On Effective Capacity in Time-Varying Wireless Networks

Hongxia Sun **Carey Williamson**
Department of Computer Science
University of Calgary
Calgary, AB, Canada T2N 1N4
Email: {sunh,carey}@cpsc.ucalgary.ca

Abstract

In some networks, the physical transmission capacity can vary unpredictably with time. This stochastic variation may degrade system performance, reducing the effective capacity of the network. Traditional performance modeling ignoring this variation may overestimate system performance. In this paper, we investigate the impacts from stochastic capacity characteristics, using simulation. We explore the effects of selected parameters, including the mean, variance, frequency, and correlation of capacity variation. The simulation results show that higher frequency and higher variance capacity changes have adverse impacts on effective capacity. However, correlations in the capacity value process or the traffic arrival process are beneficial. In general, the overall system performance in a stochastic capacity network depends on the interactions between traffic and capacity, and the relative time scales of these processes.

Keywords: Networks, Stochastic Capacity, Simulation, Blocking Probability

1 Introduction

In many computer systems, the available system capacity can vary unpredictably with time. Two simple examples are Web server farms and grid computing centers, where the failure of a computing node can result in the loss of jobs from the system. Furthermore, the temporary removal of computing nodes from the system (e.g., planned maintenance), even if scheduled in advance to avoid job losses, has an impact on the queueing delay and blocking rate experienced by arriving jobs.

Many other examples of stochastic capacity systems arise in computer networks [3, 15, 20]. For example, in a reservation-based network with multiple priority levels, high priority calls such as emergency services take precedence over ordinary traffic. The network capacity available for low priority traffic thus varies with time based on high priority traffic demands. In multi-hop wireless ad hoc networks, system capacity (e.g., throughput) is strongly dependent on the number of hops in the routing path [13]. As nodes move and routes change, the effective system capacity also varies. In cellular networks, capacity variation arises from the mobility of users (e.g., handoffs [4]), and the time-varying characteristics of the wireless propagation environment [19]. This phenomenon applies to wireless LANs and CDMA systems.

Investigating performance in such systems requires considering not only the input traffic demands but also the underlying characteristics of the capacity variation process. The capacity variation may even depend on the interactions between the traffic and the system itself. For example, in a CDMA system, there is a "soft capacity" limit for active calls that is determined from intra-cell and inter-cell interference [2]. This dynamic "soft limit", rather than the number of physical channel elements, determines the instantaneous capacity of the system.

Networks with time-varying capacity tend to have higher call blocking rates and higher outage probabilities than traditional fixed-capacity networks. In other words, the "effective capacity" is somehow lower.

Evaluating the performance of stochastic capacity networks requires the combination of channel-level models for capacity variation and user-level models for subscriber traffic. In such a system, capacity is a stochastic process rather than a fixed value. The performance analysis of such networks is of interest since it may yield deeper insights into traffic control and network design issues.

In this paper, we use simulation to study the impacts of the capacity variation process on system performance. We focus on the capacity value process, the capacity timing process, and their interactions with the offered traffic. Our simulation models allow general distributions for the traffic and capacity models.

Our paper makes two main contributions. First, we present a simulation framework for the performance analysis of stochastic capacity networks. This model provides greater flexibility to investigate impacts from stochastic system characteristics than is possible with a Markov capacity model. Second, we explore the impacts of selected parameters in the stochastic capacity process, including the mean, variance, frequency, and correlation of the capacity variation process. The simulation results show that the frequency and variance of the capacity variation process have the most pronounced (adverse) impact on system performance, while correlation in the capacity variation process is actually beneficial.

The rest of this paper is organized as follows. Section 2 reviews prior related work. Section 3 presents our methodology for studying stochastic capacity networks. Experimental methodology is provided in Section 4, with simulation results presented in Section 5. Section 6 concludes the paper.

2 Related Work

Our work draws upon ideas from *performability* modeling [14, 21], which takes into account both performance and availability of a system. Traditional performance modeling ignores stochastic variation of a system's shared resources, and may overestimate system performance. Conversely, availability analysis tends to be conservative. Performability modeling can provide a more complete picture for system performance analysis.

Trivedi *et al.* [22] give an example of performability modeling in wireless communication systems. The authors use a hierarchical composite Markov chain to obtain a loss formula for a system with channel failures. Two kinds of traffic, new call arrivals and handoff call arrivals, are considered. This model is also extended to a TDMA system consisting of base repeaters with a control channel.

A common assumption in most of these dimensioning models is that the stochastic processes (e.g., new calls, handoff calls, failure events, repair time) are memoryless (i.e., obey exponential distributions). However, many processes in communication networks, such as data call arrivals and the call handoff process, exhibit non-exponential distributions.

Stochastic Petri Nets have been used to model non-exponential characteristics [7, 11, 18]. Trivedi *et al.* [8, 23] provide examples of performance modeling by extending a Markov Chain model to a Markov Regenerative Process, where handoff traffic is modeled with a general distribution. For analytical tractability of the performability model, at most one non-exponential distribution is allowed in the model.

