# Impact of Stochastic Traffic Characteristics on Effective Capacity in CDMA Networks

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## Abstract

*In this paper, a comprehensive system model is built to evaluate system performance for data services in CDMA networks. Unlike traditional analyses, we model both system capacity and traffic demands using stochastic processes.*

*Call-level simulation is conducted based on the proposed analytical model. The simulation results show that stochastic traffic characteristics can affect the system performance significantly. Traffic correlation is beneficial for the same system load level. Moreover, the simulation results illustrate that using a simple activity factor to model the traffic process can cause capacity overestimation.*

**Keywords:** CDMA, Effective Capacity, Modeling, Simulation

## 1. Introduction

In a CDMA network, the available system capacity usually varies with time. The capacity variation arises from the mobility of users, traffic burstiness caused by data services, and the time-varying characteristics of the wireless propagation environment [8]. In a CDMA system, there is a "soft capacity" limit for active calls that is determined by intra-cell and inter-cell interference [5]. This dynamic "soft limit" determines the instantaneous capacity of the system.

Networks with time-varying capacity tend to have higher call blocking rates and higher outage probabilities than fixed-capacity networks. In other words, the "effective capacity" of the system is usually lower. Evaluating performance in such stochastic capacity networks requires considering not only the traffic demands but also the underlying characteristics of the capacity variation process. The effective capacity of the system may even depend on the interactions between traffic and the system itself [9].

Although there has been extensive research on system capacity of CDMA networks, the system is not well modeled in that most studies oversimplify the input traffic characteristics and the capacity variation process. Moreover, most prior studies ignore the effects of interactions between network traffic and the stochastic capacity process.

In this paper, we analyze effective capacity of a CDMA network. A comprehensive system model is built for the analysis. In this model, we consider network traffic and system capacity as stochastic processes. Based on the proposed analytical model, we conduct call-level simulation to evaluate system performance. Our simulation results illustrate that the stochastic characteristics of network traffic can significantly affect the effective capacity of the system. Moreover, the simulation results also show that the overall system performance depends on the interactions between the stochastic traffic process and the capacity variation process. The correlations in the processes are beneficial to the system.

The rest of this paper is organized as follows. Section 2 reviews the prior related work. Section 3 introduces our analytical model. Section 4 presents system analysis based on the analytical model. Section 5 describes the evaluation methodology used in our simulation study. Section 6 presents the simulation results. Finally, Section 7 concludes the paper.

## 2. Related work

Effective capacity in CDMA networks has been a popular research topic for years. Two main analytical methodologies are typically used in the investigation.

The first method models interference as a stochastic process, and abstracts the traffic process using a simple *traffic activity factor*. Several authors [3, 4] have used this method to evaluate the system performance. Conversely, the second method considers the network input traffic as a stochastic process, such as a Poisson process, and defines the system capacity as a fixed value over time. This method was used for studies presented in [1, 6, 7].

As introduced in Section 1, a CDMA network is a stochastic capacity system. Evaluating networks with time-varying capacity requires the combination of channel-level models for capacity variation and user-level models for subscriber traffic. The oversimplified models used in prior studies may overestimate or underestimate system performance.

Our work differs from the foregoing studies in two important ways. First, we use stochastic processes to model the system capacity and the input traffic demands. We believe that the stochastic models are more accurate than simplified fixed values to represent the real CDMA networks. Second, using stochastic models for network traffic and system capacity makes it possible for us to explore impacts of interactions between these two factors. Our simulation results show that the interactions between network traffic and capacity variation processes can affect system performance.

## 3. Analytical methodology

Figure 1 provides a conceptual overview of our methodology for studying the system performance of CDMA networks. The network outage probability, a user-perceived performance metric, is used to evaluate the CDMA system. It can implicitly reflect the effective capacity in the system, since higher effective capacity corresponds to lower outage probability. Note that our analysis focuses on the reverse-link capacity.

