Joint Network-Centric and User-Centric Radio Resource Management in a Multicell System*

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Abstract
A pricing mechanism to mediate (and allocate resources) between conflicting user and network objectives has been recently proposed [1, 2] in a single-cell system. In this short paper, we extend the results to a multicell system where the autonomous base station assignment and power control are formulated as a non-cooperative game among users. The network prices the resources using two strategies: global pricing that maximizes the revenue and minimax pricing that trades off the revenue for an even resource distribution.

Index Terms
Power Control, Pricing, Utility, Radio Resource Management, Revenue Maximization

I. INTRODUCTION
Pricing, and more generally microeconomic principles, have recently emerged as powerful tools for resource allocation in wireless networks [3–6]. For example, pricing was used as a policing mechanism to improve user behavior and system efficiency for the up-link of a CDMA data system in [3, 4]. In [5], pricing was a potential simplification of explicit admission control. Pricing in [6] was applied for the down-link of a CDMA voice system to maximize the total utilities or the total revenues. In our most recent work [1, 2], we have considered joint user-centric and network-centric radio resource management for an uplink single-cell CDMA system where pricing played the role of a mediating mechanism between the user and network. In the single-cell system, each user adjusted its transmitter power unilaterally to maximize its net utility, defined as utility minus its payment. On the other hand, the network chose the unit price that maximized the total revenue. The net result is a tradeoff between the two seemingly conflicting user and network objectives.

In this paper, we extend the work in [1, 2] for a single-cell system to a multicell system. Each individual user has to adjust its transmitter power based on the base station it is assigned to. Different base station assignments will lead to different power control results. In this paper, we let the user choose the base station where the user’s net utility is maximized. Therefore, the power control and base station assignment are integrated in the user-centric optimization. For the network-centric optimization, we apply two approaches: one is global pricing where the network seeks a unit price for global revenue maximization and the other is minimax pricing where a unit price is assigned based on maximizing the revenue at the base station with the smallest local optimum unit price.

The paper is organized as follows. In Section II, we define in a multicell CDMA system the user metric (utility function) and the network metric (revenue) as well as the pricing (or payment) function that mediates between the user objectives and the network objective. We present in Section III our joint user-centric and network-centric optimization problems. Our numerical results are presented in Section IV.

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II. SYSTEM MODEL

We consider the up-link of a CDMA system with \( K \) cells serving \( N \) mutually interfering users that are randomly located throughout the service area.

A. User Metric: Utility Function

We assume that there is no base station diversity, i.e., one user is connected to only one base station at any time. The quality of service (QoS) received by user \( i \) can be translated quantitatively into a utility function. While several notions of utilities are possible [3–8], we use the one chosen here [7] since it combines the two important criteria of wireless transmission: throughput denoted as \( T \) and transmitter power denoted as \( p \). The transmitter power vector is denoted as \( \mathbf{p} = (p_1, p_2, ..., p_N) \). The utility function \( U_i(a_i, \mathbf{p}) \) of user \( i \) when it is assigned to base station \( a_i \) is defined as the average number of information bits of user \( i \) received correctly at base station \( a_i \) per Joule of battery energy expended. It is generally given as:

\[
U_i(a_i, \mathbf{p}) \triangleq \frac{T_i(a_i, \mathbf{p})}{p_i},
\]

where \( T_i(a_i, \mathbf{p}) \) is the throughput of user \( i \) received at base station \( a_i \). Data bits are packed into frames of \( M \) bits containing \( L < M \) information bits per frame, where \( M - L \) bits are used for error detection. The signal of user \( i \) is transmitted at a rate of \( R_i \) bits per second. The received signal to interference plus noise ratio (SINR) of user \( i \) at base station \( a_i \) is given as:

\[
\gamma_i(a_i, \mathbf{p}) = \frac{W}{R_i} \left( \sum_{j \neq i} h_{a_i,j} p_j + \sigma^2 \right) \triangleq G_i \frac{h_{a_i,i} p_i}{T_i(a_i, \mathbf{p})},
\]