The network capacity process may be even more complicated since it is affected by traffic, channel assignment, user mobility, and routing protocols. A Markov process may be inadequate to describe the capacity process, and may introduce modeling errors. In our study, we use a flexible model to reflect general stochastic characteristics of capacity. Stochastic characteristics of the capacity timing process are also considered.

Some papers in the literature consider capacity variation in wireless networks [6, 22]. An example is the dynamic control strategy where call admission decisions are made based on instantaneous SINR (Signal to Noise plus Interference Ratio) [6]. However, these approaches are not able to study effects from temporal correlations and from the interactions between traffic characteristics and the network capacity. Grossglauser *et al.* [12] considered the impacts of bandwidth fluctuations over multiple time scales. However, their work focuses solely on admission control. The performance was analyzed using a decomposition approach.

The queueing theory literature has studied queues with time-varying load or capacity [1, 10, 17]. To complement and extend these theoretical studies, we use simulation to investigate the effects of different stochastic capacity parameters on the effective capacity of telecommunication networks.

In our study, we build traffic and capacity models for a general system. The capacity model considers characteristics such as mean, variance, and correlation structure. Therefore, our results provide a broad view of capacity impacts, in terms of distributional and temporal characteristics. The interactions between traffic and capacity are also studied.

3 System Model and Assumptions

3.1 Overview

Figure 1 provides an overview of our methodology for studying stochastic capacity networks. First, we formalize the stochastic characteristics of capacity. We model the network, the traffic, and the capacity using stochastic processes such as a Markov process, or a semi-Markov process. Next, we combine these processes to form the stochastic system. We build a simulation environment to investigate the call block-

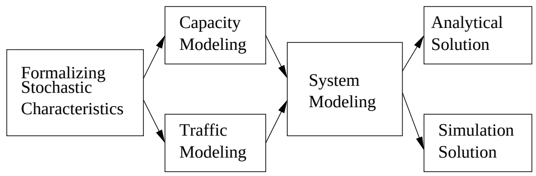

Figure 1. Overview of Modeling Methodology

ing performance for a wide range of network traffic and capacity characteristics.

The simulation results lead to general observations about important network properties. We discuss the impacts on call blocking performance from stochastic characteristics, such as the mean, variance, and correlation structure of the capacity process.

We study not only the impacts from the capacity process, but also from the interactions between capacity and traffic processes. The results show that traffic and capacity characteristics both affect overall system performance.

3.2 Capacity Model

As stated previously, the capacity of a network may vary randomly with time because of stochastic traffic effects, the channel status, and the protocols used for bandwidth allocation, channel assignment, power control, and mobility management. In this section, we develop an abstract model for these stochastic capacity characteristics.

For flexibility and generality, we propose a novel two-part model to describe capacity variations. Two independent random processes characterize the capacity evolution. A *timing process* determines when the next capacity change occurs, while a *value process* determines the next capacity value attained.

In the following, we construct our stochastic capacity model. A semi-Markov model [5] is built to represent the timing and value processes.

In our model, we assume that the capacity value process is insensitive to the sojourn time in each state. Given this independence, we can study separately the impacts from capacity changes with respect to their duration or value. As these two parameters are strongly related to the system state and control strategies, it is possible to construct such a capacity model from real system parameters. Dynamic channel assignment is one example for this kind of process: assignment decisions may occur at times determined by a general distribution, while the number of channels may be independent of the state duration.

Suppose that the system has discrete changes in capacity. Let $C(t)$ denote the capacity value at time t. The set $\{t_i\}$ represents the instants of state transitions for the capacity value process.

3.3 Traffic Model

Different traffic types exhibit different stochastic properties [9, 16]. In our model, network traffic consists of call arrivals. Mathematically, this process is described as a point process. Another process that affects traffic characteristics is the holding time for a call. In traditional traffic models, the holding times are exponentially distributed and i.i.d. In our work, we also allow this process to have a general (non-exponential) distribution.

The arrivals and departures form the traffic process in our system. It is an occupancy process in the sense that it represents the number of simultaneously active calls in the network. We describe this traffic process as an occupancy function, where $N(t)$ denotes the number of active calls at time t.

A simple example of a traffic model is a Poisson process, in which the interarrival times are exponentially distributed with mean $\frac{1}{\lambda}$, and holding times are exponential distributed with mean $\frac{1}{\mu}$. In a non-blocking network, the corresponding occupancy process $N(t)$ satisfies:

$$P\{N(t) = n\} = \frac{(\frac{\lambda}{\mu})^n}{n!}\, e^{-\frac{\lambda}{\mu}} \quad (1)$$

4 Experimental Methodology

In the rest of this paper, we investigate the impacts of time-varying capacity on network performance, using a call-level simulation study. This section describes the experimental setup for our simulation study, while Section 5 presents the simulation results.

