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# An SSMP Traffic Model Based on Network Measurements

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# An SSMP Traffic Model Based on Network Measurements

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**Abstract** *This paper gives an application of the knowledge of the parameters which have the greatest influence on the occupancy and the loss of a finite capacity queue. We show that it is possible to fit the decisive parameters of an SSMP(N) (Special Semi-Markov Process with N states) to those of the measured data, which has been measured on a LAN-Network located at the EPFL (Swiss Federal Institute of Technology). The SSMP is a discrete-time process and is a generalization of the Markov Modulated Poisson Process: each state is characterized by a general probability density function The example taken to verify this affirmation is the comparison of the expected cell loss in a SSMP(N)/G/1/c queue and the expected cell loss of the converted LAN traffic/G/1/c queue which can be used as model of a LAN-MAN interconnection. The comparisons show that it is possible to correctly model the slotted traffic during a short period of time.*

## 1 Introduction

In this paper, a method for fitting the most relevant network parameters, typically delay jitter and cell loss of a finite capacity queue, is applied. The chosen configuration was a Local Area Network (LAN)-Wide Area Network (WAN) interconnection. Starting from measurements made on the Swiss Federal Institute of Technology network, we noticed the slotted traffic at the Interworking Unit LAN-WAN was bursty and correlated. It was well known that such traffic streams do not form a renewal process [1]. It has been shown that it is very difficult to obtain a good statistic of the LAN traffic as described in [2] but the aim of this work is to model correctly the slotted traffic at the Interworking Unit during a short period of time. To model this traffic, an accurate stochastic process can be used: the Semi-Markov Process (SMP) [3,4]. The SMP is a Markov modulated doubly stochastic process. The Special Semi-Markov Process (SSMP), a special class of the SMP, is an equivalent of the Discrete Time Markovian Arrival Process [5]. It is very well suited to input data traffic modeling [6] as well as other services; for example, the traffic from multimedia communication, which is an aggregation of different services, can be accurately fitted to an SSMP. The statistical multiplexer is a well known and accurate model for superimposing different traffic streams. Its output process, the traffic descriptor of the multimedia communication, is an SSMP as well. The superimposed input traffic stream is an SSMP and its transition matrix is given by the Kronecker product of the transition matrices of the simple traffic stream. The number of arriving cells in each phase is given by the Kronecker sum [7]. Obviously, the state space of the multimedia traffic descriptor becomes enormous. When focusing only on the most relevant network parameters, typically delay jitter and cell loss, the state space can be drastically reduced.

## 2 Measurements and data analysis

The broadcast nature of most LANs makes the measurement process not too difficult a task. Passive collection of packets can be performed by a computer by just sensing the LAN cable while in promiscuous mode (this mode allows the workstation to peek at packets on the network without retrieving them). This allows the measurer to peek at all packets passing by and timestamp them without removing them from the network. Two approaches exist to processing the data. It can be done while collecting it (this is called the on-the-fly approach) or data can be saved to disk for analysis (this is termed retrospective analysis). If collecting packets is not difficult, problems arise afterwards in any of the two analysis approaches. Consider a computer performing the measurement. It can be a workstation or some dedicated hardware. If this computer is performing any task during measurement, then it will loose all packets that pass by while it is performing that task*. This is the main reason for having non zero packet loss rates. Whichever configuration is used, the measurer will have to perform certain tasks. Consider the on-the-fly processing approach. Data processing is directly performed while measuring and this may require heavy computations. Hence, such an approach is only valid for multi-processor hardware if loss rate has to be low. Retrospective analysis is better for the single processor measurer, since no computation will take place during measurements. However, when performing long measurements, the memory buffers will have to be periodically emptied and saved to disk. This will cause a loss rate that may be non negligible since disk operations are lengthy. In order to minimize the losses, a double-buffer technique [8] was used : a large buffer stores the time-stamped packets. When the buffer is full, another buffer is filled while the first one is being saved to disk by a low priority process. With this configuration, time stamps are as accurate as the workstation clock. The latter is usually fast enough to obtain accurate time stamping. The sole exceptions are some Sun workstations where the clock resolution is about 20 msec.

