On the Tradeoff Between Blocking and Dropping Probabilities in CDMA Networks Supporting Elastic Services

Gábor Fodor[1], Miklós Telek[2], and Leonardo Badia[3]

[1] Ericsson Research, SE-164 80 Stockholm, Sweden
Gabor.Fodor@ericsson.com
[2] Budapest University of Technology and Economics, H-1111 Budapest, Hungary
telek@hit.bme.hu
[3] Consorzio Ferrara Ricerche, 44100 Ferrara, Italy
lbadia@ing.unife.it

Abstract. This paper is a sequel of previous work, in which we proposed a model and computational technique to calculate the Erlang capacity of a single CDMA cell that supports elastic services. The present paper extends that base model by taking into account two important features of CDMA. First, we capture the impact of *soft blocking* by modeling the neighbor cell interference as a lognormally distributed random variable. Secondly, we model the impact of the outage by taking into account that in-progress sessions can be *dropped* with a probability that depends on the current load in the system. We then consider a system with elastic and rigid service classes and analyze the trade-off between the total (soft and hard) blocking probabilities on the one hand and the throughput and the session drop probabilities on the other.

1 Introduction

The teletraffic behavior of code division multiple access (CDMA) networks has been the topic of research ever since CDMA started to gain popularity for military and commercial applications, see for instance Chapter 6 of [1] (and the references therein) that are concerned with the Erlang capacity of CDMA networks. The paper by Evans and Everitt used an $M/G/\infty$ queue model to assess the uplink capacity of CDMA cellular networks and also presented a technique to calculate the outage probability [2]. These classical papers have focused on "rigid" traffic in the sense that elastic or best effort traffic whose bit rate can dynamically change was not part of the models. Subsequently, the seminal paper by Altman proposed a Shannon like capacity measure called the "best effort capacity" that explicitly takes into account the behavior of elastic sessions [3].

The importance of modeling outages and *session drops* and their impacts on the Erlang capacity in cellular networks in general and in CDMA in particular has been emphasized by several authors, see for instance [2] and more recently [7]. Session drops are primarily caused by outages, when the desired signal-to-noise ratio for a session stays under a predefined threshold during such a long time that the session gets interrupted. However, sessions can be dropped by a load control algorithm (typically located in the radio network controller in WCDMA) to preserve system stability. Session

F. Boavida et al. (Eds.): NETWORKING 2006, LNCS 3976, pp. 954–965, 2006.

interruptions are perceived negatively by end users - more negatively than blocking a session - and therefore their probability should be minimized by suitable resource management (including admission control) techniques.

The purpose of this paper is to develop a model that can be used to analyze the trade-off between the blocking and dropping probabilities in CDMA in the presence of elastic traffic. We build on the model developed for elastic traffic in previous work [4] and extend it with allowing for a state dependent soft blocking and capturing the fact that sessions are sometimes dropped. The main assumption that we make is that the session drop probability is connected to the load of the system. When the load is high, the interference from neighbor cells leads to outages with a higher probability than when it is low. For elastic sessions, fast rate and power control attempts to reduce the transmission rates and the required received power at the base station, as long as the transmission rates stay above the session specific so called *guaranteed bit rate* (GBR). Therefore, it seems intuitively clear that there is a trade-off between how conservative the admission control algorithm is (on the one hand) and what is the average bit rate of elastic sessions and what session drop probabilities users experience (on the other hand). The contribution of the paper is to propose a model that can be used for the analysis of this trade-off.

2 Revisiting CDMA Uplink Equations and State Space Structure

The basic CDMA uplink equations that serve as a starting point for this paper are described in details in [3] and [4]. In this section we summarize these results and refer to these references for the derivation of them.

2.1 Revisiting the Basic CDMA Equations

We consider a single CDMA cell at which sessions belonging to one of I service classes arrive according to a Poisson arrival process of intensity λ_i $(i = 1, \ldots, I)$. Each class is characterized by a peak bit-rate requirement $\hat{R}_i$ and an exponentially distributed nominal holding time with parameter μ_i. When sending with the peak rate for a session, the required target ratio of the received power from the mobile terminal to the total interference energy at the base station is given by $\tilde{\Delta}_i = \frac{\hat{R}_i E_i}{W N_0}$. Here E_i/N_0 is the class-wise signal energy per bit divided by the noise spectral density that is required to meet a predefined QoS (e.g. bit error rate, BER) and $W/\hat{R}_i$ is the CDMA *processing gain*.

