Joint Link Quality and Power Management Over Wireless Networks With Fairness Constraint and Space–Time Diversity

Zhu Han, *Student Member, IEEE,* and K. J. Ray Liu, *Fellow, IEEE*

***Abstract*—In multiaccess wireless networks, dynamic allocation of resource such as link qualities and transmitted powers is an important means to combat time-varying fading environments and cochannel interferences (CCIs). In most prior work, every link's quality is maintained by having a fixed signal-to-interference-noise-ratio (SINR) requirement. We discover that such a constraint is too strong and can degrade the performance of entire wireless networks, because a user with a bad channel response requires too much transmitted power and, therefore, causes unnecessary CCI to other users. In this paper, we alleviate this constraint and explore the time and multiuser diversity. For each user, the time-average link quality is maintained as a constant to ensure fairness. For the whole system, we want to minimize the overall transmitted power. In order to solve this problem, each user provides the system with a SINR range that is acceptable, according to the channel conditions and transmission history. Then, the system allocates the resources according to these ranges, channel conditions, and other practical constraints. Each time, some users may sacrifice their performances to reduce the overall network transmitted power. These users' temporary sacrifices will improve the system performance and will be paid back in the long term. This scheme can be conceived of as "water filling" the wireless network resources to different users at different times. In addition, by combining the proposed scheme with beamforming, we can have one more degree of freedom to combat CCIs in different directions of arrivals and different channel conditions over time.**

***Index Terms*—antenna arrays, communication networks, diversity methods, power control, resource management.**

I. Introduction

TWO KEY challenges for mobile wireless networks are the time-varying nature of the channels and cochannel interferences (CCIs). Because of the effects such as cochannel users, multipath fading, shadowing, path losses, directions of arrivals (DOA), and noise levels, the signal-to-interference-noise ratio (SINR) at the output of the receiver can fluctuate in the order of tens of decibels. A common strategy to combat these detrimental effects is the dynamic allocation of resources such as link qualities and transmitted powers based on the channel conditions. Link qualities such as bit-error rate (BER), transmission rate, distortion, or other quantities of quality of service (QoS) can be closely related to the received SINR level. The system can determine a targeted SINR (threshold) for each user to ensure his link quality. In power control, the goal is to assign the minimal transmitted power levels to the mobile units and at the same time to manage the mutual interferences, so that each mobile unit can meet its SINR requirement for the desired link quality. Such a process improves the qualities of weak links, but at the same time increases CCIs during the deep fading. All these resources are interrelated and there are tradeoffs to allocate them in the interference limited wireless networks. Moreover, there are other constraints, such as fairness and practical implementation constraints, so how to optimally allocate these resources has become an important wireless research issue.

Resource allocation for the wireless networks has been extensively studied in the literature. In [1]–[7], classical power-control algorithms are presented and their convergence is proved. In [8]–[15], the authors study combining rate adaption and power control to optimize the system performance. In [16]–[19], beamforming, power control, multiuser detection, and base station assignment are combined for cellular wireless communication system. In [20] and [21], the problem of optimal resource allocation is considered from the information theoretic point of view. Throughput capacity and delay-limited capacity are extensively studied. In [22]–[24], dynamic programming is considered for integrating link adaptation and power control to improve the overall throughput. In [25] and [26], game theory is introduced to the power-control problem. The utility functions are designed for users to compete with each other for resources. The system is balanced in some equilibrium.

In the traditional power control, the overall transmitted power is minimized, while each user modifies his transmitted power, so that his received SINR is larger than or equal to a fixed and predefined targeted SINR threshold that required maintaining his link quality. However, a user with a bad channel response will transmit a very high power; therefore, he can cause unnecessary CCI to other users. As a result, the overall network performance is degraded. In this paper, by alleviating the fixed link quality constraint and exploring the time and multiuser diversity, we develop adaptive joint link quality and power-management schemes with fairness constraint for both the uplink and the downlink. These schemes encourage some users to sacrifice their performances in a short period, with the incentive that the overall network transmitted power can be reduced and the users' temporary sacrifices will be paid back in the long term.

In the proposed schemes, each user provides the system with a SINR range that he can accept each time. Then, the system employs adaptive algorithms to assign different users their

Manuscript received June 16, 2003; revised December 29, 2003 and March 11, 2004.

The authors are with the Electrical and Computer Engineering Department, Institute for Systems Research, University of Maryland, College Park, MD 20742 USA (e-mail: hanzhuglue.umd.edu; kjrliu@glue.umd.edu).

Digital Object Identifier 10.1109/TVT.2004.830976

targeted SINRs, according to their acceptable SINR ranges, channel conditions, and other practical constraints. Different users may have different assigned SINRs each time, while each user's time-average SINR is maintained as a constant to ensure fairness for the link quality for which the user has paid. In order to ensure fairness, users adjust their acceptable SINR ranges, according to their channel conditions and transmission histories. If a user has a smaller assigned SINR now, he will provide the system with a higher acceptable SINR range in the future, such that the system has to assign a higher SINR to him. The scheme can be conceived as "water filling" the wireless network resources to different users at different times, according to their channel conditions. Moreover, the joint consideration of the proposed scheme and beamforming can be interpreted as to combat CCIs in different DOAs and different channel conditions over time. As will be shown in the simulation results, the proposed schemes reduce up to 60% of the overall transmitted power and increase the maximal achievable SINR by up to 6 dB, compared with the previous work [16], [17]; thus, the schemes greatly increase the network performance.

This paper is organized as follows. In Section II, we present the system model and, in Section III, we first explain the traditional power-control problem and note its shortcomings. We develop adaptive algorithms to reduce the overall transmitted power by alleviating the fixed link quality constraint and exploring time diversity. We discuss downlink cases and note the differences from the uplink cases. In Section IV, joint beamforming and our proposed scheme is presented and, in Section V, we have simulation studies. In Section VI, we have conclusions.

II. System and Channel Models

Consider M cochannel links that may exist in distinct cells of multicell networks. Each link consists of a mobile user and his assigned base station. Assume that coherent detection is possible, so that it is sufficient to model this system by an equivalent baseband model. Each link is affected by propagation loss, shadowing fading, and multipath Rayleigh fading. For uplink, the output signal at the ith base station can be expressed as

$$x_i(t)=\sum_{m=1}^{M}\sum_{l=1}^{L}\sqrt{P_mG_{mi}\rho_{mi}}\alpha_{mi}^l g_m(t-\tau_{mi}^l)s_m(t-\tau_{mi}^l)+n_i(t) \tag{1}$$

where L is the maximal number of multipath, P_m is the mth user's transmitted power, G_{mi} and ρ_{mi} are the path loss and the log-normal shadow fading from the mth user to the ith base station, respectively, α_{mi}^l is the Rayleigh fading for the lth path, $g_m(t)$ is the shaping function, $s_m(t)$ is the mobile's message symbol, τ_{mi}^l is the transmission delay, and $n_i(t)$ is the thermal noise. We assume that the channels change slowly and are stable over a frame with hundreds of symbols. We also assume that the multipath delay is far less than one symbol duration, i.e., $\tau_{ii}^l \approx 0$, $\forall i, l$ (the delay from the mobile user to his assigned base station), and the delay from the user to any other cell $\tau_{mi}^l, m \neq i$ is uniformly distributed in $[0,T]$, where T is the sample duration.

Define the impulse response from the mth mobile user to the ith base station by

$$h_{mi}=\sum_{l=1}^{L}\alpha_{mi}^l r_{mi} \tag{2}$$

where r_{mi} includes the effects of transmission delay, transmitter filter, receiver filter, and shaping function. Then, we can express the sampled received signal at time k as

$$x_i(k)=\sum_{m=1}^{M}h_{mi}\sqrt{P_mG_{mi}\rho_{mi}}s_m(k)+n_i(k) \tag{3}$$

where $n_i(k)$ is the sampled thermal noise. The ith user's SINR can be written as

$$\Gamma_i=\frac{P_i\rho_{ii}G_{ii}|h_{ii}|^2}{\sum\limits_{m\neq i}P_m\rho_{mi}G_{mi}|h_{mi}|^2+N_i} \tag{4}$$

where $N_i = E(|n_i|^2)$.

Now we discuss the downlink cases. One issue that complicates the downlink problem is the possible lack of direct measurements of downlink channel responses at the base stations, especially for frequency-division-duplex (FDD) systems. The other issue is the lack of efficient downlink algorithms, even though the downlink channel responses are available. To obtain the optimal power control involves a complicated multivariable optimization. In this paper, we use the virtual uplink power-control technique [17], which just involves simple computations. The received signal at the mth mobile receiver is given by

$$\begin{aligned}&\tilde{y}_m(t)\\&=\sum_{i=1}^{M}\sum_{l=1}^{L}\sqrt{\tilde{P}_i\tilde{G}_{im}\tilde{\rho}_{im}}\tilde{\alpha}_{im}^l\tilde{g}_{im}(t-\tilde{\tau}_{im}^l)\tilde{s}_i(t-\tilde{\tau}_{im}^l)+\tilde{n}_m(t)\end{aligned} \tag{5}$$

where $\tilde{s}_i$ is the message signal transmitted from the ith base station to its associated mobile user; $\tilde{n}_m$ is the thermal noise at the mth mobile user; $\tilde{P}_i$ is the signal power; and $\tilde{G}_{im}$, $\tilde{\rho}_{im}$, $\tilde{\alpha}_{im}^l$, $\tilde{g}_{im}$, and $\tilde{\tau}_{im}^l$ have the same definitions as those of the uplink cases. The impulse response from the ith base station to the mth mobile user is defined as

$$\tilde{h}_{im}=\sum_{l=1}^{L}\tilde{\alpha}_{im}^l\tilde{r}_{im} \tag{6}$$

where $\tilde{r}_{im}$ includes the effects of receiver matched filter, shaping function, and transmitter filter. Then, the sampled received signal vector is given by

$$\tilde{y}_m(k)=\sum_{i=1}^{M}\tilde{h}_{im}\sqrt{\tilde{P}_i\tilde{\rho}_{im}\tilde{G}_{im}}\tilde{s}_i(k)+\tilde{n}_m(k). \tag{7}$$

The SINR at the mth mobile receiver can be expressed as

$$\tilde{\Gamma}_m=\frac{\tilde{P}_m\tilde{\rho}_{mm}\tilde{G}_{mm}|\tilde{h}_{mm}|^2}{\sum\limits_{i\neq m}\tilde{P}_i\tilde{\rho}_{im}\tilde{G}_{im}|\tilde{h}_{im}|^2+\tilde{N}_m} \tag{8}$$

where $\tilde{N}_m$ is the thermal noise power at the mth mobile user.

