Application Notes

Hai-Lin Liu and Fangqing Gu
Guangdong University of Technology, Guangzhou, CHINA

Yiu-Ming Cheung
Department of Computer Science, Hong Kong Baptist University, Hong Kong, CHINA

Shengli Xie
Guangdong University of Technology, Guangzhou, CHINA

Jun Zhang
Department of Computer Science, Sun Yat-Sen University, Guangzhou, CHINA

On Solving WCDMA Network Planning Using Iterative Power Control Scheme and Evolutionary Multiobjective Algorithm

I. Introduction

Due to the increasing demand for mobile radio services, 3G wireless network planning has been becoming one of the most important research fields. 3G system, e.g. WCDMA, is based on Code Division Multiple Access [1], which is quite different from Time Division Multiple Access (TDMA) as used in 2G system. In the 3G network planning, not only are coverage, capacity and quality of the signal interrelated, but multi-rate and mixed-business also utilize the common carrier at the same time. As a result, it makes the 3G network planning become more challenging. In this paper, we will only concentrate on the WCDMA network planning. Since the WCDMA systems have self-interference and the effects of cell-breathing, it makes the coverage, capacity and interference of the base stations (BSs) restrain each other [2], [3]. That is, the area actually covered by a BS depends on the Quality of Service (QoS) and the traffic demand distribution. Therefore, the relationship between coverage, capacity and interference should be fully taken into account in the planning process.

In the past few years, a number of models have been developed for the WCDMA network planning, which can be roughly summarized into two categories. In the first category, the models only consider the location of the BS [4]–[8], [10], [32]. For example, Amaldi [4] planned the location of the BSs by considering the quality constraints for downlink (i.e. BS to user). In [5], the model is extended to the uplink (i.e. user to BS), which is more stringent than the downlink for symmetric traffic. Also, the models considering both downlink and uplink were presented in [6], [7]. Furthermore, Yang et al. [32] presented a programming model which takes into account soft handover [10] and the fast transmission power control. By contrast, the models in the other category consider not only the locations of the BSs, but also the BSs' configuration parameters [11]–[15]. For example, Gu et al. [11] proposed a multiobjective optimization model for WCDMA network planning, in which the antenna height and sector configuration are both considered. Furthermore, one of the most comprehensive models presented in [12] discussed a mathematical programming model to support the decisions, e.g. where to install new BSs, and how to select their configuration (i.e. antenna height and tilt, sector orientations, etc.), so as to find a trade-off between maximizing coverage and minimizing cost. This model has considered not only the configuration parameters of the BSs, but also the signal quality constraints in both uplink and downlink directions.


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In the WCDMA network planning, the most time-consuming procedure is to guarantee the QoS of the connection. There are many measures presented for this purpose. A simple and commonly adopted model proposed in [16], [17] assumes that the interference due to the neighboring cells (i.e. intercell interference) can be expressed as a fraction of the interference due to the other connections in the same cell (i.e. intracell interference). This model is suitable for homogeneous distribution of traffic demand, but not for the inhomogeneous one. In the literature, two power control mechanisms have been presented to minimize the interference and guarantee the quality. In the first one [18], [19], the transmitted power is adjusted so that the power received on each connection is equal to a given value. Therefore, whether a connection is active or not just depends on the mobile station positions. However, this simple mechanism may allocate more radio resources than necessary. In the second one [12], the transmitted power is adjusted so that the signal-to-interference ratio (SIR) is equal to the target value. This mechanism is more efficient than the first one because it allows for the use of lower power. Nevertheless, it is more complex because the power emitted by each station depends on that emitted by all the others. Moreover, some dimension reduction strategies have been addressed in [20]–[22] for systems equipped with

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omnidirectional antenna, but few studies have been conducted on the systems equipped with directive antenna.

In this paper, we will propose a novel WCDMA network planning model based on iterative power control scheme and optimize it by utilizing a multiobjective evolutionary algorithm based on decomposition. The main contributions of this paper are four-fold:

1) Propose a simple, but effective model: We pre-determine the maximum influence region of each BSs' sector. Then, the total interference is approximated with the interference due to the signals transmitted by the emitter (i.e., mobile stations in the uplink and base stations in the downlink) in the same maximum influence region. This model neglects the interference due to the channels without maximum influence region, thus simplifying the WCDMA planning model without degrading the performance evidently.
2) Develop an iterative power control scheme for directive antenna: In this scheme, when a single transmitted power is changed, we only update the transmitted power of the active connections in the same cell. Such power control method significantly reduces the complexity of the model.
3) Sample a small, but representative set of combination levels of configuration parameters: In the proposed model, each BS is equipped with directive antenna and four configuration parameters (i.e., antenna height, antenna tilt, sector orientation, and pilot signal power) are considered. However, since there are too many combination levels of configuration parameters, it is very difficult to find the best one from them. To overcome this problem, a representation method based on orthogonal design is proposed in this paper.
4) Apply a novel multiobjective evolutionary algorithm to solve this model: The evolutionary algorithm, as one of the most powerful tool to solve the complex optimization problems, has been widely used in the various fields [23]–[26]. Accordingly, we present a multiobjective evolutionary algorithm based on decomposition [27] to solve this combinatorial optimization problem. Simulation results have shown the effectiveness of the proposed algorithm by providing a set of high quality solutions.

The remainder of this paper is organized as follows: Section II proposes the mathematical model based on the local interference for network planning problem and describes the iterative power control scheme. In Section III, we code the solution with a novel representation strategy based on orthogonal design and present a multiobjective evolutionary algorithm to solve this model. Computational results are reported in Section IV. Finally, a conclusion is drawn in Section V.

II. The Model Based on Local Interference and Iterative Power Control Scheme

In WCDMA network planning problem, it needs to select a subset of candidate sites (CSs) to install BSs with suitable configuration parameters and assign the test points (TPs) to an available BS. In this section, we will present a model for the WCDMA network planning. Accordingly, a set of TPs and a set of CSs are given as follows:

TP: The service area is divided into some square grids. As shown in Fig. 1, the centroid of a grid is regarded as a TP. The ith TP is denoted as TP i with $i \in I = \{1,2,3,\cdots m\}$, where m is the number of TPs. Moreover, the traffic demand of TP i is represented by u_i^u in the uplink and u_i^d in the downlink. It can simply correspond to the number of the active connections. Then the total traffic demand of TP i is $u_i = u_i^u + u_i^d$.