where \( h_{a_i,i} \) is the path gain from the \( i^{th} \) user to the \( a_i^{th} \) base station. \( \sigma^2 \) is the additive white Gaussian noise (AWGN) power. \( G_i = W/R_i \) is the processing gain of the \( i^{th} \) signal with \( W \) being the common chip rate of user \( i \). \( T_i(a_i, \mathbf{p}_{-i}) = \sum_{j \neq i} h_{a_i,j} p_j + \sigma^2 \) denotes the interference plus noise level before spreading at base station \( a_i \) for user \( i \) and \( \mathbf{p}_{-i} = (p_1, p_2, ..., p_{i-1}, p_{i+1}, ..., p_N) \) denotes the transmitter power vector without the power of the \( i^{th} \) user. We assume perfect error detection and automatic retransmission request (ARQ): a frame with error is retransmitted until received correctly. Then the throughput is equal to \( T_i(a_i, \mathbf{p}) = \frac{L}{M} R_i f(\gamma_i(a_i, \mathbf{p})) \); where the efficiency function \( f(\gamma_i(a_i, \mathbf{p})) = [1 - 2\text{BER}(\gamma_i(a_i, \mathbf{p}))]^{3/2} \), with BER(\( \gamma_i(a_i, \mathbf{p}) \)) being the bit error rate. Note that the efficiency function is an approximation to the frame success rate (FSR) that yields the desirable properties of \( U_i(a_i, \mathbf{p}) = 0 \) when \( p_i = 0 \) and \( p_i = \infty \) (see [3, 4, 7] for details).

B. Network Metric: Revenue

With the existence of a pricing scheme, a natural metric of the network satisfaction is its revenue. Revenue is the product of price per unit service and the amount of service provided. The amount of service provided is proportional to the throughput for a fixed time frame. We assume a fixed time frame for our system, and in this fixed time frame, the network charges each user proportional to its throughput. We assume that the network broadcasts a common unit price \( \lambda \) to all the users. Given a base station and power vector assignment, the payment by each user is explicitly a function of \( \lambda \) and is given as:

\[
r_i(\lambda) \triangleq \lambda T_i(a_i, \mathbf{p}).
\]

Further, if we denote \( \beta_k \) as the set of users connected to the base station \( k \) (\( i \in \beta_k \) if and only if \( a_i = k \)), the revenue collected by the base station \( k \) is defined as:

\[
\rho_k(\lambda) \triangleq \sum_{i \in \beta_k} \lambda T_i(a_i, \mathbf{p}).
\]
The revenue that the network collects is:

\[ \rho(\lambda) = \sum_{k=1}^{K} \rho_k(\lambda) = \sum_{i=1}^{N} \rho_i(\lambda). \]

In the context of this paper, we propose pricing as a mediator between possibly conflicting user and network objectives. While such a pricing scheme can be expressed in terms of monetary units, the actual transformation remains a topic of future study.

### III. Joint User and Network Optimization

#### A. User Optimization: Autonomous Base Station Assignment and a Non-cooperative Power Control Game

With the network broadcasted unit price \( \lambda \), the user objective is for each user to unilaterally maximize its net utility, defined as the difference between its utility and its payment:

\[
\text{[User Problem]} \quad \max_{p_i, a_i} U_i^{\text{net}}(a_i, p_i, p_{-i}, \lambda) = \max_{p_i, a_i} \left\{ U_i(a_i, p) - \lambda T_i(a_i, p) \right\}, \quad \forall i.
\]

Given the minimum and maximum power constraints denoted as \( p_i^{\text{min}} \) and \( p_i^{\text{max}} \) and the total number of base stations denoted as \( K \), \( S_i = [p_i^{\text{min}}, p_i^{\text{max}}] \) and \( A = \{1, 2, ..., K\} \) in the above equation is the strategy space for the transmitter power and the base station assignment of the \( i \)th user. Unlike the user-centric problem in a single-cell system where each user maximizes its net utility over its transmitter power only, the user-centric objective is to optimize the net utility over two dimensions: its transmitter power and its base station assignment. The transmitter power takes continuous values and the base station assignment takes discrete value only. Searching over all possible base station assignments and performing net utility optimizations over transmitter powers for every combination would be computationally intensive. We can greatly simplify the **User Problem** by virtue of the following theorem:

**Theorem III.1**: Given an interference vector \( p_{-i} \), the following is true:

\[
\max_{p_i, a_i} U_i^{\text{net}}(a_i, p_i, p_{-i}, \lambda) = \max_{p_i, a_i} \max_{a_i} U_i^{\text{net}}(a_i, p_i, p_{-i}, \lambda), \quad \forall i.
\]

