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An Admission Control-based Benefit Optimization Model for Mobile Communications: the Effect of a Decision Time Budget

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Abstract In mobile communication systems, a soft handoff (SHO) technique is used to optimize the quality and capacity of communications. However, because the handoff process incurs a high overhead there must be a tradeoff between the system capacity and the handoff overhead. In this paper, we propose a benefit optimization model for mobile communications. The model tries to maximize the overall system capacity by considering SHO process overhead and quality of service requirements jointly. We first construct a framework of admission policies and devise an appropriate admission control policy, which is then used to analyze the system benefit. The service rate is defined by three measures: the call blocking ratio, system load, and admit-to-existence ratio; while the solution quality is defined by the gap between the upper bound and lower bound of the objective function value. By applying iteration-based Lagrangian relaxation as a solution approach, a time budget is allocated to each iteration so that admission control can be implemented. To fulfill the continuous admission process requirements in the long-term, users' demands are randomly distributed via a simulation process. The goal of this paper is to investigate the effect of the admission control policy on the system benefit, service rate and solution quality. Experiment results are presented to demonstrate the efficacy of both the proposed model and the solution approach.

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1 Introduction

The rapid evolution of wireless communications has created almost limitless opportunities for new digital networks with greatly enhanced capabilities. For example, future applications of multimedia data services will provide more capacity, higher data rates, and better quality of service (QoS). Call admission control (CAC) is a widely used mechanism that regulates a network's operations with an optimal condition. As a result, existing mobile users (EMUs) can be guaranteed uninterrupted service, and as many new mobile user (NMU) requests as possible can be accommodated. The larger the number of users admitted, the greater will be the system benefit. On the other hand, the distribution of the user requests among cells is uneven, so it is difficult to optimize the overall capacity of the system [1]. In CDMA systems, for example, soft handoff (SHO) plays an important role, as it enables mobile users (MUs) near cell boundaries to use the same signals to transmit to and receive from more than one base station (BS). The process is called the SHO to distinguish it from the conventional hard handoff (HHO) process. By combining the signals from several BSs with macrodiversity, the signal-to-interference ratio (SIR), which is defined as a QoS threshold, can be improved to extend cell coverage.

Under the SHO function, if there are EMUs in the handoff region, some of the EMUs controlled by a cell that is heavily loaded can be compulsorily handed off to an adjacent cell that is lightly loaded [2]. To handle SHO call requests, [3] proposed a CAC policy that gives SHO calls priority over new calls and stream-type data traffic. Another study [4] developed an adaptive channel reservation (ACR)-based CAC scheme that prioritizes SHO calls. Using power control to enforce SHO has been proposed as another possible solution to local traffic imbalance among cells. In [5], Sang et al. presented a scalable cross-layer framework to improve global resource utilization with uneven arrivals and departures of the MUs. The overall system capacity can be optimized by using the SHO process to handle CAC globally [6].

However, SHO operations still incur an overhead because a large number of messages must be passed between MUs and BSs. Hence, there must be a tradeoff between the system capacity and the handoff overhead. To improve the handoff performance, [7] used a dynamic programming technique to reduce the network overhead by integrating handoff and power control. In [8], Sheu and Wu applied grey prediction theory to reduce the overhead, and formulated the overhead problem as a minimum-cost model [9]. Alpcan and Basar [10] proposed a game-theoretic power control scheme to reduce the handoff overhead in multi-cell CDMA networks.

To deal with the overhead issue, Chu et al. [11] proposed a framework of CAC policies. The framework comprises two types of call requests, EMU and NMU requests, as shown in Fig. 1. EMUs (ongoing users) are in the system before CAC is implemented, while NMUs are waiting to be admitted. It is assumed that an NMU can only be homed to its controlling BS or blocked, while EMUs can be re-homed to any adjacent BS that has a light load in order to accommodate more users. Ergo, we

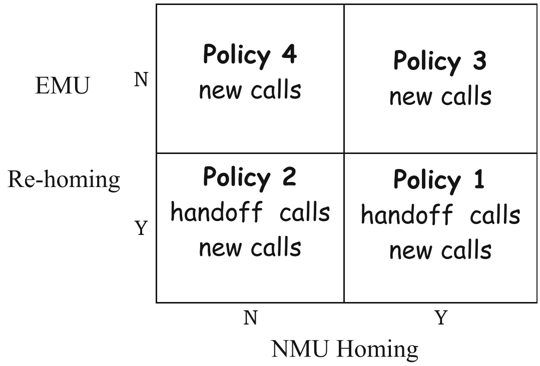


Fig. 1 The framework of admission control policies

denote “Homing” as the CAC policy for NMU call requests, and “Re-homing” as the CAC policy for EMU call requests. In the figure, “Y” means the user can be admitted to one of the BSs that cover it, and “N” means the user can only be admitted by the nearest BS or blocked. If the CAC focuses on an EMU with one of the “N” Re-homing policies (Policy 3 or Policy 4), it will only target new calls irrespective of which NMU homing policy is applied. Two types of calls (new and handoff calls) must be dealt with if focusing on EMUs with one of the “Y” Re-homing policies (Policy 1 or Policy 2), which are applied during the SHO operation.

To maximize the system capacity, CAC controls the users’ power and data rates; therefore, the throughput maximization problem can be formulated as a classic optimization problem. Several studies [12–16] formulate frequency, capacity assignment, and network survivability problems as combinatorial optimization models. The objective of frequency assignment is to minimize the number of frequencies used, while capacity assignment tries to maximize the number of channels allocated to users. Han [12] modeled the frequency reassignment problem as an integer programming problem and proposed installing new BSs to support capacity expansion. In [13, 15], tabu search techniques are used, while [14] employs branch-and-cut techniques. Han’s work focuses on prospective resource planning, not on admission control operations. The survivability problem in mobile communication networks is caused by base station failure events. To address the problem, the CAC-based performance model proposed in [16], relocates mobile/portable BSs to expand the system’s capacity.