Since relying on the operating system for timestamping results in a loss of timing accuracy an improved solution involves dedicated hardware for timestamping. Such a solution has been recently introduced by Leland and Wilson [2].

### 2.1 Tcpdump

Since no hardware was available for the measurements to be performed, the use of a software measurer was decided on. The Lawrence Berkeley Laboratory of the University of California,

* Buffering packets in the I/O interface is not a solution because time stamping cannot be performed accurately

Berkeley developed such a measuring tool named *Tcpdump*. It is based on SMI's *etherfind* that was written at Lawrence Berkeley Laboratory as part of a research project to investigate and improve tcp and internet gateway performance.

Tcpdump prints out the headers of packets on a network interface that match a Boolean expression. It is very easy to filter traffic out in order to watch some specific traffic (i.e. going through a specific port, arriving at a particular host). The tcpdump distribution that is available via anonymous ftp from host `ftp.ee.lbl.gov` also contains some utilities for easier processing of the data.

The first thing to be done was to evaluate tcpdump's performance. For this purpose, a small client-server program has been written. The goal was to generate a known traffic on the network where each packet was numbered so that it was possible to tell which packet was either lost by the network or missed by tcpdump. Tcpdump proved to be quite reliable on either Ethernet or FDDI networks.

### 2.2 Measurements performed

Some of the measurements that have been conducted within the scope of this work have been stored for later use. The selected one is a 24-hour trace file of the external traffic of three laboratories of the Electrical Engineering Department (EPFL) representing an amount of approximately 50 w These measurements have been taken between August 30, 1993 8:15 am and August 31, 1993 8:15 am .

### 2.3 Arrival distribution

Part of this work consists of offering tools for basic traffic statistics computation. The metrics chosen are based on existing works [2,8,9]. Therefore, the analysis software offers the possibility of computing the statistics described below.

The most immediate metric that can be computed is the distribution of arrivals versus time, which can be computed over many time scales. Studies of this distribution show what has been pointed out in previous works [2,8,9]; that is that the traffic shows burstiness over many time scales and whatever the resolution at which computation is performed, the traffic consists of time intervals where the load is high followed by intervals where load is much lower.

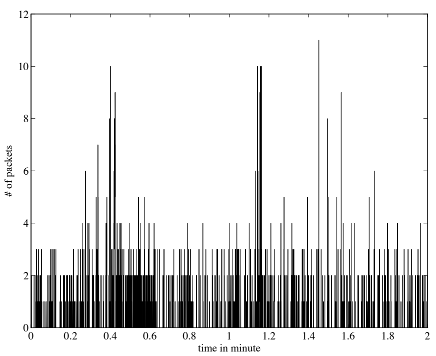


Figure 1: Arrival distribution versus time for a 2-minute portion of the 24-hour trace. Resolution is 20 ms.

As an example, figure 1 shows the arrival distribution computed over a 2-minute period in the 24-hour trace (actually between 10:25 am and 10:27 am).

### 2.4 Interarrival distribution

A more important metric is the distribution of packet interarrival time. This distribution is computed at the same resolution as the arrival distribution. It can easily be seen that a large majority of packets have a very small interarrival time. This confirms the fact that computer network traffic is very bursty, i.e. when a packet is observed going from host A to host B, then there is a very high probability that in a very short time interval, a packet going either from A to B or from B to A will be observed.

Figure 2 shows the interarrival distribution computed for a 10-minute period in the 24 hours trace (actually between 10:25 am and 10:35 am) at a resolution of 0.5 msec. The large peak that is observed between 1 and 1.5 milliseconds corresponds to the interarrival of large packets (that are an important component of the total traffic). This is deduced from their transmission time on a 10 Mbits/sec Ethernet network.

