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The effect of call admission policies on the system benefit of CDMA communication networks

Kuo-Chung Chu · Frank Yeong-Sung Lin · Lun-Ping Hung

Abstract Previous studies of call admission control (CAC) in mobile communication networks focused on call blocking and call dropping mechanisms. However, achieving global optimization of the system benefit is a complicated process. In this paper, we propose a benefit optimization model that accommodates as many users as possible, while simultaneously maintaining system-wide quality of service (QoS) in terms of admission control. To clarify the CAC concept, we construct a framework of CAC policies, derive associated interference models based on the framework, and then investigate the effects of the policies on the system benefit. In addition, to solve the complicated integer programming problem, we adopt the Lagrangean relaxation approach, and employ Lagrangean multipliers to perform sensitivity analysis of several parameters. The contribution of this study is twofold: the novel problem formulation and the improvement in the system benefit. The computational results demonstrate that the system accrues more benefit as new traffic is loaded and the number of users increases. Meanwhile, the sensitivity analysis shows that proper assignment of the strength of power-controlled signals is a key factor in the global optimization of the system benefit.

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1 Introduction

Because of the tremendous improvements in wireless and mobile communications, the diffusion of, and demand for, mobile communication services are growing rapidly. Code division multiple access (CDMA)-based mobile wireless communication systems provide an environment for mobile commerce applications. A key attribute of CDMA is that it can operate in single cell/sector clusters, with each cell/sector using the same carrier frequency. Unlike FDMA and TDMA, CDMA does not specify an upper limit of available channels. As all users share the entire frequency spectrum rather than divided frequency or time, the system's capacity is bounded by interference, which may comprise inter-cellular and intra-cellular interference, as well as background noise. Inter-cellular interference is caused by mobile users (MUs) served by neighboring cells/base stations, while MUs in the coverage of their homing cells/base stations simultaneously generate intra-cellular interference. The capacity limit depends on the interference that occurs at each base station (BS).

In CDMA systems, multi-access interference is a function of the number of users. Such interference is a limiting factor in ensuring quality of service (QoS), so there must be a tradeoff between the system capacity and the level of communication quality. Because of spectrum sharing in CDMA systems, channel assignment based on the allocation of transmission power results in interference with other MUs. However, to guarantee QoS, the interference incurred

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at a BS must be lower than a pre-defined threshold [1–3]. The lower the interference experienced by BSs, the greater will be the capacity of the system. Although several ways to increase CDMA capacity have been proposed, multi-user detection and smart antenna/sectorization are the most popular technologies [4, 5]. Multi-user detection can mitigate interference between intra-cellular MUs [5, 6]. Call admission control (CAC) is also widely used to allocate channel resources and manage system capacity efficiently. The objective of CAC (a.k.a. connection admission control) is to ensure QoS.

Several studies, e.g., [7–11], formulate frequency and capacity assignment problems as combinatorial optimization models. The goal of frequency assignment is to minimize the number of frequencies used, while capacity assignment tries to maximize the number of channels allocated to users. Both problems are NP-hard. Han [7] dealt with the frequency reassignment problem by installing new BSs to expand the system's capacity. He modeled the problem as an integer programming problem, and solved it with decomposition-based heuristics. Other solutions to the frequency reassignment problem include tabu search techniques [8, 11] and branch-and-cut techniques [10]. All of the above works focus on traditional telecommunication systems rather than CDMA-based third generation systems and beyond.

In a CDMA network, the CAC mechanism relies on the network's "soft capacity", which is determined by the level of multi-access interference and is usually characterized by the signal-to-interference ratio (SIR). Essentially, CAC regulates network operations with an optimal condition that guarantees uninterrupted service for existing mobile users (EMUs), while accommodating as many new mobile user (NMU) requests as possible. For example, [12] proposed adaptive channel reservation mechanism to support soft handoff calls with a higher admission priority than ordinary new call requests. Therefore, the more users admitted, the more benefit the system will accrue. Current CAC research focuses on the analysis of QoS in terms of the following issues: (1) how different types of traffic affect the performance delay [13] and capacity [14]; and (2) the development of power control mechanisms to enhance capacity [2, 15] and reduce call blocking/forced terminations [16].

Usually, call blocking and call dropping measures are used for admission control. Call blocking occurs when an NMU is denied access to the system, while call dropping is invoked when an EMU's call is forcibly terminated during the handoff process. CAC policy is crucial to guaranteeing two factors; (1) the grade of service (GoS), i.e., the call blocking probability and forced termination probability of EMUs; and (2) the QoS, i.e., the SIR. The traffic type affects the performance delay, while the power control mechanism reduces call blocking and the number of forced terminations. Few studies have addressed the issue of benefit optimization in terms of CAC. However, in [15], the author notes that CDMA capacity is bounded on the uplink (UL) connection. The approach performs capacity analysis of the UL connection because the non-orthogonality that leads to limited capacity is on the UL.

In this paper, we analyze the total system benefit rather than the typical performance issue. The objective is to accommodate as many users as possible. To clarify the concept of CAC, we construct a framework of admission control policies, and derive associated interference models based on the framework. Specifically, the benefit model is formulated as a mathematical optimization problem. To solve the complicated integer programming problem in the model efficiently, we adopt Lagrangean relaxation (LR) as the solution approach, and use the Lagrangean multipliers to perform sensitivity analysis of several parameters.

The remainder of this paper is organized as follows. In Sect. 2, we discuss the admission control problem in CDMA networks. In Sect. 3, we model the benefit optimization problem in terms of an admission control mechanism, and propose a solution approach. In Sect. 4, we describe the experiments conducted to determine the effect of CAC policies on the system benefit, and discuss the sensitivity analysis results. Then, in Sect. 5, we summarize our findings.

2 Admission control in CDMA networks

2.1 Problem definition

Theoretically, CDMA does not stipulate an upper limit on the number of available channels, since all users share the entire frequency spectrum. However, as channel assignment based on allocating transmission power results in interference with other MUs, the system capacity is strictly interference limited. The interference is comprised of inter-cellular and intra-cellular interference, as well as background noise. Inter-cellular interference is caused by MUs served by neighboring cells, while MUs in the coverage of their homing cells generate intra-cellular interference. To ensure QoS, the interference incurred at a BS must be lower than a pre-defined threshold [2, 4]. The interference model is thus a key component of CDMA capacity management. The SIR of a message received by a BS affects the connection quality; thus, the SIR is a capacity function factor. CAC plays an important role in guaranteeing QoS and serving as many users as possible. Because CDMA capacity is bounded on the UL connection, the goals of UL CAC are to prevent the system from becoming overloaded, and to provide uninterrupted service for EMUs. In this paper, we propose a strategic-based benefit model in terms of CAC policy, instead of a theoretic-based propagation model. Without loss of generality, we ignore the shadowing effect, and