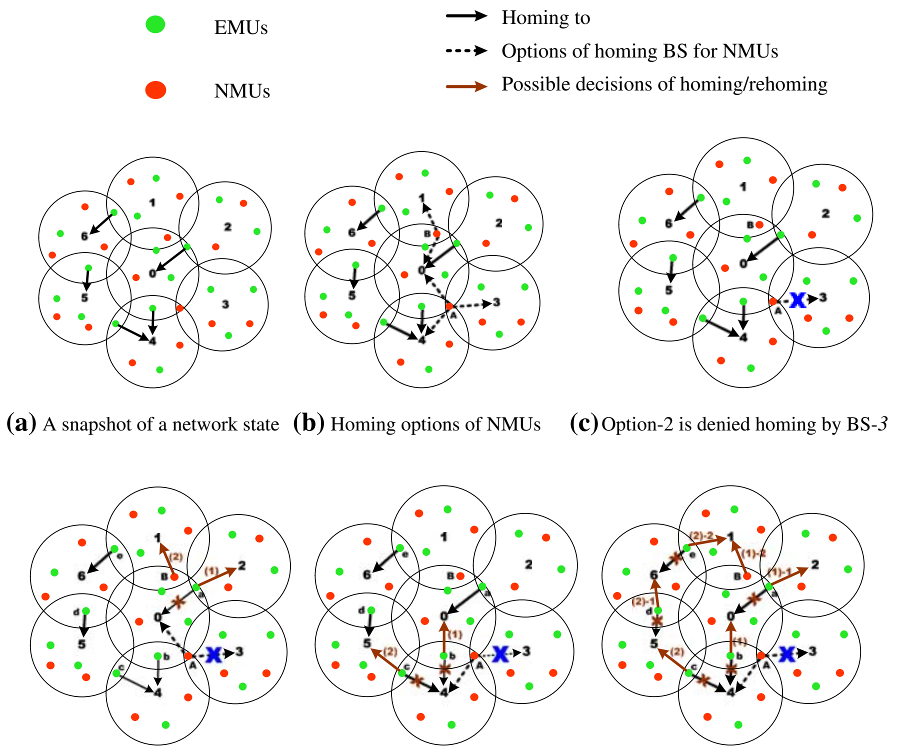
In this paper, we consider CDMA system benefit management and the SHO overhead jointly in order to optimize the system capacity. To this end, based on Policies 1 and 2 in [11], we propose an admission control-based optimization model subject to QoS requirements. Because of the uncertainty about the number of call requests and the call holding times, CAC-based long-term benefit management is by nature a stochastic problem instead of a deterministic one. We analyze the overall system benefit by implementing continuous and individual admission processes, but the fading issue in the propagation model of traditional communication theory is not discussed. In addition, we use the probability distribution to simulate the number of call arrivals and the call holding times, and apply the proposed benefit optimization model to evaluate the system benefit of the individual admission process.

The remainder of this paper is organized as follows. Section 2 provides an overview of CDMA admission control, including an example to explain the SHO concept. In Sect. 3, we describe the proposed admission control-based benefit management model. The solution approach of the model is given in Sect. 4. In Sect. 5, we discuss the results of computational experiments. Section 6 contains some concluding remarks.

2 Admission Control in CDMA Networks

2.1 Possible Admission Control Decisions

Accommodating as many call requests as possible with guaranteed QoS is a non-trivial task. To achieve the optimization goal, the CAC algorithm should re-home EMUs covered by at least two BSs/cells to adjacent BSs whose QoS system loads are light. The adjacent BSs, in turn, may re-home the MUs to other adjacent BSs. For example, let there be seven BSs, configured as shown in Fig. 2, and let i denote BS identification $i \in \{0, 1, 2, 3, 4, 5, 6\}$. A circle represents the coverage (service)



(a) A snapshot of a network state **(b)** Homing options of NMUs **(c)** Option-2 is denied homing by BS-*3*

(d) Option-2 homes to BS-*0* **(e)** Option-3 homes to BS-*4* **(f)** Recursive rehoming of option-3

Fig. 2 Possible admission control decisions area of BS-i. The EMUs (green points) and NMUs (red points) are served by the respective BSs that cover them, unless otherwise specified. Assuming the capacity supported by each BS is limited to five users, CAC tries to accommodate as many users as possible, subject to QoS constraints. Thus, some EMUs should be further rehomed to adjacent BSs that are lightly loaded.

Figure 2a shows a snapshot of a network state where five EMUs covered by at least two BSs are homed to the BS indicated by the solid arrow; while, in Fig. 2b, NMUs “A” and “B” are covered by at least two BSs that initiate call requests. NMU A has three homing options (CAC decisions), 1, 2, and 3, which home to BS-*0*, BS-*3*, and BS-*4*, respectively. As shown in Fig. 2c, option-2 is denied because BS-*3* has reached its capacity limit of five users. In Fig. 2d, if option-1 is chosen, EMU “a”, which was previously homed to BS-*0*, must be rehomed to BS-*2*. In Fig. 2e, if the CAC decision of NMU “A” is option-3, either EMU “b” or EMU “c” will be rehomed to an adjacent cell. In Fig. 2f, the adjacent BSs, in turn, will recursively re-home the EMUs to other adjacent cells via path (1) or path (2). Clearly, this is a complicated process in terms of global optimization.

2.2 Interference Model

Theoretically, there is no upper limit of available channels in CDMA, since all users share the entire frequency spectrum, instead of dividing the frequency or time. However, as channel assignment based on the allocation of transmission power results in interference with other MUs, the system’s capacity is strictly limited by such interference. In fact, some works, e.g., [17, 18, 19] suggest that CDMA capacity is bounded on the uplink connection, and the SIR of the BS affects the connection quality.

CAC plays an important role in guaranteeing QoS. On the uplink (UL), the goal of CAC is to prevent the system from being overloaded, and to provide uninterrupted service for EMUs. It is assumed that the following conditions exist: 1) perfect power control; 2) the UL is completely separate from the downlink (DL); and 3) fading is not considered. To satisfy the QoS requirements of the whole system, the sources of interference for each BS must be taken into account, and the handoff of EMU connections must be managed effectively.

Since the capacity of CDMA systems is bounded by interference, defining an interference model is a key capacity management issue. Denote B and T as the set of BSs and the set of MUs, respectively. We consider the CAC problem in terms of user types and call types, as shown in Fig. 1. To differentiate EMUs from NMUs, we denote T' and T'' as the set of EMUs and NMUs, respectively, where $T = T' \cup T''$. We also use P to denote the power received by a BS from an MU that is homed to the BS with perfect power control. The total interference is comprised of background noise N_0, intra-cellular interference (1), and inter-cellular interference (2), where D_{jt} is the distance between BS $j \in B$ and MU $t \in T$; and z_{jt} is a decision variable, which is 1 if MU t is admitted by BS j and 0 otherwise. G, κ, and ρ represent the processing gain, attenuation factor, and voice activity factor, respectively. The MUs served by a BS generate intra-cellular interference, while MUs served by neighboring BSs cause inter-cellular interference. In a CDMA environment, all users communicate at the same time and the same frequency; therefore, each user's transmission power is regarded as a part of other users' interference. The SIR of the BS affects the connection quality, as shown in (3), where the denominator is the total interference. In this situation, the interference experienced by the BS must be lower than a pre-defined maximum acceptable interference threshold $(E_b/N_{\text{total}})_{\text{req}}$ to ensure communication QoS, as shown in (4), where E_b and N_{total} denote the energy the BS received and the total noise respectively. We consider re-homing the EMUs and homing the NMUs jointly in such cases. For various reasons, EMUs may be either re-homed to an adjacent cell or forcibly terminated in order to grant access to more NMUs.