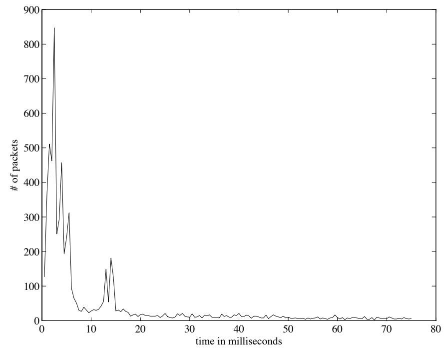


Figure 2: Interarrival distribution versus time for a 10-minute portion of the trace. Resolution is 0.5 ms.

### 2.5 Packet size distribution

The next statistic that is computed is the distribution of packet size. Figure 3 shows such a distribution computed for the whole 24-hour period of measurements. The most important characteristics is the importance of very small packets, that are mostly logins, acknowledgments and interactive session traffic. The next important component are very large packets that results from file transfers.

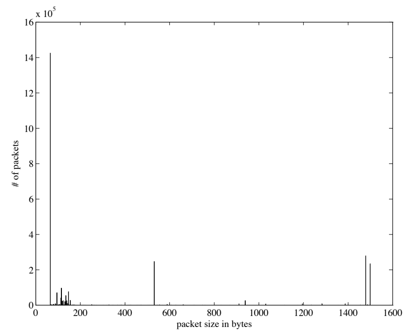


Figure 3: Packet size distribution for the full 24-hour trace

## 3 Interconnection

As the interconnection of LANs located on various sites becomes increasingly important, the study of interactions between LANs and wider area networks becomes of utmost importance. The goal of this work is to provide experimental data to verify models of such interconnections and more specifically to evaluate the model developed in [10]. This section will present the traffic conversion mechanism assuming conversion from a LAN similar to Ethernet to a MAN such as DQDB.

### 3.1 Packet Conversion

This subsection describes how packets are affected by the network interconnection. It is assumed that the WAN splits variable length packets into fixed-size cells. This is depicted in figure 4. The mechanism is as follows. An *Initial Media access control Protocol Data Unit* (IMPDU) is created by adding a header and a trailer to the incoming packet. The IMPDU is then split into segments to which headers and trailers are added to make up cells.

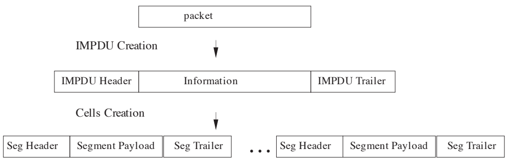


Figure 4: Splitting of a variable length packet into fixed-size cells.

It is important to know that before creating the IMPDU, the Cyclic Redundancy Check (CRC) is checked. Hence the cells corresponding to a packet cannot be sent before the packet has entirely arrived. Figure 5 depicts this situation. Part (a) represents the incoming traffic of LAN, part (b) shows the IMPDU creation (assuming a higher rate) and part (c) shows the cells that are emitted on the MAN.

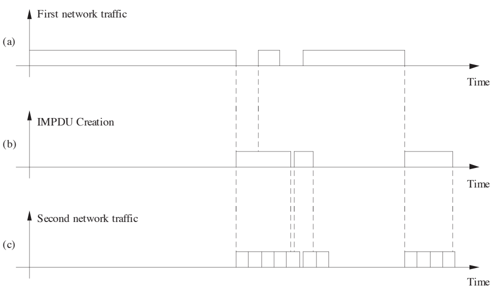


Figure 5: Conversion of LAN traffic (a) to MAN traffic (c). Packets are first encapsulated in an IMPDU (b) before being segmented and emitted.

It has been seen in [19], [20] that the LAN-MAN interconnection can be modeled by a queue.

