Output Traffic Characterization of Policers and Shapers with Long-Range Dependent Input Traffic

Stefano Bregni, *Senior Member, IEEE,* Paolo Giacomazzi, Gabriella Saddemi

Politecnico di Milano, Dept. of Electronics and Information, Piazza Leonardo Da Vinci 32, 20133 Milano, ITALY
Tel.: +39-02-2399.3503 – Fax: +39-02-2399.3413 – E-mail: {bregni,giacomaz,saddemi}@elet.polimi.it

***Abstract* — Long-range dependence (LRD) is a largely verified property of Internet traffic, which severely affects network queuing. An approach for guaranteeing performance requirements is controlling the statistical profile of input traffic by policing or shaping regulators. In this paper, it is investigated by simulation how the $1/f^{\alpha}$ spectrum of LRD traffic is altered when this is regulated by either policers or shapers. Traffic spectral analysis is carried out mainly by the Modified Allan Variance, a time-domain quantity with demonstrated superior accuracy in fractional-noise parameter estimation. The queuing behaviour of LRD regulated traffic in FIFO schedulers is also investigated. Conditions under which service level agreements based on delay bounds can be violated, by varying α in input LRD traffic, are examined.**

***Index Terms* — Communication system traffic, fractional noise, Internet, long-range dependence, queuing analysis, traffic control (communication).**

I. Introduction

Internet traffic exhibits self-similarity and long-range dependence (LRD) on various time scales [1]—[3]. These properties emphasize long-range time-correlation between packet arrivals. Fractional noise and fractional Brownian motion models are often used to describe such behaviour of Internet traffic series, e.g. cumulative or incremental bit count transmitted over time.

In a self-similar random process, a dilated portion of a realization, by the scaling Hurst parameter H, has the same statistical characterization than the whole. On the other hand, LRD is usually equated to an asymptotic power-law decrease of the power spectral density (PSD) $\sim f^{-\alpha}$ (for $f\to 0$) or, equivalently, of the autocovariance function. Under some common hypotheses [2], the integral of a LRD process is self-similar with H related to α (e.g., fractional Brownian motion, integral of fractional Gaussian noise).

It has been pointed out [4]—[7] that traffic LRD contributes to build up long queues in network buffers. In the case of fractional Gaussian traffic, for example, it has been found [4][5] that the queue tail is Weibull distributed, i.e. the buffer occupancy X exceeds a given threshold x with asymptotic probability $P\{X > x\} \sim exp(-\beta x^{1-\alpha})$, where β is a positive function of α and of other network parameters.

The Weibull queue length distribution departs significantly from the exponential distribution resulting with Poisson input traffic. In particular, the closer α is to 1, the slower the queue distribution decreases, making higher the queuing delay. Therefore, the network delay performance depends considerably on actual values of the H and α parameters, among others.

Guaranteeing performance requirements, e.g. delay bounds, calls for a strict control of the statistical profile of offered traffic. A common approach is to control it by *policing* or *shaping regulators*, after the leaky bucket scheme proposed in [8]. Both types of regulators control the average rate and burstiness of the through traffic. Traffic exceeding one or both these parameters is either *dropped* (policer) or *delayed* (shaper).

Enforcing average rate and burstiness of input flows may allow attaining given network performance targets [9]. Though, several authors proved that it is difficult to cope with LRD using leaky-bucket regulators [10]—[16]. Some, based on analysis, claim that LRD cannot be cancelled [11][13][14]. Others, based on simulation, assert that LRD can be reduced by policers and shapers, although only by dropping or delaying a very large fraction of packets [10][12]. Such contradictions stem mainly from the difficulty of studying analytically the traffic output by a regulator, which is both non linear and with memory, fed with LRD input traffic. Simulation as well is made cumbersome by the asymptotical definition of LRD for $f\to 0$.

In our previous paper [17], we presented a thorough simulation study, which confirmed that leaky-bucket policers can hardly weaken traffic LRD and that, consequently, it is difficult to match service delay bounds if α increases.

In this paper, we further investigate this matter, now extending the scope to shapers. By simulation, it is studied how the $1/f^{\alpha}$ spectrum of LRD traffic is altered when this is regulated by either policers or shapers, comparing their behaviour. Traffic spectral analysis is carried out mainly by the Modified Allan Variance, a time-domain quantity with demonstrated superior accuracy in fractional-noise parameter estimation. The queuing behaviour of LRD regulated traffic in downstream FIFO schedulers is also investigated. Conditions are examined, under which a Service Level Agreement (SLA) based on delay bounds can be violated by varying α in input LRD traffic, although regulated by either a policer or shaper.

II. Self-Similarity and Long-Range Dependence

A random process $X(t)$ (e.g., cumulative packet arrivals in time interval $[0, t]$), is said to be *self-similar*, with scaling parameter of self-similarity or Hurst parameter $H>0$, $H\in\Re$, if

$$X(t) =_d a^{-H} X(at) \tag{1}$$

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for any a>0, where $=_d$ denotes equality for all finite-dimensional distributions [1][2]. In other terms, the statistical description of $X(t)$ does not change by *scaling* its amplitude by a^{-H} and its time by a.

