\lambda_{ab}) = 1 - \int_0^{\infty} \left[1 - Q\left(\frac{\ln x - \bar{Y}_f}{\sigma_f}\right)\right]^{L-1} \frac{1}{\sqrt{2\pi} \sigma_x} \exp\left(-\frac{(\ln x - \bar{Y}_k)^2}{2\sigma^2}\right) dx
\]  
(5)

where \( Q(x) = \int_x^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) dx \). Let \( w = \frac{\ln x - \bar{Y}_f}{\sigma_f} \) and transform Eq. (5) into the Hermite integration form, which can be calculated by the Hermite polynomial approach. We have

\[
F_S(\lambda_{ab}) = 1 - \int_{-\infty}^{\infty} f(w) \exp(-w^2) dw = 1 - \sum_{n=1}^{\infty} f(w_n) h
\]  
(6)

where

\[
f(w) = \frac{1}{\sqrt{2\pi}} \left[1 - Q\left(\frac{\ln x - \bar{Y}_f}{\sigma_f}\right)\right] \left[1 - Q\left(\sqrt{2} w\right)\right]^{L-1}
\]  
(7)

and \( w_n \) and \( h \) are roots and weight factors of the n-th order Hermite polynomial.

**SIR-macrodiversity** Assume SIR in each branch \( (S_k/I_k, k = 1, \ldots, L) \) are i.i.d. random variables. Then the average CCI probability with SIR selection diversity is

\[
F_{SIR}(\lambda_{ab}) = \text{Prob}(\max(\frac{x_{l_1}}{I_{l_1}}, \ldots, \frac{x_{l_k}}{I_{l_k}}) \leq \lambda_{ab}) = [\text{Prob}(\frac{x_{l_k}}{I_{l_k}} \leq \lambda_{ab})]^L
\]  
(8)

In the case of no macrodiversity, the CCI probability formula is the same for S-diversity,
$S/I$-diversity, and $S+I$-diversity. By letting $L=1$ in Eq. (5), we can simplify the CCI probability with no diversity as

$$F_{SIR}(\lambda_m) = Q\left(\frac{\ln \frac{\ln T}{\lambda_m}}{\sqrt{\sigma_t^2 + \sigma_f^2}}\right).$$ (9)

According to the Eqs. (8) and (9), the CCI probability of the SIR-macrodiversity in the presence of log-normal shadowing is then written as

$$F_{SIR}(\alpha_m) = \left[Q\left(\frac{\ln \frac{\ln T}{\lambda_m}}{\sqrt{\sigma_t^2 + \sigma_f^2}}\right)\right]^L$$ (10)

$(S+I)$-macrodiversity. Following a similar procedure given in [11], we derive the performance of the $(S+I)$-macrodiversity as follows. It is easy to see that the $L$-branch CCI probability can be written as

$$F_{S+I}(\lambda_{th}) = 1 - \sum_{l=1}^{L} \left\{ \text{Prob}(\frac{S_i}{I_i} \geq \lambda_{th} | S_i + I_i \geq S_j + I_j, j = 1, ..., L, j \neq i) \times \text{Prob}(S_i + I_i \geq S_j + I_j, j = 1, ..., L, j \neq i) \right\}$$

Let $U = S_i + I_i$ and $V = S_j / I_j$. Then the above equation is reduced to

$$F_{S+I}(\lambda_{th}) = 1 - \int_{0}^{\infty} \int_{0}^{\infty} f_{U,V}(u,v)[\text{Prob}(S_j + I_j \leq v)]^{L-1} du dv$$ (11)

Note that $\text{Prob}(S_i + I_i \leq v)$ is just the cdf of $U$ and $f_{U,V}(u,v)$ is the composite pdf of random variables $U$ and $V$. The relation between $f_{U,V}(u,v)$ and the composite pdf of random variables $S_i$ and $I_i$ is

$$f_{U,V}(u,v) = \frac{v}{(u+1)^2} f_{S_i,I_i}(\frac{uV}{u+1}, \frac{v}{u+1}).$$ (12)

As in the case of $S$-diversity, we use a log-normal random variable with area mean $\bar{Y}$ and logarithmic variance $\sigma$ to approximate the composite pdf of the sum of multiple log-normal interferers. Combining the pdf of the desired signal power (described in Eq. (4)), we then express Eq. (12) as

$$f_{U,V}(u,v) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{-(\ln u - \bar{Y})^2}{2\sigma^2}\right) \exp\left(-\frac{-(\ln v - \bar{Y})^2}{2\sigma^2}\right)$$ (13)
Since both $S_j$ and $I_j$ are log-normal distributed, we again use a log-normal random variable with area mean $Y_c$ and logarithmic variance $\sigma_c$ to approximate $S_j + I_j$. Then

$$\text{Prob}(S_j + I_j \leq y) = 1 - Q\left(\frac{\ln(y)}{\sigma_c}\right)$$  \hspace{1cm} (14)

Substituting Eqs. (13), (14) into (11), we express the CCI probability in a Hermite form as follows.

$$F_{S+I}(\lambda_n) = 1 - \int_{-\infty}^{\infty} f(w) \exp(-w^2) dw = 1 - \sum_{i=1}^{\infty} f(w_i)h_i$$  \hspace{1cm} (15)

where

$$f(w) = \frac{L}{\sqrt{\pi}} \sum_{i=1}^{\infty} \exp\left[-(z - \frac{\ln(z)}{\sqrt{2} \sigma_z} + \frac{\sigma_z}{\sqrt{2} \sigma_z})^2\right][1 - \frac{\ln(\exp(\sqrt{2} \sigma_z) + 1 - \frac{\sigma_z}{\sqrt{2} \sigma_z} \sigma_z)}{\sigma_z}]^{L-1} dz$$  \hspace{1cm} (16)

where $w_i$ and $h_i$ are the roots and weight factors of the $n$-th order Hermite polynomial.

3.1.2 Results

Consider a dual slope path loss model, $P_r/P_t = \frac{1}{r^{(1+\frac{g}{2})}}$, where $P_r/P_t$ is the ratio of received power to the transmitted power, $r$ is the distance, $a=b=2$ and $g=0.6$ times of the cell radius in our case. Assume the receiver is located at the cell boundary $R$ and the interferers are $4.5R$ away. Although Figure 5 shows that under the worst case scenario, the first-tier interferers can be as large as six. In reality, however, the number of interferers is usually small since we have a sectored system. Even if we assume that all cells on the circle have an interferer, there are, on average, only two interferers. Fig. 6 compares, in the presence of one interferer with $8$ dB shadowing spread, the $S$-macrodiversity, $S+I$-macrodiversity, and $SIR$-macrodiversity (i.e. Eqs. (6), (10), and (15)).

The results show that under a $5\%$ CCI probability, the SIR thresholds for the $SIR_-, S$, and $(S+I)$-diversity are $15$ dB, $11$ dB and $10$ dB. In other words, with a probability of $0.95$ the SIR of the network exceeds $15$ dB, $11$ dB, and $10$ dB for the three types of macrodiversity. Compared with the case of no diversity ($5$ dB), the gains of the three diversity schemes are $10$ dB, $6$ dB and $5$ dB. If the CCI probability is set to $10\%$, then the SIR thresholds for $SIR_-, S$, and $(S+I)$-diversity become $18$ dB, $15$ dB, and $14$ dB. Compared with the case of no diversity ($9$ dB), the gains are $9$ dB, $6$ dB, and $5$ dB for the three diversity schemes. The results indicate that all three diversity schemes have significant performance gains over the case of no diversity. The gains of $(S+I)$- and $S$-diversity are similar. $(S+I)$-diversity can be considered as a good
approximation for the S-macrodiversity. The gain of SIR-diversity is significantly higher. But a precise SIR measurement is difficult to achieve.

Since (S+I)-macrodiversity is the simplest to implement, we show some additional results based on this scheme. Figure 7 shows, in the presence of two interferers, the performance gain of the (S+I)-diversity as a function of the number of diversity branches. At the 5% CCI probability, 2-branch has 4 dB gain over the case of no diversity; 3-branch has a gain of 6 dB. Figure 8 describes how the performance gain is affected by the number of interferers. The case we study is a 3-branch (S+I)-diversity. Compared with the case of one interferer, two interferers degrade the performance by 1.7 dB, and three interferers degrade the performance by 4.5 dB.

![Graph showing performance comparison of SIR-macrodiversity and S-macrodiversity and S+I macrodiversity](image)

Figure 6 Performance comparison of SIR-macrodiversity and S-macrodiversity and S+I macrodiversity in the presence of one log-normal shadowing interferer, where the shadowing spread for is 8 dB for both the desired signal and interferer.
Figure 7 Comparison of L-branch (L = 1, 2, 3) S+1-macrodiversity in the presence of two log-normal shadowed interferers, where the shadowing spread for all is 8 dB.

Figure 8 Effects of the number of interferers on the performance of 3-branch S+1 macrodiversity, where the shadowing spread for all is 8 dB.
3.2 Converting Capacity Gain into Handoff Reduction

In a traditional cellular system, a mobile unit immediately requires a handoff as it crosses a cell boundary. But a mobile unit in MAWCC can travel a much longer distance before a handoff is needed. There are two reasons for this.

1. The inherent imperfect packing of DCA allows a mobile unit to travel a greater distance before violating the reuse distance constraint. For example, suppose a cellular system imposes a reuse distance of 4 during call setup. Due to imperfect packing, the real average reuse distance is increased to 5 (Figure 9)\(^2\). (The maximum packing efficiency depends on the complexity of the algorithm (see [12]).) In a conventional DCA system, this is just bandwidth waste. But in MAWCC, this lost bandwidth is converted into handoff reduction and allows a mobile unit to travel one more cell without violating the interference requirement.

2. Macrodiversity increases the system's capacity. This capacity gain can be converted into handoff reduction, as shown below.

In the following we offer a simplified analysis to show the tradeoff between capacity gain and handoff reduction.

\[
\text{reuse distance requirement} = 4
\]

```
1 1 1 1 1 1 1 1
```

\[\text{no other cell in between can use the same channel}\]

Figure 9  Due to the nature of imperfect packing in DCA, a channel can travel a distance more than a cell without violating the reuse distance requirement.

3.2.1 A Renewal Model

In MAWCC, connections using the same channel can be likened to particles moving in a chamber. Handoffs are needed when particles collide (Fig. 10). An exact analysis of this model may not be possible. In the following we study a simplified one-dimensional case shown in Fig.\(^2\)

This does not imply the overall capacity is less than a conventional system. The capacity loss due to imperfect packing in DCA is well compensated by a higher trunking efficiency (see [6,12]).
where all users move along a line. Assume the system uses a timid DCA policy where a reuse distance limit \( R \) is imposed when a call is newly set up. Let \( H \) denote the *handoff distance* (the *minimum* reuse distance), meaning a handoff is required when the distance between any two users (particles) is less than \( H \). Obviously the condition \( R \geq H \) must hold. For example, in a conventional 7-cluster cellular system \( R = 4.5 \). If we assume a user needs a handoff when he/she gets to the cell boundary, then \( H = 3.5 \).