## 4 Important Queuing Parameters to be observed

In this section, we resume quickly the results obtained in [10] in order to support the following developments. We consider the mean cell delay and the cell loss during a busy period (beginning at time $-\tau^*$ and ending at time $\tau^*$) of a queuing system. Let *N(t)* denote the number of cells in the queuing system at time t and *U(t)* the number of arriving minus the number of served cells at time t. Furthermore, we assume the queuing system's capacity to be limited to c places is defined as:

$$\psi(\omega) = \frac{1}{2\tau}\int_{-\tau^*}^{\tau^*} N(t)e^{-i\omega t}dt \qquad (1)$$

where $\psi(0) = \boldsymbol{E}\left[N \middle| -\tau^* < t < \tau^*\right]$. $\boldsymbol{E}$ is the operator of the expected value and let $\phi_U(\omega)$ be the spectral density of the process *U(t)*. Then, it can be proven that [10]:

$$\psi(0)\overline{\psi}(0) = \left(\boldsymbol{E}\left[N \middle| -\tau^* < t < \tau^*\right]\right)^2 \tilde{\propto}\ 2\pi\tau^*\left(\phi_U(0) + 2\pi\eta^2\right) \qquad (2)$$

with $\boldsymbol{E}[U(t)] = \eta$, independent of t because the process *U(t)* has been assumed to be wide sense stationary and ergodic. Equation 2 shows that the spectral density at frequency 0 of the process *U(t)* , the expected value of U(t) and the duration of the busy period ($2\tau^*$) have a decisive influence on the queuing system occupation. $\phi_U(0)$ is equal to the integral over lags of the autocovariance function of the process *U(t)*. A similar result for the mean cell loss can be derived [10] during the busy period.

## 5 Fitting procedure to the SSMP model

### 5.1 Spectral estimation

For reliable spectral estimates we would wish for large amount of data. In our case, we consider two minutes of Ethernet-traffic on a 34 Mb/s DQDB-line, which gives approximately $9.6*10^6$ slots. Two main techniques are available for the spectral estimation, non-parametric spectral estimation and parametric spectral estimation. The first method is appropriate when the amount of data is sufficiently large. The most popular methods for nonparametric estimation are:

- periodogram spectral estimator
- averaged periodogram estimator
- minimum variance estimator

These algorithms have the great advantage of making no assumptions concerning the signal nature except that it is wide sense stationary. The inconvenience is the tradeoff between the bias and the variance. If the spectral estimator yields a good estimate of the average (low bias), then we can expect much variability from one data realization to the next (high variance). e other hand, if we choose a spectral estimator with low variability, then on average the spectral estimate may be poor. The only way out of this dilemma is to increase the data record length. In our case, the data record length can be as large as we want. Hence, the chosen method was the averaged periodogram spectral estimator.

### 5.2 SSMP Process

Due to the slotted nature of the future broadband networks (such as Asynchronous Transfer Mode, ATM and Distributed Queue Dual Bus, DQDB), we must choose adequate models which fit as well as possible the behavior of the traffic flowing on these future networks. In this paper, we suggest the use of a Semi-Markov Process (SMP) for modeling different traffic sources; this general process has interesting properties which we will discover in the following pages.

The SMP was introduced by Lévy [3] and Smith [4] independently as a new class of stochastic processes. These processes are a generalization of both continuous and discrete parameter Markov process with countable state spaces. Here, we consider only the discrete case.

As said before, we assume that the time is slotted. The Markov chain is modulated and can change its state at defined times: t, t+1, ... Between time t and t+1, the chain remains in the same state. In each state, the cells are generated according a distribution $\beta_i$ which is dependent of the visited state as well as the one to be visited next. The Special Semi-Markov Process (SSMP) is an SMP whose the distribution $\beta_i$ in a given state depends only on the present state. When $\beta_i$ is a Poisson distribution, the SSMP is then called Modulated Markov Poisson Process (MMPP)[14].

### 5.3 Moments

The k$^{\text{th}}$ moment of the random variable (RV) $X_t$ is, by definition

$$E\left[X_t^k\right] = \sum_{x_1 \geq 0} x_1^k \, pr\left(X_t = x_1\right)$$

$X_t$ is the RV representing the number of cells arriving during the interarrival [t-1,t), $X_t$ can be positive or equal to zero. In the case of an SSMP Process, the k$^{\text{th}}$ moment is

$$E\left[X_t^k\right] = \vec{\pi}_t \Lambda_t^{(k)} \vec{\mathbf{e}}$$

with $\pi_t = \left(pr\left(\mathrm{Y_t} = 1\right), \ \ldots \ , pr\left(\mathrm{Y_t} = n\right)\right)$ which is the modulator's state probability vector; ($Y_t$=i) is the modulator's state $i$, $i \in \{1,\ldots,n\}$ at time t. For the SSMP process, $\Lambda_t^{(r)}$ is equal to

$$\Lambda_t^{(r)} = diag\left(E\left(X_t^r \mid Y_t = 0\right),\ldots,E\left(X_t^r \mid Y_t = n\right)\right)$$