In practice, the class of self-similar (H-SS) processes is usually restricted to that of *self-similar processes with stationary increments* (H-SSSI processes), which are "integral" of some stationary process. For example, consider the δ-increment process of $X(t)$, defined as $Y_\delta(t) = X(t)-X(t-\delta)$ (e.g., packet arrivals in the last δ time units). For a H-SSSI process $X(t)$, $Y_\delta(t)$ is stationary and $0 < H < 1$ [2].

Long-range dependence of a process is defined by an asymptotic power-law decrease of its autocovariance and PSD [1][2]. Let $Y(t)$ be a 2nd-order stationary random process. $Y(t)$ exhibits LRD if its autocovariance follows asymptotically

$$R_Y(\delta) \sim c_1 |\tau|^{\alpha-1} \quad \text{for } \tau \to +\infty,\ 0<\alpha<1 \tag{2}$$

or, equivalently, its two-sided PSD follows asymptotically

$$S_Y(f) \sim c_2 |f|^{-\alpha} \quad \text{for } f \to 0,\ 0<\alpha<1 \tag{3}$$

In general, a random process with non-integer power-law PSD is also known as fractional (not necessarily Gaussian) noise. It can be proven [2] that H-SSSI processes $X(t)$ with $1/2 < H < 1$ have LRD increments $Y(t)$, with

$$\alpha = 2H - 1 \tag{4}$$

III. Regulating Input Traffic for Guaranteeing QoS

The quality of Internet end-to-end services (QoS) can be guaranteed in terms of bandwidth, jitter limits and delay bounds [18]. QoS guarantees may apply either to single [19] (*IntServ model*) or aggregate flows (*DiffServ model*).

A. Service Level and Traffic Conditioning Agreements

In either case, the customer contracts with the Internet Service Provider (ISP) for the transport of flows under a SLA, which specifies quantities defining the QoS that the ISP must meet. In this paper, we focus on statistical delay bounds [20], commonly defined as maximum fraction of packets $p_{\max}$ allowed to exceed a given end-to-end delay threshold $d_{\max}$.

The contract between customer and ISP includes a *Traffic Conditioning Agreement* (TCA), which describes the statistical profile of traffic allowed to enter the network, in order to guarantee the SLA. The ISP allocates resources based on TCA parameters, which usually include [21]: average rate r [byte/s], burst size b [byte], peak rate [byte/s], minimum policed unit [byte] and maximum packet length [byte]. The ISP may act conservatively, allocating the declared peak data rate, or more aggressively, taking advantage of statistical multiplexing [20][22]–[26]. In any case, the ISP must meet the SLA.

To enforce the TCA, a common solution is using traffic regulators based on the leaky bucket scheme. If the source traffic complies with the TCA (*in-profile* traffic), the regulator transfers it unaltered. Otherwise, if traffic is violating the TCA (*out-of-profile*), the regulator drops it (*policing*) or delays it (*shaping*) in an internal buffer, until it is possible to inject it into the network without violating the TCA.

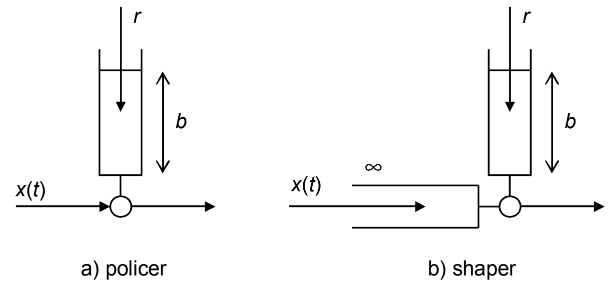

Fig. 1: Policing (a) and shaping (b) traffic regulators.

B. Traffic Regulators: Policers and Shapers

We adopted a fluid traffic model [5], where traffic units are bits. As shown in Fig. 1a, the leaky bucket policing regulator has a counter of credits (tokens) with maximum value b [bit] (*token bucket size*). The credit counter is increased every $1/r$ s, where r is the *token rate*. One bit of offered traffic is allowed to pass through the regulator if the counter is positive (then, the counter is decremented). Otherwise, if the counter is equal to zero, the bit is dropped.

Fig. 1b shows a shaping regulator. The credit counter works as for the policer. An incoming bit passes through the regulator instantaneously if, at its arrival, the counter is positive and the infinite input buffer is empty. Otherwise, if the buffer is not empty and/or the counter is null, the incoming bit is stored. When the input buffer is not empty, one bit is fetched from the buffer as soon as a token is generated.

The r and b parameters of both types of regulators have an intuitive physical meaning. The r parameter controls the average rate of the through traffic, as the regulator cannot output more than r bit/s on the average. The b parameter controls the length of output traffic bursts. If the token counter is full (i.e., it holds b tokens), the regulator can output a burst of b bits at maximum rate. Then, it must stop to wait further tokens.