Furthermore, the base station assignment based on the net utility maximization is equivalent to the one based on maximizing SINR:

\[
a_i^* = \arg \max_k U_i^{\text{net}}(k, p_i, p_{-i}, \lambda) \equiv \arg \max_k \gamma_i(k, p).
\]

The proof of the above theorem is shown in Appendix A. The implication of the above theorem is that the base station assignment of any user \( i \) based on its net utility maximization is equivalent to the one based on maximizing its SINR. Further, the net utility maximization via joint power control and base station assignment is equivalent to doing base station assignment first and then power control. The user problem can be regarded as a non-cooperative game and we now present some properties of this game.

1) **Nash Equilibrium and Its Existence**: If all the users’ optimization attempts settle down, the game achieves an equilibrium called the Nash equilibrium with the equilibrium power vector and base station assignment vector \( (p^*(\lambda), a^*(\lambda)) \), where power vector is defined as \( p^* = (p_1^*, p_2^*, ..., p_N^*) \) and base station assignment vector is defined as \( a^* = (a_1^*, a_2^*, ..., a_N^*) \). Formally, the Nash equilibrium power and base station assignment vector is the one at which no single user can improve its net utility by unilaterally changing its power and its base station assignment. Mathematically,

\[
p_i^* = \arg \max_{\xi_i \in S_i} U_i^{\text{net}}(a_i^*, \xi_i, p_{-i}^*, \lambda), \quad \text{where} \quad a_i^* = \arg \max_k \gamma_i(k, p^*), \quad \forall i.
\]
Theorem III.2: A Nash equilibrium exists for the multi-cell non-cooperative power control game if BER(\(\gamma\)) decays exponentially in SINR denoted by \(\gamma\). □

The proof of the above theorem is similar to that of the existence of a Nash equilibrium in a single-cell system shown in [1].

2) Iterative Algorithm and Its Convergence: The iterative algorithm for the user-centric optimization is for each user in a round-robin way first to do the base station assignment based on maximizing its SINR, then to find the transmitter power that optimizes its net utility.

The base station assignment is based on maximizing SINR at a given interference vector. The base station update rule is:

\[
a_i(t + 1) = \arg \max_k \gamma_i(k, p(t)) = \arg \max_k G_i \frac{h_{ki}}{I_i(k, p_{-i}(t))}.
\]

(10)

With \(p(t)\) denoting the power vector at the \(t\)th iteration, the power update rule for the next iteration is:

\[
p_i(t + 1) = \arg \max_{\xi_i \in S_i} U_{\text{net}}(a_i(t + 1), \xi_i, p_{-i}(t), \lambda), \forall i.
\]

(11)

The power update rule for all the users can be expressed in general as:

\[
p(t + 1) = X(p(t)),
\]

(12)

where \(p(t) \in \mathbb{R}^N\) and \(X(\cdot) \in \mathbb{R}^N\) is the mapping corresponding to the update rule. It is shown in Appendix B that for all \(p \in S \triangleq S_1 \times S_2 \times \ldots \times S_N\), the update rule function \(X(\cdot)\), has the following properties:

1) Positivity: \(X(p) > 0\);

2) Monotonicity: If \(p > p'\), then \(X(p) \geq X(p')\);

3) Scalability: \(\forall \alpha > 1, \alpha X(p) > X(\alpha p)\).

These properties satisfy those of a standard interference function for distributed power control (see [9]). We can apply the results in [9] directly and prove the following theorem:

Theorem III.3: Given any unit price \(\lambda\), starting from any initial point \(p^0 \in S, a^0 \in A^N\), the iteration specified by \(p(t + 1) = X(p(t))\), always converges to a unique Nash equilibrium. □

In summary, the user-centric optimization realizes autonomous base station assignment and power control, i.e., for every given value of unit price \(\lambda\), the resulting power and base station assignment vector converge to the fixed values denoted as \(p^*(\lambda)\) and \(a^*(\lambda)\) respectively.

B. Network Optimization

We will discuss in the following two different network problems characterized by strategies for finding the optimum unit price.