If the process is wide sense stationary, the k$^{\text{th}}$ moment of $X_t$ can be written

$$E\left[X^k\right] = \vec{\pi} \, \Lambda^{(k)} \vec{\mathbf{e}}$$

$\vec{\mathbf{e}}$ is the unity vector

$$\vec{\mathbf{e}} = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

### 5.4 Autocovariance function

The general expression of the autocovariance function of the RV $X_t$ is [15]

$$cov\left(X_{t+\tau}^s, X_t^k\right) = E\left[X_{t+\tau}^s X_t^k\right] - E\left[X_{t+\tau}^s\right] E\left[X_t^k\right]$$

For an SSMP process $cov\left(X_{t+\tau}^s, X_t^k\right)$ becomes

$$cov\left(X_{t+\tau}^s, X_t^k\right) = \vec{\pi}_t \Lambda_t^{(k)} \left(\mathbf{A}(t+\tau,t) - \vec{\mathbf{e}}\vec{\pi}_{t+\tau}\right) \Lambda_{t+\tau}^{(s)} \vec{\mathbf{e}}$$

with

$$\left(\mathbf{A}(t+\tau,t)\right)_{kj} = a_{kj}(t+\tau,t) = pr\left(Y_{t+\tau} = j \mid Y_t = k\right) \qquad 1 \leq k, j \leq n$$

which are the elements of the Markov chain transition matrix, and if the process is wide sense stationary

$$cov\left(X_\tau^s, X_0^k\right) = \vec{\pi} \, \Lambda^{(k)} \left(\mathbf{A}^{|\tau|} - \vec{\mathbf{e}}\vec{\pi}\right) \Lambda^{(s)} \vec{\mathbf{e}}, \; |\tau| \geq 1$$

### 5.5 Spectrum estimation

By the Wiener-Khintchine theorem [11], we know that the power spectral density can be found if the autocovariance function of the RV is known

$$\phi(\omega) = \sum_{\tau=-\infty}^{\infty} cov(X_\tau, X_0) \, e^{-i\omega\tau}$$

$cov(X_\tau, X_0)$ is known from the formulas in §5.4, after replacing its value

$$\phi(\omega) = cov(X_0, X_0) + \sum_{j=1}^{N} \left( \frac{2\alpha_j \left(1 - \left|\lambda_j\right| e^{-i\varphi_j} cos(\omega)\right)}{1 + \left|\lambda_j\right|^2 e^{-2i\varphi_j} - 2\left|\lambda_j\right| e^{-i\varphi_j} cos(\omega)} - 2\alpha_j \right)$$

with $\lambda_j$ the j$^{\text{th}}$ eigenvalue of the transition probabilities matrix except the first one (which is always equal to 1 in a stochastic matrix), and $\varphi_j$ the phase. $\alpha_j$ is constant. $\phi(\omega)$ is a pair and real function because $cov(X_\tau, X_0)$ is a pair function.

## 5.6 Optimization

According the chapter 4, it is necessary to find a Markov chain which matches the decisive parameters. The distribution and the spectral density is known for an SSMP as seen in chapter V. The problem is to define an objective function (OF) which gives an idea of the "goodness" of the traffic characterization by the SSMP. The chosen OF is

$$OF = \sum_i W_s(i) \,.\, d\big(\textbf{measured spectrum}, \textbf{SSMP spectrum}\big) + \sum_j W_d(j) \,.\, d\big(\textbf{measured distribution}, \textbf{SSMP distribution}\big)$$