$$\frac{1}{G}\rho P\left(\sum_{t\in T} z_{jt} - 1\right) \tag{1}$$

$$\frac{1}{G}\rho P\sum_{\substack{j'\in B\\ j'\neq j}}\sum_{t\in T}\left(\frac{D_{jt}}{D_{j't}}\right)^{\kappa} z_{j't} \tag{2}$$

$$\frac{P}{N_0 + (\rho P/G)\left(\sum_{t\in T} z_{jt} - 1\right) + (\rho P/G)\sum_{\substack{j'\in B\\ j'\neq j}}\sum_{t\in T}\left(\frac{D_{jt}}{D_{j't}}\right)^{\kappa} z_{j't}} \tag{3}$$

$$\left(\frac{E_b}{N_{\text{total}}}\right)_{\text{req}} \leq \frac{(P/N_0)}{1 + (\rho/G)(P/N_0)\left(\sum_{t\in T} z_{jt} - 1\right) + (\rho/G)(P/N_0)\sum_{\substack{j'\in B\\ j'\neq j}}\sum_{t\in T}\left(\frac{D_{jt}}{D_{j't}}\right)^{\kappa} z_{j't}} \tag{4}$$

3 Admission Control-based Benefit Optimization Model

3.1 The Admission Control Mechanism

We use stochastic way to simulate the call number of arrival and departure for a serial of CAC decisions, and solve each CAC by deterministic-based Lagrangian relaxation to optimize the revenue in each CAC process. In the system, new call requests are Poisson distributed with mean rate λ, and the call holding time is assumed to be exponentially distributed with mean τ. In a specific time slot (budget η), time $\Gamma - 1$, and Γ are, respectively, the start and stop points of the time slot, as shown in Fig. 3. At time Γ, λ_Γ, α_Γ, γ_Γ, and ε_Γ are the number of arriving calls, the number of admitted calls, the number of remain/ongoing calls, and the total number of existing calls, respectively. Ergo, at time Γ, the CAC mechanism (5) can be defined as a function of $\lambda_{\Gamma-1}$ and $\varepsilon_{\Gamma-1}$, where $\lambda_{\Gamma-1}$ is the number of new calls arrived before time $\Gamma - 1$, and $\varepsilon_{\Gamma-1} = (\alpha_{\Gamma-1} + \gamma_{\Gamma-1})$ is the sum of admitted calls ($\alpha_{\Gamma-1}$) and ongoing calls ($\gamma_{\Gamma-1}$) after time $\Gamma - 1$. We implement the mechanism (5) by the proposed CAC-based benefit optimization model in Equation (IP) in Sect. 3.3, where T is the set of users in the system. The combination of both stochastic and deterministic ways is our novel approach, which is different from traditional stochastic one that confidence interval is provided in the same CAC scenario for

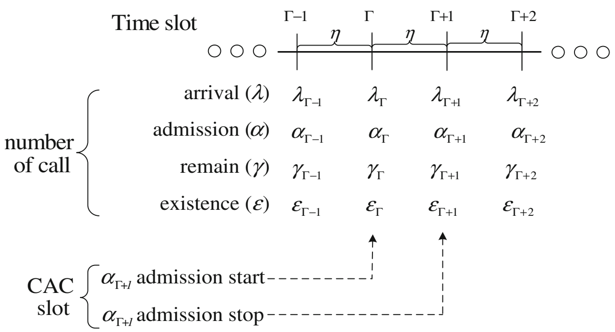


Fig. 3 The timing diagram of admission control

different arrivals (…, $\lambda_{\Gamma-1}$, λ_Γ, $\lambda_{\Gamma+1}$…). In this study, the generated arrivals are for a serial of CAC decisions, each of them has diverse scenario, such as user number in the system, strength of interferences, number of available channels.

$$\alpha_\Gamma = CAC(\lambda_{\Gamma-1}, \varepsilon_{\Gamma-1}) \tag{5}$$

In Fig. 4, λ_Γ denotes the number of call requests that arrived between time $\Gamma - 1$ and Γ, but they are queued until time Γ before being admitted. At time Γ, the requests are admitted by CAC $\alpha_\Gamma = CAC(\lambda_{\Gamma-1}, \varepsilon_{\Gamma-1})$ in (5). Denote $\varepsilon_{\Gamma-1}$ as the number of calls that are still ongoing after time $\Gamma - 1$. Some of them are expected to end in time τ (i.e. after time Γ), depending on exponential distribution. We denote the call holding time as X. Therefore, the probability that calls will be completed within η (the time budget allocated to implement CAC) is $p(X \le \eta) = 1 - e^{-\eta/\tau}$; and the probability that calls will still be ongoing after η is $1 - p(X > \eta) = e^{-\eta/\tau}$. Then, at time Γ, the number of calls still ongoing (remaining calls) is $\gamma_\Gamma = \lfloor \varepsilon_{\Gamma-1} \cdot e^{-\eta/\tau} \rfloor$, where $\lfloor\rfloor$ is a floor function. The call holding time, which is decided entirely by the users instead of by a pre-set timeout value, is distributed exponentially. However, in our simulation, we specify a decision time budget η, and use the equation $\gamma_\Gamma = \lfloor \varepsilon_{\Gamma-1} \cdot e^{-\eta/\tau} \rfloor$ to simulate how many calls will still be ongoing after the budget is exhausted. The initial values are $\alpha_0 = 0$, $\gamma_0 = 0$, $\varepsilon_0 = 0$. To clarify the CAC mechanism, we provide an example of calculating the number of calls with $\lambda = 30$, $\tau = 90$, and $\eta = 3$ in Table 1. At the end of time slot 3, for example, 39 ($\alpha_3 = 39$) of the 45 arriving calls ($\lambda_2 = 45$) at the end of time slot 2 are

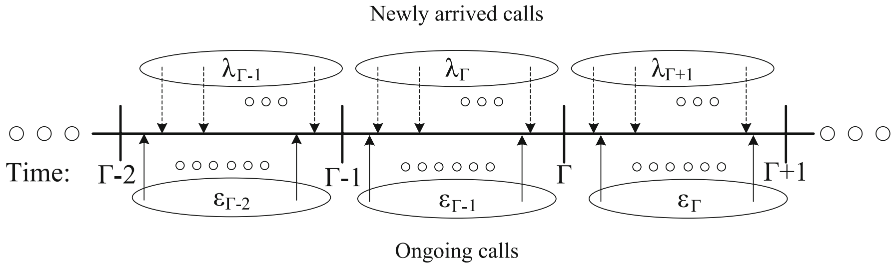


Fig. 4 The difference between newly arrived calls and ongoing calls

Table 1 Calculating the number of calls with $\lambda = 30$, $\tau = 90$, and $\eta = 3$

Time slot (t)	0	1	2	3	4	6	•	•
Arrival (λ_Γ)	26	34	45	28	22	31		
Admission (α_Γ)	0	25	30	39	24	19	•	•
Remain (γ_Γ)	0	0	24	52	88	108	•	•
Existing (ε_Γ)	0	25	54	91	112	127		

admitted. In addition, 52 ($\gamma_3 = 52$) of the 54 EMU calls ($\varepsilon_2 = 54$) at the end of time slot 2 are still ongoing after time budget η, where $52 = \lfloor 54e^{-3/90} \rfloor$. Thus, the total number of existing calls at end of time slot 3 is 91 (39 + 52).

