Cross-Layer QoS Provisioning in Packet Wireless CDMA Networks

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Abstract—In this paper, quality of service (QoS) guarantees for multimedia traffic are provided by means of cross-layer optimization in code division multiple access (CDMA) networks. We develop optimal connection admission control (CAC) schemes with both physical layer signal-to-interference ratio (SIR) and network layer blocking probability QoS constraints. Packet traffic is modeled as Markov modulated Poisson process (MMPP). We show that the cross-layer CAC problem in packet CDMA networks has the nearly complete decomposability structure, based on which we propose two CAC algorithms that require much less computation than some existing schemes and can have good approximation to the optimal solutions. The effectiveness of the proposed schemes is demonstrated by numerical examples.

I. INTRODUCTION

With the growing demand for bandwidth-intensive multimedia application (e.g., video) in code division multiple access (CDMA) networks, quality of service (QoS) provisioning is becoming increasingly important. There are different QoS metrics at different layers of wireless CDMA networks. At the network layer, QoS metrics are blocking probabilities of connections. At the physical layer, the QoS requirements are usually characterized by signal-to-interference ratio (SIR).

Two recent papers study the admission control problem by considering physical layer QoS and network QoS jointly [1], [2]. Optimal admission policies are designed to maximize the network utilization (minimize blocking probabilities) with constraints on SIR and blocking probabilities. Although [1], [2] guarantee both physical layer QoS and network QoS by means of cross-layer optimization, only constant bit rate traffic is considered. However, in order to provide integrated services, next generation wireless mobile networks are required to support packet traffic [3], where a connection may change the radio resource consumption and the QoS requirements during its lifetime. Therefore, the schemes in [1], [2] may result in low network utilization with variable bit rate packet traffic. To tackle the low utilization problem, authors in [4] introduce a small SIR outage probability for packet traffic in the cross-layer CAC design. It is shown that the network utilization can be increased significantly in [4] by exploiting the Markov modulated Poisson process (MMPP) packet traffic models. The difficulty of the schemes in [4], however, lies in their computational complexity, which makes them unfeasible for large-scale realistic networks.

In this paper, we show that the cross-layer CAC problem in packet CDMA networks has the nearly complete decomposability (NCD) structure, based on which we propose two CAC algorithms that require much less computation than the schemes in [4] and can have good approximation to the optimal solutions.

1) In the first proposed scheme, a conservative approach to the constraint of SIR outage probability, $P_{\text{out}}$, is used, where the SIR outage probability can be guaranteed at all time instants.

2) The second proposed scheme considers an aggressive approach to the constraint of $P_{\text{out}}$ to increase the network utilization. In this scheme, the SIR outage probability constraint may be violated at some time instants, but the long term SIR outage probability can be guaranteed.

We show the effectiveness of the proposed schemes by numerical examples using voice and Star Wars video traffic. By exploiting the NCD structure of the cross-layer CAC problem, the proposed schemes can dramatically reduce the computational complexity and have good approximation to the optimal solutions.

The rest of this paper is organized as follows. Section II describes the physical layer and traffic models. The admission control scheme with SIR outage is presented in Section III. Section IV illustrates the nearly complete decomposability of the admission control problem. The admission control schemes with reduced complexity are presented in Section V. Section VI illustrates the performance of the proposed schemes by numerical examples. Finally, we conclude this study in Section VII.

II. CDMA PHYSICAL LAYER MODEL AND TRAFFIC MODEL

A. Fading Channel and Linear Multiuser Detector Physical Layer Model

Consider a synchronous CDMA system with spreading gain $N$ and $K$ users. Each user generates MMPP traffic in the system. An important physical layer performance measure of class $j$ users is the signal-to-interference, $\text{SIR}_j$, which should be kept above the target value $\omega_j$. The signature sequences of all users are independent and randomly chosen. A class $j$ connection in state $m_j$ is assigned $R_{jm}(t)$ signature sequences
and transmits at $R_{jm}(t)$ times the basic rate (obtained using the lowest spreading gain $N$). Due to multi-path fading, each user appears as $L$ resolvable paths or components at the receiver. The path $l$ of user $k$ is characterized by its estimated average channel gain $h_{kl}$ and its estimation error variance $\xi_{kl}^2$. Linear minimum mean square error (LMMSE) detectors are used at the receiver to recover the transmitted information.

