Investigating Self-Similarity and Heavy-Tailed Distributions on a Large-Scale Experimental Facility

Patrick Loiseau, Paulo Gonçalves, *Member, IEEE*, Guillaume Dewaele, Pierre Borgnat, *Member, IEEE*, Patrice Abry, *Senior Member, IEEE*, and Pascale Vicat-Blanc Primet, *Member, IEEE*

***Abstract*—After the seminal work by Taqqu *et al.* relating self-similarity to heavy-tailed distributions, a number of research articles verified that aggregated Internet traffic time series show self-similarity and that Internet attributes, like Web file sizes and flow lengths, were heavy-tailed. However, the validation of the theoretical prediction relating self-similarity and heavy tails remains unsatisfactorily addressed, being investigated using either numerical or network simulations, or from uncontrolled Web traffic data. Notably, this prediction has never been conclusively verified on real networks using controlled and stationary scenarios, prescribing specific heavy-tailed distributions, and estimating confidence intervals. With this goal in mind, we use the potential and facilities offered by the large-scale, deeply reconfigurable and fully controllable experimental Grid5000 instrument, combined with state-of-the-art estimators, to investigate the prediction's observability on real networks. To this end, we organize a large number of controlled traffic circulation sessions on a nationwide real network involving 200 independent hosts. We use a FPGA-based measurement system to collect the corresponding traffic at packet level. We then estimate both the self-similarity exponent of the aggregated time series and the heavy-tail index of flow-size distributions, independently. Not only do our results complement and validate, with a striking accuracy, some conclusions drawn from a series of pioneering studies, but they also bring in new insights on the controversial role of certain components of real networks.**

***Index Terms*—Heavy-tailed distributions, large-scale experiments, monitoring, network traffic, self-similarity.**

I. Motivations

THE comprehension and prediction of network traffic is a constant and central preoccupation for Internet service providers. Challenging questions, such as the optimization of network-resource utilization that respect application constraints and the detection (and ideally the anticipation) of anomalies and congestion, contribute to guarantee a better quality of service (QoS) to users. From a statistical point of view, this is a challenging and arduous problem that encompasses several components: network design, control mechanisms, transport protocols, and the traffic's nature itself. In the last decade, great attention has been devoted to the statistical study of network time series and random variables. When collected at the core of networks, they are valuable fingerprints of the system's state and evolution. With this in mind, the pioneering work by [1] and [2] evidenced that the Poisson hypothesis, a relevant and broadly used model for phone networks, fails at describing computer network traffic. Instead, self-similarity was shown to be a much more appropriate paradigm, and since then, many authors have reported its existence in a wide variety of traffic [3]–[6]. Following up this prominent discovery, the theoretical work by Taqqu *et al.* constituted another major breakthrough in computer network traffic modeling, identifying a plausible origin of self-similarity in traffic time series [2], [7], [8]. It posits that the heavy-tail nature of some probability distributions, mainly that of flow-size distributions, suffices to generate traffic exhibiting long-range dependency, a particular manifestation of self-similarity [9]. To support their claim, they established a closed-form relation connecting the heavy-tail thickness (as measured by a tail index) and the self-similarity exponent.

Notwithstanding the mathematical soundness of the heavy tail/LRD model, its validity has only been partially or approximately corroborated empirically using either real traffic traces or simulated traces. The first pitfall lies in the definition of long-range dependency itself, which, as we will see, is a scale invariance property that holds only asymptotically for long observation durations. Its consistent measurement requires that experimental conditions remain constant and that no external activity disturbs the traffic's characteristics. In those conditions, finding a scale range that limits itself to stationary data and is sufficiently wide to endorse reliable self-similarity measurements is an intricate task.

Second, even though real traffic traces have led to check the validity of the relation between the tail index and the self-similarity exponent, it only allowed to validate the model for a unique set of parameters values, corresponding to a particular network configuration. An extensive test in order to verify that the self-similarity exponent obeys the same rule when the tail index is forced to vary over some interval of interest has never been performed on a large-scale real network platform.

Finally, the exact role of the exchange protocol, viewed as a subsidiary factor from this particular model, is still controversial

Manuscript received May 30, 2008; revised June 04, 2009; approved by IEEE/ACM Transactions on Networking Editor P. Barford. First published March 01, 2010; current version published August 18, 2010. This work was supported by the French Ministry of Research under the Grid'5000 Project, the INRIA Aladdin ADT, an INRIA GridNet-FJ grant, the NEGST CNRS-JSP Project, and the European Commission under the FP6-IST-045256 Project EC-GIN.

P. Loiseau was with École Normale Supérieure de Lyon (LIP), Université de Lyon, 69364 Lyon cedex 07, France. He is now with INRIA Paris-Rocquencourt, 78153 Le Chesnay Cedex, France (e-mail: patrick.loiseau@inria.fr).

P. Gonçalves and P. Vicat-Blanc Primet are with INRIA, École Normale Supérieure de Lyon (LIP), Université de Lyon, 69364 Lyon cedex 07, France. (e-mail: Paulo.Goncalves@ens-lyon.fr; Pascale.Primet@ens-lyon.fr).

G. Dewaele is with Laboratoire de Physique, École Normale Supérieure de Lyon, Université de Lyon, 69364 Lyon cedex 07, France (e-mail: Guillaume.Dewaele@ens-lyon.fr).

P. Borgnat and P. Abry are with Laboratoire de Physique, CNRS, UMR 5672, École Normale Supérieure de Lyon, Université de Lyon, 69364 Lyon cedex 07, France. (e-mail: Pierre.Borgnat@ens-lyon.fr; Patrice.Abry@ens-lyon.fr).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TNET.2010.2042726

[10]–[12]. Due to the lack of flexible, versatile, and realistic experimental environments, part of this metrology questioning has been addressed by researchers of the network community, using simulators, emulators, or production platforms. However, these tools have limitations of their own, which make studies difficult and yield only incomplete results.

In the present work, we use the potential and the facilities offered by the very large-scale, deeply reconfigurable, and fully controllable experimental instrument Grid5000 [13] to empirically investigate the scope of applicability of the theorem proposed by Taqqu *et al.* [2], [7], [8].

Under controlled experimental conditions, we first prescribe the flow-size distribution to different tail indices and compare the measured traffic's self-similar exponents to their corresponding theoretical predictions. Our main goal is not to check the goodness of fit of the ON/OFF models to traffic data, but rather to demonstrate that imposing such models on the sources of a real network facility is sufficient to produce LRD, as predicted by Taqqu's theorem. Then, we elucidate the role of the protocol and of the rate-control mechanism on traffic's scaling properties. In the course of our approach, we resort to efficient estimators of the heavy-tail index and of the self-similarity exponent derived from recent advances in wavelet-based statistics and time-series analysis. In our opinion, this revisited investigation is the prerequisite to a rigorous methodological approach to assess the actual applicability conditions of this theoretical bond regarding real applications. That is why we deemed important to start with an advisedly *elementary* and yet *realistic* traffic pattern. The originality of our approach lies in the combination of well-suited ingredients:

- a large-scale real experimental platform;
- a fully controllable environment;
- state-of-the-art estimators whose utilization is appropriately adapted to the experimental conditions.