Let n_i be the number of ongoing sessions of class i. We will refer to vector $\underline{n} = \{n_i\}$ as the *state* of the system. We now assume that arriving sessions are blocked by a suitable admission control algorithm that prevents the system from reaching the state in which the power that should be received at the base station would go to infinity. In other words, a suitable admission control algorithm must prevent the system to reach its *pole capacity* (as defined by Equation (8.10) of [8] and (5) of [3]).

The power P_i that is received at the base station from the mobile terminal for session i must fulfill (see [4]):

$$P_i = \left(P_N + \frac{P_N \cdot \Psi}{1 - \Psi}\right) \cdot \Delta_i = \frac{P_N \cdot \Delta_i}{1 - \Psi}; \Psi \triangleq \Psi(\underline{n}) = \sum_{\ell=1}^{I} n_\ell \cdot \Delta_\ell; \Delta_i \triangleq \frac{\tilde{\Delta}_i}{1 + \tilde{\Delta}_i} \quad (1)$$

Table 1. Model (Input) Parameters

I	Number of service classes
$\hat{R}_i$	Peak bit rate associated with class-i sessions
λ_i	Arrival intensity of sessions belonging to class-i
$1/\mu_i$	Mean (nominal) holding time of sessions belonging to class-i
$\hat{a}_i$	Maximum slow down (using the terminology of [3]) of $\hat{R}_i$
φ	Parameter of the other cell (sector) interference (see Equation (4))
E_i/N_0	Normalized signal energy per bit requirement of class-i

In practice, $\hat{\Psi}$ is defined such that the noise rise in the system stays under some predefined threshold, typically less than 7dB. In the single class case it means that the number of admitted sessions must fulfill: $n_1 < \lfloor \hat{\Psi}/\Delta_1 \rfloor$.

2.2 The Impact of Slow Down

Recall that the required target ratio (Δ_i) depends on the required bit-rate. Explicit rate controlled elastic services tolerate a certain slow down of their peak bit-rate ($\hat{R}_i$) as long as the actual instantaneous bit rate remains greater than $\hat{R}_i/\hat{a}_i$. When the bit rate of a class-i session is slowed down to $\hat{R}_i/a_i$, $(0 < a_i \le \hat{a}_i)$ its required Δ_{a_i} value becomes:

$$\Delta_{a_i} = \frac{\tilde{\Delta}_i}{a_i + \tilde{\Delta}_i} = \frac{\Delta_i}{a_i \cdot (1 - \Delta_i) + \Delta_i}, \quad i = 1, \ldots, I, \tag{2}$$

which increases the number of sessions that can be admitted into the system, since now Ψ_a must be kept below $\hat{\Psi}$, where $\Psi_a = \sum_{i=1}^{I} n_i \cdot \Delta_{a_i}$.

We use the notation $\Delta_{min,i} = \Delta_{\hat{a}_i}$ to denote the class-wise minimum target ratios (can be seen as the minimum resource requirement), that is when the session bit-rates of class-i are slowed down to the minimum value (GBR) associated with that class. The smallest of these $\Delta_{min,i}$ values $\Delta = \min_i \Delta_{min,i}$ can be thought of as the finest "granularity" with which the overall CDMA resource is partitioned between competing sessions.

2.3 Determining the System State Space

The maximum number of sessions from each class can is given by $\hat{n}_i = \lfloor (\Delta_{min,i})^{-1} \rfloor$. Then, recall that in each $\underline{n}$ state of the system, the inequality $\sum_i n_i \cdot \Delta_{a_i} < \hat{\Psi}$ must hold. The states that satisfy this inequality are the *feasible states* and constitute the state space of the system (Θ). The feasible states, in which the acceptance of an additional class-i session would result in a state outside of the state space are the class-i *blocking states*. The set of the class-i blocking states is denoted by Θ_i. Due to the "Poisson Arrivals See Time Averages" (PASTA) property, the sum of the class-i blocking state probabilities gives the (overall) class-i blocking probability. In each feasible state, it is the task of the bandwidth sharing policy to determine the $\Delta_{a_i}(\underline{n})$ class-wise target ratios for each class. The $\Delta_{a_i}(\underline{n})$:s reflect the fairness criterion that is implemented in the resource sharing policy mentioned above. From these, the class-wise slow down factors and the instantaneous bit-rates of the individual sessions can be calculated as follows:

$$a_i(\underline{n}) = \frac{\Delta_i \cdot (1 - \Delta_{a_i}(\underline{n}))}{\Delta_{a_i}(\underline{n}) \cdot (1 - \Delta_i)}; \quad R_{a_i}(\underline{n}) = R_i / a_i(\underline{n}) \tag{3}$$

For ease of presentation, in the rest of the paper we will not indicate the dependence of a_i, Δ_{a_i} and R_{a_i} on the system state $\underline{n}$.