In a large system (both $N$ and $K$ are large) with background noise $\sigma^2$, the SIR for the LMMSE receiver of a user (say, the first one) can be expressed approximately as [5] $\text{SIR}_1 = (P_1 \sum_{i=1}^{L} |h_{1i}|^2 \eta)\left(1 + P_1 \xi_1^2 \eta\right)$, where $P_1$ is the attenuated transmitted power from user 1, $\eta$ is the unique fixed point in $(0, \infty)$ that satisfies $\eta = \left[\sigma^2 + (1/N) \sum_{k=2}^{K} (L-1) I(\xi_k^2, \eta) + I(\sum_{i=1}^{L} |h_{ki}|^2 + \xi_k^2, \eta)\right]^{-1}$ and $I(\nu, \eta) = \nu/(1 + \nu \eta)$. Assume that all users in the same class have the same average channel gain $|\bar{h}_j|^2 = \sum_{i=1}^{L} |h_{ji}|^2$, $j = 1, 2, \ldots, J$. Authors in [2] show that a minimum received power solution exists such that all users in the system meet their target SIRs if and only if

$$\omega_j < \frac{|\bar{h}_j|^2}{\xi_j^2} \quad \text{and} \quad \frac{1}{N} \sum_{j=1}^{J} \sum_{m=1}^{M_j} n_{jm} R_{jm} \eta_j < 1, \quad (1)$$

where $n_{jm}$ is the number of class $j$ users in state $m_j$ and $\eta_j = (L - 1) \omega_j \xi_j^2 / (|\bar{h}_j|^2) + (\omega_j + 1) \xi_j^2 / ((|\bar{h}_j|^2)/(1 + \omega_j))$.

### B. MMPP Traffic Models for Multimedia Traffic

Assume that there are $j, i = 1, 2, \ldots, J$, classes of statistically independent traffic in the network. Class $j$ traffic has $M_j$ states with the process, while in any state $m_j$, $1 \leq m_j \leq M_j$, behaving as a Poisson process with a state-dependent rate parameter $R_{jm}$. Transitions between states are governed by an underlying continuous-time Markov chain (or more generally a Markov renewal process). Let $\theta_{im}^j$ be the rate of transition between state $i$ and $m$.

### III. Constrained Semi-Markov Decision Process Formulation of CAC in Packet CDMA Networks

In this section, the admission control problem in packet CDMA networks is formulated as an average cost semi-Markov decision process (SMDP) [4].

### A. State Space, Decision Epochs and Actions

Define row vector $k(t) = [k_1(t), k_2(t), \ldots, k_J(t)] \in \mathbb{Z}_+^J$, where $k_j(t)$ denotes the number of class $j$ connections in the system. Define row vector $n(t) = [n_{12}(t), n_{13}(t), \ldots, n_{1M_j}(t), n_{22}(t), n_{23}(t), \ldots, n_{2M_j}(t), \ldots, n_{J2}(t), n_{J3}(t), \ldots, n_{JM_j}(t)] \in \mathbb{Z}_+^{JM}$, where $n_{jm}(t)$ denotes the number of class $j$ connections in state $m_j$ and $M = \sum_{j=1}^{J} (M_j - 1)$. The state vector of the system at decision epoch $t$ is given by $x(t) = [k(t), n(t)]$. The state space $X$ can be defined as

$$X = \{x = [k, n] \in \mathbb{Z}_+^{J+M} : \sum_{j=1}^{J} k_j \leq G, n_{jm} \leq k_j, \quad m = 2, 3, \ldots, M_j, j = 1, 2, \ldots, J\}, \quad (2)$$

where $G$ is a fixed large positive integer used to restrict the state space to be finite.

We choose the decision epochs to be the set of all connection arrival and departure instances, as well as the instances when an MMPP traffic changes states during the connection lifetime. Action $a$ at decision epoch $t$ is defined as $a(t) = [a_1(t), a_2(t), \ldots, a_J(t)]$, where $a_j(t)$ denotes the action for class $j$ connections. The action space is a set of all possible actions, which can be defined as $A = \{a : a \in \{0, 1\}^J, j = 1, 2, \ldots, J\}$.