Perfect channel allocation in a DCA network, such as MAWCC, is usually unachievable. Because of imperfect channel packing, the distance—denoted by \( d \)—between a new connection and the nearest particle will always be \( \geq R \). Let \( x \) be the random variable representing the extra distance, i.e. \( d = R + x \) (Figure 11). The average value of \( x \) is determined by the efficiency of the DCA channel assignment algorithm (for random assignment, the efficiency is about 80% of the maximum packing efficiency [12]). Although \( x \) can have a general distribution, we assume \( d \) has a negative exponential density function to reduce the computation complexity. That is,

\[
\begin{align*}
    f(d) & = 0 & & \text{if } d < R \\
    & = \mu e^{-\mu(d-R)} & & \text{if } d \geq R
\end{align*}
\]

(17)

We intend to get an estimation for the average number of collisions of a connection during its lifetime. In Figure 11, the collision rate is determined by the relative movements among particles. We simplify the analysis by assuming that only the new connection is moving and the rest are idle. This will remove the dynamics and turn the model into a static one. In this static model we can treat the new connection as a particle with a radius \( H \) and the other old connections using the same channel only as a point. After the new connection collides with its neighbor (same channel), a new channel will be used (i.e. a handoff) and the whole process will repeat. Thus the model renews itself upon collision times and the average number of handoffs follows the *renewal* formula.
Figure 10 Each active instance of a channel is likened to a particle. A handoff is needed only when the distance between two particles is less than H. We call H the handoff distance.

Figure 11 Assume the new connection moving along one direction

Let $C_y$ be the random number of collisions of the new connection after it travels a distance $y$. Let $s$ be the location of the nearest mobile unit using the same channel. Given $s$, we can write $C_y$ as

$$C_y = \begin{cases} 
0 & \text{if } s > y \\
1 + C_{y,s} & \text{if } s \leq y 
\end{cases} \quad (18)$$

Taking expectation of $C_y$ in Eq. 18 results in

$$E[C_y | s, s < y] = 1 + E[C_{y,s} | s, s < y] \quad (19)$$

Let $\overline{C}(y)$ be the average value of $C_y$, i.e. $\overline{C}(y) = E[E[C_y | s]]$. Then taking another expectation of both sides of Eq. 19 with respect to $s$ leads to

$$\overline{C}(y) = F(y) + \int_0^y \overline{C}(y-s)f(s)ds \quad (20)$$

15
where \( f() \), given in Eq. 17, is the density function of the distance \( d \) of the nearest neighbor and \( F() \) is the distribution function. The above integral equation can be solved numerically.

Let \( z \) be the total distance traveled by the new particle (connection) during its life time. Suppose that \( z \) also has a negative exponential distribution with mean \( 1/\lambda \). Since the moving particle has a radius \( H \), then the total number of collisions is \( C(z+H) \) for a given \( z \). Averaging this number with respect to \( z \), we get the average number of handoffs, denoted by \( C_{\text{ave}} \), during the life time of the new connection in Fig. 11. Which is,

\[
C_{\text{ave}} = \int_0^\infty C(z+H) \times \lambda e^{-\lambda z} dz
\]

(21)

Figure 12 plots \( C_{\text{ave}} \) against \( R \). In the figure, we assume packing efficiency = 80% [12] (meaning \( R / (R+1/\mu) = 0.8 \)). We can compute \( \mu \) for different \( R \). We also assume the average traveling distance \( 1/\lambda = 1 \). The range for \( R \) is chosen as follows. We begin with \( R = 4.5 \), the same value used in a 7-cluster cellular system [13]. In a FCA network, a handoff occurs when the mobile unit is on the boundary. That means the handoff distance \( H = 3.5 \). If we assume the macrodiversity gain = 5 dB (section 3.1), we can get a rough estimation for the new handoff distance \( H' \) using the deterministic path loss model: \( 10 \log (H/H')^4 = 5 \) and this leads to \( H' = 2.62 \). Thus within this range \( R \geq 2.62 \), the CCI performance will not be worse than that in a FCA network. Figure 12 shows the conversion between capacity and handoff reduction. At \( R = 2.6 \), the network has the highest capacity. At \( R = 4.5 \), the entire capacity gain is traded for handoff reduction.
4. Concluding Remarks

The trend toward smaller cells and multirate has put handoff and call-dropping to the forefront of all mobility management issues in wireless communications. The frequent handoffs existing in the current cellular architectures could render them incapable of supporting high-speed multirate services. In the paper we have argued for a new network architecture for wireless communications. We also showed how its capacity gain from macrodiversity can be converted into a reduction in handoffs.

The convertibility between the two offers a new direction for designing a wireless network. Consider the issue of macrocells versus microcells. Smaller cells, while offering more capacity, are unable to handle high mobility users. To deal with this problem, a common approach is to design a network with macrocells overlaying on microcells, one for high and the other for low mobility users. But the unpredictability in traffic estimation and user mobility profiles will reduce the efficiency of the partitioning scheme.

But MAWCC offers more efficient options. We can design the network with the same cell size (the small one) to support both high and low mobility users. If a user's mobility is high, the same channel will be reallocated at a greater distance away; if low, then at a shorter distance. When a high-mobility user stops and turns into a low mobility user, the reuse distance of the same channel can be shortened. The reduced mobility is then converted back into network capacity. Priority can also be included to manage mobility. For instance, if a user deems his/her call important, he/she can require the call be given high priority (of course, the user will pay more). When a high-priority user collides with a low priority user, the latter is forced to do the handoff and the former is allowed to continue with the same channel and thus experiences a lower call dropping probability.

These new options are only part of the features provided by MAWCC. Many other features in MAWCC, like location identification through macrodiversity, are also important. We will report our findings on them in a future paper.

REFERENCES


An Efficient Algorithm for Estimating the Signal-to-Interference Ratio in TDMA Cellular Systems

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ABSTRACT

A new algorithm is proposed for estimating the signal-to-interference ratio (SIR) in TDMA cellular systems. The proposed SIR estimator is evaluated for use in the IS-54/136 system and a GSM-like system, and compared with existing SIR estimation algorithms. Our results show that the proposed algorithm has better performance than existing algorithms in terms of the mean square prediction error. When the computational requirements are considered, the proposed algorithm has far less computational complexity than existing algorithms of comparable performance.

Keywords: SIR estimation, computational complexity.

1. Introduction

Many of the radio resource management algorithms used in first generation macrocellular systems employed received signal plus interference plus noise power (S+I+N) as a measure of radio link quality. This approach works well for such macrocellular systems, because the radio propagation environment is fairly predictable and the required signal-to-interference plus noise ratio, S/(I+N), of first generation systems is fairly large. However, these conditions will no longer be true for future microcellular systems, where the propagation environment is characteristically erratic and the radio receivers are designed to operate at a much lower S/(I+N). For these systems, a radio link having large (S+I+N) may be deprived of good quality because of a correspondingly low S/(I+N). Consequently, S/(I+N) is considered to be a key parameter for the more contemporary cellular radio resource management algorithms for handoffs [1], dynamic channel assignment [2, 3], and power control [4]. Many of these algorithms operate under the premise that fast and accurate measurements of the received S/(I+N) are available at either the base stations (BSs), mobile stations (MSs), or both.

Several methods have been recently proposed for TDMA cellular systems, to generate accurate, real time, estimates of the received S/(I+N). One such method has been suggested by Austin and Stüber [5] that uses the training and/or color code sequences that are typically present within each TDMA slot to obtain an unbiased estimate of the S/(I+N). The numerical examples in [5] show that the S/(I+N) can be estimated to within 2 dB in less than a second for an IS-54/136 system. The signal-to-variance (SVR) power estimator proposed in [6] is another method. This method uses the autocorrelation sequence of the received signal samples for a short time scale. The application of SVR method to a DECT system reveals that the estimator suffers from a large bias for interesting values of S/I. Another S/I estimation algorithm for TDMA cellular systems has been reported in [7]. The algorithm uses the eigenvalues of the covariance matrix of the received signal sequence to estimate the S/I. Simulation results for a GSM-like system show that the S/I can be estimated within an error of 0.3 dB in 200 ms. The method has, however, some computational burden.

This paper develops a new and efficient S/(I+N) estimation method for TDMA cellular systems. The method has low computational complexity and a lower average absolute prediction error than all of the S/(I+N) estimation algorithms discussed above. The remainder of the paper is organized as follows. Section 2 presents the discrete-time framework for the channel model and signal quality estimation, and presents the basic idea of the proposed estimation technique. Computational issues are discussed in Section 3. Section 4 summarizes the simulation results for the proposed SIR estimation technique. Finally, Section 5 provides some concluding remarks.

2. Discrete-Time Channel Model

Following [5], the overall discrete-time channel consisting of the transmit filter, channel, matched filter, and baud-rate sampler and can be modeled as an M-tap, T-spaced, transversal filter, where T is the baud duration. The overall channel taps can be described by the vector \( f = [f_1, \ldots, f_M]^T \). The received samples \( y_n \) at the output of the matched filter have the form

\[
y_n = \sum_{k=1}^{M} a_{n-k} f_k + w_n, \tag{1}
\]

where \( \{a_n\} \) is the transmitted symbol sequence and the \( w_n \) are samples of the received interference plus noise. Let \( y = [y_1, \ldots, y_L]^T \) be a length L vector of received samples. It follows that the received signal vector \( y \) is

\[
y = Af + w, \tag{2}
\]

where \( A \) is an \( L \times M \) Toeplitz matrix consisting of the transmitted symbols of the form

\[
A = \begin{bmatrix}
a_0 & a_{-1} & \cdots & a_{1-M} \\
a_1 & a_0 & \cdots & a_{2-M} \\
\vdots & \vdots & \ddots & \vdots \\
a_L & a_{L-1} & \cdots & a_{L-M} 
\end{bmatrix}, \tag{3}
\]

and \( w = [w_1, \ldots, w_L]^T \) is the vector of received interference plus noise samples. The matrix \( A \) is commonly called a convolution
matrix. If there are $N_f$ interfering BSs, then $w$ can be expressed as
\[ w = \sum_{k=1}^{N_f} A_k f_k + n, \]
where $n$ is a zero-mean, discrete-time, white Gaussian process. Since the BSs are unsynchronized in TDMA cellular systems such as IS-54/136, PDC, and GSM, the received signal sample sequences from the interfering BSs can be considered as uncorrelated and mutually uncorrelated. This implies that $w$ and $A$ are mutually uncorrelated. Furthermore, it is reasonable to assume that the channel taps, $f$, are uncorrelated with both the symbol sequence $(a_k)$ and the interference plus noise vector $w$. Assuming a zero-mean signal constellation, it follows that $y$ and $w$ are zero-mean uncorrelated random processes.