CS: Suppose there are n CSs and there is at most one BS to be installed at each CS. For convenience, we will not discriminate between the base station installed at CS and the Candidate Site. For each BS, four configuration parameters are considered in this paper. That is:

❏ Antenna height: h_b
❏ Antenna Tilt: β
❏ Sector Orientation: γ
❏ Pilot Power: $\hat{p}$.

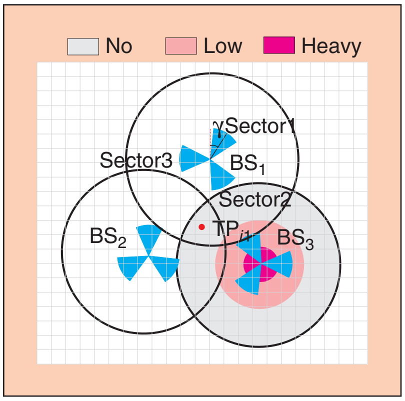

FIGURE 1 Illustration of the no-load coverage, low-load coverage, heavy-load coverage and sector orientation.

Then, a set of combination levels, i.e. $K = \{1,2,\cdots,l\}$, of the configuration parameters is given for each BS, where l is the number of the combination levels of configuration parameters. Moreover, an installation cost c_{jk} is also given to each base station installed at CS $j \in J = \{1,2,\ldots,n\}$ with combination level $k \in K$ of configuration parameters. Obviously, the installation cost varies with the BS's configuration parameters.

A. The Impact of the Configuration Parameters on Capacity

The first two configuration parameters, antenna height and antenna tilt, have an impact on propagation gain tensor. The sector orientation defines the sets of TPs within the same sector and the pilot power is utilized to determine the BS, to which each TP is assigned. The impact of these configuration parameters will be described as follows:

The antenna height and tilt have an impact on the propagation gain tensor $\mathbf{G} = [g_{ijk}]$, where $0 < g_{ijk} < 1$ is the propagation gain from TP i to BS j with the combination level k of configuration parameters. It can be estimated by using prediction tools or obtained by actual measurements. We use the COST-231 Hata model [29] and vertical diagram [28] to describe the impact of antenna height and tilt on the propagation gain in this paper. It can be represented by the attenuation in db, i.e. $g_{ijk} = 1/10^{(l_{ijk}/10)}$, where l_{ijk} is the propagation factor between TP i and BS j with configuration

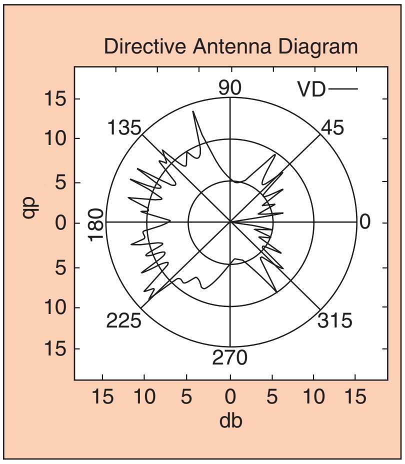

FIGURE 2 The vertical diagram of the directive antenna.

combination level k. The propagation factor can be defined as:

$$l_{ijk} = \mathrm{VD}_{ijk} + \mathrm{PL}_{ijk}, \tag{1}$$

where PL_{ijk} is the pathloss (PL) from TP i to CS j with combination level k of configuration parameters, and VD_{ijk} is the vertical diagram (VD).

The vertical diagram defines the relation between the radiant signal loss and the radial deviation from the signal main axis.

The vertical diagrams of the directive antenna are displayed in Fig. 2. Then, the vertical diagram is defined as:

$$\mathrm{VD}_{ijk} = \mathrm{VD}(\alpha_{ij} - \beta_j), \tag{2}$$

where α_{ij} is the vertical angle, in which the TP i appears to the base station j in degrees. As shown in Fig. 3, h_{bj} represents the effective antenna height of the BS in meter and β_j represents the antenna tilt of the BS j. d_{ij} is the distance from TP i to CS j. We can know from geometrical relationship that $\alpha_{ij} = \arctan((h_{bj} - h_m)/d_{ij})(180/\pi)$, where h_m is the height of the mobile station. Therefore, we have

$$\mathrm{VD}_{ijk} = \mathrm{VD}\left(\arctan\left(\frac{h_{bj} - h_m}{d_{ij}}\right)\frac{180}{\pi} - \beta_j\right). \tag{3}$$

From Eq. (3), we can see that the antenna height and tilt have an impact on the vertical diagram.

In this paper, the pathloss PL_{ijk} is formulated by the COST-231 Hata model.

$$\begin{aligned} \mathrm{PL}_{ijk} &= \mathrm{PL}(f, h_{bj}, h_m, d_{ij}) \\ &= 46.3 + 33.9\log(f) \\ &\quad - 13.82\log(h_{bj}) - a(h_m) \\ &\quad + (44.9 - 6.55\log(h_{bj}))\log(d_{ij}) \\ &\quad + C_M, \end{aligned} \tag{4}$$

where f is the frequency in MHZ, h_{bj}, h_m and d_{ij} are the same as the ones used in Eq. (3). C_M is the correction factor of area type and $a(h_m)$ is the correction function about the height of the mobile station. For medium and small cities, $a(h_m)$ is expressed by

$$\begin{aligned} a(h_m) &= (1.1\log(f) - 0.7)h_{mi} \\ &\quad - (1.56\log(f) - 0.8), \end{aligned} \tag{5}$$

while it is defined as

$$a(h_m) = \begin{cases} 8.29(\log(1.54h_m))^2 - 1.1 \\ 3.2(\log(11.75h_m))^2 - 4.97 \end{cases} \tag{6}$$

for large cities. From Eq. (1), (3), (4), we can find that the propagation gain depends on the antenna height and tilt.

Next, let us study the impact of sector orientation and pilot power on WCDMA network planning. Since it is possible to install a BS which is equipped with s identical sectors at each CS j, we suppose all the BSs are equipped with 3 identical sectors. As shown in Fig. 1, the sector orientation γ defines the angle clockwise from due north to the first sector. All TPs severed by a BS are divided into 3 cells. Clearly, the sector orientation determines which TPs are in the same cell.