3.2 Performance Measures

CAC is based on a series of events. All arriving calls are aggregated by the CAC mechanism, which considers both NMU calls and EMU calls. The total number of existing calls is the sum of admitted and remaining calls, where the number of remaining calls is calculated by the cumulative density function (cdf) of the exponential distribution. In other words, the number of existing calls depends on the call arrivals (λ_Γ), the mean of the call holding time (τ), and the time budget of CAC (η). We consider the following four performance measures.

1. Benefit: The primary goal of the CAC model is to maximize the system benefit in a near-realistic scenario. The more users admitted, the greater the benefit the system will accrue.
2. Blocking ratio (BR): At time Γ, the BR definition is simply expressed by $(\lambda_{\Gamma-1} - \alpha_\Gamma)/\lambda_{\Gamma-1}$, and the entire system BR is the average of a sequence of BRs. In other words, if we denote $\mathrm{BR}_\Gamma = (\lambda_{\Gamma-1} - \alpha_\Gamma)/\lambda_{\Gamma-1}$ at time Γ, the system $\mathrm{BR} = \sum_{i=1}^{\Lambda} \mathrm{BR}_i / |\Lambda|$, where Λ is the total number of time slots to conduct experiments. The BR is the most important measure used to evaluate the CAC mechanism. We examine the effect of time budget η on the blocking ratio and choose an appropriate value for future analysis.
3. System load (SL): The system load is defined as the total number of existing calls, i.e., the total number of EMUs ε_Γ at time Γ. As mentioned in the previous section, since ε_Γ in (5) is a parameter of the CAC mechanism, theoretically, the CAC performance is a decreasing function of SL.
4. Admit-to-existence ratio (AER): the number of calls admitted (α_Γ) is decided based on the SL and AER = $\alpha_\Gamma/\varepsilon_\Gamma$. The AER provides system state analysis, and indicates the stability of the proposed CAC mechanism. If the AER is not affected by λ, the quality of the proposed mechanism is assured.

3.3 The Benefit Optimization Model

To maximize the system benefit, the EMUs can be kept in the original home BS or re-homed to an adjacent BS, so that as many NMUs as possible can be admitted. However, a cost (f_t) is imposed to trade off the maximal capacity and the SHO overhead when the EMUs are re-homed recursively. The model's objective is to maximize the benefit, as defined in (IP). The definitions of the notations used in the model are shown in Table 3 in the Appendix. Since the maximum benefit is equivalent to the minimum benefit loss, the maximal benefit gain problem can be converted into a minimal benefit loss problem.

Objective function:

$$\begin{aligned} Z_{\mathrm{IP}} &= \max\left(\sum_{t\in T''} a_t \sum_{j\in B} z_{jt} - \sum_{t\in T'} f_t \sum_{j'\in B-\{b_t\}} z_{j't}\right) \\ &= \min\left(-\left(\sum_{t\in T''} a_t \sum_{j\in B} z_{jt} - \sum_{t\in T'} f_t \sum_{j'\in B-\{b_t\}} z_{j't}\right)\right) \end{aligned} \tag{IP}$$

The optimization model is subject to the following constraints:

QoS constraint: a QoS requirement is defined in (6), where the right-hand side is an SIR value for each connection between the MU and the BS. The value must be greater than a pre-defined QoS threshold $(E_b/N_{\mathrm{total}})_{\mathrm{req}}$.

$$\left(\frac{E_b}{N_{\mathrm{total}}}\right)_{\mathrm{req}} \le \frac{(P/N_0)}{1+(\rho/G)(P/N_0)\left(\sum_{t\in T} z_{jt}-1\right)+(\rho/G)(P/N_0)\sum_{\substack{j'\in B\\ j'\neq j}}\sum_{t\in T}\left(\frac{D_{j't}}{D_{jt}}\right)^{\kappa} z_{j't}} \quad \forall j\in B \tag{6}$$

Capacity constraint: for each BS, the total number of admitted NMUs is limited by the pre-defined threshold M_j.

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

Admission constraint: to be admitted by a BS, an NMU must be in the coverage of the BS's power transmission, where R_j is the power radius. Thus, if an NMU t is not located in the coverage region of BS j ($D_{jt} > R_j$), it cannot be admitted ($z_{jt} = 0$), as defined in (8).

$$D_{jt} z_{jt} \le R_j u_{jt} \quad \forall j \in B, t \in T \tag{8}$$

Coverage indicator: denote u_{jt} as an indicator, which is 1 if NMU t can be served by BS j and 0 otherwise. If $D_{jt} > R_j$, set $u_{jt} = 0$. With u_{jt}, the admission decision variable z_{jt} is constrained by (9).

$$z_{jt} \le u_{jt} \quad \forall j \in B, t \in T \tag{9}$$

Homing constraint: (10) guarantees that EMU $t \in T'$ can only be admitted to one BS or rejected.

$$\sum_{j\in B'} z_{jt} = 1 \quad \forall t \in T'' \tag{10}$$

Completed homing constraint: define B' as the set of $B \cup \{b'\}$, where b' is an artificial BS that carries a call rejected by admission control (CAC). Each EMU

($t \in T'$) is always admitted by constraint (11) because an uninterrupted connection is required.

$$\sum_{j \in B} z_{jt} = 1 \quad \forall t \in T' \tag{11}$$

Upper bound of the overhead to benefit ratio: in constraint (12), U is a predefined threshold of the ratio, where f_t is the handoff cost of MU t from the current controlling BS to an adjacent BS, and b_t is the BS that controls MU t. The denominator in (12) is the total benefit of the system, while the numerator expresses the total handoff cost. If the ratio is greater than U, the CAC mechanism stops all handoff processes.

$$\frac{\sum_{t \in T'} f_t \sum_{j' \in B - \{b_t\}} z_{j't}}{\sum_{t \in T''} a_t \sum_{j \in B} z_{jt}} \le U \quad \forall j \in B, t \in T \tag{12}$$

Integer property: this ensures that the decision variable z_{jt} is 0/1 in Constraint (13)

$$z_{jt} = 0 \text{ or } 1 \quad \forall j \in B, t \in T \tag{13}$$

4 Solution Approach

4.1 Lagrangian Relaxation

We use Lagrangian relaxation [20] to solve the problem (IP). Specifically, we transform the primal optimization problem (IP) into the following Lagrangian relaxation problem (LR) in which constraints (6), (7), (8), and (12) are relaxed.

$$\begin{aligned} Z_D\left(v_j^1, v_j^2, v_{jt}^3, v^4\right) = \min - &\left(\sum_{t \in T''} a_t \sum_{j \in B} z_{jt} - \sum_{t \in T'} f_t \sum_{j' \in B - \{b_t\}} z_{j't}\right) \\ &+ \sum_{j \in B} v_j^1 \left(\left(\frac{E_b}{N_{\text{total}}}\right)_{\text{req}} + \left(\frac{E_b}{N_{\text{total}}}\right)_{\text{req}} (\rho/G)(P/N_0) \left(\left(\sum_{t \in T} z_{jt} - 1 \right) \right.\right. \\ &\left.\left. + \sum_{\substack{j' \in B \\ j' \neq j}} \sum_{t \in T} \left(\frac{D_{j't}}{D_{jt}}\right)^{\kappa} z_{j't} \right) - (P/N_0) \right) + \sum_{j \in B} v_j^2 \left(\sum_{t \in T} z_{jt} - M_j \right) \\ &+ \sum_{t \in T} \sum_{j \in B} v_{jt}^3 \left(D_{jt} z_{jt} - R_j u_{jt} \right) + v^4 \left(\sum_{t \in T'} f_t \sum_{j' \in B - \{b_t\}} z_{j't} - U \sum_{t \in T''} a_t \sum_{j \in B} z_{jt} \right) \end{aligned} \tag{LR}$$

subject to (9), (10), (11), and (13).