1) Global Pricing: The network aims to find its highest revenue by searching over \(\lambda \geq 0\):

\[
\text{[Network Problem(G)] max}_{\lambda \geq 0} \rho(\lambda), \text{ where } \rho(\lambda) = \sum_{i=1}^{N} \lambda T_i(a^*(\lambda), p^*(\lambda)).
\]

(13)

Theorem III.4: The revenue \(\rho(\lambda)\) as a function of the unit price \(\lambda\) has the following desirable properties: \(\rho(\lambda) \geq 0; \rho(\lambda) = 0\) when \(\lambda = 0; \rho(\lambda) < \infty\) when the number of users \(N\) is finite; \(\rho(\lambda) \to 0\) as \(\lambda \to \infty\). □

The proof of the above theorem is very similar to that for a single-cell system [1]. These properties together with the continuity of revenue yield:

\(^1\)The base station assignment is not necessarily unique even though the power control converges to the unique power vector.
Corollary III.1: There exists an optimum unit price $\lambda_G$ which maximizes the revenue $\rho(\lambda)$. Further, both $\lambda_G$ and $\rho(\lambda_G)$ are finite.

While we do not have a formal proof for the uniqueness of the optimum unit price, all our numerical results seem to support such a hypothesis.

2) Minimax Pricing: In this pricing scheme, the network chooses the unit price in the following way. First, the optimum unit price that maximizes the revenue $\rho^k$ at the base station $k$ is found for every base station $k = 1, 2, ..., K$. Then the unit price called the minimax price denoted as $\lambda_M$ is chosen to be the smallest among the $K$ optimum unit prices obtained at each of the base stations. Mathematically, the network problem in this case can be stated as:

$$[\text{Network Problem}(M)] \min \left\{ \arg \{ \max \lambda \rho^1(\lambda) \}, \arg \{ \max \lambda \rho^2(\lambda) \}, ..., \arg \{ \max \lambda \rho^K(\lambda) \} \right\}. \quad (14)$$

It is easy to verify that $\lambda_M$ exists. Minimax pricing results in an evener distribution of achieved QoS compared to global pricing, as will be discussed in the following.

IV. Numerical Results and Discussions

We consider a multicell CDMA system with $K = 4$ base stations serving $N = 30$ users. We use a distance based path gain formula, i.e., a user at a distance $d$ from the base station has the path gain $h = \text{constant} / d^4$. We use non-coherent FSK as the modulation method. The main system parameters are listed in Table I. The locations of a randomly generated set of users in the four-cell system are as shown in Figure 1. We want to compare in the following the two network optimization strategies. We plot in Figure 2 the revenue of each base station and the total revenue as a function of the unit price, where we observe that the network collects more revenue using the global pricing scheme compared to the minimax one. We next compare the user metrics at the global optimum unit price $\lambda_G$ and the minimax pricing optimum price $\lambda_M$ as a function of distance to the assigned base station in Figure 3. We can observe that at minimax pricing $\lambda_M$, users have higher frame success rates (FSR) while they transmit at higher transmitter powers. We can see from Figure 3 (a), that under global pricing, only two users have FSRs that are significantly higher than zero. With minimax pricing, however, it is observed in this example that there are significantly more number of users with such FSRs. The utilities at $\lambda_M$ are generally higher than their counterparts at $\lambda_G$, except for one user with the best channel, as shown in Figure 3 (c). As to the payments, the network obtains its revenue mainly from the few users with best channels when using $\lambda_G$; while the network collects the revenue (though lower than the revenue got at $\lambda_G$) from more users when using $\lambda_M$. In Figure 3 (d), the network collects revenue mainly from two users at $\lambda_G$ while eight users contribute non-negligible amount of payments to the network revenue at $\lambda_M$. However, the total revenue at $\lambda_G$ is higher than that at $\lambda_M$. We can observe from Figure 4 that users who pay more obtain proportionally better service, measured in terms of their utilities, which is consistent with our main results for a single-cell system in [1]. This proportionality holds true for both global and minimax pricing strategies. The minimax pricing network optimization, however, reduces the degree of monopoly that the global pricing results in. In the global network optimization, the network is so greedy in collecting the revenue that most of the network resources are distributed to the very few users with best channels. The minimax pricing, however, reduces the degree of monopoly that the global pricing results in. The network resources are allocated to more users even though the total revenue collected is lowered. One can view this as a trade off between the network revenue and an evener distribution of network resources.
Since the throughput $T_i$ is equivalent to maximizing throughput:

$$U_i^n = T_i(a_i, p_i, p_{-i}, \lambda) = T_i(a_i, p) \left( \frac{1}{p_i} - \lambda \right),$$