### B. State Dynamics

The cumulative event rate is the sum of the rates of all constituent processes and the expected sojourn time is the inverse of the event rate $\tau_x(a) = [\sum_{j=1}^{J} \lambda_j a_j + \sum_{j=1}^{J} \mu_j k_j + \sum_{j=1}^{J} \sum_{m=1}^{M_j} \alpha_{jm}(k_j - n_{jm}) + \sum_{j=1}^{J} \sum_{m=1}^{M_j} \beta_{jm} n_{jm}]^{-1}$. The state transition probabilities of the embedded chain is

$$p_{xy}(a) =$$

\[
\begin{align*}
\lambda_j a_j r_{jm} \tau_x(a), & \quad \text{if } y = x + e_j^r + e_{jm}^r, \\
\lambda_j a_j r_{jm} \tau_x(a), & \quad \text{if } y = x + e_j^r, \\
\mu_j n_{jm} \tau_x(a), & \quad \text{if } y = x - e_j^r - e_{jm}^s, \\
\mu_j n_{jm} \tau_x(a), & \quad \text{if } y = x - e_j^r, \\
\alpha_{jm}(k_j - n_{jm}) \tau_x(a), & \quad \text{if } y = x + e_j^s, \\
\beta_{jm} n_{jm} \tau_x(a), & \quad \text{if } y = x - e_j^s, \\
0, & \quad \text{otherwise},
\end{align*}
\]

where $m = 2, 3, \ldots, M_j, j = 1, 2, \ldots, J$.

### C. Cost Function and Linear Programming Solution to the SMDP

Based on the action $a$ taken in a state $x$, a cost $c(x, a)$ occurs to the network. Authors in [1] show that the blocking probability can be expressed as an average cost criterion in the CAC setting. Following [1], we define the cost as

$$c(x, a) = \sum_{j=1}^{J} w_j (1 - a_j), \quad (4)$$

where $w_j \in \mathbb{R}_+$ is the weight associated with class $j$.

The optimal policy $u^*$ of the SMDP is obtained by solving the linear program [4].

### IV. Nearly Complete Decomposable SMDP

The SMDP introduced in Section III is $(J + \sum_{j=1}^{J} \sum_{m=1}^{M_j} m)$ dimensional for a $J$ class system. For large $J$, this leads to computational problems of excessive size. The notion of nearly complete decomposability (NCD) [6] Markov chains can be used to reduce this to a $J$-dimensional problem. Intuitively, when making a connection admission decision, the number of connections of each class in progress is important, but the number of connections of each class in the different states is not, because
these quantities oscillate too rapidly. Mathematically, the embedded Markov chain of the SMDP in packet CDMA networks has two time-scale structure — it spends most of its time jumping in the $k$ component, and only rarely jumps in the $n$ component of the state descriptor (2).

Let $S$ denote the total number of states in the embedded Markov chain of the SMDP. Mathematically, the transition probability matrix of the embedded Markov chain has the following NCD structure: $Q = B + \epsilon C$, where $B$ has a block diagonal structure.

$$B = \begin{bmatrix} B_{11} & 0 & \ldots & 0 \\ 0 & B_{22} & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & B_{HH} \end{bmatrix},$$

where $B_{ii} \in \mathbb{R}^{s_i \times s_i}, \forall i$, $\sum_i s_i = S$, is the maximum degree of coupling, and $C \in \mathbb{R}^{S \times s_i}$. $B_{ii}, \forall i$ are also infinitesimal generators. Denote the state partitions as $X_1 = (x_1, x_2, \ldots, x_{s_1})$, $X_2 = (x_{s_1+1}, x_{s_1+2}, \ldots, x_{s_1+s_2})$ and so on. The “super-states” $X_1, X_2$, etc., will be called as macro-states. In addition, the elements of $k$ in the state vector are identical within each macro-state. The above structure of $Q$ implies that the embedded Markov chain has a two time-scale structure — it spends most of its time jumping between states in a particular macro-state, and only rarely jumps between macro-states.

A process of aggregation can be applied to the $S$-state nearly completely decomposable Markov chain to approximate it with a $H$-state Markov chain. We show by an example of this NCD structure in the problem considered in this paper.