3 Modeling Soft Blocking and Session Drop

3.1 Modeling the Interference from Neighbor Cells

The interference contribution from other cells is typically quite high (around 30-40%). This is taken into account as follows. We think of the CDMA system as one that has a maximum of $\hat{n} = \frac{\hat{\Psi}}{\Delta}$ number of (virtual) channels. The neighbor cell interference ξ is a random variable of log-normal distribution with the following mean and standard deviation respectively :

$$\alpha = \frac{\varphi}{\varphi + 1} \cdot \hat{n} \quad \text{and} \quad \sigma = \alpha, \tag{4}$$

where φ is factor characterizing the neighbor cell interference and is an input parameter of the model (Table 1).

The mean value of the interference α is equal to the average capacity loss in the cell due to the neighbor cell interference and σ is chosen to be equal to α as proposed by [6] and also adopted by [5]. (When $\varphi = 0$, the neighbor cell interference is ignored in the model.)

Recall that we think of $\Psi(\underline{n})$ as the used resource in state $\underline{n}$. Then in a given state $\underline{n}$ let $b_\Psi(\underline{n})$ denote the probability that the neighbor cell interference is greater than the available capacity in the current cell that is ($\hat{\Psi} - \Psi$):

$$b_\Psi(\underline{n}) = Pr\{\xi > \hat{\Psi} - \Psi\} = 1 - Pr\{\xi < \hat{\Psi} - \Psi\} = 1 - D(\hat{\Psi} - \Psi),$$

where $D(x)$ is the cumulative distribution function of the log-normal distribution:

$$D(x) = \frac{1}{2}\left(1 + \mathrm{erf}\left(\frac{\ln(x) - N}{S\sqrt{2}}\right)\right); N = \ln\left(\frac{\alpha^2}{\sqrt{\alpha^2 + \sigma^2}}\right); S^2 = \ln\left(1 + \frac{\sigma^2}{\alpha^2}\right).$$

The impact of state dependent soft blocking resulted, e.g. by the neighbor cell interference, can conveniently be taken into account by modifying the λ_i arrival rates in each state by the (state dependent) so called passage factor: $\sigma_i(\underline{n}) = g_i(1 - b_\Psi(\underline{n})) = g_i(D(\hat{n} - \Psi(\underline{n})))$. The passage factor is the probability that a class-i session is not blocked by the admission control algorithm when such a session arrives in system state $\underline{n}$ [5].

3.2 Modeling Session Drop

When the system is in state $\underline{n}$, a class-i session leaves the system with intensity $\gamma_i(\underline{n}) \cdot \frac{\mu_i}{a_i(\underline{n})}$, where $\gamma_i(\underline{n})$ is the state dependent session drop factor. The session drop factor is such that for all i: $\gamma_i(\underline{n})\,|_{n_i=0} = 1$; and $\gamma_i(\underline{n})\,|_{n_i \neq 0} \geq 1$. Furthermore, we can assume that the drop probability for a given session does not depend on the instantaneous slow down of that session. This is because whether a session gets out of coverage or whether it gets dropped by the radio network does not depend on the slow down. The session drop probabilities, however, depend on the actual level of the noise rise, because higher noise rise level at the base station makes decoding of signals more difficult. We will thus assume that the session drop factor is a function of the macro state only and is the same for all classes : $\gamma_i(x) = f(x) = f(\Psi) \quad \forall i \in I$. That is, we assume that the session drop probability is determined by the load in the system and is equal for all service classes.

4 System Behavior

4.1 The Markovian Property and Determining the Generator Matrix

We now make use of the assumptions that the arrival processes are Poisson and the nominal holding times are exponentially distributed (see Subsection 2.1). The transitions between states are due to an arrival or a departure of a session of class-i. The arrival rates are given by the intensity of the Poisson arrival processes. Due to the memoryless property of the exponential distribution, the departure rates from each state depend on the nominal holding time of the in-progress sessions and on the slow down factor in that state. Specifically, when the slow down factor of a session of class-i is $a_i(\underline{n})$, its departure rate is $\gamma_i(\underline{n})\mu_i/a_i(\underline{n})$. Thus, the system under these assumptions is a continuous time Markov chain (CTMC) whose state is uniquely characterized by the state vector $\underline{n}$.