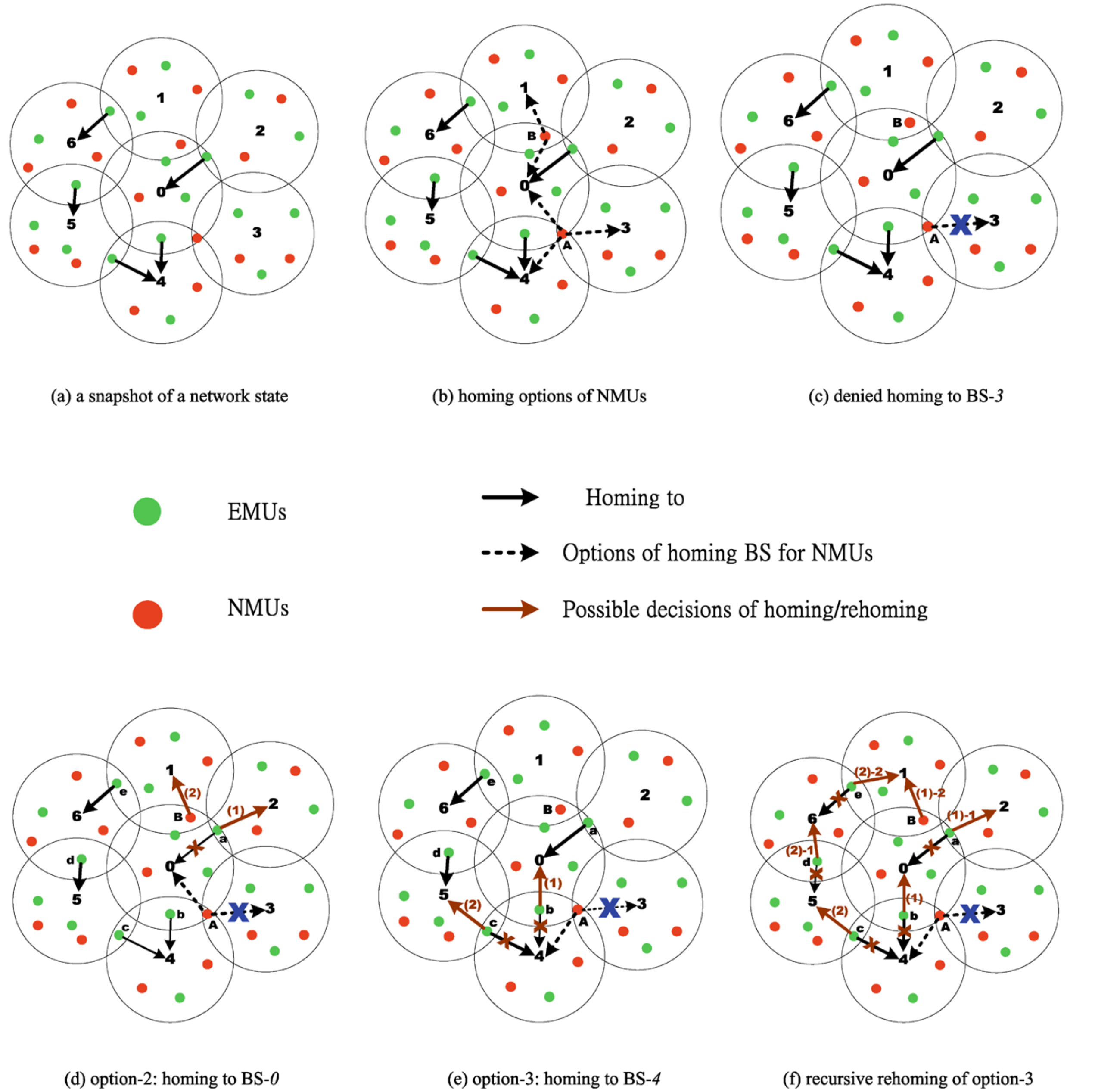


Fig. 1 Examples of possible admission control decisions

assume that the following conditions exist: (1) perfect power control; (2) the UL is perfectly separated from the downlink (DL); and (3) fading is not an issue.

Accommodating as many call requests as possible with guaranteed QoS is a non-trivial task. To achieve optimization, the CAC algorithm must re-home the EMUs covered by at least two BSs to adjacent cells that are lightly loaded and can fulfill the QoS requirement. Those cells, in turn, may re-home the MUs to other adjacent cells. For example, Fig. 1 shows a configuration with seven BSs. Let i denote the BS identification, $i \in \{0, 1, 2, 3, 4, 5, 6\}$. The coverage area of BS-i is indicated by the circle in which it is centered. Both EMUs (green points) and NMUs (red points) are served by the respective BSs that cover them, unless specified explicitly elsewhere. Assuming the capacity of each BS is limited to five users, CAC decisions try to accommodate as many users as possible, subject to QoS constraints. Thus, some EMUs must be re-homed to adjacent BSs that are lightly loaded.

In the network state shown in Fig. 1(a), suppose the five EMUs covered by at least two BSs are rehomed to the BSs indicated by the solid arrows. Figure 1(b) shows NMUs "A" and "B" initiating call requests. First, we consider NMU A, which has homing options (CAC decisions) 1, 2, and 3

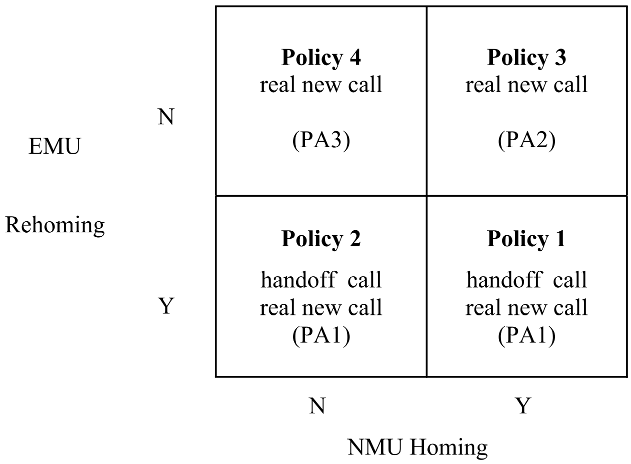


Fig. 2 Framework of admission control policies

that home to BS-0, BS-3, and BS-4 respectively. Option-2 homes to BS-3, but it is denied service because the BS has reached its capacity limit of five users, as shown in Fig. 1(c). In Fig. 1(d), if option-1 is chosen, EMU "a", which was previously homed to BS-0, must be rehomed to BS-2. In Fig. 1(e), if the CAC decision of NMU "A" is option-3, either EMU "b" or EMU "c" will be rehomed to adjacent cells. In Fig. 1(f), the cells, in turn, will recursively re-home the EMUs to other adjacent cells via path (1) or path (2). This is a complicated process in terms of global optimization.