Here, we only have to solve one subproblem (SUB) related to decision variable z_{jt}. (SUB) can be further decomposed into several independent subproblems. For any $v_j^1, v_j^2, v_{jt}^3, v^4 \ge 0$, $Z_D\left(v_j^1, v_j^2, v_{jt}^3, v^4\right)$ 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}:

$$Z_{\mathrm{SUB}} = \min \sum_{t \in T''} \left(\sum_{j \in B} \left(z_{jt} \left(-a_t + \left(\frac{E_b}{N_{\mathrm{total}}} \right)_{\mathrm{req}} (\rho/G)(P/N_0) \left(v_j^1 + \sum_{\substack{j' \in B \\ j' \neq j}} v_{j'}^1 \left(\frac{D_{jt}}{D_{j't}} \right)^{\kappa} \right) + v_j^2 + v_{jt}^3 D_{jt} - U v^4 a_t \right) - v_{jt}^3 R_j u_{jt} \right) \right) + \sum_{t \in T'} \left(\sum_{j \in B} \left(z_{jt} \left(f_t \left(1 + v^4 \right) + \left(\frac{E_b}{N_{\mathrm{total}}} \right)_{\mathrm{req}} (\rho/G)(P/N_0) \left(v_j^1 + \sum_{\substack{j' \in B \\ j' \neq j}} v_{j'}^1 \left(\frac{D_{jt}}{D_{j't}} \right)^{\kappa} \right) + v_j^2 + v_{jt}^3 D_{jt} \right) - v_{jt}^3 R_j u_{jt} \right) \right) + \sum_{j \in B} \left(v_j^1 \left(\left(\frac{E_b}{N_{\mathrm{total}}} \right)_{\mathrm{req}} - (P/N_0) - \left(\frac{E_b}{N_{\mathrm{total}}} \right)_{\mathrm{req}} (\rho/G)(P/N_0) \right) - v_j^2 M_j \right) \tag{SUB}$$

Recall that, in the proposed model, EMUs can be re-homed to another BS that can serve them. This allows more NMUs to be admitted to the system, even if the system blocked them initially. Therefore, we can decompose this sub-problem into $|T''|$ sub-problems for NMUs that request admission and $|T'|$ sub-problems for EMUs that need to be re-homed. Let

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

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

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

If k_{jt} is equal to or less than 0, we can re-home $z_{j't}$ to 1, where $j' \neq j$. However, we cannot block EMUs, so z_{jt} cannot be assigned to 0 if k_{jt} is greater than 0.

4.2 An Admission Control Algorithm

1 CAC rationale of LR: Based on the LR approach, a pre-defined time budget η, e.g., 3 s, is set to solve the Lagrangian dual problem and get primal feasible solutions iteratively. In other words, CAC must be completed within a specific time budget, the length of which determines the number of call requests admitted.

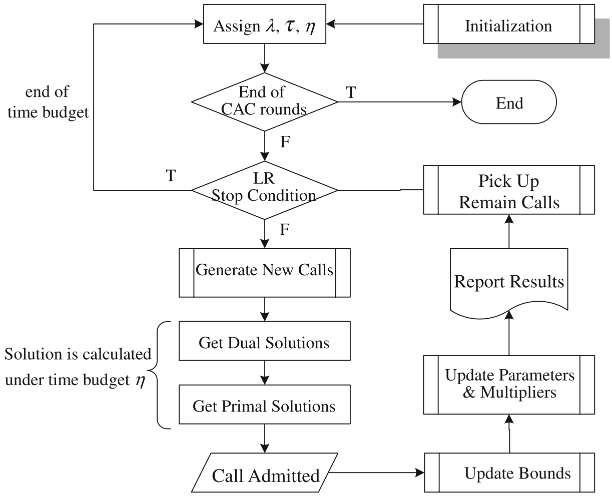


Fig. 5 The LR-based CAC procedure

2 Algorithm: The overall procedure of the LR-based CAC algorithm is shown in Fig. 5. The associated input parameters are λ (mean NMU arrival rate), τ (mean call holding time), and η (time budget for CAC). The output measures are Z_{IP} (benefit), the blocking ratio (BR), the system load (SL), and the admit-to-existence ratio (AER), which are described in Sect. 5.2. The detailed algorithms for each process in the procedure chart are given in the Appendix. The processes are initialization, generate new calls, get dual solutions, get primal feasible solutions, update bounds, pick up remaining calls, and update parameters and multipliers.

4.3 Getting Primal Feasible Solutions

According to the weak Lagrangian duality theorem, for any $v_j^1, v_j^2, v_{jt}^3, v^4 \geq 0$, the objective value of $Z_D\left(v_j^1, v_j^2, v_{jt}^3, v^4\right)$ is an LB on Z_{IP}. Based on the problem (LR), the dual problem $Z_D = \max Z_D\left(v_j^1, v_j^2, v_{jt}^3, v^4\right)$ is constructed to calculate the tightest LB subject to $v_j^1, v_j^2, v_{jt}^3, v^4 \geq 0$. The subgradient method [21] is used to solve the dual problem. Let the vector S be a subgradient of $Z_D\left(v_j^1, v_j^2, v_{jt}^3, v^4\right)$ at $\left(v_j^1, v_j^2, v_{jt}^3, v^4\right)$. In iteration k of the subgradient optimization procedure, the multiplier vector π is updated by $\pi^{k+1} = \pi^k + t^k S^k$, where t^k is the step size determined by $t^k = \delta\left(Z_{IP}^* - Z_D(\pi^k)\right) / \left\|S^k\right\|^2$. In the latter calculation, Z_{IP}^* is an upper bound (UB) on the primal objective function value after iteration k; and δ is a scalar value, where $0 \leq \delta \leq 2$.We apply the subgradient method to calculate tightest lower bound. The solutions calculated for dual problems need to be checked to ensure that all the constraints relaxed by (LR) are satisfied. Here, we propose an algorithm, A, for getting a primal feasible solution.

```
[Algorithm A]
  Step 1. Check capacity Constraint (7), for each BS. Drop an NMU,
          i.e., set z_jt =0 if it violates Constraint (7); otherwise,
          go to Step 2.
  Step 2. Ensure QoS Constraint (6) is satisfied for each BS. Drop
          the NMU, i.e., set z_jt =0 if it violates Constraint(6);
          otherwise, go to Step 3.
  Step 3. Try reinstating all new users dropped in Steps 1 & 2.
         3-1) Sequentially pick up each dropped new user.
         3-2) Home to another BS, i.e., set z_jt =1 again if this
              setting satisfies Constraint (6) and capacity
              constraint (7) 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 covered by more than one BS.
         4-2) Re-home the selected users to an adjacent BS if
              Constraints (6), (7), and (12) are all 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 this setting satisfies Constraints (6)
              and (7) for each BS; otherwise go to Step 5.
  Step 5. End algorithm A.
```