The pilot power is used to allocate each TP to a certain active BS. As shown in Fig 1, TP_{i1} may be covered by the BS 1, 2 and 3. It is allocated to the BS, from which TP_{i1} receives the maximum pilot power. That is, for each TP $i \in I$, it will be allocated to BS $\tilde{j}$ so that

$$\tilde{j} = \arg\max_{j \in J} \hat{p}_j g_{ijk}, \tag{7}$$

where $\hat{p}_j$ is the pilot power of BS j. Therefore, it not only depends on the TP's position, but also the pilot power of the BS to which each TP is allocated.

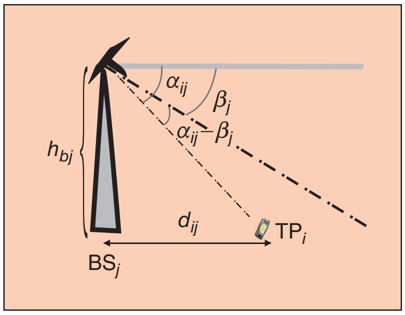

FIGURE 3 The antenna tilt and the angle of incidence.

B. The Interference in Uplink and Downlink Based on Maximum Influence Region

The signal quality is usually measured by the SIR, which can be expressed as:

$$\mathrm{SIR} = \frac{W}{R}\frac{p_{\mathrm{receive}}}{\omega I_{\mathrm{in}} + I_{\mathrm{out}} + \eta}, \tag{8}$$

where W is the system chip rate, e.g., W = 3840 Chip/s for WCDMA, R is the user data rate, η denotes the thermal noise power, and p_{receive}, represented by red arrows in Fig. 4, is the received signal power. ω is the orthogonality loss factor. In the uplink case, the user channels are not orthogonal and $\omega = 1$, while in the downlink case, the user channels are orthogonal in the same cell but the multi-path interference makes $0.4 < \omega < 0.9$ [28]. As shown in Fig. 4, I_{in}, represented by the green arrow, is the total interference due to the signals transmitted by the mobile stations in the same cell (i.e. intracell interference) and I_{out}, represented by the black arrow, is the interference due to signals of the other mobile station (i.e. intercell interference) in the uplink. Correspondingly, in the downlink case, I_{in} is the total interference due to the signals transmitted by the same BS and I_{out} is that due to signals transmitted by the other BSs.

From the theoretical viewpoint, the intercell interference I_{out} is the total interference due to the signals transmitted by all the mobile stations which are not in the same cell in the uplink and the signals transmitted by all other BSs in the downlink. However, we can neglect the interference source which is away from the user [10]. Therefore, we define a maximum influence region with no-load coverage area for sector σ of CS j. It is the TPs which can be potentially covered by the sector σ of BS $j \in J$ with combination level $k \in K$ of configuration parameters. A pool I^{σ}_{jk} is formed with these TPs. It is computed as follows: First of all, we ignore all other BSs. That is, we assume there is only one BS j. If TP i is included in sector σ and the pilot power received at TP i from BS j is greater than minimum allowable value $\hat{p}_{\min}$, i.e.

$$\hat{p}_j g_{ijk} > \hat{p}_{\min}, \tag{9}$$

TP i may be covered by sector σ of BS j. Usually, the actual coverage of sector σ of BS j is smaller than I^{σ}_{jk}. At the same time, a set $J_i, i \in I$ is determined, which is used to store the indices of sectors which can affect TP i. In addition, we allocate each TP to a certain active BS according to Eq. (7). These TPs which are allocated to the same sector and within its no-load coverage area are regarded as a cell, denoted as C^{σ}_{jk}. The more detailed information about computing I^{σ}_{jk}, j_i and C^{σ}_{jk} will be described in Section II-D1. Then, we estimate the intercell interference I_{out} for TP i with the total interference due to the signals of the TPs in $I^{\sigma i}_{jk}$ but not in $C^{\sigma i}_{jk}$, where σ_i is the sector containing TP i. Hence, we only consider the local interference due to the channels which are fallen into the maximum influence region.

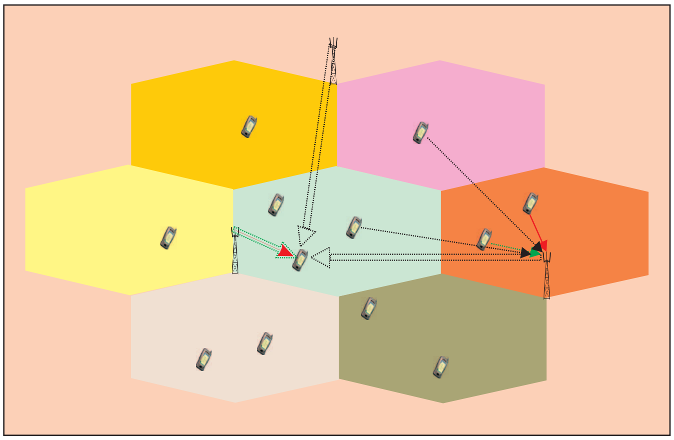

FIGURE 4 Illustration of intracell interference and intercell interference in uplink and downlink.

C. Multiobjective Optimization Model for WCDMA Network Planning

To describe the programming model, a binary variable matrix $\mathbf{X} = [x_{jk}]_{n \times l}$ is utilized to denote the state of each CS, where $x_{jk} \in \{0,1\}$, $j \in J, k \in K$, satisfies:

$$x_{jk} = \begin{cases} 1 & \text{if a BS installed in CS } j \text{ with combination level } k \\ 0 & \text{otherwise.} \end{cases}$$

Meanwhile, a binary variable matrix $\mathbf{S} = [s_{ij}]$ denotes the state of each connection. $s_{ij} = 1$ if and only if the connection between TP i and CS j satisfies the quality requirements in the uplink and downlink directions. That is,

$$s_{ij} = \begin{cases} 1 & \text{if the conection between TP } i \text{ and BS } j \text{ is active} \\ 0 & \text{otherwise,} \end{cases}$$

where $i \in I$, $j \in J$.

We formulate the WCDMA network planning as a multiobjective optimization problem. The system capacity $T_{\text{cap}}(\mathbf{X},\mathbf{S})$ and installation cost $C_{\cos}(\mathbf{X},\mathbf{S})$ considered in this paper are:

$$\max T_{\text{cap}}(\mathbf{X},\mathbf{S}) = \sum_{i \in I} \sum_{j \in J_i} u_i s_{ij} \tag{10}$$

$$\min C_{\cos}(\mathbf{X},\mathbf{S}) = \sum_{j \in J} \sum_{k \in K} c_{jk} x_{jk}. \tag{11}$$

Also, suppose each TP $i \in I$ can be assigned to one BS at most, i.e.

$$\sum_{j \in J_i} s_{ij} \le 1 \quad \forall\, i \in I, \tag{12}$$

where $\sum_{j \in J_i} s_{ij} = 1$ means that TP i is served; otherwise, it is not served.

