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An argument for reduction of simulation complexity

Sireen Malik, Ulrich Killat

Hamburg University of Technology, Denickestrasse 17, 21073-Hamburg, Germany
E-mail:{s.malik, killat}@ tuhh.de

One way of creating Long Range Dependent (LRD) traffic is by the superposition of a large number of on-off sources. We show that a small number of sources is enough to generate LRD traffic thus addressing the scalability issue of the network simulation methodology. Our strategy lies in increasing the activity of each source thus reducing the required number of sources for producing target traffic. However, this impacts the burstiness of the source. We first build a Semi-Markov (SM) model for the arrival process and show that while the first moment of the traffic remains independent of the burstiness, the second order moments depend on it. This dependence directly influences the performance parameters. A Quasi Birth Death model (SM/M/1 queue) is used to study the impact of burstiness on the mean packet delay. We show the same dependency in the aggregate traffic and then define a criterion for reduction of simulation complexity. Our results show that 24 times reduction in the number of typical sources is easily possible.

1 Introduction

The Internet traffic is Long Range Dependent (LRD) in its nature [1,2]. LRD is attributed mainly to the session characteristics, or the user behavior. Various methods to generate LRD traffic have been proposed. A summary is presented in [3]. A sophisticated approach is the generation of traffic by the superposition of on-off sources [4]. If either, or both, the on- and off-times are heavy-tailed distributed then the resulting traffic is LRD in nature.

Large capacity networks carry large volumes of traffic. A large number of traffic sources would be required to simulate a high speed network. However, each source puts a demand on the computer resources (CPU and memory). Therefore, the available finite computing resources bound the number of sources that can be simulated. The scalability argument is true for every type of traffic source. A real scenario is considered to lay out the problem clearly and emphasize the importance of the solution. The more commonly available Linux kernel allows 4GBytes (8GBytes in future) of memory access in typical simulation platforms. We do not consider the “hard-disk swapping memory” as the simulation times become unacceptably large when it is used. The kernel and relevant applications/drivers/programs use 1GBytes of the total available memory leaving 3GBytes for the simulator. So the first obvious question is that how much traffic could be simulated with the available 3GBytes? The estimates show that each traffic source in our simulator consumes approx. 20KBytes of memory. This means that approx. 150,000 sources can be simulated. Each source is tuned to produce the traffic of a “typical” user which is approx. 12Kbps. This means that with 150,000 sources we can simulate up to 1.8Gbps of total traffic. That is the limit.

So how do we increase the capacity of the system to simulate bigger and faster networks? What are the possible solutions? A solution is to reduce the memory requirement of each source. We have dealt with that in [5]. This paper presents yet another solution based on the “reduction” of the number of sources required to produce the target traffic. For example, if we could some how double the amount of traffic produced by each source then we would need half the number of sources required to produce the same target traffic. In the context of the above discussion, if each source produced 24Kbps instead of 12Kbps then we could simulate 3.6Gbps of traffic with the same available memory! So theoretically if we could make the activity of each source 150,000 times higher then we would need just one source to produce 1.8Gbps of traffic!

However, this is not possible. There are limitations. We will show in this paper that the activity of a source *can* be increased and, therefore, a significant reduction in the total number of sources required to produce the same target traffic can be achieved *up to* a certain point without any significant deviations in the important traffic and performance parameters. However, beyond that point, increasing the activity of a source has a direct impact on the traffic statistics. It was observed in [6] that the Throughput (TP), Co-efficient of Variation (CV), Hurst parameter (H) and Mean Packet Delay (MPD) remain independent from the number of sources up to a certain point of aggregation but beyond that point H and MPD show dependence. However, no explanation for this phenomenon was given. In this paper we explore the theoretical background for this transition while giving readers a deeper understanding of the LRD traffic. We will show that this is linked with the burstiness of the source.

The traffic produced by the source has long range correlations, or has a LRD character. We use a Semi-Markov (SM) model to describe the correlated arrival process. The SM model is used to quantify the first and second order moments of the arrival process. We show that the second order moments of the arrival process depend upon the burstiness of the source. We use plots of CV and Auto-Covariance (ACV) to show that reduced burstiness causes the arrival process to lose memory.