III. Joint Adaptive Link Quality and Power Management

In this section, we will first review the traditional power-control problem and indicate the disadvantages of this kind of approach. Then, we give the reformulated problems for both uplink and downlink cases. Adaptive algorithms are developed to solve the problems.

A. Traditional Power Control

In the traditional uplink power control, the transmitted power of each mobile user is selected, so that each user has $\Gamma_i \geq \gamma_i$ for $i = 1, \ldots, M$, while the overall transmitted power used by all mobile users is minimized. Here, γ_i is a fixed and predefined targeted SINR threshold to maintain the required link quality. Given that the path gains and the transmitted powers are nonnegative, the matrix version of the traditional power-control formulation with the fixed link quality is given by

$$\min_{P_i} \sum_{i=1}^{M} P_i \quad \text{subject to } (\mathbf{I}-\mathbf{DF})\mathbf{P} \geq \mathbf{u} \tag{9}$$

where $\mathbf{u} = [u_1, \ldots, u_M]^T$ with $u_i = \gamma_i N_i/\rho_{ii}G_{ii}$, $\mathbf{P} = [P_1, \ldots, P_M]^T$, $\mathbf{D} = \mathrm{diag}\{\gamma_1, \ldots, \gamma_M\}$, and

$$[\mathbf{F}]_{ij} = \begin{cases} 0 & \text{if } j = i, \\ \frac{\rho_{ji}G_{ji}|h_{ji}|^2}{\rho_{ii}G_{ii}|h_{ii}|^2} & \text{if } j \neq i. \end{cases} \tag{10}$$

If the spectral radius of $\mathbf{DF}$, $\rho(\mathbf{DF})$, i.e., the maximal eigenvalue of $\mathbf{DF}$, is inside the unit circle, the system has feasible solutions, i.e., there exists a positive power allocation that $\Gamma_i \geq \gamma_i$ for $i = 1, \ldots, M$. By the Perron–Frobenius theorem [35], the optimum power vector for this problem is $\hat{\mathbf{P}} = (\mathbf{I}-\mathbf{DF})^{-1}\mathbf{u}$. The optimal solution of the power vector is achieved when the equations of the constraint are held, i.e., $\Gamma_i = \gamma_i, \forall i$. It has been shown that this is a nondeterministic polynomial (NP) hard problem [36]. Many adaptive algorithms [1], [4], [5], [16] have been developed to decrease the system complexity by updating the transmitted powers in a distributed manner.

In the traditional power-control scheme mentioned above, each user adjusts his transmitted power to maintain the fixed and predefined SINR thresholds. When these targeted SINR thresholds are small and CCIs are minor, the system works perfectly well. However, when the targeted SINR thresholds become large, each user transmits a higher power and causes higher CCI to other users. The overall transmitted power will start to increase rapidly. If the targeted SINR thresholds are larger than some specific levels, CCIs will be so large that no feasible solutions exist, i.e., no matter how large the transmitted powers are, the receivers cannot get enough SINR levels. The reason for such a problem is that the user with the bad channel condition transmits too much power and, thus, introduces unnecessarily high CCI to other users. Consequently the overall system performance is reduced. Therefore, having the fixed and predefined targeted SINR thresholds constraint as the problem defined in (10) is not a good approach for wireless resource allocations.

B. Proposed Approach for Uplink

In this paper, we alleviate the constant SINR constraint by allowing users to have the time-varying SINR thresholds, according to their channel conditions. We assume that the ith user can accept the instantaneous SINR threshold within a range from $\gamma_i^{\min}$ to $\gamma_i^{\max}$, according to his channel condition, while the overall network link quality is kept higher than or equal to a value for adequate overall network performances. Each time, the users with bad channel conditions sacrifice their SINRs (because such levels of SINRs may not improve anything for these users significantly) and are assigned with lower SINR thresholds. At the same time, the users with good channel conditions get higher SINRs. Consequently, they have better link qualities. For each user, the time average link quality is kept as a constant to ensure the fairness for which the user has paid. Each time, some users may sacrifice their performances to reduce the overall network transmitted power. These users' temporary sacrifices will be paid back in the long term. The scheme can be conceived as "water filling" wireless network resources in the time domain and to the different users, according to users' channel conditions. The user's link quality can have different definitions for different scenarios. For example, for adaptive modulation systems, the throughput and BER can be approximated by simple exponential expressions in [8] and [10]. For adaptive coding systems and multimedia transmissions, the coding performance and distortion can also be approximated as functions of γ_i [29]. In this paper, we define the link quality as γ_i directly, which fits the situations such as power-limited communications [4]. For the other link quality functions, the schemes described in the rest of this paper can be easily extended in the similar way. The matrix version of this problem formulation can be expressed as

$$\min_{P_i,\gamma_i} \sum_{i=1}^{M} P_i \quad \text{subject to } \begin{cases} (\mathbf{I}-\mathbf{DF})\mathbf{P} \geq \mathbf{u} \\ \sum_{i=1}^{M} \gamma_i \geq \psi \\ \gamma_i^{\min} \leq \gamma_i \leq \gamma_i^{\max} \\ E(\gamma_i) = \gamma_i^{\mathrm{ave}} \end{cases} \tag{11}$$

where γ_i^{ave} is the time average ith link's quality and ψ is the network overall link quality that our system needs to guarantee, which is at least as large as that of the traditional power control in (9) and is also the sum of time average throughput, i.e., $\psi = \sum_{i=1}^{M} \gamma_i^{\mathrm{ave}}$.

It is worthwhile to emphasize that the inequality $(\mathbf{I}-\mathbf{DF})\mathbf{P} \geq \mathbf{u}$ is a bilinear matrix inequality (BMI) [30]. If we fix the powers, the targeted SINRs are linearly constrained; if we fix targeted SINRs, the powers are linearly constrained. However, if both are considered, it is a BMI problem. In the previous works [1], [16], each user's targeted SINR is the same; thus, the inequality constraint is linear. While in the proposed scheme, users can select different γ_i, so the constraint is not linear any more. A BMI problem is nonconvex and can have multiple local optima.

The time-diversity fairness constraint $E(\gamma_i) = \gamma_i^{\mathrm{ave}}$ in (11) involves optimizations at different times. The difficulties to solve it analytically by techniques such as dynamic programming lie in how to represent the channel models with CCIs and

TABLE I
ADAPTIVE ALGORITHM FOR MOVING ACCEPTABLE SINR RANGE

Initialization:	$\gamma_i^{min}(0)=\hat{\gamma}_i^{min}$; $\gamma_i^{max}(0)=\hat{\gamma}_i^{max}$; $\gamma_i^{mid}=\gamma_i^{ave}$.
Iteration:	$\gamma_i^{mid}(n)=\gamma_i^{mid}(n-1)+\beta(\gamma_i(n)-\gamma_i^{ave})$; $\gamma_i^{min}(n+1)=\min(\max(\gamma_i^{ave}-\gamma_i^{mid}(n)+\hat{\gamma}_i^{min},\hat{\gamma}_i^{min}),\hat{\gamma}_i^{max})$; $\gamma_i^{max}(n+1)=\max(\min(\hat{\gamma}_i^{max}-\gamma_i^{mid}(n)+\gamma_i^{ave},\hat{\gamma}_i^{max}),\hat{\gamma}_i^{min})$.

the computational complexity with a large number of users. In this paper, we develop a moving SINR window algorithm and a projected gradient algorithm to heuristically solve (11). The basic idea is to first change the acceptable SINR ranges, according to the transmission histories and channel conditions, so that the fairness constraint is satisfied. Then, within these SINR ranges, a projected gradient algorithm finds the allocation that produces the minimal overall transmitted power.