Further, as there is at most one BS with combination level k of configuration parameters to be installed in each CS j, we have

$$x_j = \sum_{k \in K} x_{jk} \le 1 \quad \forall\, j \in J. \tag{13}$$

If $x_j = 1$, it implies that there is a BS installed in CS j. Otherwise, no BS is installed in CS j.

Furthermore, a TP i can be assigned to a CS $j \in J$ only if a BS has been installed in CS j. That is,

$$s_{ij} \le x_j \quad \forall\, i \in I, j \in J. \tag{14}$$

In addition, SIR has to be maintained for all active connections in order to satisfy the QoS in the network. The interference is composed of intracell interference, intercell interference and noise power. From Eq.(8), the SIR in the uplink can be expressed as:

$$\frac{W}{R_i^u} \frac{p_i^u g_{ijk} s_{ij}}{I^u_{\text{in},i} + I^u_{\text{out},i} + \eta_{bj}} = \text{SIR}_j^u s_{ij} \tag{15}$$

for $i \in I$, $j \in J$, where

$$I^u_{\text{in},i} = \sum_{t \in C^{\sigma_i}_{jk}} u_t^u p_t^u g_{tjk} s_{tj} - p_i^u g_{ijk},$$

$$I^u_{\text{out},i} = \sum_{t \in I^{\sigma_i}_{jk}, t \notin C^{\sigma_i}_{jk}} u_t^u p_t^u g_{tjk}$$

are the intracell and intercell interference of the connection between TP i and CS j, respectively. p_i^u is the transmit power from a mobile at TP i and $\eta_{bj} = -105$ dbm is the thermal noise at BS j. SIR_j^u is the lower bound on SIR of BS j. We assume that all BSs have the same lower bound on SIR, i.e. $\text{SIR}_j^u = 6$ db, $j \in J$. R_i^u is the user data rate of a mobile station in TP i and let it be the same value, i.e. $R_i^u = 12.2$ kbit/s for different TPs in uplink. $I^{\sigma_i}_{jk}$ is the set of all TPs that are fallen into the no-load coverage area of sector σ_i containing TP i, and $C^{\sigma_i}_{jk}$ is the cell containing TP i. The numerator of the left-hand-side term corresponds to the power of the relevant signal arriving from TP i at CS j. $u_t^u p_t^u g_{tjk}$ indicates the total power received at the BS j from TP t. Thus, $I^u_{\text{in},i}$ amounts to the total interference due to all other active connections within the cell $C^{\sigma_i}_{jk}$, and $I^u_{\text{out},i}$ is the total interference due to the channels within no-load coverage area $I^{\sigma_i}_{jk}$ but not in $C^{\sigma_i}_{jk}$.

Since the power that the mobile station can emit is nonnegative and there exists an upper bound on the maximum power $P^u_{\max}$, we have:

$$0 \le p_i^u \le p^u_{\max} \quad \forall\, i \in I. \tag{16}$$

The interference at TP i in the downlink direction is from the active BSs j_i. That is, we only consider the interference from the BSs which are close to TP i. Then, the signal quality constraint for each connection in the downlink direction can be expressed as:

$$\frac{W}{R_i^d}\frac{p_{ji}^d g_{ijk} s_{ij}}{\omega I_{\text{in},i}^d + I_{\text{out},i}^d + \eta_{mi}} = \text{SIR}_i^d s_{ij} \quad (17)$$

for $i \in I,\ j \in J$, where

$$I_{\text{in},i}^d = \sum_{t \in C_{jk}^{\sigma_i}} u_t^d p_{jt}^d g_{ijk} s_{tj} - p_{ji}^d g_{ijk} + \hat{p}_j g_{ijk}$$
$$= p_j^{d\sigma_i} g_{ijk} - p_{ji}^d g_{ijk}$$
$$I_{\text{out},i}^d = \sum_{l \in J_i, l \neq j} p_l^{d\sigma_i} g_{ilk}$$

represent the intercell and intracell interferences in the downlink direction, respectively. p_{ji}^d is the power assigned from BS j to a mobile station at TP i and $p_j^{d\sigma_i}$ is the total power of the sector whose maximum influence region contains TP i of BS j. R_i^d is the user data rate provided that all the mobile stations have the same value $R_i^d = 64$ kbit/s. $\text{SIR}_i^d = 4$ db is the lower bound on SIR in downlink. $\eta_{mi} = 108$ dbm is the thermal noise at TP i and $\omega = 0.5$ is the orthogonality loss factor. For any active connection between a BS installed in CS j and TP i, the summation term of $I_{\text{in},i}^d$ expresses the power distributed to the TPs falling in the sector σ_i and severed by CS j. $\hat{p}_j$ is the pilot signals of BS j. $I_{\text{out},i}^d$ is the interference due to the signals transmitted by the neighbor BSs J_i.

Obviously, the power that a BS can assign to a connection is nonnegative and there exists an upper bound on the maximum power $p_{j\max}^d$. We have:

$$0 \le p_{ji}^d \le p_{j\max}^d \quad \forall i \in I. \quad (18)$$

The limit on the total power that each BS j can emit is given by the following inequality:

$$0 \le p_j^{d\sigma} = \hat{p}_j + \sum_{i \in C_{jk}^{\sigma}} p_{ji}^d s_{ij} \le p_{j\max}^d \quad (19)$$

for $j \in J, \sigma = 1,2,3$, where $p_{j\max}^d$ is the upper bound on the total power emitted by BS j in downlink.

Finally, we consider the rate of coverage as follows:

$$\frac{T_{\text{cap}}}{\sum_{i \in I} u_i} \ge 0.9. \quad (20)$$

This model is a complex constrained combinational optimization problem. To solve this problem, we propose an iterative power control method to compute the power p_i^u and $p_{ji}^d, i \in I,\ j \in J$, and then check the constraints (12)–(19) to determine the state s_{ij} of each connection.

D. Fix S As Given X by Using the Iterative Power Control Scheme

A subset $\mathcal{J}$ has been selected from the set CS J and a definite configuration parameters combination level k is chosen for each BS installed at CS $j \in \mathcal{J}$. That is, x_{jk} is determined. There are three basic procedures to assign a TP i to a suitable BS and determine the power in the uplink and downlink directions.