2.2 Call admission policies

To maintain QoS for the whole system, a number of interference sources for each BS must be taken into account, and the handoff of EMU connections must be managed effectively. We summarize CAC in terms of user types, namely EMU and NMU call requests; and call types, comprised of handoff and real new calls. For simplicity, we focus on the handoff of EMUs (the re-homing policy) and the call requests of NMUs (homing policy). Figure 2 illustrates the framework of CAC policies (polices 1 to 4) in terms of user types. If the BS that receives the strongest signal is an NMU's controlling BS, the NMU is re-homed to that BS; otherwise, it is blocked. Meanwhile, EMUs can be re-homed to an adjacent cell that has a light load in order to accommodate more users. Thus, CAC must handle real new calls and handoff calls simultaneously.

If the system ignores the EMU re-homing policy, the CAC will only target real new calls, irrespective of which NMU homing policy is applied. This kind of CAC policy comprises policy 3 and policy 4, which are based on policy approaches (PA) PA2 and PA3 respectively. In contrast, we consider EMU re-homing in order to accommodate as many users as possible and optimize the system benefit globally. As handoff calls must be differentiated from real new calls, we propose using PA1 to optimize the system benefit.

2.3 Interference models

Since the capacity of CDMA systems is bounded by interference, capacity management depends on how an interference model is defined. In this section, we present three SIR models for voice traffic: without re-homing of EMUs, with re-homing of EMUs, and multi-user detection. We consider the CAC problem in terms of the user type and the call type. Denote B and T as the set of BSs and the set of MUs respectively. To differentiate between EMUs and NMUs, we use T' and T'' to denote the set of EMUs and the set of NMUs respectively, where $T = T' \cup T''$. In addition, α represents the voice activity factor, and D_{jt} is the distance between BS j and MU t. Denote P as the power received by a BS from an MU that is homed to the BS with perfect power control, G as the processing gain, E_b as the bit energy that the BS receives, N_0 as the background noise, and N_{total} as the total noise. The models are functions of the distance, voice activity, attenuation factor, and inter-cellular/intra-cellular interference. An SIR value is expressed by the power (P) over interference, which includes the N_0 and intra-cellular/inter-cellular interference. N_0 is divided into a numerator and a denominator, denoted by P/N_0 in the models. The CAC policies use the respective SIR models; for example, (1) for PA2 and PA3, and (2) for PA 1. Equation (3) is expressed without intra-cellular interference for comparison with (2) and (3). We use (2) to implement a benefit analysis algorithm. Next, we describe the three interference models. The SIR level in each model must be higher than the pre-defined QoS threshold $(E_b/N_{total})_{req}$.

Without re-homing of EMUs The interference model (1) is used to manipulate CAC, where δ_{jt} and z_{jt} denote the decision variables of the EMUs and NMUs respectively. Without considering EMU re-homing, δ_{jt} is always set at 1. Meanwhile, $z_{jt} = 1$ if MU t is admitted, and 0 otherwise. The second and third terms of the denominator are the intra-cell interference and inter-cell interference respec tively.

$$\left(\frac{E_b}{N_{total}}\right)_{req} \leq \frac{\frac{P}{N_0}}{1 + \frac{\alpha}{G}\frac{P}{N_0}(\sum_{t\in T'}\delta_{jt} + \sum_{t\in T''} z_{jt} - 1) + \frac{\alpha}{G}\frac{P}{N_0}\sum_{\substack{j'\in B\\ j'\neq j}}(\sum_{t\in T'}(\frac{D_{j't}}{D_{jt}})^{\tau}\delta_{j't} + \sum_{t\in T''}(\frac{D_{j't}}{D_{jt}})^{\tau} z_{j't})} \tag{1}$$

With re-homing of EMUs In this case [17], we consider the re-homing of EMUs and the homing of NMUs jointly. For various reasons, EMUs may be either re-homed to an adjacent cell or forcibly terminated in order to grant access to more NMUs. Thus, the cost of re-homing EMUs must be considered. In the interference model presented in (2), one decision variable, z_{jt}, is sufficient.

$$\left(\frac{E_b}{N_{total}}\right)_{req} \le \frac{\frac{P}{N_0}}{1+\frac{\alpha}{G}\frac{P}{N_0}(\sum_{t\in T} z_{jt}-1)+\frac{\alpha}{G}\frac{P}{N_0}\sum_{\substack{j'\in B\\ j'\neq j}}\sum_{t\in T}(\frac{D_{j't}}{D_{jt}})^{\tau} z_{j't}} \tag{2}$$

Multi-user detection Although several approaches have been proposed to reduce interference, multi-user detection and smart antenna are the most popular technologies [4, 5]. Multi-user detection can mitigate the effects of interference on intra-cellular MUs. A concise model is defined in (3).

$$\left(\frac{E_b}{N_{total}}\right)_{req} \le \frac{\frac{P}{N_0}}{1+\frac{\alpha}{G}\frac{P}{N_0}\sum_{\substack{j'\in B\\ j'\neq j}}\sum_{t\in T}(\frac{D_{j't}}{D_{jt}})^{\tau} z_{j't}} \tag{3}$$

3 The benefit model

3.1 Problem formulation

The usual measures of CAC are call blocking and call dropping. The former means an NMU request is denied access to the system, while the latter means an EMU call is forcibly terminated in the handoff process. CAC policy is crucial to guaranteeing both the QoS and the GoS, i.e., the call blocking probability and forced termination probability of EMUs.

Based on the CAC framework described in Sect. 2, we propose a benefit model that attempts to accommodate as many users as possible. We model the benefit optimization problem as a mathematical formulation, and analyze the system benefit derived by several PAs. In addition, we consider the re-homing of EMUs and the homing of NMUs jointly, and try to increase the system capacity. The goals of CAC are to prevent the system from becoming overloaded, and to provide uninterrupted service to EMUs. The related notations are defined in Table 1.

To maximize the system benefit, the EMUs can be kept in their original home BSs or re-homed to adjacent BSs. The goal is to maximize utilization of the system capacity by admitting as many NMUs as possible. However, as re-homing an EMU incurs an overhead, there is a tradeoff between the system capacity and the overhead. In the model, a penalty (f_t) is imposed when an EMU is re-homed. The objective is to maximize the benefit, as defined in the (IP), where the benefit model is expressed in terms of loss minimization instead of maximization gain.

