A Maximum-Throughput Call Admission Control Policy for CDMA Beamforming Systems

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***Abstract*— A throughput-maximization call admission control (CAC) policy is proposed for CDMA beamforming systems in which the QoS requirements in both physical and network layers can be guaranteed. While the existing cross-layer CAC policies rely on a separate reduced-outage-probability (ROP) algorithm to guarantee the physical layer QoS requirement, which adds to system complexity and reduces spectral efficiency, the proposed CAC policy can maintain arbitrary outage probability constraints as well as all the other QoS requirements without the aid of any ROP algorithm. The optimal CAC policy, obtained by formulating a constrained semi-Markov decision process (SMDP), is able to optimize the overall system throughput across different layers. Numerical examples demonstrate that the proposed policy is capable of achieving a significant performance gain, in terms of lowered blocking and outage probabilities as well as increased system throughput.**

I. Introduction

Recently, the problem of ensuring quality-of-service (QoS) requirements in both physical and network layers by designing a cross-layer CAC policy is receiving much attention. In [1]- [2], optimal semi-Markov decision process (SMDP)-based CAC polices are presented for the case of single-antenna systems, which lacks the tremendous benefits provided by multiple antennas. In this paper, we investigate the optimal CAC policy for a CDMA multiple-antenna system.

In multiple antenna systems, the spatial channel response, parameterized by the angle-of-arrival (AoA) information may be employed at the receiver to suppress interference. The resulting signal-to-interference ratio (SIR) is a random process determined by the realizations of AoAs. The large fluctuations in this spatially filtered SIR can lead to a significant outage probability in the physical layer, defined as the probability that the target SIR cannot be satisfied. Outage probability constraints are discussed in [2]. However, the CAC policy in [2] considers a single antenna system, which relies on a specific large system analysis. Furthermore, existing methods for cross-layer admission control in the current literature, e.g., [1] [2], treat the SIR as quasi-static and do not work well for multiple antenna systems. Therefore, designing an optimal CAC policy for multiple antenna systems can be a very challenging problem since the outage probability must be controlled jointly with the network layer operation.

In [3] [4], suboptimal CAC policies are derived for CDMA beamforming systems, in which a separate reduced-outage-probability (ROP) algorithm is required to mitigate the outage probability. Several efficient ROP algorithms are proposed in [3], which can reduce the outage probability to a tolerably small level. These ROP algorithms, however, either introduce cost in system resources, such as reduced spectral efficiency and increased computation complexity, or degrade the network layer performance [3]. Furthermore, in [1]- [4], only network layer optimization is considered, which is inferior to the CAC policy jointly optimized across physical and network layers. This motivates our research on a throughput-maximization CAC policy for multiple antenna systems without the aid of a ROP algorithm.

An exact outage probability is derived in the presence of both voice activity and multiple antennas. Based on this outage probability, the optimal CAC problem is obtained by formulating a constrained semi-Markov decision process, which can guarantee arbitrary outage probability constraints without the aid of a ROP algorithm. The proposed policy optimizes the overall system throughput across physical and network layers. To the best of our knowledge, the CAC design which maximizes the overall system throughput across different layers has not been addressed in the literature.

To highlight the maximum-throughput CAC design, error-control schemes such as automatic retransmission request (ARQ) are ignored in this paper. However, in our companion paper [5], an optimal admission control (AC) policy as well as a low-complexity suboptimal version are developed that incorporate a truncated ARQ scheme [5]. In summary, this paper differs from [5] in the following ways: a) In this paper we study a connection-oriented network in which voice activity factor is employed to increase the user capacity, while in [5], a connectionless communication is assumed in which no activity factor is considered; b) In this paper we focus on the optimal CAC design by incorporating the outage probability as well as all the other QoS constraints into the Markov decision process, while in [5] we mainly emphasize the formulation of the constrained admission control problem by considering the impact of ARQ.

The rest of this paper is organized as follows. The signal model and problem formulation are presented in Section II. Section III investigates the physical layer performance and provides an analytical expression for outage probability. Optimal CAC policies for multiple-class systems are proposed in Section IV. Numerical results are presented in Section V.

