7

OPTIMAL RESOURCE ALLOCATION OF DAS

Lin Dai

Contents

The distributed antenna system (DAS) has emerged as a promising candidate for the future, beyond 3G or 4G mobile communications thanks to its open architecture and flexible resource management. The distributed characteristic of the antennas provides a more efficient utilization of space resources; however, it also raises a crucial challenge for the advanced resource allocation. In this chapter, the optimal resource allocation for DAS networks is investigated. We start with an overview of the current adaptive techniques for wireless systems. The resource allocation strategies in distributed channels are then proposed, and the performance comparison with equal allocation helps us understand why an adaptive resource allocation is indispensable to the DAS. It is further extended to the multi-user scenario and the optimal resource allocation among multiple users is discussed. The chapter concludes by presenting some open research issues in the realization of resource allocation for DAS networks.

7.1 RESOURCE ALLOCATION FOR WIRELESS SYSTEMS

Future wireless networks are expected to support a wide variety of communication services, such as voice, video, and multimedia. However, the wireless environment provides unique challenges to the reliable communication: time-varying nature of the channel and scarcity of the radio resources such as power and bandwidth. Therefore, it is of great interest to investigate how to efficiently allocate the limited radio resources to meet diverse quality-of-service (QoS) requirements of users and maximize the utilization of available bandwidth based on the channel states of users. In this section, we will present an optimal resource allocation framework for the wireless system, and based on it, some adaptive techniques will be introduced.

7.1.1 Optimal Framework of Resource Allocation

There are tremendous ways to perform resource allocation. For instance, adaptive power and rate allocation can provide significant performance gain in fading channels [1]. In code division multiple access (CDMA) systems, the radio resources are usually allocated to the users by regulating their transmit power and spreading gains [2]. In general, if we consider a wireless network with $\mathcal{K}$ users, each with a utility function $U_k(.)$ and a constraint $S_k(.) \leq q_k$, the problem of optimal resource allocation can be formulated as

$$\begin{aligned} &\text{Maximize} \quad \sum_{k=1}^{\mathcal{K}} U_k(P_k, R_k, L_k, \Phi_k) \\ &\text{Subject to} \quad S_k(P_k, R_k, L_k, \Phi_k) \leq q_k, \qquad k = 1, \ldots, \mathcal{K}, \end{aligned} \tag{7.1}$$

where the utility of user k $U_k(.)$ is a function of the allocated resources including: the transmit power P_k, the modulation and coding level R_k, the packet length L_k and Φ_k. Φ_k represents the available resources in specific systems, which can be the number of spreading codes assigned to user k in CDMA systems; the number of subcarriers in orthogonal frequency division multiplexing (OFDM) systems; the number of antennas in multiple-input multiple-output (MIMO) systems; or the number of time slots in time division multiple access (TDMA) systems. q_k is the required QoS for user k, i.e., the required rate, error probability, and delay constraints, etc.

From (7.1) it can be seen that the optimal resource allocation is essentially an optimization problem of maximizing the network utility $\sum_{k=1}^{\mathcal{K}} U_k(.)$, over the available resources, subject to the constraints of all users. Obviously, in wireless systems where users may have diverse QoS requirements and distinct channel statistics, optimal resource allocation can bring huge performance gain.

Optimal resource allocation for a specific user can be performed in time, space, or frequency domain. For example, the transmit power and rate can be adjusted among different fading states (time domain), different antennas (space domain), or different subcarriers (frequency domain) to maximize the throughput or minimize the error rate. Optimal resource allocation among multiple users, however, will be much more complex because the feasible solution field may not always exist. Maximizing the network utility $\sum_{k=1}^{\mathcal{K}} U_k(.)$ does not guarantee that the utility of each user is maximized; on the contrary, sometimes it is achieved by scarifying some users' performance. Therefore, a tradeoff between efficiency and fairness usually has to be addressed in multi-user resource allocation.

7.1.2 Adaptive Techniques

We have shown that in wireless systems, resources should be adaptively allocated according to users' QoS requirements and channel statistics. In this section, we will further introduce some adaptive techniques and show how to perform resource allocation in specific systems.

7.1.2.1 Adaptive Power and Rate Allocation

Adaptive power and rate allocation was proposed a long time ago as an effective means to overcome the detrimental effect of time-varying channels [1, 3–5]. Later, information-theoretic work showed that to maximize the ergodic capacity of a single-user fading channel with channel state information (CSI) at both the transmitter and receiver, the optimal power and rate allocation is a water-filling procedure over the fading states [6]. The ergodic capacity region of a fading multiple-access channel (MAC) and the corresponding optimal power and rate allocation, which is a multi-user version of the single-user water-filling procedure, were obtained in [7] using the polymatroidal structure of the region. [8] further derived the optimal power allocation for maximizing the delay-limited capacity. It was shown that with the proposed channel inversion strategy, there is zero outage probability and the end-to-end delay is independent of the channel variation. The price is that huge power has to be consumed to invert the channel when it is in an unfavorable state.

Another line of work focused on practical schemes, which typically assume a finite number of power levels and modulation and coding schemes [9–15]. For example, adaptive modulation and coding (AMC) has been studied extensively [10–14] and adopted at the physical layer in several standards, e.g., 3GPP, 3GPP2, IEEE 802.11a, IEEE 802.15.3, and IEEE 802.16 [16–18]. Recent work includes the cross-layer optimization combining AMC at the physical layer and automatic request protocol (ARQ) or finite-length queue at the link layer [19, 20], and the joint optimization of rate and packet length in cooperative ad hoc networks [21].

7.1.2.2 Adaptive Resource Allocation for MIMO Systems

MIMO systems have recently attracted tremendous interest due to their ability in providing great capacity improvements [22, 23]. Different from the traditional power and rate allocation in fading channels, which is performed in time domain, the resources in MIMO systems are usually allocated among the antennas or in space domain.

It has been shown that the optimal power allocation among the multiple antennas is the water-filling strategy [22]. However, to perform this optimal allocation requires full

CSI at the transmitter. Later work focused on transmit beamforming and precoding with limited feedback [24–27], where the transmitter uses a small number of feedback bits to adjust the power and phases of the transmit signals. To further reduce the amount of feedback and complexity, per-antenna rate and power control was proposed [28–32]. By adapting the rate and power for each antenna separately, the performance (error probability [31] or throughput [28–30]) can be improved greatly at a slight cost of complexity.

Antenna selection was proposed to reduce the number of radio frequency (RF) chains and the receiver complexity. Various criteria for receive antenna selection or transmit antenna selection have been presented, aiming at minimizing the error probability [33–40] or maximizing the capacity bounds [41,42]. It was shown that only a small performance loss is suffered when the transmitter/receiver selects a good subset of the available antennas based on the instantaneous CSI. However, recently it is found that in the correlated scenario, proper transmit antenna selection can not just be used to decrease the number of RF chains, but as an effective means to bring the performance gain [43]. When the channel links present spatial correlation (due to the lack of spacing between antennas or the existence of small angular spread), the degrees of freedom of the channel are usually less than the transmit antennas. Therefore, by the use of transmit antenna selection, the resources are allocated only to the "good" subchannels so that a capacity gain can be achieved.

Most of the above work focused on the peer-to-peer link in the single-user scenario. Resource allocation in a multi-user MIMO scenario is still quite an open issue. [44,45] both considered a multi-user MIMO system and focused on multi-user precoding and turbo space–time multi-user detection, respectively. More recent work includes a cross-layer resource allocation in downlink multi-user MIMO systems [46].

7.1.2.3 Adaptive Resource Allocation for OFDM Systems

OFDM was proposed to combat the intersymbol interference (ISI) problem [47]. Later it was found that adaptive rate allocation can be perfectly performed in OFDM systems, where subcarriers with higher channel gains carry more bits while the ones in deep fade carry few or even zero bits [48,49]. Similar to the per-antenna rate and power allocation, here the rate of each subcarrier is adjusted according to the CSI following the water-filling principle. The optimal power allocation has also been studied [50,51]. Significant performance gain can be achieved through the power and rate adaptation.

In MIMO systems, it is not straightforward to extend the per-antenna rate and power allocation to the multi-user scenario as there is no bijective mapping between the transmit antenna set and the subchannel set. Some complicated interference cancellation techniques have to be developed. In multi-user OFDM systems, however, thanks to the orthogonality among the subcarriers, each subcarrier can be allocated to a user with the best channel condition. Here multi-user diversity gain is further achieved based on the low probability that all the users' signals on the same subcarrier are in deep fading [52–55]. Some recent work includes the adaptive resource allocation for MIMO-OFDM systems [56] and cross-layer optimization for multi-user OFDM systems [57].

7.1.2.4 Adaptive Resource Allocation for CDMA Systems

The available resources in CDMA systems include transmit power and spreading codes. Joint power allocation and base station assignment problems were first analyzed in [58,59]. In these works, the objective is the minimization of the total transmit power subject to the QoS requirements of the sources, without considering the allocation of the spreading gains. Another line of work focuses on multiple classes of service, where users are allocated different class-dependent spreading gains to maximize the throughput [60,61]. The joint optimal allocation of power and spreading gains was considered in [2, 62–66], in which an optimization problem is usually formulated to optimize the total transmit power or the sum of the transmission rate (or say, the network throughput) under the constraint on the maximum transmission power of each user or the minimum spreading gain (or both).

Recently, utility-based power control has received significant attention, where a game theoretic approach is applied to the power control problem for CDMA data networks. Here, the optimization objective is neither the total transmit power nor the sum rate. Instead, a utility function is proposed which quantifies the level of satisfaction a user gets from using the system resources [67], and the resources are allocated to optimize the network utility. Its attractiveness comes partially from the distributed nature: each user can maximize its own utility in a distributed fashion. See [67,68] and references therein for more details.

7.1.2.5 Channel-Aware Scheduling

Efficient resource allocation for multiple users is always an interesting but challenging issue. As we have introduced, in OFDM (or CDMA) wireless systems, subcarriers (or spreading codes) are assigned to users according to their QoS requirements and channel conditions. Another option, however, is to allocate all the system resources to different users, in different time slots. This leads to the so-called *scheduling* problem. In the earliest work on scheduling for wireless systems, the time-varying nature of wireless channels was not taken into full consideration [69,70]. The channel is usually simplified as an "ON-OFF" model and the focus is on the queue statistics. Knopp and Humblet [71] first proposed to always schedule the user with the best channel and showed that significant throughput gain can be brought by multi-user diversity "when there are many users who fade independently; at any one time there is a high probability that one of the users will have a strong channel" [72]. Obviously, the more users scheduled, the higher throughput that can be obtained.

There have been numerous works on how to exploit this multi-user diversity gain [73–77]. However, to directly implement the idea of multi-user diversity will result in unfairness if users' fading statistics are not identical: The user with a statistically stronger channel has a higher opportunity in acquiring the system resources. From a system aspect, efficiency and fairness are both crucial issues in resource allocation and should be carefully addressed. Several definitions of fairness have been proposed, such as max-min fairness [78] and proportional fairness [79,80]. A scheduler combined with multi-user diversity and proportional fairness has been proposed in [81], which is also the baseline scheduler for the downlink of IS-856. Asymptotic analysis of scheduling can be found in [82].

So far we have presented the optimal resource allocation framework and introduced some representative adaptive techniques. In next section, we will focus on distributed antenna systems (DASs) and illustrate how to efficiently allocate resources in distributed channels.

7.2 RESOURCE ALLOCATION IN DISTRIBUTED CHANNELS

In DASs, many remote antenna ports are distributed over a large area and connected to a central processor by fiber, coax cable, or microwave link [83]. Basically, resource allocation of DASs is also performed among the antennas, similar to that of the MIMO systems. However, due to some special characteristics of distributed channels, resource allocation is indispensable to a DAS and is not just for performance enhancement. It will be shown that the performance severely deteriorates without proper resource allocation. In this section, we consider the downlink resource allocation in the single-user scenario, i.e., how to assign the transmission phases, rate, and power of different distributed antennas to a specific user. Multi-user resource allocation will be discussed in Section 7.3 from a system perspective.

7.2.1 System and Channel Model

Consider a DAS with $\mathcal{M}$ remote antennas which are randomly distributed around $\mathcal{K}$ users each equipped with n colocated antennas. Here the cells are divided not geographically, but according to the user demands, which are called "virtual cell" [83]. As shown in Figure 7.1, the remote antennas serving for user k form the k-th virtual cell. When user k moves, the remote antennas in the k-th virtual cell will be dynamically modified to adapt to the changes of user k. The central processor continuously tracks the channel between user k and each remote antenna and selects the best m remote antennas to form the virtual cell of user k.