Instead of having fixed $\gamma_i^{\min}$ and $\gamma_i^{\max}$, we assume that the ith user can select SINR level $\gamma_i^{\min}(n)\le\gamma_i(n)\le\gamma_i^{\max}(n)$ at time n and the targeted time average SINR is $\gamma_i^{\rm ave}$. Each time, $\gamma_i^{\min}(n+1)$ and $\gamma_i^{\max}(n+1)$ are modified by the current $\gamma_i(n)$. When $\gamma_i(n)$ is smaller than $\gamma_i^{\rm ave}$, $\gamma_i^{\min}(n+1)$ and $\gamma_i^{\max}(n+1)$ are increased, so that there is a higher probability that $\gamma_i(n+1)$ is larger than $\gamma_i^{\rm ave}$; otherwise, $\gamma_i^{\min}(n+1)$ and $\gamma_i^{\max}(n+1)$ are decreased. $\gamma_i^{\min}(n+1)$ and $\gamma_i^{\max}(n+1)$ are bounded by $\hat{\gamma}_i^{\min}$ and $\hat{\gamma}_i^{\max}$, which are the minimal and maximal SINRs that are fixed and predefined by the system. In order to track the history of γ_i, we define

$$\gamma_i^{\rm mid}(n)=\gamma_i^{\rm mid}(n-1)+\beta(\gamma_i(n)-\gamma_i^{\rm ave}),\ \ 0<\beta<1 \quad (12)$$

where β is a delay sensitive factor. If a user's payload is a voice traffic and cannot suffer much delay, β should select a relatively larger number, such that the link quality will be compensated quickly. If a user's payload is a data traffic and can suffer some delay, β can select a relatively small number, so that the user can wait until the channel becomes better to transmit. When $\gamma_i^{\rm mid}(n)=\gamma_i^{\rm ave}$, the time average SINR requirement is satisfied. Each time, $\gamma_i^{\min}(n)$, $\gamma_i^{\max}(n)$, and $\gamma_i^{\rm mid}(n)$ are updated by each user in Table I.

When $\gamma_i(n)$ is continuously less than $\gamma_i^{\rm ave}$ for some time, $\gamma_i^{\min}(n)$ is increased to $\gamma_i^{\rm ave}$. Then, the next $\gamma_i(n+1)\ge\gamma_i^{\rm ave}$, consequently, $\gamma_i^{\rm mid}(n)$ stops increasing. The same analysis can be applied to $\gamma_i^{\max}(n)$. Since $\gamma_i^{\min}(n)$ and $\gamma_i^{\max}(n)$ are bounded and linearly modified by $\gamma_i^{\rm mid}(n)$, $\gamma_i^{\rm mid}(n)$ is also bounded. Rearrange $\gamma_i^{\rm mid}(n)$ in (12) and average over times, we have

$$\frac{\sum_{n=1}^{N}\gamma_i(n)}{N}=\gamma_i^{\rm ave}+\frac{(\gamma_i^{\rm mid}(N)-\gamma_i^{\rm ave})}{\beta N}. \quad (13)$$

Since $\gamma_i^{\rm mid}(N)$ is bounded, the second term on the right-hand side decreases to zero as $N\to\infty$, so we prove that $\lim_{N\to\infty}\sum_{n=1}^{N}\gamma_i(n)/N=\gamma_i^{\rm ave}$, i.e., the proposed algorithm guarantees fairness.

Now, we can construct the adaptive algorithm to adjust each user's targeted SINR threshold to reduce the overall transmitted power. We need to find out which users cause larger CCIs and contribute more to the overall transmitted power. If these users can sacrifice their targeted SINRs a little bit, the overall transmitted power will be reduced significantly. $P_{\rm sum}$ can be written as $P_{\rm sum}=\mathbf{1}^T(\mathbf{I}-\mathbf{DF})^{-1}\mathbf{u}$. From [28], we know that $P_{\rm sum}$ is a convex and increasing function of γ_i, when the other $\gamma_j,\ j=1\ldots M,\ j\ne i$ are fixed. Take derivatives of γ_i of $P_{\rm sum}$; then we have the ith element of gradient $\mathbf{g}=[g_1\ldots g_M]^T$ of the overall uplink transmitted power $P_{\rm sum}$ as

$$\begin{aligned}g_i&=\frac{\partial P_{\rm sum}}{\partial\gamma_i}\\&=\mathbf{1}^T\left[(\mathbf{I}-\mathbf{DF})^{-1}\frac{\partial\mathbf{u}}{\partial\gamma_i}-(\mathbf{I}-\mathbf{DF})^{-1}\frac{\partial(\mathbf{I}-\mathbf{DF})}{\partial\gamma_i}(\mathbf{I}-\mathbf{DF})^{-1}\mathbf{u}\right]\\&=\mathbf{1}^T(\mathbf{I}-\mathbf{DF})^{-1}[\hat{\mathbf{D}}_i\mathbf{FP}+\hat{\mathbf{u}}_i]\end{aligned} \quad (14)$$

where $\hat{\mathbf{D}}_i$ is a $M\times M$ matrix, $\hat{\mathbf{u}}_i$ is a $M\times 1$ vector, and

$$[\hat{\mathbf{D}}_i]_{jk}=\begin{cases}1, & \text{if } i=j=k\\ 0, & \text{otherwise.}\end{cases}$$

$$[\hat{\mathbf{u}}_i]_j=\begin{cases}\frac{N_i}{(\rho_{ii}G_{ii}|h_{ii}|^2)}, & \text{if } j=i\\ 0, & \text{otherwise.}\end{cases}$$

Reorder (14) and we have

$$g_i=\frac{c_i\left(N_i+\sum_{j\ne i}P_j\rho_{ji}G_{ji}|h_{ji}|^2\right)}{\rho_{ii}G_{ii}|h_{ii}|^2}=\frac{c_iP_i}{\Gamma_i} \quad (15)$$

where Γ_i is the SINR detected at the base station's antenna output for the ith user, $c_i=\mathbf{1}^T(\mathbf{I}-\mathbf{DF})^{-1}\mathbf{v}_i$, and $[\mathbf{v_i}]_j=1$, if $j=i$; $[\mathbf{v_i}]_j=0$, otherwise. c_i reflects te severeness of CCIs and tells which user causes more CCI to other users. When CCIs are small, $c_i\approx c_j,\ \forall i,j$. Since we only care about the direction of the gradient and do not care about the amplitude, we can ignore the value of c_i when CCIs are small. By using this gradient, we know how to reduce the overall transmitted power.

Since each user can have his targeted SINR threshold in a range from $\gamma_i^{\min}(n)$ to $\gamma_i^{\max}(n)$, $\forall\ i$ at time n, if we do not have any more constraint, every user will have $\gamma_i^{\min}(n)$ as his targeted SINR threshold, so that the transmitted powers are minimized. However, the network performance is consequently degraded, so we assume the overall link quality of the network $\sum_{i=1}^{M}\gamma_i(n)\ge\psi$. Because we optimize the overall transmitted power $P_{\rm sum}$, which is an increasing function of γ_i [28], the optimal solution will occur when $\sum_{i=1}^{M}\gamma_i(n)=\psi$. If we change each user's targeted SINR according to (15), the constraint $\sum_{i=1}^{M}\gamma_i(n)=\psi$ will not hold. We have to modify the gradient by projecting the gradient onto the plane where the constraint holds. Define the modified gradient as $\mathbf{q}=[q_1\ldots q_M]^T$. By the definition of a projection, vector $\mathbf{q}$ is the vector closest to $\mathbf{g}=[g_1\ldots g_M]^T$ in space Ω, where $\sum_{i=1}^{M}\gamma_i=0$, i.e.,

TABLE II
ADAPTIVE ALGORITHM FOR UPLINK

Initialization:	$\gamma_1(0)=\gamma_1^{ave},\ldots,\gamma_M(0)=\gamma_M^{ave}$.
Adaptive Threshold Allocation	do { $\mathrm{g}=\bigtriangledown P_{sum}$; $\mathrm{q}=\mathrm{projection(g)}$; $\gamma_i(n)=\gamma_i(n)-\mu \mathrm{q}_i\ \forall\ i$; if $(\gamma_i(n)>\gamma_i^{max}(n))$, $\gamma_i(n)=\gamma_i^{max}(n)$; if $(\gamma_i(n)<\gamma_i^{min}(n))$, $\gamma_i(n)=\gamma_i^{min}(n)$.} while $(\gamma_i(n)$ is not convergent.)
Power Update Iteration:	$\mathrm{D}=\mathrm{diag}(\gamma_1(n),\gamma_2(n),\ldots,\gamma_M(n))$; $\mathrm{P}=\mathrm{DFP}+\mathrm{u}$.
SINR Range Update:	Update $\gamma_i^{mid}(n),\gamma_i^{min}(n)$, and $\gamma_i^{max}(n)$.

$\mathbf{q}=\arg\min_{\forall \mathbf{x}\in\Omega}\|\mathbf{g}-\mathbf{x}\|^2$, where $\mathbf{x}$ is a vector in Ω and $\sum_{i=1}^{M}x_i=0$. The distance between $\mathbf{q}$ and $\mathbf{x}$ is given by

$$\|\mathbf{g}-\mathbf{x}\|^2=\sum_{i=1}^{M-1}(x_i-g_i)^2+(x_M-g_M)^2. \tag{16}$$

We take derivatives with respect to each argument x_i for (16). Then, we set these derivatives to zeros to get the optimal projection $\mathbf{q}$ of $\mathbf{g}$ onto Ω. We write the equations in matrix form as $q_m=-\sum_{i=1}^{M-1}q_i$ and

$$\begin{bmatrix} q_1\\ q_2\\ \vdots\\ q_{M-1}\end{bmatrix}=\frac{1}{M}\begin{bmatrix} M-1 & -1 & \ldots & -1\\ -1 & M-1 & \ldots & -1\\ \vdots & \vdots & \ddots & \vdots\\ -1 & -1 & \ldots & M-1\end{bmatrix}\times\begin{bmatrix} g_1-g_M\\ g_2-g_M\\ \vdots\\ g_{M-1}-g_M\end{bmatrix}. \tag{17}$$

Now we can construct an adaptive algorithm to move along the projected gradient $\mathbf{q}$ to reduce the overall transmitted power, as summarized in Table II. We initialize the algorithm with $\gamma_1(0)=\gamma_1^{\mathrm{ave}},\ldots,\gamma_M(0)=\gamma_M^{\mathrm{ave}}$. The initialization is assumed to be feasible. μ is a small constant, whose value decides the rate of convergence and the variance of the final result. The convergence criteria for the adaptive algorithm can be implemented according to the Karush–Kuhn–Tucker(KKT) conditions [40]. For the specific problem in (11), the KKT conditions are given by the following theorem.