We believe that based on these supervised studies, the causes of a possible breakdown of Taqqu's relation in real-world traffic will have to be sought elsewhere, and in particular, the protocol in itself should not be solely incriminated.

The article is organized as follows. Section II summarizes related works. Section III elaborates on theoretical foundations of the present work, including a concise definition of parameters of interest. In Section IV, we develop the specificities of our experimental testbed and describe our experimental designs. Section V presents and comments the results. Conclusions and perspectives are drawn in Section VI.

II. Related Work

Without giving a full bibliography on the subject (many can be found in [4], [5], and [14]), there have been extensive reports on heavy-tailed distributions and self-similarity in network traffic. As most of them are based on measurements and on analyses of real-world traces from the Internet, they only permit the experimental validation of a single point on the prediction curve of Taqqu's theorem, corresponding to one particular configuration. As it was presented before, the question here is more on the relation between these two properties. This relation is rooted in the seminal work in [2] and [7] about the M/G/N queueing models with heavy-tailed distributions of the ON periods. Nonetheless, the first experimental works by Crovella *et al.* [3], [11] hinted that this theoretical relation holds for Internet traffic and, later on, for more general types of traffic as well [10], [12]. However, due to the impossibility of controlling important parameters when monitoring the Internet, only the compatibility of the formula could be tested against real data. Still, there is no statistically grounded evidence that self-similarity measured in network traffic is due solely to this equality. Moreover, study of self-similarity at large scales is very sensitive to inevitable nonstationarities (day and week periodicities for instance) and to fortuitous anomalies existing on the Internet (see, for instance, [15]). It seems that the question has since never received a full experimental validation that relies on both a real large-scale platform and a proper usage of the right estimators. In order to obtain such a validation, it is important to be able to make the heavy-tail index vary. There have been only a few attempts to validate the relation under these conditions. One is conducted in [11], which uses a network simulator and where some departure from the theoretical prediction is reported (Fig. 3 in this article). This deviation is probably caused by the limited length of the simulation and also by the bias introduced by the chosen scaling estimator (R/S and Variance-Time) when used on short traces. Actually, the main restriction of simulators lies in their scalability limitation and in the difficulty of their validation. Indeed, the network is an abstraction, protocols are not production code, and the number of traffic sources or bitrates that can be simulated depends on the computing power of the machine.

Large-scale experimental facilities are alternatives that may overcome the limitations of both the Internet and simulators, as they allow controlling network parameters and traffic generation, including statistics and stationarity issues. Emulab [16] is an experimental network facility where network protocols and services are run in a fully controlled and centralized environment. The emulation software runs on a cluster where nodes can be configured to emulate network links. In an Emulab experiment, the user specifies an arbitrary network topology, having a controllable, predictable, and reproducible environment. He has full root access on PC nodes, and he can run the operating system of his choice. However, the core network's equipment and links are emulated. The RON testbed [17] consists of about 40 machines scattered around the Internet. These nodes are used for measurement studies and evaluation of distributed systems. RON does not offer any reconfiguration capability at network- or node-level. The PlanetLab testbed [18] consists of about 1000 PCs on 500 sites (every site runs two PCs) connected to the Internet (no specific or dedicated link). PlanetLab allows researchers to run experiments under real-world conditions and at a very large scale. Research groups are able to request a PlanetLab slice (virtual machine) in which they can run their own experiments.

Grid5000 [13], the experimental facility we use in the present work, proposes a different approach where the geographically distributed resources (large clusters connected by ultra high-end optical networks) are running actual pieces of software in a real wide-area environment. Grid5000 allows reproducing experimental conditions, including network traffic and CPU usage.

This feature warrants that evaluations and comparisons are conducted according to a strict and scientific method. Grid5000 proposes a complementary approach to PlanetLab in terms of both resources and experimental environment.

III. Theory

Taqqu's theorem relates two statistical properties that are ubiquitously observed in computer networks: self-similarity, defined at the level of the traffic's aggregated time series, and heavy-tailedness that involves the grouping of packets. Simplistically, network traffic is described as a superposition of flows (without any notion of users, sessions, etc.), which allows us to adopt the following simple two-level model: 1) packets are emitted and grouped in flows whose length (or number of packets) follows a heavy-tailed distributed random variable [19]–[21]; 2) the sum over those flows approximates network traffic on a link or a router. This crude description is coherent with current (yet more elaborate) statistical models for Internet traffic [20], [21].

After a succinct definition of these two statistical properties, we present the corresponding parameter-estimation procedures that we use in our simulations. They were chosen among those reckoned to present excellent estimation performance.

A. Self-Similarity and Long-Range Dependency

1) Definition: Taqqu's theorem implies that Internet time series are relevantly modeled by fractional Brownian motion (fBm), the most prominent member of a class of stochastic processes, referred to as *self-similar processes with stationary increments* (H-sssi, in short). A process X is said to be H-sssi if and only if it satisfies [9]

$$X(t) - X(0) \stackrel{\text{fdd}}{=} X(u+t) - X(u) \quad \forall t, u \in \mathbb{R} \tag{1}$$

$$X(t) \stackrel{\text{fdd}}{=} a^H X\left(\frac{t}{a}\right) \quad \forall t, a > 0,\ 0 < H < 1 \tag{2}$$

where $\stackrel{\text{fdd}}{=}$ means equality for all finite dimensional distributions. Equation (1) indicates that the increments of X form a stationary process (while X itself is not stationary). Essentially, self-similarity expressed in (2) means that no characteristic scale of time plays a specific role in the analysis or description of X. As a corollary, (2) implies that $\mathbb{E}X(t)^2 = \mathbb{E}X(1)^2 t^{2H}$, underlining both the scale-free and the nonstationary natures of the process.

It turns out that the covariance function of the increment process, $Y(t) = X(t+1) - X(t)$, of a H-sssi process X satisfies, for $|\tau| \to +\infty$

$$\mathbb{E}Y(t)Y(t+\tau) \sim \mathbb{E}X(1)^2 H(2H-1)|\tau|^{2H-2}. \tag{3}$$

When $1/2 < H < 1$ (hence $-1 < 2H - 2 < 0$), the resulting slow power-law decay of the covariance function is referred to as long-range dependency [9], [14].

Long-range dependency and self-similarity designate two different notions, albeit often confused. The latter is associated to nonstationary time series such as fBms, while the former is related to stationary time series such as the fBm's increments. In the present work, given that Taqqu's theorem predicts that the cumulated sums of aggregated Internet time series are self-similar, we adopt the same angle and discuss the results in terms of self-similarity of the integrated traces.

2) Self-Similarity Parameter Estimation: In [22], it was shown that wavelet transform provides a relevant procedure for the estimation of the self-similarity parameter. This procedure was shown to be particularly efficient at analyzing Internet time series in [5] and [6] and has thus been massively used in this context.