Particularly, user k receives signals from the m remote antennas of its virtual cell. Assume a flat fading and quasi-static channel model and perfect symbol synchronization

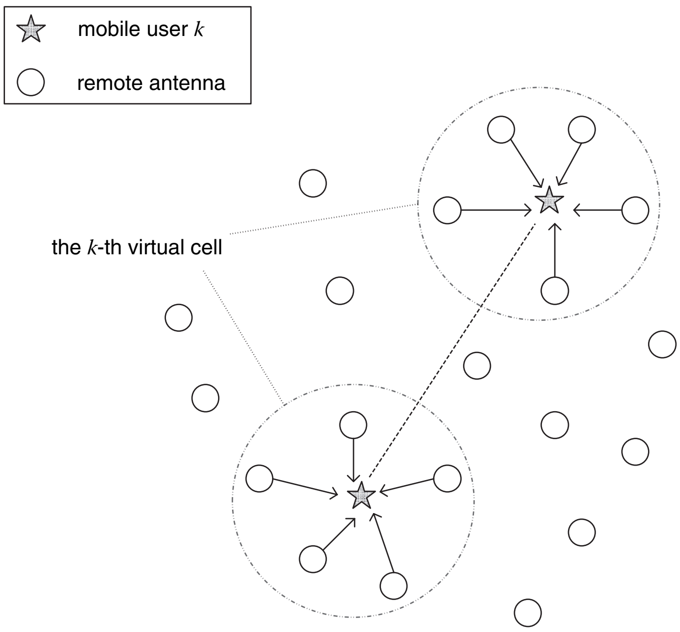

Figure 7.1 System Model of DAS

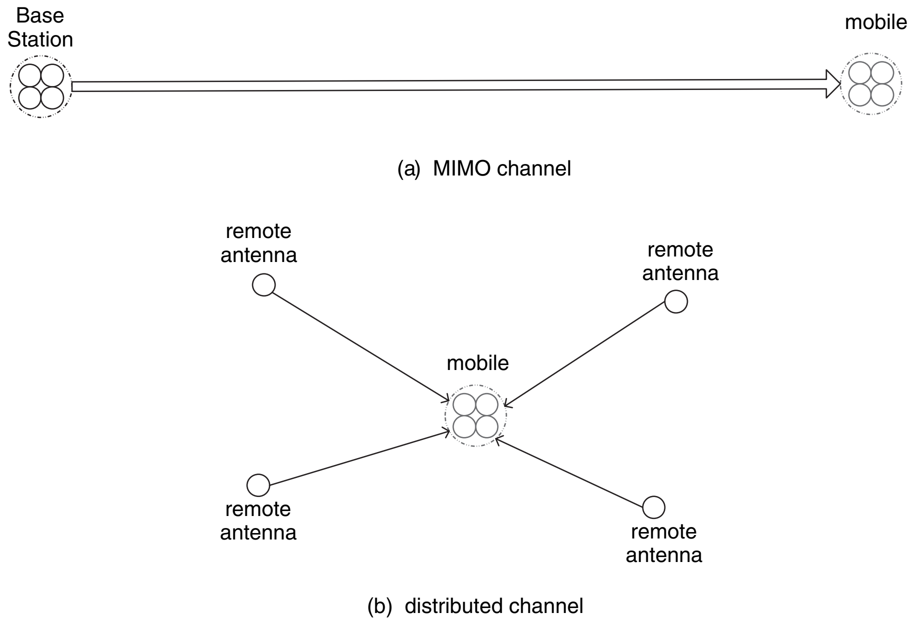

Figure 7.2 MIMO Channel Vs. Distributed Channel

at the receiver. The discrete model of the received complex signal vector can be written as

$$\mathbf{y} = \mathbf{Hx} + \mathbf{z} = \mathbf{R_r^{1/2}H_wFx} + \mathbf{z}, \tag{7.2}$$

where $\mathbf{z}$ is the noise vector with i.i.d. $\mathcal{CN}(0, \sigma^2)$ entries. The small-scale fading is denoted by an $n \times m$ matrix $\mathbf{H_w}$ with i.i.d. $\mathcal{CN}(0, 1)$ entries. $\mathbf{R_r}$ denotes the $n \times n$ antenna correlation matrix at the receiver (where n antennas are colocated) [84]. $\mathbf{F}$ is an $m \times m$ diagonal matrix.

Equation (7.2) is reminiscent of a MIMO channel model [85]. The only difference is that the transmit correlation matrix $\mathbf{R_t}$ is replaced by a diagonal matrix $\mathbf{F}$. Illustrated in Figure 7.2 is a comparison between a MIMO channel and a distributed channel. It can be seen that in a MIMO system, the antennas are colocated at both the base station and the user. Therefore, the transmit signals experience similar large-scale fading and resource allocation here is usually adopted to overcome the spatial correlation, which leads to insufficient degrees of freedom of the channels. However, in distributed channels, the signals transmitted from different remote antennas suffer from distinct degrees of large-scale fading, which is denoted by this $m \times m$ diagonal matrix $\mathbf{F}$. In particular, $\mathbf{F} = diag(f_1, \ldots, f_m) = diag(\sqrt{\varsigma_1 d_1^{-\alpha}}, \ldots, \sqrt{\varsigma_m d_m^{-\alpha}})$, where d_i is the access distance between the user and the i-th remote antenna. α is the path loss exponent and ς_i represents the effect of log-normal shadowing, $i = 1, \ldots, m$. In the following discussions, we normalize $trace(\mathbf{FF}^*)$ to be m and let $\eta = \|f_1\|^2 : \|f_2\|^2 : \cdots : \|f_m\|^2$.[1] We will show that due to the existence of $\mathbf{F}$, equally allocating resources among the transmit antennas, which is often adopted in MIMO systems, will lead to severe performance degradation. Adaptive resource allocation is highly desired in a DAS.

[1] Throughout the chapter, "$*$" represents the conjugate and transpose operator.

7.2.2 Water-Filling and Equal Power Allocation

To understand why resource allocation is requisite in a DAS, we start with a simple power allocation problem in a multiple-antenna channel. For simplicity, let us assume that the receive antennas at the user are uncorrelated, i.e., $\mathbf{R_r} = \mathbf{I_n}$. The mutual information is then given by

$$I(\mathbf{Q}) = \log_2 \det\left(\mathbf{I_n} + \frac{1}{\sigma^2}\mathbf{H_w F Q F^* H_w^*}\right), \tag{7.3}$$

where $\mathbf{Q} = \mathrm{E}(\mathbf{xx}^*)$ is the transmit covariance matrix.

Without the CSI at the transmitter, equal power allocation, i.e., $\mathbf{Q} = \frac{P_t}{m}\mathbf{I_m}$, would be optimal [22,23]. In this case, we have

$$C = \log_2 \det\left(\mathbf{I_n} + \frac{\rho}{m}\mathbf{H_w F F^* H_w^*}\right) = \log_2 \det\left(\mathbf{I_m} + \frac{\rho}{m}\mathbf{F^* H_w^* H_w F}\right), \tag{7.4}$$

where $\rho = P_t/\sigma^2$ is the average receive single-to-noise ratio (SNR). Since $\mathbf{H_w^* H_w}$ is Hermitian, it can be diagonalized as $\mathbf{H_w^* H_w} = \mathbf{U_h^* \Lambda_h U_h}$, with a unitary matrix $\mathbf{U_h}$ and a nonnegative diagonal matrix $\mathbf{\Lambda_h}$. Let $\mathbf{X} = \mathbf{\Lambda_h^{1/2} U_h F} = \mathbf{V_x^* \Lambda_x^{1/2} U_x}$, we see that

$$C_{eq} = \sum_{i=1}^{r} \log_2\left(1 + \frac{\rho}{m}\lambda_i\right), \tag{7.5}$$

where λ_i is the i-th eigenvalue of $\mathbf{X^*X}$ and $r = min(m, n)$.

On the other hand, if CSI is available at the transmitter, [22] has shown that the water-filling policy would maximize the capacity, which requires

$$\tilde{\mathbf{Q}} = \mathbf{U_x Q U_x^*} = diag(\mu - \sigma^2\lambda_i^{-1})^+, \tag{7.6}$$

where μ is chosen to satisfy $\sum_{i=1}^{m} \tilde{Q}_{ii} = P_t$, and the capacity is then given by

$$C_{wf} = \sum_{i=1}^{r} (\log_2(\mu\lambda_i/\sigma^2))^+. \tag{7.7}$$

When $\mathbf{X^*X}$ is of full rank and well-conditioned, the water-filling strategy allocates nearly an equal amount of power to all the dimensions, and the capacity is approximated by

$$C_{wf} = \sum_{i=1}^{r} \log_2\left(1 + \frac{\rho}{r}\lambda_i\right). \tag{7.8}$$

Comparing (7.8) and (7.5), we can see that the water-filling strategy can achieve a power gain of a factor of m/r over the equal power allocation. This implies that when there are more transmit antennas than receive antennas, CSI at the transmitter is highly desired so that the transmit energy can be effectively allocated to only r degrees of freedom instead of being spread out equally across all m directions. Figure 7.3 presents the 10% outage capacity results of the water-filling strategy and the equal power allocation in iid. MIMO channels (i.e., $\mathbf{F} = \mathbf{I_m}$). Only a slight capacity gain can be observed with the water-filling strategy when both the number of transmit antennas and receive antennas

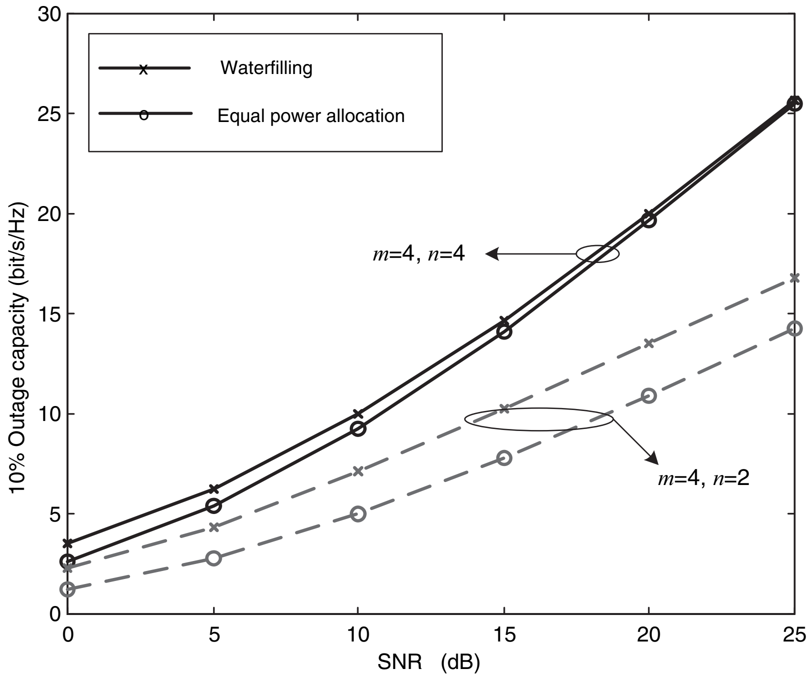

Figure 7.3 10% Outage Capacity Comparison of Water-Filling Strategy and Equal Power Allocation in MIMO Channels

are equal to four. However, the capacity gap is significantly enlarged if there are not as many receive antennas as transmit antennas.

In fact, if we notice that $\mathbf{X}^*\mathbf{X}$ is usually ill-conditioned in distributed channels, we will find that the water-filling strategy can bring even more substantial capacity gains. Again, assume $m = n = 4$ and consider two types of distributed channels with $\eta_1 =$ 500:100:20:1 and $\eta_2 =$ 1000:100:10:1. Obviously, in the first case two subchannels are significantly better than the others and $\mathbf{X}^*\mathbf{X}$ is rank deficient. The second case is even more asymmetric, and $\mathbf{X}^*\mathbf{X}$ is severely ill-conditioned. Figure 7.4 shows the capacity gains of the water-filling strategy over the equal power allocation, i.e., $(C_{wf} - C_{eq})/C_{eq} \times 100\%$, in both cases. For comparison, the results in MIMO channels are also provided. In distributed channels, the water-filling strategy performs much better than the equal power allocation. In a low SNR regime, over 50% capacity gains can be achieved by the water-filling strategy. This gain, however, will diminish when the SNR is high enough.

Based on the above discussions, we can conclude that resource allocation is highly desired in a DAS. In MIMO systems, all the subchannels suffer from nearly the same large-scale fading; hence, the equal power allocation can provide comparable performance, especially when $m = n$.[2] In DASs, however, due to the large differences among subchannels, equal allocation incurs a significant capacity loss. CSI is highly desired at the transmitter to perform the adaptive resource allocation.[3]

[2] Note that here, no space correlation is assumed.

[3] Throughout this chapter, perfect CSI is always assumed available at the receiver.

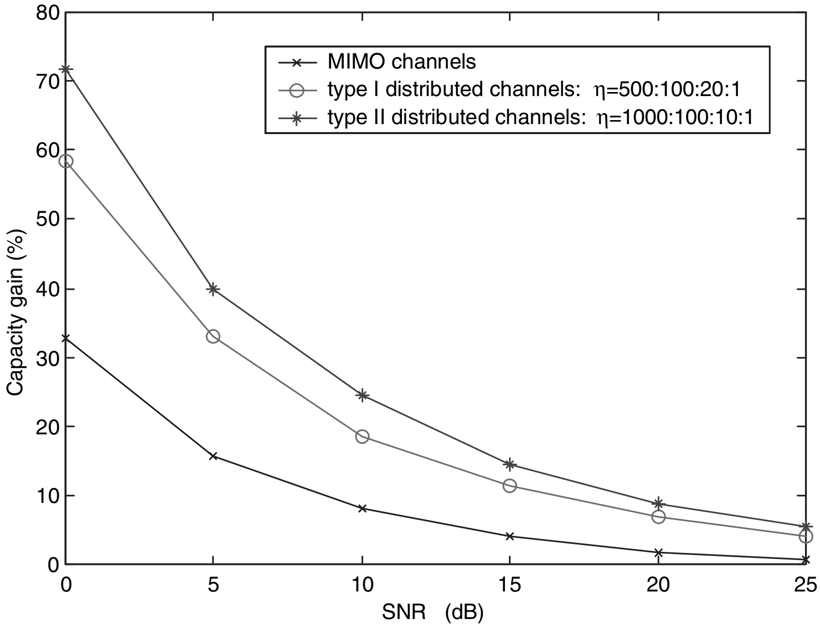

Figure 7.4 Capacity Gains of Water-Filling Strategy Over Equal Power Allocation in Distributed Channels and MIMO Channels. $m = n = 4$

7.2.3 Full CSI at the Transmitter

So far we have shown that CSI at the transmitter plays an important role in distributed channels. In a DAS, the signals transmitted from different remote antennas suffer from distinct degrees of large-scale fading. Therefore, CSI is required at the transmitter to ensure that the resources are allocated only to those "good" subchannels. In this subsection, we will focus on the case with full CSI at the transmitter.[4]

7.2.3.1 Transmit Precoding

As we know, with full CSI, i.e., **H**, at the transmitter, the water-filling strategy can achieve the optimal capacity. Therefore, a natural way is to design a precoding matrix based on this water-filling principle.