**Example 1:** For simplicity, we assume that there is one class of MMPP traffic with arrival rate $\lambda$ and service rate $\mu$. The MMPP has two states, $x_1$ and $x_2$. The initial state is $x_1$ with probability 1. The rate from $x_1$ to $x_2$ is $\beta$ and the rate from $x_2$ to $x_1$ is $\alpha$. In addition, we assume that at most 2 connections are allowed in the system. As shown before, the state of this system can be defined as a doublet $(k, n)$, where $k$ denotes the number of connections in the system and $n$ denotes the number of connections in state $x_2$ among $k$ connections. The resultant two-dimensional state space, with transitions between state superimposed, appears in Fig. 1. The infinitesimal generator of the embedded Markov chain is

$$Q = \begin{bmatrix} -\lambda & \lambda & 0 & 0 & 0 \\ \mu & q_1 & \alpha & \lambda & 0 \\ \mu & 0 & q_2 & \lambda & 0 \\ 0 & 2\mu & 0 & q_3 & 2\alpha \\ 0 & \mu & 2\mu & \beta & q_4 & \alpha \\ 0 & 0 & 2\mu & 0 & 2\beta & q_5 \end{bmatrix},$$

where $q_1 = -\alpha - \mu - \lambda$, $q_2 = -\beta - \lambda$, $q_3 = -2\mu - 2\alpha - \lambda$, $q_4 = -2\mu - \beta - \alpha - \lambda$, and $q_5 = -2\beta - 2\mu$. This matrix can be written as

$$Q = B + \epsilon C,$$

where $B$ has a block diagonal structure

$$B = \begin{bmatrix} -2\alpha & 2\alpha & 0 \\ \beta & -\beta - \alpha & \alpha \\ 0 & 2\beta & -2\beta \end{bmatrix},$$

and $C = \begin{bmatrix} -1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{\lambda \epsilon^1 c_1 c_2} & \frac{\mu c_1 c_2}{\lambda \epsilon^1 c_1 c_2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{\lambda \epsilon^1 c_1 c_2} & \frac{1}{\mu c_1 c_2} & 0 & \frac{1}{\lambda} & 0 & 0 & 0 & 0 & 0 \\ \frac{2}{\lambda \epsilon^1 c_1 c_2} & \frac{1}{\mu c_1 c_2} & \frac{1}{\lambda} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{\lambda \epsilon^1 c_1 c_2} & \frac{\mu c_1 c_2}{\lambda \epsilon^1 c_1 c_2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{\lambda \epsilon^1 c_1 c_2} & \frac{1}{\mu c_1 c_2} & \frac{1}{\lambda} & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{\lambda \epsilon^1 c_1 c_2} & \frac{1}{\mu c_1 c_2} & \frac{1}{\lambda} & 0 & 0 & 0 \\ \frac{1}{\lambda \epsilon^1 c_1 c_2} & \frac{1}{\mu c_1 c_2} & \frac{1}{\lambda} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

where $c_1 = (\lambda + \mu), c_2 = (\lambda + 2\mu)$, and $c_3 = (\lambda + 3\mu)$.

We can see that $B_{11} \in \mathbb{R}^{1 \times 1}, B_{22} \in \mathbb{R}^{2 \times 2}$ and $B_{33} \in \mathbb{R}^{3 \times 3}$ are also infinitesimal generators. Denote the state partitions as macro-state $X_1 = \{(0, 0)\}, X_2 = \{(1, 0), (1, 1)\}$, $X_3 = \{(2, 0), (2, 1), (2, 2)\}$. Note that the number of connections $k$ in the system does not change within a macro-state, but the number of connections in the $x_2$ state $(n)$ does. In addition, because $1/\lambda$ and $1/\mu$ are the mean connection inter-arrival and service times, which are usually large values compared to $1/\alpha$ and $1/\beta$, the coupling parameter $\epsilon = \lambda \mu (\lambda + \mu) (\lambda + 2 \mu) (\lambda + 3 \mu)$ is small.

**V. REDUCED COMPLEXITY CONSTRAINED SMDP FORMULATION OF CAC**

Since the embedded Markov chain of the SMDP formulated in Section III for packet CDMA networks has the nearly com-
plete decomposability (NCD) structure, in this section, we formulate the CAC problem as a reduced complexity constrained SMDP by exploiting this NCD structure.