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II. Signal Model

A. Signal model in the physical layer

We consider an uplink CDMA beamforming system in which M antennas are employed at the BS and a single antenna is employed for each user. A single-cell, power-controlled synchronous CDMA system is assumed which supports J classes of users. Different classes of users are characterized by different QoS requirements.

Without loss of generality, class 1 is assumed to be voice traffic. We use α_i to represent the voice activity indicator for voice user i, $i = 1, .., n_s^1$, where α_i can be one or zero corresponding to an active or inactive status for user i, respectively. It is assumed that the voice activity indicators have independent and identical distributions with success rate p_v.

A system state, denoted by s, is defined as

$$s = [n_s^1, .., n_s^J]$$

where n_s^j is the number of accepted users for class j. The total number of accepted users in the system can be obtained by summing the users in all the classes, i.e., $K = \sum_{j=1}^{J} n_s^j$. In the following, we derive the SIR for a given system state s.

Let $\vec{a}_k$ denote the normalized array response vector for user k, where $k = 1, .., K$. The array response vector contains the relative phases of the received signals at each array element, which depend on the array geometry as well as the angle of arrival (AoA) for user k, denoted by θ_k.

To characterize the fraction of user i's signal passed by the beamforming weights, the beamforming pattern for a desired user k can be accomplished by

$$\phi_{ik}^2 = \left|\vec{\omega}_k^H \vec{a}_i\right|^2 \quad (1)$$

where $\vec{\omega}_k$ denotes the beamforming weight vector for a desired user k, and $(.)^H$ denotes conjugate transpose.

We assume the signature sequences of the interfering users appear as mutually uncorrelated noise. As shown in [6], the received signal-to-interference ratio (SIR) for a desired user k, where $k = 1, .., K$, can be written as

$$SIR_k = \frac{B}{R_k} \frac{p_k \phi_{kk}^2}{\sum_{i \neq k} p_i \phi_{ik}^2 + \eta_0 B} \quad (2)$$

where B and R_k denote the bandwidth and data rate for user k, respectively, and the ratio $\frac{B}{R_k}$ represents the processing gain; $p_k = P_k G_k^2$ denotes the received power for user k, in which P_k and G_k denote the transmitted power and link gain, respectively; the transmitted power for an inactive user is set to zero; η_0 denotes the one-sided power spectral density of background additive white Gaussian noise (AWGN). In the following, we consider a spatially matched filter receiver, i.e., $\mathbf{w}_k = \mathbf{a}_k$.

QoS requirements in the physical layer

In a wireless communication network, we must allow for outage, defined as the probability that a target SIR cannot be satisfied. The QoS requirement in the physical layer can be represented by target outage probabilities. In this paper, we consider two types of outage probability constraints: worst-state-outage-probability (WSOP) constraint, denoted by ρ_w, and average-outage-probability (AOP) constraint, denoted by ρ_{av}. The WSOP is defined as the maximum outage probability among all the feasible system states for a long term, while the AOP is defined as the long-run average outage probability.

B. Signal model in the network layer

The arrival process of the aggregate connections is modeled by a Poisson process with rate λ_j for each class j, where $j = 1, .., J$. We assume that the duration time of a connection follows an exponential distribution with mean duration $\frac{1}{\mu_j}$, and the angle-of-arrival (AoA) of mobile users follows a uniform distribution within the service area.

The QoS requirements in the network layer can be represented by the target blocking probability, denoted by Ψ_j for class j.

The connection delay constraints are neglected in this paper in order to highlight the optimal CAC policy which can guarantee an exact outage probability constraint. However, the CAC policy can be easily extended to include delay constraints.

C. Problem formulation

The overall system throughput, defined as the number of correctly received connections per second, can be evaluated by [7]

$$\text{Throughput} = \sum_j (1 - P_b^j)(1 - P_{out}^{av})\lambda_j \quad (3)$$

where P_b^j and P_{out}^{av} denote the blocking probability for class j and average-outage-probability, respectively.

In this paper, we aim to derive an optimal CAC policy R^*, which incorporates the benefits provided by multiple antennas and voice activity. The objective is to maximize the overall system throughput, while simultaneously guaranteeing QoS requirements in terms of target average-outage-probability, target worst-state-outage-probability and target blocking probability. If one of the above probability constraints is not required, simply set the constraint of that probability to one.

