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Is CoV(t)-based Modeling Sufficient for Traffic Characterization in Network Links ?

Ludovic Noirie, Georg Post
Alcatel-Lucent Bell Labs, Nozay, France
Email: {ludovic.noirie; georg.post}@alcatel-lucent.fr

Abstract— For performance evaluation and dimensioning of packet-based networks, engineers need simple, efficient and realistic traffic models. The traffic volume on a packet link, observed at different time scales t , has previously been modeled as a stationary stochastic process based on the Coefficient of Variation $CoV(t)$. In this paper we try to supply the missing information about the *shape* of the distribution functions, required to fully characterize the traffic in network links. Applying the maximum entropy principle, we show that the knowledge about the mean rate μ and the value of $CoV(t)$, associated with the information about the link capacity C , gives truncated Gaussian distributions that are bathtub-shaped at short time-scales and bell-shaped at long-time-scale, leading to quite accurate modeling of the traffic volume distributions at all time-scales t . We illustrate this with some real traffic and some simulated traffic.

Keywords- network dimensioning; traffic modeling; traffic simulation; coefficient of variation;

I. INTRODUCTION

For performance evaluation and correct dimensioning of future packet-based transport networks, engineers need accurate but simple traffic models ([1]). In a previous work [2], we proposed a traffic model that balances the simplicity of use and the accuracy with real traffic, based on the mean rate μ and the coefficient of variation $CoV(t)$ of the traffic volume at different time scales t . Using few parameters, it considers the self-similar nature of the observed Internet traffic at long time scales [3], like the Fractional Brownian Motion model [4], and it was validated on real traffic traces from [5]. An approximation procedure superposing ON/OFF sources was derived from this CoV(t)-based traffic model to generate traffic for performance evaluation.

In [2], a justification for the use of CoV(t)-based traffic model was that, in transport networks, numerous individual flows are aggregated, so the knowledge of the first two statistical moments is enough with a Gaussian distribution assumption. But what happens with a smaller number of flows? Moreover, the traffic is transported in a link with fixed-capacity C . Thus at very short time-scales, the traffic volume distribution is ON/OFF, which is very different from the Gaussian distribution. So, in this paper, we try to answer the following question: is CoV(t)-based modeling sufficient for traffic characterization in network links?

The paper is organized as follows. After summarizing in Section §II the CoV(t)-based traffic model of [2], we use the maximum entropy principle [6] to derive the most probable – or “expected” – distributions given the knowledge we have (mean rate μ , $CoV(t)$, link capacity C). They are simply truncated Gaussian-type that could be bathtub-shaped or bell-shaped according to the value of $CoV(t)$. In Section §IV we show that the distributions from real traffic [5] are close to the “expected” distributions. In Section §V, we demonstrate by simulations that the traffic generator defined in [2], when constrained in a link of capacity C , gives also similar distributions. Finally, we conclude in Section §VI.

II. COV(T)-BASED TRAFFIC MODELING

In this section we summarize the general CoV(t)-based traffic model and the simplified version as defined in [2].

A. General CoV(t)-based Model

Considering the traffic volume $X(t)$ generated in a period of time-scale t , CoV(t)-based traffic models require only the first two statistical moments: mean $m(t)$ and variance $\sigma^2(t)$. With stationarity, $m(t) = \mu \times t$ with the mean rate μ . The variance is linked to the Coefficient of Variation (CoV):

$$CoV(t) = \sigma(t)/m(t). \quad (1)$$

B. Simplified CoV(t)-based Model

For short time scales, the traffic behaves like an ON/OFF source. So, with the link utilization ratio $\rho = \mu / C$, one has:

$$CoV(t) \underset{t \rightarrow 0}{\approx} CoV(0) = \sqrt{1/\rho - 1}, \quad (2)$$

while at long time scales t , $\sigma(t)$ increases like t^H , where $H \in [0.5, 1[$ is the Hurst parameter (see [3], [4]), so one has:

$$\partial \log CoV(t) / \partial \log t \underset{t \rightarrow \infty}{\approx} H - 1. \quad (3)$$

The simplified CoV(t)-based traffic model of [2] joins these two asymptotic behaviors at the transition time scale t_0 :

$$\left\{ \begin{array}{l} \forall t \leq t_0, CoV(t) = CoV(0) \\ \forall t \geq t_0, CoV(t) = CoV(0) \times (t/t_0)^{H-1} \end{array} \right. \quad (4)$$

This traffic model is represented on Fig. 1 in log-log scales. Its parameters can be derived from experiments or deduced from the type of application generating the traffic.