4.1 Simulation Model

Our work is carried out using call-level simulation. The two inputs provided to the simulation are a call workload file and a network capacity file. These correspond to the traffic process and the stochastic capacity process described in Section 3.

The call workload file is a time-ordered sequence of call arrival events. Each call specifies its source node, destination node, arrival time, and duration. Each call requires one unit of network capacity (bandwidth). Workload files are generated using the call workload models indicated in the top part of Table 1. We use

Table 1. Factors in Simulations

Factor		Levels
Stochastic Traffic	Arrival process	Poisson, Self-similar
	Holding time	Exponential, Constant
Stochastic Capacity	Timing process	Deterministic, Exponential, Self-similar
	Value process	Normal

workload files with 100,000 calls. We consider this trace length adequate to highlight performance differences among the different stochastic characteristics evaluated.

The network capacity file is a time-ordered sequence of capacity change events. Capacity files are generated using the models indicated in the lower part of Table 1. We use capacity files with 10,000 capacity change events. In some simulations, only the initial portion of the capacity file is needed, depending on the frequency of capacity changes being modeled.

4.2 Experimental Design and Metrics

Table 2 shows the workload parameters and levels used in our simulation experiments. We explore the impact of different stochastic parameters as well as different statistical distributions on the call-level performance, under a broad range of assumptions about the network capacity variation.

There are two QoS related performance metrics in stochastic capacity networks, namely blocking probability and outage probability. In our simulation, the primary performance metric is the call blocking probability, which characterizes the user-perceived performance. This metric implicitly reflects the effective capacity in such systems, since higher effective capacity corresponds to lower call blocking rates. Low call blocking rates (e.g., 2% or less) are desirable in commercial systems.

5 Simulation Results

5.1 Effects of Capacity Value Process

Figure 2 provides an overview of our simulation results. In this graph, the call blocking rate is plotted versus the offered load in Erlangs. These simulation results represent the average (and 95% confidence intervals) from 10 different simulation runs each with 100,000 calls. The call arrival process is Poisson, and the call holding times are exponentially-distributed with a mean of 30 seconds. The network capacity varies stochastically, with a capacity change every 120

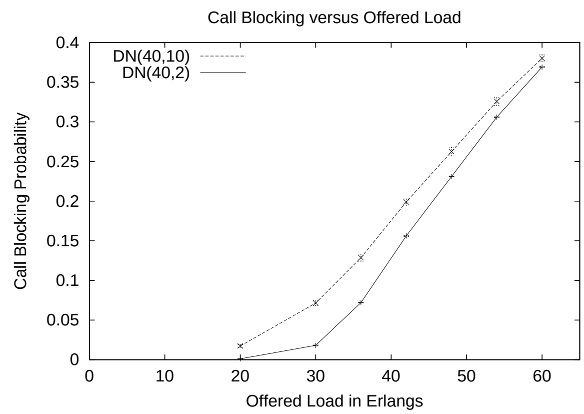

Figure 2. Blocking Rate versus Offered Load

seconds. The capacity (in calls) is drawn from a Normal distribution with a mean of 40, and a standard deviation of either 2 (lower line in Figure 2) or 10 (upper line). We use the notation $DN(X, Y)$ to denote that the network capacity changes on a deterministic (D) schedule, with the capacity value drawn from a Normal distribution $N(X, Y)$ with mean X and standard deviation Y.

Figure 2 shows that the call blocking rate increases with offered load, as expected. Call blocking is negligible at or below a load of 20 Erlangs, especially when the capacity variation is low. Higher variation in the capacity value process leads to higher call blocking. When the offered load is 30 Erlangs (75% average load), call blocking is noticeable, and the influence of the variance of the capacity process is more pronounced. As the network approaches saturation, higher variation in capacity leads to more blocked calls. Under overload (average load exceeding 40 Erlangs), the call blocking rates are excessively high (e.g., exceeding 10%), and the impact of capacity variation is less pronounced.

Next, we vary the frequency of capacity changes in the network, to study its effect on the blocking performance. We also change the mean and the variance of the capacity value process.

Figure 3 shows the simulation results for three dif-

Table 2. Workload Parameters in Simulations

Parameter		Level
Call arrival rate (per sec)		0.1, 1.0
Mean holding time (sec)		30
Time between capacity changes (sec)		10, 15, 30, 60, 120
Capacity value (calls)	Mean	30, 40, 50
	Variance	2, 5, 10
Long-range dependence (H)		0.5, 0.7, 0.9

ferent values of mean capacity (30, 40, and 50 calls), while Figure 4 shows the results for low, medium, and high variance in the capacity value process. For these results, the network capacity values are drawn from a Normal distribution with the indicated mean and standard deviation.