Theorem 1: The convergence criteria of the proposed algorithm in Table II is: when γ_i hits the boundary, the projected gradient q_i will point inside the range; otherwise, $q_i=0$, i.e.,

$$\begin{cases} q_i\geq 0, & \text{if } \gamma_i=\gamma_i^{\min}(n)\\ q_i\leq 0, & \text{if } \gamma_i=\gamma_i^{\max}(n)\\ q_i=0, & \text{otherwise.}\end{cases} \tag{18}$$

Under such conditions, the algorithm cannot further decrease the overall transmitted power and falls into a local minimum.

Proof: Each time, we know the acceptable SINR ranges for different users and the fact that the optima occur when $\psi=\sum_{i=1}^{M}\gamma_i$. We can rewrite the optimization problem in (11) as

$$\min_{\gamma_i}\ f=\mathbf{1}^T(\mathbf{I}-\mathbf{DF})^{-1}\mathbf{u}$$

$$\text{subject to}\begin{cases} h=\psi-\sum_{i=1}^{M}\gamma_i=0\\ g_1^i=\gamma_i-\gamma_i^{\max}(n)\leq 0,\ \forall i\\ g_2^i=\gamma_i^{\min}-\gamma_i\leq 0,\ \forall i.\end{cases} \tag{19}$$

Write the Lagrange multiplier for this constrained optimization problem as

$$L(\gamma_i,\lambda,u_1^i,u_2^i)=f+\lambda h+\sum_{i=1}^{M}u_1^ig_1^i+\sum_{i=1}^{M}u_2^ig_2^i \tag{20}$$

where λ, u_1^i, and u_2^i, $\forall i$ are the Lagrange coefficients. Assume that the local minimum occurs at $[\gamma_1^*\ldots\gamma_M^*]^T$. The KKT conditions are that there are u_1^i, u_2^i, and λ, such that the following conditions hold at γ_i^*, $\forall i$:

$$\begin{aligned}\bigtriangledown f+\bigtriangledown h^T\lambda+\sum_{i=1}^{M}\bigtriangledown g_1^{i\,T}u_1^i+\sum_{i=1}^{M}\bigtriangledown g_2^{i\,T}u_2^i&=\mathbf{0}\\ \forall i,\ u_1^{i\,T}g_1^i=0,\ u_2^{i\,T}g_2^i&=0\\ \forall i,\ u_1^i\geq 0,\ u_2^i&\geq 0\end{aligned} \tag{21}$$

where $\bigtriangledown g_1^i=1$ and $\bigtriangledown g_2^i=-1,\forall i$. We have $\mathbf{q}=\bigtriangledown f+\bigtriangledown h^T\lambda$ at point γ_i^*, $\forall i$. When $\gamma_i^{\max}(n)>\gamma_i^*>\gamma_i^{\min}(n)$, we select $u_1^i=0$ and $u_2^i=0$. Under this condition, q_i needs to be zero. If $\gamma_i^{\max}(n)=\gamma_i^*$, we select $u_2^i=0$. Because $q_i\leq 0$ and $\bigtriangledown g_1^i=\mathbf{1}$, we can have $u_1^i\geq 0$. If $\gamma_i^{\min}(n)=\gamma_i^*$, we select $u_1^i=0$. Because $q_i\geq 0$ and $\bigtriangledown g_2^i=-\mathbf{1}$, we can have $u_2^i\geq 0$. So we prove that the equations in (18) satisfies the KKT conditions in (21). □

The power-update step in Table II can be implemented in a distributed iteration manner as in [1], which only needs local channel information. In each update, the targeted SINRs are calculated at the base station and then the powers are updated according to the targeted SINRs in the distributed iterations [1], [4], [5], [16]. The power-update equation in the algorithm in Table II has been proved [16] to fit the *standard function* [1]. The power-update step converges to a unique solution when the targeted SINRs are feasible. In the proposed algorithm, the targeted SINRs are selected, so that the overall transmitted power is reduced. Starting from any feasible initialization, γ_i is always within the feasible range $|\rho(\mathbf{DF})|<1$, so the power update step converges.

TABLE III
ADAPTIVE ALGORITHM FOR DOWNLINK

Initialization:	$\gamma_1(0) = \gamma_1^{ave}, \ldots, \gamma_M(0) = \gamma_M^{ave}$.

Adaptive Threshold Allocation	do {
	 $\tilde{g} = \nabla \tilde{P}_{sum}$;
	 $\tilde{q} = \mathrm{projection}(\tilde{g})$;
	 $\gamma_i(n) = \gamma_i(n) - \mu \tilde{q}_i, \ \forall \ i$;
	 if $(\gamma_i(n) > \gamma_i^{max}(n)), \quad \gamma_i(n) = \gamma_i^{max}(n)$;
	 if $(\gamma_i(n) < \gamma_i^{min}(n)), \quad \gamma_i(n) = \gamma_i^{min}(n)$.}
	 while ($\gamma_i(n)$ is not convergent.)

Iteration:	
Virtual Uplink Power Update:	$P = D\tilde{F}^T P + u$.
Downlink Power Update:	$\tilde{P} = D\tilde{F}\tilde{P} + \tilde{u}$.
SINR Range Update:	Update $\gamma_i^{mid}(n), \gamma_i^{min}(n)$, and $\gamma_i^{max}(n)$.

C. Proposed Approach for Downlink

Similar to the uplink cases, we develop the proposed link quality and power-management algorithm for the downlink cases. Define $\tilde{P}_i$ as the downlink transmitted power. The optimization problem is

$$\min_{\tilde{P}_i, \gamma_i} \sum_{i=1}^{M} \tilde{P}_i \quad \text{subject to} \begin{cases} (\mathbf{I} - \mathbf{D}\tilde{\mathbf{F}})\tilde{\mathbf{P}} \geq \tilde{\mathbf{u}} \\ \sum_{i=1}^{M} \gamma_i \geq \psi \\ \gamma_i^{\min} \leq \gamma_i \leq \gamma_i^{\max} \\ E(\gamma_i) = \gamma_i^{\text{ave}} \end{cases} \tag{22}$$

where $\tilde{\mathbf{u}} = [\tilde{u}_1 \ldots \tilde{u}_M]^T$ with $\tilde{u}_i = \gamma_i \tilde{N}_i / \tilde{\rho}_{ii} \tilde{G}_{ii} |\tilde{h}_{ii}|^2$, $\tilde{\mathbf{P}} = [\tilde{P}_1 \ldots \tilde{P}_M]^T$, $D = \text{diag}\{\gamma_1 \ldots \gamma_M\}$, and

$$[\tilde{\mathbf{F}}]_{ji} = \begin{cases} 0, & \text{if } j = i, \\ \frac{\tilde{\rho}_{ij} \tilde{G}_{ij} |\tilde{h}_{ij}|^2}{\tilde{\rho}_{jj} \tilde{G}_{jj} |\tilde{h}_{jj,}|^2}, & \text{if } j \neq i. \end{cases} \tag{23}$$

Similar to the uplink cases, the overall transmitted power $\tilde{P}_{\text{sum}} = \sum_{i=1}^{M} \tilde{P}_i$ is a convex and increasing function of γ_i if $\gamma_j, \ j \neq i, \ j = 1 \ldots M$ is fixed [28]. By using the similar deductions of the overall transmitted power as those in the uplink cases, the mth gradient element $\tilde{\mathbf{g}}_m$ of the overall downlink transmitted power is given by

$$\tilde{g}_m = \frac{\tilde{c}_m \tilde{P}_m}{\tilde{\Gamma}_m} \tag{24}$$

where $\tilde{\Gamma}_m$ is the SINR detected at the mth mobile user and $\tilde{c}_m = \mathbf{1}^T (\mathbf{I} - \mathbf{D}\tilde{\mathbf{F}})^{-1} \mathbf{v}_m$.

For the discussion of downlink in this section, we still assume that the SINR as the link quality index and the overall network link quality is greater than or equal to ψ each time. We can use (17) to get the projection of the gradient, such that $\sum_{i=1}^{M} \gamma_i(n) = \psi$ holds. For each user, we use the same moving SINR window algorithm to ensure fairness as that for the uplink cases.

If the uplink and downlink are reciprocal, such as time-divided-duplex (TDD) systems, we can use uplink channel responses as downlink channel responses and construct a virtual uplink [17] whose channel responses are similar to those of the downlink. Then, we find the powers and targeted SINRs at the base stations of the virtual uplink. Finally, we use the same powers and targeted SINRs for the real downlink. In order to update the transmitted power, we use the algorithm in [17]: downlink SINR is measured in each mobile user; knowing his previous transmitted power and targeted SINR, the mobile user uses a feedback channel to update the transmitted power from the base station. The algorithm is summarized in Table III.

IV. Joint Consideration With Beamforming

The antenna array-processing techniques, such as beamforming, can efficiently improve the received SINRs and system performances [16], [17], [19]. The antenna arrays point their beams toward the directions of the desired signals while trying to null the CCIs. In this section, we jointly consider the proposed schemes in the previous section with beamforming and explain why such joint schemes are superior to the traditional joint power-control and beamforming schemes [16], [17].