Let $d_X(j,k) = \langle \psi_{j,k}, X \rangle$ denote the (discrete) wavelet transform coefficients, where the collection $\{\psi_{j,k}(t) = 2^{-j/2}\psi_0(2^{-j}t - k), k \in \mathbb{Z}, j \in \mathbb{Z}\}$ forms a basis of $L^2(\mathbb{R})$ [23]. The reference template ψ_0 is termed mother-wavelet and is characterized by its number of vanishing moments $N_\psi > 1$, an integer such that $\int t^k \psi_0(t)\, dt \equiv 0, \forall k = 0, \ldots, N_\psi - 1$. Then, the variance of the wavelet coefficients of a H-sssi process decomposition, verifies [22]

$$\mathbb{E}|d_X(j,k)|^2 = \mathbb{E}|d_X(0,0)|^2 2^{j(2H+1)} \tag{4}$$

and, provided $N > H + 1/2$, the sequence $\{d_X(j,k), k = \ldots, -1, 0, 1, \ldots\}$ forms a stationary and weakly correlated time series [6]. These two central properties warrant that the empirical mean $S(j) = n_j^{-1} \sum_k |d_X(j,k)|^2$ (n_j being the number of available coefficients at scale 2^j) is a good estimate of the ensemble average $\mathbb{E}|d_X(j,k)|^2$. Equation (4) indicates that self-similarity transposes to a linear behavior of $\log_2 S(j)$ versus $\log_2 2^j = j$ plots, often referred to as logscale diagrams (LDs) in the literature [5], [6]. A (weighted) linear regression of the LD within a proper range of octaves j_1, j_2 is used to estimate H.

In [5], [6], and [22], the estimator's performance is both theoretically and practically quantified and is proved to compare satisfactorily against the best parametric techniques. Moreover, this estimator is endowed with a practical robustness that comes from its extra degree of freedom N_ψ. In practice, the main difficulty lies in the correct choice of the regression range $j_1 \le j \le j_2$. This will be discussed in Section V in the light of actual measurements.

By principle, the wavelet coefficients at coarser scales (i.e., for large values of j_2) convey information about a signal in the limit of long observation periods. Therefore, analyzing the LD in the large-scales region is a straightforward manner to tackle the time limit issue of Taqqu's result mentioned in Section III-C.

B. Heavy Tail

1) Definition: A (positive) random variable $\mathbf{w}$ is said to be heavy-tailed with tail exponent $\alpha > 0$ (and noted α-HT) when the tail of its cumulative distribution function $F_{\mathbf{w}}$ is characterized by an algebraic decrease [24]

$$P(\mathbf{w} > w) = 1 - F_{\mathbf{w}}(w) \sim L(w) \cdot w^{-\alpha} \text{ for } w \to \infty \tag{5}$$

where $L(w)$ is a slowly varying function (i.e., $\forall a > 0, L(aw)/L(w) \to_{w \to \infty} 1$). An α-HT random variable $\mathbf{w}$ has finite moments up to order α. For instance, when $1 < \alpha < 2$,

$\mathbf{w}$ has finite mean but infinite variance. A paradigm for α-HT positive random variable is given by the Pareto distribution

$$F_{\mathbf{w}}(w) = 1 - \left(\frac{k}{w+k}\right)^{\alpha} \tag{6}$$

with $k > 0$ and $\alpha > 1$. Its mean reads: $\mathbb{E}\mathbf{w} = k/(\alpha - 1)$.

2) Tail-Exponent Estimation: Estimation of the tail exponent α for α-HT random variables is an intricate issue that received considerable theoretical attention in the statistics literature: Measuring the tail exponent of a heavy-tailed distribution amounts to evaluating, from observations, how fast the probability of rare events decreases in (5). Once random variables are known to be drawn from an *a priori* distribution, such as the Pareto form (6) for example, parametric estimators exist and yield accurate estimates of the tail index α (see, e.g., [25]). However, if the actual distribution of observations does not match the *a priori* expected α-HT model, parametric estimators fail at measuring the tail decay.

For this reason, the nonparametric empirical estimator of α proposed in [26] will be preferred. The principle of this estimator is simple and relies on the Fourier mapping between the cumulative distribution function $F_{\mathbf{w}}(w)$ and the characteristic function $\chi_{\mathbf{w}}(s)$ of a random variable

$$\chi_{\mathbf{w}}(s) = \int e^{-isw}\, dF_{\mathbf{w}}(w). \tag{7}$$

By a duality argument, the tail exponent α that bounds the order of finite moments of $F_{\mathbf{w}}$

$$\alpha = \sup_r \{r > 0 : \int |w|^r\, dF_{\mathbf{w}}(w) < \infty\} \tag{8}$$

transposes to the local Lipschitz regularity of the characteristic function $\chi_{\mathbf{w}}$ at the origin, according to

$$\alpha = \sup_r \{r > 0 : 1 - \Re\chi_{\mathbf{w}}(s) = \mathcal{O}(s^r) \text{ as } s \to 0^+\} \tag{9}$$

where $\Re$ stands for the real part. It is easy to recognize in this power law behavior of $\Re\chi_{\mathbf{w}}(s)$ a scale-invariance property of the same type as that of relation (3), which is conveniently identifiable with wavelet analyses. Hence, computing the discrete wavelet decomposition of $\Re\chi_{\mathbf{w}}$, and retaining only the wavelet coefficients that lie at the origin $k = 0$, yields the following multiresolution quantity:

$$d_{\chi_{\mathbf{w}}}(j, 0) = \mathbb{E}\Psi_0(2^j \mathbf{w}) \leq C 2^{j\alpha} \text{ for } j \to -\infty \tag{10}$$

where $\Psi_0(\cdot)$ denotes the Fourier transform of analyzing wavelet $\psi_0(\cdot)$. Now, let $\{w_0, \ldots, w_{n-1}\}$ be a set of i.i.d. α-HT random variables, and replace the ensemble average in (10) by its empirical estimator, the estimate $\widehat{\alpha}$ simply results from a linear regression of the form

$$\begin{aligned}\log \widehat{d}^{(n)}_{\chi_{\mathbf{w}}}(j, 0) &= \log n^{-1} \sum_{i=o}^{n-1} \Psi(2^j w_i) \\ &\approx \widehat{\alpha} j + \log C \text{ as } j \to -\infty.\end{aligned} \tag{11}$$

The estimator was proved to converge for all heavy-tailed distributions, with a reduced variance of estimation in $\mathcal{O}(n^{-1})$ (where n is the sample size). It was moreover shown to be robust for all $\alpha > 0$, even for α close to 1^+, when the apparent data mean instability is responsible for the slow convergence of usual empirical estimates. We refer the interested reader to [26], where the robustness and effective use of this estimator are thoroughly studied. Yet, let us mention the existence of a theoretical scale range where the linear model of (11) holds true, which is very helpful for practitioners to adequately adjust their linear fitting over a correct scale range.

C. Taqqu's Theorem

A central result for interpreting the statistical modeling of network traffic is a celebrated theorem due to Taqqu *et al.* [2], [7], [8], in which the heavy-tailedness of flow sessions has been put forward as a possible explanation for the occurrence of self-similarity of Internet traffic.

The original result considers a M/G/N queueing model served by N independent sources, whose activities $Z_i(t)$, $i \in \{1, \ldots, N\}$, are described as binary ON/OFF processes. The durations of the ON periods (corresponding to a packet-train emission by a source) consists of i.i.d. positive random variables τ_{ON}, distributed according to a heavy-tail law P_{ON}, with exponent $\alpha = \alpha_{\mathrm{ON}}$. Intertwined with the ON periods, the OFF periods (a source does not emit traffic) have i.i.d. random durations τ_{OFF} drawn from another possibly heavy-tailed distribution P_{OFF} with tail index $\alpha = \alpha_{\mathrm{OFF}}$. Thus, the $Z_i(t)$ consist of a 0/1 reward-renewal processes with i.i.d. activation periods.