The received signal plus interference plus noise power, and the received interference plus noise power, are $\sigma_2^2 = \frac{1}{L} E[y^H y]$ and $\sigma_2^2 + N = \frac{1}{L} E[w^H w]$, respectively. Assuming ergodicity, the ensemble averages can be replaced by time-averages so as to obtain the unbiased estimates of $S$ and $I+N$, denoted by $\hat{\sigma}_S^2$ and $\hat{\sigma}_{I+N}^2$, respectively. That is
\[ \hat{\sigma}_S^2 = \frac{1}{L} \overline{y^H y} \quad \hat{\sigma}_{I+N}^2 = \frac{1}{L} \overline{w^H w}. \]

2.1 Estimating (I+N)

Suppose that $A$ has more rows than columns, i.e., $L > M$. Let $\mathcal{R}(A)$ and $\mathcal{N}(A)$ denote the range space and null space of $A$, respectively, where $\mathcal{R}(A)$ and $\mathcal{N}(A)$ are defined with respect to the left eigenvectors. Also, let $Q = \dim(\mathcal{R}(A))$ and $P = \dim(\mathcal{N}(A))$. Then $Q + P = L$, $Q \leq M$ and $P \geq L - M$. Let $\{e_1, \ldots, e_P\}$ be the orthonormal basis for $\mathcal{N}(A)$ and $\{e_{P+1}, \ldots, e_L\}$ be the orthonormal basis for $\mathcal{R}(A)$. Since $\mathcal{N}(A) = \mathcal{R}(A)^\perp$, there exists a unique $x \in \mathcal{N}(A)$ and $z \in \mathcal{R}(A)$ such that $w = x + z$, where $x$ is the orthogonal projection of $w$ onto $\mathcal{N}(A)$. We can express $x$ as
\[ x = \sum_{i=1}^{P} e_i \langle e_i, w \rangle, \]
where $\langle \cdot, \cdot \rangle$ denotes the inner product and $(x, w) = x^H w$. From Bessel’s inequality
\[ \|x\|^2 = \sum_{i=1}^{P} |\langle e_i, w \rangle|^2 \leq \|w\|^2, \]
where $\|x\|^2 = (x, x) = x^H x$. Now consider
\[ E[x^H x] \equiv E[\|x\|^2] = \frac{1}{L} \sum_{i=1}^{P} |\langle e_i, w \rangle|^2 \]
\[ = \frac{1}{L} \sum_{i=1}^{P} E[|\langle e_i, w \rangle|^2]. \]

However,
\[ E[|\langle e_i, w \rangle|^2] = \left[ \sum_{j=1}^{L} |\langle e_{i,j}, w \rangle|^2 \right] \]
\[ = \left[ \sum_{j=1}^{L} \sum_{k=1}^{L} |\langle e_{i,k}, w_j \rangle|^2 \right]. \]

2.2 Estimating $S/(I+N)$

After obtaining an estimate for the interference plus noise power, $S/(I+N)$ can be estimated if the signal power can be separated from the interference plus noise power. The signal plus interference plus noise power is
\[ \sigma_3^2 + (I+N) = \frac{1}{L} E[y^H y] \]
\[ = \frac{1}{L} E[r^H A^H Af + w^H w] \]
\[ = \frac{1}{L} E[r^H A^H Af] + \sigma_2^2 + N, \]
where the second equality follows from the assumption that $w$ is zero-mean and uncorrelated with $A$ and $f$. The first term in (14) is the signal power, $\sigma_3^2$. Hence, an SIR estimator can easily be formed by
\[ \hat{\text{SIR}} = \left( \frac{\hat{\sigma}_3^2 + (I+N)}{\hat{\sigma}_2^2 + N} - 1 \right) = \frac{\hat{\sigma}_3^2}{\hat{\sigma}_2^2 + N}, \]
where $\hat{\sigma}_3^2 + (I+N)$ is obtained by replacing ensemble average in (14) with a time-average, i.e., $\hat{\sigma}_3^2 + (I+N) = \frac{1}{L} \overline{y^H y}$. When (15) is combined with (13), the SIR estimator becomes
\[ \hat{\text{SIR}} = \frac{1}{\frac{1}{L} \overline{y^H y} - 1}. \]

Finally, if (I+N) and (S+I+N) are estimated for $N$ different input vectors, then (16) has the more general form
\[ \hat{\text{SIR}} = \frac{\sum_{i=1}^{N} |\langle e_i, y_i \rangle|^2}{\sum_{i=1}^{N} \sum_{k=1}^{P_i} |\langle e_{i,k}, y_i \rangle|^2} - 1. \]
3. Computational Issues

As mentioned earlier a fast and accurate estimate of \((I+N)\) requires that \( \mathcal{N}(A) \) be as large as possible. Assume that \( \{c_1, \ldots, c_P\} \) is the basis for \( \mathcal{N}(A) \) found by Gaussian elimination. To obtain an orthonormal basis for \( \mathcal{N}(A) \), we need to orthonormalize \( \{c_1, \ldots, c_P\} \). This orthonormalization can be computationally intensive, because we try to choose \( P \) as large as possible to obtain a better estimate of \( \sigma_i^2 \). The number of floating point multiplications and additions required for this orthonormalization process is proportional to \( P^2 \).

Instead of projecting \( y \) onto \( \mathcal{N}(A) \), we can project it onto \( \mathcal{R}(A) \). We can uniquely write \( y = x + v \), where \( x \in \mathcal{N}(A) \) and \( v \in \mathcal{R}(A) \). Then, we have

\[
\|y\|^2 = \|x\|^2 + \|v\|^2
\]

by the Pythagorean Theorem. Also, observe that \( w = x + z \), where \( x \in \mathcal{N}(A) \) and \( z \in \mathcal{R}(A) \), since the projection of \( w \) and \( y \) onto \( \mathcal{N}(A) \) are the same. By using the projection of \( v \) onto \( \mathcal{N}(A) \) and (18), \( \|v\|^2 \) can be expressed as

\[
\|v\|^2 = \|y\|^2 - \sum_{i=p+1}^{L} |\langle e_i, y \rangle|^2.
\]

Hence, the SIR estimate can be obtained as

\[
\text{SIR} = \frac{\sum_{i=1}^{N} \|y_i\|^2}{\sum_{i=1}^{N} \frac{1}{2} \|x_i\|^2 - 1} = \frac{\sum_{i=1}^{N} \|y_i\|^2}{\sum_{i=1}^{N} \frac{1}{2} (\|y_i\|^2 - \|v_i\|^2)} - 1
\]

\[
= \frac{\sum_{i=1}^{N} \|y_i\|^2}{\sum_{i=1}^{N} \frac{1}{2} \|y_i\|^2 - \sum_{k=p+1}^{L} |\langle e_k, y \rangle|^2} - 1
\]

We do the above modifications because it is computationally easier to obtain an orthonormal basis for \( \mathcal{R}(A) \) than \( \mathcal{N}(A) \). Actually, the columns of \( A \) are readily available as a basis for \( \mathcal{R}(A) \). The columns of \( A \) have to be orthonormalized by using Gram-Schmidt process to obtain an orthonormal basis for \( \mathcal{R}(A) \). The computational complexity of this orthonormalization procedure is determined by the number of columns of \( A \), yielding \( M^2L \) multiplications and \( \frac{1}{2} M(M+1)L \) additions. Hence, a significant computational saving is realized by choosing \( P = \dim(\mathcal{N}(A)) \) as large as possible, i.e., we choose \( L \) as large as possible relative to \( M \).

4. Training Sequence Based Signal Quality Estimation

The analysis to this point has assumed that all received symbol sequences are known. In practice, only the training and colour code sequences are known in each TDMA burst. These known sequences will be used to construct the convolution matrix \( A \) described in the above analysis. We now determine the performance of the proposed S/(I+N) estimator, using only the training and colour code sequences in IS-54/136 and GSM-like systems. These sequences are used for BS and sector identification, symbol synchronization, sample timing, and channel estimation.

The next section compares the performance of the proposed SIR estimation algorithm with existing SIR estimation algorithms. The final form of the SIR estimator in (20) projects the received signal vectors are onto the signal subspace. Hence, the proposed algorithm is called Signal Projection (SP). In [7], the SIR estimation method proposed by Austin and Stüber [5] is called the Interference Projection (IP) method, and the SIR estimation method proposed in [7] is called the Subspace Based (SB) SIR estimator. These names will be used in the sequel.

4.1 Simulation Results

The performance of the (I+N) and S/(I+N) estimators, developed in the previous section, were tested through the software simulation for both an IS-54/136 system [8] and a GSM-like system. With IS-54/136, π/4-DQPSK modulation is used with a symbol rate of 24.3 ks/s. Each frame has 6 bursts of 162 symbols, as shown in Fig. 1, where each burst has a duration of 6.67 ms. Here we assume that a MS has correctly determined its serving BS (meaning that the colour code is known) and is operating in half-rate mode (meaning that it receives one burst per frame). Consequently, in each frame the 14-symbol training sequence and 6-symbol colour code sequences are known.

The GSM system uses Gaussian minimum shift keying (GMSK) with a raw bit rate of 270.8 kb/s. Each frame has 8 slots and each burst contains 148 symbols with a 26-symbol training sequence located in middle of the burst, for a burst duration of 0.577 ms as shown in Fig. 2. For simplicity we define a GSM-like system that replaces GMSK with BPSK, but otherwise has the same frame structure as GSM. Our simulations assume a two-equal-ray, baud-spaced, Rayleigh fading channel with uncorrelated taps for both the IS-54/136 and GSM-like systems. It is not important to use the same channel model for both systems, because our intention is not to make comparisons between systems. Rather, we wish to assess the relative performance of the SIR estimators when they are applied to each system.

1) IS-54/136 System: For the IS-54/136 system, two cases are examined; one uses the training sequences only and the other uses both the training and colour code sequences. From the training sequence, a 13x2 Toeplitz matrix is obtained. Additive white Gaussian noise at 20 dB below the interference power was also included. In all the simulations the true S/I is 5 dB, and the same experiment was run 500 times (with a different seed) with the results averaged to obtain a good approximation for mean SIR estimation error \( E[|S/I - \text{SIR}|] \).