The above optimal CAC problem is a constrained optimization problem, which can be solved by formulating a semi-Markov decision process [9].

In the following, we first analyze the outage probability in the physical layer, which is then passed to the network layer to decide CAC. In the network layer, the optimal CAC problem can be formulated as a semi-Markov decision process (SMDP), and then solved by linear programming methodology.

III. Performance analysis in the physical layer: power solution and outage probability

In this section, we investigate the power solution and outage probability for a given system state s, where $s = [n_s^1, .., n_s^J]$.

A. Power solution

In the physical layer, we aim to derive a power solution which minimizes the total transmitted power while guaranteeing SIR requirements, i.e., $\min \sum_{k=1}^{K} P_k$ subject to $SIR_k \geq \gamma_k$, where $k = 1, .., K$, SIR_k is given in (2), and γ_k denotes the target SIR. For the above criterion, we also find the maximum number of users of each class that can be simultaneously supported while meeting their constraints [10].

As shown in [10], at the optimal power solution, all SIR constraints are met with equality,

$$\gamma_k = \frac{B}{R_k} \frac{p_k \phi_{kk}^2}{\sum_{i \neq k} p_i \phi_{ik}^2 + \eta_0 B}. \quad (4)$$

By grouping the above K equations, we have the following matrix form

$$[\mathbf{I}_K - \mathbf{Q}_s \mathbf{F}_s]\mathbf{p}_s = \mathbf{Q}_s \mathbf{u}_s \quad (5)$$

where subscript s refers to the given state $s = [n_s^1, .., n_s^J]$, $\mathbf{I}_K$ is a $K-$dimensional identity matrix, power vector $\mathbf{p}_s = [p_1, .., p_K]^t$, $\mathbf{u}_s = \eta_0 B[1, .., 1]^t$,

$$\mathbf{Q}_s = \text{diag}\left\{ \frac{\frac{\gamma_1 R_1}{B}}{1 + \frac{\gamma_1 R_1}{B}}, .., \frac{\frac{\gamma_K R_K}{B}}{1 + \frac{\gamma_K R_K}{B}} \right\} \quad (6)$$

and

$$\mathbf{F}_s = \begin{bmatrix} F_{1,1} & F_{1,2} & ... & F_{1,K} \\ F_{2,1} & F_{2,2} & ... & F_{2,K} \\ ... & ... & ... & ... \\ F_{K,1} & F_{K,2} & ... & F_{K,K} \end{bmatrix} \quad (7)$$

in which $F_{ij} = \frac{\phi_{ij}^2}{\phi_{ii}^2}$.

To ensure a positive solution for power vector $\mathbf{p}_s$, we require the following feasibility condition [8],

$$\upsilon(\mathbf{Q}_s \mathbf{F}_s) < 1 \quad (8)$$

where $\upsilon(.)$ denotes the maximum eigenvalue, which is real-valued since the matrices are symmetric.

Under the above condition, the power solution can be obtained as

$$\mathbf{p}_s = [\mathbf{I}_K - \mathbf{Q}_s \mathbf{F}_s]^{-1} \mathbf{Q}_s \mathbf{u}_s \quad (9)$$

where $(.)^{-1}$ denotes matrix inverse.

B. Outage probability

In the above power solution, (8) represents a sufficient and necessary condition which guarantees a positive power solution to meet the target SIRs. Due to randomly distributed AoAs and user mobility, $\upsilon(\mathbf{Q}_s \mathbf{F}_s)$ is a random process which depends on the realizations of AoAs. Therefore, for a given state s, the condition in (8) cannot be satisfied at all time instances, which introduces a non-zero outage probability.

The outage probability for state $s = [n_s^1, .., n_s^J]$ can be obtained by

$$P_{out}(s) = \text{Prob}\{\upsilon(\mathbf{Q}_s \mathbf{F}_s) \geq 1\} \quad (10)$$

where Prob$\{A\}$ denotes the probability of event A.