$W_s$ is the cost function for the spectrum and $W_d$ the cost function for the distribution. With these cost functions, it's possible to give more importance to the low frequencies and to the first moments of the Markov chain; $d(\mathbf{x},\mathbf{y})$ is the distance between two vectors $\mathbf{x}$ and $\mathbf{y}$. For our calculations, the Euclidean distance has been chosen. The aim of the algorithm described here is to minimize OF. The parameters affecting OF are the transition probabilities and the distribution parameters in each state in the Markov chain. In fact, this problem is an optimization problem, well known in the operational research field. In order to find the global minimum, the two best known available methods are: the Simulated Annealing technique and the Tabu Search technique. In the combinatorial optimization, the use of approximate algorithms (heuristics) is classic; the best known problem is surely the traveling salesman problem[16]. Unlike the Simulated Annealing technique which tries to exploit an analogy with the thermodynamics, the Tabu Search technique looks more like an intelligent search which may in some sense imitate human behavior. In this paper, we will shortly describe the Tabu search technique applied to our problem.

## 5.7 Tabu Search

What is the aim of the Tabu Search technique ? If V is a set of vectors (**s**) which provide solutions when a certain, well defined function is applied; then the Tabu Search helps us to find an $\mathbf{s}^*$ in V for which f($\mathbf{s}^*$) is minimum [17]. In our case, the set V is a [(n-1).(n-1) + l.n] dimensional space where the $a_{ij}$ (transition probabilities) vary between 0 and 1, and the l parameters of each distribution are "a priori" not limited. Because of that, it will be necessary to introduce artificial boundaries in order to obtain a closed space V. An iterative procedure will move from **s** to **s**' in V by a modification **m**: **s**'=**s**+**m**. It has to be noticed that the **m** vector has to be chosen in the set of acceptable modifications. The descent methods have the property to accept only better solutions than the previous ones, in other words, **s**' is accepted only if f(**s**')>f(**s**) and the procedure works until f(**s**')<f(**s**). A disadvantage of these methods is the possibility of being trapped in a local minimum which can be far from the global minimum. In order to find the global minimum, it is necessary to accept a solution which is worse than the previous one. The Simulated Annealing and the Tabu Search algorithms accept such solutions in their hunt. With the Simulated Annealing, a worse solution is accepted with a certain probability evolving with the number of iterations. With the Tabu Search algorithm, the modifications we have made in the previous steps are forbidden. So it has to choose the other possibilities to continue the search. Among the remaining solutions, all can be worse than the one we have visited. So we establish a list T with the i last modifications called tabu conditions. If the algorithm searches in one direction and i>0 it cannot search in the opposite direction the next step, for example. It is easy to see that the periodicity of the given solution can only be > i. In our problem, we consider that the n.l distribution parameters are given. In fact, we examine each situation sequentially because of the problem's nature, V is then reduced to (n-1).(n-1) dimensions. The modification introduced is a variation of each transition probability $a_{ij}$ : $a_{ij} + \varepsilon,\ a_{ik} - \varepsilon\ \forall i, j, k$ with k≠j. When the best solution is found, the optimal $\varepsilon$ is searched according to a dichotomic law.

# 6 Numerical Examples

Figure 6 shows the measured spectrum of the Ethernet traffic on the EPFL-network on August the 30 at 6:52 pm - 6:54 pm. We have selected a situation where the traffic was heavy. In fact it is the worst case situation which is interesting (for network dimensioning, for example).

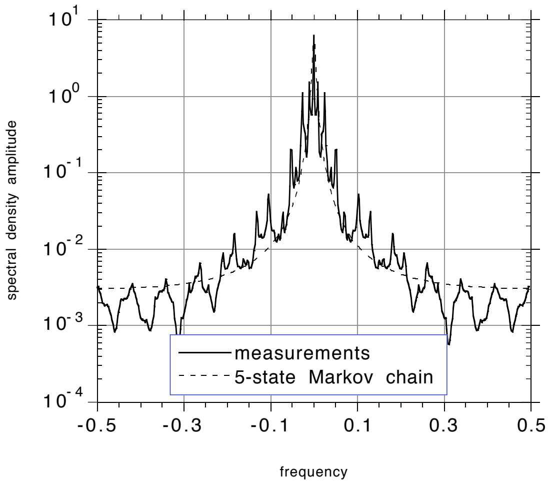


Figure 6: spectral density amplitude, parameters fitting 5-state Markov Process 1: $W_s(i) = 100 * e^{|i|*4.6/256} + 100 * \delta(0)$