In both of these plots, the horizontal axis represents the time between capacity changes in network (i.e., the inverse of the frequency of capacity changes). The capacity changes exactly every T seconds, where T is indicated along the axis. The left end of the axis represents high frequency changes (every 10 seconds), while the right end represents low frequency changes (every 120 seconds). The mean call holding time is 30 seconds with an average Poisson arrival rate of 1 call per second (a load of 30 Erlangs).

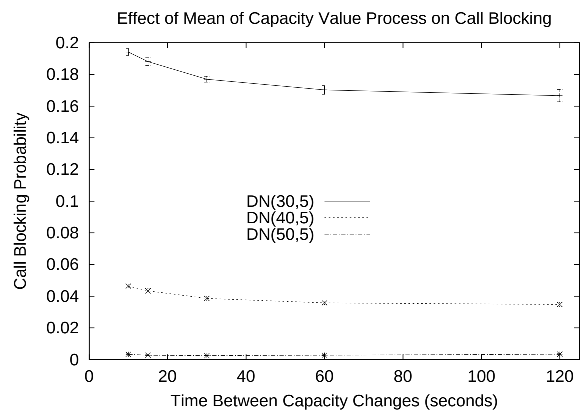

Figure 3. Effect of Capacity Value Mean

Figure 3 and Figure 4 together illustrate several observations. First, the larger the mean capacity is, the lower the blocking rate is (see Figure 3). This result is obvious. Second, higher variance in the capacity value process causes higher call blocking (see Figure 4). Again, this result is fairly obvious. Third, the frequency of capacity changes has a noticable impact on call blocking when the load is high (the DN(30,5) case in Figure 3) or when there is high variance in the capacity process (the DN(40,10) case in Figure 4).

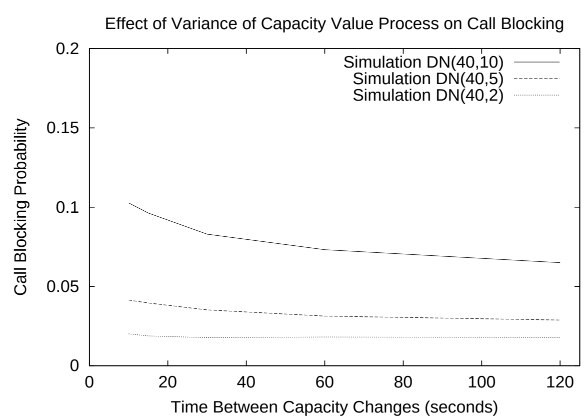

Figure 4. Effect of Capacity Value Variance

These results show that the effective capacity of a stochastic capacity system is lower than that in a fixed capacity system. The reduction in effective capacity is more acute when the capacity is highly variable. Higher variability could arise from higher variance in the capacity value process, higher frequency capacity changes, or both. These observations fit the general expectations.

Figure 5 shows the impact of the distribution used for the capacity value process. Three distributions are considered, all with a mean of 40 and a standard deviation of 5. The first is a Normal distribution DN(40,5). The second is a uniform distribution between 31 and 49 (inclusive), denoted DU(31,49). The third is a trimodal distribution DT(33,40,47) with 40 as the mode (50% of the time), and two other values

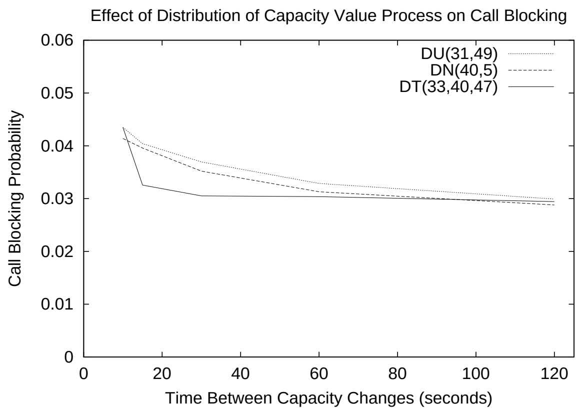

Figure 5. Effect of Capacity Value Distribution

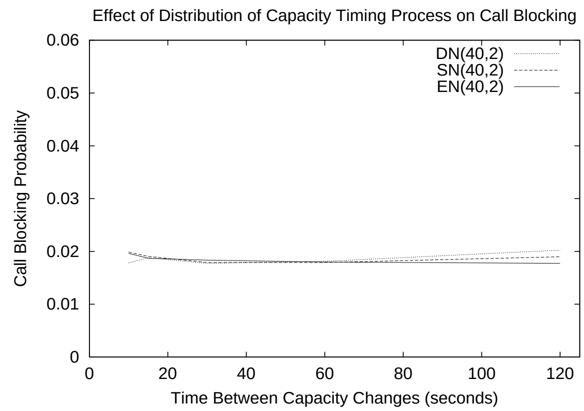

Figure 6. Effect of Timing of Capacity Changes

(33 and 47) each occurring 25% of the time. All simulations use the same traffic workload (30 Erlangs), and deterministic timing for capacity changes.