Now, let $Y_N(t) = \sum_{i=1}^{N} Z_i(t)$ denote the aggregated traffic time series, and define the cumulative process $X_N(Tt)$

$$X_N(tT) = \int_0^{Tt} Y_N(u) \mathrm{d}u = \int_0^{Tt} \left(\sum_{i=1}^{N} Z_i(u)\right) \mathrm{d}u. \tag{12}$$

Taqqu's theorem (cf. [7]) states that when taking the limits $N \to \infty$ (infinitely many users) and $T \to \infty$ (infinitely long observation duration) in this order, then $X_N(tT)$ behaves as

$$X_N(tT) \sim \frac{\mathbb{E}\tau_{\mathrm{ON}}}{\mathbb{E}\tau_{\mathrm{ON}} + \mathbb{E}\tau_{\mathrm{OFF}}} NTt + C\sqrt{N} T^H B_H(t). \tag{13}$$

In this relation, C is a constant and B_H denotes a fractional Brownian motion with Hurst parameter

$$H = \frac{3 - \alpha^*}{2} \quad \text{where } \alpha^* = \min(\alpha_{\mathrm{ON}}, \alpha_{\mathrm{OFF}}, 2). \tag{14}$$

The order of the limits is critical to obtain this asymptotic behavior; this has been discussed theoretically elsewhere and is beyond the issues we address here. The main conclusion of Taqqu's theorem is that, in the limit of (infinitely) long observations, fractional Brownian motions superimposed to a deterministic linear trend are relevant asymptotic models to describe the cumulated sum of aggregated traffic time series. Moreover, (14) shows that only heavy-tailed distributions with infinite variance (i.e., $1 < \min(\alpha_{\mathrm{ON}}, \alpha_{\mathrm{OFF}}) < 2$) can generate self-similarity associated to long-range dependency (i.e., $H > 1/2$).

Conversely, when both activity and inactivity periods have finite variance durations, $\alpha^* = 2$ and consequently $H = 1/2$, which means no long-range dependency.

IV. Experimental Setup

To study the practical validity of Taqqu's result, we use the potential and facilities offered by the very large-scale, deeply reconfigurable, and fully controllable experimental instrument Grid5000 to overcome the previously mentioned limitations of emulation, simulation, or measurement in production networks. Moreover, we deliberately chose to work with the simplest network configurations that permit a thorough investigation of Taqqu's theorem—namely, an elementary network topology encompassing multiple independent sources, whose throughputs aggregate on a single hop, and a traffic generation without congestion. This way, we isolate the nature of the flows' distributions as the main entry for Taqqu's relation. After a general overview of Grid5000, the metrology platform is described. Finally, the designing of a large set of experiments, aimed at studying the actual dependency between the network traffic's self-similarity and the heavy-tailedness of flow-size distributions, is detailed.

A. Overview of the Grid5000 Instrument

Grid5000 is a 5000-CPU nationwide Grid infrastructure for research in Grid computing [13], providing a scientific tool for computer scientists similar to the large-scale instruments used by physicists, astronomers, and biologists. It is a research tool featuring deep reconfiguration, control, and monitoring capabilities designed for studying large-scale distributed systems and for complementing theoretical models and simulators. As much as 17 French laboratories are involved, and nine sites host one or more clusters of about 500 cores each. A dedicated private optical networking infrastructure—provided by RENATER, the French National Research and Education Network—interconnects the Grid5000 sites. Two international interconnections are also available: one at 10 Gb/s interconnecting Grid5000 with DAS3 in the Netherlands and one at 1 Gb/s with Naregi in Japan. In the Grid5000 platform, the network backbone is composed of private 10-Gb/s Ethernet links connected to a DWDM core with dedicated 10-Gb/s lambdas with bottlenecks at 1 Gb/s in Lyon and Bordeaux in France (see Fig. 1).

Grid5000 offers every user full control of the requested experimental resources. It uses dedicated network links between sites and allows users to reserve the same set of resources across successive experiments, to run their experiments in dedicated nodes (obtained by reservation), and to install and run their own experimental condition injectors and measurement software. Grid5000 exposes two tools to implement these features: OAR is a reservation tool, and Kadeploy is an environment-deployment system. OAR offers an accurate reservation capability (CPU/Core/Switch reservation) and integrates the Kadeploy system. With Kadeploy, each user can make his own environment and have a total control on the reserved resources. For instance, software and kernel modules for rate limitation, QoS mechanisms, or congestion-control variants can be deployed automatically within the native operating system of a large number of communicating nodes. OAR also permits users to reserve

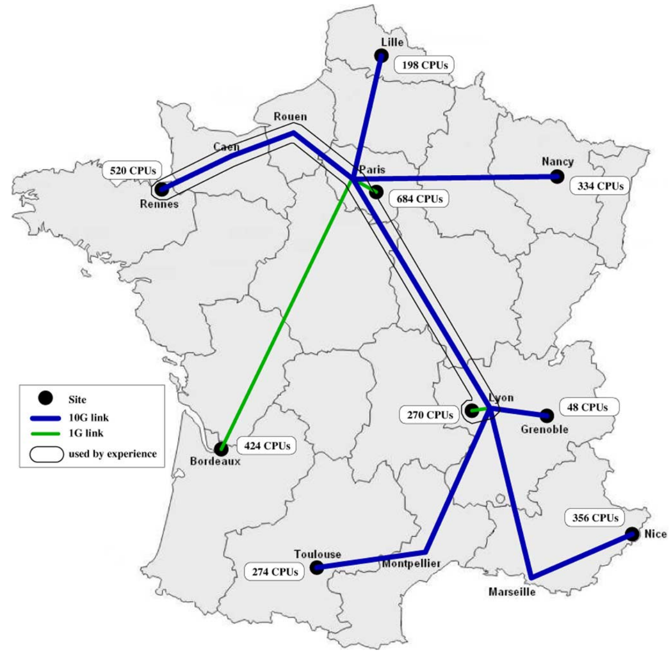

Fig. 1. Grid5000 backbone.

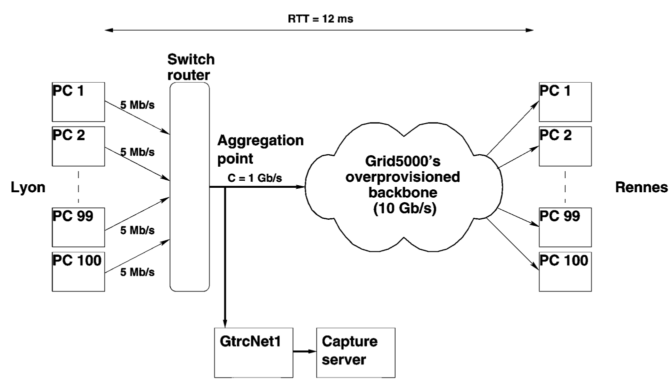

Fig. 2. Metrology platform overview.

equipment for several hours. As a consequence, Grid5000 enables researchers to run successive experiments reproducing the exact experimental conditions several times, a task that is almost impossible with shared and uncontrolled networks. This also ensures large-duration observation windows under stationary conditions, which cannot be achieved on the Internet. As a private testbed, Grid5000 makes the installation of experimental hardware—e.g., the traffic capture instrument at representative traffic aggregation points—quite easy.