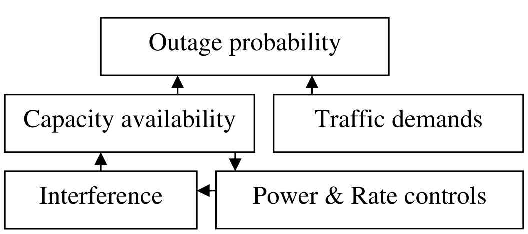


**Figure 1. Overview of Modeling Methodology**

The system outage probability mainly depends on two factors: time-varying system capacity and stochastic traffic demands. In our study, we define our traffic demand model on a per-user basis, to reflect the user service pattern.

For a CDMA network, the system capacity is interference-limited [3]. Hence, it is necessary to include an interference model, as shown in Figure 1, when analyzing the system capacity. Moreover, the power and rate control mechanisms are also factored into the interference model by normalizing the interference contributions from individual users.

The following subsections provide detailed descriptions for each module in Figure 1.

### 3.1. Traffic model

For data services in CDMA networks, ON-OFF traffic source is typical. Traffic measurements for CDMA cellular networks have shown that both active (ON) period and idle (OFF) periods follow heavy-tailed distributions. We incorporate this observation in our traffic model.

The Probability Density Function (PDF) for heavy-tailed distribution is:

$$P(x) = \frac{\alpha\beta^{\alpha}}{x^{\alpha+1}} \qquad (1)$$

where $0 < \alpha < 2$.

The parameter $\alpha$ is known as the tail index, and $\beta$ represents the smallest possible value of the random variable. As $\alpha$ decreases, the tail of the distribution becomes heavier.

### 3.2. Interference model

The interference model includes three key factors: wireless propagation environment, signals from active users, and background noise.

Given two cells $C_i$ and $C_j$, the number of active users in each cell is $N_i$ and $N_j$. User $k$ is power controlled by its base station $i$, and is at distance $d_{k,i}$ from $i$. The propagation loss in cell $C_i$ is generally modeled as:

$$L_{k,i} = d_{k,i}^{-l} \cdot 10^{\xi_{k,i}/10} \qquad (2)$$

where $\xi_{k,i}$ is a random variable that models the shadowing effect between user $k$ and base station $i$, typically following a zero-mean Gaussian distribution with standard deviation $\eta$. $l$ is the path loss constant.

We assume that the shadowing process is slow enough so that it can always be compensated by the power control. A fast power control mechanism is also assumed so that we can simplify the stochastic interference process without involving multi-path fading in the analysis.

The normalized interference caused by user $k$ for cell $C_j$ is given by:

$$I_{k,i}^{(k)} = \frac{d_{k,j}^{-l} \cdot 10^{\xi_{k,j}/10}}{d_{k,i}^{-l} \cdot 10^{\xi_{k,i}/10}} \quad (3)$$

Thus, the interference for cell $C_j$ caused by all active users in cell $C_i$ can be calculated [2] using:

$$I_{i,j} = e^{(\eta \cdot ln(10)/10)^2} \cdot N_i \cdot \frac{1}{A_i} \cdot \int\int_{C_i} (\frac{d_{k,i}}{d_{k,j}})^l \cdot dA \quad (4)$$

where $A_i$ is the area of cell $C_i$. Assuming users are uniformly distributed in each cell, Equation 4 is simplified to:

$$I_{i,j} = \rho \cdot \sum_{k \in C_i} f_{k,j} \cdot N_i \quad (5)$$

where $\rho = e^{(\eta \cdot ln(10)/10)^2}$, and $f_{k,j} = \int\int_{C_i} (\frac{d_{k,i}}{d_{k,j}})^l \cdot dA$. $f_{k,j}$ represents the impact of interference caused by each active user. It can be seen that the inter-cell interference experienced by cell $C_j$ depends on the number of active users in cell $C_i$ and their corresponding interference.