Figure 5 shows that different statistical distributions produce different results. This is because the capacity process is composed of two processes: the value process and the timing process. The joint stochastic capacity process does not necessarily have the same equivalent mean when the distribution changes, even though the timing process is the same and the capacity values have the same mean and variance. The influence of the distribution is small though, compared to that of the mean and the variance.

5.2 Effects of Capacity Timing Process

Figure 6 shows the effect of the capacity timing process on the blocking performance. We consider three different distribution models for the timing between capacity change events: Deterministic, Exponential, and Self-Similar. The Deterministic model (D) has a capacity change event every T seconds. The Exponential model (E) has capacity change events at random times, following a Poisson process. The time between capacity change events is exponentially distributed, with a mean of T seconds. The Self-Similar model (S) assumes that capacity change events occur in a bursty fashion, similar to a self-similar (fractal) process. The mean time between capacity change events is T seconds. All results use a Normal(40,2) distribution for the network capacity value process.

Figure 6 shows that the distribution used for the capacity timing process has negligible impact on the call blocking performance. This observation is consistent with the underlying theory: the steady-state probability of the semi-Markov process is insensitive to the high order statistics of the state sojourn times [5]. Here, the timing structure of capacity changes determines the sojourn times for the semi-Markov capacity model. Therefore, only the mean sojourn time matters, not the distribution. This property simplifies our study of the capacity timing process, which is Deterministic in all remaining experiments.

5.3 Effect of Correlations

Figure 7 shows the effects of correlations in the capacity value process. We generate a capacity value process with deterministic timing structure, but with long-range dependence (LRD) in the capacity value process. That is, the process exhibits both short-range and long-range correlations in the capacity values, with the long-range correlations decaying hyperbolically as in a self-similar process. We generate this capacity process using a Hurst parameter $H = 0.9$, to represent a high degree of LRD. To study the impact of the correlations, we generate a second capacity value process with little or no correlation structure. We do so by shuffling the capacity value trace into random order. This shuffling preserves the mean and variance of the capacity value process, but changes the correlation structure.

Figure 7 shows results from simulations with these two processes. We find that correlation in the capacity value process is beneficial: the call blocking rates for the correlated capacity value process are lower than those for the shuffled trace, suggesting that the correlated trace represents a larger effective capacity.

The difference is most pronounced for low frequency capacity changes, where the blocking rate differs by almost a factor of two. This difference can be explained based on the interactions with the traf-

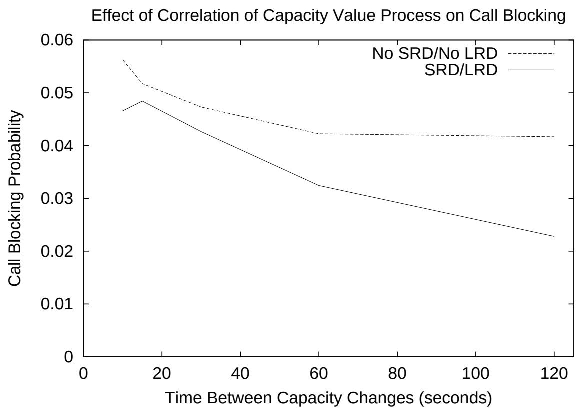

Figure 7. Effect of Capacity Correlations

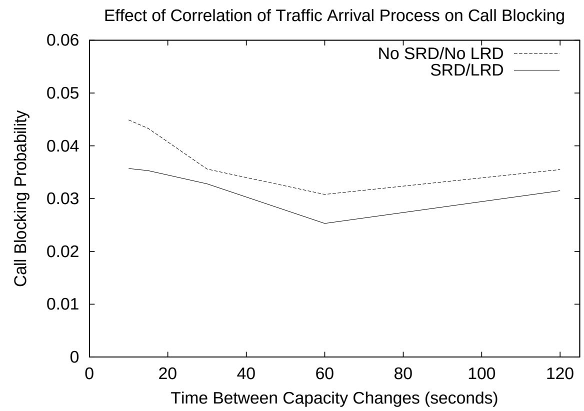

Figure 8. Effect of Traffic Correlations

fic process. Because correlated capacity values produce more gradual changes in capacity, the network is better able to serve the arriving traffic. This relates to the relative time scales of variations in traffic and capacity. Later in the paper, we will use R to represent the ratio of traffic arrival events per capacity change event, and show how effective capacity varies as a function of R.

From the simulation results, we see that capacity variation interacts with the traffic process itself. We thus continue our study of correlation effects by considering correlations in the traffic process as well.

We first consider traffic correlations in isolation, assuming an uncorrelated capacity value process, namely DN(40,5). We generate a bursty self-similar traffic arrival process from a synthetically-generated LRD count process with $H = 0.9$, and use this as our first traffic scenario. The second traffic scenario is generated from the first by randomly shuffling the (correlated) inter-arrival times used in the trace, but preserving the order and durations of the calls. Both scenarios offer the same average load (30 Erlangs), but the second process has much weaker correlation structure in the arrivals than does the first process.