4.2 Determining the Generator Matrix

For ease of presentation, but without losing generality, we use an example to illustrate the structure of the generator matrix. Assume that $\hat{a}_1 = 1$, $\hat{a}_2 > 1$ and $\hat{a}_3 > 1$. In this case, the task of the bandwidth sharing policy simplifies to determining $\Delta_{a,2}$ and $\Delta_{a,3}$ for each state, from which $\hat{a}_2$ and $\hat{a}_3$ follows.

Based on the considerations of the preceding subsections, we see that the generator matrix $\mathbf{Q}$ possesses a nice structure, because only transitions between "neighboring states" are allowed in the following sense. Let $q(n_1, n_2, n_3 \to n_1', n_2', n_3')$ denote the transition rate from state (n_1, n_2, n_3) to state (n_1', n_2', n_3'). Then the non-zero transition rates between the feasible states are (taking into account the impact of the passage factors and session drop factors):

$$
\begin{aligned}
q(n_1, n_2, n_3 \to n_1 + 1, n_2, n_3) &= \lambda_1 \sigma_1(n_1, n_2, n_3) \\
q(n_1, n_2, n_3 \to n_1, n_2 + 1, n_3) &= \lambda_2 \sigma_2(n_1, n_2, n_3) \\
q(n_1, n_2, n_3 \to n_1, n_2, n_3 + 1) &= \lambda_3 \sigma_3(n_1, n_2, n_3) \\
q(n_1, n_2, n_3 \to n_1 - 1, n_2, n_3) &= n_1 \gamma_1(n_1, n_2, n_3)\mu_1 \\
q(n_1, n_2, n_3 \to n_1, n_2 - 1, n_3) &= n_2 \gamma_2(n_1, n_2, n_3)\mu_2 / a_2(n_1, n_2, n_3) \\
q(n_1, n_2, n_3 \to n_1, n_2, n_3 - 1) &= n_3 \gamma_3(n_1, n_2, n_3)\mu_3 / a_3(n_1, n_2, n_3)
\end{aligned}
$$

The first three equations represent the state transitions due to session arrivals, while the second three equations represent the transitions due to session departures. Here we utilized the fact that Class-1 sessions cannot be slowed down, while Class-2 and Class-3 sessions can be slowed $a_2 : 1 \leq a_2 \leq \hat{a}_2$, and $a_3 : 1 \leq a_3 \leq \hat{a}_3$ respectively.

4.3 Determining the Blocking Probabilities and Session Drop Probabilities

From the steady state analysis, the blocking and dropping probabilities directly follow. The hard blocking probabilities can be easily calculated, because we assume that the sessions from each class arrive according to a Poisson process: $P_{hard,i} = \sum_{\underline{n} \in \Theta_i} \pi(\underline{n})$. The total blocking probabilities include the soft blocking probabilities in each state and the hard blocking probabilities: $P_{total,i} = 1 - \sum_{\underline{n} \in \Theta} \pi(\underline{n}) \sigma_i(\underline{n})$. Finally, the class-wise dropping probabilities can be calculated using the following observation. Since the dropping related departure rate from state $\underline{n}$ is $(\gamma_i(\underline{n}) - 1) \cdot \frac{n_i \mu_i}{a_i(\underline{n})}$, the long-term fraction of the dropped sessions must be proportional to $\frac{\gamma_i(\underline{n})-1}{\gamma_i(\underline{n})} \cdot \frac{n_i \mu_i}{a_i(\underline{n})}$. Weighing this quantity with the stationary probability distribution of the system and normalizing yields:

$$P_{drop,i} = \frac{\sum_{\underline{n} \in \Theta} \pi(\underline{n}) \cdot \frac{\gamma_i(\underline{n}) - 1}{\gamma_i(\underline{n})} \cdot \frac{n_i \mu_i}{a_i(\underline{n})}}{\sum_{\underline{n} \in \Theta} \pi(\underline{n}) \cdot \frac{n_i \mu_i}{a_i(\underline{n})}}. \tag{5}$$

In the next section we will show how this intuitively clear formula can be verified by defining a trapping state in this system.

5 Solution Based on the Tagged Customer Approach

The calculation of the (mean and the distribution of the) time to completion of successful sessions requires some additional effort. As we shall see, the method we follow here can also be used to verify the dropping probability calculations as suggested by Equation (5).

5.1 Session Tagging and Modifying the State Space

In order to calculate the moments and the distribution of the holding time of successful (not dropped) sessions we modify the state space by introducing a trapping (absorbing) state and make the following considerations.