Unlike prior studies that model the network traffic using a simple traffic activity factor, we use an ON/OFF stochastic process $X(t)$ for our traffic model, as introduced in Section 3.1. Therefore, the interference is a function of time:

$$I_{i,j}(t) = \rho \cdot \sum_{k \in C_i} f_{k,j} \cdot X_{k,i}(t) \quad (6)$$

The total inter-cell interference is given by:

$$I_j^{inter}(t) = \rho \cdot \sum_{C_i \in C, C_i \neq C_j} \sum_{k \in C_i} f_{k,j} \cdot X_{k,i}(t) \quad (7)$$

where $C$ is the set of all neighboring cells of cell $C_j$.

From Equation 3, the intra-cell interference for a specific user $U$ in cell $C_j$ is given by:

$$I_j^{intra}(t) = \sum_{k \in C_j, k \neq U} X_{k,j}(t) \quad (8)$$

### 3.3 Stochastic system capacity

The system capacity of a CDMA network is determined based on the Signal-to-Interference-plus-Noise-Ratio (SINR). Given an active user $U$ in cell $C_j$, the SINR for user $U$ is given by:

$$r(t) = \frac{1}{R/W \cdot (I_j^{(intra)}(t) + I_j^{(inter)}(t)) + N_0/P} \quad (9)$$

where $N_0$ is the variance of white Gaussian noise, and $P$ is the mean transmission power. $R/W$ is the ratio of rate and bandwidth in the system. Substituting Equation 7 and Equation 8 into Equation 9, we have:

$$r(t) = \frac{W/R}{N_0/P + Y + Z} \quad (10)$$

where

$$Y = \sum_{l \in C_j, k \neq U} X_{k,j}(t) \quad (11)$$

and

$$Z = \sum_{C_i \in C, C_i \neq C_j} \sum_{k \in C_i} f_{k,j} \cdot \rho \cdot X_{k,i}(t). \quad (12)$$

To meet the Quality of Service (QoS) requirements, the SINR must be maintained above a certain threshold. Given the threshold $\Gamma$ and the number of active users $N_j$, we have:

$$\sum_{k \in C_j} X_{k,j}(t) \cdot (N_j - 1)/N_j \leq W/R \cdot (1/\Gamma - N_0/P) - \sum_{C_i \in C, C_i \neq C_j} \sum_{k \in C_i} f_{k,j} \cdot \rho \cdot X_{k,i}(t) \quad (13)$$

Effective capacity refers to the average number of active users that the system can accommodate based on the QoS requirements. It is determined from the SINR constraints for the users. The evolution of this constraint limits the traffic processes in the home cell so that the aggregate capacity demand is below the available capacity provided. The available capacity is a time-varying process, which depends on inter-cell interference and system parameters (such as bandwidth and transmission rate).

Effective capacity is determined by the available capacity process and the traffic demand process. The available capacity increases when inter-cell interference decreases, and thus the system can accommodate more users. The traffic process in the home cell could be an independent random process. Therefore, effective capacity also depends on interactions of these two random processes. Our study shows that not only the long term distribution of these random processes impacts the effective capacity, but also the temporal correlation and frequency of the value-changing function impact the effective capacity.

## 4 System analysis

In this section, we study the effective capacity by analyzing the outage probability.

Equation 13 allows us to separate the impacts of traffic generated by users in the home cell from those for traffic generated by neighboring cells. This separation facilitates our study on effect of user behavior, namely traffic stochastic characteristics, user distribution and density.

The left-hand side of Equation 13, and the second item on the right-hand side, are superpositions of many ON/OFF processes, while the channel fading process can be seen as "rewards" for each ON-period. Let $A(t)$ be the aggregate stochastic process on the left side of Equation 13, and let $C(t)$ be the aggregate stochastic process on the right side of Equation 13. The outage probability is the probability that the traffic demands $A(t)$ exceed the available capacity $C(t)$.