For any fixed transmitter power vector $p$ and unit price $\lambda$, the base station assignment based on maximizing net utility is equivalent to maximizing throughput:

$$\arg \max_k U_i^n(k, p_i, p_{-i}, \lambda) \equiv \arg \max_k T_i(k, p).$$

Since the throughput $T_i$ is a monotone increasing function of SINR $\gamma_i$, the base station assignment is equivalent to maximizing SINR: $\arg \max_k T_i(k, p) \equiv \arg \max_k \gamma_i(k, p)$. Therefore, the proposed equivalence

$$a^*_i = \arg \max_k U_i^n(k, p_i, p_{-i}, \lambda) \equiv \arg \max_k \gamma_i(k, p)$$

is proved.

For a fixed interference level $p_{-i}$, it can be shown that:

$$a^*_i = \arg \max_k \gamma_i(k, p) = \arg \max_k \frac{h_{ki}}{I_i(k, p_{-i})} p_i = \arg \max_k \frac{h_{ki}}{I_i(k, p_{-i})}, \quad \forall p_i \in S_i.$$

We can conclude that

$$\max_{p_i, a_i} U_i^n(k, p_i, p_{-i}, \lambda) \equiv \max_{p_i} \left( \max_{a_i} U_i^n(k, p_i, p_{-i}, \lambda) \right),$$

with base station assignment given by:

$$a^*_i \equiv \arg \max_k U_i^n(k, p_i, p_{-i}, \lambda) \equiv \arg \max_k \gamma_i(k, p);$$

thereby completing the proof.

### APPENDIX B

**Proof of Power Update Rule Being a Standard Interference Function**

The proof of positivity follows from the fact that power is always non-negative and zero power is a local minimum instead of a maximum of the objective function $U_i^n$.

To prove the monotonicity and the scalability, we proceed as follows. We solve the first order necessary condition $\frac{\partial U_i^n}{\partial p_i} = 0$ and replace $p_i$ with the update rule $X_i(p)$. We consider the Taylor series expansion to the exponential function and obtain:

$$1 - \lambda X_i(p) = \frac{1}{M} \sum_{n=0}^{\infty} \frac{1}{(n+1)!} \left[ \frac{\nu G h_{ki}}{I_i(k, p_{-i})} \right]^n [X_i(p)]^n = \sum_{n=0}^{\infty} \beta_n(p) [X_i(p)]^n,$$

where $k = a_i(p)$ is the base station assignment when the power vector is $p$ and each coefficient $\beta_n(p) = \frac{1}{M(n+1)!} \left[ \frac{\nu G h_{ki}}{I_i(k, p)} \right]^n$ is positive. We define $\Psi_L(\xi)$ as $\Psi_L(\xi) = 1 - \lambda \xi$, the function on the LHS of equation (20). We also define $\Psi_R(\xi; p)$ as $\Psi_R(\xi; p) = \sum_{n=0}^{\infty} \beta_n(p) \xi^n$, the function on the RHS of equation (20). Note that the solution to equation (20) is $X_i(p)$ that satisfies $\Psi_L(X_i(p)) = \Psi_R(X_i(p); p)$.

To prove monotonicity, we need to show that if $p > p'$, then $X_i(p) \geq X_i(p')$. Let us denote $j = a_i(p')$ as the base station assignment for the $i$th user when the power vector is $p'$, which might not be the same as
$k$, the base station assignment for power vector $p$. Since base station assignment is based on SINR maximization, from equation (17), we obtain $\frac{h_{i k}}{I_{i (k, p_{-i})}} > \frac{h_{i k}}{I_{i (k, p_{-i})}}$. On the other hand, $p' < p$ leads to $I_i (k, p'_{-i}) < I_i (k, p_{-i})$, which implies $\frac{h_{i k}}{I_{i (k, p_{-i})}} > \frac{h_{i k}}{I_{i (k, p_{-i})}}$. Combining the two inequalities together, we obtain $\frac{h_{i k}}{I_{i (k, p')_{-i}}} > \frac{h_{i k}}{I_{i (k, p_{-i})}}$, which is equivalent to $\beta_n (p') > \beta_n (p)$. Now let us prove the monotonicity by contradiction. Assume that $X_i (p) < X_i (p')$ when $p > p'$. Then we can derive $\Psi_L (X_i (p')) < \Psi_L (X_i (p))$ since $\Psi_L (\xi)$ is a monotone decreasing function. Further, since $\Psi_R (\xi, p)$ is a monotone increasing function and $\beta_n (p') > \beta_n (p)$, it follows that $\Psi_R (X_i (p'), p') > \Psi_R (X_i (p), p)$. We can see from the above two inequalities that it is impossible to satisfy both $\Psi_L (X_i (p)) = \Psi_R (X_i (p), p)$ and $\Psi_L (X_i (p')) = \Psi_R (X_i (p'), p')$, thus resulting in a contradiction. Therefore we prove monotonicity.