C. Guaranteeing Quality of Service with LRD Traffic

These regulators can enforce the traffic average rate and burst length, but it is not clear if they are capable of adjusting the α parameter too. This problem is important, as the high sensitivity of delay tails to α makes difficult to match delay SLA, if the α parameter of fractional traffic is not controlled.

This issue has been addressed in [17] for a policing regulator. It has been shown that it is difficult to change the α parameter of traffic without dropping a very large fraction of traffic. It has been also shown that an increase of α in input traffic, even without altering the average rate, can cause a violation of delay SLA in downstream schedulers.

IV. Estimating Parameters H and α of LRD Data Using the Modified Allan Variance

For estimating H and α parameters of LRD traffic series, we used the Modified Allan Variance (MAVAR), recently proposed also as traffic analysis tool [27][28].

A. The Modified Allan Variance

MAVAR is a well-known time-domain quantity, originally

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conceived in 1981 for frequency stability characterization of precision oscillators [29]—[33] by modifying the definition of the Allan Variance (AVAR). MAVAR has been demonstrated to feature superior spectral sensitivity and accuracy in fractional-noise parameter estimation, coupled with excellent robustness against nonstationarities in data analyzed (e.g., drift and steps) [28]. This section briefly recalls few MAVAR properties most relevant to our aim.

Given a finite set of N samples $\{x_k\}$ of a signal $x(t)$, evenly spaced by sampling period τ_0, MAVAR can be estimated using the ITU-T standard estimator [29]

$$\mathrm{Mod}\,\sigma_y^2(\tau) = \frac{\sum_{j=1}^{N-3n+1}\left[\sum_{i=j}^{n+j-1}\left(x_{i+2n} - 2x_{i+n} + x_i\right)\right]^2}{2n^4\tau_0^2\,\left(N-3n+1\right)} \quad (5)$$

where the observation interval is $\tau = n\tau_0$ and $n = 1, 2, ..., \lfloor N/3 \rfloor$.

The MAVAR is a kind of variance of the second difference of input data, including an internal average over n adjacent samples. A recursive algorithm for fast computation of this estimator exists [29], which cuts down the number of operations needed for all values of n to $\sim N^2$ instead of $\sim N^3$.

It should be noted that the point estimate (5) is a random variable itself. Along a plot of MAVAR(τ), confidence intervals are negligible for short τ and widen moving to longer τ, where fewer terms are averaged [34]—[36]. In our results, therefore, we excluded MAVAR values computed for largest n.

B. Power-Law Random Processes

It is convenient to extend the LRD power-law model of spectral density (3). As customary in characterization of phase and frequency noise of precision oscillators [37], we deal with random processes $x(t)$ whose one-sided PSD is modelled as

$$S_x(f) = \begin{cases} \sum_{i=1}^{P} h_{\alpha_i} \big/ f^{\alpha_i} & 0 < f \le f_\mathrm{h} \\ 0 & f > f_\mathrm{h} \end{cases} \quad (6)$$

where P is the number of noise types considered, α_i and h_{α_i} are model parameters (α_i, $h_{\alpha_i} \in \Re$) and f_h is the upper cut-off frequency. Such random processes are commonly referred to as *power-law* or *fractional noise* (not necessarily Gaussian).

Power-law noise with $0 \le \alpha_i \le 4$ was revealed in practical measurements of various physical phenomena, such as phase noise of precision oscillators [29][37] and Internet traffic [1][2], whereas P should be not greater than few units for the model being useful. If the process $x(t)$ is LRD with PSD (3), then this model still applies, for P=1 and $0 < \alpha_i < 1$ (at least asymptotically). Although values $\alpha_i \ge 1$ yield model pathologies, such as infinite variance and even non-stationarity, this model is common, considering also that real-world measurements have finite duration and bandwidth.

Under this general hypothesis of power-law PSD, by letting P=1, α=α_i and in the whole range of MAVAR convergence $0 \le \alpha < 5$, MAVAR is found to follow a simple power law (ideally asymptotically for $n \to \infty$, $n\tau_0 = \tau$, but in practice for n>4), i.e.

$$\mathrm{Mod}\,\sigma_y^2(\tau) \sim A_\mu \tau^\mu\ , \quad \mu = -3 + \alpha \quad (7).$$

If P>1, it is immediate to generalize (7) to summation of powers $\sum_i A_{\mu_i}\tau^{\mu_i}$. This is a fundamental result. If $x(t)$ obeys (6), a log-log plot of Mod $\sigma_y^2(\tau)$ looks ideally as a piecewise function made of P straight segments, assuming sufficient separation between components, whose slopes μ_i can be estimated to yield exponents $\alpha_i = 3+\mu_i$ of the fractional noise terms that are dominant in different ranges of τ. If we consider a LRD process with PSD (3), characterized by Hurst parameter $1/2 < H < 1$, from (4) and (7) we obtain

$$\begin{aligned} H &= \mu/2 + 2 \\ \alpha &= \mu + 3 \end{aligned} \quad (8).$$

In papers [27][28], these estimates of H and α were demonstrated to be very accurate and robust against nonstationarities in the processed data (drifts, periodic trends and steps).