Then, assuming a markovian service process, we use a SM/M/1 model - a Quasi Birth Death (QBD) process - to calculate the MPD for a typical user. We show that the MPD of a typical web-user is well bounded by an SM/M/1 queue. This acts as a bench mark. Then we show that the simulation complexity reduction strategy causes the queuing to transit from a QBD type SM/M/1 model to a Birth Death (BD) type M/M/1 model - the arrival processes becomes memoryless. The simulation reduction strategy causes the correlation in the arrival process to disappear so that M/M/1 becomes a valid queue model at the other extreme. The queue occupancy in M/M/1 type of a system is much lower than that of a SM/M/1 type thus MPD in the earlier case are much smaller. Then we study the first and second order moments of the aggregate traffic (multiples sources) and show that the same dependency exists between the burstiness of the source and the correlations in the traffic. We will use H parameter that measures the degree of LRD. A weaker H indicates a weaker correlation structure. Based on these observations, we formulate a simulation complexity reduction rule. We reduce the number of sources only to a point that keeps the correlation structures in the arrival process intact leading to typical MPD's. Beyond this point the MPD's would be smaller as LRD in the arrival process becomes weaker as compared to the LRD of a typical user - the simulation complexity reduction strategy will not be correct any more.

In section 2. we give an insight into the simulation complexity reduction strategy. In section 3. a brief intro to the Matrix Exponential (ME) type of distributions is given. We will discuss the heavy-tailed Truncated Power Tail (TPT) distribution in this section that would also facilitate the discussion in the following sections. In section 4. the SM arrival process for a single source is presented. Section 5. contains the Quasi Birth Death (QBD) model and its solution methodology. In the last section, we discuss the simulation setup and then the results.

2 Simulation complexity reduction argument

We briefly discuss the details of the HTTP-TCP source [7] that is used in the context of this discussion. It is modeled as an on-off source. It generates very realistic web-traffic as the actual transport of HTTP web-pages is done by TCP. On getting a user request, the HTTP protocol at the session level fetches the requested web page and passes it to TCP. TCP transports the web page from the web-server to the user. Because of its prevalence, HTTP-1.1 is considered at the session layer. It sends the web pages through a persistent connection. This means that a single connection is used to transport all the files in the web page. Let V be the average file size that the web server generates. Let Z be the average number of objects per web page. If F denotes the average web-page size then $F = V * Z$. The transmission of an average web page by TCP level is done on average in T_{on} time. After the download of a web page, the connection is closed and the user remains inactive for an average T_{off} time, the user think-time, before making the next request. Each web user cycles through this on and off behavior. The on-time is heavy-tailed distributed because of the heavy-tailed web-page sizes distribution. We assume that the off-time is negative exponentially distributed. Assuming that in an appropriately dimensioned network there are negligible packet losses, in [7] the authors came up with the following expression for the throughput of a single traffic source.

$$TP = \frac{F}{N * RTT + T_{off}}, \tag{1}$$

where RTT is the Round Trip Time and N is the average number of $RTT's$ required to transport an average web page of size F. Therefore, the source on-time, $T_{on} = N * RTT$. Let M be the total number of sources. Then the aggregate throughput (TP) resulting from M sources, or typical users, is given as:

$$TP = M * \frac{F}{N * RTT + T_{off}}. \tag{2}$$

The idea of reduction in the complexity of simulation is that by reducing T_{off} the activity of one source can be increased so that a smaller number of sources is required to produce the target traffic. Let $W \leq M$ be the reduced number of sources. We define Z as the aggregation level. Then:

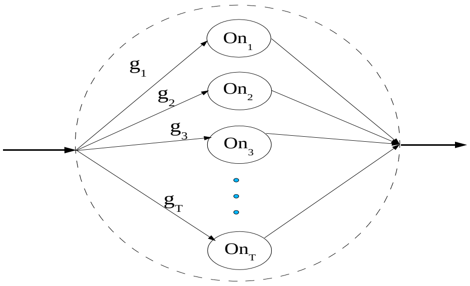

Figure 1. TPT distribution with T states.

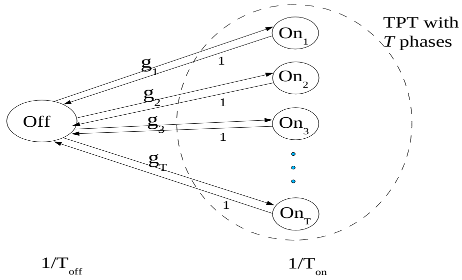

Figure 2. On-Off source.