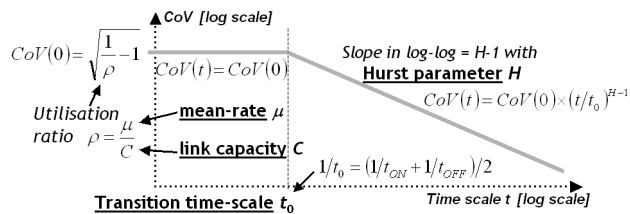


Figure 1. Simplified CoV(t)-based traffic model

III. APPLICATION OF MAXIMUM ENTROPY PRINCIPLE

In this section, we apply the Maximum Entropy Principle (MEP) with the limited knowledge of the CoV(t)-based traffic model to derive the most probable – or “expected” – distributions of the traffic volume at different time-scales.

A. Maximum Entropy Principle (MEP) for Networks

The MEP method, as described in chapter 11 of [6], dates back to Gibbs who laid the foundations of thermodynamics, derived from statistical mechanics. It is useful when one has limited knowledge about a complex system to derive the “expected” or “most likely” probability distributions of the states of this system. For example, in a system of many atoms to be described from a mechanical point of view, only the mean energy per atom may be known. The MEP method derives the distribution of energies that is overwhelmingly the most likely one, namely the Maxwell-Boltzmann (exponential) distribution which has the temperature as its parameter.

Transport networks are also very complex systems, with too many parameters to control (numerous traffic flows, users, nodes, applications, protocols, etc.), so one cannot have the full knowledge about the traffic transported in the network. MEP can help us to estimate what are the most probable (“expected” in the following) distributions of the traffic volumes, with the limited knowledge we have.

B. Knowledge with CoV(t)-based Traffic Model

At any time-scale t , using the CoV(t)-based traffic model of §II.A, we know the mean traffic volume $m(t) = \mu \times t$ and the variance $\sigma^2(t)$ with (1). Using only this knowledge without any assumption about bounds, the MEP method leads to a pure Gaussian distribution ([6]), which is not realistic because it predicts negative traffic volumes. Indeed, we also know that the traffic volume $X(t)$ generated over a period of duration t is positive and limited by the capacity C of the link:

$$\forall t, 0 \leq X(t) \leq C.t. \quad (5)$$

C. “Expected” Traffic Volume Distributions

Knowing the inputs of $m(t)$, $\sigma^2(t)$, and (5), we apply the MEP method described in chapter 11 of [6]. The solving is straightforward and leads to Gaussian-type distribution truncated to the range of (5). With the normalizations $x = X(t)/(C.t) \in [0,1]$ and $\eta = CoV(t)/CoV(0) \in [0,1]$, the “expected” probability distribution of the traffic volume for given ρ and η values is:

$$p_{\rho,\eta}(x) = \frac{\exp(-\beta_1 \cdot (x - \rho) - \beta_2 \cdot (x - \rho)^2)}{\int_0^1 \exp(-\beta_1 \cdot (u - \rho) - \beta_2 \cdot (u - \rho)^2) du}, \quad (6)$$

with parameters β_1 and β_2 verifying:

$$\beta_1 = p_{\rho,\eta}(1) - p_{\rho,\eta}(0), \quad (7)$$

$$2 \cdot \eta^2 \cdot \rho \cdot (1 - \rho) \cdot \beta_2 = 1 - (1 - \rho) \cdot p_{\rho,\eta}(1) - \rho \cdot p_{\rho,\eta}(0). \quad (8)$$

The study of (6), (7) and (8) leads to the following results:

- $(\frac{1}{2} - \rho)$ and β_1 have the same sign,
- the shapes are symmetrical when changing ρ by $1 - \rho$,
- if $\rho = 1/2$ and $\eta = \eta_0(1/2) = 1/3$ then $\beta_1 = \beta_2 = 0$, giving the uniform distribution,
- if $\rho \neq 1/2$ and $\eta = \eta_0(\rho)$ with

$$\eta_0^2(\rho) = 1 - \frac{1 - 2\rho}{\rho(1 - \rho)} \cdot \frac{1}{\beta_1} \quad \text{and} \quad \rho = \frac{1}{\beta_1 + \frac{1}{1 - e^{\beta_1}}}, \quad (9)$$

then $\beta_1 \neq 0$, $\beta_2 = 0$, giving an exponential distribution,

- if $\eta < \eta_0(\rho)$ then $\beta_2 > 0$, giving a truncated concave (bell, $\exp[-x^2]$) Gaussian distribution, which tends to the pure Gaussian distribution obtained by removing the input (5) in the MEP method, when $\eta \rightarrow 0$,
- if $\eta > \eta_0(\rho)$ then $\beta_2 < 0$, giving a truncated convex (bathtub, $\exp[+x^2]$) Gaussian distribution that tends to the discrete ON/OFF distribution when $\eta \rightarrow 1$.

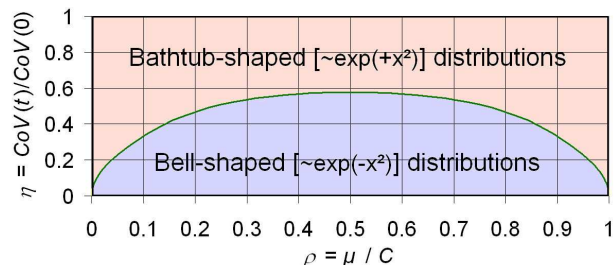
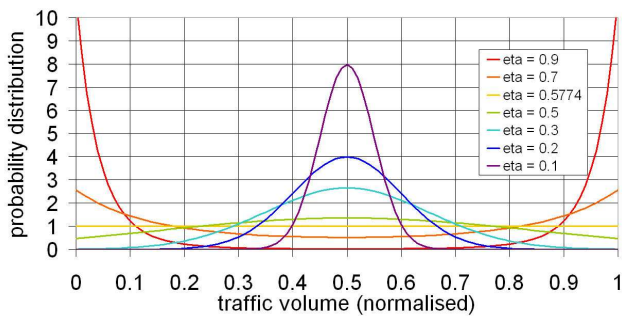
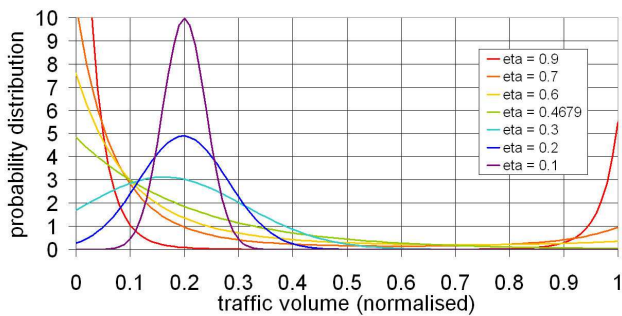


Figure 2. Shape of the traffic volume distributions according to the utilisation ratio ρ and $\eta = CoV(t)/CoV(0)$

In Fig.2, we identified the regions where the distributions are bell-shape or bathtub-shaped, respectively to the values of ρ and η , the frontier being given by (9). In Fig.3 and Fig.4, we represented the values of $p_{\rho,\eta}(x)$ for $\rho = 0.5$ and $\rho = 0.2$, for some values of η . For $\rho = 0.8$, the distribution shapes are the left-right mirror images of the ones of Fig.4.

Figure 3. Expected traffic volume distributions for $\rho = 0.5$ Figure 4. Expected traffic volume distributions for $\rho = 0.2$

IV. MEASURED REAL TRAFFIC

In this section we analyze the traffic volume distributions at different time-scales t on a measured real-traffic trace, to compare them with the bathtub or bell shapes of expected distributions in section §III.