We will continue to think of an elastic session as one that brings with itself an exponentially distributed amount of work and, if admitted into the system, stays in the system until this amount of work is completed or the session gets dropped. The method we follow here is based on (1) *tagging* an elastic session arriving to the system, which, at the time of arrival is in one of the feasible states; and (2) carefully examining the possible transitions from the moment this tagged call enters the system until it acquires the required service or gets dropped and therefore leaves the system. Finally, un-conditioning on all possible entrance state probabilities, the distribution of the best effort service time can be determined.

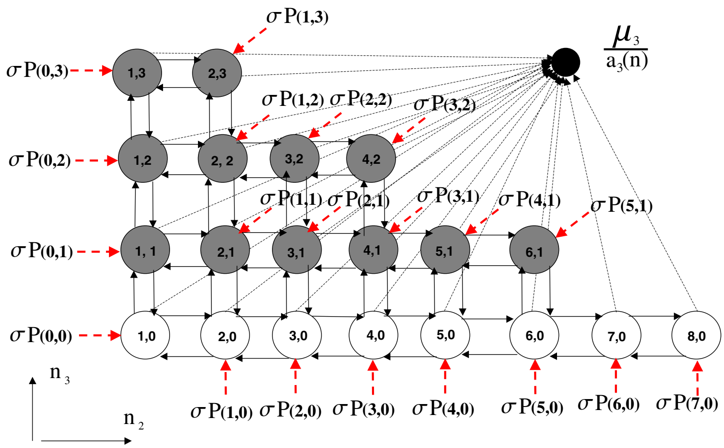

Fig. 1. Modified state space with a trapping state that represents successful session termination. The transition rates to this trapping state correspond to the transition rates with which the tagged session enters the trapping state. The initial probability vector can be determined from the steady state by normalization and taking into account the 'thinning' affect of the passage factors.

For the purpose of illustration, we again concentrate on the part of the state space in which $n_1 = 8$ and tag a class-3 session. Figure 1 shows the state transition diagram from this tagged session's point of view an infinitesimal amount of time after this tagged session entered the system. Since we assume that at least the tagged session is now in the system, we exclude states where $n_3 = 0$. Figure 1 also shows the entrance probabilities for each state, with which the tagged session finds the system in *that* state. Thus, in Figure 1, the tagged arriving session will find the system in state (n_2, n_3) with probability $P(n_2, n_3)$, and will bring the system into state $(n_2, n_3 + 1)$ unless (n_2, n_3) is a Class-3 hard blocking state. For non hard blocking states the entrance probabilities have to be "thinned" with the passage factor (i.e. $\gamma(n_1, n_2, n_3)$). In order for the entrance probabilities to sum up to 1, they need to be re-normalized since we have excluded entrances in the hard blocking states.

In this modified state space, we also define a $trapping$ $(absorbing)$ $state$. Depending on how this trapping state is interpreted and how the transition rates into that state is defined, we can calculate the moments and the distribution of the holding time of successful sessions and the time until dropping of dropped sessions as well.

We first discuss the case of successful sessions. In this case, the trapping state corresponds to the state which the tagged session enters when the workload is completed ("the file has been transferred successfully"). The transition rates from each state are given by $\mu_3/a(\underline{n})$. The time until absorption corresponds to the time the tagged session spends in the system provided that it is not dropped. Indexing the modified state space in a similar manner as the original state space, the new generator matrix $\tilde{\mathbf{Q}}_\mathbf{S}$ will have the following structure:

$$\tilde{\mathbf{Q}}_\mathbf{S} = \begin{bmatrix} B_S & b_S \\ 0 & 0 \end{bmatrix} \tag{6}$$

where the B_S matrix represents the transitions between the non-trapping states, the b_S vector contains the transitions to the trapping state, the 0 vector indicates that no transitions are allowed $from$ the trapping state. When the trapping state represents the state that the tagged session enters when it is dropped, the transition rates to the trapping state are given by $\frac{\gamma_3(\underline{n})-1}{a_3(\underline{n})}\mu_3$ and the generator matrix takes the following form:

$$\tilde{\mathbf{Q}}_{\mathbf{D}} = \begin{bmatrix} B_D & b_D \\ 0 & 0 \end{bmatrix} \tag{7}$$

where the B_D matrix represents the transitions between the non-trapping states, and the b_D vector contains the transitions to the trapping state. Once the structure of the expanded state space and the associated transition rates together with the (thinned) initial probability vector, $P_R(0)$, are determined, we can determine the r^{th} moment of T_S:

$$E[T_S^r] = r! \cdot P_R^t(0) \cdot (-B_S)^{-r} \cdot e \tag{8}$$

We note that the procedure to calculate the moments of T_D is the same as that for T_S, except that we now have to make use of the B_D matrix instead of B_S. The distributions of T_S and T_D are given by:

$$Pr\{T_S < x\} = 1 - P_R^t(0) \cdot e^{xB_S} \cdot e; \quad Pr\{T_D < x\} = 1 - P_R^t(0) \cdot e^{xB_D} \cdot e.$$