Truncated Power Tail distribution: Consider Fig. 1. Let *T* be the truncation level, or the number of states in the TPT distribution. This is a hyper-exponential distribution in which the probability of entering state *i* is given as g_i and the leaving rate of state *i* is given as r_i:

$$g_i = \frac{\theta^{i-1}(1-\theta)}{1-\theta^T}, \quad i = 1, ..., T, \qquad r_i = \frac{1}{\gamma^{i-1}} . \frac{1-\theta}{1-\theta^T} . \frac{1-(\theta\gamma)^T}{1-\theta\gamma} . \frac{1}{E(X)} \quad i = 1, ..., T. \tag{8}$$

The probability g_i of entering into a state *i* decays geometrically by a factor $\theta < 1$ (in this paper we used $\theta = 0.5$ as given in [10]). The state holding time (inverse of r_i) grows geometrically by a factor $\gamma = 1/\theta^{1/\alpha}$, where α is the *shape-parameter* of the TPT distribution. The reliability function for such a distribution is given as:

$$R_T(x) = \frac{1-\theta}{1-\theta^T} \sum_{j=0}^{T-1} \theta^j e^{-(\frac{\mu x}{\gamma^j})} \tag{9}$$

This reliability function shows *power-law* behavior $R(x) \sim x^{-\alpha}$ for several orders of magnitude before it drops exponentially [11]. The higher the number of states, or the truncation level, the later the drop-off occurs. This imparts the LRD character to the traffic. The relevant matrices are given as:

$$\mathbf{p} = \frac{1-\theta}{1-\theta^T}[\theta^0, ..., \theta^{T-1}], \quad \mathbf{B} = \mu \begin{bmatrix} \frac{1}{\gamma^0} & 0 & ... & 0 \\ 0 & \frac{1}{\gamma^1} & ... & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \frac{1}{\gamma^{T-1}} \end{bmatrix}, \quad \mathbf{V} = \frac{1}{\mu} \begin{bmatrix} \gamma^0 & 0 & ... & 0 \\ 0 & \gamma^1 & ... & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \gamma^{T-1} \end{bmatrix} \tag{10}$$

4 Semi-Markov process

A typical user is modeled as an on-off source as discussed in section 2. The on-off model is shown in Fig. 2. The TPT distribution considered in the previous section is used as the on-times distribution (right hand side, same as Fig. 1.). Heavy-tailed sized pages are then produced in the on-phase. These pages are transported to the user through packets which, under our assumption, have negative exponentially distributed inter-arrival times, or the packet generation process is poissonian. Then a user stays in the on-phase for a time that is a function of the web-page size chosen from the TPT distribution and r, the packet generation rate in the on-state. As defined in section 2. the user is in the on-state for T_{on} mean time. The user goes into the off-state after downloading the page. As defined in section 2. the user is in the off-state for T_{off} mean time. We consider the off-phase as negative exponential distributed (left hand side of Fig. 2). The off-time is tied to the burstiness of the source through (5).

There are several approaches to model an on-off source, however, because of the mathematical tractability of ME algebra we choose to model the source as an SM process that captures the concept of *correlations* in traffic [12] i.e., the idea that the next customer enters the system in a state that *depends* upon the leaving state of the last customer. We will use the ME algebra discussed in the previous section to generate the first and second order moments for the on-off type of traffic source. However, the assumption of independence considered in the last section has to be modified that means that entrance vector **p** must be replaced.

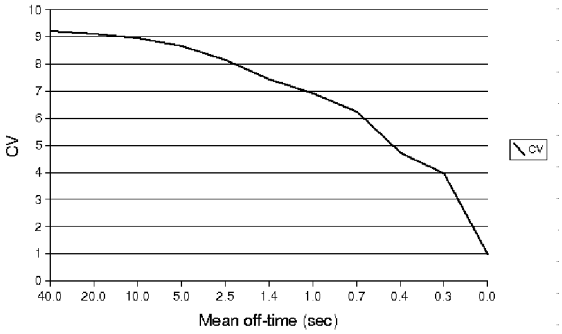

Figure 3. Impact of off-time on CV of SM arrival process

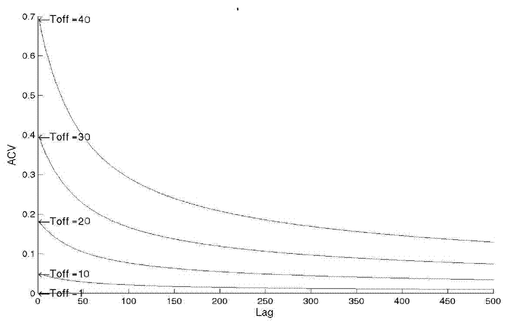

Figure 4. Impact of off-time on ACV of SM arrival process

starts to lose dependence structures. At $b = 0$, the correlations disappear and the process becomes memoryless $(CV = 1)$.