5 Computational Experiments

5.1 Environment and Parameters

The locations of all BSs, EMUs, and NMUs are generated in a uniform distribution. For statistical analysis purposes, there are 500 consecutive time slots in the experiment. The experimental parameters are $P/N_0 = 10$ db, $E_b/N_{\text{total}} = 1$ db, $M_j = 120$, $R_j = 4$ km, $G = 156.25$, $U = 0.5$, $a_t = 10$, $f_t = 2$, $\kappa = 4$, $\rho = 0.3$, [11, 19, 22]. Our objective is to determine the effect of the following three factors on the performance measures. 1) Whether CAC is fulfilled subject to the time budget η, where 3, 6, 9, and 12 s are selected. 2) Whether the mean call holding time is another key factor that directly affects the number of remaining calls; here we choose 60, 70, 80, and 90 s. 3) Whether the mean arrival rate (λ) has a major effect on the admission performance. To evaluate the overall system and determine how arrivals affect the admission performance, we examine three cases with $\lambda = 100, 150, 200$, respectively.

5.2 Performance Analysis

1. Expected benefit ($\mu_{Z_{IP}}$): The benefit is calculated by the problem (IP). The expected benefit for each mean arrival rate is shown in Fig. 6. For $\eta = 3$, $\mu_{Z_{IP}}$ varies from 965 to 1,005 for $\lambda = 100$, from 1,020 to 1,405 for $\lambda = 150$, and from 920 to 1,400 for $\lambda = 200$. By increasing η (6, 9, 12), $\mu_{Z_{IP}}$ varies within the

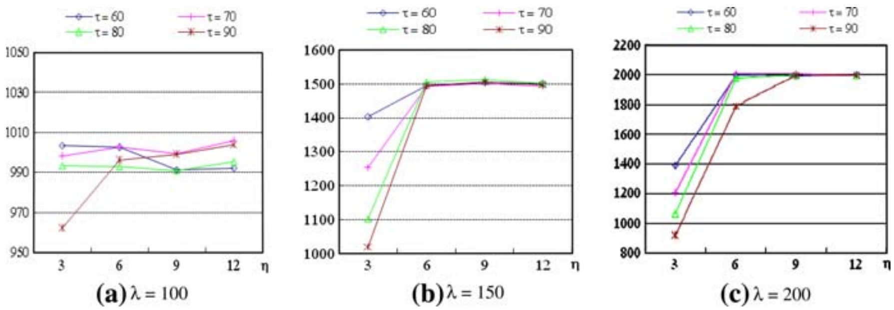


Fig. 6 The effect of the time budget on the mean benefit

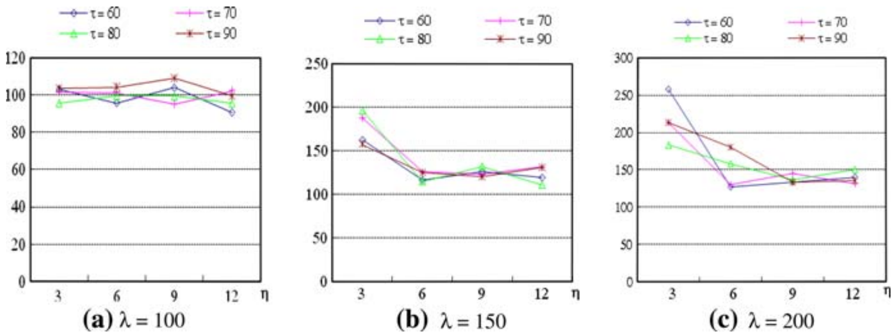


Fig. 7 The effect of the time budget on the standard deviation of the benefit

range 994 to 1,002 for $\lambda = 100$, as shown in Fig. 6b, and converges to 1,500 for $\lambda = 150$. For $\lambda = 200$, $\mu_{Z_{\mathrm{IP}}}$ varies from 1,800 to 2,000, and converges to 2,000 for both $\eta = 9$ and $\eta = 12$, as shown in Fig. 6c. In summary, $\mu_{Z_{\mathrm{IP}}}$ generally converges to an optimal value as η increases. To verify the optimality of the proposed CAC mechanism, we also analyze the standard deviation ($\sigma_{Z_{IP}}$) of $\mu_{Z_{\mathrm{IP}}}$. For $\lambda = 100$, $\sigma_{Z_{IP}}$ varies from 90 to 110 in Fig. 7a, and converges to a steady value near 125 when η is larger than or equal to 6 in Fig. 7b. In Fig. 7c, $\sigma_{Z_{IP}}$ converges to a smaller value between 140 and 260 as η increases. Although $\eta = 9$ and $\eta = 12$ are calculated with optimal revenue and have smaller standard deviations, to achieve the CAC goal, our analysis suggests using a smaller value of n. In this paper, we consider that $\eta = 6$ is the proper value in the proposed CAC.

2. Mean blocking ratio (μ_{BR}): Fig. 8 shows that μ_{BR} is a decreasing function of the time budget (η) in all cases. Unavoidably, the larger the given value of λ, the larger the μ_{BR} value calculated. By using the suggested value of $\eta = 6$, we observe that μ_{BR} is in the range 0.00 to 0.08 in Fig. 8a, in the range 0.00 to 0.10 in Fig. 8b, and in the range 0.05 to 0.28 in Fig. 8c. Figure 8 also shows the effect of the time budget on the standard deviation of the mean blocking ratio. The deviation approaches zero for both $\lambda = 100$ and $\lambda = 150$ when η is equal to or larger than 6, and decreases to less than 0.05 with $\eta = 6$ for $\lambda = 200$. The