5.2 Verifying Equation (5): An Alternative Way to Calculate the Dropping Probabilities

The trapping state approach can also be used to determine the dropping probabilities, which can be used to verify results obtained from Equation (5). In order to do this, we consider the modified state space with two trapping states illustrated in Figure 2. From each state, the tagged class-i session can enter any of the two trapping states corresponding to the case when the tagged session successfully terminates or gets dropped. The generator matrix of this state space is given by:

$$\tilde{\mathbf{Q}}_{\mathbf{i}} = \begin{bmatrix} B_i & b_{S,i} & b_{D,i} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{9}$$

where $\underline{b}_{drop,i}$ is the column vector containing the transition rates to the trapping state representing the session drops. The B_i matrix has to be determined considering the total transition rates to the two trapping states.

The class-wise dropping probabilities can be calculated using Equation (10):

$$P_{drop,i} = P_R^t(0) \cdot (-B_i)^{-1} \cdot \underline{b}_{D,i}, \tag{10}$$

6 Numerical Results

6.1 Input Parameters

The input parameters for the two cases that we study are summarized by Table 2. In Case I, Class-1 is a rigid class, whereas in Case II, Class-1 is elastic with a maximum slow

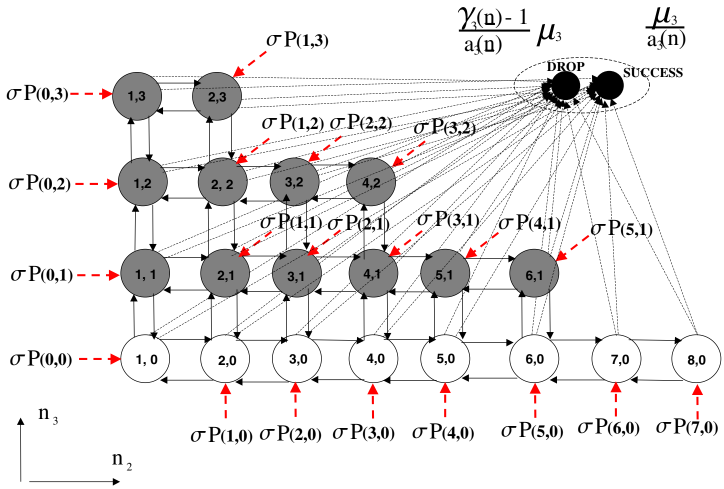

Fig. 2. Modified state space with two trapping states representing successfully terminated and dropped sessions respectively. Seen from the transient states, the total transition rates with which the tagged session enters either of these states is the sum of the two transition rates. This modified state space can be used to determine the probabilities of success and drop.

down factor $\hat{a}_1 = 3$. In both cases we change the maximum slow down factor of Class-2 $\hat{a}_2 = 1 \dots 4$. ($\hat{a}_2$ is changed along the x axis in each Figure.) The offered traffic is set to 2.72 Erlang per each class and the required Δ_i value for sessions of each class is ≈ 0.15. The function $\gamma_i(\underline{n}) = f(\underline{n})$ is set such that it does not depend on the slow down factors, according to the discussion at the end of Section 3.2. Specifically, in this paper we choose the following dropping factor: $f(\underline{n}) = 1 + \nu \ln(1 + n_1 \cdot \Delta_1 + n_2 \cdot \Delta_2)$, expressing that the dropping factor is a function of the total load in the system (see also Table 2).

6.2 Numerical Results

Blocking Probabilities. Figures 3-4 and Figures 5-6 show the impact of state dependent blocking on the total blocking probabilities. State dependent blocking implies that the admission control takes into account the instantaneous value of the noise rise at the base station rather than just the state of the own cell. This increases the class-wise total blocking probabilities from around 7% and 2% to 10% and 6% in Case I when $\hat{a}_2 = 4$. We also note that when both classes are rigid (Case I, $\hat{a}_2 = 1$), the total blocking values are high, but these high values are brought down to reasonably low blocking probability values when either one and especially when both classes tolerate slowing down of the instantaneous transmission rates (Case II, $\hat{a}_2 = 4$).

Dropping Probabilities. Figures 7-8 and Figures 9-10 show the impact of soft blocking on the session drop probabilities. First, we note that the session drop probabilities slightly (less than 2%) increase as traffic becomes more elastic. The reason is that the system utilization increases when traffic is elastic and the system operates in "higher states" with a higher probability than when traffic is rigid.