Figs. 3 and 4 plot the mean absolute SIR estimation error against the averaging time for the SP, IP and, SB estimators for one and 6 co-channel interferers, respectively. Fig. 3 shows that IP performs poorly compared to SP and SB for all MS speeds. The SIR is very large initial SIR estimation errors in the order of 100 dB (not shown), but later converges and is almost as good as SP. The SIR can be estimated with SP to within an average error of 0.5 dB at 100 km/h and 1 dB at 5 km/h. Comparison of Figs. 3 and 4 shows that all the SIR estimators perform slightly better when the number of interferers increases. Although not shown, the performance of the SIR estimators were found to be insensitive to the true S/I.

One may think that the 6-symbol colour code could improve the performance of the estimation algorithm. SP estimation was performed with 6-symbol colour code in addition to the 14 symbol training sequence. The simulation results are shown in Fig. 5 which makes comparisons with the first case where the
colour code was not used. The colour code does not provide any significant improvement because, in this case, \( L = 5 \) and \( P = 3 \) which are not large enough to improve the SIR estimate.

2) GSM System: Figs. 6 and 7 show the mean absolute SIR estimation error against the averaging time for the SP and SB estimators. The SP estimator is seen to perform slightly better than SB estimator. As before, the SB estimator has very large mean error at the beginning (not shown), but begins to converge after four or five bursts. Figs. 6 and 7 show that the SIR can be estimated within an average error of 0.3 dB at 100 km/h after 300 ms and 1 dB at 5 km/h after one second.

4.1.1 Computational complexity of SP vs SB

Although the SP and SB estimators have similar performance, the real benefit of SP is its computational efficiency. As mentioned in Section III, SP requires \( M^2L \) multiplications and \( \frac{1}{2}M(M + 1)L \) additions for each estimate. On the other hand, SB requires the eigenvalues of an \( L \times L \) Hermitian matrix, \( L \) different values of a circularity test function, together with a search algorithm for a vector of length \( L \). Finding the eigenvalues of a matrix is computationally intensive. As described in [9], the QR algorithm is the most efficient and widely used method to calculate the eigenvalues of a matrix. Basically, the QR algorithm is an iterative procedure where the covariance matrix, \( B \), is factored as \( B = QR \) with \( R \) upper triangular and \( Q \) orthogonal. The iteration continues with \( B_m = Q_m R_m \) and \( B_{m+1} = R_m Q_m \), where \( B_1 = B \). The sequence \( \{B_m\} \) will converge to a triangular matrix with the eigenvalues of \( B \) on its diagonal. Each iteration of the QR algorithm requires \( O(L) \) multiplications and additions for a tridiagonal matrix. A symmetric matrix can be transformed to a Hessenberg (tridiagonal in this case) matrix with a cost of \( O(L^3) \) multiplications and additions.

The number of iterations required in the QR algorithm depends on the eigenvalues of the matrix. The convergence properties of the QR method are discussed in [9]. The following theorem is taken from [9].

**Theorem 1** Let \( B \) be a real matrix of order \( n \), and let its eigenvalues \( \{\lambda_i\} \) satisfy

\[
|\lambda_1| > |\lambda_2| \cdots > |\lambda_n| > 0.
\]

Then iterates \( B_m \) of the QR method will converge to an upper triangular matrix \( D \), which contains the eigenvalues \( \{\lambda_i\} \) in the diagonal positions. If \( B \) is symmetric, the sequence \( \{B_m\} \) converges to a diagonal matrix. For the speed of convergence,

\[
\|D - B_m\| \leq c \max_i \left| \frac{\lambda_{i+1}}{\lambda_i} \right|,
\]

The covariance matrix used in SB algorithm (theoretically) has the following eigenvalues

\[
\lambda_i = \begin{cases} 
\sigma_i^2 + \sigma_{i+N}^2 & \text{if } i = 1, \ldots, M \\
\sigma_{i+N}^2 & \text{otherwise}
\end{cases}
\]

as described in [7]. In the simulations \( M = 2 \) and \( Q \leq M \), and \( L = 13 \). Hence, \( \max_i |\lambda_{i+1}/\lambda_i| = 1 \), which implies that the algorithm convergences very slowly. Actually, the number max \( |\lambda_{i+1}/\lambda_i| \) is not 1, but close to 1, in the simulations. In our simulation of SB algorithm, the number of floating point operations (flops\(^1\)) was calculated for the eigenvalue computation of each covariance matrix without balancing. The average number of flops is obtained afterwards, which is 106000 flops. This is considerably large number compared to \( M^2L = 52 \) flops needed for the SP method.

5. Concluding Remarks

A computationally simple and fast estimation technique was developed to estimate \( S/(I+N) \) in TDMA wireless systems that employ known sequences of training symbols. The performance of the new estimator was evaluated for various situations through software simulations. The proposed estimation technique outperforms all other known techniques in the literature with respect to both accuracy and computational complexity.

**References**


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\(^1\)One flop is one floating point multiplication and one floating point addition.
Figure 1: IS-54 frame structure showing the relative locations of the training and colour code sequences (not to scale).

<table>
<thead>
<tr>
<th>IS-54 frame (6 time slots)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
</tr>
<tr>
<td>14 symbols</td>
</tr>
<tr>
<td>Training Sequence</td>
</tr>
<tr>
<td>2.75 ms</td>
</tr>
</tbody>
</table>

Figure 2: GSM frame structure showing the relative location of the training sequence (not to scale).

<table>
<thead>
<tr>
<th>GSM frame (8 time slots, 4.615ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
</tr>
<tr>
<td>61 symbols</td>
</tr>
<tr>
<td>Synchronization word</td>
</tr>
<tr>
<td>0.577 ms GSM time slot</td>
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Figure 3: Mean SIR estimation error against the averaging time; \( N_f = 1 \) and S/I=5 dB.

Figure 4: Mean SIR estimation error against the averaging time; \( N_f = 6 \) and S/I=5 dB.

Figure 5: Mean SIR estimation error against the averaging time; \( N_f = 6 \) and S/I=5 dB.

Figure 6: Mean SIR estimation error against the averaging time; \( N_f = 1 \) and S/I=5 dB.

Figure 7: Mean SIR estimation error against the averaging time; \( N_f = 6 \) and S/I=5 dB.
An Efficient Algorithm for Estimating the
Signal-to-Interference Ratio in TDMA Cellular
Systems†

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Abstract

A new algorithm is proposed for estimating the signal-to-interference ratio (SIR) in TDMA cellular systems. The SIR estimator is evaluated for use in the IS-54/136 system and a GSM-like system, and compared with existing SIR estimation algorithms. The algorithm is shown to offer comparable performance to the best known SIR estimation schemes in terms of the mean square prediction error, but with a significantly reduced computational complexity.

Keywords: SIR estimation, signal projection

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I Introduction

Signal-to-interference plus noise ratio, $S/(I+N)$, is a key parameter for contemporary cellular radio resource management algorithms for handoffs [1], channel assignment [2, 3], and power control [4]. Many of these algorithms assume that fast and accurate measurements of $S/(I+N)$ are available at the base stations (BSs), mobile stations (MSs), or both. Several methods have recently been developed generate accurate, real time, estimates of $S/(I+N)$ in TDMA cellular systems. One method by Austin and Stüber [5] uses the training and/or color code sequences that are typically present within cellular TDMA slots to obtain an unbiased estimate of $S/(I+N)$. The signal-to-variance (SVR) power estimator in [6] is another method that uses the autocorrelation sequence of the received signal samples over a short time scale. The application of SVR method to a DECT system reveals that the estimator has a large bias for interesting values of $S/I$. Still another method for TDMA cellular systems estimates $S/I$ by using the eigenvalues of the covariance matrix of the received signal sequence [7].

This paper develops a fast and efficient $S/(I+N)$ estimation technique for TDMA cellular systems. The method has a computational complexity that is comparable to the method in [5] and a average absolute $S/(I+N)$ prediction error that is comparable to the method in [7]. Section II presents the system and channel model, and the proposed $S/(I+N)$ estimation technique. Computational issues are discussed in Section III. Section IV summarizes the simulation performance results, followed by concluding remarks in Section V.

II Discrete-Time Channel Model

Following [5], the overall discrete-time channel consisting of the transmit filter, channel, matched filter, and baud-rate sampler and can be modeled as an $M$-tap, $T$-spaced, transversal filter, where $T$ is the baud duration. The overall channel taps are described
by the vector $\mathbf{f} = [f_1, \ldots, f_M]^T$. The $n$th received sample at the matched filter output is $y_n = \sum_{k=1}^{M} a_{n-k} f_k + w_n$, where $\{a_n\}$ is the transmitted symbol sequence and the $\{w_n\}$ are samples of the received interference plus noise. Let $\mathbf{y} = [y_1, \ldots, y_L]^T$ be a length $L$ vector of received samples. Then, $\mathbf{y} = \mathbf{A}\mathbf{f} + \mathbf{w}$, where $\mathbf{A}$ is an $L \times M$ Toeplitz convolution matrix consisting of the transmitted symbols and $\mathbf{w} = [w_1, \ldots, w_L]^T$ is the vector of received interference plus noise samples. If $\alpha = [\alpha_1 \ldots \alpha_{L+M-1}]$ is the length-$(L+M-1)$ training sequence that is embedded in each TDMA time slot, then $\mathbf{A}$ has the form

$$
\mathbf{A} = \begin{bmatrix}
\alpha_M & \alpha_{M-1} & \cdots & \alpha_1 \\
\alpha_{M+1} & \alpha_M & \cdots & \alpha_2 \\
\vdots & \vdots & \ddots & \vdots \\
\alpha_{M+L-1} & \alpha_{M+L-2} & \cdots & \alpha_L
\end{bmatrix}.
$$

Note that it is not necessary that $\mathbf{A}$ be formed from known training symbols. The matrix $\mathbf{A}$ could also be formed by using decisions on the transmitted symbols [5]. Assuming $N_I$ interfering co-channel signals, $\mathbf{w} = \sum_{k=1}^{N_I} A_k f_k + \mathbf{n}$, where $\mathbf{n}$ is a zero-mean, discrete-time, white Gaussian process. Since the BSs are unsynchronized in TDMA cellular systems such as IS-54/136, PDC, and GSM, the received signal sample sequences from the co-channel signals can are uncorrelated and mutually uncorrelated, implying that $\mathbf{w}$ and $\mathbf{A}$ are mutually uncorrelated. Furthermore, it is reasonable to assume that the channel taps, $\mathbf{f}$, are uncorrelated with both the symbol sequence $\{a_k\}$ and the interference plus noise vector $\mathbf{w}$. Assuming a zero-mean signal constellation, $\mathbf{y}$ and $\mathbf{w}$ are zero-mean uncorrelated random processes, i.e., $E[y_j y_k^*] = 0$ and $E[w_j w_k^*] = 0$ for $j \neq k$.