Table 1 The notations used in the proposed model

Notation	Description
B	The set of candidate locations for base stations (BSs)
b'	An artificial BS that carries a rejected call when the admission control function rejects the call request
B'	The set of $B \cup \{b'\}$
b_t	The controlling BS of mobile user (MU) t
T	The set of MUs
T'	The set of existing mobile users (EMUs)
T''	The set of new mobile users (NMUs) whose admittance to the cell is to be determined
G	The processing gain
P	The power a BS receives from an MU that is homed to the BS with perfect power control
E_b	The energy received by a BS
N_{total}	The total noise
N_0	The background noise
α	Voice activity factor
τ	Attenuation factor
U	The predefined threshold of the ratio of the handoff cost to the total benefit derived by admitting an NMU
D_{jt}	The distance between BS j and MU t
M_j	The upper bound on the number of MUs that can be active at the same time in BS j
μ_{jt}	An indicator function, which is 1 if MU t can be serviced by BS j, and 0 otherwise
a_t	The benefit derived by admitting MU $t \in T''$ to the system, where $a_t = 10$
R_j	The upper bound of the power transmission radius of BS j
f_t	The handoff cost of MU t from the currently assigned BS to another BS, where $f_t = 2$
z_{jt}	A decision variable, which is 1 if MU t is serviced by BS j and 0 otherwise

$$\text{(IP)} \quad Z_{\text{IP}} = \max\left(\sum_{t\in T''} a_t \sum_{j\in B} z_{jt} - \sum_{t\in T'} f_t \sum_{j'\in B-\{b_t\}} z_{j't}\right)$$
$$= \min\left(-\left(\sum_{t\in T''} a_t \sum_{j\in B} z_{jt} - \sum_{t\in T'} f_t \sum_{j'\in B-\{b_t\}} z_{j't}\right)\right)$$

subject to

$$\left(\frac{E_b}{N_{total}}\right)_{req} \le \frac{\frac{P}{N_0}}{1+\frac{\alpha}{G}\frac{P}{N_0}(\sum_{t\in T} z_{jt}-1)+\frac{\alpha}{G}\frac{P}{N_0}\sum_{\substack{j'\in B\\ j'\neq j}}\sum_{t\in T}(\frac{D_{j't}}{D_{jt}})^{\tau} z_{j't}} \quad \forall j \in B \tag{4}$$

$$\sum_{t\in T} z_{jt} \le M_j \quad \forall j \in B \tag{5}$$

$$D_{jt} z_{jt} \le R_j \mu_{jt} \quad \forall j \in B, t \in T \tag{6}$$

$$z_{jt} \le \mu_{jt} \quad \forall j \in B, t \in T \tag{7}$$

$$\sum_{j\in B'} z_{jt} = 1 \quad \forall t \in T'' \tag{8}$$

$$\sum_{j\in B} z_{jt} = 1 \quad \forall t \in T' \tag{9}$$

$$\frac{\sum_{t\in T'} f_t \sum_{j'\in B-\{b_t\}} z_{j't}}{\sum_{t\in T''} a_t \sum_{j\in B} z_{jt}} \le U \quad \forall j \in B, t \in T \tag{10}$$

$$z_{jt} = 0 \quad \text{or} \quad 1 \quad \forall j \in B, t \in T \tag{11}$$

Constraint (4) is adapted from (2) to guarantee the QoS. A capacity constraint is given in (5). Constraints (6) and (7) ensure that a user can only be serviced in the coverage area of the BS. Constraint (8) requires that an NMU can only be homed to one physical BS or rejected. Constraint (9) ensures that EMUs are always admitted to the system. The cost threshold of re-homing EMUs is given in Constraint (10), while Constraint (11) ensures the integer property of the decision variable z_{jt}. To solve the complicated integer programming problem efficiently, we adopt the Lagrangean relaxation (LR) approach [18, 19]. Brief descriptions of the LR approach and the solution procedure are given in the Appendix.

3.2 An algorithm for finding primal feasible solutions

According to the weak Lagrangean duality theorem, for any $(v_j^1, v_j^2, v_{jt}^3, v^4) \ge 0$, the objective value of $Z_{\mathrm{D}} = \max Z_{\mathrm{D}}(v_j^1, v_j^2, v_{jt}^3, v^4)$ is an lower bound (LB) of Z_{IP}. Based on the problem (LR), the following dual problem (D) is constructed to calculate the tightest LB.

(D) $\quad Z_{\mathrm{D}} = \max Z_{\mathrm{D}}(v_j^1, v_j^2, v_{jt}^3, v^4)$,

subject to $(v_j^1, v_j^2, v_{jt}^3, v^4) \ge 0$.

Then, the subgradient method [20] is applied to solve the dual problem. Let the vector S be a subgradient of $Z_{\mathrm{D}}(v_j^1, v_j^2, v_{jt}^3, v^4)$ at $(v_j^1, v_j^2, v_{jt}^3, v^4)$. In iteration k of the subgradient optimization procedure, the multiplier vector π is updated by $\pi^{k+1} = \pi^k + t^k S^k$; t^k is the step size determined by $t^k = \rho(Z_{\mathrm{IP}}^* - Z_{\mathrm{D}}(\pi^k))/\|S^k\|^2$, where Z_{IP}^* is an upper bound (UB) on the primal objective function value after iteration k; and ρ is a constant, where $0 \le \rho \le 2$.

After finding the optimal solution to the Lagrangean dual problem, we get a set of decision variables. However, the solution is not feasible for the primal problem because some of the constraints are not satisfied. Thus, minor modifications of the decision variables must be made to obtain a primal feasible solution of problem (IP). Generally speaking, a UB of the problem (IP), is the best primal feasible solution, while the solution to the Lagrangean dual problem guarantees the LB of (IP). By solving the Lagrangean dual problem iteratively, and getting a primal feasible solution, we derive the LB and the UB respectively. Thus, the gap between the UB and LB, computed by (UB − LB)/LB × 100%, illustrates the optimality of the problem solution. The smaller the gap computed, the better will be the optimality of the solution. To derive a primal feasible solution, we present an algorithm called *getting the primal feasible solution* (GPFS).

Algorithm *GPFS*

Step 1. Check capacity Constraint (5), for each BS. Drop an NMU, i.e., set $z_{jt} = 0$, if it violates Constraint (5); otherwise, go to Step 2.

Step 2. Ensure that QoS Constraint (4) is satisfied for each BS. Drop an NMU, i.e., set $z_{jt} = 0$, if it violates Constraint (4); otherwise, go to Step 3.

Step 3. Try to re-add all new users dropped in Steps 1 & 2 to system.

- (3-1) Select dropped new users sequentially.
- (3-2) Home to another BS, i.e., set $z_{jt} = 1$ again, if the setting satisfies Constraint (4) as well as the capacity Constraint (5) for each BS; otherwise go to Step 4.

Step 4. Re-home EMUs in adjacent BSs in order to grant access to more new users.

- (4-1) Sequentially select EMUs that are covered by more than one BS.
- (4-2) Re-home the selected users in an adjacent BS if Constraints (4), (5), and (10) are satisfied for each BS; otherwise go to Step 5.
- (4-3) Admit new users that are still blocked, i.e., set $z_{jt} = 1$ again, if the setting satisfies Constraints (4) and (5) for each BS; otherwise go to Step 5.