1) TP Allocation

We first determine I_{jk}^{σ} and C_{jk}^{σ} for $j \in J, k \in K, \sigma = 1,2,3$ and j_i for each TP i. That is, we find the maximum influence of each sector of every BS and the cells. Specifically, it can be achieved by Algorithm 1.

2) Power Control in Uplink Direction

The problem is to determine the minimum transmit power for mobile station such that constraint (15) is satisfied. Let $Q_{ij} = W / \text{SIR}_j^u R_i^u$, then the Eq. (15) can be converted into the following linear equations:

$$(1 + Q_{ij}) p_i^u g_{ijk} - \sum_{t \in C_{jk}^{\sigma_i}} u_t^u p_t^u g_{tjk} s_{tj} = \eta_{bj}^{\sigma_i} \quad (21)$$

for $i \in I,\ j \in J$, where

$$\eta_{bj}^{\sigma_i} = \eta_{bj} + I_{\text{out},i}^u = \eta_{bj} + \sum_{t \in I_{jk}^{\sigma_i}, t \notin C_{jk}^{\sigma_i}} u_t^u p_t^u g_{tjk}. \quad (22)$$

It is the system interference at the sector σ_i containing TP i of BS j, which is composed of the thermal noise and the interference from the mobile stations in the maximum influence region of the sector σ_i at BS j, but not in the same cell.

Algorithm 1: Allocate TP to BS.

Input: The state of each BS: $\mathbf{X}$;
The set of the TP: I;
The set of the CS: J.
Output: $I_{jk}^{\sigma}, C_{jk}^{\sigma}, J_i$.
for $i \in I$ **do**
for $j \in J$ **do**
if $x_{jk} = 1$ **then**
Compute the propagation gain g_{ijk} and the received pilot power $\hat{p}_{ji} = \hat{p}_j g_{ijk}$;
if $\hat{p}_{ji} > \hat{p}_{\min}$ **then**
$I_{jk}^{\sigma i} := I_{jk}^{\sigma i} \cup i$; $J_i := J_i \cup j$;
end if
end if
end for
$\tilde{j} = \arg\max_{j \in J} \hat{p}_{ji}$ by Eq. (7);
$C_{jk}^{\sigma i} := C_{jk}^{\sigma i} \cup i$.
end for

Eq. (21) can be extended by the equation $c = \sum_{t \in C_{jk}^{\sigma_i}} u_t^u p_t^u g_{tjk} s_{tj}$ with an additional variable c. Substituting this into Eq. (21) we have that

$$p_i^u g_{ijk} = \frac{c + \eta_{bj}^{\sigma_i}}{1 + Q_{ij}}$$

and

$$c = \sum_{t \in C_{jk}^{\sigma_i}} u_t^u p_t^u g_{tjk} s_{tj}$$
$$= (c + \eta_{bj}^{\sigma_i}) \sum_{t \in C_{jk}^{\sigma_i}} \frac{u_t^u s_{tj}}{1 + Q_{tj}}.$$

Solving the above equation for c yields $c = \beta \eta_{bj}^{\sigma_i} / (1 - \beta)$ with $\beta = \sum_{t \in C_{jk}^{\sigma_i}} u_t^u s_{tj} / (1 + Q_{tj})$. Hence, we have

$$p_i^u = \frac{\eta_{bj}^{\sigma_i}}{g_{ijk}(1 + Q_{ij})\left(1 - \sum_{t \in C_{jk}^{\sigma_i}} \frac{u_t^u s_{tj}}{1 + Q_{tj}}\right)},$$
$$i \in C_{jk}^{\sigma_i}. \quad (23)$$

From Eq. (23) we have that p_i^u depends on the spreading gain Q_{ij}, the propagation gain g_{ijk}, the system interference $\eta_{bj}^{\sigma_i}$, and the connection state $s_{tj}, t \in C_{jk}^{\sigma_i}$. It is independent of the variables p_i^u in the same cell. In addition, from the third factor in the denominator of Eq. (23), there is no feasible power allocation if

$$\sum_{t \in C_{jk}^{\sigma_i}} u_t^u s_{tj} \ge 1 + Q_{tj}$$

and all user data rate and QoS parameters are equal, i.e. $Q_{tj} = Q$ for all $t \in C_{jk}^{\sigma_i}$. In WCDMA system, if $W = 3.84$ Mhz and the user data rate $R_i^u = 12.2$ kbit/s in uplink and $\text{SIR}_j^u = 6$ db

Algorithm 2: Power control in uplink direction: p_i^u

Input: $I_{jk}^{\sigma}, C_{jk}^{\sigma}$ obtained by Algorithm 1;
The propagation gain $G=[g_{ijk}]$.
Output: The state of the connection S_{ij};
The transmitted power p_i^u.
Initial the maximum number of iteration *maxiter* and the transmitted power of the each mobile station p_i^u;
for $n=1$: *maxiter* **do**
  Compute the system interference η_{bj}^{σ} by Eq. (22)
  for each C_{jk}^{σ} **do**
    Check the connection state $S_{tj}, t \in C_{jk}^{\sigma}$; Compute the transmitted power p_t^u by Eq. (23) of the mobile stations in TP $t \in C_{jk}$ with $s_{tj}=1$;
  end for
end for

$$p_{ji}^{d} = \frac{\omega \sum_{t \in C_{jk}^{\sigma_i}} \frac{u_t^d s_{tj} \eta'_{mh}}{\Phi_t + \omega} + \eta'_{mi}\left(1 - \omega \sum_{t \in C_{jk}^{\sigma_i}} \frac{u_t^d s_{tj}}{\Phi_t + \omega}\right)}{(\Phi_i + \omega)\left(1 - \omega \sum_{t \in C_{jk}^{\sigma_i}} \frac{u_t^d s_{tj}}{\Phi_t + \omega}\right)}. \tag{26}$$

$= 3.9811$, then $Q \approx 79$. That is, there is no way to accommodate more than 79 users at the desired QoS requirement in uplink direction.