B. Metrology Platform

Using the facilities offered by Grid5000, a platform for metrology has been designed and schematized in Fig. 2. Before describing the monitoring facilities and the developed data processing software, let us present the effective topology used for this experiment.

1) Experimental System Description: Unless explicitly mentioned, all our experiments consist in producing data-flow transfers between many independent client nodes (sources) and many independent server nodes (destinations). We chose

$N = 100$ nodes able to reach transmission rates up to $C_a = 1$ Gb/s in both directions. Aggregated traffic is captured on a backbone link of capacity $C = 1$ Gb/s shared by all the source–destination pairs (see Fig. 2), and we ensure that our controlled traffic undergoes no other bottleneck in the network.

For our experiments, we used nodes from the Grid5000 clusters of Lyon (clients) and Rennes (servers). The average RTT was stable and equal to 12 ms, which leads to a bandwidth-delay product of 1.5 MB. In our forthcoming scenarios, TCP and UDP transfers are made using *iperf* [27] on Sun Fire V20z (bi-opteron) workstations of Grid5000 [13], running GNU/Linux 2.6.18.3 kernels with standard TCP and UDP modules. Iperf is a traffic-generation tool that allows users to tune the different TCP and UDP parameters and to evaluate their impact on network performance.

This single-bottleneck topology was intentionally chosen since our main goal was not to study the queueing effect of successive routers in a multiple-hops network. We believe that, without loss of generality, the simplicity of this test topology suffices at properly creating the realistic experimental conditions for investigating the limits of Taqqu's theorem.

2) Capture System: To measure the traffic at packet level, we designed a specific system combining packet capture, header extraction, and dedicated data-analysis software. Packets are first captured by mirroring the traffic of the access link connecting the Lyon site to the rest of Grid5000. Only the outgoing traffic from the Lyon site to Grid5000 is mirrored, connecting a 1-Gb/s fiber port to a 1-Gb/s copper port directed to the monitoring system.

This system is composed of a GtrcNET-1 device [28], developed by AIST GTRC, and based on a FPGA that has been programmed to extract and aggregate packet headers and send them to an attached server. This header aggregation reduces the number of interrupts of the computer that receives the traffic to analyze, decreasing the local loss probability. In the packet-capture system, the GtrcNET-1 is configured to extract a 52-byte header (composed of 14, 20, and 18 bytes of Ethernet, IP, and TCP headers, respectively) from the packets arriving at the 1-Gb port. Headers are added a timestamp each, encapsulated by groups of 25 into a UDP packet, and then sent to another gigabit port. Timestamps have a 60-ns (2^{-24} s) resolution.

The concatenated headers are stored in a computer with a quad-core processor running at 2.66 GHz, 4 GB memory, two Ethernet gigabit ports, 300 GB SAS disk for the system, 1 RAID controller with 5×300 GB SAS disk in a RAID 0 array offering 1500 GB for storing capture files. We developed a driver that reads GtrcNET-1 packets, deencapsulates time-stamped packet headers, and writes them to a file in the pcap format.

3) Data Processing and Flow Reconstruction: We use a series of tools over the captured IP traffic traces to go from the packet-level traces to the aggregated traffic and the flow statistics that are needed in this work. A first step is to handle the captured IP traffic traces. Second, we reconstruct the flows from the packets.[1]

[1]Using standard flow-monitoring tools, such as Netflow or Sflow, would not be sufficient here since we need statistical characterization at both packet level (for H-sssi) and flow level (for α-HT).

IP traffic traces, saved in standard pcap format by the capture device, are first processed by `ipsumdump`, a program developed at the University of California, Los Angeles (UCLA) [29], able to read the pcap format and to summarize TCP/IP dump files into a self-describing binary format. Thanks to this tool, we retrieve the needed information from our traces: timestamps, source and destination IPs, port numbers, protocol, payload size, TCP flags, and sequence numbers. The information is condensed into a binary file that is easier to parse and does not depend on specific capture hardware anymore.

Second, we have developed a collection of tools working on the `ipsumdump` binary format directly, which performs a variety of useful data operations on the traces. Among those, the following are of relevant interest: computation of the aggregated traffic time series (used for self-similarity estimation); extraction of traffic subtraces for conditioned study, based on the random sampling of flows or packets or on parameter filtering (e.g., traffic from/to a list of IPs, traffic on given ports, traffic using a specific protocol); and reconstruction of the flows existing in the traces.

The question of flows reconstruction is an intricate problem and an important and difficult aspect when one wants to study the impact of their distribution's heavy-tailedness [14], [30]–[32]. It is necessary to recompose each flow from the intertwined packet streams measured on an aggregated link. This means that we must identify and group all the packets pertaining to the same set, while considering a significantly large number of flows to guarantee statistical soundness. This constraint faces the arduous issues of loss-free capture and of dynamic table updating.

In our tool, flows are classically defined as a set of packets that share the same 5-uplet comprising: source and destination IPs and ports and protocol. However, because there is a finite number of ports, it is possible for two different flows to share the same 5-uplet and thus to get grouped in a single flow. To avoid this, we set a `timeout` threshold: A flow is considered as finished if its packet train undergoes an interruption lasting more than `timeout`. Any subsequent packet with the same 5-uplet will tag the beginning of a new flow. Naturally, a proper choice of `timeout` is delicate, but that is the only solution that works for any kind of flows. For TCP flows, though, things are easier, as we can use the SYN or SYN/ACK flags to initiate a flow (closing any currently open flow with the same 5-uplet), and the FIN or RCT flag to close the flow, dispensing with `timeout`. Note that `timeout` remains necessary when the FIN packet is accidently missing.

Flow reconstruction (with `timeout`) is then performed in a table that contains all currently open flows, using hash functions to speed up the access. The relatively modest trace bitrate allows keeping the whole table in memory. Since the TCP sequence numbers and the payload size for TCP packets are captured, it is possible to search for dropped or reemitted packets during the flow reconstruction and take that into account. Elementary statistics on the flows are then available: number of packets, number of bytes, duration of the flow, etc.

Altogether, the data processing tools extract the two elements needed for this study: the aggregated time series at packet level and the experimental flow-size distribution of any traffic that will be sent through, and monitored in, Grid5000's metrology platform.

C. Rate-Limitation Mechanisms

The last major aspect of the experimentation is the careful design of traffic generation. In real networks, flows are not the fluid ON/OFF flows of the $M/G/N$ model: Packets composing the flows are sent entirely, one after the other, at the wire bitrate. Following up, a critical feature to consider in network experiment design is the mechanism of traffic generation, especially the rate at which the packets are sent. An important parameter is the aggregation level of traffic K, defined as the ratio between the bottleneck capacity C and the access link's nominal capacity $C_{\rm a}$. In xDSL context and more generally in the Internet, it is not rare to have K over 1000, while in the datacenter context, K is around 1 or 10. In our Grid5000 setup, the K factor is close to 1. To obtain a K factor larger than 100 (so as to mimic the natural rate limit due to the bandwidth of users' uplink in an Internet configuration) and to impose an aggregated throughput average lower than $C = 1$ Gb/s, the sources' rate has to be limited to at most 10 Mb/s.