As shown in Figure 7.5, at the transmitter, the information is split into m parallel data streams and encoded separately. After being modulated, those streams are multiplied by a linear transformation matrix $\mathbf{L} \in \mathbf{C}^{m\times m}$ and then transmitted through m remote antennas. Based on the water-filling principle, **L** is given by [86]

$$\mathbf{L} = \mathbf{V}\mathbf{D}^{1/2}\mathbf{W} \tag{7.9}$$

where the columns of **V** are eigenvectors of $\mathbf{H}^*\mathbf{H}$. $\mathbf{D} = diag(m(\mu - \lambda_i^{-1})/\rho)^+$ and **W** is a unitary matrix. It can be easily proved that (7.9) satisfies the constraint condition

[4] Although the subsection is entitled "full CSI at the transmitter," the resource allocation can be performed at the receiver. The receiver then feeds back the allocation results, instead of the exact CSI information, to the transmitter.

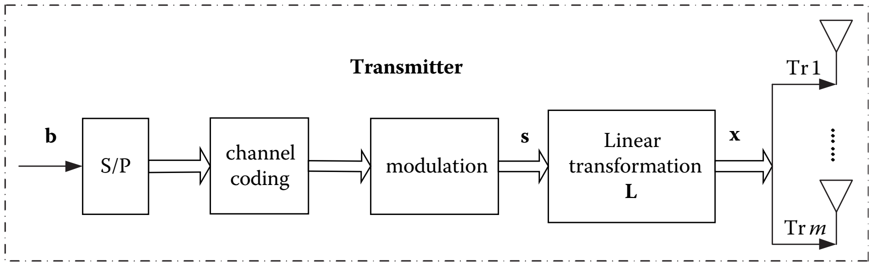

Figure 7.5 Transmitter Structure with Precoding

$tr(\mathbf{LQL}^*) = tr(\mathbf{Q})$ and achieves the optimal capacity given by (7.7). Although the capacity is maximized as long as **W** is a unitary matrix, **W** should be carefully selected for particular coding and modulation beacuse the error performance depends on **W**. We search the optimal **W** to minimize the pairwise error probability, namely, to maximize the minimum distance between received vectors.

Figure 7.6 presents the frame error rate (FER) comparison of this precoding scheme and the equal power allocation in MIMO channels. QPSK modulation is assumed at the transmitter with $m = 2$ remote antennas. Maximum likelihood detection (MLD) is adopted at the receiver. From Figure 7.6 it can be seen that a significant performance gain is brought by precoding at the transmitter. For instance, a 3 dB gain can be observed at the FER of 0.1 with $n = 2$ receive antennas, and this gain increases to 10 dB when there are less antennas at the receiver, say, $n = 1$.

Au: Does QPSK = quadratic phase shift keying? Please spell out.

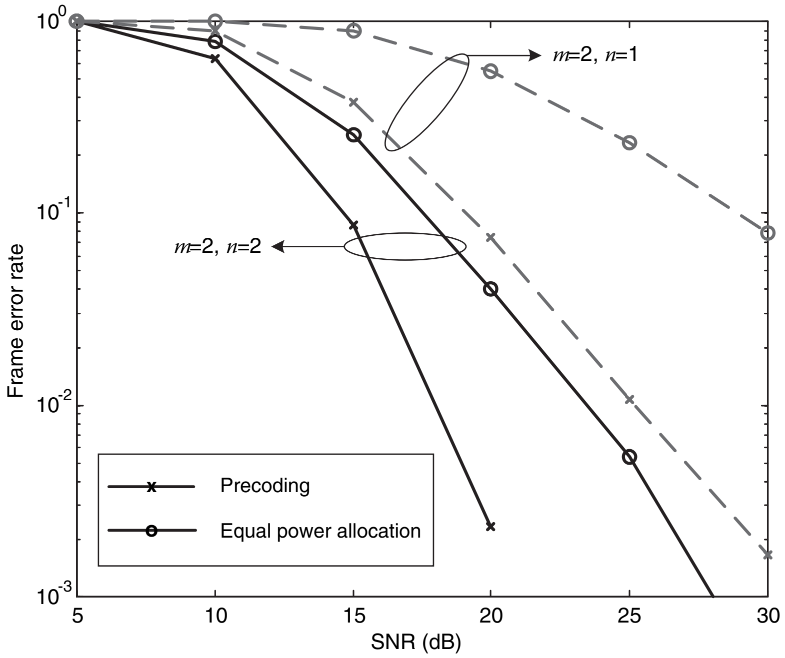

Figure 7.6 FER Comparison of the Precoding Scheme and Equal Power Allocation in MIMO Channels With QPSK Modulation and MLD

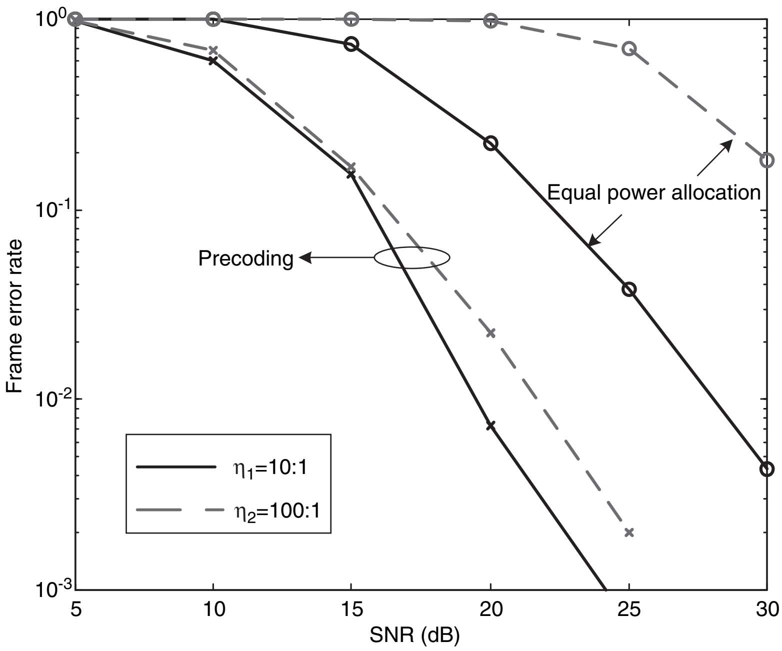

Figure 7.7 FER Comparison of the Precoding Scheme and Equal Power Allocation in Distributed Channels With QPSK Modulation and MLD. $\boldsymbol{m = n = 2}$

The performance gap is even larger in distributed channels. As shown in Figure 7.7, when $\eta_1 = 10:1$, an 8 dB gain can be achieved by the precoding scheme over the equal allocation one. As the variance of subchannels increases, the performance of the equal power allocation deteriorates rapidly. When $\eta_2 = 100:1$, the equal power allocation cannot work at all. In contrast, only slight performance degradation is observed with the precoding scheme.

Despite the superior performance, the precoding scheme requires either full CSI or an updated linear precoding matrix $\mathbf{L}$ to be fed back to the transmitter, both of which will incur a large amount of feedback. Thus, the transmission phase of each remote antenna is adjusted based on the feedback information, which makes this scheme highly sensitive to the feedback errors.

7.2.3.2 Per-Antenna Rate and Power Adaptation

With full CSI at the transmitter, the water-filling based precoding scheme has been able to achieve huge performance gains, especially in distributed channels. However, this precoding scheme requires a large amount of feedback and is quite sensitive to the feedback errors, which restricts its application in the practical scenarios. In this subsection, we will introduce a more robust resource allocation strategy, where the transmission rate and power are adjusted in a *per-antenna* manner.

As shown in Figure 7.8, the coding, modulation, and average transmit power of each remote antenna are adjusted based on the feedback information. Here we define a *mode* as a combination of specific coding and modulation. Let M_i denote the mode of the i-th antenna and the corresponding spectral efficiency is denoted by $R(M_i)$. Given the total

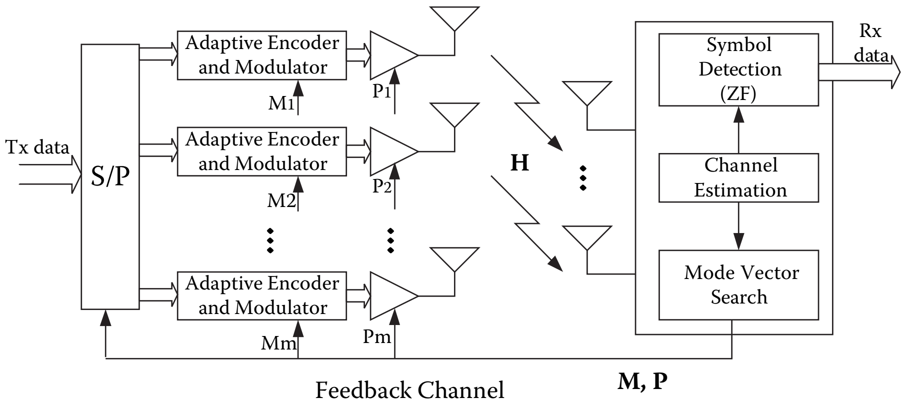

Figure 7.8 Transmitter and Receiver Structures With Per-Antenna Rate and Power Allocation

required spectral efficiency R_t, we define the mode vector as $\mathbf{M} = [M_1, \ldots, M_m]$ such that $R_t = \sum_{i=1}^{m} R(M_i)$. Likewise, with the total transmit power P_t, we define the power allocation vector as $\mathbf{P} = [P_1, \ldots, P_m]$ such that $P_t = \sum_{i=1}^{m} P_i$, where P_i denotes the average power radiated by the i-th transmit antenna. Although full CSI is required to optimize the mode vector $\mathbf{M}$ and the power allocation vector $\mathbf{P}$, this can be performed at the receiver and only the optimized results on $\mathbf{M}$ and $\mathbf{P}$ are fed back to the transmitter.

There are numerous ways to optimize the mode vector $\mathbf{M}$ and the power allocation vector $\mathbf{P}$, based on different objectives. Here we take the example of minimizing bit error rate (BER) to illustrate how to design the optimization criterion. In particular, define the active antenna set as $\mathcal{A} = \{i | R(M_i) > 0, \forall i\}$. Denote the BER of the i-th antenna after detection as BER_i. Zero-forcing (ZF) is assumed at the receiver and denote the nulling vector of the i-th substream as $\mathbf{w}_i^{\mathcal{A}} (i \in \mathcal{A})$. The total transmit power can then be expressed as

$$P_t = \sigma^2 \sum_{i \in \mathcal{A}} \xi(M_i, BER_i) \|\mathbf{w}_i^{\mathcal{A}}\|^2 R(M_i), \tag{7.10}$$

where $\xi(M_i, BER_i)$ represents the required E_b/N_0 in additive white Gaussian noise (AWGN) for the target BER_i, with the mode M_i. It can be approximated by $\xi(M_i, BER_i) \approx K(M_i) \cdot F(BER_i)$, where $K(M_i)$ is the coefficient in terms of mode and $F(BER_i)$ is a monotonously decreasing function of BER_i [31]. To optimize the BER performance, we should minimize the maximum BER_i because the overall BER performance is mainly dictated by the worst one. Therefore, the optimal mode vector $\tilde{\mathcal{M}}$ and antenna set $\tilde{\mathcal{A}}$ can be finally obtained as

$$\tilde{\mathcal{A}}, \tilde{\mathcal{M}} = \underset{\mathcal{A}, \mathbf{M}}{\operatorname{argmin}} \sum_{i \in \mathcal{A}} \|\mathbf{w}_i^{\mathcal{A}}\|^2 K(M_i) R(M_i) \tag{7.11}$$

and the corresponding power allocation vector $\tilde{\mathbf{P}}$ satisfies

$$\tilde{P}_i = \begin{cases} P_t \frac{\|\mathbf{w}_i^{\mathcal{A}}\|^2 K(M_i) R(M_i)}{\sum_{k \in \mathcal{A}} \|\mathbf{w}_k^{\mathcal{A}}\|^2 K(M_k) R(M_k)} & i \in \mathcal{A} \\ 0 & i \notin \mathcal{A}. \end{cases} \tag{7.12}$$

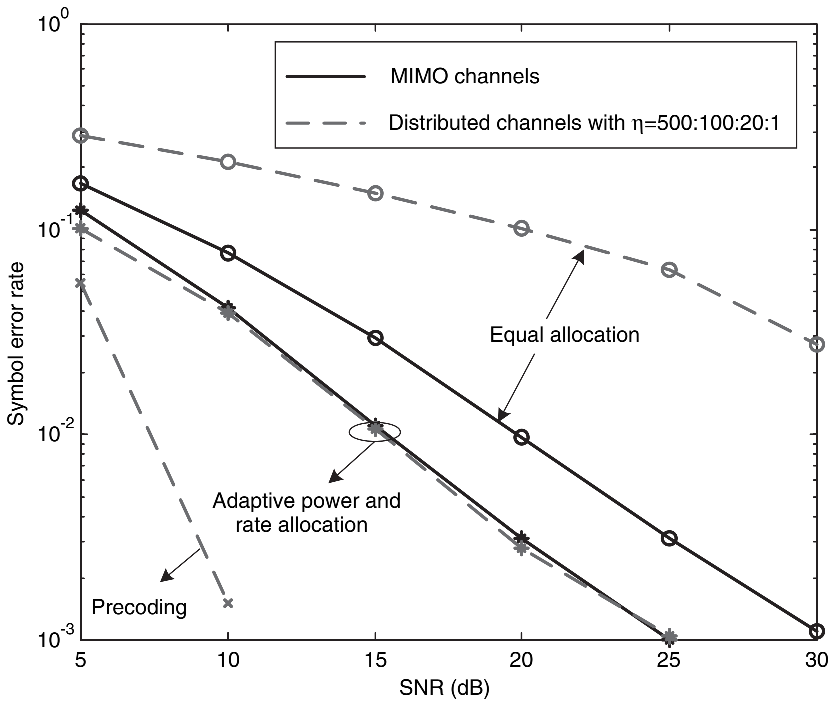

Figure 7.9 SER Comparison of Per-Antenna Adaptive Rate and Power Allocation, Equal Allocation and Precoding. $m = n = 4$

The transmission rate and power of each antenna can be determined by (7.11 to 7.12). Because the number of available modes is usually small and the power quantization requires only limited bits, the amount of feedback information can be sharply reduced compared to the precoding case. Figure 7.9 shows the symbol error rate (SER) performance of this per-antenna adaptive rate and power allocation strategy. Here four antennas are assumed at both the transmitter and the receiver, i.e., $m = n = 4$. Three modes are considered: uncoded BPSK, uncoded QPSK and uncoded 16 QAM. The total spectral efficiency R_t is constrained to be 4 b/s/Hz. For comparison, the SER curves of the precoding scheme and the equal allocation are also provided.