Figure 8 shows the simulation results for these two traffic processes. There are two main observations in this figure. First, the frequency of capacity changes impacts performance for these traffic scenarios. However, it shows non-monotonic behavior with respect to the frequency of capacity variation (a new observation). Second, the correlated traffic has a lower blocking rate.

Figure 9 demonstrates the impacts of call holding time distributions. The two traffic files have the same mean holding time, but different distributions. One has constant holding times, while the other follows an exponential distribution. The two traffic streams have exactly the same arrival processes. Four different versions of these processes are obtained by shuffling the correlated arrival sequence at different granularities. This generates four arrival processes with different correlation structure. We denote them along the x-axis from weakest to strongest. For this experiment only, network capacity is fixed (constant) at 40 calls.

Figure 9 shows that as the correlation in the traffic arrival process changes, the relative order of the two lines changes. The traffic with constant holding time (SC) has higher blocking when arrivals are weakly correlated, but call blocking drops when the degree of correlation increases. The traffic with exponential holding time (SE) has lower blocking when there are weak correlations in the arrivals. The blocking rate still drops as correlations grow stronger, but the drop is slower than that for the first traffic stream, leading to the crossover between the two lines.

We can explain this phenomenon based on the peakedness characteristics of the joint traffic process. Higher variability in holding times weakens the correlations in the occupancy process.

Table 3 shows equivalent means and standard deviations at two different correlation levels. Again, we see that the stronger the correlation is, the lower the blocking is. This means that effective capacity of the system benefits from correlations in the capacity value process and the traffic arrival process.

The foregoing results in Figure 7 and Figure 9 show that the frequency of capacity changes affects the system in two different ways: when the capacity value process is correlated, and when the traffic itself is correlated. In the first case, the favorable effect of correlated capacity is evident with low frequency capacity changes. Conversely, in the second case, frequent ca-

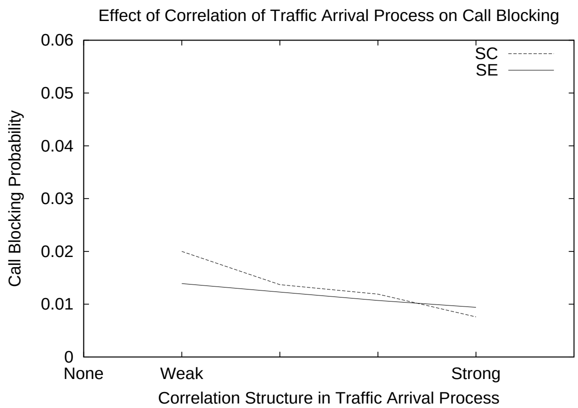

Figure 9. Effect of Traffic Correlations and Holding Time Distribution

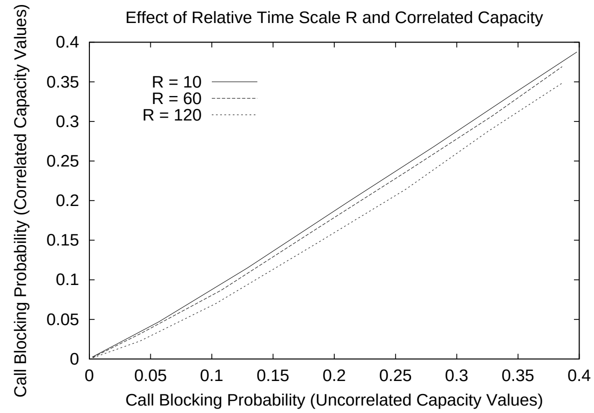

Figure 10. Effect of Relative Time Scale with Correlated Capacity

pacity changes disrupt the correlation of the traffic process, leading to higher blocking. Due to these opposing effects, the non-monotonic behavior emerges for self-similar traffic in Figure 8.

5.4 Traffic and Capacity Interactions

The foregoing experiments demonstrate subtle interactions between the traffic process and the capacity process in a stochastic capacity system. Based on these observations, we see that impacts from stochastic factors in a capacity varying system are complicated. However, the basic factors that determine system performance are rather simple. They are the equivalent means and variances of the capacity and traffic processes. Distributions and correlations can also affect the performance.

The main factor that adds complexity to our study is the stochastic transient effects. However, these effects could be large or small, depending on the relative time scales for the traffic and capacity processes.

We return to this issue in this section, using a ratio R that expresses the expected number of call arrivals per capacity change event. This metric expresses the relative time scales of the two processes. Three graphs are displayed here to illustrate the impacts on the call blocking performance.

Figure 10 illustrates the relationships between two capacity value processes. Both have exactly the same mean and variance, but one exhibits correlation in its capacity values while the other does not. Both axes represent the blocking probability for Poisson traffic, with the mean offered load varying from 20 Erlangs to 60 Erlangs. Points appearing exactly on the diagonal in the graph indicate that there is no observable performance difference between correlated and uncorrelated capacity systems.