The system interference $\eta_{bj}^{\sigma_i}$ and s_{tj} in Eq. (23) are not available in advance. Hence, an iterative approach is presented to solve it. It is composed of three procedures as follows:

1) As $p_i^u, i \in I$, is given, we can easily obtain the system interference η_{bj}^{σ} for each cell of the active BSs according to Eq. (22).
2) For each cell C_{jk}^{σ}, check the connection state $s_{tj}, t \in C_{jk}^{\sigma}$ to guarantee the SIR constraint (16). We always give priority to TPs with a greater propagation gain. Specifically, we sort the TPs $i \in C_{jk}^{\sigma}$ in descending order according to the propagation gain g_{ijk}, and then compute the transmitted power of the TPs one by one according to Eq. (23). If the transmitted power of mobile stations in TP t satisfies the SIR constraint, i.e. $p_t^u < p_{\max}^u$, then $s_{tj}=1$, otherwise, $s_{tj}=0$.
3) For each cell C_{jk}^{σ}, compute the transmitted power of the mobile stations in TP $t \in C_{jk}^{\sigma}$ with $s_{tj}=1$ by Eq. (23).

More precisely, the power control in uplink is described in Algorithm 2, where *maxiter* is the maximum number of the iteration. We set it at 3 and let the initial transmitted power of each mobile station be zero in this paper.

3) Power Control in Downlink Direction:

A similar procedure is also used to estimate the emitted power in the downlink direction. Let $\Phi_i = W / \mathrm{SIR}_i^d R_i^d$, and we can transform the SIR constraint (17) into the following linear equations:

$$(\Phi_i + \omega) p_{ji}^d - \omega \sum_{t \in C_{jk}^{\sigma_i}} u_t^d p_{jt}^d s_{tj} = \eta'_{mi} \tag{24}$$

for $i \in I$, $j \in J$ where

$$\eta'_{mi} = \frac{\eta_{mi} + \hat{p}_j g_{ijk} + \sum_{l \in J_i, l \neq j} p_l^{d\sigma_i} g_{ilk}}{g_{ijk}}. \tag{25}$$

As discussed in the uplink power control method, Eq. (25) can be extended by the equation $c = \sum_{t \in C_{jk}^{\sigma_i}} u_t^d p_{jt}^d s_{tj}$ with an additional variable c. Substituting this into Eq. (24), we have that

$$p_{ji}^d = \frac{\omega c + \eta'_{mi}}{\Phi_i + \omega}$$

and

$$c = \omega c \sum_{t \in C_{jk}^{\sigma_i}} \frac{u_t^d s_{tj}}{\Phi_t + \omega} + \sum_{t \in C_{jk}^{\sigma_i}} \frac{u_t^d s_{tj} \eta'_{mt}}{\Phi_t + \omega}.$$

Hence, p_{ji}^d can be calculated as shown in (26) at the top of this page.

From Eq. (26), we can find that p_{ji}^d depends on η'_{mt} and s_{tj}, $t \in C_{jk}^{\sigma_i}$. It is independent of the variable p_{ji}^d in the same cell. Hence, we can use the similar method described above to solve it. Please note that there is no way to accommodate more than 23 users at the desired QoS requirement.

As a result, the state of the connection s_{ij} just depends on the values of the BSs' state $\mathbf{X}$. It means that s_{ij} can be expressed as a latent function of $\mathbf{X}$, denoted as $s_{ij} = f_{ij}(\mathbf{X}) \in \{0,1\}$. Moreover, the constraints (12)–(19) are satisfied when we solve the state of the connection s_{ij}. Then, the model can be formulated as follows:

$$\begin{aligned} \max T_{\text{cap}}(\mathbf{X}) &= \sum_{i \in I} \sum_{j \in J_i} u_i f_{ij}(\mathbf{X}) \\ \min C_{\cos}(\mathbf{X}) &= \sum_{j \in J} \sum_{k \in K} c_{jk} x_{jk} \\ s.t. \frac{T_{\text{cap}}}{\sum_{i \in I} u_i} &\geq 0.9. \end{aligned} \tag{27}$$

III. MOEA/D-M2M for WCDMA Network Planning

A. Presentation Based on Orthogonal Design

Four configuration parameters for each BS are taken into account in this paper. Sine each BS has a specific lower bound of the antenna height according to the terrain variation, the antenna height is just a fine adjustment configuration. We consider the antenna height above the lower bound in meter, i.e. $h \in \{0,1,2,3,4,5\}$. It is assumed that the antenna tilt of each sector of a BS also has six possible values in degree, i.e. $\beta_i \in \{0,3,6,9,12,15\}$ with $i=1,2,3$. The sector orientation which defines the sets I_{jk}^{σ} and C_{jk}^{σ} has the following six possible values in degree: $\gamma \in \{0,20,40,60,80,100\}$. The pilot power $\hat{p}$ also has six possible values in watt $\hat{p}$ $\{1,1.2,1.4,1.6,1.8,2\}$. This indicates that there are $6^6 = 46656$ combinations levels of configuration parameters for each BS. The search space of configuration parameters combinations of the model is 46656^n. It is very time consuming to find the best configuration combination level. Therefore, it is desirable to sample a small, but representative set of combination levels. The orthogonal design [30] is used to reduce the search space of the model in this paper. A series of orthogonal array are provided in [30]. Orthogonal array $L_{36}(6^6)$ is utilized in this paper. Then, there are only 36 combination levels for each BS. It greatly reduces the search space of the model.

We propose an encoding method based on orthogonal design. Specifically, a vector $\mathbf{y} = (y_1, y_2, \cdots, y_n)$ records the combination level of BSs' configuration parameters in a solution. $y_j = k$ expresses that a BS is installed in CS j with combination level k of configuration parameters, i.e. $x_{jk}=1$. For example, $y_2 = 10$ implies that a BS is installed

Algorithm 3: MOEA/D-M2M for WCDMA network planning problem.

Input: The WCDMA planning problem;
max_gen: the maximum number of generations;
T: the number of the subproblems;
N: the size of the subpopulation.
Output: All the nondominant solutions in $\cup_{k=1}^{T} P_k$.
Initialization: Generate $2NT$ initial individuals $\{y^1, \cdots, y^{2NT}\}$ by the problem specific method described above, evaluate their objective values and then use these initial individuals to set $P_1, \ldots, P_T$. The current generation set: gen = 1.
while gen < max_gen **do**
  Generation of New Solutions:
  Set $\Pi = \emptyset$;
  for $k \leftarrow 1$ **to** T **do**
    for each $y \in P_k$ **do**
      Randomly choose y' from P_k;
      Apply crossover and mutation operators on y and y' to generate a new solution z;
      Compute the objective values of z;
      $\Pi := \Pi \cup \{z\}$
    end for
  end for
  Updating the subpopulations:
  $Q := \Pi \cup (\cup_{k=1}^{T} P_k)$;
  Use Q to set $P_1, \ldots, P_T$.
end while
Find all the nondominated solutions in $\cup_{k=1}^{T} P_k$ and output them.

in CS 2 with configuration combination level 10. The 10th row of the orthogonal array $L_{36}(6^6)$ is (2,4,5,6,1,2). The information of the configuration parameters of BS 2 is available. That is, $h = 1$, $\beta_1 = 9$, $\beta_2 = 12$, $\beta_3 = 15$, $\gamma = 0$ and $\hat{p} = 1.2$. Moreover, if there is no BS installed in CS j, $y_j = 0$. We have that $y_j \in \{0, 1, \cdots, l\}$ for $j \in J$.