Au: Does BPSK = binary phase shift keying? Please spell out.

Au: Does QAM = quadratic amplitude modulation? Please spell out.

From Figure 7.9 it can be seen that in MIMO channels, a 5 dB gain can be achieved by the adaptive power and rate allocation over the equal one at the SER of 10^{-3}. When the variance of subchannels increases significantly, i.e., in distributed channels with $\eta = 500 : 100 : 20 : 1$, the performance of the equal allocation deteriorates sharply while the adaptive one still works well. A closer observation shows that in this case the adaptive power and rate allocation scheme always chooses the best antenna using 16QAM or the best two antennas using QPSK, because the degrees of freedom of the channel never exceed two. It can be also seen that the performance of the precoding scheme is significantly better than the adaptive one, which is partially attributed to the optimal transmission phase and partially to the optimal MLD receiver. Nevertheless, considering that the precoding scheme requires a large amount of feedback and is sensitive to the feedback error, the adaptive power and rate allocation scheme is still highly attractive in a DAS.

7.2.4 Long-Term Channel Statistics at the Transmitter

So far we have discussed the resource allocation schemes based on full CSI, which require the adaptation results to be updated for each channel instance. In this section, we will further show that in distributed channels, resources can be adaptively allocated based only on the *long-term channel statistics*, i.e., $\mathbf{F}$ and $\mathbf{R_r}$ in (7.2), instead of the instantaneous CSI, with only negligible performance loss.

7.2.4.1 Antenna Selection

As explained in the system model, in the downlink of DASs, the central processor usually selects the "best" m antennas for user i's data transmission. A natural question is how to optimally choose those m antennas. There have been numerous papers on antenna selection algorithms (see Section 7.1.2 for an overview). However, most of them are based on the instantaneous CSI at the transmitter. In the following we will introduce an optimal antenna selection criterion for capacity maximization assuming that only the long-term channel statistics, i.e., $\mathbf{F}$ and $\mathbf{R_r}$ in (7.2), are available.

Define the selected transmit antenna subset and selected receive antenna subset as $\mathbf{\Lambda_t}$ and $\mathbf{\Lambda_r}$, respectively, which are both unordered sets with m and n selected antennas. Let $\mathbf{R}_{\Lambda_r}$ denote the cross-correlation matrix of those n selected antennas, and $\mathbf{F}_{\Lambda_t}$ denote the large-scale fading of the m selected antennas. These matrices can be obtained by eliminating the columns and rows of the nondesired antennas from $\mathbf{R_r}$ and $\mathbf{F}$, respectively. Assume that m and n are selected to ensure that $\mathbf{R}_{\Lambda_r}$ and $\mathbf{F}_{\Lambda_t}$ are both of full rank. Now let $\tilde{\mathbf{H}}$ represent the $n \times m$ channel gain matrix between m selected transmit and n selected receive antennas. Then,

$$\tilde{\mathbf{y}} = \tilde{\mathbf{H}}\tilde{\mathbf{x}} + \tilde{\mathbf{z}} = \mathbf{R}_{\Lambda_r}^{1/2}\tilde{\mathbf{H}}_{\mathbf{w}}\mathbf{F}_{\Lambda_t}\tilde{\mathbf{x}} + \tilde{\mathbf{z}}. \tag{7.13}$$

Assume equal power allocation among those selected transmit antennas. By applying eigenvalue decomposition to $\mathbf{R}_{\Lambda_r}$, we can obtain

$$C = \log_2\det\left[\mathbf{I_n} + \frac{\rho}{m}\tilde{\mathbf{H}}\tilde{\mathbf{H}}^*\right] = \log_2\det\left[\mathbf{I_n} + \frac{\rho}{m}\hat{\mathbf{H}}_{\mathbf{w}}\mathbf{Q_t}\hat{\mathbf{H}}_{\mathbf{w}}^*\mathbf{Q_r}\right], \tag{7.14}$$

where $\mathbf{Q_r}$ is a diagonal matrix whose diagonal entries are the eigenvalues of $\mathbf{R}_{\Lambda_r}$, and $\mathbf{Q_t} = \mathbf{F}_{\Lambda_t}\mathbf{F}_{\Lambda_t}^*$. $\hat{\mathbf{H}}_{\mathbf{w}} = \mathbf{U_r^*}\tilde{\mathbf{H}}_{\mathbf{w}}$, where $\mathbf{U_r}$ is a unitary matrix whose columns are the eigenvectors of $\mathbf{R}_{\Lambda_r}$. Clearly, $\hat{\mathbf{H}}_{\mathbf{w}}^*\hat{\mathbf{H}}_{\mathbf{w}}$ has the same eigenvalues as $\tilde{\mathbf{H}}_{\mathbf{w}}^*\tilde{\mathbf{H}}_{\mathbf{w}}$.

When $m = n$, from (7.14) we have

$$C \approx m\log_2\left(\frac{\rho}{m}\right) + \log_2\det\left[\hat{\mathbf{H}}_{\mathbf{w}}\hat{\mathbf{H}}_{\mathbf{w}}^*\right] + \log_2\det[\mathbf{Q_t}] + \log_2\det[\mathbf{Q_r}] \tag{7.15}$$

at high values of ρ. From (7.15) to maximize the capacity, we should maximize the determinants of $\mathbf{Q_t}$ and $\mathbf{R}_{\Lambda_r}$. In other words, the optimal transmit (or receive) antenna set $\mathbf{\Lambda_t}$(or $\mathbf{\Lambda_r}$), in terms of capacity maximization, should be selected to maximize the determinant of the corresponding matrix $\mathbf{Q_t}$(or $\mathbf{R}_{\Lambda_r}$). When $n \neq m$, however, it is difficult to obtain a closed form of the exact capacity expression. In [43], lower and upper bounds were developed which converge to the same limit. Both bounds can be maximized according to the following antenna selection criterion.

Antenna Selection Criterion: *The optimal selected transmit antenna subset* $\mathbf{\Lambda_r^*}$ *and receive antenna subset* $\mathbf{\Lambda_t^*}$ *that maximize the capacity are given by*

$$\mathbf{\Lambda_r^*} = \underset{\mathbf{\Lambda_r}}{\text{argmax}}\ \det(\mathbf{R}_{\mathbf{\Lambda_r}}), \quad \textit{and} \quad \mathbf{\Lambda_t^*} = \underset{\mathbf{\Lambda_t}}{\text{argmax}}\ \det(\mathbf{F}_{\mathbf{\Lambda_t}}\mathbf{F}^*_{\mathbf{\Lambda_t}}). \tag{7.16}$$

The above criterion is based on the assumption that both $\mathbf{F}_{\mathbf{\Lambda_t}}\mathbf{F}^*_{\mathbf{\Lambda_t}}$ and $\mathbf{R}_{\mathbf{\Lambda_r}}$ are of full rank. For the cases when $\mathbf{F}_{\mathbf{\Lambda_t}}\mathbf{F}^*_{\mathbf{\Lambda_t}}$ and $\mathbf{R}_{\mathbf{\Lambda_r}}$ are singular, the criterion is also applicable if we substitute $\det(\mathbf{R}_{\mathbf{\Lambda_r}})$ and $\det(\mathbf{F}_{\mathbf{\Lambda_t}}\mathbf{F}^*_{\mathbf{\Lambda_t}})$ in (7.16) by $\prod_{i=1}^{rank(\mathbf{R}_{\mathbf{\Lambda_r}})} q_r^{(i)}$ and $\prod_{i=1}^{rank(\mathbf{F}_{\mathbf{\Lambda_t}}\mathbf{F}^*_{\mathbf{\Lambda_t}})} q_t^{(i)}$, respectively.

Then we can describe a selection process according to the above criterion, namely, long-term selection algorithm (LtSA). This algorithm consists of creating all possible antenna sets $\mathbf{\Lambda_t}$ (or $\mathbf{\Lambda_r}$) with m (or n) out of $\mathcal{M}$ transmit (or $\mathcal{N}$ receive) antennas. The corresponding $\det(\mathbf{F}_{\mathbf{\Lambda_t}}\mathbf{F}^*_{\mathbf{\Lambda_t}})$(or $\det(\mathbf{R}_{\mathbf{\Lambda_r}})$) are computed and the one with the best measure, as described in the criterion, is selected.

The capacity cumulative density function (cdf) curves of the LtSA in distributed channels are provided in Figure 7.10 and Figure 7.11 for $\mathcal{M} = n = 6$ with an SNR of 10 dB. Here, we only consider antenna selection at the transmitter side with m ranging from 2 to 6. For comparison, the capacity cdf results of the instantaneous selected algorithm (ISA), which is based on the exact CSI, are also presented. From Figure 7.10, the LtSA incurs only a negligible capacity loss compared to ISA. When $m = 4$ or 5, the gap between the capacity of the ISA and LtSA is so slight that the two curves overlap. With a smaller m, say, $m = 2$, a 10% outage capacity of the LtSA is only 0.5 b/s/Hz less than that of the ISA. Figure 7.11 presents the capacity comparison in a more asymmetric distributed channel, i.e., $\eta = 1000 : 500 : 200 : 100 : 50 : 1$. In this case, the LtSA can always achieve almost

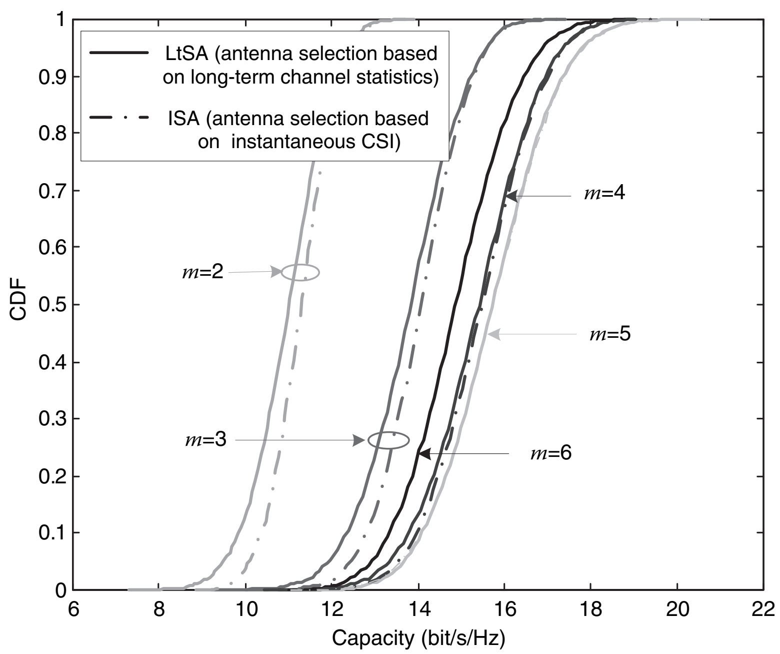

Figure 7.10 Capacity cdf Curves of LtSA and ISA in Distributed Channels With $\eta = 50 : 40 : 30 : 20 : 10 : 1$. $\mathcal{M} = n = 6$. SNR = 10 dB

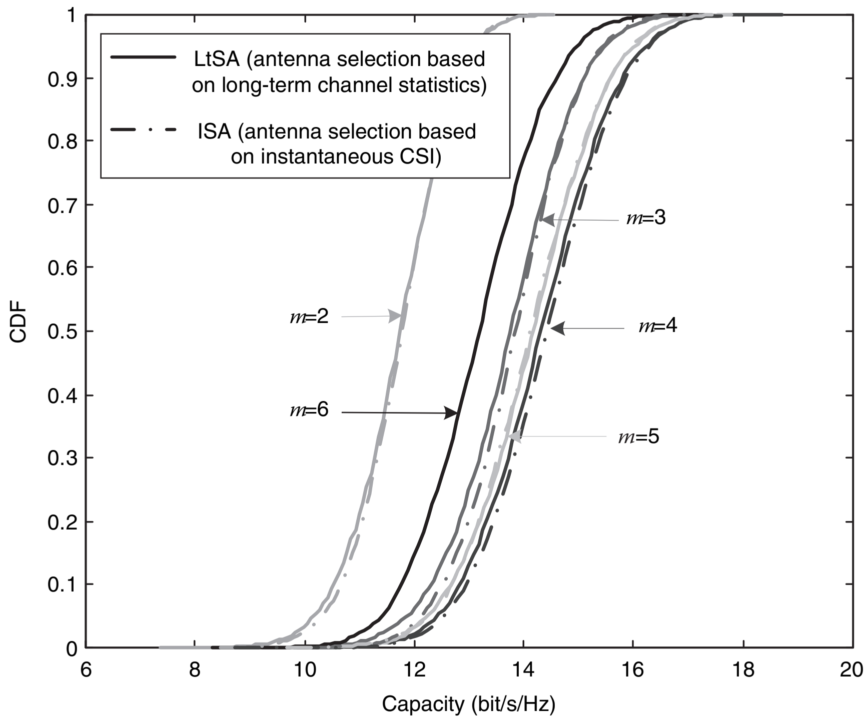

Figure 7.11 Capacity cdf Curves of LtSA and ISA in Distributed Channels With $\eta = 1000 : 500 : 200 : 100 : 50 : 1$. $\mathcal{M} = n = 6$. SNR = 10 dB

the same capacity as the ISA. As a result, we conclude that in distributed channels, antenna selection can be performed based on the long-term channel statistics instead of the instantaneous CSI with a very slight capacity loss, but significant complexity reduction.