To prove scalability, we need to show that $\alpha X_i (p) > X_i (\alpha p)$, $\forall \alpha > 1$. Replacing $p$ with $\alpha p$ in the equation (20), we obtain:

$$1 - \lambda X_i (\alpha p) = \sum_{n=0}^{\infty} \beta_n (\alpha p) X_i^n (\alpha p) ;$$

where $\beta_n (\alpha p) = \frac{1}{M(n+1)!} \left[ \frac{\nu \xi}{I_i (\xi, \alpha p)} \right]^n$. We denote $l = a_i (\alpha p)$ as the base station assignment for the $i^{th}$ user when the power vector is $\alpha p$, which might not be the same as $k$, the base station assignment when the power vector is $p$. Since the base station assignment is based on maximizing SINR, from equation (17), we obtain $\frac{h_{i k}}{I_{i (l, \alpha p_{-i})}} > \frac{h_{i k}}{I_{i (l, p_{-i})}}$. On the other hand, $I_i (k, \alpha p_{-i}) < a I_i (k, p_{-i})$ for $\alpha > 1$, which implies $\frac{h_{i k}}{I_{i (k, \alpha p_{-i})}} > \frac{h_{i k}}{\alpha I_{i (k, p_{-i})}}$. Combining the above two inequalities, we obtain the following (by the definition of $\beta_n (\cdot)$),

$$\beta_n (\alpha p) > \frac{\beta_n (p)}{\alpha^n} .$$

Putting the inequality into equation (21), we get

$$1 - \lambda \left[ \frac{X_i (\alpha p)}{\alpha} \right] > \sum_{n=0}^{\infty} \beta_n (p) \left[ \frac{X_i (\alpha p)}{\alpha} \right]^n \forall \alpha > 1 .$$

We will again prove scalability by contradiction. We assume $\frac{X_i (\alpha p)}{\alpha} \geq X_i (p)$ for $\alpha > 1$. We can derive for both the LHS and RHS of the inequality (23) the following inequalities:

$$LHS = 1 - \lambda \left[ \frac{X_i (\alpha p)}{\alpha} \right] \leq 1 - \lambda \alpha X_i (p) \leq 1 - \lambda X_i (p);$$

$$RHS = \sum_{n=0}^{\infty} \beta_n (p) \left[ \frac{X_i (\alpha p)}{\alpha} \right]^n \geq \sum_{n=0}^{\infty} \beta_n (p) X_i^n (p) .$$

From equations (23), (24) and (25), it follows that $1 - \lambda X_i (p) > \sum_{n=0}^{\infty} \beta_n (p) X_i^n (p)$, i.e., $\Psi_L (X_i (p)) > \Psi_R (X_i (p), p)$, which is in contradiction to $\Psi_L (X_i (p)) = \Psi_R (X_i (p), p)$. Therefore $\frac{X_i (\alpha p)}{\alpha} < X_i (p)$ for $\alpha > 1$ and thus scalability is proved.

REFERENCES

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<th>Parameter</th>
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<td>Transmission Rate $R$</td>
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<td>Total Bits per packet $M$</td>
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<td>Information Bits per packet $L$</td>
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<td>AWGN Power at receiver $\sigma^2$</td>
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Fig. 1. The locations of a randomly generated set of users (denoted as +) in a four-cell (base stations are denoted as $\Delta$) system.


Fig. 2. Comparison of revenue via global pricing and minimax pricing.

Fig. 3. Comparison of the user metrics with global and minimax pricing.
Fig. 4. Proportionality between QoS (utility) achieved and payment.