Finally, let us notice that this procedure is analogous to that of the wavelet second-order log-scale diagram technique [1][2][38], which analyzes data over a range of scales, by observing the power-law behaviour (i.e., estimating the slopes) of the wavelet detail variances across octaves.

V. Model and Synthesis of Input Traffic

In this paper, we focus on fractional Gaussian traffic, because for this type of LRD traffic the queue tail distribution has been derived analytically (Weibull) [4][5]. Our procedure, detailed in [17], generates pseudorandom sequences fGt$_\mathrm{R}$(α, m_x, σ_x^2), with PSD $\propto 1/f^\alpha$, normally-distributed samples, mean m_x and variance σ_x^2, rectified to avoid negative samples.

VI. Simulation Results: Shaper vs. Policer Behaviour

We generated fGt$_\mathrm{R}$ sequences $\{x_k\}$ made of $N = 2^{23}$ samples, representing the incremental data count [bit/s] input at each time unit into the regulator under study. We set the time unit $\tau_0 = 1$ ms, the mean $m_x = 2279$ bit per time unit (i.e., 2.279 Mbit/s) and the deviation $\sigma_x = 773.9$ bit per time unit (i.e., 773.9 kbit/s), as in [5]. We varied α in range $0 \le \alpha < 1$.

The traffic $x(t)$ was fed into the regulator. Then, we characterized the output traffic, observing how it is affected for various values of the token rate r and size b. Traffic was analyzed both in the time and frequency domains, respectively by means of MAVAR and classic FFT-based power spectrum estimation (periodogram over 1024 points, having divided the sequence in 8192 segments with Welch data windowing [39]).

A. Impact of Policers and Shapers on Traffic 1/f$^\alpha$ Spectrum

Figs. 2 and 3 show the PSD and MAVAR, respectively, computed on the traffic sequence at the output of a policer and a shaper, with threshold $b = 14202$ bit and for various values of the ratio $r/m_x > 1$ of the token rate to the input traffic mean rate, fed with fGt$_\mathrm{R}$ input traffic with $\alpha = \alpha_\mathrm{IN} = 0.50$.

For both the policer and the shaper, curves for $r/m_x = \infty$ were computed directly on the input sequence $x(t)$, which in this case transits through the policer unaffected, as obvious. Values $r/m_x \ge 1.1$ may be reasonable default settings of the

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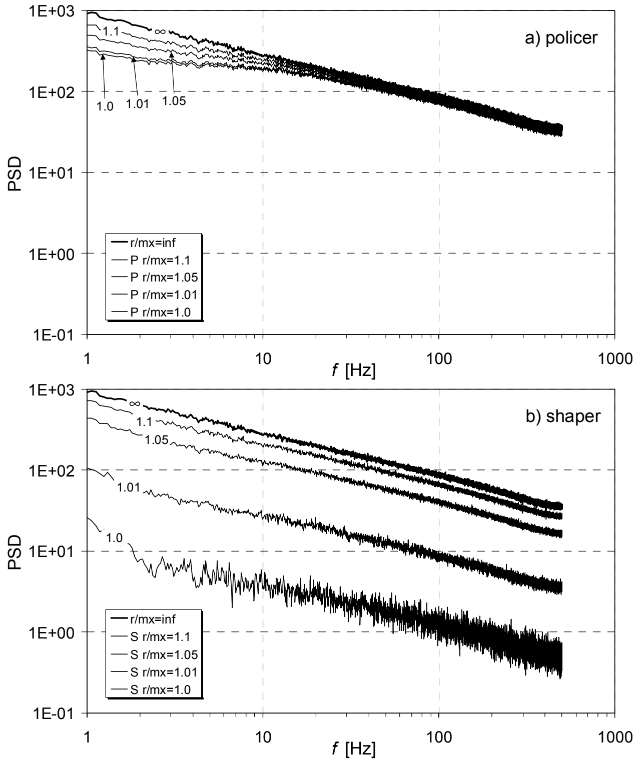

Fig. 2: PSD of traffic output by a) policer and b) shaper (b=14202 bit, r) with fGt$_R$ input traffic (α_{IN}=0.50, m_x=2.279 kbit/ms, σ_x=773.9 bit/ms, τ_0=1 ms).