Given an ON/OFF process $X(t)$, $X(t) = 1$ means that there is a call active at time $t$. It can be deemed as a reward at time $t$. Since each user generates its own call sequence, it has its own reward. At time $t$, the superposition process $A(t)$, or cumulative call count, is $\sum_{i=1}^{M} X_i(t)$, where $M$ is the total number of users counted in the process. The aggregate cumulative call count in time interval $[0, T]$ is given by:

$$X_M(T) = \int_0^T (\sum_{i=1}^{M} X_i(t)) \cdot dt \tag{14}$$

This is an aggregate stochastic process. It is proved in [10] that the process stochastically behaves in accordance with the following theorem:

**Theorem 4.1** *For large $M$ and $T$, the aggregate cumulative call process behaves statistically like*

$$TM \cdot \frac{\mu_1}{\mu_1 + \mu_2} \cdot t + T^H \sqrt{M} \sigma_{lim} B_H(t) \tag{15}$$

*where* $H = \frac{3-\alpha_{min}}{2}$, $\sigma_{lim}^2 = \frac{2\mu_{max}^2 a_{min}}{(\mu_1+\mu_2)^3 \Gamma(4-\alpha_{min})}$ *with* $\alpha_{min} = \min(\alpha_{on}, \alpha_{off})$, $a_{min} = \beta^{\alpha_{min}} \frac{\Gamma(2-\alpha_{min})}{\alpha_{min}-1}$.

$B_H(t)$ represents fractional Brownian motion, which is the only Gaussian process with stationary increments that is self-similar. The covariance function is:

$$E(B_H(s) B_H(t)) = \frac{1}{2}(s^{2H} + t^{2H} - |s-t|^{2H}) \tag{16}$$

More precisely, Equation 15 can be expressed in the following way:

$$\lim_{T\to\infty} \lim_{M\to\infty} \frac{X_M(T) - TM\frac{\mu_1}{\mu_1+\mu_2} t}{T^H \sqrt{M}} = \sigma_{lim} B_H(t) \tag{17}$$

where the limit refers to convergence in the sense of the finite-dimensional distributions.

Now the effective capacity can be analyzed by finding outage probability under the requested threshold. For simplicity, we assume that all users have homogeneous traffic characteristics in the following analysis. It is not difficult to extend the analysis using an aggregate process for traffic with different patterns.

By moving the second item on the right side of Equation 13 to the left side, we have:

$$\sum_{k \in C_j} X_{k,j}(t) \cdot \frac{(K-1)}{K} + \sum_{C_i \in C, C_i \neq C_j} \sum_{k \in C_i} f_{i,j} \cdot \rho \cdot X_{k,i}(t) \leq W/R \cdot (1/\Gamma - N_0/P) \tag{18}$$

The right side of Equation 18 is now a constant, and the left side is a combinational process consisting of two fractional Brownian motion processes with different weights $\sigma_{lim}$. We can rewrite it as follows:

$$(\sigma_{lim}^{intra} + \sigma_{lim}^{inter}) B_H(t) \leq W/R \cdot (1/\Gamma - N_0/P) \tag{19}$$

where $\sigma_{lim}^{inter}$ is for the inter-cell aggregated process, and $\sigma_{lim}^{intra}$ is for the intra-cell aggregated process.

The outage probability is the probability that the value of the joint process on left side exceeds the constant on right side of Equation 19. We express this as:

$$\text{Prob}[(\sigma_{lim}^{intra} + \sigma_{lim}^{inter}) B_H(t) - W/R \cdot (1/\Gamma - N_0/P)] \tag{20}$$

It can be seen that the density function of $B_H(t)$ determines this probability. As the converged equivalent Hurst parameter $H$ of $B_H(t)$ is known, assume that there exists an equivalent cumulative distribution function of $B_H(t)$:

$$F_B(t) = (b/t)^{-2H} \tag{21}$$

where $b$ is a constant. Then, the outage probability is obtained:

$$P(B_H(t) > w_{lim}) = (b/w_{lim})^{2H} \tag{22}$$

where

$$w_{lim} = \frac{W/R \cdot (1/\Gamma - N_0/P)}{\sigma_{lim}^{intra} + \sigma_{lim}^{inter} \cdot \rho} \tag{23}$$

Note that the condition that the aggregate processes can be represented by fractional Brownian motion is that the number of ON/OFF processes and the rescale time interval are approximately infinite. Therefore, this outage probability can be seen as a lower bound in a heavily loaded network (i.e., many users in the home cell and in the neighboring cells). We consider this case as our performance bound.