The above outage probability ignores the voice activity. With voice activity, the outage probability in (10) for state $s = [n_s^1, .., n_s^J]$ is modified to

$$P_{out}(s) = \sum_{m=0}^{n_s^1} p(m) \text{Prob}\{\upsilon(\mathbf{Q}_{s_m} \mathbf{F}_{s_m}) \geq 1\} \quad (11)$$

where $p(m)$ denotes the probability that m out of n_s^1 users are active at the current time instant, which is the probability-density-function of a Binomial distribution with parameter p_v. $\mathbf{Q}_{s_m}$ and $\mathbf{F}_{s_m}$ are the parameter matrices defined in (6) and (7) for a state $s_m = [m, n_s^2, .., n_s^J]$, where $m = 1, .., n_s^1$.

Equation (11) gives the outage probability for a system state s. This state outage probability is then employed to ensure QoS for an optimal CAC policy.

IV. Optimal call admission control policy

To derive an optimal CAC policy for multiple-class networks, we need to solve a constrained optimization problem as presented in Section II-C. This constrained optimization problem can be achieved by formulating the CAC problem as a semi-Markov-decision-process (SMDP) if the Markovian property holds, and then solved by linear programming (LP) [1].

In view of the assumptions that the amount of time the process stays in some state is exponentially distributed and that the next state visited is independent of the duration of that stay, the process has the Markovian property that the future behavior of the process depends only on the present state and is independent of the past history [9]. In this sense, the CAC problem can be formulated as a SMDP, which includes the following components: state space, decision epoch, action space, dynamic statistics, policy, performance criterion, expected cost function and constraints [2]. The detailed SMDP formulation can be found in [9]. By considering the signal model and optimization problem discussed in Section II-C, the components of our formulated SMDP is derived as follows.

A. State space

The state space comprises of any state vector s, whose state outage probability, given in (11), is less than the WSOP constraint, i.e.,

$$S = \left\{ s = [n_s^1, .., n_s^J], \text{ where } P_{out}(s) \leq \rho_w \right\}. \quad (12)$$

where ρ_w denotes the WSOP constraint. It is obvious that the state space formulated as the above ensures that the worst-state-outage-probability (WSOP) constraint can be satisfied for a long term.

For a system without WSOP constraint, i.e., $\rho_w = 1$, the above state space would have a size of infinity. To formulate a finite-size state space, as shown in [2], we can limit the number of users by a large number G,

$$S = \{s = [n_s^1, .., n_s^J], \sum_j n_s^j < G\}.$$

where G can be decided by the system.

Let $s(t)$ denote the system state at time t, where $s(t) \in S$. Since the arrivals and departures are random, $\{s(t)\}_{t \in IR_+}$ is a finite-size stochastic process [2].

B. Decision epoch and action space

Decision epochs are chosen to be the set of all arrival and departure instances.

At each decision epoch, t_k, $k = 1, 2, ..$, the network makes a decision for each possible user arrival or departure that may occur in the time interval $(t_k, t_{k+1}]$. An action a at decision epoch t is denoted by $a(t) = [a_1(t).., a_J(t)]$, where $a_j(t)$ can be 1 or 0, corresponding to decisions of acceptance or rejection, respectively.

For any $s \in S$, the admissible action space A_s is defined as

$$A_s = \{a \in A : a_j = 0, \text{ if } s + (0,..,\underbrace{1}, ..,) \notin S \text{ and } (a_1,..,a_J) \neq (0,..,0) \text{ if } s = (0,..,0)\} \quad (13)$$

which ensures that after taking this action, the next transition state is still in state space S. In addition, we impose the condition that $(a_1,..,a_J) \neq (0,..,0)$ if the system is in state $s = (0,..,0)$.

C. Dynamic statistics

Dynamic statistics can be characterized by expected holding time and transition probability. The expected holding time $\tau_s(a)$ is the expected time until the next decision epoch after action a is chosen in the present state s,

$$\tau_s(a) = \left(\sum_{j=1}^{J} \lambda_j a_j + \sum_{j=1}^{J} \mu_j n_s^j \right)^{-1}.$$

Transition probability, denoted by $p_{sy}(a)$, is the probability that the state at the next decision epoch is y if action a is selected at the current state s, which can be represented by

$$p_{sy}(a) = \begin{cases} \lambda_j a_j \tau_s(a) & \text{if } y = s + e_j^s \\ \mu_j n_s^j \tau_s(a) & \text{if } y = s - e_j^s \end{cases}$$

in which e_j^s represents vector with a dimension of J, which contains only zeros except for position j which contains a 1.