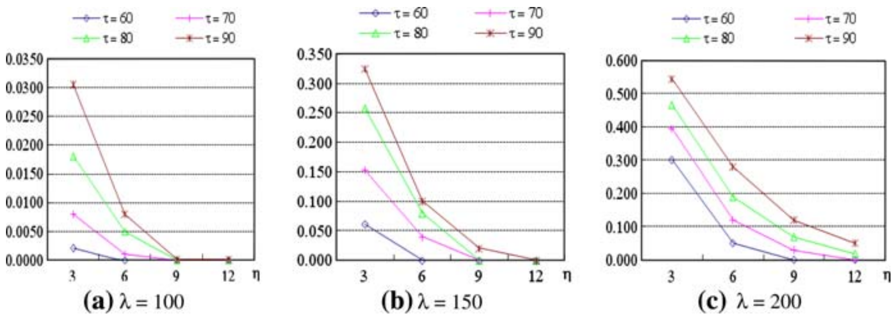


Fig. 8 The effect of the time budget on the mean blocking ratio

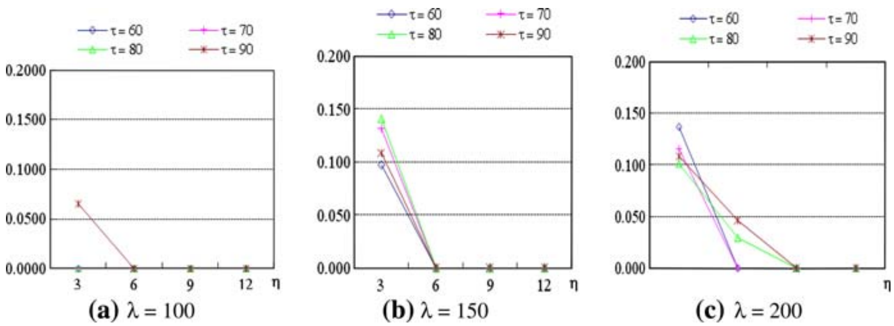


Fig. 9 The effect of the time budget on the standard deviation of the mean blocking ratio

analysis of the mean call blocking ratio conforms with the result of the mean benefit, i.e., it yields a better mean blocking ratio with $\eta = 6$.

3. Mean system load (μ_{SL}): Fig. 9 shows that the mean system load μ_{SL} is a decreasing function of the time budget (η), irrespective of the values of the mean call holding time (τ) and the mean arrival rate (λ). Since the call holding time is assumed to be exponentially distributed, the number of remaining calls (γ_Γ) decreases as the time budget increases, where γ_Γ affects the number of EMU calls (ε_Γ). In the case of $\lambda = 100$ in Fig. 10a, μ_{SL} is in range 2,000–2,800 for $\eta = 3$, while it is nearly 750 for $\eta = 12$. For $\lambda = 150$ in Fig. 10b, μ_{SL} is nearly 3,000 for $\eta = 3$ and nearly 1,000 for $\eta = 12$. In the case of $\lambda = 200$ in Fig. 10c, μ_{SL} decreases by 50% (from 2,800 to 1,400)

We also examine the effect of the time budget on the standard deviation of the mean blocking ratio. As shown in Fig. 11, the deviations vary for each value of λ. Generally speaking, the deviations become smaller as η increases. This implies that no matter which τ is selected, we can achieve a stable mean system load. The time budget is one of the key factors that affect the system's loading; and a small mean arrival rate ($\lambda = 100$) is more significant than a large mean arrival rate ($\lambda = 150$, 200).

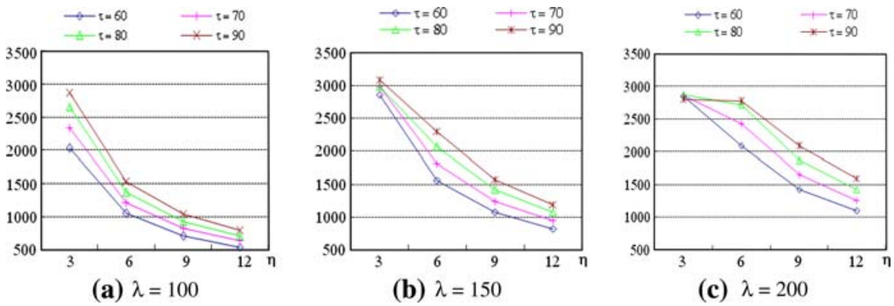


Fig. 10 The effect of the time budget on the mean system load

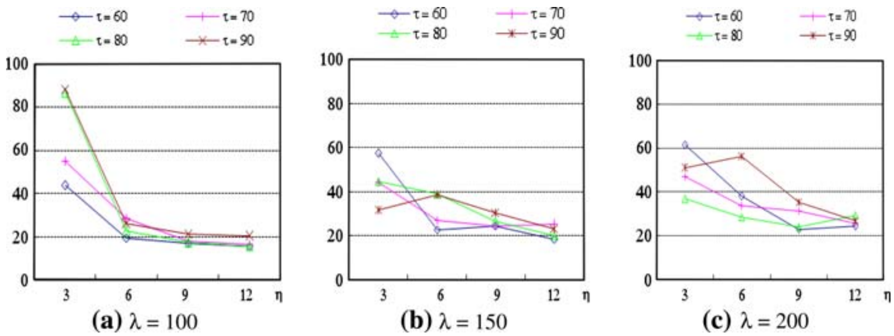


Fig. 11 The effect of the time budget on the standard deviation of the mean system load

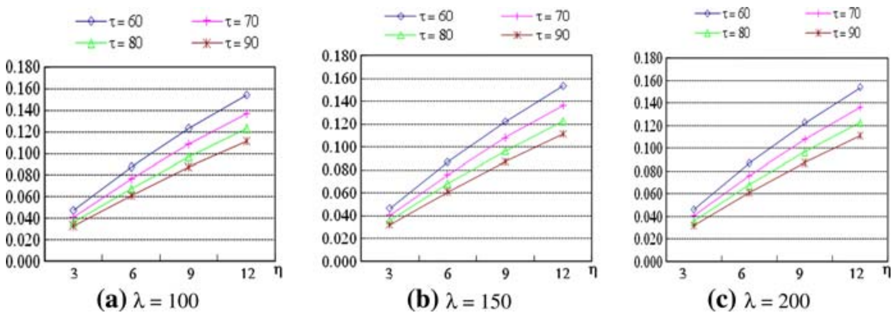


Fig. 12 The effect of the time budget on the mean AER

4. Mean of the admit-to-existence ratio (μ_{AER}):μ_{AER}, which is a stable measure of all the analyzed cases, is a monotonically increasing function of the time budget (η). We evaluated three cases of the mean arrival rate (λ) and found that the results were almost the same, as shown in Fig. 12a–c. Another interesting finding is that the difference in μ_{AER} for the four values of τ varies from $\eta = 3$ to $\eta = 12$. For $\eta = 3$, the difference in μ_{AER} is in the range 0.03–0.05, while it is in the range 0.11–0.15 in the case of $\eta = 12$. Although the time budget and the mean call holding time jointly affect the AER ratio, the former is more