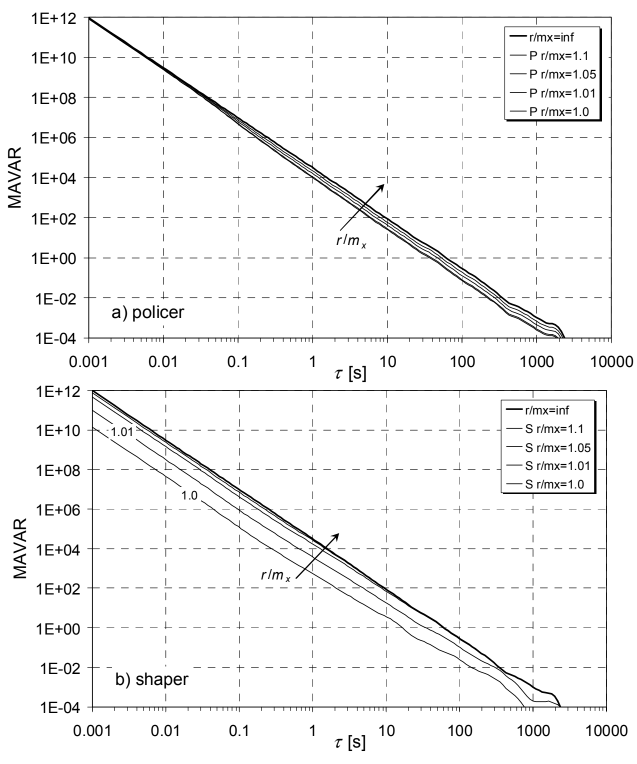

Fig. 3: MAVAR of traffic output by a) policer and b) shaper (b=14202 bit, r) with fGt$_R$ input traffic (α_{IN}=0.50, m_x=2.279 kbit/ms, σ_x=773.9 bit/ms, τ_0=1 ms).

Table 1: Values of α_{OUT} estimated from MAVAR results in Fig. 3 (α_{IN}=0.50).

r/m_x	Policer α_{OUT}	Shaper α_{OUT}
∞	0.491	0.491
1.1	0.455	0.527
1.05	0.423	0.580
1.01	0.384	0.634
1.0	0.372	0.685

Note: α_{OUT} estimated by linear regression in interval 0.001 s < τ < 300 s.

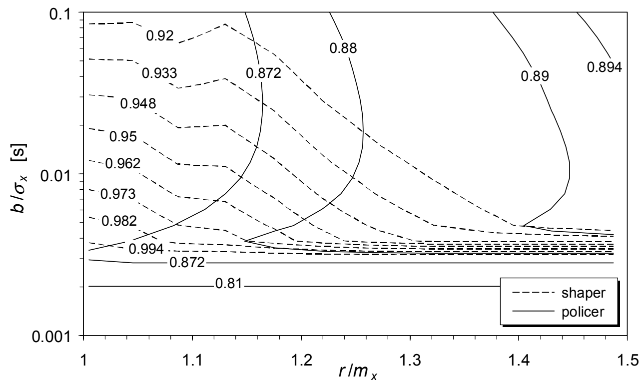

Fig. 4: *Loci* of the (r/m_x, b/σ_x) pairs for which the same α_{OUT} was estimated on the traffic output by a regulator fed with fGt$_R$ (α_{IN}=0.90).

regulator, when the token rate is much greater than the source mean rate and the regulator drops or delays traffic only seldom. In this case, the customer is complying with the TCA and the regulator does not drop or delay traffic significantly: both PSD and MAVAR of the output traffic nearly coincide with those of the input traffic. Decreasing further the ratio r/m_x, we notice that the spectrum of the through traffic begins to be affected significantly. Nevertheless, the policer and the shaper exhibit different behaviours.

When $r/m_x > 1$, both regulators work in a quasi-linear mode: the output PSD and MAVAR do not depart much from a simple power law (linear trend in the log-log plot), although with changed slope. In other words, policers and shapers somehow alter the parameter α of the through traffic, but they do not distort much the power-law spectral nature of traffic.

When $r/m_x < 1$, the customer exceeds the TCA limits and regulators severely cut the traffic rate. The policer drops a significant or even most part of the traffic. The shaper, on the contrary, delays traffic in the infinite input buffer, loaded with coefficient $\rho = m_x/r > 1$. Therefore, the queue does not stabilize on a stationary probability distribution, but it grows indefinitely: after a brief initial transient, the shaper simply squeezes a uniform flow at constant rate r. For this reason, we restricted spectral analysis of output traffic by PSD and MAVAR to the case $r/m_x > 1$.

We estimated average slopes of MAVAR curves in Fig. 3 by linear regression in interval 0.001 s < τ < 300 s, getting the estimates $\alpha = \alpha_{OUT}$ reported in Table 1 for both the policer and the shaper. By examining these α values, it is interesting to note that the policer and the shaper exhibit opposite behaviours: for $r/m_x \geq 1$, the policer slightly diminishes the value of α of through traffic, while the shaper increases it. Therefore,

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policers seem to slightly decorrelate traffic, while shapers do the opposite enhancing LRD of through traffic.

Further results shown in Fig. 4 sustain this claim. In these simulations, regulators were fed with fGt_R traffic with $\alpha = \alpha_{IN} = 0.90$. Then, we varied both parameters r and b of the regulator in a wide interval. The α parameter of the output traffic was estimated by linear regression on MAVAR curves in the same interval 0.001 s < τ < 300 s as in Table 1 (we excluded safely the last decade because of lower confidence).