D. Policy, performance criterion and expected cost function

For each given state $s \in S$, an action $a \in A_s$ is chosen according to a policy $R_s \in \mathbf{R}$, where $\mathbf{R}$ is the set of all admissible policies. A policy defines a mapping rule from the state space to the action space [2], i.e.,

$$\mathbf{R} = \{R : S \rightarrow A | R_s \in A_s, \forall s \in S\}.$$

In this paper, we take the average cost as the performance criterion. For any policy R with an initial system state s_0, where $s_0 \in S$, the average cost can be expressed as

$$J_R(s_0) = \lim_{t\rightarrow\infty} \frac{1}{T} E\left\{ \int_0^T c(s(t), a(t))dt \right\} \quad (14)$$

where $E[.]$ denotes expectation, and $c(s(t), a(t))$ is the expected cost function which represents the expected cost until the next decision epoch when $a(t)$ is chosen at the current system state $s(t)$.

If the average cost in (14) represents blocking probability, the expected cost function, denoted by $c_b^j(s, a)$, can be written as [1]

$$c_b^j(s, a) = (1 - a_j) \quad (15)$$

where a_j denotes the action for class j traffic.

If the average cost in (14) represents average-outage-probability, expected cost function, denoted by $c_{out}(s, a)$, can be expressed as

$$c_{out}(s, a) = P_{out}(s) \quad (16)$$

which is given in (11).

If the average cost in (14) represents throughput, according to the definition of throughput in (3), the expected cost function, denoted by $c_{thr}(s, a)$, can be expressed as

$$\begin{aligned} c_{thr}(s, a) &= \sum_{j=1}^{J} \lambda_j (1 - c_b^j(s, a))(1 - c_{out}(s, a)) \\ &= \sum_{j=1}^{J} \lambda_j a_j (1 - P_{out}(s)) \end{aligned} \quad (17)$$

where the last equation is obtained by using Equations (15) and (16).

The optimal policy can be chosen according to a certain performance criterion, such as minimizing-blocking-probability or maximizing-throughput. In this paper, we aim to find an optimal policy R^* which maximizes the throughput for any initial system state, i.e.,

$$R^* = \arg\max_{R\in\mathbf{R}} \lim_{t\rightarrow\infty} \frac{1}{T} E\left\{ \int_0^T \sum_{j=1}^{J} \lambda_j a_j (1 - P_{out}(s))dt \right\}.$$

Under the assumption that the embedded chain is a unichain [9], which is a common assumption in the CAC problem, an optimal CAC policy exists and can be obtained by solving the SMDP [2].

E. Constraints

In the optimal CAC problem, we have blocking probability, average outage probability and worst-state outage probability constraints.

The worst-state outage probability constraint can be satisfied by restricting the state space in (12), so only the blocking probability constraint and average-outage-probability constraint need to be considered.

From (14) and (15), the achieved long-run blocking probability can be expressed as

$$\begin{aligned} P_b^j &= \lim_{T\rightarrow\infty} \frac{1}{T} E\left\{ \int_0^T c_b^j(s(t), a(t)) \right\} dt \\ &= \lim_{T\rightarrow\infty} \frac{1}{T} E\left\{ \int_0^T (1 - a_j)dt \right\} \\ &\leq \Psi_j, \ j = 1,.., J \end{aligned} \quad (18)$$

where Ψ_j denotes the blocking probability constraint for class j.

From (14) and (16), the achieved long-run average-outage-probability (AOP) can be represented by

$$\begin{aligned} P_{out}^{av} &= \lim_{T\rightarrow\infty} \frac{1}{T} E\left\{ \int_0^T P_{out}(s(t), a(t))dt \right\} \\ &\leq \rho_{av} \end{aligned} \quad (19)$$

where ρ_{av} denotes the AOP constraint.