Step 5. End algorithm *GPFS*.

4 The effect of call admission policies on the system benefit

4.1 Experiment environment

Table 2 details the parameters used in the experiment for the problem (IP). The parameter α is set at 0.3 and the number of BSs ($|B|$) is 16, deployed with 4×4 BS array. To analyze how $|T'|$ affects the admission of new users, three cases of $|T'|$ are considered with 50, 60, and 70 users respectively. We analyze the long-term system benefit. The experiment is a snapshot of existing/ongoing calls and newly initiated calls. The values of λ are the arrival rates in a given unit of time. To determine how traffic demand affects the benefit contribution, $|T''|$ is generated by a Poisson arrival process with three mean arrival rates (λ), $\lambda = 100$, 150, and 200. The generated locations of EMUs and NMUs are distributed uniformly in the coverage areas of the BSs; and between 6 (100/16) and 13 (200/16) new users are generated in the coverage of each BS. For each EMU and NMU combination, we use the Lagrangean relaxation approach to solve the problem (IP) for benefit analysis.

4.2 Output measures and results

(1) Solution gap Table 3 summarizes the statistics of the gaps for the worst, average, and best cases of the 500 tests with respect to λ, $|T'|$, and policy approaches (PAs). PA1 yields a better optimal solution than PA2 and PA3. The results range from 0.00% to 2.34% for the average case, while the worst case is 8.77%. An analysis of the improvement over PA2 and PA3 is given in Fig. 3. The biggest improvement is $(0.63 - 0.03)/0.63 \times 100\% = 95\%$ in the case of $\lambda = 150$ compared to PA3 with $|T'| = 70$.

(2) Number of iterations Given a time budget of 30 seconds, the analysis calculates the total number of iterations of the LR algorithm. The smaller the number of iterations, the more efficient the algorithm is deemed to be. Figure 4 shows the percentiles of the iterations calculated. Irrespective of whether λ or $|T'|$ is used, PA1 achieves 95% optimality in less than 50 iterations. For PA2 and PA3, the number of iterations increases as λ and $|T'|$ increase. The extent of the increase of PA3 is more significant than that of PA2.

(3) Service rate The service rate is defined by the ratio of the total number of admitted NMUs to the total number of users (including $|T'|$ and $|T''|$) in the system. Table 4 summarizes the statistics of the service rate for the worst, average, and best cases of 500 tests with respect to λ, $|T'|$, and PA. Fortunately, all the service rates in the best case are 1.0. We also compare the service rates of the average and worst cases shown in Fig. 5(a). For the worst case, irrespective of which PA is applied, λ has a more significant impact than $|T'|$. For PA3, the service rate is reduced from 1.0 to 0.71, 1.0 to 0.67, and 0.94 to 0.57 for $|T'| = 50$, 60, and 70 respectively. Figure 5(b) shows an analysis of the improvement. The more new users admitted, the better the service rate will be.

(4) Benefit contribution We analyze the performance of CAC policy in terms of the benefit contribution. The aggregate benefit contributed by the three PAs is shown in Table 5. When $\lambda = 100$ and $|T'| = 70$, the benefits contributed by PA1, PA2, and PA3 are 502340, 502330 and 502220 respectively. In the scenarios where $\lambda = 150$ and $\lambda = 200$, PA1

Table 2 The parameters used in the experiment

Notation	Value
S/N_0	7 db
E_b/N_{total}	6 db
M_j	120
τ	4
G	156.25
a_t	10

Table 3 Statistics of the gaps, in percentages, with respect to λ, $|T'|$, and PAs

λ		100			150			200		
Algorithm		PA1	PA2	PA3	PA1	PA2	PA3	PA1	PA2	PA3
W*	50	0.00	0.00	0.00	1.34	2.48	11.18	7.08	14.29	31.98
	60	0.00	0.00	0.00	1.86	4.26	16.49	8.37	16.96	38.64
	70	0.74	1.48	9.63	2.01	11.36	25.76	8.77	29.83	39.04
A*	50	0.00	0.00	0.00	0.01	0.02	0.08	0.30	0.88	3.24
	60	0.00	0.00	0.00	0.02	0.08	0.31	0.46	1.44	5.00
	70	0.00	0.00	0.02	0.03	0.15	0.63	0.70	2.34	7.65
B*	50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

The exact error gap is less than 0.001%. For ease of presentation, only two decimal places are reported

*W, A, and B denote the worst, average, and best cases respectively

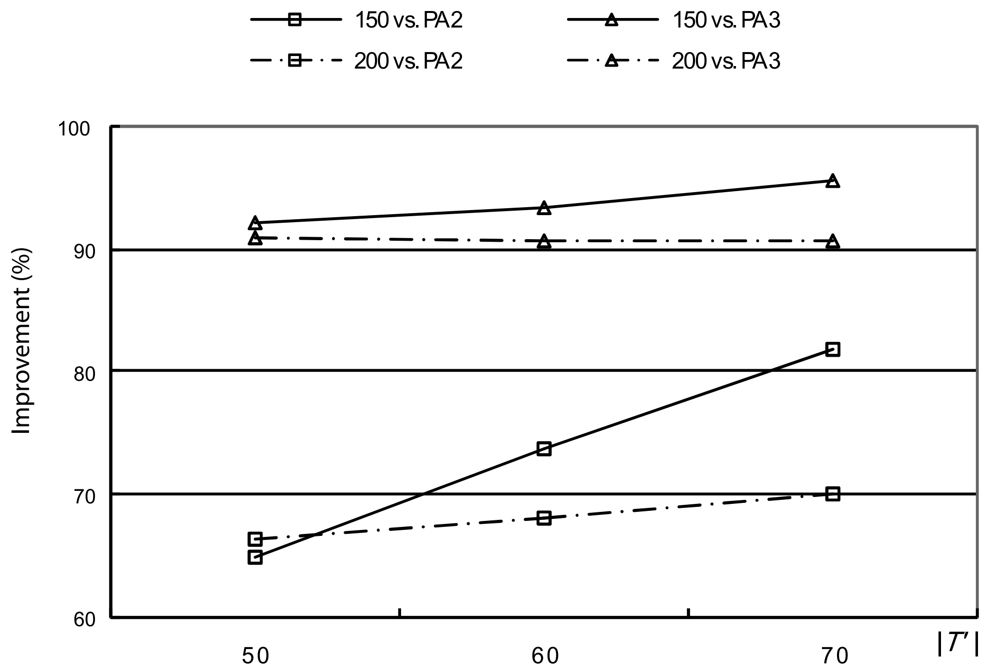
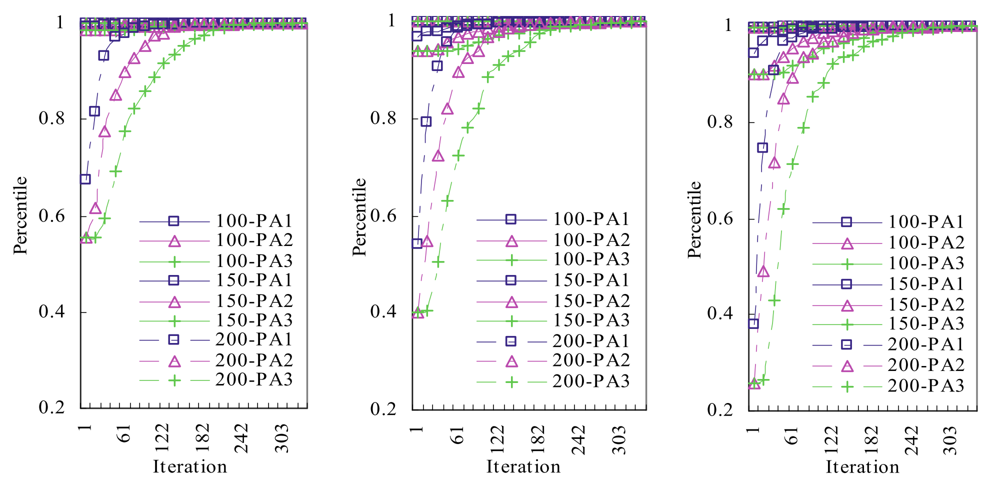