4.1 Some additional comments

Whereas the regular assumption is that in the sub-states of the TPT distribution packets are produced according to a Poisson process, we point out that in reality there are correlations in the packet generation process. The basic reason behind is that in real networks close to 90% packet are transported by TCP which does introduce burstiness on its own. In [5] we modeled TCP as an on-off source which emits a window of packets in a RTT. We showed that while LRD structure comes from the heavy-tailed file-size distribution, TCP introduces multi-fractal structures in the small time scales [13] through the RTT distribution. This aspect of the traffic is not captured by the above model. It only captures the mono-fractal or the LRD behavior in the scope of this paper.

At this point we also briefly discuss the *Hurst parameter* (0.5<*H*<1). The long range dependence is the same as the *second order asymptotic self-similarity.* As $H \to 1$, it indicates a greater degree of LRD. $H = 1$ indicates a purely fractal process. $H = 0.5$ indicates the absence of LRD and the process is called Short Range Dependent (SRD). Poisson process has *H=0.5* and is SRD. The most popular way to estimate *H* is based on the wavelet transform (WT) method [13]. It is to be noted that the scale parameter α of a heavy-tailed distribution and *H* are tied through the following expression [14]:

$$H = \frac{3 - \alpha}{2}. \tag{17}$$

5 Quasi Birth Death process

We are interested in finding the mean number of customers in the system as well as the mean response time for a typical web user. We want to study the SM/M/1 queue, however, we discuss a more general ME/ME/1 queue which can then be easily adapted to any arrival and service processes. Fig. 5. is a model for general ME/ME/1 type of queue where both arrival and service processes are of ME type. Its generator is given as [15]:

$$\mathbf{Q} = \begin{bmatrix} A_{0,0} & A_{0,1} & 0 & 0 & 0 & ... \\ A_{1,0} & A_1 & A_0 & 0 & 0 & ... \\ \vdots & 0 & A_2 & A_1 & A_0 & ... \\ \vdots & \vdots & 0 & A_2 & A_1 & ... \\ \vdots & \vdots & \vdots & \vdots & \vdots & ... \end{bmatrix}. \tag{18}$$

The left most column for the states with queue-length 0, the next for queue-length 1, etc. The upper diagonal consists of *forward* transition rates, while the lower one gives the *backward* transition rates. The middle diagonal gives the $local$ transitions of the state. $\mathbf{A}_i$ and $\mathbf{A}_{i,j}$ are all matrices which take their form from the arrival and service processes. $\mathbf{A}_0$ expresses the forward transitions, $\mathbf{A}_1$ the local transitions and $\mathbf{A}_2$ the backward transitions. We just assume at this stage to develop a more general solution:

* *arrival process* is represented by a ME type of distribution given by $<\mathbf{p_a},\mathbf{B_A}>$,

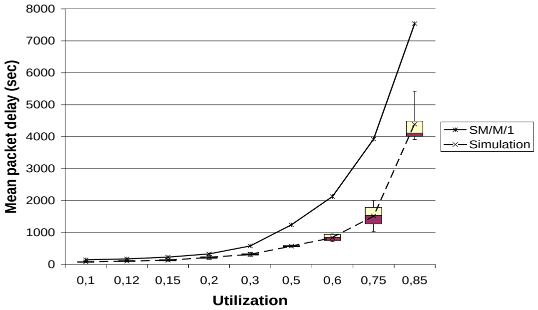

Figure 7. SM/M/1 MPD's.

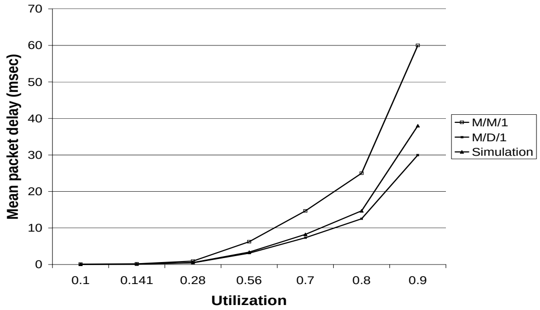

Figure 8. M/M/1 and M/D/1 MPD's.

where C is the capacity of the server. A packet that arrives in the system sees $E[N]$ packets already in the system. Now it is a straight forward to plug in the matrices of the SM process of the section 4. as the arrival process, and the exponential distribution as the service process in the QBD construction of (18) to obtain the performance measures.