End-host-based mechanisms can control the individual flows in a scalable and simple way [33]. When considering packets of constant size, we can enforce data rates over a large period of time by imposing the interpackets' intervals. In end-host systems, four different beat times are controllable: 1) userland timers; 2) TCP self-clocking, i.e., RTT of the transfer's path; 3) OS's kernel timers; and 4) packet-level clocking. In our experiments, we used three rate-limitation approaches that act at different timescales: The first one is based on packet-level clocking (packet spacer), the second one on the OS's kernel timers (Token Bucket), the last one on TCP self clocking, which is the RTT of the transfer's path (window size limitation).

The first two methods rely on Linux's traffic-shaping mechanism: with the `tc` utility [34], the qdisc associated to a network interface (the queue in which packets are put before being sent to the network card) is configured. The PSP (PSPacer) [35] qdisc spaces packets by inserting IEEE 802.3x PAUSE packets. These PAUSE packets are discarded at the input port of the first switches. With this mechanism, packets are regularly spaced and short bursts are avoided. The second method resorts to HTB (Hierarchical Token Bucket) qdisc [36] that uses a bucket constantly filled by tokens at the configured target rate. With this qdisc, the average rate limit can be overridden during short bursts.

The third and last method modifies the TCP window size to slow down the throughput. The formula $\mathrm{window\_size} = \mathrm{target\_throughput} \times \mathrm{RTT}$ determines the TCP window size to use to limit the sending rate to $\mathrm{target\_throughput}$. This mechanism works well if the window size is not too small, which requires the target's throughput and the RTT to not be too small. As the TCP limitation acts for each TCP connection, many sources located on the same node can have independent rate limitation, which is not the case for qdisk-based limitation mechanisms. To limit the rate of a 1-Gb/s source to 5 Mb/s with full-size (1500 bytes) Ethernet packets and a RTT of 12 ms, the window size has to be set to 7.5 kB (corresponding to five full-size Ethernet packets).

TABLE I
FIXED EXPERIMENTAL GLOBAL PARAMETERS

	description
Client nodes	Sun Fire V20z (bi-opteron)
Kernel	GNU/Linux 2.6.18.3
TCP variant	Bic, with SACK
iperf version	2.0.2
Topology	Butterfly
Bottleneck	1 Gb/s
RTT	12 ms
Sources nb.	100
Source rate	5 Mb/s
Exp. duration	8 hours
Flows nb.	5.10^6
Aggregation time	$\Delta = 100\ \mu$s
Flow timeout	`timeout`= 100 ms

D. Experiments Description

Using the facilities offered by Grid5000, our metrology facilities, and the rate-control mechanisms for traffic generation, several experiments were performed, and we elaborate here on their rationale. First, the general experimental conditions are presented (see Table I).

The primary interest here is the effect of flow-size distributions on self-similarity, when each client behaves like an ON/OFF source model, where an ON period corresponds to a flow emission, and an OFF period to a silent source. The ON (respectively OFF) lengths are random variables drawn independently and identically distributed, following the specific probability distribution $P_{\rm ON}$ (respectively $P_{\rm OFF}$) we want to impose on the flow durations $\tau_{\rm ON}$ (respectively, on the silent periods, $\tau_{\rm OFF}$). The emission of packets in each flow is controlled by one of the methods described in previous section, each source rate being limited to 5 Mb/s to avoid congestion at the 1-Gb/s bottleneck.

Let us emphasize that even though we impose a rate control (at the TCP window or at packet level) to avoid congestion, our TCP sources remain realistic. Indeed, they are ack-clocked, they are regulated by slow-start and congestion-avoidance algorithms of a real GNU/Linux protocol implementation, and they are subject to real packet regulation. On average, each packet goes through two layer-3 equipments (IP routers), four layer-2 equipments (1 Gb/s or 10 Gb/s Ethernet switches) and three layer-1 equipments (Optical CrossConnect).

All experiments consist of one trace of 8-h traffic generation, representing a total of approximately $n = 5.10^6$ flows. As explained before, flows are reconstructed from the traces, and we extract their flow sizes (in packets) $W = \{w_i, i = 1, \ldots, n\}$, as well as the OFF time series corresponding to the interflow times for each source. Grouping and counting the packets in each contiguous time interval of width $\Delta = 100\ \mu$s yields the aggregated traffic's time series $X^{(\Delta)}(t)$.

In order to clearly define the terms of application of Taqqu's theorem on real traffic traces, as well as to identify possible interactions with other factors, we designed four series of experiments whose parameters are summarized in Table II.

- **Experiment A**: This is the cornerstone experiment to check relation (14). Distribution of the ON periods are prescribed to Pareto laws with mean $\mu^{\rm ON} = 0.24$ s (corresponding to a mean flow size of $\langle P \rangle = 100$ packets). The experiment is performed 10 times with different prescribed

TABLE II
SUMMARY OF EXPERIMENTAL CONDITIONS

	Proto	Band lim	α_{ON}	α_{OFF}	$\langle P \rangle$	meas param
A	TCP	PSP HTB TCP	1.1 – 4	-	100	$\widehat{H}$ $\widehat{\alpha}$
	UDP	iperf				
B	TCP	TCP	1.1 – 4	-	100 1000	$\Delta_{j_1}^{\langle P \rangle}$
C	TCP	TCP	-	1.1 – 4	1000	$\widehat{H}$
D	TCP	TCP	1.1 – 4	-	100	$\widehat{h}_{\mathrm{loc}}$
	UDP	iperf				

tail index α_{ON}, varying from 1.1 to 4. OFF periods are kept exponentially distributed with mean $\mu^{\mathrm{OFF}} = \mu^{\mathrm{ON}}$. For each value of α_{ON}, an experimental point $(\hat{\alpha}_{\mathrm{ON}}, \hat{H})$ is empirically estimated. Moreover, to evaluate the possible influence of the protocol, and of the workload-generation mechanism, the same series of experiments is reproduced with TCP (window-size limitation) and with UDP (user-level packet pacing) first, and then using PSP, HTB, and TCP throughput controls. The exact same trial of random variables defining the flow lengths is used for all experiments that imply the same probability law P_{ON}.

- **Experiment B**: Under similar conditions as in series A, the mean of the ON periods takes on two different values $\mu^{\mathrm{ON}} = 0.24$ s and $\mu^{\mathrm{ON}} = 2.4$ s, corresponding to mean flow sizes $\langle P \rangle = 100$ and $\langle P \rangle = 1000$ packets, respectively. The objective is here to relate $\langle P \rangle$ to the lower scale bound $\Delta_{j_1} = 2^{j_1}\Delta$ defining a sensible regression range to estimate H.
- **Experiment C**: The protocol (TCP), the throughput-limitation mechanism (TCP window limitation), and the mean flow size ($(\langle P \rangle = 1000)$ being fixed, we now investigate the role of the OFF-periods distribution on the self-similar exponent H. Distributions of the OFF periods are prescribed to Pareto laws with mean $\mu^{\mathrm{OFF}} = 2.4$ s. The experiment is repeated with different prescribed tail index α_{OFF}, varying from 1.1 to 4. ON periods are kept exponentially distributed with mean $\mu^{\mathrm{ON}} = \mu^{\mathrm{OFF}}$. For each value of α_{OFF}, an experimental point $(\hat{\alpha}_{\mathrm{OFF}}, \hat{H})$ is empirically estimated.
- **Experiment D**: The last series of experiments aims at investigating self-similarity at finer scales (lower than the RTT scale) and whose origin is distinct from long-range-dependance phenomena. The variable parameter is the tail index, as in experiment A, whereas the scaling-law index will be estimated in the short timescales limit, in order to characterize the traffic's burstiness from process $X^{(\Delta)}$. Under the same experimental conditions as in series A, we evaluate how the protocol (TCP versus UDP) entails a significant change in the traffic's burstiness.