Fig. 4 plots the *loci* of the (r, b) pairs, for which the same value α_{OUT} was estimated on the output traffic of policers and shapers, having normalized r to the input traffic average m_x and b to the input traffic deviation σ_x. In this graph, curves are labelled by the value α_{OUT}. Let us notice that $\alpha_{OUT} < \alpha_{IN}$ for the policer and $\alpha_{OUT} > \alpha_{IN}$ for the shaper. Moreover, we observe that the function $\alpha_{OUT}(r, b)$ is not trivial. For large values of r/m_x and b/σ_x, we have $\alpha_{OUT} \cong \alpha_{IN}$. For the policer, α_{OUT} decreases as r/m_x and b/σ_x get smaller, while the opposite happens for the shaper. Finally, $\alpha_{OUT}(r, b)$ is not monotonic.

B. Impact on Queuing Delay of Regulated Traffic

As recalled in Sec. I and III.C, the α parameter of traffic has great importance for the provisioning of network resources. Therefore, we simulated scenarios where traffic regulated by a policer or a shaper is fed into a FIFO scheduler.

In these simulations, the traffic $x(t)$ at the input of the regulator has the same average rate m_x and deviation σ_x set in previous experiments. The rate and threshold of both the policer and the shaper are set to $r = 3$ Mbit/s (i.e., $r/m_x = 1.31$) and $b = 14202$ bit (i.e., $b/\sigma_x = 18.3$ ms), respectively. With these settings, both the policer and the shaper affect α negligibly (cf. Figs. 3, 4 and Table 1). The FIFO scheduler has an output line with capacity $C = 2.532$ Mbit/s (i.e., $m_x/C = 0.90$).

Fig. 5 plots the probability $P(d>D)$ that traffic experiences a delay d greater than D, measured from the input of the regulator to the output of the FIFO scheduler, for six different values of the α parameter of the input traffic (viz. $\alpha = 0.0$, 0.2, 0.4, 0.5, 0.6 and 0.8), for both a policer and a shaper. Confidence intervals are negligible.

Let us assume that the network operator and the customer stipulated a TCA with $r = 3$ Mbit/s and $b = 14202$ bit. Moreover, the SLA specifies that the probability that the delay d in the scheduler exceeds D=30 ms is $P\{d>30 \text{ ms}\} \leq 0.002$. Finally, let us assume that the customer supplies fGt_R traffic $x(t)$ with m_x and σ_x as in previous simulations, with $\alpha = 0.4$. By inspection of Fig. 5, we conclude that the SLA is fulfilled, because $P(d>30 \text{ ms})$ is just smaller than 0.002.

Nevertheless, if the customer supplies $x(t)$ with same m_x and σ_x but with $\alpha \geq 0.5$, we observe again from Fig. 5 that the SLA is now violated, as the probability of exceeding delay 30 ms $P\{d>30 \text{ ms}\}$ results much greater than 0.002 (actually 10 or 100 times greater). In this case, both the policer and the shaper are unable to alter the α parameter of traffic and the result is a disruption of the required quality of service.

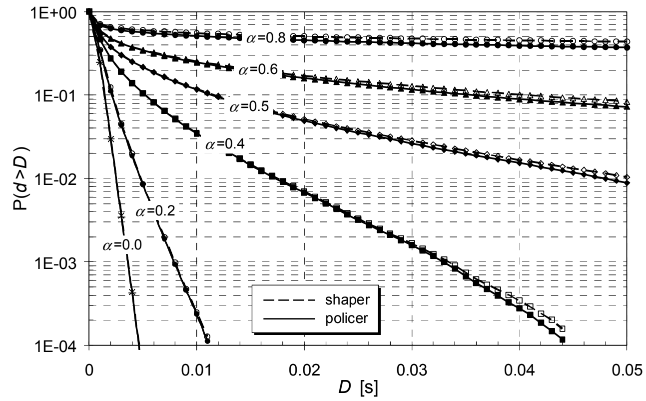

Fig. 5: Probability of exceeding delay D in a FIFO queue following a regulator (m_x=2279 bit/ms, σ_x=773.9 bit/ms, τ_0=1 ms, r/m_x=1.31, b/σ_x=18 ms).

VII. Conclusions

In this paper, we investigated by simulation how policing and shaping regulators alter the $1/f^{\alpha}$ power-law spectrum of LRD traffic. Spectral analysis of traffic was carried out mainly in the time domain by means of the Modified Allan Variance, because of its demonstrated superior accuracy in fractional-noise parameter estimation.

We found that policers and shapers may alter the LRD of regulated traffic, depending in particular on ratio r/m_x, but they do exhibit opposite behaviours. Policers slightly diminish the value of α of through traffic (i.e., they decorrelate it), while shapers increase α (i.e., they enhance LRD of through traffic). These behaviours have been observed when the regulator rate is greater than the input traffic mean rate (r/m_x>1), that is when the regulator operates in the "normal" condition where the customer fulfils the TCA, by feeding the network with an average traffic smaller than or equal to the contracted rate.