We consider a system with antenna arrays at the base stations only. There are P elements for each antenna array. For uplink, the sampled received signal vector $\mathbf{x}_i(k)$ can be expressed as

$$\mathbf{x}_i(k) = \sum_{m=1}^{M} \mathbf{h}_{mi} \sqrt{P_m \rho_{mi} G_{mi}} s_m(k) + \mathbf{n}_i(k) \tag{25}$$

where $\mathbf{h}_{mi} = [h_{mi}^1, \ldots, h_{mi}^P]^T$, $h_{mi}^p = \sum_{l=1}^{L} \alpha_{mi}^l a_{mi}^p(\theta_l) r_{mi}^p$, $a_{mi}^p(\theta_l)$ is the pth antenna element response to the signal from the direction θ_l, and $\mathbf{n}_i(k)$ is the sampled thermal noise vector.

With adaptive beamforming, the output of each antenna array element is combined together with beamforming weight vector $\mathbf{w}_i$. The aim is to adjust the weight vector to achieve the maximal SINR at the output of the combiner. If the channel response from the desired user is known, the minimal variance distortion response (MVDR) solution to this problem can be used to minimize the total interferences at the output of beamformer, while the gain for the desired user is kept as a constant [34]. For uplink, the MVDR problem can be defined as

$$\min_{\mathbf{w}_i} \|\mathbf{w}_i^H \mathbf{x}_i\|^2 \quad \text{subject to } \|\mathbf{w}_i^H \mathbf{h}_{ii}\|^2 = 1, \ i = 1, \ldots, M.$$

Define the correlation matrix as $\mathbf{\Phi}_i = E[\mathbf{x}_i \mathbf{x}_i^H]$. The optimal weight vector is given by

$$\hat{\mathbf{w}}_i = \frac{\mathbf{\Phi}_i^{-1} \mathbf{h}_{ii}}{\mathbf{h}_{ii}^H \mathbf{\Phi}_i^{-1} \mathbf{h}_{ii}}. \tag{26}$$

TABLE IV
JOINT BEAMFORMING AND PROPOSED RESOURCE ALLOCATION

Initialization: $\gamma_i(0) = \gamma_i^{ave}, \ \forall i.$
Iteration:
1.Beamforming: find the optimal $\mathtt{w}_i, \ \forall i$
2.Adaptive Threshold Allocation: find the targeted SINR $\gamma_i, \ \forall i.$
3.Power Update: update powers by $\mathtt{w}_i$ and $\gamma_i, \ \forall i.$
SINR Range Update: Update $\gamma_i^{mid}(n), \gamma_i^{min}(n),$ and $\gamma_i^{max}(n), \ \forall i.$

Assuming that the transmitted signals from different sources are uncorrelated and zero mean and that the additive noise is spatially and temporally white, we can write the ith user's power at the beamformer output of the ith base station as

$$E[\|\mathbf{w}_i^H\mathbf{x}_i\|^2] = P_i\rho_{ii}G_{ii} + \sum_{m\neq i} P_m\rho_{mi}G_{mi}\|\mathbf{w}_i^H\mathbf{h}_{mi}\|^2 + \mathbf{w}_i^H\mathbf{N}_i\mathbf{w}_i \quad (27)$$

where $\mathbf{N}_i$ is the noise correlation matrix. The effective SINR at the ith base station's beamformer output is given by

$$\Gamma_i = \frac{P_i\rho_{ii}G_{ii}}{\sum_{m\neq i} P_m\rho_{mi}G_{mi}\|\mathbf{w}_i^H\mathbf{h}_{mi}\|^2 + \mathbf{w}_i^H\mathbf{N}_i\mathbf{w}_i}. \quad (28)$$

For the downlink case, the complexity of beamforming may increase because the calculations for the beamformer weight vectors need the knowledge of downlink channel responses for the whole network. This requires channel measurements at the mobile users and feedback mechanisms to send the information to the base stations, which will cost too much overhead and reduce the capacity. In order to calculate the downlink beamforming weight vectors, we can only measure the channel response from the base station to its assigned mobile user. We try to maximize the received power at the desired mobile user with a fixed norm downlink beamforming vector as

$$\tilde{\mathbf{w}}_m = \arg\max \|\tilde{\mathbf{w}}^H\tilde{\mathbf{h}}_{mm}\|^2 \qquad \text{subject to } \|\tilde{\mathbf{w}}\|^2 = 1 \quad (29)$$

where $\tilde{\mathbf{w}}_m$ is the downlink beamforming weight vector for the mth user and $\tilde{\mathbf{h}}_{mm} = [\tilde{h}_{mm}^1, \ldots, \tilde{h}_{mm}^P]^T$ with $\tilde{h}_{mm}^p$ as the channel response from the pth antenna.

It is well known that the beamforming can effectively reduce CCIs in different DOAs. However, if the desired users are almost at the same direction, the beamforming is less effective, because the beam pattern cannot distinguish the desired signals from the undesired interferences. Under this condition, some of the cochannel users will cause severe CCIs to the others. In the traditional joint power-control and beamforming schemes with the fixed link quality requirement, in order for the system to operate well all the time, the worst case scenario has to be considered to choose the users' link qualities. In our proposed joint schemes, each user's time average link quality is maintained instead. When beamforming cannot improve SINRs of some users, these users can sacrifice their temporary link qualities with the incentive that their link qualities can be compensated back, when the DOAs change better and beamformers become more effectively. Consequently, the overall transmitted power can be reduced a lot. It can be interpreted as the system to "water-fill" the users' link qualities, according to the different channel conditions, as well as the different DOA's over time. Therefore, our proposed schemes have one more degree of freedom to reduce the overall transmitted power. The proposed joint beamforming and resource-allocation scheme is shown in Table IV.

In the rest of this section, we will analyze a two-user example to illustrate the underlying reason for the performance improvements. Consider a network with two users and one base station. For the uplink, the two users' SINRs are given by

$$\begin{cases} \Gamma_1 = \frac{P_1\rho_1G_1}{\|\mathbf{w}_1^H\mathbf{h}_2\|^2 P_2\rho_2G_2 + \mathbf{w}_1^H\mathbf{N}_1\mathbf{w}_1} \\ \Gamma_2 = \frac{P_2\rho_2G_2}{\|\mathbf{w}_2^H\mathbf{h}_1\|^2 P_1\rho_1G_1 + \mathbf{w}_2^H\mathbf{N}_2\mathbf{w}_2} \end{cases}$$

where P_i, ρ_i, G_i, and $\mathbf{N}_i$ are the power, shadow fading, propagation gain, and thermal noise matrix, respectively; $\mathbf{w}_i$ is the ith user's beamforming weight vector; and $\mathbf{h}_i$ is the fading and array response for the ith user. The overall transmitted power can be written as

$$P_1 + P_2 = \frac{1}{1 - \Gamma_1\Gamma_2\|\mathbf{w}_1^H\mathbf{h}_2\|^2\|\mathbf{w}_2^H\mathbf{h}_1\|^2} \times \left(\frac{\Gamma_1\mathbf{w}_1^H\mathbf{N}_1\mathbf{w}_1}{\rho_1G_1} + \frac{\Gamma_2\mathbf{w}_2^H\mathbf{N}_2\mathbf{w}_2}{\rho_2G_2}\right)$$

where $\|\mathbf{w}_1^H\mathbf{h}_2\|^2$ and $\|\mathbf{w}_2^H\mathbf{h}_1\|^2$ represent the effects of beamformers to suppress the interferences. In the previous joint power-control and beamforming scheme [16], $\Gamma_1 = \Gamma_2$. Under this condition, in order to have a feasible solution of positive power allocation, the following condition must be satisfied at any time:

$$\Gamma_1 = \Gamma_2 < \frac{1}{\sqrt{\|\mathbf{w}_1^H\mathbf{h}_2\|^2\|\mathbf{w}_2^H\mathbf{h}_1\|^2}}. \quad (30)$$

Because the channel responses $\mathbf{h}_1$ and $\mathbf{h}_2$ change randomly, the beamformers cannot be very effective for some channel responses at some time. Consequently, the system has to be designed for the worst case situation, the overall transmitted power cannot be reduced, and the maximal achievable targeted SINR is low. The underlying reason is that there is no freedom to optimize the overall transmitted power by adjusting each user's targeted SINR. In the proposed scheme, $E(\Gamma_1) = E(\Gamma_2)$ over time. When the beamformers cannot reduce the interferences well, i.e., the term $\|\mathbf{w}_1^H\mathbf{h}_2\|^2\|\mathbf{w}_2^H\mathbf{h}_1\|^2$ is large, our proposed algorithm cleverly reduces the targeted SINRs (the value of $\Gamma_1\Gamma_2$ will be reduced), so that the overall transmitted power is reduced. The DOAs are frequently changed by the reflections around the moving users. The algorithm waits to increase the targeted SINRs and compensate the previous losses, until the