A. States, Decision Epochs, Actions and State dynamics

In the reduced complexity problem, only the number of connections in each class appears in the state vector of the system, which is given by \( x(t) = k(t) = [k_1(t), k_2(t), \ldots, k_J(t)] \). As in the original problem, we choose the decision epochs to be the set of instances when the state of the system changes, i.e., the connection arrival and departure instances. The actions that can be chosen is the same as before, accept and reject for each class of traffic. The resulting process consists of only an arrival process with rate \( \sum_{j=1}^J \lambda_j \), if a class \( j \) connection be admitted and a departure process with rate \( \sum_{j=1}^J \mu_j k_j \). The sojourn time is \( \tau_x(a) = \left[ \sum_{j=1}^J \lambda_j a_j + \sum_{j=1}^J \mu_j k_j \right]^{-1} \). The state transition probabilities of the embedded chain is

\[
p_{xy}(a) = \begin{cases} 
\lambda_j a_j \tau_x(a), & \text{if } y = x + e_j^x, \\
\mu_j k_j \tau_x(a), & \text{if } y = x - e_j^x, \\
0, & \text{otherwise.}
\end{cases}
\]  

(6)

In the reduced complexity problem, the connection blocking probability constraints can be considered the same way as before. However, the constraint of the SIR outage probability can not be formulated the same way as before. We present two approaches to the constraint of the SIR outage probability: conservative approach and aggressive approach, which are described in the following subsections.

B. The Conservative Approach to the Constraint of the SIR Outage Probability

In the conservative approach, which we call CON-CAC, the SIR outage probability is guaranteed in each state and the system will never go into any state for any period of time where the SIR outage probability will be violated. Before defining the state space of the reduced complexity problem in this approach, we need to derive the SIR outage probability in a given state.

The stationary state probabilities in the original problem with state vector \([k, n]\) is

\[
\phi(k, n) = \prod_{j=1}^J \prod_{m=1}^{M_j} \left( k_j - \sum_{l=1}^{m-1} n_{jl} \right) \left( \pi_{jm} \right)^{n_{jm}},
\]  

(7)

where \( \pi_{jm} \) is the stationary state probabilities of class \( m \) MMPP being in state \( m \). The SIR outage probability in the reduced complexity problem for a given state \( x = k \) is

\[
\psi(x) = \psi(k) = \sum_{n_{11}=0}^{k_1} \sum_{n_{12}=0}^{k_2} \ldots \sum_{n_{Jm_j}=0}^{k_J} \phi(k, n) \delta \left( \frac{1}{N} \sum_{j=1}^J \sum_{m=1}^{M_j} n_{jm} R_{jm} y_j - 1 \right).
\]  

(8)

The state space of the reduced complexity problem is restricted such that the SIR outage probability of any given state is not violated.

\[
X = \{ x = [k_1, k_2, \ldots, k_J] \in \mathbb{Z}_+^J : \psi(k) \leq \zeta \}.
\]  

(9)

The reduced complexity policy can be obtained from the solution of the following linear program:

\[
\min_{z_{xa} \geq 0, x \in X, a \in A_x} \sum_{x \in X} \sum_{a \in A_x} w_j (1 - a_j) \tau_x(a) z_{xa}
\]

subject to

\[
\sum_{a \in A_y} z_{ya} - \sum_{x \in X} \sum_{a \in A_x} p_{xy}(a) z_{xa} = 0, y \in X
\]

\[
\sum_{x \in X} \sum_{a \in A_x} z_{xa} \tau_x(a) = 1,
\]

\[
\sum_{x \in X} \sum_{a \in A_x} (1 - a_j) z_{xa} \tau_x(a) \leq \gamma_j, j = 1, 2, \ldots, J.
\]  

(10)

C. The Aggressive Approach to the Constraint of the SIR Outage Probability

In the aggressive approach, which we call AGG-CAC, the SIR outage probability is satisfied over long periods of time, but can be violated in some states for short periods. The SIR outage probability in AGG-CAC is given as

\[
F_{\text{out}}^{\text{red}} = \sum_{x \in X} \sum_{a \in A} \psi(x) \tau_x(a).
\]  

(11)

The state space of the reduced complexity problem is defined as

\[
X = \{ x = [k_1, k_2, \ldots, k_J] \in \mathbb{Z}_+^J : \sum_{j=0}^{J} k_j \leq G \},
\]  