Table 2. Model (Input) Parameters

I	2
$\hat{R}_i$	128 [kbps]
λ_i	87.2613 [1/s]
μ_i	32.03 [1/s]
$\hat{a}_1$	1 (Case I); 3 (Case II)
$\hat{a}_2$	$1 \ldots 4$ (along the x axis)
φ	0.25
E_i/N_0	7 [dB]
Dropping factor	$f(\underline{n}) = 1 + \nu \ln(1 + n_1 \cdot \Delta_1 + n_2 \cdot \Delta_2)$,$\nu = 1$; [9]

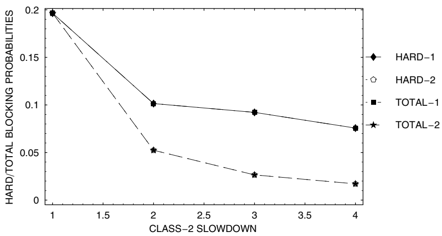

Fig. 3. Case I, no soft blocking, blocking probabilities (total and hard blocking probabilities being equal)

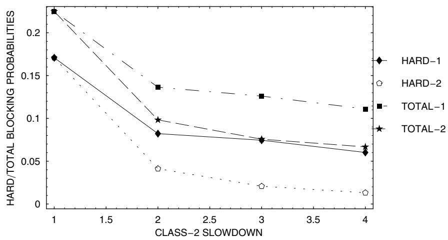

Fig. 4. Case I, soft blocking, blocking probabilities

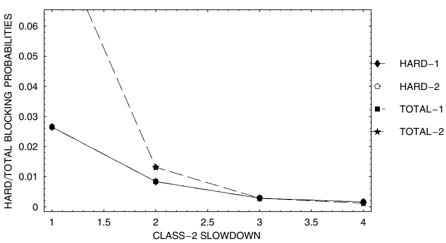

Fig. 5. Case II, no soft blocking, blocking probabilities (total and hard blocking probabilities being equal)

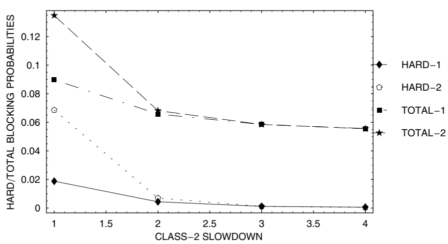

Fig. 6. Case II, soft blocking, blocking probabilities

We also see that state dependent blocking decreases the session drop probabilities in both cases (for example from around 7% to 5% in Case I when $\hat{a}_2 = 4$). This is because soft blocking entails that in average there are fewer sessions in the system that decreases session drops.

Mean Holding Time of the Successful (Not Dropped) Sessions. Figures 11-12 show the mean holding times of successful sessions (normalized to the nominal expected holding time, that is when the slow down factors are 1). In Case I, Class-1 sessions are