From Figure 7.10 and Figure 7.11 it can be also seen that in distributed channels, transmit antenna selection can bring significant capacity gains. In Figure 7.10, the highest capacity is achieved when $m = 5$ instead of 6. In distributed channels, there are usually insufficient degrees of freedom of the channel. By allocating the transmit power to only the "good" subchannels, the optimal transmit antenna selection actually performs like a water-filling strategy. In Figure 7.11, the number of degrees of freedom of the channel further decreases to around 4. Therefore, choosing the best 4 transmit antennas can achieve the highest capacity.

7.2.4.2 Adaptive Power Adaptation

In Section 7.2.4.1, we have shown how to choose m antennas for downlink transmission based on the long-term channel statistics. In this section, we will further present an adaptive power allocation scheme which also requires only the information of $\mathbf{F}$ instead of the full CSI.

In particular, recall that for a channel model given by (7.2), the mutual information can be written as

$$I(\mathbf{Q}) = \log_2 \det\left(\mathbf{I_n} + \frac{1}{\sigma^2}\mathbf{H_w}\mathbf{F}\mathbf{Q}\mathbf{F}^*\mathbf{H_w^*}\right) \tag{7.17}$$

by assuming that the receive antennas at the user are uncorrelated, i.e., $\mathbf{R_r} = \mathbf{I_n}$, and $\mathbf{Q} = \mathrm{E}(\mathbf{xx}^*)$ is the transmit covariance matrix. Let $\boldsymbol{\Omega} = (1/\sigma^2)\mathbf{QF}^*\mathbf{H}_\mathbf{w}^*\mathbf{H_w F}$. We have

$$\mathrm{E}\{I(\mathbf{Q})\} \le \mathrm{E}\left\{\log_2 \prod_{i=1}^{m}(1+\Omega_{ii})\right\} \le \prod_{i=1}^{m}\log_2 \mathrm{E}\{1+\Omega_{ii}\} = \prod_{i=1}^{m}\log_2\left(1+\frac{nP_i}{\sigma^2}\|f_i\|^2\right). \quad (7.18)$$

The suboptimal power allocation scheme that maximizes the upper bound in (7.18) can be solved using the water-filling principle [87], i.e.,

$$P_i = \left(\mu - \frac{\sigma^2}{n\|f_i\|^2}\right)^+, \quad (7.19)$$

$i = 1, \ldots, m$, where μ is chosen to satisfy $\sum_{i=1}^{m} P_i = P_t$.

Clearly the power allocation given by (7.19) requires only the long-term channel statistics, i.e., $\|f_i\|^2$, $i = 1, \ldots, m$. Figure 7.12 provides the capacity cdf results of the adaptive power allocation in distributed channels with $\eta = 500 : 100 : 20 : 1$ and SNR = 10dB. Despite a slight capacity loss, say, 0.3 b/s/Hz at 10% outage, compared to the optimal water-filling strategy, significant capacity gains can be achieved over the equal power allocation. This performance degradation becomes negligible in a more asymmetric channel. As shown in Figure 7.13, the adaptive power allocation achieves almost the same capacity as the optimal water-filling strategy in distributed channels with $\eta = 1000 : 100 : 10 : 1$.

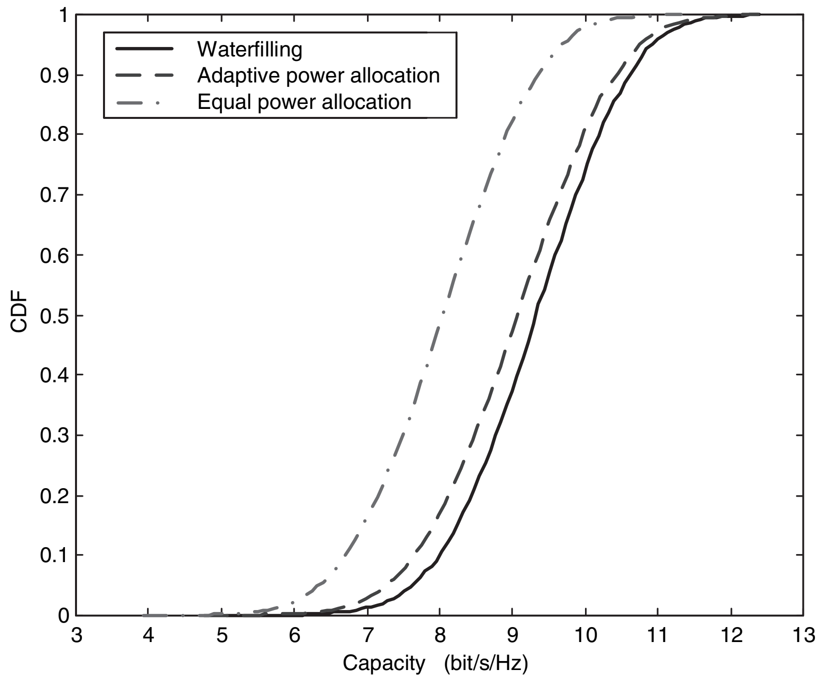

Figure 7.12 Capacity cdf Curves of Waterfilling, Adaptive Power Allocation and Equal Power Allocation in Distributed Channels With $\eta = 500 : 100 : 20 : 1$ and SNR = 10 dB. $m = n = 4$

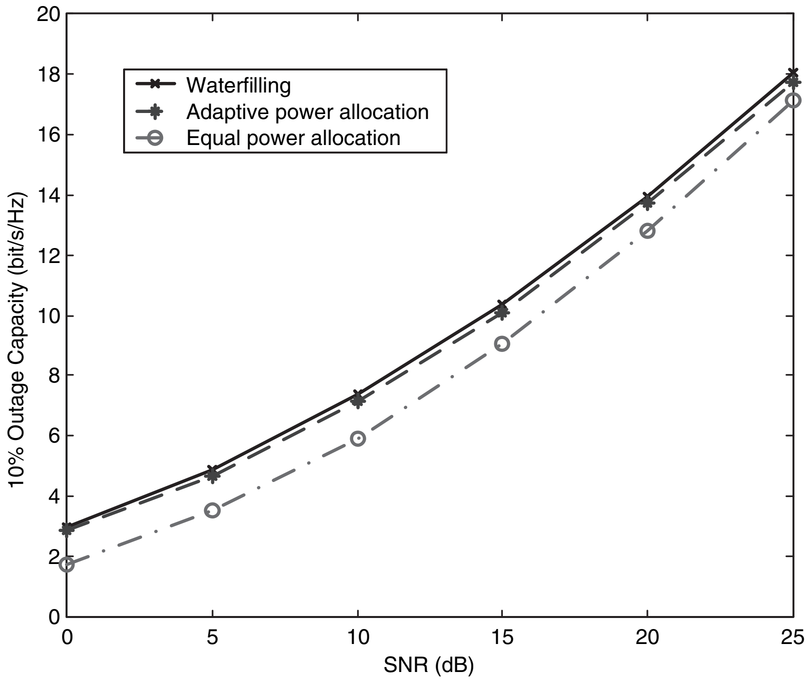

Figure 7.13 10% Outage Capacity Comparison of Waterfilling, Adaptive Power Allocation and Equal Power Allocation in Distributed Channels With $\eta = 1000 : 100 : 10 : 1$ and SNR = 10 dB. $m = n = 4$

7.2.5 Summary

In this section, we discussed the resource allocation strategies in distributed channels. The information-theoretic results demonstrated that resource allocation is indispensable to DASs due to the large differences among subchannels. Transmit precoding and the per-antenna rate and power allocation schemes were introduced, which adaptively allocate resources among the remote antennas according to the full CSI. Superior performance has been shown in distributed channels, where equal allocation suffers from severe performance degradation. We further showed that in a DAS, resource allocation can be performed based on only the long-term channel statistics with a negligible capacity loss compared to the ones with full CSI.

Performance evaluation of the above schemes in more practical scenarios, i.e., with the effect of Doppler spread and frequency selectivity, still needs further investigation. Additionally, a two-dimensional resource allocation would be interesting if OFDM is adopted. The cross-layer joint optimization with some link layer techniques such as ARQ is also an attractive issue.

7.3 MULTI-USER RESOURCE ALLOCATION IN DASs

In Section 7.2, we introduced the adaptive resource allocation strategies in the context of a single-user scenario. In this section, we will turn to a network of multiple users and study the optimal multi-user resource allocation strategy for DASs.

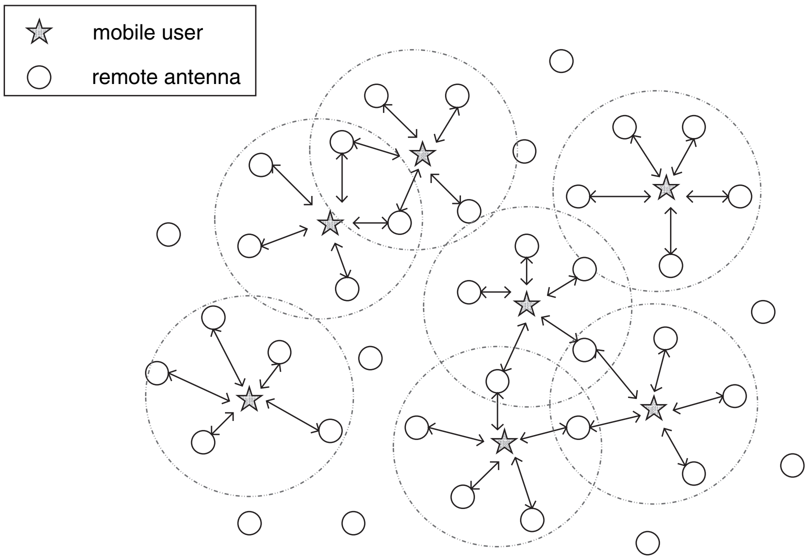

Figure 7.14 A Multiuser DAS Network. The Circle Represents the Virtual Cell for Each User

In a multi-user DAS network, each user has its own virtual cell and different remote antennas may transmit to (or receive from) different user sets. As shown in Figure 7.14, instead of a one point to multipoint (in downlink) or multipoint to one point (in uplink) channel, here both downlink and uplink resource allocation should be performed based on a multipoint-to-multipoint channel, which is much more complex than the traditional resource allocation in cellular systems. It can be also seen that in a DAS, each remote antenna connects to only a small set of users (instead of the whole user set in cellular systems). Likewise, each user only receives signals from its own virtual cell. This can actually bring significant performance gains, as we will show later. However, it also requires a more complicated resource allocation strategy.

In particular, in a multi-user DAS network, the first issue to be addressed is interference management. The signals transmitted to and from different users need to be distinguished using code division, frequency division, time division, or space division so as to avoid strong interference. Then based on some specific multiplexing/multiple-access scheme, the system resources, such as power, antennas, codes, etc., can be adaptively allocated among multiple users according to their channel states and QoS requirements. In Section 7.3.1, we will focus on a CDMA-based DAS system, i.e., transmit signals to and from users are assigned with different spreading codes. The optimal power allocation strategy will be introduced for the downlink transmission. In Section 7.3.2 opportunistic transmission will be applied to a DAS and the fairness issue will be also addressed.

7.3.1 CDMA-Based Resource Allocation

Au: What is PN? Please spell out.

Let us consider a downlink CDMA-based DAS where the transmit signal to each user is a PN code modulated bit stream with a spreading factor (or processing gain) of ϕ. Assume that each user has only one antenna and maximum ratio combining (MRC) is adopted. The power of the pilot channel, P, is equal to the total allocated power of each user. As explained previously, in DASs each signal from remote antennas to a user propagates through a distinct path and arrives at the user with independent fading. Therefore, some form of resource allocation is required. In the following, we focus on the optimal power allocation.

Assume that the power allocated to user k from antenna $l_{k,i}$ is $\varpi^2_{k,l_{k,i}} \cdot P$, where $l_{k,i}$ and $\varpi_{k,l_{k,i}}$ represent the i-th antenna in user k's virtual cell and its corresponding weight, respectively. Clearly, we have $\forall k$, $\sum_{i=0}^{m-1} \varpi^2_{k,l_{k,i}} = 1$. Then, the received signal of user 0 is given by

$$x(t) = \sum_{i=0}^{\mathcal{M}-1} \sum_{k=0}^{K_i-1} \psi_k \sqrt{P} \varpi_{k,i} \gamma_{0,i} b_k \left(\lfloor \frac{t-\tau_{0,i}}{T} \rfloor \right) c_k(t-\tau_{0,i})$$
$$+ \sum_{i=0}^{\mathcal{M}-1} \sqrt{P} \gamma_{0,i} b'_i \left(\lfloor \frac{t-\tau_{0,i}}{T} \rfloor \right) c'_i(t-\tau_{0,i}) + n(t), \tag{7.20}$$

where the first and second items represent the data and pilot signals received by user 0, respectively. In particular, ψ_k is the voice activity variable with an activity factor of ν. $b_k(\cdot)$ denotes the transmitted bit of user k in duration T and $c_k(\cdot)$ is the spreading code used by user k. $b'_i(\cdot)$ and $c'_i(\cdot)$ represent the bit and the spreading code used by the pilot of antenna i. K_i is the number of users that communicate with antenna i. $\gamma_{0,i}$ represents the channel gain between user 0 and antenna i, which includes the effect of both the large-scale fading and the small-scale fading. $\tau_{0,i}$ is the propagation delay from antenna i to user 0, $i = 0, \ldots, \mathcal{M}-1$. By regarding the signals from different antennas in user 0's virtual cell to user 0 as multiple paths of the desired signal, we can separate the paths with a RAKE receiver. The E_b/I_0 at the receiver can then be derived as [83]

$$\frac{E_b}{I_0} = \sum_{j=0}^{m-1} \left(\frac{E_b}{I_0} \right)_j = \frac{\phi \cdot \sum_{j=0}^{m-1} \varpi^2_{0,j} \|\gamma_{0,j}\|^2}{(\nu\mathcal{K}/\mathcal{M}+1) \sum_{i=0}^{\mathcal{M}-1} \|\gamma_{0,i}\|^2}. \tag{7.21}$$

It can be easily proved that the optimal weight vector to maximize (7.21) is given by

$$\varpi_{0,i} = \begin{cases} 1, & i = \operatorname{argmax} \left\|\gamma_{0,j}\right\|^2 \\ 0, & \text{otherwise} \end{cases} \tag{7.22}$$

$i = 0, \ldots, m-1$. Obviously this is the well-known selective transmission scheme, i.e., the transmit power is allocated to the antenna with the best channel. Figure 7.15 shows the curves of outage probability versus the number of users per antenna. Here we consider a three-tier hexagonal model, i.e., $\mathcal{M} = 37$. Both the effect of path loss and shadow fading are included with the path loss exponent $\alpha = 4$ and the standard variance of the log-normal shadowing variable $\sigma_s = 8$ dB. Additionally, the voice activity factor $\nu = 0.375$ and the spreading factor $\phi = 127$. Assume adequate performance (i.e., BER $\leq 10^{-3}$) is achieved with $E_b/I_0 = 7$ dB. Figure 7.15 shows that the downlink capacity[5] decreases rapidly as m increases. This is because the received signal power at the user is the sum

[5] Here the "downlink capacity" is defined as the number of users that can be supported by the system at a certain outage probability. For example, from Figure 7.15 it can be seen that when $m = 1$, at an outage probability of 10^{-3}, 18 users can be supported. This number drops to 10 when m increases to 4.