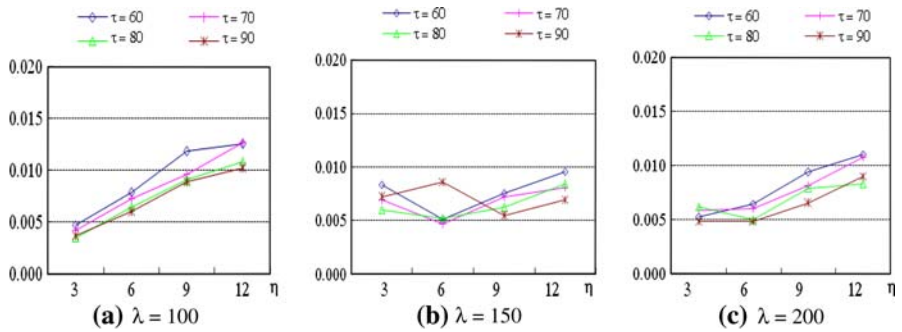


Fig. 13 The effect of the time budget on the standard deviation of the mean AER

significant because the difference is more discernible with a larger value of η. With regard to the effect of the time budget on the standard deviation of the mean AER, the larger the budget allocated, the greater will be the deviation, as shown in Fig. 13. The deviations are in the range 0.003–0.013 for $\lambda = 100$, 0.005–0.009 for $\lambda = 150$, and 0.005–0.011 for $\lambda = 200$. Selecting $\eta = 6$ achieves CAC, and the deviation of the mean AER is insignificant.

5. Solution quality: This quality is defined as a gap, i.e., 100%*(UB-LB)/LB. Table 2 summarizes the gaps for solving the benefit optimization problem. In Table 2 (a), all gaps are 0.00%, except for 3.04% on average for $\eta = 3$, $\tau = 90$. In Table 2 (b), all gaps are 0.00%, except for case $\eta = 3$, where the maximum gap is 32.42 in the average case and 2.21 in the best case. Unfortunately, as shown in Table 2 (c), these is a maximum gap of 54.37% on average for $\eta = 3$, $\tau = 90$. However, by choosing the suggested value $\eta = 6$, the maximum gap can be reduced to 10.89%. Thus, to a certain extent, the optimality of the proposed solution is confirmed. In summary, the values in Table 2 represent the

Table 2 Error gaps for solving the benefit optimization problem by CAC

%		(a) $\lambda = 100$				(b) $\lambda = 150$				(c) $\lambda = 200$			
		τ				τ				τ			
η		60	70	80	90	60	70	80	90	60	70	80	90
3	B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.21	0.00	0.00	0.00	18.03
	A	0.06	0.00	0.00	3.04	6.14	15.33	25.79	32.42	32.02	39.42	46.64	54.37
6	B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.35	10.89
9	B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

B, best case; A, average case

gaps between the proposed solution and the real-optimal solution. The value "0.00" verifies getting a real-optimal solution.

6 Concluding Remarks

6.1 Research Contribution

The research contribution of this paper is twofold: (1) the problem formulation, and (2) the performance analysis. The SHO is an essential and complicated process. It plays a key role in maximizing the system capacity because it enables the system to accommodate as many users as possible. Thus, admission control can be treated as a decision about homing new calls and re-homing existing calls; however, to maximize the overall system benefit, user demands (calls) around BSs must be managed effectively. In addition, SHO operations incur a substantial overhead because a large number of messages must be passed between the MUs and BSs. Hence, there must be a tradeoff between the system capacity and the handoff overhead. In this paper, we propose an admission control-based benefit optimization model that considers benefit management and SHO overhead jointly, subject to QoS requirements. To solve the optimization problem, we use an iteration-based Lagrangian relaxation approach; and to derive an optimal solution, the smallest possible error gap is calculated. Constructing respective interference models and choosing reasonable parameters to run the proposed model, our approach can be applied to other systems.

6.2 Implications

Our experiment results demonstrate that the time budget for admission decisions is a key factor that affects the system load. Moreover, a small mean arrival rate is more significant than a large mean arrival rate. The budget is a more significant factor than the mean call holding time, since the difference is more noticeable when a larger amount of time is allowed for admission decisions. CAC decisions are made in consecutive time slots so that an appropriate decision time budget can be derived and the system benefit can be optimized. The concept and solution approach of our proposed benefit management model have reference value for researchers who wish to investigate a variety of resource allocation problems.

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Appendix

See Table 3

Table 3 Definitions of notations

Symbol	Definition
T'	A set of EMUs
T''	A set of NMUs
T	$T = T' \cup T''$
B	A set of BSs
$(E_b/N_{\text{total}})_{\text{req}}$	The pre-defined threshold of the bit energy to noise ratio, which is a QoS value
P	The power received by a BS from an MU with perfect power control
N_0	Background noise
b'	An artificial BS used to carry a rejected call
B'	The set of $B \cup \{b'\}$
M_j	The pre-defined threshold for the total number of admitted NMUs
Rj	The power radius of a BS
u_{jt}	An indicator, which is 1 if MU t can be served by BS j, and 0 otherwise
D_{jt}	The distance between BS j and MU t
f_t	The handoff cost of MU t from the currently assigned BS to an adjacent BS
z_{jt}	The admission decision variable
κ	The attenuation factor
ρ	The voice activity factor
G	The processing gain
a_t	The benefit contributed by an MU t if it is admitted to the system
b_t	The controlling BS initially assigned to MU t

[Algorithm 1] (Initialization):

a) Given BS locations (set B);
b) Uniformly generate users (set T);
c) Calculate the distance D_{jt};
d) Set $UB^* = 0$, $LB^* = -\infty$;
e) Set initial Lagrangian Multipliers $\pi^0 = 0$, where π is a multiplier vector;
f) Set iteration counter $k=0$, improvement counter $m=0$, and scalar of step size $ss_0 = 2$;
g) Set the number of CAC rounds (T)

[Algorithm 2] (Generate New Calls):

a) Generate the number of new calls (λ_Γ);
b) Set NewCallCount=0;
c) Do {
   Randomly select a user;
   If (isNewCallFlag=0 && isRemainCallFlag=0)
      {Set isNewCallFlag=1;}
   NewCallCount= NewCallCount+1;
  }Until NewCallCount= λ_Γ;

```
[Algorithm 3] (Get Dual Solutions):
      a) k = k+1, m = m+1;
      b) Get dual decision variables to calculate LB^k on Z_IP

[Algorithm 4] (Get Primal Feasible Solutions):
      a) Get primal feasible solutions to calculate UB^k on Z_IP
         subject to constraints

[Algorithm 5] (Update Bounds):
     a) Check LB
             If LB^k > LB*, then LB* = LB^k;
     b) Check UB
             If UB^k < UB*, then UB* = UB^k;

[Algorithm 6] (Pick UP RemainCalls):
      a) Calculate the number of terminated calls (TerminatedCalls);
      b) Do {
        Randomly select a user;
        If (isRemainCallFlag=1) {Set isRemainCallFlag =0;}
        TerminatedCount= TerminatedCount +1;
       }Until TerminatedCount = TerminatedCalls;

[Algorithm 7] (Update Parameters & Multipliers):
      b) If (m = update_counter_limit) {ss_k = ss_k/2; m = 0;}
         π^{k+1} = max{0, π^k + t^k · S^k};
```

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