Fig. 3 Solution gap improvement of PA1 in the average case with respect to (λ vs. PA) and $|T'|$



(a) $|T'|$=50 (b) $|T'|$=60 (c) $|T'|$=70

Fig. 4 Percentiles of iterations subject to a time budget, given $|T'|$

Table 4 Statistics of the service rates with respect to λ and PAs

λ		100			150			200		
Algorithm		PA1	PA2	PA3	PA1	PA2	PA3	PA1	PA2	PA3
W*	50	1.00	1.00	1.00	0.98	0.93	0.92	0.77	0.72	0.61
	60	1.00	1.00	1.00	0.97	0.92	0.85	0.72	0.69	0.67
	70	0.99	0.99	0.94	0.81	0.77	0.78	0.80	0.63	0.57
A*	50	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.96
	60	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.98	0.94
	70	1.00	1.00	1.00	1.00	1.00	0.99	0.97	0.97	0.92
B*	50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	60	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	70	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

*W, A, and B denote the worst, average, and best cases respectively

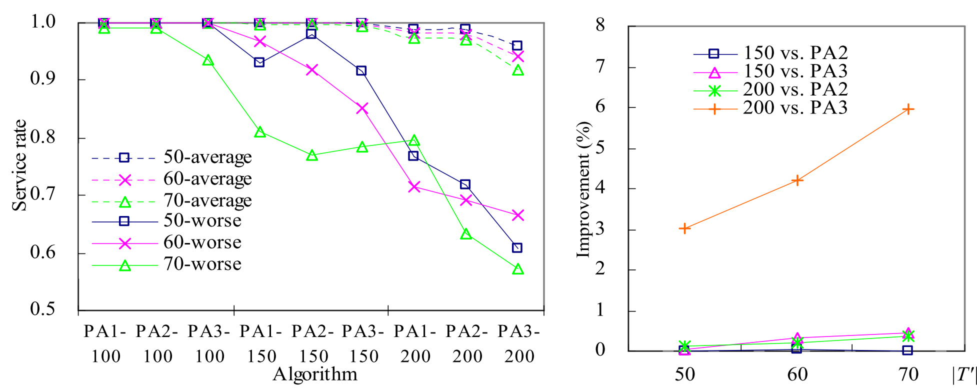
Table 5 Aggregate benefit contributed by the three PAs with respect to λ and $|T'|$

λ		100		
Algorithm		PA1	PA2	PA3
$\lvert T'\rvert$	50	502350	502350	502350
	60	502350	502350	502350
	70	502340	502330	502220
λ		150		
Algorithm		PA1	PA2	PA3
$\lvert T'\rvert$	50	749940	749850	749350
	60	749820	749350	747400
	70	749770	748800	745030
λ		200		
Algorithm		PA1	PA2	PA3
$\lvert T'\rvert$	50	999540	993400	968620
	60	997780	987510	950330
	70	995260	978190	923200

always yields higher benefits than PA2 and PA3. We also compare the benefit improvements of PA1 over PA2 and PA3 with respect to λ, as shown in Fig. 6. In the case of $\lambda = 200$, the improvement is up to 8% better than PA3 for $|T'| = 70$. This indicates that the more new traffic is loaded and the more EMUs that exist, the greater will be the benefit contribution. No matter what value of λ is applied, PA1 outperforms the other two policies.

In summary, the service rate of PA1 increases as more traffic is loaded into the system. The phenomenon is more significant in the worst-case scenario because there may be several users located in the handoff area; hence, some of them can be handed off from a heavily loaded BS to a lightly loaded one. This implies that PA1 is more suitable for severely/heavily loaded environments. In addition, the users generated by the high values of λ are uniformly distributed in the coverage of a 4×4 BS array, so, the values are feasible. In the same environment, if the system is heavily loaded (with larger λ), more users will probably be located in the handoff area; however, by applying PA1, they can be

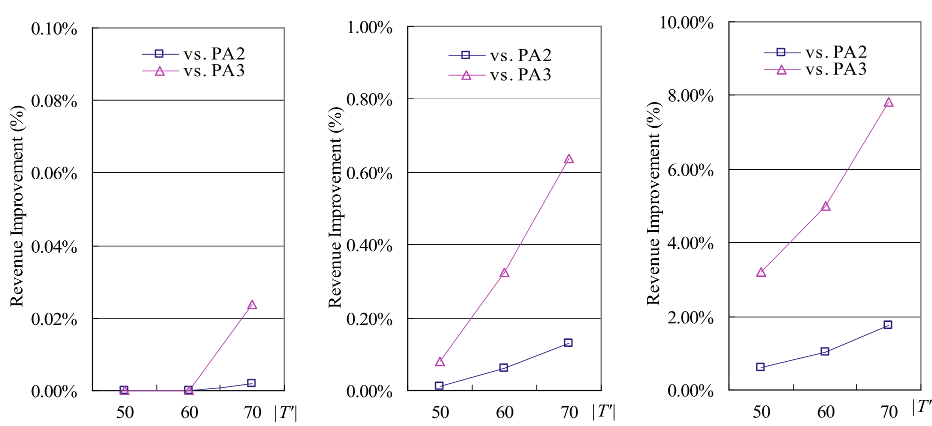
Fig. 5 Comparison of the service rates



(a) as a function of λ and PA

(b) improvement in the average case

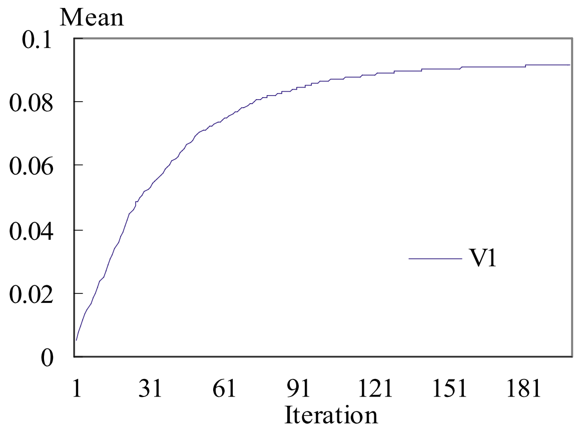
Fig. 6 Benefit improvement of PA1 over PA2 and PA3, given λ