# 5 Evaluation methodology

## 5.1 Simulation model

We use call-level simulation to investigate the impacts of traffic characteristics on the effective capacity in CDMA networks.

Our simulator consists of three modules as shown in Figure 2. The user traffic generator generates time-ordered call sequences with specified stochastic characteristics. In general, the traffic pattern follows an ON-OFF process. For simplicity, handoff traffic or traffic with different services is integrated into the traffic model.

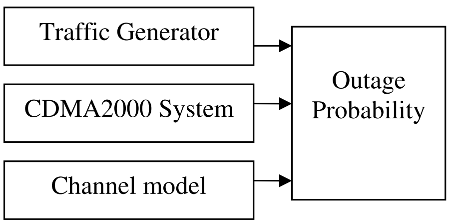


**Figure 2. Simulation Model**

A seven-cell CDMA2000 system is simulated in the system model. The user data rate is varied from 9.6 Kbps to 1.03 Mbps. A chip rate of 3.68 Mcps is used on a 5 MHz reverse channel. Fast power control mechanism is assumed.

The wireless channel model provides a channel fading model and a user location information. The channel fading model is based on path loss with log-normal shadowing, which uses an autoregressive (AR) model. User information includes mobility pattern and location information for each user.

Table 1 summarizes the related system parameters used in our experiments.

**Table 1. Parameter settings**

| Factor | Value |
|---|---|
| Path loss coefficient | 4 |
| Variance in shadow fading | 3dB |
| System processing gain | 15.1dB |
| SINR threshold | 9.2dB |
| $P/N_0$ | 19dB |

## 5.2 Experimental design

Three sets of experiments are conducted to investigate the system performance with different stochastic parameters and statistical distributions. The outage probability is used as the primary performance metric in all experiments.

The first set of experiments uses Pareto distribution for both active and idle periods. $H_1$ is the Hurst parameter used for the active period distribution, while $H_2$ is the Hurst parameter used for the idle period distribution. There are 60 users in the home cell and a total of 240 users in the 6 neighboring cells. Each user generates 10,000 data service calls. We then explore the impact of the Hurst parameter on the system performance.

The second set of experiments evaluates the effects of different statistical distributions. We consider four groups of distributions for ON-OFF periods: Pareto-Pareto, Exponential-Pareto, Deterministic-Pareto, and Exponential-Exponential.

The third set of experiments studies the impact of correlation. In the experiments, we first generate two long-range dependent (LRD) traffic processes using a Hurst parameter $H = 0.8$ and $H = 0.9$. We generate another two traffic processes with little or no correlation structure. We do so by shuffling the two original processes separately into random order. This shuffling preserves the mean and variance of the original processes, but changes the correlation structure. The number of users in the home cell of an active user is varied from 50 to 90, while the number of users in neighboring cells is fixed at 240.

Table 2 summarizes the factors and their levels.

**Table 2. Traffic factors and levels**

| Factors | | Levels |
|---|---|---|
| ON | Distributions | Deterministic, Exponential, Pareto |
| OFF | Distributions | Deterministic, Exponential, Pareto |
| $H_1$ | | 0.6 to 0.9 in steps of 0.05 |
| $H_2$ | | 0.7, 0.75, 0.8 |

# 6 Simulation results

## 6.1 Effect of Hurst parameter

Figure 3 shows the impact of the Hurst parameter. The horizontal axis shows the Hurst parameter for the call ON (active) period, while the vertical axis represents the outage probability. Three lines are shown on the graph, representing different Hurst values for the OFF (idle) period.