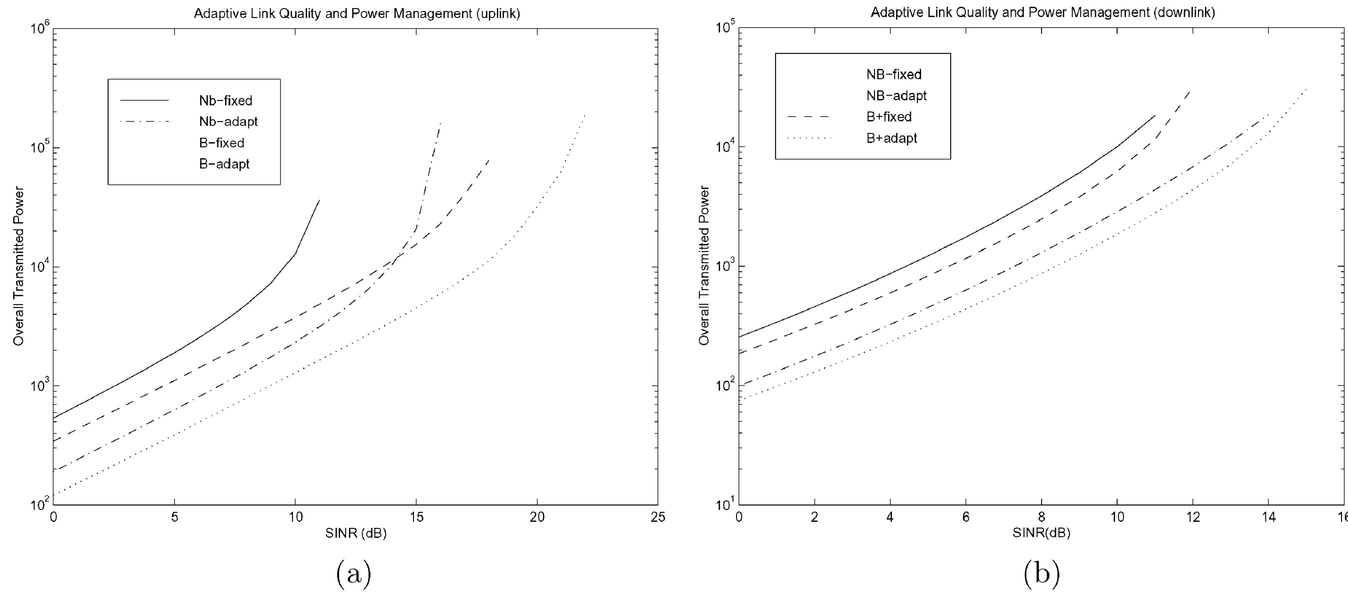

Fig. 1. Overall transmitted power as a function of average targeted SINR.

beamformers become more effectively for distinguishing the interfering users. This is why the joint schemes can be used to combat CCIs more efficiently, which will be shown in the simulation results in the next section.

V. Simulation Results

In order to evaluate the performances of the proposed algorithms, a network with 50 hexagonal cells is simulated. The radius of each cell is 1000 m. Two adjacent cells do not share the same channel. One base station is placed at the center of each cell and one user is located randomly within the cell with the uniform distribution. The uplink and downlink work in TDD. In the simulations, we consider three multipath Rayleigh fadings with equal powers. The delay spread between different paths is far less than one symbol duration. The angle of arrival for each path is a uniform random variable in $[0, 2\pi]$. Each base station has one traditional antenna or four-element antenna arrays. $\beta = 0.1$ and $N_i = 10^{-3}$. The channel fading is stable within each frame and is independent between frames. We have 10 000 simulation runs to ensure an accurate enough confidence interval.

Path loss is due to the decay of the intensity of a propagating radio wave. In the simulations, we use the two-slope path-loss model [32], [33] to obtain the average received power as a function of distance. According to this model, the average path loss is given by

$$G = \frac{K_0}{r^{b_1}\left(1 + \frac{r\lambda_c}{(4h_b h_m)}\right)^{b_2}} \tag{31}$$

where K_0 is a constant, r is the distance between the mobile user and the base station, $b_1 = 2$ is the basic path-loss exponent, $b_2 = 2$ is the additional path loss component, h_b is the base station antenna height, h_m is the mobile antenna height, and λ_c is the wavelength of the carrier frequency. We assume that the mobile antenna height is 2 m and the base station antenna height is 50 m. The carrier frequency is 900 MHz.

In the urban microcell system, the link quality is also affected by the shadowing of the line-of-sight path from terrain, buildings, and trees. The shadowing is generally modeled as log-normal distribution[41]. The probability density function (pdf) is given by

$$\mathrm{pdf}(\rho) = \frac{1}{\sqrt{2\pi}\sigma\rho}\exp\left\{-\frac{(\log\rho - \xi)^2}{2\sigma^2}\right\}, \qquad \rho > 0 \tag{32}$$

where ξ is related to the path loss and σ is the shadow standard deviation. In the simulation, for each link, 3-dB log-normal shadow fading is considered.

Fig. 1 illustrates the overall transmitted power as a function of the average targeted SINR and Fig. 1(a) shows the uplink case. We compare performances of the fixed SINR assignment algorithm [16] and those of the proposed adaptive-resource management, with and without beamforming. Here, we assume that each user has the same desired time average SINR threshold $\gamma_1^{\mathrm{ave}} = \ldots = \gamma_M^{\mathrm{ave}}$. For the SINR range, we assume $\hat{\gamma}_i^{\min} = \gamma_i^{\min}(0) = \gamma_i^{\mathrm{ave}} - \Delta\gamma$ and $\hat{\gamma}_i^{\max} = \gamma_i^{\max}(0) = \gamma_i^{\mathrm{ave}} + \Delta\gamma$, where $\Delta\gamma$ is defined as window size and $\Delta\gamma = 5$ dB. The solid curve (NB-fixed) shows the algorithm with the fixed SINR assignment and without beamforming [16]. The dashed-dotted curve (NB-adapt) shows the adaptive link quality and power management without beamforming. The dashed curve (B-fixed) shows the algorithm with the fixed SINR assignment and with beamforming [16]. The dotted curve (B-adapt) shows the adaptive link quality and power management with beamforming. The simulation results show that, compared with the fixed SINR assignment algorithm [16], the proposed algorithms significantly reduce the overall transmitted power by 60% and extend the maximal achievable SINR by 6 dB by using the adaptive link quality and power management alone. Beamforming can further reduce

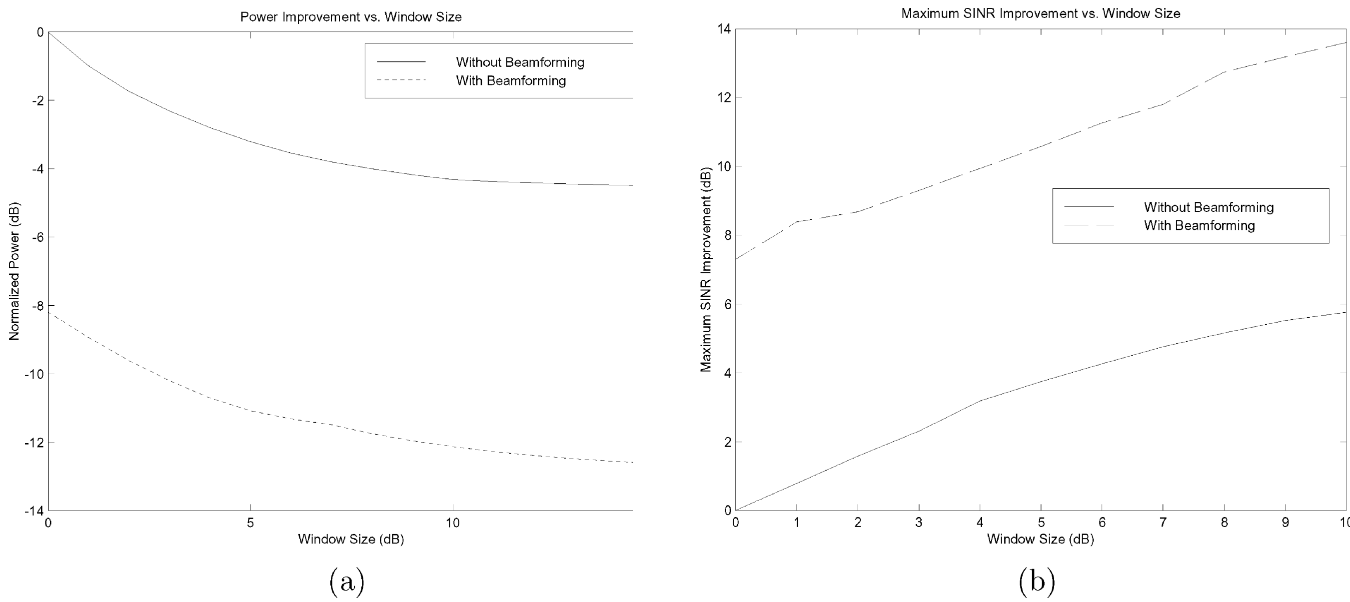

Fig. 2. Effects of window size.

the overall power by 60% and the maximal achievable SINR is improved by another 7 dB. Joint beamforming and our proposed algorithms can further reduce CCIs, especially at the higher SINR area, where CCIs become more severe. Fig. 1(b) shows the downlink case. We compare the performances of the adaptive downlink algorithm and those of the fixed SINR assignment [17] with beamforming and without beamforming. Here, similar as the uplink, we select $\Delta\gamma = 5$ dB. We use the simplifications mentioned in the previous section. From Fig. 1(b), we can see that the adaptive SINR threshold allocation can have 60% reduction of the overall transmitted power, which in turn reduces CCIs and increases the network capacity. Furthermore, the feasible SINR areas are extended by 4 dB. The beamforming can further reduce the overall power by 40%, but at the higher SINR area, because of the simplification of downlink beamforming algorithm, the advantage of beamforming is decreasing. From the simulation results, we can see that it is an efficient method to combat the time-varying nature of channel and CCIs by dynamically allocating resources.