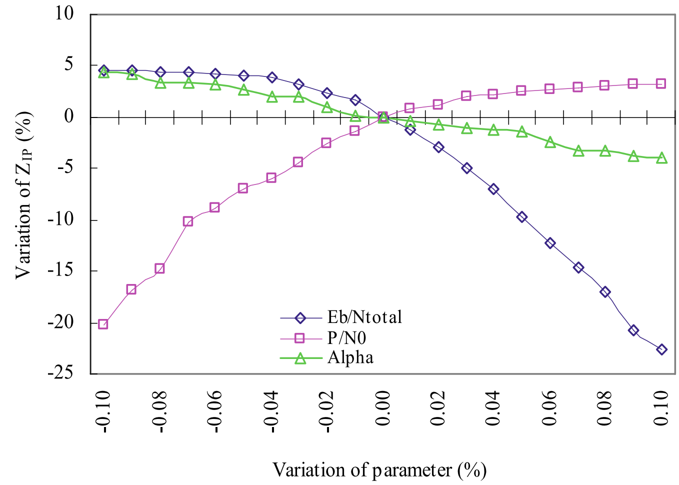
(a) λ=100

(b) λ=150

(c) λ=200



(a) for Lagrangean multipliers V1



(b) for various parameters on Z_{IP}

Fig. 7 Sensitivity analysis of the benefit model

handed off from a saturated-BS to an unsaturated-BS. This explains why PA1 is better than PA2 and PA3 in terms of benefit improvement.

4.3 Sensitivity analysis

Although four constraints in the benefit model are relaxed, only one multiplier, V1, related to SIR Constraint (4) is calculated with non-zero values. The other threes multipliers—V2 related to Constraint (5), V3 related to Constraint (6), and V4 related to Constraint (10)—are all zero. This means the three constraints are irrelevant to the benefit analysis. Thus, our sensitivity analysis focuses on the SIR constraint in (4) as shown in Fig. 7. In Fig. 7(a), the V1 values converge to 0.92 in less than 200 iterations, which demonstrates the good performance of the proposed GPFS algorithm.

We also assess the impact of three other parameters on the total benefit, namely the threshold E_b/N_{total}, the power strength P/N_0, and the voice activity factor (AF) α. Figure 7(b) shows the variations of Z_{IP} when the parameters change. The results derived by adjusting the parameters E_b/N_{total} and P/N_0 are almost symmetric. The total benefit varies from $+4.5\%$ to -22.5% as the value of E_b/N_{total} adjusts from -10% to $+10\%$, while the variations range from -20.3% to $+2.35\%$ when P/N_0 changes from -10% to $+10\%$. The effect of the voice activity factor on the benefit is moderate (from $+4.38\%$ to -3.95%) compared to that of the other two parameters. In summary, to accommodate as many users as possible, the strength of the power-controlled signal must be properly assigned.

5 Conclusion

Increasing system capacity is an important issue in mobile wireless communication systems. However, accommodating as many call requests as possible with guaranteed QoS is a nontrivial task. In this paper, we propose a benefit optimization model based on admission control policy, and present an efficient solution algorithm that distributes the system load among cells. To achieve the optimization goal, the algorithm re-homes the MUs covered by at least two BSs, to lightly loaded adjacent cells that meet the QoS requirement. These cells, in turn, may re-home the MUs to other adjacent cells. We find that the benefit improvement as up to 8% better than previously reported results. This suggests that the more new traffic that is loaded and the more EMUs that exist, the greater will be the benefit contribution.

As an engineering guideline, we suggest using approach PA1 because it outperforms the other two approaches. Specifically, it admits more NMUs by re-homing EMUs to adjacent cells that are lightly loaded. The superiority of PA1 is evident when the system is heavily loaded. Even though the numbers of EMUs and NMUs increase, more benefit is contributed, and the service rate is better under PA1. Furthermore, sensitivity analysis results show that proper assignment of the strength of power-controlled signals is a key factor in accommodating as many as users as possible. In addition, our proposed analysis approach can be generalized to other systems, only if the SIR model constraints are replaced to respective systems.

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Appendix

Lagrangean relaxation (LR), a general solution approach for solving mathematical optimization problems, is used to decompose such problems and exploit their special structure. The procedure of the LR method is as follows: relax complicating constraints, multiply the relaxed constraints by the corresponding Lagrangean multipliers, and then add them to the primal objective function. Accordingly, the primal optimization problem can be transformed into an LR problem by decomposing it into several independent sub-problems that can be solved optimally. To obtain optimal solutions, we must iteratively adjust the Lagrangean multipliers to optimally solve the Lagrangean dual problem. In addition, by calculating the multipliers in all the procedures, sensitivity analysis of associated constraints can be further investigated.

LR has the following significant advantages. (1) It is a very flexible approach that decomposes models in several ways and applies LR to each decomposition. (2) By decomposing problems, it solves core sub-problems as stand-alone models. (3) It permits us to develop bounds on the value of the optimal objective function and quickly generate good solutions with associated performance guarantees. (4) Based on LR, we can develop effective heuristic methods for solving complex combinatorial optimization problems.

Even though LR is a standard solution technique that can solve a wide range of combinatorial optimization problems, to solve those problems efficiently and effectively, the following non-trivial tasks must also be considered. (1) In the problem formulation stage, the first step is to find a suitable formulation that can be decomposed into subproblems and solved by LR. This may require many attempts to reformulate the problem by trial and error. (2) In the solution procedure stage, it is necessary to decide which constraints should be relaxed and how a number of critical parameters can be carefully determined, so that the optimal solution and a high convergence rate can be derived. These remain open issues. (3) How to apply Lagrangean multipliers and develop an efficient algorithm to get primal feasible solutions is a challenging issue. We use Lagrangean multipliers for sensitivity analysis so that the corresponding constraints can be evaluated for decision support.