F. Deriving an optimal policy by solving the SMDP

As formulating the admission problem as a SMDP, an optimal CAC policy can be obtained by using the decision variables $z_{sa}, s \in S, a \in A_s$, in solving the following linear programming (LP) problem:

$$\max_{z_{sa} \geq 0, s, a} \sum_{s \in S} \sum_{a \in A_s} \sum_{j=1}^{J} \lambda_j a_j (1 - P_{out}(s)) \tau_s(a) z_{sa} \quad (20)$$

subject to the set of constraints

$$\begin{aligned} \sum_{a \in A_m} z_{ma} - \sum_{s \in S} \sum_{a \in A_s} p_{sm}(a) z_{sa} &= 0, m \in S \\ \sum_{s \in S} \sum_{a \in A_s} \tau_s(a) z_{sa} &= 1 \\ \sum_{s \in S} \sum_{a \in A_s} (1 - a_j) \tau_s(a) z_{sa} &\leq \Psi_j, \ j = 1, .., J \\ \sum_{s \in S} \sum_{a \in A_s} P_{out}(s) \tau_s(a) z_{sa} &\leq \rho_{av} \end{aligned}$$

In the above LP formulation, $\tau_s(a) z_{sa}$ represents the steady-state probability that the system is at state s and an action a is chosen. The first constraint is the balance equation, and the second constraint ensures the sum of all the steady-state probabilities to be one. The latter two constraints represent the QoS requirements in terms of blocking probability and average-outage-probability, respectively. The worst-state-outage-probability constraint, if any, is already included in the state space S as discussed in (12).

Since the sample path constraints are included in the above linear programming approach, the optimal policy resulting from the SMDP is a randomized policy [2]: the optimal action $a^* \in A_s$ for state s, where A_s is the admissible action space, is chosen probabilistically according to the probabilities $z_{sa} / \sum_{a \in A_s} z_{sa}$.

We remark that the above randomized CAC policy allows for resources to be more flexibly reserved for potential arriving traffic, and as a result can optimize the long-run performance.

V. Numerical examples

In the following examples, a circular antenna array with a uniformly distributed AoA is employed at the BS. The total bandwidth is $B = 3.84MHz$. A two-class system is considered in which the SIR requirements are given by $\gamma_1 = 10$ and $\gamma_2 = 5$, and the rate for each class is set to $R_1 = 48$ kbps and $R_2 = 144$ kbps, respectively. The arrival and departure rates for class 1 and class 2 are denoted by $\lambda_1 = 1$, $\lambda_2 = 0.5$, $\mu_1 = 0.25$, and $\mu_2 = 0.1375$, respectively.

As shown in [4], compared with beamforming systems, single antenna systems encounter an infeasibility problem more easily, i.e., the QoS requirements may not be satisfied by any CAC policy. Since we aim to compare the performance between single and multiple antenna systems in a quantitative way, this infeasibility situation should be avoided. Therefore, in this paper, we employ a relatively relaxed blocking probability constraints, which are set to 0.25 and 0.45 for classes 1 and 2, respectively. However, the conclusions derived in this paper can be generalized to any QoS constraints.

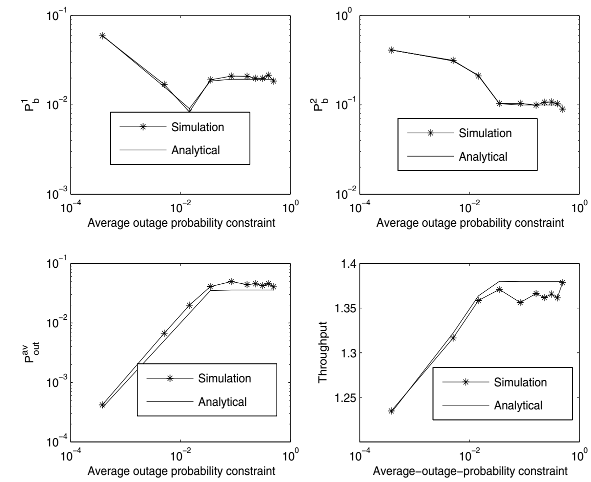

Fig. 1. Performance comparison between simulation and analytical results with $p_v = 1$.

We now investigate the long-run average performance in terms of blocking probability, average outage probability and overall system throughput.