Figure 3 shows that the outage probability increases when $H_1$ increases and $H_2$ decreases. These results are

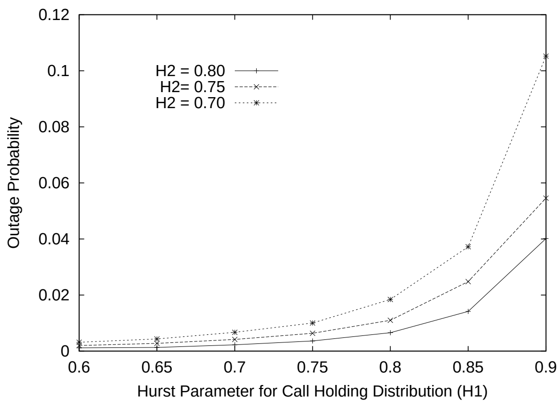


**Figure 3. Outage Probability versus Hurst Parameter**

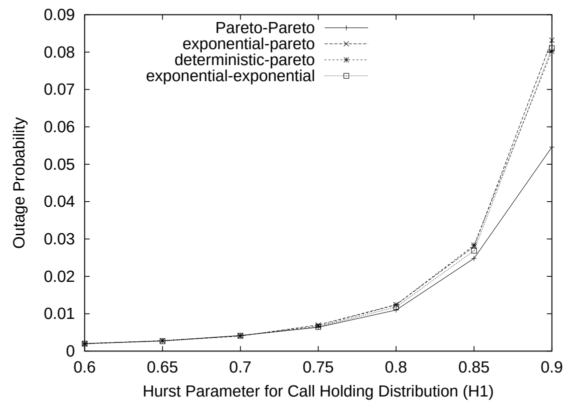


**Figure 4. Outage Probability versus Traffic Distribution**

understandable, since increasing $H_1$ or decreasing $H_2$ implies higher traffic load level in the network.

We compare our simulation results with the results calculated using traffic activity factors. Similar to the approach in [1, 3], we estimate the available capacity using:

$$N_j \leq \frac{W}{a \cdot R} \cdot (1/\Gamma - N_0/P) + 1 - \rho \cdot \sum_{C_i \in C, C_i \neq C_j} f_{i,j} \cdot N_i \tag{24}$$

where $a = \frac{E[T_{on}]}{E[T_{on}]+E[T_{off}]}$ [4]. The outage probability is then calculated based on this constant capacity. Traffic is modeled using a stochastic process in the calculation.

Table 3 shows the effective capacity (EC) calculated using Equation 24. It can be found that for each traffic load level, the estimated capacity using the activity factors approach is large enough to accommodate the 60 users. Therefore, the outage probability is zero for all tested load levels. Obviously, for data traffic, the traditional method overestimates the effective capacity in the network.

**Table 3. Estimated capacity using traffic activity factor**

| $H_2$ | 0.75 | | | | | | |
|---|---|---|---|---|---|---|---|
| $H_1$ | 0.90 | 0.85 | 0.80 | 0.75 | 0.70 | 0.65 | 0.60 |
| EC | 89 | 123 | 151 | 176 | 198 | 218 | 235 |

This result clearly illustrates that the traffic activity factor is not appropriate to reflect all impacts from traffic. While the activity factor for voice traffic is usually set to 0.375, choosing an activity factor for data traffic is not straightforward. For the foregoing comparison, we use the approach in [4] to calculate the activity factor.

## 6.2 Effect of traffic distribution

Figure 4 shows impacts from different distributions for data calls. For the Pareto-Pareto combination, $H_1$ is varied from 0.6 to 0.9, while $H_2$ is fixed at 0.75. Other distribution combinations preserve the same mean holding time and the same mean idle time as those used in the Pareto-Pareto combination.

Figure 4 shows that when the ON/OFF processes follow the Pareto distribution, the network usually has lower outage probability. This phenomenon is more evident with increased network load level. The other three distribution combinations perform closely.