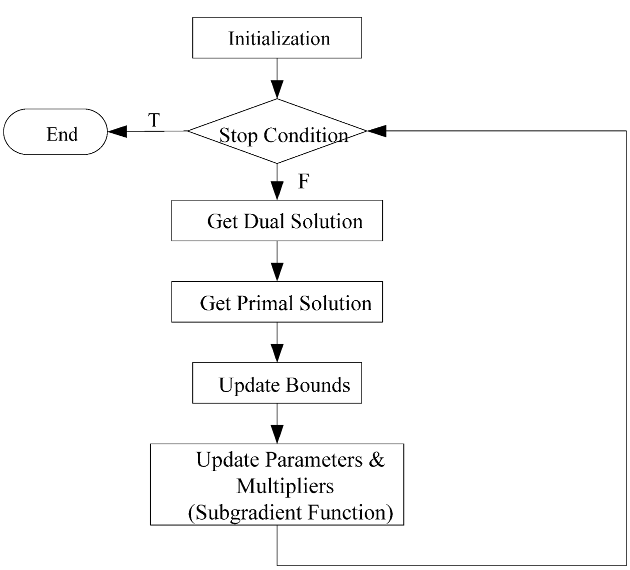

Fig. 8 The overall procedure of the LR approach

Based on the LR procedure, we relax Constraints (4), (5), (6), and (10) in the primal optimization problem (IP), which is then transformed into the following LR problem (LR).

$$
\begin{aligned}
&Z_{\mathrm{D}}(v_j^1, v_j^2, v_{jt}^3, v^4)\\
&\quad = \min -\Bigg(\sum_{t\in T''} a_t \sum_{j\in B} z_{jt} - \sum_{t\in T'} f_t \sum_{j'\in B-\{b_t\}} z_{j't}\Bigg)\\
&\qquad + \sum_{j\in B} v_j^1 \Bigg(\bigg(\frac{E_b}{N_{total}}\bigg)_{req}\\
&\qquad + \bigg(\frac{E_b}{N_{total}}\bigg)_{req} (\alpha/G)(P/N_0)\Bigg(\bigg(\sum_{t\in T} z_{jt} - 1\bigg)\\
&\qquad + \sum_{\substack{j'\in B\\ j'\neq j}} \sum_{t\in T} \bigg(\frac{D_{j't}}{D_{jt}}\bigg)^{\tau} z_{j't}\Bigg) - (P/N_0)\Bigg)\\
&\qquad + \sum_{j\in B} v_j^2 \bigg(\sum_{t\in T} z_{jt} - M_j\bigg)\\
&\qquad + \sum_{t\in T} \sum_{j\in B} v_{jt}^3 (D_{jt} z_{jt} - R_j \mu_{jt})\\
&\qquad + v^4 \Bigg(\sum_{t\in T'} f_t \sum_{j'\in B-\{b_t\}} z_{j't} - U \sum_{t\in T''} a_t \sum_{j\in B} z_{jt}\Bigg),
\end{aligned}
$$

subject to (7), (8), (9), and (11).

Next, the subproblem (SUB) related to decision variable z_{jt} has to be solved. For any $v_j^1, v_j^2, v_{jt}^3, v^4 \geq 0$, $Z_{\mathrm{D}}(v_j^1, v_j^2, v_{jt}^3, v^4)$ is a lower bound (LB) on Z_{IP}. The tightest LB can be calculated iteratively by the subgradient method.

Subproblem (SUB) related to decision variable z_{jt}:

$$
\begin{aligned}
Z_{\mathrm{SUB}} = \min \sum_{t\in T''} \Bigg(\sum_{j\in B} \Bigg(z_{jt}\Bigg(-a_t\\
&+ \bigg(\frac{E_b}{N_{total}}\bigg)_{req} (\alpha/G)(P/N_0)\Bigg(v_j^1 + \sum_{\substack{j'\in B\\ j'\neq j}} v_{j'}^1 \bigg(\frac{D_{jt}}{D_{j't}}\bigg)^{\tau}\Bigg)\\
&+ v_j^2 + v_{jt}^3 D_{jt} - U v^4 a_t\Bigg) - v_{jt}^3 R_j \mu_{jt}\Bigg)\Bigg)
\end{aligned}
$$

$$+ \sum_{t\in T'}\left(\sum_{j\in B}\left(z_{jt}\left(f_t(1+v^4)\right.\right.\right.$$

$$+ \left(\frac{E_b}{N_{total}}\right)_{req}(\alpha/G)(P/N_0)\left(v_j^1 + \sum_{\substack{j'\in B\\ j'\neq j}} v_{j'}^1\left(\frac{D_{jt}}{D_{j't}}\right)^{\tau}\right)$$

$$\left.\left.\left.+ v_j^2 + v_{jt}^3 D_{jt}\right) - v_{jt}^3 R_j \mu_{jt}\right)\right)$$

$$+ \sum_{j\in B}\left(v_j^1\left(\left(\frac{E_b}{N_{total}}\right)_{req} - (P/N_0)\right.\right.$$

$$\left.\left. - \left(\frac{E_b}{N_{total}}\right)_{req}(\alpha/G)(P/N_0)\right) - v_j^2 M_j\right)$$

In the model, the EMUs can be re-homed to another BS that can serve them. Thus, more NMUs can be admitted, even if they were originally blocked by the system. We can further decompose the problem (SUB) into $|T''|$ sub-problems for NMUs that want to be admitted, and $|T'|$ sub-problems for EMUs that we must re-home. Let

$$h_{jt} = -a_t + \left(\frac{E_b}{N_{total}}\right)_{req}(\alpha/G)(P/N_0) \times \left(v_j^1 + \sum_{\substack{j'\in B\\ j'\neq j}} v_{j'}^1\left(\frac{D_{jt}}{D_{j't}}\right)^{\tau}\right) + v_j^2 + v_{jt}^3 D_{jt} - U v^4 a_t - v_{jt}^3 R_j \mu_{jt}$$

If h_{jt} is equal to or less than 0, we assign z_{jt} to 1; otherwise, we assign z_{jt} to 0. We then consider the $|T'|$ sub-problems of EMUs. Let

$$k_{jt} = f_t(1+v^4) + \left(\frac{E_b}{N_{total}}\right)_{req}(\alpha/G)(P/N_0) \times \left(v_j^1 + \sum_{\substack{j'\in B\\ j'\neq j}} v_{j'}^1\left(\frac{D_{jt}}{D_{j't}}\right)^{\tau}\right) + v_j^2 + v_{jt}^3 D_{jt} - v_{jt}^3 R_j \mu_{jt}$$

If k_{jt} is equal to or less than 0, we can re-home these $z_{j't}$ to 1, which is $j' \neq j$. However, we can not block EMUs, so z_{jt} can not be assigned to 0 if k_{jt} is greater than 0. In this situation, the re-homing cost f_t is 0.

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