In Figure 10, the line closest to the diagonal represents $R = 10$. Next is the one for $R = 60$. The third line is for $R = 120$. In general, the blocking performance for the two different capacity value processes deviates further from the diagonal when R increases. The larger R is, the greater is the performance difference seen with the correlated capacity model.

Figure 11 highlights the impact of R on correlated traffic processes, with mean capacity varying from 30 to 50 calls. The two traffic processes used in the figure have the same mean and variance, but different correlation structure in the arrival process. Similar to the cases shown in Figure 10, correlation improves system performance compared to the uncorrelated case. That is, the lines are all below the diagonal, illustrating lower blocking for correlated traffic than for uncorrelated traffic. However, unlike Figure 10, increasing R *reduces* the effects of traffic correlations. In particular, the line farthest from the diagonal is the case $R = 10$, and the closest one is $R = 60$.

Figure 12 is used to study the effect of R for a general traffic scenario offering a load of 30 Erlangs. The horizontal axis shows the blocking probability for the original traffic in a fixed capacity network, for which the Erlang B formula can be used. The vertical axis presents the blocking probability in a stochastic capacity network. It is clear that capacity changes cause higher blocking, since the lines all appear above the diagonal of the graph. In the simulations, we adjust the capacity change frequency to represent $R = 10$, $R = 60$, and $R = 120$. The larger R is, the less

Table 3. Equivalent Means and Standard Deviations for Traffics with two Correlation Levels

Arrivals	Traffic1(SC)		Traffic2 (SE)	
	Mean	Standard Deviation	Mean	Standard Deviation
Strongly correlated	30.3065	2.4959	30.2403	2.5886
Weakly correlated	30.3306	3.1106	30.2413	2.8826

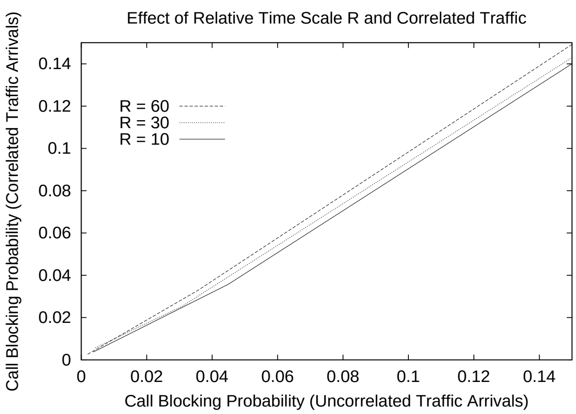

Figure 11. Effect of Relative Time Scale with Correlated Traffic

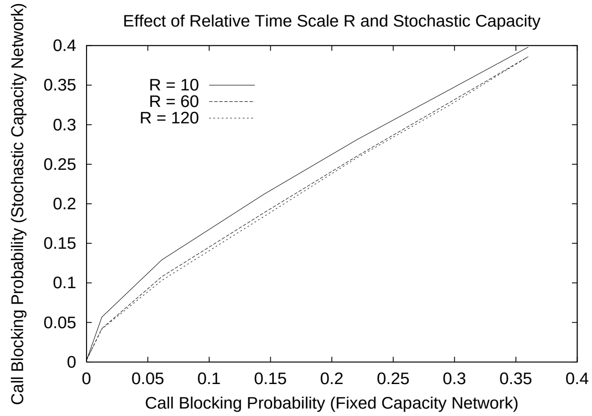

Figure 12. Effect of Relative Time Scale on Stochastic Capacity System

pronounced is the impact of the stochastic capacity characteristics.

The observations in this section indicate that when analyzing effective capacity for a stochastic capacity network, interactions among the stochastic characteristics must be considered. These effects exhibit different behaviors in different situations. The graphs illustrate the interactions between the traffic and capacity processes. These performance differences will manifest themselves especially in heavy loaded networks.

6 Summary and Conclusions

This paper studies the call-level performance of a network with stochastic capacity variation. We treat this as a performability modeling problem.

Our work explores this problem using simulation. Stochastic characteristics of the capacity process are considered in the experiments. The simulations are conducted for a broad set of traffic and capacity assumptions.

Our simulation results show that the stochastic properties of the capacity variation process strongly influence the effective capacity of the system. The most influential characteristics are the mean and the variance of the capacity value process. High variance or high frequency capacity changes reduce the effective capacity of a system, leading to higher call blocking rates. However, correlations in the capacity value process or the traffic arrival process are beneficial.

Our ongoing work is developing mathematical models to explain our observations about effective capacity in stochastic capacity networks. We are also applying our stochastic capacity models to cellular CDMA networks. Factors such as mobility, power control, and dynamic channel assignment protocols are under consideration.

References

[1] I. Adan and V. Kulkarni, "Single-server Queue with Markov Dependent Inter-arrival and Service Times", *Queueing Systems*, Vol. 45, pp. 113-134, 2003.