II-A Estimating (I+N)

Suppose that $\mathbf{A}$ has more rows than columns, i.e., $L > M$. Let $\mathcal{R}(\mathbf{A}^T)$ and $\mathcal{N}(\mathbf{A}^T)$ denote the left range space and left null space of $\mathbf{A}$, respectively. Also, let $Q = \dim(\mathcal{R}(\mathbf{A}^T))$ and $P = \dim(\mathcal{N}(\mathbf{A}^T))$. Then $Q + P = L$, $Q \leq M$ and $P \geq L - M$. 

3
Let \( \{e_1, \ldots, e_P\} \) be the orthonormal basis for \( \mathcal{N}(A^T) \) and \( \{e_{P+1}, \ldots, e_L\} \) be the orthonormal basis for \( \mathcal{R}(A^T) \). Since \( \mathcal{N}(A^T) = \mathcal{R}(A^T)^\perp \), there exists a unique \( x \in \mathcal{N}(A^T) \) and \( z \in \mathcal{R}(A^T) \) such that \( w = x + z \), where \( x \) is the orthogonal projection of \( w \) onto \( \mathcal{N}(A^T) \). We can express \( x \) as

\[
x = \sum_{i=1}^{P} e_i \langle e_i, w \rangle
\]  

(2)

where \( \langle \cdot, \cdot \rangle \) denotes the inner product and \( \langle x, w \rangle = x^H w \). From Bessel's inequality

\[
\|x\|^2 = \sum_{i=1}^{P} |\langle e_i, w \rangle|^2 \leq \|w\|^2
\]  

(3)

where \( \|x\|^2 = \langle x, x \rangle = x^H x \). Now consider

\[
E[\|x\|^2] = E[\sum_{i=1}^{P} |\langle e_i, w \rangle|^2] = \sum_{i=1}^{P} E[|\langle e_i, w \rangle|^2] .
\]  

(4)

However,

\[
E[|\langle e_i, w \rangle|^2] = E[\sum_{j=1}^{L} e_{i,j}^* w_j \sum_{k=1}^{L} e_{i,k}^* w_k^*] 
= \sum_{j=1}^{L} \sum_{k=1}^{L} e_{i,j}^* e_{i,k}^* E[w_j w_k^*] 
= \sum_{j=1}^{L} |e_{i,j}|^2 \sigma_{j+N}^2 = \sigma_{i+N}^2
\]  

(5)

where the second last equality follows from the assumption that \( E[w_j w_k^*] = 0 \) for \( j \neq k \). We have \( \sigma_{i+N}^2 = \frac{1}{P} E[x^H x] \) by combining (4) and (5). Replacing the ensemble average with a time-average in this expression yields the unbiased estimate

\[
\hat{\sigma}_{i+N}^2 = \frac{1}{P} x^H x = \frac{1}{P} \sum_{i=1}^{P} |\langle e_i, w \rangle|^2
\]  

(6)

which effectively forms the time-average of \( P \) samples of \( w \). Since \( e_i \in \mathcal{N}(A^T) \), \( i = 1, \ldots, P \)

\[
\langle e_i, y \rangle = \langle e_i, Af + w \rangle = e_i^H Af + e_i^H w = e_i^H w = \langle e_i, w \rangle,
\]  

(7)

Thus, (6) becomes

\[
\hat{\sigma}_{i+N} = \frac{1}{P} \sum_{i=1}^{P} |\langle e_i, y \rangle|^2
\]  

(8)
In [5], the estimate $\hat{\sigma}^2_{I+N}$ is generated by projecting the received signal vector onto a single vector, say $c$, in $\mathcal{N}(A^T)$; however, our new approach projects the received signal vector onto the entire subspace $\mathcal{N}(A^T)$, yielding a much faster estimate.

An alternative form of the (I+N) estimator that may have some computational advantages (discussed in Sect. III) is obtained by projecting $y$ onto $\mathcal{R}(A^T)$ instead of $\mathcal{N}(A^T)$. We can uniquely write $y = x + v$, where $x \in \mathcal{N}(A^T)$ and $v \in \mathcal{R}(A^T)$. Then,

$$||y||^2 = ||x||^2 + ||v||^2$$  \hspace{1cm} (9)

by the Pythagorean Theorem. Also, $w = x + z$, where $x \in \mathcal{N}(A^T)$ and $z \in \mathcal{R}(A^T)$, since the projection of $w$ and $y$ onto $\mathcal{N}(A^T)$ are the same. By using the projection of $v$ onto $\mathcal{N}(A^T)$ and (9), $||x||^2$ can be expressed as

$$||x||^2 = ||y||^2 - \sum_{i=P+1}^{L} |\langle e_i, y \rangle|^2.$$  \hspace{1cm} (10)

Hence, the SIR estimate can be obtained as

$$\text{SIR} = \frac{\sum_{i=1}^{N} ||y_i||^2}{\sum_{i=1}^{N} \frac{1}{L} ||x_i||^2} - 1 = \frac{\sum_{i=1}^{N} ||y_i||^2}{\sum_{i=1}^{N} \frac{1}{L} (||y_i||^2 - ||v_i||^2)} - 1 = \frac{\sum_{i=1}^{N} ||y_i||^2}{\sum_{i=1}^{N} \frac{L}{L-Q} (||y_i||^2 - \sum_{k=P+1}^{L} |\langle e_k, y_i \rangle|^2)} - 1.$$  \hspace{1cm} (11)

Since the SIR estimator in (11) projects the received signal vectors onto the signal subspace, the proposed algorithm is called Signal Projection (SP).

II-B Estimating $S/(I+N)$

After obtaining an estimate of (I+N), $S/(I+N)$ can be estimated if the signal power can be separated from the interference plus noise power. The signal plus interference plus noise power is

$$\sigma^2_{S+I+N} = \frac{1}{L} E[y^H y] = \frac{1}{L} E[f^H A^H Af + w^H w] = \frac{1}{L} E[f^H A^H Af] + \sigma^2_{I+N},$$  \hspace{1cm} (12)
where the second equality follows from the assumption that \( w \) is zero-mean and uncorrelated with \( A \) and \( f \). The first term in (12) is the signal power, \( \sigma_s^2 \). Hence, an SIR estimator can easily be formed as

\[
\text{SIR} = \left( \frac{\hat{\sigma}_S^2 + \mathbb{E}\{\mathbf{y}^H \mathbf{y}\}}{\hat{\sigma}_I^2 + \mathbb{E}\{\mathbf{y}^H \mathbf{y}\}} - 1 \right) = \frac{\hat{\sigma}_S^2}{\hat{\sigma}_I^2 + \mathbb{E}\{\mathbf{y}^H \mathbf{y}\}},
\]

(13)

where \( \hat{\sigma}_S^2 + \mathbb{E}\{\mathbf{y}^H \mathbf{y}\} \) is obtained by replacing ensemble average in (12) with a time-average, i.e., \( \hat{\sigma}_S^2 + \mathbb{E}\{\mathbf{y}^H \mathbf{y}\} = \frac{1}{L} \mathbf{y}^H \mathbf{y} \). When (13) is combined with (8), the SIR estimator becomes

\[
\text{SIR} = \frac{\frac{1}{L} \mathbf{y}^H \mathbf{y}}{\frac{1}{L} \sum_{i=1}^{P} \mathbb{E}\{\mathbf{y}^H \mathbf{y}\}^2} - 1.
\]

(14)

If \((I+N)\) and \((S+I+N)\) are estimated for \(N\) different training bursts, then (14) has the more general form

\[
\text{SIR} = \frac{\sum_{i=1}^{N} \frac{1}{L} \mathbf{y}^H \mathbf{y}_i}{\sum_{i=1}^{N} \frac{1}{L} \sum_{k=1}^{P} \mathbb{E}\{\mathbf{y}^H \mathbf{y}\}} - 1.
\]

(15)

Finally, we note that the number of \( T \)-spaced channel taps, \( M \), is needed in the \( S/(I+N) \) estimator when forming the matrix \( A \). However, to mitigate the effects of ISI, a typical radio receiver employs an equalizer that is designed for some particular value of \( M \); sometimes the channel will be underequalized or overequalized. This same value of \( M \) could be used to form the \( A \) matrix. Such an approach has the practical benefit of tuning the \( S/(I+N) \) estimate to what the radio receiver, i.e., the equalizer, actually sees.

### III Computational Issues

The estimate \( \hat{\sigma}_I^2 + \mathbb{E}\{\mathbf{y}^H \mathbf{y}\} \) in (15) improves with increasing \( P \). Assume that \( \{c_1, \ldots, c_P\} \) is the basis for \( \mathcal{N}(A^T) \) found by Gaussian elimination. An orthonormal basis for \( \mathcal{N}(A^T) \) can be obtained by orthonormalizing \( \{c_1, \ldots, c_P\} \). The number of flops\(^2\) required to

\(^1P \) is ultimately limited by the length of the training sequence, \( L + M - 1 \).

\(^2\)One flop is one floating point multiplication and one floating point addition.
do so is proportional to $P^2$, where $P \geq L - M$. For situations where the matrix $A$ is derived from a training sequence, the orthonormalization only needs to be done once and, in fact, the basis vectors $\{e_1, \ldots, e_P\}$ can be precomputed and stored at the receiver. However, for situations where the matrix $A$ is generated from decisions on random symbols, the $S/(I+N)$ estimate in (11) may be preferred over the one in (15), because fewer computations are required to obtain an orthonormal basis for $\mathcal{R}(A^T)$ than $\mathcal{N}(A^T)$. In fact, the columns of $A$ are readily available as a basis for $\mathcal{R}(A^T)$. They just need to be orthonormalized by using the Gram-Schmidt process. The computational complexity of this orthonormalization procedure is determined by the number of columns of $A$, yielding $M^2L$ multiplications and $\frac{1}{2}M(M+1)L$ additions. Hence, a significant computational saving is realized for large $P$, i.e., when $L$ is chosen as large as possible relative to $M$.