(12)

where \( G \) is a large positive integer to restrict the state space to be finite. The linear program for obtaining the reduced complexity policy becomes

\[
\min_{z_{xa} \geq 0, x \in X, a \in A_x} \sum_{x \in X} \sum_{a \in A_x} w_j (1 - a_j) \tau_x(a) z_{xa}
\]

subject to

\[
\sum_{a \in A_y} z_{ya} - \sum_{x \in X} \sum_{a \in A_x} p_{xy}(a) z_{xa} = 0, y \in X
\]

\[
\sum_{x \in X} \sum_{a \in A_x} z_{xa} \tau_x(a) = 1,
\]

\[
\sum_{x \in X} \sum_{a \in A_x} (1 - a_j) z_{xa} \tau_x(a) \leq \gamma_j, j = 1, 2, \ldots, J.
\]

(13)
VI. Numerical Examples - Voice and Star Wars Video Traffic

Two classes of voice traffic and one class of video traffic are considered with arrival rates $\lambda_1$, $\lambda_2$ and $\lambda_3$, respectively. The service rates are $\mu_1$, $\mu_2$ and $\mu_3$. Each voice traffic is modeled as an MMPP that has two states with the transmission rates in one state being zero. The rate from $x_{j1}$ to $x_{j2}$ is $\alpha_j$ and the rate from $x_{j2}$ to $x_{j1}$ is $\beta_j$, $j = 1, 2$, for the voice traffic. An MMPP with 8 states is used to model the video traffic. We choose the infinitesimal generating matrix in Table III of [8] for a full motion coded movie Star Wars. The transmission rate $R_{31}$ in the first state of the video traffic corresponds to an equivalent spreading gain $N = 32$. The transmission rates in other states are: $R_{sm} = mR_{31}$, $m = 2, 3, \ldots, 8$. The target SIRs for three classes are equal, $\omega_1 = \omega_2 = \omega_3 = 10$. The channel parameters are chosen as follows: $L = 1$ (flat fading), $|\tilde{h}_1|^2 = |\tilde{h}_2|^2 = |\tilde{h}_3|^2 = 1$, $\xi_1^2 = 0.02$, $\xi_2^2 = \xi_3^2 = 0.05$.

We compare the results from the original optimal scheme in Section III, which is called OPT-CAC to those from CON-CAC and AGG-CAC using nearly complete decomposability approximation. Table I illustrates the parameters in the experiment and the numerical results. SIR outage constraint is 0.005 and $\lambda_1, \mu_1$ are fixed in this experiment. The blocking probability is obtained from different values of $\alpha_1$ and $\beta_1$. We observe that the NCD solution can have good approximation to the optimal solution. Table I also indicates that the NCD solution performs better when the MMPP changes states faster ($\alpha$ and $\beta$ are large).

Table II shows the comparison of the computation complexity of the proposed schemes. In particular, we are interested in the CPU time required in solving the linear program. We run the algorithms on a PC with 1.6G Hz Pentium 4 CPU with 256M memory. Both CON-CAC and AGG-CAC need much less CPU time than OPT-CAC. The NCD solutions reduce the computation complexity significantly.

We compare the conservative approach to the SIR outage probability, CON-CAC with the aggressive approach, AGG-CAC. Fig. 2 shows the network utilization in CON-CAC and AGG-CAC. The SIR outage probability constraint is 0.01 in both CAC schemes. We observe that CON-CAC has lower network utilization than AGG-CAC. This is because CON-CAC can guarantee the SIR outage probability in any state and is conservative in admitting connections. In contrast, in AGG-CAC, the SIR outage probability can be violated in some states, but is satisfied over long periods of time, which can increase the network utilization.

VII. Conclusions

In this paper, the cross-layer optimal connection admission control problem in packet CDMA networks was formulated as an average cost Markov decision process (SMDP). We have shown that the SMDP has the nearly complete decomposability structure. Then we proposed two cross-layer CAC schemes that can dramatically reduce the computational complexity and have good approximation to the optimal solutions. The effectiveness of the approaches was demonstrated by numerical examples.

### Table I

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<th>$\alpha_1$</th>
<th>$\beta_1$</th>
<th>$P_b$(OPT-CAC)</th>
<th>$P_b$(AGG-CAC)</th>
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### Table II

<table>
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<td>CON-CAC</td>
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<td>AGG-CAC</td>
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Fig. 2. Network utilization in CON-CAC and AGG-CAC

### References