Consider a system with a small average-outage-probability constraint and a relatively relaxed worst-state-outage-probability constraint. We investigate a system with WSOP constraint of 0.5, and AOP constraint varies over $[10^{-4}, 10^{-2}]$. Figure 1 shows the analytical and simulated performance in terms of blocking probability, outage probability and throughput for a two-antenna system, in which P_b^j and P_{out}^{av} denote the achieved blocking probability and average-outage-probability, respectively. The analytical results are derived from linear programming, while the simulation results are obtained by Monte-Carlo simulation. It is observed that the simulation results are very close to the analytical results, which justifies the accuracy of our derived optimal CAC policy.

From Figure 1, we observe that the blocking probability for class 1 is not monotonically reduced with ρ_{av}. At a point of $\rho_{av} = 5 \times 10^{-2}$, the blocking probability is increased compared with $\rho_{av} = 10^{-2}$. This is because under this certain ρ_{av}, to achieve a maximum throughput, more space should be reserved for class 2 users by blocking class 1 connections. Although the blocking probability for a certain class may not be monotonically reduced, the overall blocking probability as well as the throughput do follow a monotonous rule with ρ_{av}.

Figure 2 compares the analytical performance for single antenna and two-antenna systems, obtained through linear programming (LP) approach, in which P_b is obtained by $(P_b^1 + P_b^2)/2$.

As mentioned before, allowing for outage probability in the physical layer can reduce the overall blocking probability and improve the throughput. For single antenna systems, the outage is introduced by employing voice activity, while for beamforming systems, outage is introduced by both voice activity and randomly distributed AoAs. Therefore, allowing outage for multiple antenna systems provides a more flexible way to handle QoS requirements. For example, when average-outage-probability (AOP) constraint is relaxed from 10^{-4}

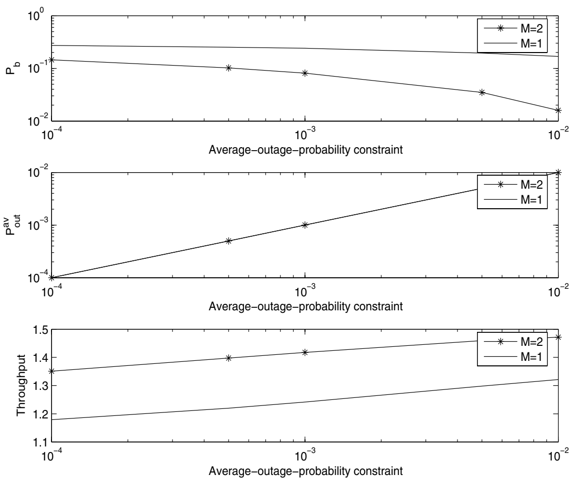

Fig. 2. Performance comparison between single antenna and two-antenna systems with $p_v = 3/8$.

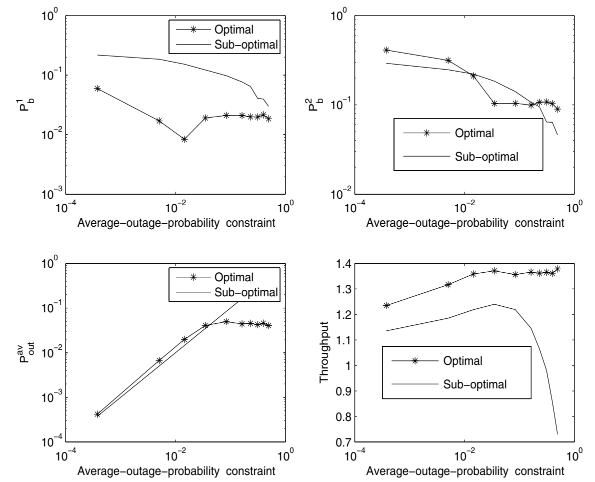

Fig. 3. Comparison between the optimal and sub-optimal CAC policies with $p_v = 1$.

to 10^{-2}, the overall blocking probability for single antenna system can be reduced from 0.27 to 0.17, i.e., reduced by 37%, while for a two-antenna sysstem, the blocking probability can be reduced from 0.14 to 0.016, i.e., reduced by 88%.