Specifically for series A and C, where ON and OFF periods are statistically forced, it is crucial for those experiments to guarantee a loss-free traffic. Should this not be the case, flow lengths and/or silence periods may deviate from the prescribed distributions due either to packet drops and reemission or to exponential backoffs.

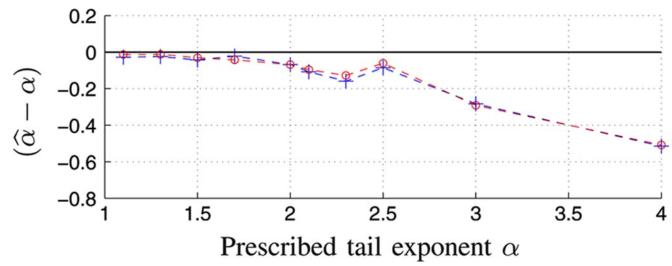

Fig. 3. Difference between the prescribed HT index α and the actually estimated HT index $\hat{\alpha}$ for the set of different values of α used in experiment series A (see Table II) for two different protocols: TCP $(+)$ and UDP $(\circ)$.

V. RESULTS AND DISCUSSION

A. Verifying Taqqu's Relation

For every trace, we use the wavelet-based methodologies described in Section III for heavy-tail and self-similarity analyses. The estimated tail index $\hat{\alpha}$ (corresponding to either $\hat{\alpha}_{\mathrm{ON}}$ or $\hat{\alpha}_{\mathrm{OFF}}$, clear from the context of Table II) results from the linear regression of (11) applied to the flow-size sequence W (or to the OFF times series), where a sixth-order derivative of a Gaussian wavelet is systematically used. The self-similarity index $\hat{H}$ is estimated from the LD plots of the aggregated time series $X^{(\Delta)}$, using a standard Daubechies wavelet with three vanishing moments [23].

1) Tail-Index Estimates: Proceeding with experiment A, for different values of the tail index of the flow-size distribution, Fig. 3 displays the differences between the prescribed value α and the actually estimated value $\hat{\alpha}$. The two experimental curves, corresponding to the TCP and UDP protocols respectively, superimpose almost perfectly. Beyond coherence with the fact that the exact same trial of random variables defining the flow lengths is used in both cases, such a concordance demonstrates that the flow reconstruction procedure, for both TCP or UDP packets grouping, is fully operative, notably including a relevant `timeout` adjustment (`timeout` = 100 ms).

Fig. 3 shows an increasing difference $(\hat{\alpha} - \alpha)$ with α as well. In our understanding, this is not caused by an increasing bias of the HT estimator, which is known to perform equally well for all α values. It is rather caused by the natural difficulty of prescribing large values of α over a fixed duration, principally when the mean of the distribution is kept constant. Indeed, as α increases, large flows become rarer, and the number of observed elephants during the constant duration (8 h) of the experiments decreases, progressively deviating from a statistically relevant sample. A second explanation lies in the estimation issue: As the distribution's mean is fixed, the maximum observed value decreases and reduces the domain where the distribution asymptotically behaves as a power law. This observation is fully consistent with arguments developed in [37]. In our numerical studies, we will then systematically compare the estimated H to $\hat{\alpha}$ rather than to the prescribed α.

2) Gaussianity: Before verifying the presence of long-range dependency in the aggregated traffic's time series, we first need to verify the normal assumption (recall that the increment process of a fBm is a stationary and Gaussian process). Thus,

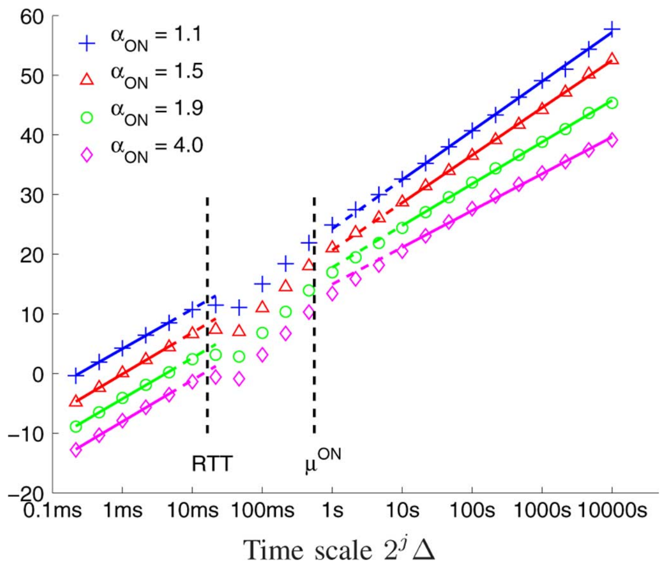

Fig. 4. Wavelet log-diagrams $\log S(j)$ versus time scale j of aggregated traffic (aggregation interval $\Delta = 100\ \mu$s). Log-diagrams correspond to four time series obtained under similar experimental conditions with the protocol TCP, with four different values of $\alpha_{\rm ON}$: 1.1 (+), 1.5 ($\triangle$), 1.9 ($\circ$), and 4.0 ($\Diamond$). For the sake of readability, curves were vertically shifted to avoid overlapping.

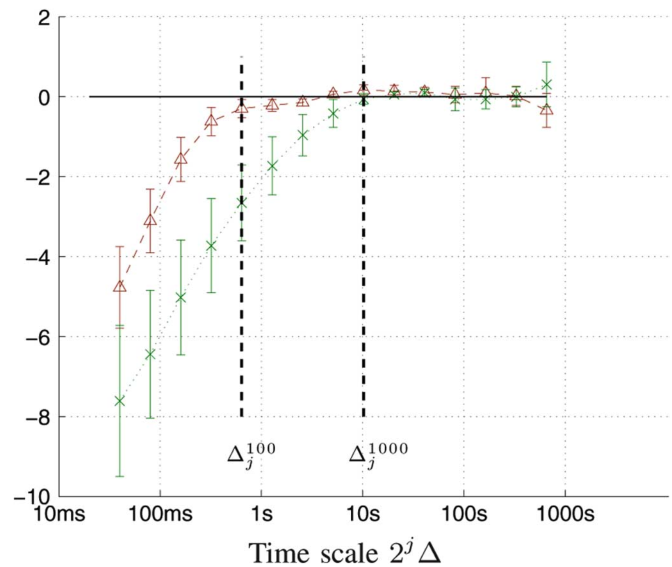

Fig. 5. Averaged normalized log-diagrams for two different mean sizes $\langle P\rangle$ of the transmitted flows: ($\times$) $\langle P\rangle = 1000$ packets – ($\triangle$) $\langle P\rangle = 100$ packets.

for each trace described in Table II, the Kurtosis index[2] of the aggregated traffic's time-series distribution was computed at several different aggregation intervals. As the Kurtosis index was always found to lie between 3.0 and 3.1, for aggregation intervals larger than $\Delta = 10$ ms, we conclude that the aggregated traffic's time series is a reasonably Gaussian process beyond this limit.