B. Crossover and Mutation

We choose the single-point crossover to create the offsprings. Given two solutions, this crossover operator creates a random integer number u between 1 and $n-1$ and swaps u leftmost bits of each solution. For example, given parents $\mathbf{y}^1 = (0, 10, 30, 0, 5)$ and $\mathbf{y}^2 = (0, 0, 0, 11, 12)$, the children will be $\mathbf{y}^c = (0, 10, 0, 11, 12)$ if $u = 2$.

The mutation operator is used to escape a possible local optimum and find a new neighborhood with a potentially more promising solution. For each solution $\mathbf{y}^c$ generated by the crossover operation, our implementation alters each component by selecting a random number between 1 and n. If the hth component of $\mathbf{y}^c$ is selected to be mutated, then

$$y_h^c = k,$$

where k is randomly selected from $\{0, 1, \cdots, l\}$.

C. MOEA/D-M2M

Multiobjective evolutionary algorithm, as one of the most powerful tool to solve the complex optimization problems, especially the combinatorial optimization problems, has been widely used in the various fields [23]–[26]. A number of multiobjective evolutionary algorithms have been proposed in the past few years, such as NSGA-II [31], MOEA/D [32], MOEA/D-M2M [27] and so on. MOEA/D-M2M has strong ability to maintain the diversity of the population [27]. There are a few of Pareto solutions in this optimization problem, the diversity of the population is more important, we therefore take MOEA/D-M2M to solve the problem described above.

In MOEA/D-M2M, the multiobjective optimization problem is decomposed into a number of simple multiobjective optimization subproblems, which are then solved in a collaborative manner. T direction vectors $\mathbf{v}^1, \ldots, \mathbf{v}^T$ are uniformly chosen from the unit circle in the first quadrant, where T is the number of the subproblems. Then, the first quadrant R_+^2 is divided into T subregions $\Omega_1, \ldots, \Omega_T$, where $\Omega_k (k = 1, \ldots, T)$ defined as

$$\Omega_k = \{\mathbf{u} \in R_+^2 \mid \langle \mathbf{u}, \mathbf{v}^k \rangle \leq \langle \mathbf{u}, \mathbf{v}^j \rangle\}$$

for any $j = 1, \ldots, T$. $\langle \mathbf{u}, \mathbf{v}^j \rangle$ is the acute angle between $\mathbf{u}$ and $\boldsymbol{v}^j$. In other words, $\mathbf{u}$ is in Ω_k if and only if $\mathbf{v}^i$ has the smallest angle to $\mathbf{u}$ among all the T direction vectors. For each subregion, there is a subpopulation with N individuals to optimize it.

The initial population is generated as follows: For each element y_j, $(j = 1, 2, \cdots, n)$, of individual solution $\mathbf{y}$, if rand < 0.4 then $y_j = 0$, where rand is a random number generated by a uniform random number generator in [0, 1]. That is, there is no BS installed in CS j; Otherwise, y_j is set at a random integer number within the range of $\{1, 2, \cdots, l\}$.

In each generation, MOEA/D-M2M maintains T subpopulations: $P_1, \ldots, P_T$. Each subpopulation is utilized to optimize one subregion in the objective space. Specifically, the MOEA/D-M2M works as Algorithm 3. MOEA/D-M2M utilizes a number of individual solutions to initialize and update $P_1, \ldots, P_T$. This procedure can be realized by Algorithm 4, where $|P_k|$ is the number of the individuals in P_k.

IV. Experimental Results

This section will present some numerical results obtained from the application of the MOEA/D-M2M to some synthetic but realistic instances. The aim of these numerical experiments is not only to demonstrate the effectiveness and rationality of the proposed model, but also to show the effectiveness of the MOEA/D-M2M to solve the combinatorial optimization problems.

A. Instance Generator

These instances were generated by the instance generator tool described in [12]. It simulates the traffic demand distribution of service area and the CSs' location which is usually selected by service providers considering traffic intensity in the area. A square service area $D \times D$ was considered in each instance. As shown in Fig. 5, we divided the service area into $d \times d$ smaller regions and regarded the center of each region as a TP. We assumed that the numbers of the TP with high, medium and low traffic demand is m_h, m_m and m_l, respectively.

The traffic demand of each TP was given as follows: We first selected the TPs which were assigned with the high traffic demand. A weight ω_i with initial value 1 was associated to each TP i, $i = 1, 2, \cdots, m$. TPs were iteratively picked with a probability $p_i = \omega_i / \sum_{i=1}^{m} \omega_i$. After each iteration, the weight ω_i of the selected TP was set at zero, and the weights of the neighboring TPs which had not been selected were increased by 1. Once all m_h TPs with

Algorithm 4: Allocation of individuals to subpopulations.

Input: Q: a set of individual solutions their objective values.
Output: $P_1, \ldots, P_T$.
for $k \leftarrow 1$ **to** T **do**
  Initialize P_k as the solutions in Q whose normal objective values are in Ω_k;
  if $|P_k| < N$ **then**
    randomly select $N - |P_k|$ solutions from Q and add them to P_k.
  end if
  if $|P_k| > N$ **then**
    rank the solutions in P_k using the constraint nondominated sorting method [31] and remove from P_k the $S - |P_k|$ lowest ranked solutions.
  end if
end for

high traffic demand had been selected, the m_m TPs with medium traffic demand and the m_l TPs with low traffic demand were selected with the same procedure.

The positions of CSs were also randomly selected in the set of crossing points of the regular grid. The adopted procedure was similar to the previous one. That is, each grid point was assigned a weight that equals to the sum of the traffic demand of neighboring TPs. After each iteration, the weight of the selected grid point was set at zero. To make the numerical results easily readable, we adopted the same cost for all BSs and separately reported the system capacity (i.e. the number of the user served) and the installation cost (i.e. the number of the active BSs). In the following sections, we present the numerical results obtained with the medium and large size instances.