Next, we compare our proposed optimal CAC policy with the sub-optimal CAC policy derived in [4]. For the sub-optimal CAC policy, a ROP algorithm is required to mitigate the outage probability. In the following example, a ROP algorithm, proposed in [3], is employed, in which the CAC policy is derived with an increased virtual target SIR. By using this suboptimal CAC policy, the average-outage-probability can be reduced to an arbitrarily small level by adjusting the ROP parameter.

Figure 3 compares the blocking probability, average-outage-probability and system throughput for sub-optimal and optimal CAC policies for a two-antenna system. It is observed that for a given average-outage-probability constraint, the proposed optimal CAC policy can achieve a dramatic performance gain in terms of lower blocking probability and improved system throughput. For example, with an AOP constraint of 0.035, compared with the suboptimal CAC policy, the proposed optimal CAC policy can reduce the blocking probability from 0.15 to 0.06, i.e., reduced by 60%, and increase the throughput from 1.24 to 1.37 connections/second, i.e., increased by 10%. With an increased AOP constraint, this performance gain becomes even larger. The optimal CAC policy is performed without the aid of any ROP algorithm, and as a result, saves substantial system complexity.

VI. Conclusions

An optimal CAC policy is proposed for CDMA beamforming systems, which can maximize the overall system throughput while simultaneously guaranteeing all the QoS requirements. Compared with the existing policies, the proposed optimal CAC policy is capable of achieving a significant performance gain in terms of blocking probability, outage probability and system throughput. The multiple QoS requirements can be flexibly handled by employing the tradeoff between network and physical layer performance. Unlike the existing suboptimal CAC policies, in which a separate ROP algorithm must be employed to control the outage, our proposed CAC policy can guarantee an arbitrary outage probability constraint without the aid of any ROP algorithm, which saves a lot of system resources.

Acknowledgment

This research has been partially supported by Natural Sciences and Engineering Research Council Discovery Grant 41731.

References

[1] C. Comaniciu and H. V. Poor, "Jointly optimal power and admission control for delay sensitive traffic in CDMA networks with LMMSE receivers", *IEEE Trans. Signal Processing*, vol. 51, no. 8, pp. 2031-2042, August 2003.

[2] F. Yu, V. Krishnamurthy, and V. C. M Leung, "Cross-layer optimal connection admission control for variable bit rate multimedia trafiic in packet wireless CDMA networks", *IEEE Trans. Signal Processing*, vol. 54, no. 2, pp. 542-555, Feburary 2006.

[3] W. Sheng and S. D. Blostein, "Reduced-Outage-Probability Algorithms for Cross-Layer Call Admission Control in CDMA Beamforming Systems", *Proc. IEEE Globecom 2006*, December 2006.

[4] W. Sheng and S. D. Blostein, "Cross-layer call admission control for a CDMA uplink employing a base-station antenna array", *To appear in Proc. IEEE Globecom 2007*, November 2007.

[5] W. Sheng and S. D. Blostein, "An Optimal Admission Control Policy for CDMA Multiple Antenna Systems with QoS Constraints", *To Appear in Proc. IEEE WCNC 2008*, March 2008.

[6] F. R. Farrokhi, L. Tassiulas and K. J. R. Liu, "Joint optimal power control and beamforming in wireless networks using antenna arrays", *IEEE Trans. Communications*, vol. 46, no. 10, pp. 1313-1324, October 1998.

[7] Q. Liu, S. Zhou, and G. B. Giannakis, "Cross-layer combining of adaptive modulation and coding with truncated ARQ over wireless links", *IEEE Trans. Wireless Commun.*, vol. 3, no. 5, pp. 1746-1755, Sep. 2004.

[8] G. Song and K. Gong, "Performance comparison of optimal beamforming and spatial matched filter in power-controlled CDMA Systems", *Proc. ICC 2002*, vol. 1, pp. 455-459, 2002.

[9] H. C. Tijms, Stochastic modelling and analysis: a computational approach, U.K.: Wiley, 1986.

[10] A. Sampath, P. S. Kumar and J. M. Holtzman, "Power control and resource management for a multimedia CDMA wireless system", *Proc. PIMRC'95*, vol. 1, pp. 21-25, 1995.