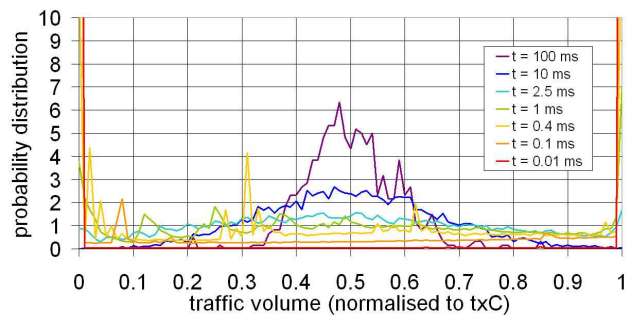
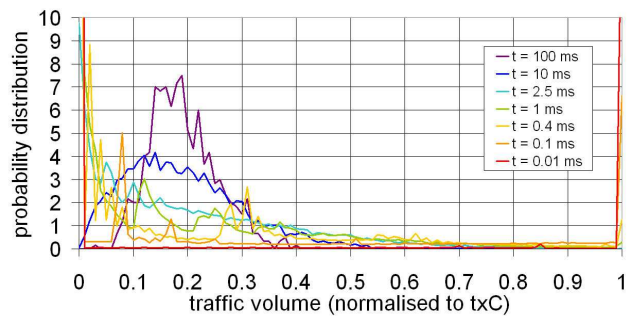
A. Measured Real Traffic Trace

The traffic trace was measured by the University of Stuttgart ([5]) on a 100 Mbit/s Ethernet link in the “Selfnet” network, on October 31st, 2004, from 18:00 to 22:00. It has been used in [2] to validate the simplified CoV(t)-based traffic model (see this paper for more details). We divided the 4-hour trace into 240 minutes, on which we evaluate the traffic volume distributions at different time-scales t .

B. Measured Traffic Volume Distributions

The 240 different minutes show similar behavior for the distributions of traffic volume according to the time-scales t . Here we represent the distributions of traffic volume for 18:29 (Fig. 5) with utilization ratio close to 0.5 ($\rho = 0.502$), and for 19:28 (Fig. 6) with utilization ratio close to 0.2 ($\rho = 0.192$), about the same values as figures of Section §III. In both cases the shapes are similar to the theoretically expected ones of Fig. 3 and Fig. 4, with:

- bell shapes for $t \geq 2.5$ ms,
- bathtub shapes for $t \leq 1$ ms, tending to the ON/OFF distribution at $t = 0.01$ ms,
- transition through the constant distribution in Fig. 5 and an exponential distribution in Fig. 6 as expected for respectively $\rho = 0.5$ and $\rho = 0.2$, in both cases between 1 ms and 2.5 ms.

Figure 5. Measured traffic volume distributions at 18:29 ($\rho = 0.50$)Figure 6. Measured traffic volume distributions at 19:28 ($\rho = 0.19$)

For $t \leq 1$ ms, some regular peaks appear in the distribution, strongly visible at $t = 0.4$ ms. When considering the line-rate, the time-scale value and the positions of the peaks, the first one corresponds to the case of one single 1500B packet in the time-scale window, the second one to two such packets, etc. Thus the packet size distribution has an impact on the distributions of the traffic volumes at short time-scales. One can also note for long time-scales a slight asymmetry in the shape that is not in the “expected” distributions of section §III. Despite this asymmetry and the effect of the dominant packet size, we can conclude that the measured distributions are globally like the ones theoretically expected from the maximum entropy principle.

V. SIMULATED TRAFFIC

In this section, by constraining the CoV(t)-based traffic model generator of [2] with the link capacity C , we compare the simulated traffic volume distributions with the expected ones of Section §III and the measured ones of Section §IV.

A. CoV(t)-based Traffic Model Generator

A fitting procedure was described in [2] that emulates the simplified CoV(t)-based traffic model with a set of ON/OFF sources, over the time-scale range $[0, 10^N \times t_0]$, t_0 being the transition time-scale and N the number of decades for fitting self-similar behavior. It uses the four parameters of the simplified CoV(t)-based traffic model, plus the number $n+1$ of the ON/OFF sources to superpose and the target number N of decades for fitting self-similar behavior. As shown in [2], this procedure gives the right $CoV(t)$ values over the desired time-scale range. But has this generated traffic the expected shapes of the traffic volume distributions?

For $t \rightarrow 0$, because the generator superposes $n+1$ ON-OFF sources, it has not the expected 2 levels of a pure ON-OFF source, but it has 2^{n+1} levels, some of which exceeding the link-capacity bound. To repair this effect, we filter this emulated traffic through buffering, with a fixed output transmission rate equal to the link capacity C , and a minimum output packet duration set to a fraction of the transition time-scale t_0 . In this paper, we simplify the packet generation to cells of fixed size. One may easily emulate a packet size distribution closer to that of real traffic.