Section IV will show that the Subspace Based (SB) SIR estimator in [7] and the SP estimator have comparable performance. However, the real benefit of SP is its computational efficiency. For a given matrix $A$, SP requires $M^2L$ multiplications and $\frac{1}{2}M(M+1)L$ additions obtain the orthonormal basis for $\mathcal{R}(A^T)$. On the other hand, for each $S/(I+N)$ estimate SB requires the eigenvalues of an $L \times L$ Hermitian covariance matrix $B$, $L$ different values of a sphericity test function, together with a search algorithm for a vector of length $L$. Finding the eigenvalues of a matrix is computationally intensive. As described in [9], the $QR$ algorithm is the most efficient and widely used method to calculate the eigenvalues of a matrix. Basically, the $QR$ algorithm is an iterative procedure where the matrix $B$ is factored as $B = QR$ with $R$ upper triangular and $Q$ orthogonal. Each iteration of the $QR$ algorithm requires $O(L^3)$ multiplications and additions. This cost can be reduced to $O(L^2)$, if $B$ is transformed to a Hessenberg matrix at a cost of $O(L^3)$ multiplications and additions. For a tridiagonal matrix, $QR$ algorithm requires $O(L)$ multiplications and additions in each iteration. For systems that use real data symbols, it is possible to transform $B$ to
a tridiagonal form by transforming it to a Hessenberg matrix, since \( B \) is symmetric\(^3\).

The number of iterations of the \( QR \) method depends on the eigenvalues of the matrix \( B \). If the eigenvalues, \( \{\lambda_i\} \), are listed in order of descending magnitude, i.e., \(|\lambda_1| > |\lambda_2| \cdots > |\lambda_L| > 0\), then convergence is rapid only if the quantity \( \max_i |\lambda_{i+1}/\lambda_i| \) is small [9]. The covariance matrix used in SB algorithm has the following theoretical values for the eigenvalues

\[
\lambda_i = \begin{cases} 
\sigma^2_{S_i} + \sigma^2_{I+N} & \text{if } i = 1, \ldots, Q \\
\sigma^2_{I+N} & \text{otherwise}
\end{cases}
\]  

(16)

as described in [7]. In a typical application \( M = 2 \) and \( Q \leq M \), and \( L = 13 \). Hence, \( \max_i |\lambda_{i+1}/\lambda_i| = 1 \), implying a slow convergence rate\(^4\). For these parameters our simulations showed that an average of 106000 flops was required to obtain the eigenvalues for each sample covariance matrix.

IV Training Sequence Based Signal Quality Estimation

The performance of our new (I+N) and \( S/(I+N) \) estimators were evaluated by software simulation for both an IS-54/136 system [8] and a GSM-like system. The IS-54/136 system uses \( \pi/4 \)-DQPSK modulation with a symbol rate of 24.3 ks/s. Each frame has 6, 6.67 ms, slots of 162 symbols. For IS-54/136, we assume that a MS has correctly determined its serving BS (meaning that the colour code is known) and is operating in full-rate mode (meaning that it receives two bursts per frame). Consequently, in each burst the 14-symbol training sequence and 6-symbol colour code sequences are known. The GSM system uses Gaussian minimum shift keying (GMSK) with a raw bit rate of 270.8 kb/s. Each frame has 8, 0.577 ms, slots each

\[^3\]Hessenberg form of a symmetric matrix is tridiagonal
\[^4\]Since a sample covariance matrix is used rather than the true covariance matrix, \( \max_i |\lambda_{i+1}/\lambda_i| \) is not 1 but close to 1.
containing 148 symbols with a 26-symbol training sequence. For simplicity, we actually uses GSM-like system that replaces GMSK with BPSK, but is otherwise the same as GSM.

Our simulations assume a two-equal-ray, baud-spaced, Rayleigh fading channel with uncorrelated taps for both the IS-54/136 and GSM-like systems. It is not important to use the same channel model for both systems, because our intention is not to make comparisons between systems but to compare the relative performance of the different SIR estimators when they are applied to each system. Additive white Gaussian noise at 20 dB below the interference power was also included. In all simulations the true S/I is 5 dB and there are six equal power co-channel interferers.

1) IS-54/136 System: Two cases are examined; one uses the training sequence only and the other uses both the training and colour code sequences. Fig. 1 plots the mean absolute SIR estimation error E[|S/I − SIR|] against the averaging time for the SP, IP and, SB estimators. The IP estimator is seen to perform poorly compared to the SP and SB estimators for all MS speeds. The SB estimator has a large initial error, but converges and offers comparable performance to the SP estimator. After one second, the SP can estimate the SIR to within an average error of 0.5 dB at 100 km/h and 1 dB at 5 km/h. Although not shown, the performance of the SIR estimators are insensitive to the true S/I. Fig. 2 shows the error variance of the estimator. Finally, Fig. 3 shows the results when the SP estimator uses both the 14-symbol training sequence and the 6-symbol colour code sequence. Use of the colour code sequence does not provide any significant improvement because, in this case, L = 5 and P = 3 which are not large enough to improve the SIR estimate.

2) GSM-like System: Fig. 4 shows the mean absolute SIR estimation error against the averaging time for the SP and SB estimators. Once again, the SP and SB estimators have comparable performance, while the SB estimator has a large initial error. After one second, the SIR can be estimated to within an average error of about 0.3 dB
V Concluding Remarks

A computationally simple and fast signal projection $S/(I+N)$ estimation technique was developed and applied to TDMA cellular systems. The new estimation technique was shown offer comparable performance to the best known $S/(I+N)$ estimation techniques in the literature, but with a significantly reduced computational complexity.

References


Figure 1: Mean SIR estimation error against the averaging time for the IS-54/136 system.
Figure 2: Error variance against the averaging time for the IS-54/136 system.
Figure 3: Mean SIR estimation error against the averaging time for the IS-54/136 system.
Figure 4: Mean SIR error against the averaging time for a GSM-like system.
Figure 5: Error variance against the averaging time for a GSM-like system.
MODELING MOBILITY IN POWER CONTROL

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Abstract

One of the elements missing in most literature related to power control is mobility. Without it, the performance of a power control scheme and its convergence cannot be reliably predicted. In the paper we use random walk to model mobility. Combining the mobility model with a conventional CCI analysis, we study linear power control in a more dynamic environment.

1. Introduction

Power control schemes generally fall into two categories, depending on the goal. The first group aims at a better signal to interference ratio (SIR). These schemes usually take all interfering parties into consideration in order to determine the power level of each. Although they can be implemented in either a centralized [1,2] or a distributed fashion [3-5] their complexity is quite high. So far few of this kind have been implemented in real systems. The second group [6-7] aims mainly at reducing the power consumption of a mobile unit and extending the battery life between recharges. These schemes use only the received signal power (at a mobile unit or base station) to determine the transmitting power. Because of their low complexity, most power control schemes implemented in the field belong to this type.

To design and evaluate the performance of a power control scheme, an accurate analytical model is required. But the models encountered in the literature so far lack one key element of a mobile system: mobility. Which is the focus of the paper. For simplicity and practicality, we will focus on the second group of power control schemes; the main goal of which is to extend the battery life. If done correctly, however, they can also reduce the SIR [6,7]. In this paper we intend to explore

1. the effect of mobility on power control,
2. the effect of number of interferers,
3. the effect of the slope of a linear power control scheme,
4. the inter-relationship between minimizing SIR and minimizing power consumption.

2. Channel Model and Mobility Model

2.1 Channel Model

A three-stage channel model has been widely used which has the following elements: (i) path loss, (ii) shadowing, and (iii) amplitude fading. We explain how this model should be formulated for our later study.

Path Loss is a large-scale attenuation. It varies with the distance between transmitter and receiver. A two-slope path loss model has been proposed in which the received area mean power of a mobile unit, \( \gamma_d \), is given below. (The subscript "d" stands for the "desired" signal, i.e. the signal of the mobile unit. The subscript "i" used later represents the "interfering" signal.)

\[
\gamma_d = \frac{t_r C}{(r_0)^a (1+r_d(g))^b} \tag{1}
\]

where \( t_r \) is the transmitted power, \( C \) is a constant including the effect of antenna gain, \( r_0 \) is the distance between the transmitter and receiver, \( g \) is the turning point, \( a \) is the basic attenuation coefficient, and \( b \) is the additional attenuation coefficient.

Shadowing The slowly varying local mean power, \( \Omega_d \), used to characterize the effect is usually assumed to have a log-normal probability density function (pdf). That is

\[
f_{\Omega_d}(\Omega_d) = \frac{1}{\sqrt{2\pi} \sigma_d \Omega_d} \exp\left[\frac{-(\ln \Omega_d - \ln \gamma_d)^2}{2\sigma_d^2}\right] \tag{2}
\]

where \( \sigma_d \) is the shadowing and \( \gamma_d \) is the area mean power determined by Eq. (1).

Fading Given the local mean power, \( \Omega_d \), two models—Rician fading and Rayleigh fading—are traditionally used to model instantaneous signal power \( \Omega_d \). Let \( x_d \) be the instantaneous signal amplitude, then \( \Omega_d = (x_d)^2/2 \). For Rician fading, the pdf of the instantaneous signal amplitude \( x_d \) is given as

\[
f_{x_d}(x_d|\Omega_d, A_d) = \frac{x_d}{\Omega_d} \exp\left[-\frac{(x_d^2+A_d^2)}{2\Omega_d}\right] I_0\left(\frac{A_d x_d}{\Omega_d}\right) \tag{3}
\]

where \( I_0 \) is the zeroth order modified Bessel function of the first kind, \( A_d \) is the line of sight (LOS) component, \( K_d \), the Rice factor, is equal to \( (A_d)^2/2\Omega_d \), and \( \Omega_d \) is the average scattering power and can be computed from \( \Omega_d = \Omega_d/(K_d + 1) \). From Eq. (3) we can find the pdf of \( \Omega_d \) as

\[
f_{\Omega_d}(\Omega_d|\Omega_d) = \frac{x_d}{\Omega_d} \exp\left[-\frac{(K_d x_d^2)}{2\Omega_d}\right] I_0\left(\frac{4K_d x_d^2}{\Omega_d}\right) \tag{4}
\]
In the case of no LOS, i.e. $K_e=0$, the pdf of $p_s$ turns into

$$f_{p_s}(p_s | p_{od}) = \frac{1}{p_{od}} \exp\left(\frac{-p_s}{p_{od}}\right)$$

This is usually called the Rayleigh fading environment.

The above three-stage model applies for both the power of the mobile unit and its interferers.

**Co-channel Interference**

Let $p_i$, $1 \leq i \leq n$, be the instantaneous power of the $n$ interferers, and $p_s$ the sum of the random variables of $p_i$, i.e. $p_s = \sum_{i=1}^{n} p_i$. The co-channel interference (CCI) probability, denoted by $F(CI)$, is defined as the probability that $(p_s / p_s^0)$ is smaller than a threshold $\eta$.