[2] R. Akl and A. Parvez, "Impact of Interference Model on Capacity in CDMA Cellular Networks", *Proceedings of 8th World Multi-Conference on Systemics, Cybernetics, and Informatics*, July 2004.

[3] F. Ashtiani, J. Salehi, and M. Aref, "A Flexible Dynamic Traffic Model for Reverse Link CDMA

Cellular Networks", *IEEE Transactions on Wireless Communications*, Vol. 3, No. 1, pp. 159-164, January 2004.

[4] N. Bortolini, "Handoff and Optimal Channel Assignment in Wireless Networks", *Mobile Networks and Applications*, Vol. 6, No. 6, pp. 511-524, November 2000.

[5] X. Cao, "Semi-Markov Decision Problems an Performance Sensitivity Analysis", *IEEE Transactions on Automatic Control*, Vol. 48, No. 5, pp. 758-769, 2003.

[6] F. Chiti, R. Fantacci, G. Mennuti, and D. Tarchi, "Dynamic SIR-based Admission Control Algorithm for 3G Wireless Networks", *Proceedings of International Conference on Communications* Anchorage, Alaska, May 2003.

[7] H. Choi, V. Kulkarni, and K. Trivedi, "Markov Regenerative Stochastic Petri Nets", *Performance Evaluation*, Vol. 20, No. 1-3, pp. 337-357, 1994.

[8] S. Dharmaraja, K. Trivedi, and D. Logothetis, "Performance Modeling of Wireless Networks with Generally Distributed Handoff Interarrival Times", *Computer Communications*, Vol. 126, No. 15, September 2003.

[9] A. Eckberg, "Generalized Peakedness of Teletraffic Processes", *Frontiers in Queueing: Models, Methods and Problems* (J. Dshalalow, ed.), CRC Press, Boca Raton, 1995.

[10] A. Field, P. Harrison, J. Bradley, and U. Harder, "Modeling Techniques and Tools for Computer Performance Evaluation", *Performance Evaluation*, Vol. 54 No. 2, pp. 77-206, October 2003.

[11] R. German, *Performance Analysis of Communication Systems: Modeling with Non-Markovian Stochastic Petri Nets*, Wiley, 2000.

[12] M. Grossglauser and D. Tse, "A Time-Scale Decomposition Approach to Measurement-Based Admission Control", *IEEE/ACM Transactions on Networking*, Vol. 11, No. 4, pp. 550-563, August 2003.

[13] A. Gupta, I. Wormsbecker, and C. Williamson, "Experimental Evaluation of TCP Performance in Multi-hop Wireless Ad Hoc Networks", *Proceedings of IEEE/ACM MASCOTS*, Volendam, Netherlands, pp. 3-11, October 2004.

[14] B. Haverkort, R. Marie, R. Gerardo, and K. Trivedi, *Performability Modelling: Techniques and Tools*, Wiley, New York, 2001.

[15] I. Koo, S. Bahng, and K. Kim, "Resource Reservation in Call Admission Control Schemes for CDMA Systems with Non-Uniform Traffic Distribution among Cells", *Proceedings of IEEE Vehicular Technology Conference*, Vol. 1, pp. 22-25, April 2003.

[16] S. Moln and G. Miklos, "Peakedness Characterization in Teletraffic", *PICS*, pp. 97-110, 1998.

[17] N. Nain, R. Nunez-Queija, "An M/M/1 Queue in a Semi-Markovian Environment", *Performance Evaluation Review*, Vol. 29, No. 1, pp. 268-278, June 2001.

[18] A. Puliafito, M. Scarpa, and K. Trivedi, "Petri Nets with k Simultaneously Enabled Generally Distributed Timed Transitions", *Performance Evaluation*, Vol. 32, No. 1, pp. 1-34, Feb. 1998.

[19] D. Shen and C. Ji, "Capacity Trade-offs for Heterogeneous Traffic over Large scale Fading Channels in CDMA Networks", *Proceedings of IEEE International Conference on Communications*, Vol. 6, pp. 1718-1722, 2001.

[20] J. Siwko and I. Rubin, "Connection Admission Control for Capacity-Varying Networks with Stochastic Capacity Change Times", *IEEE/ACM Transactions on Networking*, Vol. 9, No. 3, pp. 351-360, June 2001.

[21] K. Trivedi, *Probability and Statistics with Reliability, Queuing, and Computer Science Applications*, Wiley, New York, 2001.

[22] K. Trivedi, X. Ma, and S. Dharmaraja, "Performability Modeling of Wireless Communication Systems", *International Journal of Communication Systems*, Vol. 16, pp. 561-577, May 2003.

[23] W. Xie, H. Sun, Y. Cao, and K. Trivedi, "Modeling of User Perceived Web Server Availability", *Proceedings of International Conference on Communications*, Anchorage, Alaska, May 2003.