The spectral density amplitude of the measurements is given in figure 8 (straight line) with the cost function for the spectrum $W_s(i) = 100 * e^{-|i|*4.6/256} + 100 * \delta(0)$ . $\delta(0)$ is the Dirac distribution. The expected value of the measured converted traffic is **E**[X]=0.0618, and $\phi(0)$=6.165. With a Poissonian model, it is very easy to fit the correct parameters because only the expected value can be fitted. In order to fit the correct parameters of a 5-state Markov chain, the method described in §5.6 has been used and a transition probability matrix such as the one below was obtained:

$$\mathbf{A} = \begin{pmatrix} 0.95106 & 0.00009 & 0.04715 & 0.00072 & 0.00098 \\ 0.00092 & 0.99244 & 0.00089 & 0.00534 & 0.00041 \\ 0.54829 & 0.4237 & 0.00876 & 0.00784 & 0.01141 \\ 0.00002 & 0.89857 & 0.03925 & 0.00371 & 0.05845 \\ 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

with the state-space: {1, 0, 0, 0, 0}. Such a Markov chain has an expected value **E**[X]=0.08305. To validate our results, it was necessary to compare the cell loss probability of the SSMP/G/1/c queue (c is the number of places in the buffer) with the fitted parameters and the measured converted traffic in the same queue and make a statistical study of the lost cells. The cell loss probability of the SSMP/G/1/c queue is calculated with a general server but in our tests, the server is geometric. It is therefore possible to vary the service time, or, in our case, the probability that the residual time equals 1: p(Rt=1). Figure 7 shows a good agreement between the cell loss probability of the SSMP/G/1/c queue and the cell loss of the measured converted traffic/G/1/c queue. In comparison, we show that the Poisson process is not adequate for the characterization of the converted LAN-traffic which is not a new result because of the correlation of such a traffic. We notice that the calculation of the cell loss probability in a SSMP/G/1/c queue can be found in [18].

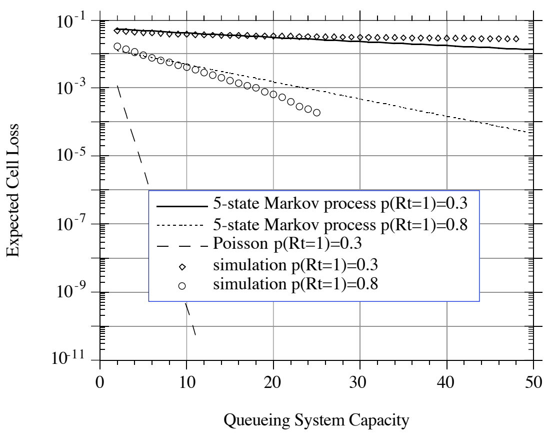


Figure 7: Comparison of the expected cell loss

## 7 Conclusion

In this paper, we have considered the expected loss of a finite capacity queue. The queue behavior strongly depends on the following parameters: distribution and the spectrum density around zero of the difference between arrivals and service. This difference is assumed to be ergodic and wide sense stationary. The aim was to demonstrate through a practical example that the parameters taken into consideration play an important role in the evaluation of the expected loss in a finite capacity queue; real LAN traffic was measured in this way. The model considered to characterize the measured converted LAN-traffic was the SSMP process; this process is especially well suited for characterizing multimedia traffic. The suitability of the SSMP for modeling LAN traffic has been evaluated through simulations performed with real traffic samples obtained from an operational EPFL network. Through comparisons between the expected loss in a SSMP/G/1/c queue and in a "measured converted LAN-traffic"/G/1/c queue, we found a very good agreement over timescales up to the order minutes if the SSMP parameters are correctly fitted of course.

## 8 Acknowledgments

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