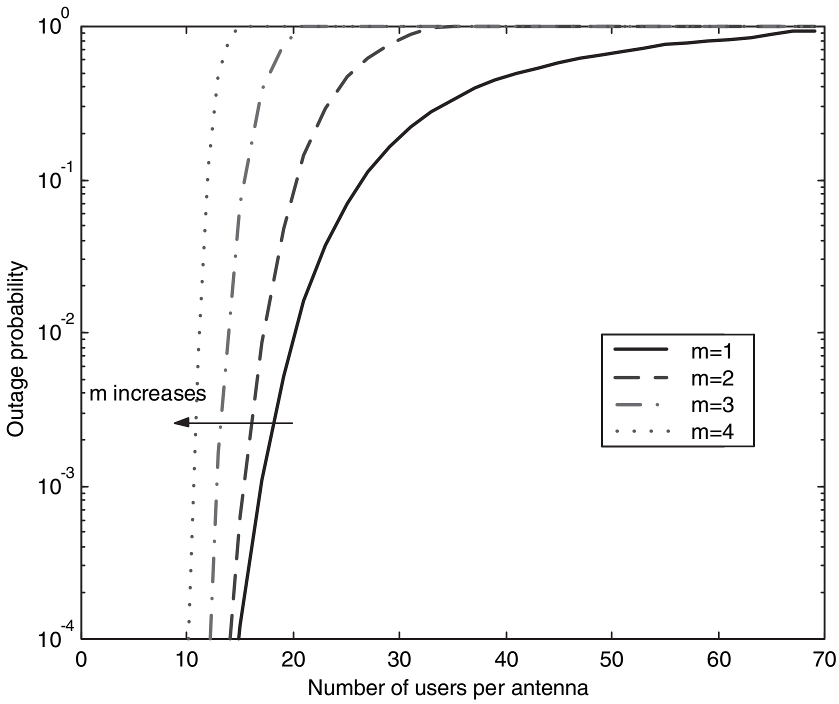

Figure 7.15 Outage Probability Vs. the Number of Users Per Antenna in a CDMA-Based DAS. Selective Transmission ($m = 1$) Performs the Best

of the power received from each involved antenna. By assuming that the total power allocated to each user is a constant, which implies that the total interference is fixed, it is clear that distributing the transmit power among several antennas will cause a decrease of the received SIR. Therefore, selective power allocation performs the best.

The above conclusion is drawn based on the assumption that only the optimal transmit power allocation is performed. If the phases of the transmit signals can be also jointly adjusted, the downlink capacity can be dramatically improved with an increase of m.

In particular, assume that the desired signals from the antennas in user 0's virtual cell are jointly adjusted so that they arrive at user 0 in phase and simultaneously. The received E_b/I_0 of user 0 can then be derived as

$$\frac{E_b}{I_0} \approx \frac{\phi\left(\sum_{j=0}^{m-1} \varpi_{0,j}\|\gamma_{0,j}\|\right)^2}{(\nu\mathcal{K}/\mathcal{M}+1)\sum_{i=0}^{\mathcal{M}-1}\|\gamma_{0,i}\|^2}. \tag{7.23}$$

It can be proved that when $\varpi_{0,i} = \frac{\|\gamma_{0,i}\|}{\sqrt{\sum_{j=0}^{m-1}\|\gamma_{0,j}\|^2}}$, i=0, ..., $m-1$, the received E_b/I_0 is maximized and given by

$$E_b/I_0 = \frac{\phi}{(\nu\mathcal{K}/\mathcal{M}+1)} \cdot \frac{\sum_{i=0}^{m-1}\|\gamma_{0,i}\|^2}{\sum_{i=0}^{\mathcal{M}-1}\|\gamma_{0,i}\|^2}. \tag{7.24}$$

Equation (7.24) shows that E_b/I_0 will increase as m increases. Here the power weight of each antenna is proportional to the channel gain. Therefore, it is also called

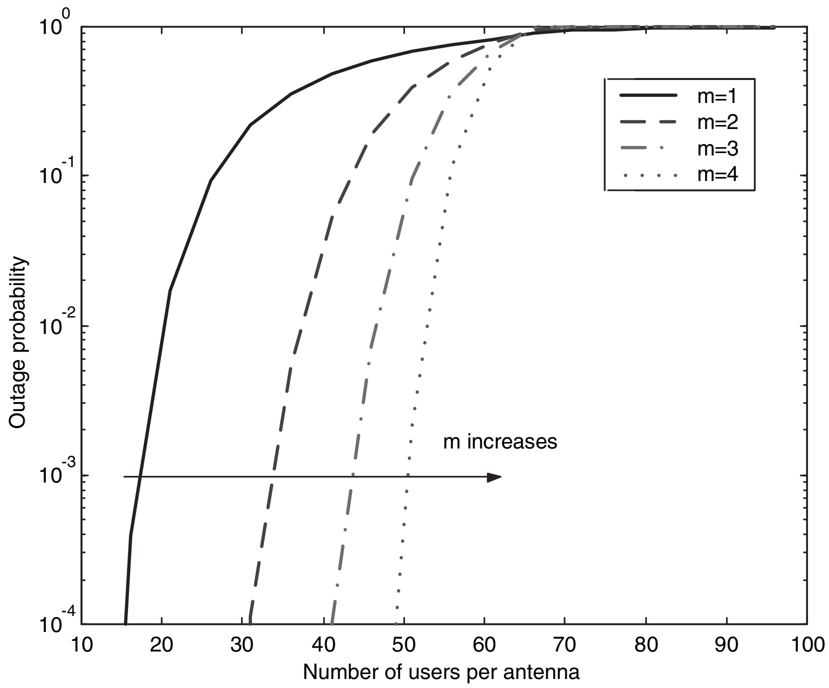

Figure 7.16 Outage Probability Vs. the Number of Users Per Antenna in a CDMA-Based DAS With Maximum Ratio Transmission

maximum ratio transmission. As shown in Figure 7.16, a substantial capacity gain can be achieved with the increase of m. Nevertheless, the maximum ratio transmission requires the transmit power and phases to be jointly adjusted, according to the instantaneous CSI of users, which will incur a huge amount of feedback information and is quite sensitive to the feedback errors. This greatly restricts its application in fast fading channels.

So far we have studied the optimal power allocation strategy in a CDMA-based DAS network. It is shown that if the transmit phases are not jointly adjusted, selective transmission, i.e., to put all the transmit power on the best remote antenna, is the optimal. Otherwise, maximum ratio transmission achieves the highest capacity where the transmit power of each antenna is proportional to its channel gain. Actually, the selective transmission strategy follows the water-filling principle. With one antenna at the mobile user, only one degree of freedom of the channel is provided, no matter how many remote antennas are included. Therefore, the water-filling strategy in this case suggests that the transmission power should always be allocated to the antenna with the best channel. On the other hand, the maximum ratio transmission is reminiscent of beamforming, although there are no real beams towards users.

7.3.2 Opportunistic Transmission

In Section 7.3.1, we assume that each user is assigned with equal transmit power P, and a spreading code with the same spreading factor ϕ. In this way the system resources are equally allocated to users and the optimal power allocation is performed among multiple

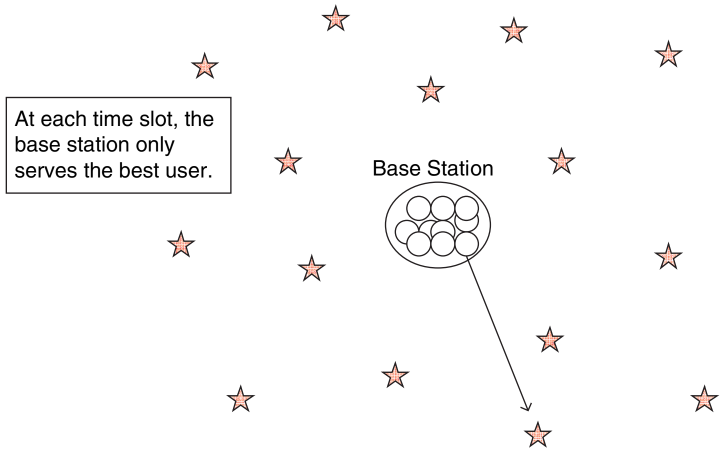

Figure 7.17 Opportunistic Transmission in Cellular Systems

antennas of each user's virtual cell. In this subsection, we will further address how to efficiently and fairly allocate resources among multiple users.

Opportunistic transmission has been proposed in [71], where in each time slot the system resources are allocated only to the user with the highest instantaneous channel gain. As illustrated in Figure 7.17, the base station tracks the channel variations of all users and schedules transmissions to the best one. Because users are expected to experience independent fading, opportunistic transmission can adaptively exploit the time-varying channel conditions of users and achieve the *multi-user diversity* gain; the network throughput will increase with the number of users [72].

Despite the substantial throughput gain brought by multi-user diversity, opportunistic transmission may not work well when multiple antennas are employed at base stations [72,88]. As we know, multi-user diversity gain has its root in the independent fluctuation of channels of different users, which in some extent exploits the channel fading. However, the conventional multi-antenna transmission techniques aiming at maximizing the diversity gain, i.e., space–time coding, beamforming, etc., are designed to counteract the adverse effect of fading. Therefore, by decreasing the channel fluctuations of different users, opportunistic transmission with multiple antennas may lead to an even lower throughput than the one in the single-antenna scenario.[6]

In the above work, only the channel fluctuations introduced by small-scale fading are taken into account. In cellular systems, power control is usually adopted to counteract the large-scale fading, such as path loss and log-normal shadowing. Otherwise, the users close to the base station will always occupy the system resources and severely impair the performance of the users far away from the base station.[7] In a DAS, however, the large-scale fading can be exploited to *amplify* the fluctuations.

[6] To address this issue, [75] proposed to induce large channel fluctuations by using multiple antennas, which is called *opportunistic beamforming using dumb antennas*. In this case, the phases and power allocated to transmit antennas randomly vary and at any time the transmission is scheduled to the user, which is currently closest to the beam. In this way the rate of channel fluctuations is artificially increased.

[7] Viswanath et al. [75] proposed a proportional fair opportunistic scheduler to avoid such cases, where data is transmitted to a user when it hits its own "peak." We will discuss it in detail later.

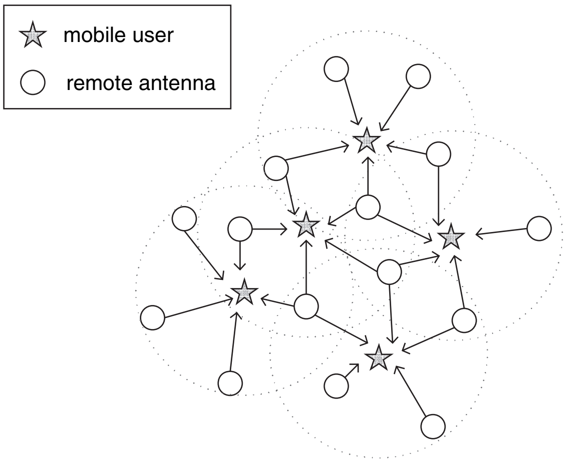

Figure 7.18 Each User Receives Independent Fading Signals from the *m* Remote Antennas of Its Virtual Cell

We take the example of downlink transmissions. As shown in Figure 7.18, each user receives independent fading signals from the m remote antennas of its virtual cell. Assume only one antenna is employed at the mobile user. From (7.2) we know that for user k, the m-dimension channel vector is given by $\mathbf{h}_k = [f_{k,1}\gamma_{k,1}, \ldots, f_{k,m}\gamma_{k,m}]$, where $f_{k,i}$ and $\gamma_{k,i}$ represent the large-scale fading and small-scale Rayleigh fading of the channel from user k to the i-th remote antenna, respectively. In cellular systems, antennas are colocated at the base station and the large-scale fading has been counteracted. Therefore, we have $\| f_{k,i}\| = 1$, for any $k = 1, \ldots, \mathcal{K}$, and $i = 1, \ldots, m$.