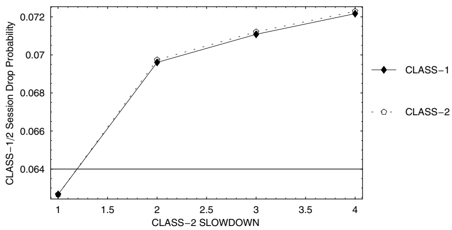

Fig. 7. Case I, no soft blocking, session drop probability

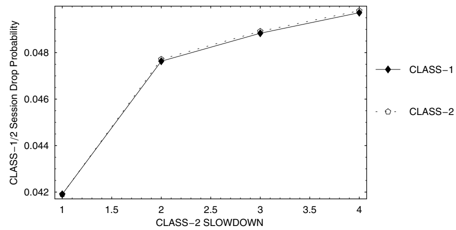

Fig. 8. Case I, soft blocking, session drop probability

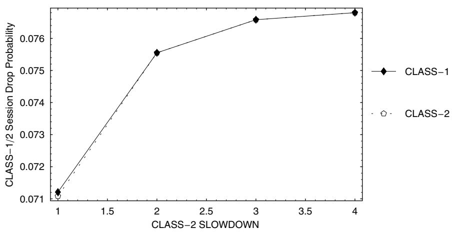

Fig. 9. Case II, no soft blocking, session drop probabilities

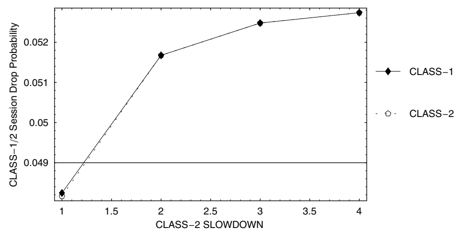

Fig. 10. Case II, soft blocking, session drop probabilities

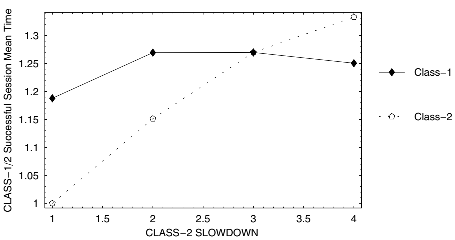

Fig. 11. Case II, no soft blocking, successful sessions' mean holding time

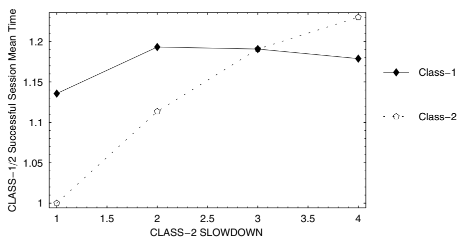

Fig. 12. Case II, soft blocking, successful sessions' mean holding time

rigid and there is no increase in their mean holding times. In this case, Class-2 sessions benefit from soft blocking (keeping in mind that we are now only taking into account the sessions that are successful). Their holding time is somewhat lower in the case of soft blocking.

7 Conclusions

In this paper we have proposed a model to study and analyze the trade-off between the blocking and dropping probabilities in CDMA systems that support elastic services. The model of this present paper captures the impact of state dependent blocking, which is a consequence of the CDMA admission control procedure that takes into account the actual noise rise value at the base station (including the interference coming from surrounding cells) rather than just the state of the serving cell. Session drops happen with a probability that increases with the overall system load.

As traffic becomes more elastic, the session drop probability increases, but this increase can be compensated for by a suitable admission control algorithm. Such state dependent admission control algorithms increase the blocking probabilities somewhat, but this increase can be mitigated if sessions tolerate some slow down of their sending rates. Thus, the design of the CDMA admission control algorithm should take into account the actual traffic mix in the system and the per-class blocking and session drop probability targets.

An important consequence of the presence of elastic traffic is that the blocking probabilities decrease as the maximum slow down factors increase. This is a nice practical consequence of one of the key findings in [3], namely that the Erlang capacity increases. Another consequence of elasticity is that the dropping probabilities increase somewhat, but this increase is not significant (the exact value would depend on the model assumptions, for instance the value of ν).

References

1. A. J. Viterbi, ”CDMA - Principles of Spread Spectrum Communication”, *Addison-Wesley*, ISBN 0-201-63374-4, 1995.
2. J. S. Evans and D. Everitt, ”On the Teletraffic Capacity of CDMA Cellular Networks”, *IEEE Trans. Vehicular Techn.*, Vol. 48, pp. 153-165, No. 1, January 1999.
3. E. Altman, ”Capacity of Multi-service Cellular Networks with Transmission-Rate Control: A Queueing Analysis”, *ACM Mobicom '02*, Atlanta, GA, September 23-28, 2002.
4. G. Fodor and M. Telek, ”Performance Anlysis of the Uplink of a CDMA Cell Supporting Elastic Services”, in the Proc. of *IFIP Networking 2005*, Waterloo, Canada, Springer LNCS 3462, pp. 205-216, 2005.
5. V. B. Iversen, V. Benetis, N. T. Ha and S. Stepanov, ”Evaluation of Multi-service CDMA Networks with Soft Blocking”, *Proc. ITC Specialist Seminar*, pp. 223-227, Antwerp, Belgium, August/September 2004.
6. A. Mäder and D. Staehle, ”An Analytic Approximation of the Uplink Capacity in a UMTS Network with Heterogenous Traffic”, 18^{th} *International Teletraffic Congress (ITC 18)*, Berlin, September 2003.
7. T. Bonald and A. Proutière, ”Conservative Estimates of Blocking and Outage Probabilities in CDMA Networks” *Performance 2005*, Elsevier Science, June 2005.
8. H. Holma and A. Toskala, ”WCDMA for UMTS - Radio Access for Third Generation Mobile Communications”, Wiley, ISBN 0 471 72051 8, First Edition, 2000.
9. W. Ye and A. M. Haimovich, ”Outage Probability of Cellular CDMA Systems with Space Diversity, Rayleigh Fading and Power Control Error”, *IEEE Communications Letters*, Vol. 2, No. 8, pp. 220-222, August 1999.