In Fig. 2, we show the effects of window size $\Delta\gamma$ on the performance of the proposed algorithms in uplink. In Fig. 2(a), we normalize the overall transmitted power with the previous scheme [16] and compare that for various window sizes. We can see that the proposed algorithm can reduce about 4 dB of the overall transmitted power. When the window size increases, the speed of power reduction decreases and power stops decreasing, after the window size is greater than some value. This is because of the constraint that each user's time-average SINR is a constant. A user with a good channel condition now gets a higher SINR. In the future, the user has to pay back and be assigned with a lower SINR. When the proposed algorithm is combined with beamforming, the point where the overall transmitted power stops decreasing moves to a higher $\Delta\gamma$. In Fig. 2(b), we compare the maximal SINR improvement versus window size. We can see that the proposed algorithm can increase the maximal SINR by up to 6 dB. The increasing speed of the maximal achievable SINR is reduced as the window size increasing. Here, again, joint beamforming and the proposed resource-allocation algorithm has a better performance.

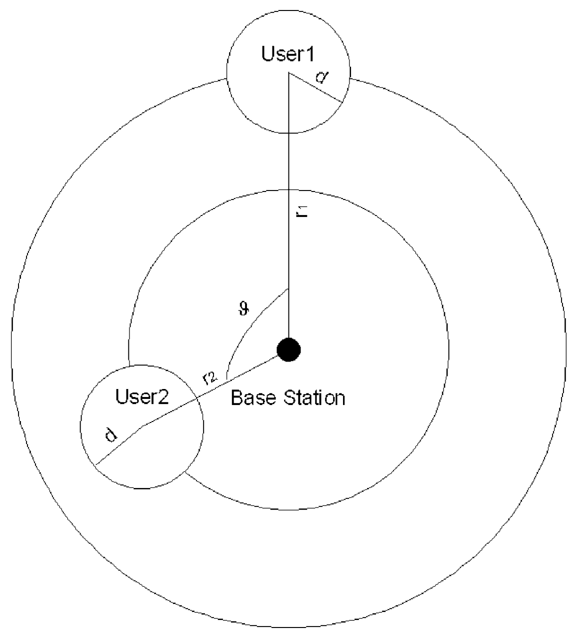

Fig. 3. Simulation system setup 2.

In order to further show that joint beamforming and the proposed resource allocation can combat CCIs in different DOAs and different channel conditions over time, an uplink network with two mobile users and one base station is set up as shown in Fig. 3. The distances between the two mobile users and the base station are r_1 and r_2, respectively. The difference between two users' DOAs is ϑ and the multipath fading is modeled by Jakes model [42]. Three multipath discrete scatterers are uniformly randomly placed on a disk with radius $d = 10$ m centered at each mobile user. We select $\Delta\gamma = 5$ dB and $P = 4$. The other settings are the same as before.

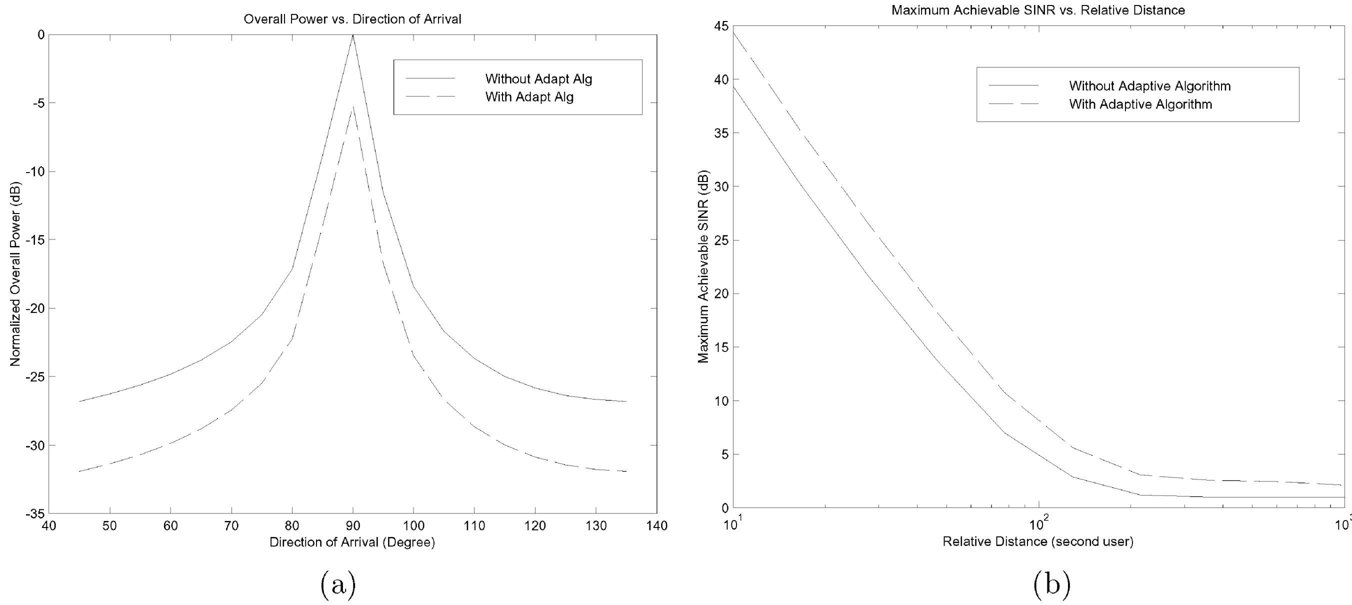

Fig. 4. Performance improvement by joint considering beamforming.

In Fig. 4(a), we compare the overall transmitted power versus DOA. Here, the first user is located at 90° and $r_1 = 1000$ m. The second user is located in different DOA and $r_2 = 50$ m. We can see that even when DOAs for the two users are almost the same (the second user is located from 85° to 95°), the proposed algorithm can still reduce the overall transmitted power by about 5 dB. When DOAs are different, the joint beamforming and proposed resource allocation can further reduce the overall transmitted power. In Fig. 4(b), we compare the maximal achievable SINR versus the relative distance (r_2). Here, the first user is located at 90° and $r_1 = 1000$ m. The second user is located at 90° and r_2 varies from 10 to 1000 m. In this situation, both users suffer severe CCIs from each other's transmitted powers. The maximal achievable SINR reduces sharply with increasing of r_2. When r_2 is small, the proposed algorithm can improve the performance by 6 dB, compared to the fixed SINR assignment algorithm. When r_2 is almost equal to r_1, the proposed algorithm can still improve the performance by about 2 dB, which is due to the constantly changing DOAs of the multipath.

VI. Conclusion

In summary, by adaptively managing the link quality and transmitted power, we minimize the overall transmitted power while each user's time-average link quality is maintained as a constant to ensure fairness. We develop the schemes to ensure fairness and to encourage some users to sacrifice their resource demands in a short period of time, with the incentive being that the system performance can be improved and their sacrifices can be compensated in the future. It can be conceived that the wireless network resources are "water filling" in time domain and are allocated for different users to reduce the overall network transmitted power.

In uplink cases, the proposed adaptive algorithm for uplink reduces 60% of the overall transmitted power of mobile users, compared with that of the fixed SINR threshold scheme [16], which is very critical in terms of battery lives in mobile sets. In downlink cases, the proposed adaptive algorithm significantly saves the overall transmitted power of base stations by 60%, compared with that of the algorithms in [17], which in turn increases the capacity of wireless networks. The maximal achievable SINR is extended by 4–6 dB toward higher SINR areas with better link qualities. When combining with beamforming, our scheme can combat CCIs in different DOAs and different channel conditions over time, which leads to a better utilization of the space–time characteristics of wireless communication.

References

[1] R. Yates, "A framework for uplink power control in cellular radio systems," *IEEE J. Select. Areas Commun.*, vol. 13, pp. 1341–1348, Sept. 1995.

[2] S. Ulukus and R. Yates, "Stochastic power control for cellular radio systems," *IEEE Trans. Commun.*, vol. 46, pp. 784–798, June 1998.

[3] S. Kandukuri and S. Boyd, "Optimal power control in interference-limited fading wireless channels with outage-probability specifications," *IEEE Trans. Wireless Commun.*, vol. 1, pp. 44–55, Jan. 2001.

[4] J. Zander, S. L. Kim, M. Almgren, and O. Queseth, *Radio Resource Management for Wireless Networks*. Norwood, MA: Artech House, 2001.

[5] G. J. Foschini and Z. Miljanic, "A simple distributed autonomous power control algorithm and its convergence," *IEEE Trans. Veh. Technol.*, vol. 42, pp. 641–646, Nov. 1993.

[6] M. Frodigh, "Performance bounds for power control supported DCA-algorithms in highway micro cellular radio systems," *IEEE Trans. Veh. Technol.*, vol. 44, pp. 238–243, May 1995.

[7] R. Jantti and S. L. Kim, "Second-order power control with asymptotically fast convergence," *IEEE J. Select. Areas Commun.*, vol. 18, pp. 447–457, Mar. 2000.

[8] X. Qiu and K. Chawla, "On the performance of adaptive modulation in cellular systems," *IEEE Trans. Commun.*, vol. 47, pp. 884–895, June 1999.

[9] N. Prasad and M. Varanasi, "Analysis of decision feedback detection for MIMO Rayleigh fading channels and optimum allocation of transmitter powers and QAM constellations," presented at the 39th Annu. Allerton Conf. Comm. Control, Comput., Monticello, IL, Oct. 2001.

[10] A. Goldsmith and S. Chua, "Variable-rate variable-power MQAM for fading channels," *IEEE Trans. Commun.*, vol. 45, pp. 1218–1230, Oct. 1997.