B. Simulated Traffic Volume Distributions

Fig. 7 and Fig. 8 represent the distributions of the traffic volume at different time-scales t , for utilization ratio $\rho = 0.5$ and $\rho = 0.2$, like for the expected (Section §III) and the measured (Section §IV) distributions. Hurst parameter is $H = 0.7$, close to the values measured on the real traces (see [2]). The packet size is $1/100^{\text{th}}$ of the transition time-scale t_0 .

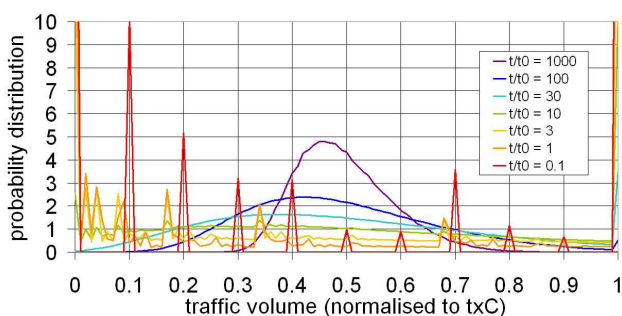


Figure 7. Simulated traffic volume distributions for $\rho = 0.5$

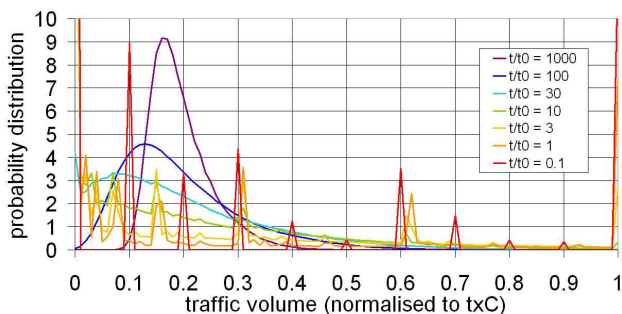


Figure 8. Simulated traffic volume distributions for $\rho = 0.2$

Like with real traffic traces, we obtain shapes similar to the theoretically expected ones. Compared to measured traffic volume distributions, the unique packet size makes more visible the peaks that also occur in simulated traffic volume distributions at small time-scales. Like in Section §IV, for long time-scales, there is the asymmetry in the shape that is not modeled in the expected distributions of Section §III. Nevertheless, we can conclude that the simulated distributions are globally like the expected ones. Most important, they are very similar to the ones measured on real traces, for all time-scales t , with peaks due to the packet size distribution and with the similar asymmetry. This validates the use of such traffic generators for simulations to evaluate network and node performance.

VI. CONCLUSION

In this paper, we used the maximum entropy principle (MEP) to determine in Section §III the “expected” probability distributions of the traffic volume at different time-scales t , under limited knowledge about the traffic: mean rate μ , coefficients of variation $CoV(t)$ and fixed link capacity C . These are the inputs of the CoV(t)-based traffic model defined in the previous work [2]. We compared the expected truncated Gaussian-type distributions with the ones observed on real traffic in Section §IV and on simulated traffic in Section §V. To answer the initial question of this paper, we can say that CoV(t)-based traffic model appear to be sufficient for traffic characterization in network links, for at least the following reasons:

- for short time-scales, it gives traffic distributions that differ a lot from pure bell-shaped Gaussian, the “expected” distributions being bathtub-shaped tending to the ON/OFF traffic,
- for all time-scales, the expected bell-shaped or bathtub-shaped distributions are close to the real-traffic ones, despite some peaks at short time-scales (explained by packet size distribution) and a slight asymmetry at long time-scale (still to be explained!),
- and it leads to a CoV(t)-based traffic generator that is able to accurately emulate real traffic both for the observed additional peaks and the asymmetry.

This CoV(t)-based traffic model generator comes from the one of [2], modified with adequate filtering (rate limited to capacity C of the input link and discrete packet size generation). It is accurate for network simulations not only because the values of $CoV(t)$ is very close to real traffic over the desired time-scale range as shown in [2], but also because the shape of the traffic volume distributions are very close to the ones of real traffic over the desired time-scales.

For further work, one may investigate why we observed a slight asymmetry in both measured and simulated traffic. Can we add pieces of knowledge in the MEP method in order to recover such kind of asymmetry ?

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