Let $\varphi_k = \mathbf{h}_k\mathbf{h}_k^*$. The variance of the sum channel gain is then given by

$$\mathrm{var}(\varphi_k) = \mathrm{var}(\|\gamma_{k,i}\|^2) \sum_{i=1}^{m} \| f_{k,i}\|^4. \tag{7.25}$$

Equation (7.25) shows that when $\| f_{k,1}\| = \cdots = \| f_{k,m}\| = 1$, φ_k has the minimum variance. By introducing different levels of large-scale fading among the different paths, the channel fluctuation will be boosted in distributed channels. Figure 7.19 presents the fluctuations of the sum channel gain φ_k in distributed channels with $\eta = 500 : 100 : 20 : 1$ and multiple-input single-output (MISO) channels (multiple antennas at the base station and one antenna at the mobile user) with $m = 4$. Obviously a much larger channel fluctuation is observed in distributed channels.

It should be noticed that the channel fluctuation is *amplified* instead of *sped up* in distributed channels, because the large-scale fading does not determine the time-varying rate of the channel. Therefore, in DASs, it is still possible that some users with good channels always occupy the system resources while others have no chances to transmit at all (for example, in a slow fading environment). To meet the fairness constraints, a proportional fair opportunistic scheduler has been proposed in [75] where the user with the largest fraction of current channel data rate to its average throughput is scheduled in each time slot, and the average throughput is updated using the following low-pass

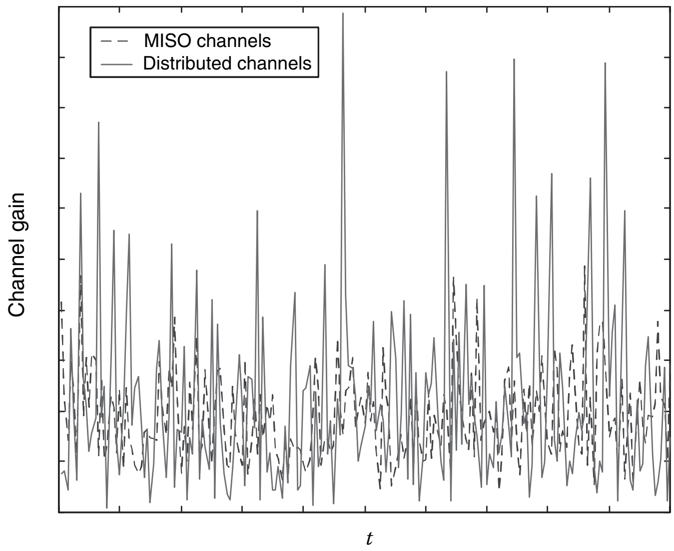

Figure 7.19 Channel Fluctuations in MISO Channels and Distributed Channels. $m = 4$ and $\eta = 500 : 100 : 20 : 1$

filter:

$$T_k[i+1] = \begin{cases} \left(1 - \frac{1}{t_c}\right) T_k[i] + \frac{1}{t_c} R_k[i] & k = k^* \\ \left(1 - \frac{1}{t_c}\right) T_k[i] & k \neq k^* \end{cases}, \tag{7.26}$$

where $R_k[i]$ is the current channel data rate of user k in time slot i. Clearly, if the scheduling time scale t_c is much larger than the correlation time scale of the channel, each user's throughput converges to the same quantity. Therefore, this scheduling algorithm can guarantee fairness in the long term.

In a DAS, the fairness performance can be further improved by scheduling multiple users simultaneously. An important characteristic of a DAS is that each user connects to only a subset of the remote antennas, i.e., the ones in its virtual cell, instead of all the antennas in the system. Therefore, the whole network usually can be decomposed into several disjoint subnetworks. As shown in Figure 7.20, assume the active user set includes users 1, 2, 4, 5, 7, 8 and 10. Obviously they can be divided into 3 subsets: {1, 2, 10}, {4, 5} and {7, 8}. The users in the same subset share part of the antennas while there are no common antennas shared by different user subsets.[8] In this case, different user subsets can be scheduled at the same time, thanks to a natural frequency reuse pattern. In cellular systems, multiple users can also be scheduled simultaneously [90]; however, either multiple spreading codes or subcarriers are required to differentiate those users, which leads to a lower spectral efficiency.

[8] Given an arbitrary active user set, the network can be decomposed into x disjoint subnetworks, $1 \leq x \leq \tilde{k}$, where $\tilde{k}$ is the number of active users. Obviously x depends on the network topology. A *network decomposition* methodology has been proposed in [89]. A similar idea can be applied to the distributed antenna case.

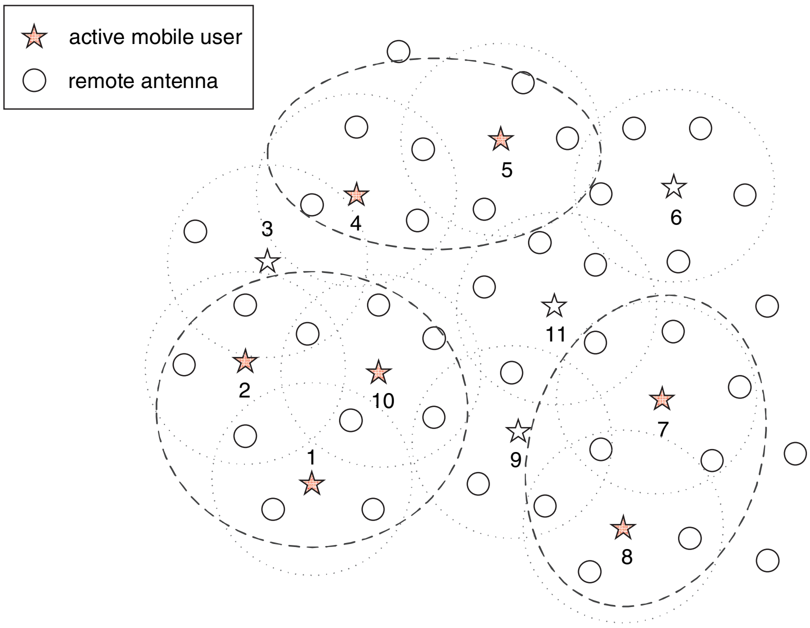

Figure 7.20 In DAS, the Active User Set can be Usually Decomposed into Several Disjoint Subsets. Multiple Users can be Scheduled at the Same Time

7.3.3 Summary

In this section, we considered the resource allocation in a multi-user DAS network. We first studied the optimal power allocation strategy for each user in a CDMA-based DAS, and then focused on efficient and fair resource allocation among multiple users. We took the example of opportunistic transmission and showed that a DAS has a great potential to fully exploit the multi-user diversity gain, and at the same time to achieve a good balance between efficiency and fairness.

In a DAS, each remote antenna connects to only a small set of users and each user only receives signals from its own virtual cell. This can bring huge performance gain, i.e., better frequency reuse, larger channel fluctuation, better interference management, and less transmit power; however, it also raises a great challenge: how to perform the resource allocation with a reasonable level of complexity, for example, in a distributed way. In addition, to perform a fair and efficient resource allocation among users, not only the channel state information but the users' QoS requirements need to be taken into consideration. A comprehensive cross-layer model for DASs would be helpful for jointly optimizing the resource allocation.

7.4 CONCLUSION

This chapter studied the optimal resource allocation strategies for DAS networks. In contrast to MIMO systems where resource allocation is usually conducted as performance enhancement, in DASs, resources must be allocated adaptively to the channel states due to the large differences among subchannels. Equal allocation will lead to severe performance degradation. Fortunately, only long-term channel statistics are required to perform the adaptive resource allocation. The resource allocation strategies in a multi-user scenario were also checked, and a DAS is able to fully exploit the multi-user diversity gain and achieve a good tradeoff between efficiency and fairness.

There are still quite a lot of open issues in this field. For example, to perform the proposed resource allocation strategies in practical scenarios, the effect of Doppler spread and frequency selectivity of the channels as well as synchronization and feedback errors needs to be taken into consideration. Furthermore, distributed algorithms have to be developed to realize the multi-user resource allocation in a large scale network, while at the same time central control is also required to balance the efficiency and fairness. Finally, the cross-layer optimization with link layer techniques such as ARQ or application layer requirements would be highly desired.

REFERENCES

[1] A.J. Goldsmith and S.G. Chua, “Variable-rate variable-power MQAM for fading channels,” *IEEE Trans. Commn.*, vol. 45, pp. 1218–1230, Oct. 1997.

[2] S.J. Oh, D. Zhang, and K.M. Wasserman, “Optimal resource allocation in multiservice CDMA networks,” *IEEE Trans. Wireless Commn.*, vol. 2, pp. 811–821, July 2003.

[3] J.K. Cavers, “Variable-rate transmission for Rayleigh fading channels,” *IEEE Trans. Commn.*, vol. 20, pp. 15–22, Feb. 1972.

[4] B. Vucetic, “An adaptive coding scheme for time-varying channels,” *IEEE Trans. Commn.*, vol. 39, pp. 653–663, May 1991.

[5] W.T. Webb and R. Steele, “Variable rate QAM for mobile radio,” *IEEE Trans. Commn.*, vol. 43, pp. 2223–2230, July 1995.

[6] A.J. Goldsmith and P.P. Varaiya, “Capacity of fading channels with channel side information,” *IEEE Trans. Inform. Theory*, vol. 43, pp. 1986–1992, Nov. 1997.

[7] D.N. Tse and S.V. Hanly, “Multiple-access fading channels – part I: polymatroidal structure, optimal resource allocation and throughput capacities,” *IEEE Trans. Inform. Theory*, vol. 44, pp. 2796–2815, Nov. 1998.

[8] S.V. Hanly and D.N. Tse, “Multiple-access fading channels – part II: delay-limited capacities,” *IEEE Trans. Inform. Theory*, vol. 44, pp. 2816–2831, Nov. 1998.

[9] C. Kose and D.L. Goeckel, “On power adaptation in adaptive signaling systems,” *IEEE Trans. Commn.*, vol. 48, pp. 1769–1773, Nov. 2000.

[10] A.J. Goldsmith and S. Chua, “Adaptive coded modulation for fading channels,” *IEEE Trans. Commn.*, vol. 46, pp. 595–602, May 1998.

[11] T. Ue, S. Sampei, N. Morinaga, and K. Hamaguchi, “Symbol rate and modulation level-controlled adaptive modulation/TDMA/TDD system for high-bit-rate wireless data transmission,” *IEEE Trans. Veh. Technol.*, vol. 47, pp. 1134–1147, Nov. 1998.

[12] M.S. Alouini and A.J. Goldsmith, “Adaptive modulation over Nakagami fading channels,” *Kluwer J. Wireless Commn.*, vol. 13, pp. 119–143, May 2000.

[13] K.J. Hole, H. Holm, and G.E. Oien, “Adaptive multidimensional coded modulation over flat fading channels,” *IEEE J. Select. Areas Commn.*, vol. 18, pp. 1153–1158, July 2000.

[14] M.B. Pursley and J.M. Shea, “Adaptive nonuniform phase-shift-key modulation for multimedia traffic in wireless networks,” *IEEE J. Select. Areas Commn.*, vol. 18, pp. 1394–1407, Aug. 2000.

[15] S.T. Chung and A. Goldsmith, “Degrees of freedom in adaptive modulation: a unified view,” *IEEE Trans. Commn.*, vol. 49, pp. 1561–1571, Sept. 2001.

Au: Author(s) needed.

[16] *Physical Layer Aspects of UTRA High Speed Downlink Packet Access (Release 4)*, 3GPP TR 25.848 V4.0.0, 2001.

Au: Author(s) needed.

[17] *Physical Layer Standard for CDMA 2000 Spread Spectrum Systems*, 3GPP2 C.S0002-0 Ver. 1.0, 1999.

[18] *IEEE Standard 802.16 Working Group, IEEE Standard for Local and Metropolitan Area Networks Part 16: Air Interface for Fixed Broadband Wireless Access Systems*, 2002.

[19] Q. Liu, S. Zhou, and G.B. Giannakis, "Cross-layer combining of adaptive modulation and coding with truncated ARQ over wireless links," *IEEE Trans. Wireless Commn.*, vol. 3, no. 5, pp. 1746–1755, Sept. 2004.

[20] Q. Liu, S. Zhou, and G.B. Giannakis, "Queuing with adaptive modulation and coding over wireless links: cross-layer analysis and design," *IEEE Trans. Wireless Commn.*, vol. 4, pp. 1142–1153, May 2005.

[21] L. Dai and K.B. Letaief, "Throughput maximization of ad-hoc wireless networks using adaptive cooperative diversity and truncated ARQ," submitted to *IEEE Trans. Commn.*, (http://www.ee.ust.hk/∼eedailin/publications.htm)

[22] E. Telatar, "Capacity of multi-antenna Gaussian channels," *AT&T Bell Labs Internal Tech. Memo*, June 1995.

[23] G.J. Foschini and M.J. Gans, "On limits of wireless communications in a fading environment when using multiple antennas," *Wireless Pers. Commn.*, vol. 6, pp. 311–335, Mar. 1998.

[24] D.J. Love, R.W. Heath Jr, and T. Strohmer, "Grassmannian beamforming for multiple-input multiple-output wireless systems," *IEEE Trans. Inf. Theory*, vol. 49, pp. 2735–2747, Oct. 2003.

[25] K.K. Mukkavilli, A. Sabharwal, E. Erkip, and B. Aazhing, "On beamforming with finite rate feedback in multiple antenna systems," *IEEE Trans. Inf. Theory*, vol. 49, pp. 2562–2579, Oct. 2003.

[26] S. Zhou, W. Wang, and G.B. Giannakis, "Quantifying the power loss when transmit beamforming relies on finite-rate feedback," *IEEE Trans. Wireless Commn.*, vol. 4, pp. 1948–1957, July 2005.

[27] D.J. Love and R.W. Heath Jr, "Limited feedback unitary precoding for spatial multiplexing systems," *IEEE Trans. Inf. Theory*, vol. 51, pp. 2967–2976, Aug. 2005.

[28] S.T. Chung, A. Lozano, and H.C. Huang, "Approaching eigenmode BLAST channel capacity using V-BLAST with rate and power feedback," in *Proc. IEEE VTC'01-Fall*, vol. 2, pp. 915–919, Oct. 2001.