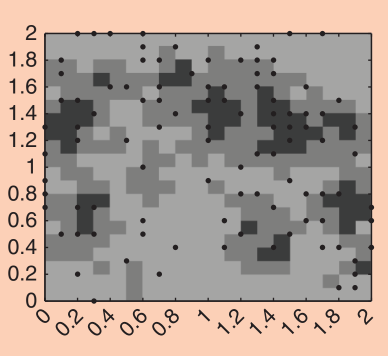

FIGURE 5 Synthetic but realistic instances, where ■: High; ■: Medium; ■: Low; •: CS.

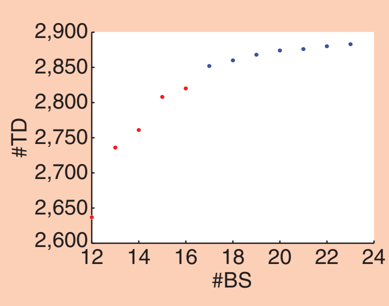

FIGURE 6 The result obtained by the algorithm on a medium size instance, where #TD denotes the number of covered the traffic demand, while #BS is the number of the active BSs.

B. The Parameters of the Instances and Algorithm

A medium size and a large size instances were pseudo-randomly generated by the tool described above. Specifically, a 2000 × 2000 meter service area was divided into 400 square regions of 100 × 100 meter in the medium size instance. The numbers of the regions with high, medium and low traffic demand were $m_h = 50$, $m_m = 150$, $m_l = 200$, respectively, and the corresponding numbers of the traffic demand per region were 12, 6 and 2 in the uplink and 7, 3, 1 in the downlink. Then, the traffic demand was 1900 in the uplink and 1000 in the downlink. The total traffic demand was 2900 in the system. Also, 100CSs, i.e. $n = 100$ were pseudo-randomly generated by using the above described method.

For the large size instance, a 3000 × 3000 meter service area was divided into 900 square regions of 100 × 100 meter. The numbers of the regions with high, medium and low traffic demand were $m_h = 100$, $m_m = 400$, $m_l = 400$, respectively, and the corresponding numbers of the traffic demand per region were 12, 5 and 2 in the uplink and 6, 3, 1 in the downlink. Then, the traffic demand was 4000 in the uplink and 2200 in the downlink. The total traffic demand was 6200 in the system. 150 CSs were pseudo-randomly generated by using the above described method.

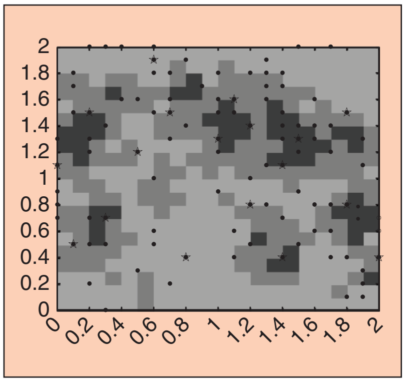

FIGURE 7 The distribution of the active BSs of the fifth solution from the left in Fig. 6, where ☆ represents the active BSs, and • represents the CSs.

We conducted the algorithm on these instances with the number of the subproblems $T = 10$ and the size of the subpopulation $N = 10$. For the medium size instance, the maximum number of generations was set at $max\_gen = 200$, while $max\_gen = 300$ for the large size instance.

C. Computational Results

1) Experimental Results on the Medium Size Instance

Fig. 6 plots the final solutions obtained by the proposed algorithm. There are a set of solutions obtained in a single run. These solutions can be roughly divided into two parts. The first part of solutions, represented with red point, require less BSs, while the other solutions, represented with blue point, have a higher coverage rate. Fig. 7 plots the distribution of the active BS of the fifth solution from the left in Fig. 6.

2) Experimental Results on the Large Size Instance

Fig. 8 plots the final solutions obtained by the proposed algorithm. Similar with the medium size instance, there are also a set of solutions obtained in a single run. These solutions can be roughly divided into two parts. The first part of solutions, represented with red point, require less BSs, while the other solutions, represented with blue point, have a higher coverage rate. Fig. 9 plots the distribution of the active BS of the eighth solution from the left in Fig. 8.

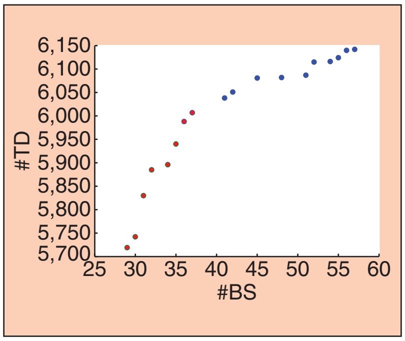

FIGURE 8 The result obtained by the algorithm on a large size instance, where #TD refers to the number of covered the traffic demand, and #BS refers to the number of the active BSs.

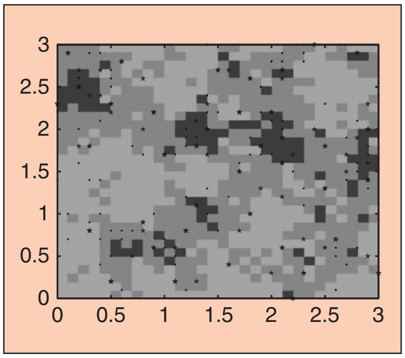

FIGURE 9 The distribution of the active BSs of the eighth solution from the left in Fig. 8, where ☆ represents the active BSs, and • represents the CSs.

V. Conclusion

In this paper we have proposed an efficient network planning model for WCDMA network planning problem. This model neglects the interference due to the channels without no-load coverage. It can greatly enhance the computational efficiency without degrading the performance evidently. Furthermore, we have presented iterative power control method for calculating the power of the channels in the uplink and downlink. When the power of a channel is changed, such a power control scheme makes us only re-compute the power of the channels in the same cell. It significantly reduces the complexity of the model. In addition, four BS's configuration parameters, i.e. the antenna height, antenna tilt, sector orientation and pilot signal power, have been taken into account in the model. Considering too many configuration parameters combination, a method based on orthogonal design has been proposed to find the better combination. Subsequently, a multiobjective evolutionary algorithm based on decomposition has been presented to solve this problem. The simulation results have shown the effectiveness of the proposed approach.

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