This phenomenon happens because the Hurst parameter affects the mean of the aggregated traffic. Theoretical analysis in Section 4 illustrates that the Hurst parameter of superposition of many ON/OFF processes is dominated by the heavier of the two tail parameters for the ON and OFF processes. With stronger correlations in the aggregate process, "Pareto-Pareto" case has lower mean traffic load than the others. Therefore, it has lower outage probability. The aggregate processes formed by other cases have little correlation because the aggregate process is weakened by the non-correlated call holding process. Therefore they have almost the same mean load. At the low end of the x-axis, they converge to the same performance.

## 6.3 Effect of correlations

Figure 5 shows the impact of process correlation.

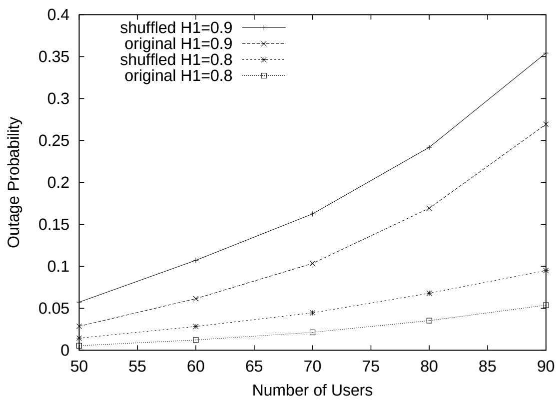


**Figure 5. Outage Probability versus Traffic Correlations**

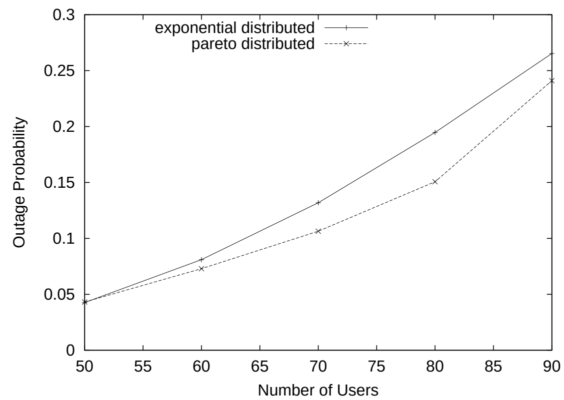


**Figure 6. Outage Probability versus Number of Users**

Two main observations are evident on the graph. First, the outage probability increases with more users. Second, the correlation structure affects system performance significantly. Traffic exhibiting long-range dependence always gains higher effective capacity than that with little correlation. The performance difference also depends on the network parameters and the traffic patterns.

Different from voice traffic, the long-range dependence property of data traffic introduces research issues on evaluating effective capacity in CDMA networks.

The LRD property of data traffic poses new challenges. In Figure 6, we illustrate the different behaviors that the correlated traffic and non-correlated traffic show under the same user activity models. To compare the fairness to the users, we assign these traffics to each group of users in network with total 240 users in their neighbors. The correlated traffic is generated using the Pareto distribution with the Hurst parameter of 0.9 for the ON process and 0.8 for the OFF process. The non-correlated traffic is generated using the exponential distribution with the same mean ON/OFF periods as those for the Pareto distributed traffic. The graph presents outage probability as a function of the number of users in the home cell. Again, it shows that correlated traffic has better performance. This implies an appropriate traffic control policy may be more efficient when considering the difference of the traffic and the integrated effect of traffic characteristics.

## 7 Conclusions

In this paper, a comprehensive system model is built to evaluate system performance for data services in CDMA networks. Unlike traditional analyses, we model both system capacity and traffic demands using stochastic processes.

Call-level simulation is conducted based on the proposed analytical model. The simulation results show that traffic stochastic characteristics can affect the system performance significantly. Traffic correlation is beneficial for the same system load level. Moreover, the simulation results illustrate that using an activity factor to model the traffic process can cause capacity overestimation.

Future work includes more accurate models for channel fading, user mobility, and dynamic traffic control protocols.

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