However, in this condition both the shaper and the policer affect only slightly (even if in opposite ways) the α exponent of traffic. This has important consequences on the possibility of controlling and guaranteeing the end-to-end quality of service stipulated in SLA. In fact, we have shown that if the α exponent of input traffic is increased, while maintaining the same average rate of input traffic, both the shaping and the policing regulators are not effective to control such increase of α. Therefore, this traffic is offered almost unaffected to downstream network schedulers, yielding possible disruptions of end-to-end delay SLA.

This result may seem negative, but it provides interesting hints for future research. In particular, it would be useful to conceive regulators able to control more effectively the α exponent of traffic. In this way, it could be possible to guarantee delay bounds even in presence of LRD traffic. Our research activity is now focused on a more complete characterization of the output of this and other types of traffic regulators, aiming at identifying schemes capable of acting more effectively on the α parameter of fractional traffic.

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REFERENCES

[1] P. Abry, R. Baraniuk, P. Flandrin, R. Riedi, D. Veitch, “The Multiscale Nature of Network Traffic”, *IEEE Signal Processing Mag.*, vol. 19, no. 3, pp. 28-46, May 2002.

[2] K. Park, W. Willinger, "Self-Similar Network Traffic: An Overview"; P. Abry, P. Flandrin, M. S. Taqqu, D. Veitch, "Wavelets for the Analysis, Estimation, and Synthesis of Scaling Data"; in *Self-Similar Network Traffic and Performance Evaluation*, K. Park, W. Willinger, Eds. Chichester, UK: John Wiley & Sons, 2000, pp. 1-88.

[3] V. Paxson, S. Floyd, “Wide-Area Traffic: the Failure of Poisson Modeling”, *IEEE/ACM Trans. Networking,* vol. 3, no. 6, pp. 226-244, 1995.

[4] N. G. Duffield, Neil O'Connell, “Large Deviations and Overflow Probabilities for The General Single Server Queue, with Applications”, *Math. Proc. Cam. Phil. Soc.*, vol. 118, pp. 363-374, 1995.

[5] I. Norros, “On The Use of Fractional Brownian Motion in the Theory of Connectionless Networks”, *IEEE J. Select. Areas Commun.*, vol. 13, no. 6, pp. 953–962, Aug. 1995.

[6] Y. Cheng, W. Zhuang, “Calculation of Loss Probability in a Partitioned Buffer with Self-Similar Input Traffic”, *Proc. IEEE GLOBECOM 2004*, Dallas, TX, USA, Nov. 2004.

[7] J. Choe, N. B. Shroff, “Queueing Analysis of High-Speed Multiplexers Including Long-Range Dependent Arrival Processes”, *Proc. IEEE INFOCOM 1999*, New York, NY, USA, March 1999.

[8] J. Turner, “New Directions in Communications (or Which Way to The Information Age?)”, *IEEE Commun. Mag.*, vol. 24, no. 10, pp. 8–15, Oct. 1986.

[9] M. Buttò, E. Cavallero, A.Tonietti, “Effectiveness of the `Leaky Bucket' Policing Mechanism in ATM Networks”, *IEEE J. Select. Areas Commun.*, vol. 9, no. 3, pp. 335–342, April 1991.

[10] F. C. Harmantzis, D. Hatzinakos, I. Katzela, “Shaping and Policing of Fractal α-Stable Broadband Traffic”, *Proc. IEEE Canadian Conf. on Elec. and Comp. Eng.*, May 2001.

[11] S. Vamvakos, V. Anantharam, “On the Departure Process of a Leaky Bucket System with Long-Range Dependent Input Traffic”, *Queueing Systems*, vol. 28, pp. 191-214, 1998.

[12] Fei Xue, S. J. Ben Yoo, “Self-Similar Traffic Shaping at the Edge Router in Optical Packet-Switched Networks”, *Proc. IEEE ICC 2002*, New York, NY, USA, 2002.

[13] S. Song, J. K. Y. Ng, B. Tang, “On the Self-Similarity Property of the Output Process from a Network Server with Self-Similar Input Traffic”, *Proc. IEEE 6th Int. Conf. on Real-Time Computing Systems and Applications*, Hong Kong, Dec. 1999.

[14] H. W. Ferng, J. F. Chang, “Characterization of the Output of an ATM Output Buffer Receiving Self-Similar Traffic”, *Proc. IEEE GLOBECOM 2001*, San Antonio, TX, USA, Nov. 2001.

[15] F. de M. Pereira, N. L. S. da Fonseca, D. S. Arantes, “Fractional Bounded Arrival Process for Self-Similar Traffic Policing”, *Proc. IEEE ICC 2003*, Anchorage, AK, USA, May 2003.

[16] N. L. S. da Fonseca, F. de M. Pereira, D. S. Arantes, “On the Performance of Generalized Processor Sharing under Long-Range Dependent Traffic”, *Proc. IEEE GLOBECOM 2002*, Taipei, Taiwan, Nov. 2002.