[29] S.T. Chung, A. Lozano, and H.C. Huang, "Low complexity algorithm for rate quantization in extended V-BLAST," in *Proc. IEEE VTC'01-Fall*, Atlantic City, NJ, vol. 2, pp. 910–914, Oct. 2001.

[30] S. Catreux, P.F. Driessen, and L. J. Greestein, "Data throughputs using multiple-input multiple-output (MIMO) techniques in a noise-limited cellular environment," *IEEE Trans. Wireless Commn.*, vol. 1, pp. 226–235, Apr. 2002.

[31] H. Zhuang, L. Dai, S. Zhou, and Y. Yao, "Low complexity per-antenna rate and power control approach for closed-loop V-BLAST," *IEEE Trans. Commn.*, vol. 51, pp. 1783–1787, Nov. 2003.

[32] Z. Zhou, B. Vucetic, M. Dohler, and Y. Li, "MIMO systems with adaptive modulation," *IEEE Trans. Veh. Technol.*, vol. 54, pp. 1828–1842, Sept. 2005.

[33] A.F. Molisch, M.Z. Win, and J.H. Winters, "Reduced-complexing multiple transmit/receive antenna systems," *IEEE Trans. on Signal Processing*, vol. 51, no. 11, pp. 2729–2738, Nov. 2003.

[34] R.W. Heath Jr. and A. Paulraj, "Antenna selection for spatial multiplexing systems based on minimum error rate," in *Proc. ICC'01*, Helsink: Finland, vol. 7, pp. 2276–2280, June 2001.

[35] X.N. Zeng and A. Ghrayeb, "Performance bounds for space-time block codes with receive antenna selection," *IEEE Trans. Inf. Theory*, vol. 50, no. 9, pp. 2130–2137, Sept. 2004.

[36] A. Ghrayeb and T.M. Duman, "Performance analysis of MIMO systems with antenna selection over quasi-static fading channels," *IEEE Trans. Veh. Technol.*, vol. 52, no. 2, pp. 281–288, Mar. 2003.

Au: Author(s) needed.

Au: Submission status update needed

Au: Submission status update needed

[37] I. Bahceci, T.M. Duman, and Y. Altunbasak, "Antenna selection for multiple-antenna transmission systems: performance analysis and code construction," *IEEE Trans. Inf. Theory*, vol. 49, no. 10, pp. 2669–2681, Oct. 2003.
[38] I. Berenguer and X. Wang, "MIMO antenna selection with lattice-reduction-aided linear receivers," *IEEE Trans. Veh. Technol.*, vol. 53, no. 5, pp. 1289–1302, Sept. 2004.
[39] D. Gore, R. Heath and A. Paulraj, "Statistical antenna selection for spatial multiplexing systems," in *Proc. ICC'02*, New York, pp. 450–454, May 2002.
[40] D.A. Gore and A.J. Paulraj, "MIMO antenna subset selection with space-time coding," *IEEE Trans. Signal Processing*, vol. 50, no. 10, pp. 2580–2588, Oct. 2002.
[41] A. Molisch, M. Win, and J. Winters, "Capacity of MIMO systems with antenna selection," in *Proc. ICC'01*, Helsinki, Finland, pp. 570–574, 2001.
[42] A. Gorokhov, D.A. Gore, and A.J. Paulraj, "Receive antenna selection for MIMO flat fading channels: theory and algorithms," *IEEE Trans. Inf. Theory*, vol. 49, no. 10, pp. 2687–2696, Oct. 2003.
[43] L. Dai, S. Sfar, and K.B. Letaief, "Optimal antenna selection based on capacity maximization for MIMO systems in correlated channels," *IEEE Trans. Commn.*, vol. 54, no. 3, pp. 563–573, Mar. 2006.
[44] K.K Wong, R.D. Murch, and K.B. Letaief, "A joint-channel diagonalization for multiuser MIMO antenna systems," *IEEE Trans. Wireless Commn.*, vol. 2, pp. 773–786, July 2003.
[45] H. Dai, A.F. Molisch, and H.V. Poor, "Downlink capacity of interference-limited MIMO systems with joint detection," *IEEE Trans. Wireless Commn.*, vol. 3, pp. 442–453, Mar. 2004.
[46] C. Wang and R.D. Murch, "Adaptive cross-layer resource allocation for downlink multi-user MIMO wireless system," in *Proc. IEEE VTC'05-Spring*, Stockholm, Sweden, vol. 3, pp. 1682–1632, June 2005.
[47] L.J. Cimini, Jr., "Analysis and simulation of a digital mobile channel using orthogonal frequency division multiplexing," *IEEE Trans. Commn.*, vol. 33, pp. 665–675, July 1995.
[48] A. Czylwik, "Adaptive OFDM for wideband radio channels," in *Proc. IEEE Globecom'96*, London, pp. 713–718, Nov. 1996.
[49] T. Keller and L. Hanzo, "Adaptive modulation techniques for duplex OFDM transmission," *IEEE Trans. Veh. Technol.*, vol. 49, pp. 1893–1906, Sept. 2000.
[50] B.S. Krongold, K. Ramchandran, and D.L. Jones, "Computationally efficient optimal power allocation algorithm for multicarrier communication systems," in *Proc. IEEE ICC'98*, Atlanta, GA, pp. 1018–1022, May 1998.
[51] T.J. Willink and P.H. Wittke, "Optimization and performance evaluation of multicarrier transmission," *IEEE Trans. Inform. Theory*, vol. 43, pp. 426–440, Mar. 1997.
[52] C.Y. Wong, R.S. Cheng, K.B. Letaief, and R.D. Murch, "Multi-user OFDM with adaptive subcarrier, bit, and power allocation," *IEEE J. Sel. Areas Commn.*, vol. 17, pp. 1747–1758, Oct. 1999.
[53] W. Rhee and J.M. Cioffi, "Increase in capacity of multiuser OFDM system using dynamic suchannel allocation," in *Proc. IEEE VTC'00-Spring*, Tokyo, pp. 1085–1089, May 2000.
[54] J. Jang and K.B. Lee, "Transmit power adaptation for multiuser OFDM systems," *IEEE J. Sel. Areas Commn.*, vol. 21, pp. 171–178, Feb. 2003.
[55] Z. Shen, J.G. Andrews, and B.L. Evans, "Adaptive resource allocation in multiuser OFDM systems with proportional rate constraints," *IEEE Trans. Wireless Commn.*, vol. 4, pp. 2726–2737, Nov. 2005.
[56] Y.J. Zhang and K.B. Letaief, "An efficient resource-allocation scheme for spatial multiuser access in MIMO/OFDM systems," *IEEE Trans. Commn.*, vol. 53, pp. 107–116, Jan. 2005.
[57] G. Song and Y. Li, "Cross-layer optimization for OFDM wireless netoworks – part I and II," *IEEE Trans. Wireless Commn.*, vol. 4, pp. 614–634, Mar. 2005.
[58] S.V. Hanly, "An algorithm for combined cell-site selection and power control to maximize cellular spread spectrum capacity," *IEEE J. Select. Areas Commn.*, vol. 13, pp. 1332–1340, Sept. 1995.

[59] R. Yates and C.Y. Huang, "Integrated power control and base station assignment," *IEEE Trans. Veh. Technol.*, vol. 44, pp. 638–644, Aug. 1995.

[60] I.C. Lin and K.K. Sabnani, "Variable spreading gain CDMA with adaptive control for true packet switching wireless network," in *Proc. IEEE ICC'95*, Seattle, WA, pp. 1060–1064, May 1995.

[61] S.J. Oh and K.M. Wasserman, "Dynamic spreading gain control in multi-service CDMA networks," *IEEE J. Select. Areas Commn.*, vol. 17, pp. 918–927, May 1999.

[62] S. Ramakrishna and J.M. Holtzman, "A scheme for throughput maximization in a dual-class CDMA system," *IEEE J. Select. Areas Commn.*, vol. 16, pp. 830–844, Aug. 1998.

[63] F. Berggren, S.L. Kim, R. Jantti, and J. Zander, "Joint power control and intracell scheduling of DS-CDMA nonreal time data," *IEEE J. Sel. Areas Commn.*, vol. 19, pp. 1860–1870, Oct. 2001.

[64] S.J. Oh, T.L. Olsen, and K.M. Wasserman, "Distributed power control and spreading gain allocation in CDMA data networks," in *Proc. IEEE INFOCOM'00*, vol. 2, pp. 379–385, 2000.

[65] A.J. Goldsmith and S.B. Wicker, "Design challenges for energy-constrained ad hoc wireless networks," *IEEE Wireless Commn.*, pp. 8–27, Aug. 2002.

[66] J.W. Lee, R.R. Mazumdar, and N.B. Shroff, "Joint resource allocation and base-station assignment for the downlink in CDMA networks," *IEEE/ACM Trans. Networking*, vol. 14, pp. 1–14, Feb. 2006.

[67] C.U. Saraydar, N.B. Mandayam, and D.J. Goodman, "Efficient power control via pricing in wireless data networks," *IEEE Trans. Commn.*, vol. 50, pp. 291–303, Feb. 2002.

[68] C. Li, X. Wang, and D. Reynold, "Utility-based joint power and rate allocation for downlink CDMA with blind multiuser detection," *IEEE Trans. Wireless Commn.*, vol. 4, pp. 1163–1174, May 2005.

[69] L. Tassiulas and A. Ephremides, "Stability properties of constrained queuing systems and scheduling policies for maximum throughput in multihop radio networks," *IEEE Trans. Autom. Contro.*, vol. 37, pp. 1936–1948, Dec. 1992.

[70] L. Tassiulas and A. Ephremides, "Dynamic server allocation to parallel queues with randomly varying connectivity," *IEEE Trans. Inf. Thoery*, vol. 39, pp. 466–4478, Mar. 1993.

[71] R. Knopp and P.A. Humblet, "Information capacity and power control in single-cell multiuser communications," in *Proc. IEEE ICC'95*, Seattle, WA, pp. , June 1995.

[72] D. Tse and P. Viswanath, *Fundamentals of Wireless Communication*. Cambridge University Press, May 2005.

[73] X. Liu, E.K.P. Chong, and N.B. Shroff, "Opportunistic transmission scheduling with resource-sharing constraints in wireless networks," *IEEE J. Select. Areas Commn.*, vol. 19, pp. 2053–2064, Oct. 2001.

[74] S. Borst and P. Whiting, "Dynamic rate control algorithm for HDR throughput optimization," in *Proc. IEEE Infocom'01*, Anchorage, AK, pp. 976–985, 2001.

[75] P. Viswanath, D.N.C. Tse, and R. Laroia, "Opportunistic beamforming using dumb antennas," *IEEE Trans. Inf. Theory*, vol. 48, pp. 1277–1294, June 2002.

[76] D. Wu and R. Negi, "Utilizing multiuser diversity for efficient support of quality of service over a fading channel," *IEEE Trans. Veh. Technol.*, vol. 54, pp. 1198–1206, May 2005.

[77] C.J. Chen and L.C. Wang, "A unified capacity analysis for wireless ystems with joint multiuser scheduling and antenna diversity in Nakagami fading channels," *IEEE Trans. Commn.*, vol. 54, pp. 469–478, Mar. 2006.

[78] D. Bertselas and R. Gallager, *Data Networks*. Englewood Cliffs, NJ: Prentice-Hall, 1987.

[79] F. Kelly, "Charging and rate control for elastic traffic," *Eur. Trans. Telecommun.*, vol. 8, pp. 33–37, 1997.

[80] F. Kelly, A. Maulloo, and D. Tan, "Rate control for communication networks: shadow prices, proportional fairness and stability," *J. Oper. Res. Soc.*, vol. 49, pp. 237–252, 1998.

[81] A. Jalali, R. Padovani, and R. Pankaj, "Data throughput of CDMA-HDR: a high efficiency, high data rate personal wireless system," in *Proc. IEEE VTC'00-Spring*, Tokyo, pp. 1854–1858, May 2000.

[82] F. Berggren and R. Jantti, “Asymptotically fair transmission scheduling over fading channels,” *IEEE Trans. Wireless Commn.*, vol. 3, pp. 326–336, Jan. 2004.

[83] L. Dai, S. Zhou, and Y. Yao, “Capacity analysis in CDMA distributed antenna systems,” *IEEE Trans. Wireless Commn.*, vol. 4, no. 6, pp. 2613–2620, Nov. 2005.

[84] D.S. Shiu, G.J. Foschini, M.J. Gans, and J.M. Kahn, “Fading correlation and its effect on the capacity of multi-element antenna systems,” *IEEE Trans. Commn.*, vol. 48, no. 3, pp. 502–513, 2000.

[85] D. Gesbert, H. Bolcskei, D.A. Gore, and A.J. Paulraj, “MIMO wireless channels: capacity and performance prediction,” in *Proc. IEEE Globecom’00*, San Francisko, pp. 1083–1088, 2000.

[86] L. Dai, S. Zhou, H. Zhuang, and Y. Yao, “A novel closed-loop MIMO architecture based on water-filling,” *Electronics Letters*, vol. 38, no. 25, pp. 1718–1720, Dec. 2002.

[87] H. Zhuang, L. Dai, L. Xiao, and Y. Yao, “Spectral efficiency of distributed antenna system with random antenna layout,” *Electronics Letters*, vol. 39, no. 6, pp. 495–496, Mar. 2003.

[88] R. Gozali, R.M. Buehrer and B.D. Woerner, “The impact of multiuser diversity on space-time block coding,” *IEEE Commn. Letters*, vol. 7, pp. 213–215, May 2003.

[89] W. Chen, L. Dai, K.B. Letaief, and Z. Cao, “A unified cross-layer framework for resource allocation in cooperative networks,” to appear in *IEEE JSAC.* (http://www.ee.ust.hk/∼eedailin/publications.htm)

[90] C. Li and X. Wang, “Adaptive multiuser opportunistic fair transmission scheduling in power-controlled CDMA systems,” in *Proc. IEEE ICASSP’04*, Montreal, Canada, vol. 4, pp. 553–556, 2004.