That is,

$$F(CI) = \Pr\{p_s / p_s^0 \leq \eta\}$$

Let $p_{od}, p_{od}^0, 1 \leq i \leq n$, be the local mean power (see Eq. 1) of the mobile unit and the $i$ interferers. Given $p_{od}, p_{od}^0$ of a Rician fading channel, we have derived [8] the exact formula for the following conditional probability $F(CI | p_{od}$ and $p_{od}^0, 1 \leq i \leq n)$ as

$$F(CI | p_{od}, p_{od}^0, 1 \leq i \leq n) = \sum_{i=1}^{n} \Psi_i \left(\frac{R_{i} + p_{od}^0}{R_{i} + p_{od}}\right)^{p_{od} - 1} \exp\left[\frac{-R_{i} / p_{od}^0}{R_{i} / p_{od}}\right]$$

where

$$\Psi_i = \frac{p_{od}^n}{p_{od}^0}$$

For a Rayleigh fading channel, the CCI probability in Equation 7 then becomes

$$F(CI | p_{od}, p_{od}^0, 1 \leq i \leq n) = \sum_{i=1}^{n} \left(\frac{p_{od}^n}{p_{od}^0}\right) \left(\frac{\eta / p_{od}^0}{\eta / p_{od}}\right)$$

We can find the final $F(CI)$ by averaging the conditional probability in Eq. 7 and 9 over $p_{od} p_{od}^0, \ldots, p_{od}^0$. That is

$$F(CI) = \int_0^\infty \ldots \int_0^\infty F(CI | p_{od}, p_{od}^0, 1 \leq i \leq n) \, dp_{od} \, dp_{od}^0 (p_{od})$$

With power control Eq. 10 must be modified slightly.

This is discussed in section 3.

**2.2 Mobility Model**

An important detail missing in conventional analyses on power control is the mobility of a mobile unit, which makes the distance between the base and the mobile unit a random variable. In the following we develop a Markov process to model mobility. A mobile unit moves constantly. In our model, we describe that movement as a random walk. Random walk has been used in several places for modeling mobility [11-12].

Although the random-walk model is inherently two dimensional, it can be approximated with a one-dimensional model for our problem. This reduction, as will be seen, greatly reduces the complexity.

Without compromising the accuracy too much, we can replace a hexagonal topology with a circle and use a polar coordinate system $(r, \theta)$. We then divide the circular cell into $N$ shells along the $r$ direction (Figure 1). Because moving along the $\theta$ direction does not change the distance, its effect would be the same as staying in the same region. Thus the $\theta$ direction can be combined with staying in the same place and gets eliminated in the model. After the elimination, the model is similar to a one-dimensional random walk. In the following we are going to use one-dimensional random walk to study the effect of mobility on power control.

Suppose every $\tau$ seconds, a mobile unit or the base station will measure the received power. The same interval $\tau$ will be used as the epoch time of the Markov model. With probability $\lambda$, the mobile unit will move one step radically, and with probability $1-\lambda$ it will stay in the same region (Figure 1.b). A large $\lambda$ implies, of course, high mobility. But if $\tau$ is large, it is also very likely that the mobile unit will change its position. Thus $\lambda$ is determined by both mobility and the frequency of power measurement.

We assume the mobile unit moves with the same probability outwards and inwards. On the boundary, the mobile unit can move into an adjacent cell at the next time interval. But as far as distance from the base station is concerned, it is the same as moving one step back. Thus we can assume that the mobile never leaves the cell and that when it reaches the boundary, it will stay in the same region with probability $1-\lambda$ or moves one step back with probability $\lambda$. We also assume the same for the innermost position.

**3. Modeling Power Control**

The received signal contains two elements: desired signal ($S$) and interference ($I$). Many algorithms have been designed to separate the two [9,10]. In the analysis we assume power is adjusted according to the $S$.
power measurements. That is, \( S \) and \( I \) can be separated. Since \( I \) is usually much smaller than \( S \), the results can also be viewed as a good approximation for the case using \((S+I)\) measurements.

The type of power control studied in the paper is linear (log-scale) power control. In such a scheme, if the received power deviates from the target value by \( \Delta \) dB then the transmitting power will be adjusted by \(-m\Delta\) dB where \( m \) is a constant. The value of \( m \) affects the performance of the power control scheme. A direct implementation of a linear scheme requires a continuous transmitting power. In practice, the transmitting power is quantized into a fixed number of levels.

We study two kinds of implementations. The first implementation, called incremental, will do the adjustment one notch at a time, depending on the value of \(-m\Delta\). The second scheme, called direct compensation, adjusts the transmitting power by the full amount \(-m\Delta\) in one step. This demands a continuous transmitting power. But in practice, it is quantized into the closest level.

### 3.1 Incremental Schemes

Let \( D_d \) be the distance of the mobile unit (desired signal) from the center of the cell. As discussed in the previous section we divide the cell radius \( R \) into \( N \) shells. Thus the value of \( D_d \) will be \( \frac{R}{N} \), \( 1 \leq R \leq N \).

The larger the \( N \), the higher the complexity of the model, but the more accurate the results. Similarly the transmitting power \( t_p \) ranging from \( t_{\text{min}} \) to \( t_{\text{max}} \) is evenly divided into \( L \) levels in the log scale. The size of every step is denoted by \( \delta \). We will discuss how to set the values of \( t_{\text{min}} \) and \( t_{\text{max}} \) in section 4. The power control system can be described by a discrete-time Markov process with state \((D_d, t)\), where the epochs of the Markov process are the times when measurements are done.

The received power, on the other hand, determines the transition probabilities between states. Suppose the current state of the system is \((D_d, t)\). Let \( \alpha(D_d, t) \) be the conditional probability that the received power exceeds \( \zeta^+ \), where \( \zeta^+ = \text{Target RSS} \) (Received Signal Strength) + \( \delta / m \). How we set the target RSS will be discussed in section 4. Then \( \alpha(D_d, t) \) is the conditional probability that given in state \((D_d, t)\) the received signal's positive deviation exceeds \( \delta \) and the transmitting power should be reduced by one notch. Similarly we define \( \alpha(D_d, t) \) as the conditional probability that the received power is below \( \zeta^- \), where \( \zeta^- = \text{Target RSS} - \delta / m \). And \( \alpha(D_d, t) \) represents the conditional probability that the received power's negative deviation exceeds \( \delta \) and the transmitting power will be reduced by one notch. Finally \( \alpha(D_d, t) \) represents the probability that no adjustment is needed. From Eq. 1 and 2, we can compute \( \alpha(D_d, t) \), \( \alpha(D_d, t) \), \( \alpha(D_d, t) \), \( \alpha(D_d, t) \) as

\[
\alpha(D_d, t) = \int_{0}^{\infty} \frac{1}{2\pi \sigma_d \Omega_d} \exp\left(\frac{-\ln \Omega_d - \ln \gamma_d}{2\sigma_d^2}\right) d\Omega_d \]

(11)

\[
\alpha(D_d, t) = \int_{0}^{\infty} \frac{1}{2\pi \sigma_d \Omega_d} \exp\left(\frac{-\ln \Omega_d - \ln \gamma_d}{2\sigma_d^2}\right) d\Omega_d
\]

where \( \gamma_d = \frac{t_p C}{(D_d)^m (1 + D_d / g)^b} \). The reason the received signal has a log-normal distribution is due to the fact that the measured power is an average of many samples. The nine neighboring states (Figure 2) and their transition probabilities are given below.

\[
\begin{align*}
\text{Prob} \{(D_d, t) \rightarrow (D_d - 1, t - \delta)\} &= \frac{1}{2} \times \alpha(D_d, t) \\
\text{Prob} \{(D_d, t) \rightarrow (D_d - 1, t)\} &= \frac{1}{2} \times \alpha(D_d, t) \\
\text{Prob} \{(D_d, t) \rightarrow (D_d - 1, t + \delta)\} &= \frac{1}{2} \times \alpha(D_d, t) \\
\text{Prob} \{(D_d, t) \rightarrow (D_d, t - \delta)\} &= (1 - \lambda) \times \alpha(D_d, t) \\
\text{Prob} \{(D_d, t) \rightarrow (D_d, t)\} &= (1 - \lambda) \times \alpha(D_d, t) \\
\text{Prob} \{(D_d, t) \rightarrow (D_d, t + \delta)\} &= (1 - \lambda) \times \alpha(D_d, t) \\
\text{Prob} \{(D_d, t) \rightarrow (D_d + 1, t - \delta)\} &= \frac{1}{2} \times \alpha(D_d, t) \\
\text{Prob} \{(D_d, t) \rightarrow (D_d + 1, t)\} &= \frac{1}{2} \times \alpha(D_d, t) \\
\text{Prob} \{(D_d, t) \rightarrow (D_d + 1, t + \delta)\} &= \frac{1}{2} \times \alpha(D_d, t)
\end{align*}
\]

(12)

Given the state transition diagram and its transition probabilities, we can determine the steady state probability \( \pi(t, D_d) \).

![Figure 2 A Markov model and its state transition diagram for mobile](image)

The interferers are modeled similarly. Given the state of the desired signal and its interferers, we use Eq. 10 to compute the conditional probability \(\mathcal{F}(CI | t, D_d, (t_{ip}, D_{ip}), \ldots, (t_{ip}, D_{ip}))\). We then weight the result by...
the steady state probabilities of all the possible states. That is,

\[ F(C|I) = \sum_{t_1=1}^{L_1} \cdots \sum_{t_L=1}^{L_L} \sum_{n=1}^{N} \sum_{D_n=1}^{N} F(C|t_d, t_1, \ldots, t_m, L, \pi(t_d, t_1, \ldots, t_m, D_d, D_1, \ldots, D_n) \quad (13) \]

Since the desired signal and its interference are commonly assumed to be independent, we have \( \pi(t_1, t_2, D_1, D_2, \ldots, D_n) = \pi(t_1, D_1) \pi(t_2, D_2) \cdots \pi(t_n, D_n) \). The complexity of the model grows with the number of interferers. We are also interested in the power consumption. For that we can compute the average power consumption \( \overline{t_d} \) using the following equation.

\[ \overline{t_d} = \sum \pi(D_d, t_d) \times t_d \quad (14) \]

3.2 Direct Compensation Schemes

Unlike an incremental scheme, a direct compensation power control scheme adjusts the transmitting power in one step. Thus non near-neighbor transitions exist in the state transition diagram (Fig. 3). Determining the transition probabilities, although tedious, is similar to procedure described in incremental schemes.