[11] Z. Han and K. J. R. Liu, "Joint adaptive power and modulation management in wireless networs with antenna diversity," presented at the IEEE 2nd IEEE Sensor Array and Multichannel Signal Processing Workshop (SAM'02) , Rosslyn, VA, Aug. 2002.

[12] S. Kim, Z. Roseberg, and J. Zander, "Combined power control and transmission rate selection in cellular networks," in *Proc. IEEE Vehicular Technology Conf.*, 1999, pp. 1653–1657.

[13] E. Armanious, D. D. Falconer, and H. Yanikomeroglu, "Adaptive modulation, adaptive coding, and power control for fixed cellular broadband wireless systems: Some new insights," *Proc. IEEE Wireless Communications and Networking Conf. (WCNC'03)*, vol. 1, pp. 238–241, Mar. 2003.

[14] C. W. Sung and W. S. Wong, "Power control and rate management for wireless multimedia CDMA systems," *IEEE Trans. Commun.*, vol. 49, pp. 1215–1226, July 2001.

[15] S. Kandukuri and S. Boyd, "Optimal power control in interference-limited fading wireless channels with outage-probability specifications," *IEEE Trans. Wireless Commun.*, vol. 1, pp. 44–55, Jan. 2001.

[16] F. Rashid-Farrokhi, L. Tassiulas, and K. J. R. Liu, "Joint optimal power control and beamforming in wireless network using antenna arrays," *IEEE Trans. Commun.*, vol. 46, pp. 1313–1323, Oct. 1998.

[17] F. Rashid-Farrokhi, K. J. R. Liu, and L. Tassiulas, "Transmit beamforming and power control for cellular wireless systems," *IEEE J. Select. Areas Commun.*, vol. 16, pp. 1437–1449, Oct. 1998.

[18] S. Papavassiliou and L. Tassiulas, "Improving the capacity of wireless networks through integrated channel base station and power assignment," *IEEE Trans. Veh. Technol.*, vol. 47, pp. 417–427, May 1998.

[19] A. Yener, D. Yates, and S. Ulukus, "Interference management for CDMA systems through power control, multiuser detection, and beamforming," *IEEE Trans. Commun.*, vol. 49, pp. 1227–1239, July 2001.

[20] D. Tse and S. Hanly, "Multi-access fading channels: Part I: Polymatroid structure, optimal resource allocation and throughput capacities," *IEEE Trans. Infom. Theory*, vol. 44, pp. 2796–2815, Nov. 1998.

[21] R. Negi and J. Cioffi, "Transmission over fading channels with channel side information and delay constraint," presented at the IEEE GLOBECOM'99, Rio de Janiero, Brazil, Dec. 1999.

[22] K. K. Leung and L. C. Wang, "Controlling QoS by integrated power control and link adaptation in broadband wireless networks," *Eur. Trans. Telecommun.*, no. 4, pp. 383–394, 2000.

[23] S. Kandukuri and N. Bambos, "Multi-modal dynamic multiple access (MDMA) in wireless packet networks," in *Proc. INFOCOM'01*, vol. 1, Anchorage, AK, Apr. 2001, pp. 199–208.

[24] M. Elaoud and P. Ramanathan, "Adaptive allocation of CDMA resources for network level QoS assurances," *Proc. MOBICOM'00*, pp. 191–199, Aug. 2000.

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

[26] M. Xiao, N. B. Shroff, and E. K. P. Chong, "Utility-based power control in cellularwireless systems," presented at the INFOCOM'01, 2001.

[27] Z. Han and K. J. R. Liu, "Adaptive SINR theshold allocation for joint power control and beamforming overal wireless network," in *Proc. IEEE Vehicular Technology Conf.*, Atalantic City, NJ, Sept. 2001, pp. 1548–1552.

[28] ——, "Power minimization under constant throughput constraint in wireless networks with beamforming," in *Proc. IEEE Vehicular Technology Conf.*, Vancouver, BC, Canada, Sept. 2002.

[29] P. Ormeci, X. Liu, D. L. Goeckel, and R. D. Wesel, "Adaptive bit-interleaved coded modulation," *IEEE Trans. Commun.*, vol. 49, pp. 1572–1581, Sept. 2001.

[30] M. Mesbahi, M. G. Safonov, and G. P. Papavassilopoulos, "Bilinearity and complementarity in robust control," in *Advances in Linear Matrix Inequality Methods in Control*. Philadelphia, PA: SIAM, 2000.

[31] A. Sampath and J. M. Holtzman, "Access control of data in integrated voice/data CMDA systems: Benefits and tradeoffs," *IEEE J. Select. Areas Commun.*, vol. 15, pp. 1511–1526, Oct. 1997.

[32] P. Harley, "Short distance attenuation measurements at 900 MHz and 1.8 GHz using low antenna heights for microcells," *IEEE Trans. Select. Areas Commun.*, vol. SAC-37, pp. 220–222, Nov. 1988.

[33] M. V. Clark , V. Erceg, and L. J. Greenstein, "Reuse efficiency in urban microcellular networks," in *Proc. IEEE Vehicular Technology Conf.*, Atlanta, GA, Apr. 1996, pp. 421–425.

[34] R. A. Monzingo and T. W. Miller, *Introduction to Adaptive Arrays*. New York: Wiley, 1980.

[35] G. Golub, *Matrix Computations*, 3rd ed. Baltimore, MD: Johns Hopkins Univ. Press, 1996.

[36] A. Mercado and K. J. R. Liu, "NP-hardness of the stable matrix in unit interval family problem in discrete time," *Syst. Control Lett.*, pp. 261–265, 2001.

[37] D. Gerlach and A. Paulraj, "Adaptive transmitting antenna arrays with feedback," *IEEE Signal Processing Lett.*, vol. 1, pp. 150–152, Oct. 1994.

[38] P. Zetterberg and B. Ottersten, "The spectrum efficiency of a base station antenna array system for spatially selective transmissions," *IEEE Trans. Veh. Technol.*, vol. 44, pp. 651–660, Aug. 1995.

[39] G. G. Raleigh, S. D. Diggavi, V. K. Jones, and A. Paulraj, "A blind adaptive transmit antenna algorithm for wireless communication," in *Proc. IEEE IEEE Int. Conf. on Communications (ICC'95)*, Seattle, WA, 1995, pp. 1949–1953.

[40] D. P. Bertsekas, *Nonlinear Programming*, 2nd ed. Belmont, MA: Athena Scienific, 1999.

[41] G. L. Stuber, *Principles of Mobile Communications*. Norwell, MA: Kluwer, 1996.

[42] W. C. Jakes, *Microwave Mobile Communications*. New York: IEEE Press, 1974.

Zhu Han (S'01) received the B.S. degree in electronic engineering from Tsinghua University, Beijing, China, in 1997 and the M.S. and Ph.D. degrees in electrical engineer from the University of Maryland, College Park, in 1999 and 2003, respectively.

From 1997 to 2000, he was a Graduate Research Assistant with the University of Maryland and from 2000 to 2002, he was an Engineer in the research and development group, ACTERNA, Germantown, MD. He currently is a Faculty Research Assistant with the University of Maryland. His research interests include wireless resource allocation and management, wireless communications and networking, game theory, and wireless multimedia.

Dr. Han is on the technical programming committee for the IEEE International Conference on Communications 2004 and 2005, the IEEE Vehicular Technology Conference Spring 2004, the IEEE Consumer Communications and Networking Conference 2005, and the IEEE Wireless Communications and Networking Conference 2005. He also is a Session Chair for the IEEE Wireless Communications and Networking Conference 2004.

K. J. Ray Liu (F'03) received the B.S. degree from the National Taiwan University, Taipei, Taiwan, R.O.C., in 1983 and the Ph.D. degree from University of California, Los Angeles (UCLA), in 1990, both in electrical engineering.

He is Professor with the Electrical and Computer Engineering Department and Institute for Systems Research, University of Maryland, College Park. He was the founding Editor-in-Chief of *EURASIP Journal on Applied Signal Processing*. His research interests span broad aspects of signal-processing algorithms and architectures, multimedia communications and signal processing, wireless communications and networking, information security, and bioinformatics, in which he has published over 280 refereed papers.

Dr. Liu is the Recipient of numerous honors and awards, including the IEEE Signal Processing Society 2004 Distinguished Lecturer, the 1994 National Science Foundation Young Investigator Award, the IEEE Signal Processing Society's 1993 Senior Award (Best Paper Award), and the IEEE 50th Vehicular Technology Conference Best Paper Award, Amsterdam, in 1999. He also received the George Corcoran Award for outstanding contributions to electrical engineering education in 1994 and the Outstanding Systems Engineering Faculty Award in 1996, in recognition of outstanding contributions in interdisciplinary research, both from the University of Maryland. He is the Editor-in-Chief of IEEE SIGNAL PROCESSING MAGAZINE and has served as an Associate Editor of IEEE TRANSACTIONS ON SIGNAL PROCESSING, a Guest Editor of a Special Issues on multimedia signal processing for PROCEEDINGS OF THE IEEE, a Guest Editor of a Special Issue on signal processing for wireless communications for IEEE JOURNAL OF SELECTED AREAS IN COMMUNICATIONS, a Guest Editor of a Special Issue on multimedia communications over networks for the IEEE SIGNAL PROCESSING MAGAZINE, and a Guest Editor of a Special Issue on multimedia over IP for the IEEE TRANSACTIONS ON MULTIMEDIA. He has served as Chairman of the Multimedia Signal Processing Technical Committee for the IEEE Signal Processing Society.