[17] S. Bregni, P. Giacomazzi, G. Saddemi, “Properties of the Traffic Output by a Leaky-Bucket Policer with Long-Range Dependent Input Traffic”, *Proc. IEEE ICC 2007*, Glasgow, UK, June 2007.

[18] T. Li, Y. Rekhter, “A Provider Architecture for Differentiated Services and Traffic Engineering (PASTE)”, *IETF RFC 2430*, Oct. 1998.

[19] R. Braden, D. Clark, S. Shenker, “Integrated Services in the Internet Architecture: an Overview”, *IETF RFC 1633*, June 1994.

[20] J. Qiu, E. Knightly, “Inter-Class Resource Sharing Using Statistical Service Envelopes”, *Proc. IEEE INFOCOM ‘99*, New York, NY, USA, Mar. 1999.

[21] S. Shenker, J. Wroclawski, “General Characterization Parameters for Integrated Service Network Elements”, *IETF RFC 2215*, Sept. 1997.

[22] E. Knightly, “Second-Moment Resource Allocation in Multiservice Networks”, *Proc. of ACM SIGMETRICS '97*, Seattle, WA, USA, June 1997.

[23] E. Knightly, “Enforceable Quality of Service Guarantees for Bursty Traffic Streams,” *Proc. of IEEE INFOCOM '98*, S. Francisco, CA, USA, Mar. 1998.

[24] P. Giacomazzi, L. Musumeci, G. Saddemi, G. Verticale, “Optimal Selection of Token Bucket Parameters for the Admission of Aggregate Flows in IP networks,” *Proc. of IEEE GLOBECOM 2006*, S. Francisco, CA, USA, Nov. 2006.

[25] P. Giacomazzi, L. Musumeci, G. Saddemi, G. Verticale, "Two Different Approaches for Providing QoS in the Internet Backbone", *Elsevier Computer Communications*, vol. 29, no. 18, pp. 3957–3969, Nov. 2006.

[26] P. Giacomazzi, L. Musumeci, G. Saddemi, G. Verticale, “Analytical Methods for Resource Allocation and Admission Control with Dual-Leaky-Bucket Regulated Traffic,” *Proc. IEEE ICC 2007*, Glasgow, UK, June 2007.

[27] S. Bregni, L. Primerano, “The Modified Allan Variance as Time-Domain Analysis Tool for Estimating the Hurst Parameter of Long-Range Dependent Traffic“, *Proc. IEEE GLOBECOM 2004*, Dallas, USA, 2004.

[28] S. Bregni, L. Jmoda, “Improved Estimation of the Hurst Parameter of Long-Range Dependent Traffic Using the Modified Hadamard Variance“, *Proc. IEEE ICC 2006*, Istanbul, Turkey, 2006.

[29] S. Bregni, "Chapter 5 - Characterization and Modelling of Clocks", in *Synchronization of Digital Telecommunications Networks*. Chichester, UK: John Wiley & Sons, 2002, pp. 203-281.

[30] D. W. Allan, J. A. Barnes, "A Modified Allan Variance with Increased Oscillator Characterization Ability", *Proc. 35th Annual Freq. Contr. Symp.*, 1981.

[31] P. Lesage, T. Ayi, "Characterization of Frequency Stability: Analysis of the Modified Allan Variance and Properties of Its Estimate", *IEEE Trans. Instrum. Meas.*, vol. 33, no. 4, pp. 332-336, Dec. 1984.

[32] L. G. Bernier, "Theoretical Analysis of the Modified Allan Variance", *Proc. 41st Annual Freq. Contr. Symp.*, 1987.

[33] D. B. Sullivan, D. W. Allan, D. A. Howe, F. L. Walls, Eds., *Characterization of Clocks and Oscillators*, NIST Tech. Note 1337, March 1990.

[34] C. A. Greenhall, "Recipes for Degrees of Freedom of Frequency Stability Estimators", *IEEE Trans. Instrum. Meas.*, 40(6), pp. 994-999, Dec. 1991.

[35] C. A. Greenhall, W. J. Riley. "Uncertainty of Stability Variances Based on Finite Differences". Available: http://www.wriley.com.

[36] W. J. Riley, "Confidence Intervals and Bias Corrections for the Stable32 Variance Functions", 2000. Available: http://www.wriley.com.

[37] J. Rutman, "Characterization of Phase and Frequency Instabilities in Precision Frequency Sources: Fifteen Years of Progress", *Proc. IEEE*, vol. 66, no. 9, pp. 1048-1075, Sept. 1978.

[38] P. Abry, D. Veitch, “Wavelet Analysis of Long-Range Dependent Traffic”, *IEEE Trans. Inform. Theory*, vol. 44, no.1, pp. 2-15, Jan. 1998.

[39] W. H. Press, B. P. Flannery, S. A. Teukolsky, W. T. Vettering, *"Numerical Recipes in C – The Art of Scientific Computing. 2nd Edition"*, Cambridge, UK: Cambridge University Press, 2002.

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