![Figure 3 A linear power control model. As shown, there are no near-neighbor transitions in the state diagram.](image)

4. Performance

We assume the cell size is \( R \) and the channel reuse distance \( D \) is \( 4R \). That is, the distance from the center of the cell to the one of the co-channel interfering cell is \( 4R \). The coverage area of each cell is divided into \( N \) shells, as shown in Fig. 1. In the analysis we choose -88 dBm as the received signal strength (RSS) target level. Then use the deterministic relationship in Eq. 1 and distance \( R \) and 4\( R \) to set \( t_{\text{min}} \) and \( t_{\text{max}} \). Once the transmitting power range is determined, it is then divided into \( L \) levels \( t_1, t_2, \ldots, t_L \). Obviously, \( t_1 = t_{\text{min}} \) and \( t_L = t_{\text{max}} \). The following parameters are used in deriving the results to be presented: \( N \) (number of shells) = 5, \( L \) (power levels) = 10, and shadowing spread \( \sigma = 8 \) dB.

In [6], the author shows that when \( m = 0.5 \) and there is a single interferer, the variance of \( S/N \) is minimized. With mobility included, our results show that this is not always true. Figure 4 shows the results of the study under the condition \( \lambda = 0.1 \). In most regions (Fig. 4), the performance of \( m = 0.25 \) is even better. But the difference between the two is small (Fig. 5).

Figure 6 shows the effect of mobility for the case of single interferer and \( m = 0.5 \). It plots the performance for different \( \lambda (0 \leq \lambda \leq 1) \). One can find that the higher the mobility (i.e. larger \( \lambda \)), the worse the performance.

Figure 7 shows the effect of interferers on power control gain. It is noticed from the results that although the CCI performance is affected by the number of interferers, the power control gain remains largely unaffected. The case we study is for \( m = 0.5 \).

Figure 8 explores the inter-relationship between CCI and power saving. It plots the average power consumption (see Eq. 14) of the mobile unit against the slope \( m \) under two different mobility factors. It shows that the power consumption is greatly lower when \( m \geq 0.5 \), and that it is minimized when \( m \) is in the range \( 0.6 \leq m \leq 0.7 \).

5. Concluding Remarks and Future Research

We have used random walk to model mobility and evaluate its effect on power control in this paper. Combining a statistical channel model and a Markov model, we have evaluated, in terms of CCI as well as power consumption, several power control schemes and their optimal operating points. The results throw new light on the performance of the power control schemes under study.

REFERENCES


FINAL REPORT FOR AWARD # 9523969

Gordon L Stuber; GA Tech Res Corp - GIT
Cellular Architectures and Resource Management

Participant individuals:
CoPrincipal Investigator(s): Chin-Tau Lea
Graduate student(s): Li-Chun Wang; Kai-Wei Ki; Mustafa Turkboylari; Chi-Jui Ho; Jinsoup Joung; Dukhyun Kim; James Caffery, Jr.; Krishna Narayanan

Participants' Detail

Partner organizations:

Activities and findings:

Research Activities:

The goal of this project was to develop new radio architectures and resource management schemes that will lead to high capacity cellular radio systems. Our objective was to develop techniques that can improve the capacity of cellular systems that are currently deployed.

A detailed study was undertaken that involved a mixture of theoretical and computer simulation work in propagation modeling, signal processing, teletraffic modeling, linear programming, detection and estimation. The work was performed by the two Principal Investigators and four Ph.D. students.

Activities were undertaken and contributions were made in the following specific areas of study

* hierarchical cellular architectures
* macrodiversity cellular architectures
* call admission control in cellular systems
* signal-to-interference ratio estimation in cellular systems

Reporting has occurred through major IEEE conference and journal publications. Our work on hierarchical cellular architectures received the Jack Neubauer Memorial Award for the best systems paper published by the IEEE Vehicular Technology Society.

Activities and findings:

Research Findings:

Radio Architectures
1. Hierarchical Cellular Architecture

An innovative hierarchical microcell/macrocell architecture has been developed. By applying the concept of "cluster planning," the proposed sectoring arrangement can provide good shielding between micro- and macro-cells. As a result, underlaid microcells can reuse the same frequencies as overlaying macrocells without decreasing the macrocell system capacity. With the proposed method, microcells not only can be gradually deployed, but they can be extensively installed to provide complete coverage and increase capacity throughout the service area. With these flexibilities, the proposed method allows existing macrocellular systems to evolve smoothly into a hierarchical microcell/macrocell architecture.

2. Macrodiversity Cellular Architectures

In a macrodiversity cellular system, switching radio links between base stations cannot be done instantaneously. Thus branch selection is usually based on the measurement of the slowly-varying local mean power rather than the rapidly-varying instantaneous signal power. We have developed an exact mathematical model to analyze the performance of a local-mean-based macrodiversity cellular system in a shadowed-Rician (desired) /shadowed-Rayleigh (interfering) channel. We have investigated the impact of both fading (Rician or Rayleigh) and shadowing in terms of co-channel interference (CCI) probability. An analytical model has also been developed to incorporate the effects of branch correlation on macrodiversity systems.

3. MAWCC: A New Network Architecture

Current cellular systems are based on the concept of cell. Although cell allows channel reuse, it has also become a metaphor for channel confinement and leads to the thorny problem of handoff and call-dropping. The problem will get much worse as cellular services move toward high-speed and multirate.

We developed a new wireless network architecture called MAWCC for its main characteristic-- MACrodiversity Without Channel Confinement. In MAWCC, mobility equals capacity. The convertibility between the two (capacity and mobility) makes MAWCC a total departure from a conventional wireless network. If offers more options for tackling the issues of mobility, handoff, and call dropping.

1. Call Admission Control

Another important element of radio resource management is call admission control. It is well known in the past that call admission control can have a big impact on the performance of a wireless network. But the nonlinear dependency of new calls and handoff calls makes the searching of a better call admission policy -- in terms of effective utilization -- a difficult task. Many studies on optimal policies have not taken the correct dependency into consideration. As a result, the reported gains in those studies can not be confirmed in a real network. We have developed a solution to the problem of finding better call admission
policies. The technique consists of three components. First, we search the policy in an approximate reduced-complexity model. Second, we modified the Linear Programming technique for the inherently nonlinear policy-search problem. Third, we verify the performance of the found policy in the exact, high-complexity, analytical model. Our results clearly demonstrate the effectiveness of the proposed technique.

We have also explored call admission control in a hierarchical cellular system. The hierarchical system we study is based on a novel "cluster planning" scheme. The original analysis of this hierarchical system showed that a significant capacity gain can be achieved by the scheme. However, this capacity is gained at the expense of the C/I (carrier to interference ratio) performance of the macrocells. By extending our cluster planning technique, we showed how to use call admission control to achieve a capacity gain without sacrificing the C/I performance of the macrocells.

2. SIR Estimation in TDMA Cellular Systems

A new algorithm to estimate the signal-to-(interference ratio plus noise) ratio \( S/(I+N) \) was developed for TDMA cellular systems. Simulation results show that the \( S/(I+N) \) can be estimated to within 0.5 dB in about 0.5 s for the IS-54/136 system and to within 0.5 dB in about 0.1 s for the GSM system. The estimator is computationally simple and outperforms all other \( S/(I+N) \) estimators that have been reported previously in the literature.

Research Training:

The research on this project has formed the basis for the Ph.D. thesis of three students:

Li-Chun Wang -- completed his Ph.D. and is now with AT&T-Labs Research, Crawford Hill Laboratory, Holmdel NJ.

Chi-Jui Ho -- currently a Ph.D. student who has passed the Ph.D. Dissertation Proposal.

Mustafa Turkboylari -- currently a Ph.D. student who has passed the Ph.D. Qualifying Exam.

The following Ph.D. students have also contributed to the project:

Kai-Wei Ki -- completed his Ph.D. and is now an Associate Professor, Taipei Institute of Technology, Taipei, Taiwan.

Jinsoup Joung -- currently a Ph.D. student who has passed the Ph.D. Qualifying Exam.

Dukhyun Kim -- completed his Ph.D. and is now with Lucent Technologies, Product Realization Center, Atlanta, GA.

James Caffery, Jr. -- completed his Ph.D. and is now an
Assistant Professor, University of Cincinnati, Cincinnati, OH.

Krishna Narayanan -- completed his Ph.D. and is now an Assistant Professor, Texas A&M University; College Station, TX.

Journal Publications:
C.-J. Ho and C.-T. Lea, "Improving Call Admission Policies in Wireless Networks", *ACM Wireless Networks*, vol. , (). Accepted

Book(s) or other one-time publication(s):

Internet Dissemination:
http://www.ee.gatech.edu/users/stuber/nsf/index.html

Publications are available in postscript form.

Other specific products:

Contributions:

Contributions within Discipline:

Spectral efficiency or capacity is of utmost importance cellular radio systems. This project has suggested some new high capacity radio architectures and methods that can be used to realized high capacity frequency reuse systems.

Our work on hierarchical (multilayer) cellular architectures has resulted in a new architecture that can be easily
applied to an existing TDMA cellular telephone systems to provide a large capacity increase. Microcells are underlaid beneath existing macrocells, and can share the same frequencies as the macrocells. The only modification required of the existing macrocellular system is a simple rotation of channel sets, a procedure that we call "cluster planning." The cluster planning technique achieves capacity gain at the expense of link quality in the existing macrocellular system. However, by using our cluster planning technique in conjunction with call admission control, it is possible to realize a capacity gain without sacrificing call quality in the existing cellular system. In order to apply call admission control, we have developed a new non-linear programming technique to optimize cellular system capacity given constraints on link quality and new call blocking probability. Our results can be easily applied to existing cellular systems.

We have introduced a new cellular architecture called MAWC (MACrodiversity Without Channel Confinement). This architecture can trade mobility for capacity in a cellular systems. The networks capacity will rise if the degree of mobility of its customers drops, and vice versa. the new architecture relies upon the combination of macrodiversity (where a call is serviced by multiple cell sites) and dynamic channel assignment (where any cell can use any frequency that does not violate the co-channel reuse constraint. In the MAWC architecture, mobile stations keep using the same channel when crossing cell boundaries. All that is changed is the radio ports used to service the call. Channel changes are only required when two mobile stations using the same channel become too close together.

We also analyzed the performance of macrodiversity cellular systems, taking into account multipath fading and correlated shadowing on the macrodiversity links. Such results are useful for analyzing cellular systems that employ soft-handoff techniques.

Finally, many of the newer types of resource management algorithms for power control, handoff and channel assignment assume that the signal-to-interference ratio (SIR) of the radio links can be monitored. In our work, we have introduced a very fast and simple method to monitor (SIR) in TDMA cellular systems.

Contributions to Education and Human Resources:

Research from the project has contributed in part to the following invited seminars and conference tutorial:


"Principles of Mobile Communications," IITESM University, Monterrey, Mexico, November 4-9, 1996.

"Wireless Personal Communications," National Tsing Hua University, Taiwan, September 22-23, 1997.

"Principles of Mobile Communications," ITESM University, Monterrey, Mexico, July 13-17, 1998.

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