6 Results

The simulation complexity reduction strategy is based on scaling of the mean off-time to increase the activity of each source thus leading to a reduced number of sources to produce the same aggregate traffic. This, however, impact the burstiness of the source. We showed earlier that as the off-time reduces the burstiness of each source reduces which leads to the decrease of correlations to the point that when $b = 0$ the SM arrival process becomes purely markovian, i.e. memoryless. We again choose $T_{on} = 0.35secs$ and make two simulation studies: one with with $Z = 1$ therefore $T_{off,w} = T_{off} = 40sec$, therefore, $b = 1$, and then with $Z = \infty$, therefore $T_{off,w} = 0$ and $b = 0$. We show that for high burstiness SM/M/1 provides a good fit and when the source has no burstiness the M/M/1 provides a good upper limit. For simulations we use the Ptolemy Simulator extended for network simulations at our department. Fig. 6. shows the simulation setup. Propagation delays $d_1 = 10msec$ and $d2 = 15msec$. Capacities C and *R* are adjusted to keep their utilization around 50%.

6.1 Impact of T_{off} or b on mean packet delay

Large $T_{off,w}$ (or $b \approx 1$): The settings for the SM arrival process given in the last sub-section are also valid here. It is to be noted that as $b \approx 1$, therefore, the source is highly bursty so long range correlations are expected to produce long MPD's. Fig. 7. shows the results of simulation compared with the model. The SM/M/1 model provides a good upper bound for the mean packet delays for a typical user.

$\mathbf{T_{off,w}} = \mathbf{0}$ (or $b = 0$) : In the previous section, we had shown that for $T_{off,w} = 0sec$ the long range correlations disappear, and the arrival process becomes memoryless thus SM to markovian transition occurs. Fig. 8 gives the comparison of MPD's of simulation with M/M/1 and M/D/1 queues. M/M/1 acts as an upper bound and M/D/1 acts as the lower. One should recall that the delays in case of deterministic delays should be half of those in the markovian case. The mean packet delays in this case are somewhere between the two bounds set by the two models as the packet sizes are neither constant nor markovian rather the packet sizes distribution has $0 < CV < 1$. This is caused by the last packet in the transmission of a file as it is not a complete packet. The end-of-file packets then give a non-deterministic character to the packet-sizes distribution, however, it is intuitive that measured results should be closer to the deterministic case. This is visible in the results.

6.2 Simulation complexity reduction argument

Having stressed the importance of burstiness in determining the important traffic parameters as well as the mean packet delay, we now turn our attention to the complexity reduction argument. The target is to find a *minimum* value of off-time (indirectly, the burstiness of the source) with which all the important parameters remain unchanged, however, the total number of sources required for producing total aggregate traffic would be minimal.

We now use a more elaborate simulation setup, given in Fig. 6. Here instead of using the open-loop source producing packets at poissonian rate, we use multiple HTTP-TCP traffic sources. An HTTP-TCP source transports the packets via TCP protocol. Thus the multi-fractal structures are expected to be present with their impact on the traffic. This means that we expect to see a difference in the TCP based traffic when $b = 0$. Whereas the SM model predicts evaporation of LRD for $b = 0$, we expect to see some correlations because of the presence of TCP. Server

in small time scales through its congestion control mechanisms. We have not modeled this aspect of the traffic. However, the reader should get an ample feel of the impact of burstiness on LRD through the models that we have presented.

How many sources? It is not trivial to model superposition of large number of SM processes (consider 2880 sources!). That approach would give ACV and CV expressions leading to a methodology for figuring out the minimum number of sources required for realistic simulations. We, however, take a simpler approach based on the burstiness factor. The last row in Table I indicates b, the burstiness of the source. We note that for $T_{off,w} \geq 5$ the burstiness remains approximately same thus showing little impact on the MPD and Hurst parameter. Thus we can reduce the off-time to a point where the change in the burstiness of source is not significant. Allowing a deviation of 10% in the MPD, we can tolerate up to 20% decrease in the burstiness. Note that $b = 0.8$ for $T_{off,w} = 1.25$. It is a simple exercise to calculate W, the reduced number of sources, from equations (3) and (5) for a given T_{on} time.

This approach is not rigorous, however, it is obvious that it is the burstiness of each source that finally impacts the second order moments of the aggregate traffic. If we do not allow the burstiness to decrease significantly despite scaling the off-time and increasing the activity of each source, the important traffic parameters would not show much impact.

7 Conclusion

We have given an explanation of how many sources are enough to make a realistic simulation. It is clear that a large number of sources only increase the complexity of simulation and are not required at all. We used a SM model for the arrival process and a QBD model for the queue to show that a reduced number of sources do not make a huge impact on the traffic and performance parameters. We have shown that 24 times reduction in simulation complexity can be easily achieved. This complexity reduction strategy opens the room for high speed networks' simulations.

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