While not a rigorous proof, this normality verification indicates that the number of used sources (100) is sufficient to meet the asymptotic conditions of an infinite number of users.

3) LD-Description: Fig. 4 shows typical LDs of aggregated traffic time series, obtained under similar conditions (experiment series A of Table II, TCP protocol, TCP window limitation), for four different values of α. Such plots enable a generic phenomenological description of LDs: Three different ranges of scales can be visually identified, whose bounds do not seem to drastically vary with α.

- **Coarse scales**: In the coarse-scale domain, a clear scaling behavior is systematically observed. As mentioned earlier, Taqqu's theorem relates heavy tails and self-similarity in the asymptotic limit of coarse scales. Therefore, the scaling exponent at coarse scales, denoted $\hat{H}$, is a candidate to match that involved in relation (14).
- **Fine scales**: At fine scales, another clear scaling behavior is also observed. However, the corresponding scaling index, denoted h, is no longer related to Taqqu's theorem's prediction, but rather to a local regularity property of the data.
- **Medium scales**: Intermediate scales mostly connect the two scaling behaviors happening for fine and coarse scales, but exhibit no noticeable scaling behavior.

[2]The Kurtosis index of a R.V. is defined as the ratio of its fourth-order moment over its square variance and takes the value 3 in the normal case.

In Fig. 4, vertical lines materialize the two transition scales between the three depicted domains and can hence be identified as characteristic timescales of the data. Let us now investigate the nature of these characteristic times.

4) Coarse-Scales Domain's Lower Bound: It is alluded in [21] that the range of scales where self-similarity can be measured is beyond a characteristic scale, referred to as the *knee* of the LD, and that it is essentially controlled by the mean flow duration. To investigate this argument in the context of our analyses, we designed two experiments series with two different values of the mean flow duration (series B of Table II). For each case, all the LDs corresponding to the different values of α are computed. To emphasize the impact of the mean flow duration, we substracted to each LD the asymptotic linear trend, obtained by linear regression between a scale Δ_{j_1}, clearly above the *knee* position, and the maximum available scale $\Delta_{j_{\max}}$. Fig. 5 shows, both for $\langle P\rangle = 100$ and $\langle P\rangle = 1000$, the mean and standard deviation over all normalized LDs. Each graph clearly exhibits a slope break: at scale $\Delta_j^{100} = 0.64$ s when $\langle P\rangle = 100$ and at scale $\Delta_j^{1000} = 10.28$ s when $\langle P\rangle = 1000$. Although for $\langle P\rangle = 100$, the knee effect slightly smooths out, the linear behavior observed for $\langle P\rangle = 1000$ clearly extends with the same slope beyond Δ_j^{1000} up to Δ_j^{100}. The measured knee position undergoes the same variations as the mean flow duration, both quantities being in the same order of magnitude: $\Delta_j^{100} \simeq \mu_{100}^{\rm ON}(0.24\ {\rm s})$ and $\Delta_j^{1000} \simeq \mu_{1000}^{\rm ON}(2.4\ {\rm s})$. This analysis confirms the intuition that the coarse-scale range, where self-similarity is to be measured, lies above the *knee* of the LD, whose position is in the same order of magnitude as the mean flow duration. The coarse scales can then be renamed the *flow scales* or the *file scales*.

5) Protocol, Rate Limitation, and Coarse Scales: As we investigate Taqqu's relation, we now focus on the coarse-scale domain. To inquire on the impact of the protocol on the coarse scales, Fig. 6 shows the LDs obtained with two different protocols: TCP and UDP (for $\alpha = 1.5$). Fig. 6 evidences the central

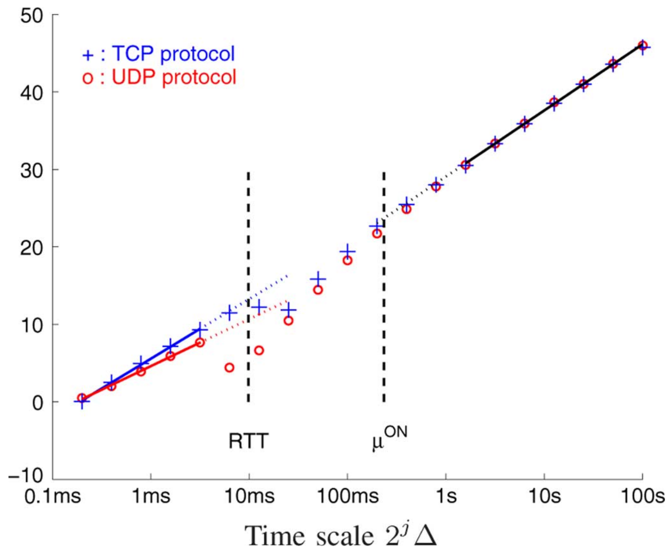

Fig. 6. Wavelet log-diagrams $\log S(j)$ versus time scale j of aggregated traffic (aggregation interval $\Delta = 100\ \mu$s). Log-diagrams correspond to two time series obtained under similar experimental conditions, for $\alpha_{\mathrm{ON}} = 1.5$, with two different protocols: TCP $(+)$ and UDP $(\circ)$.

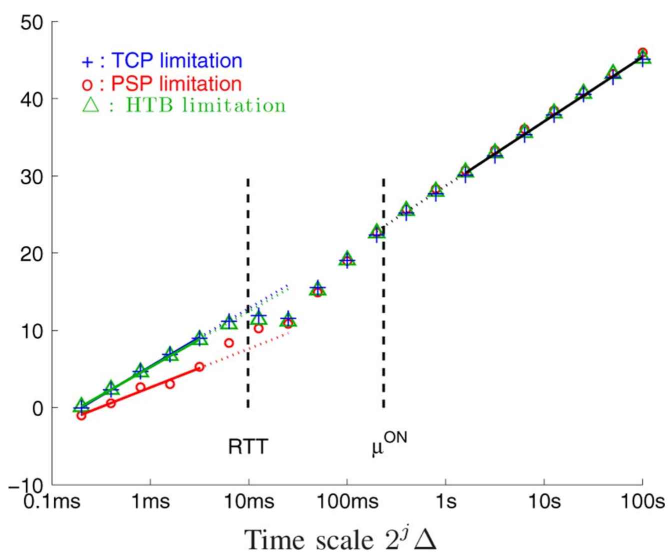

Fig. 7. Wavelet log-diagrams $\log S(j)$ versus time scale j of aggregated traffic (aggregation interval $\Delta = 100\ \mu$s). Log-diagrams correspond to three time series obtained under similar experimental conditions, for $\alpha_{\mathrm{ON}} = 1.5$, with three different rate-limitation mechanisms: TCP $(+)$, PSP $(\circ)$, and HTB $(\triangle)$.

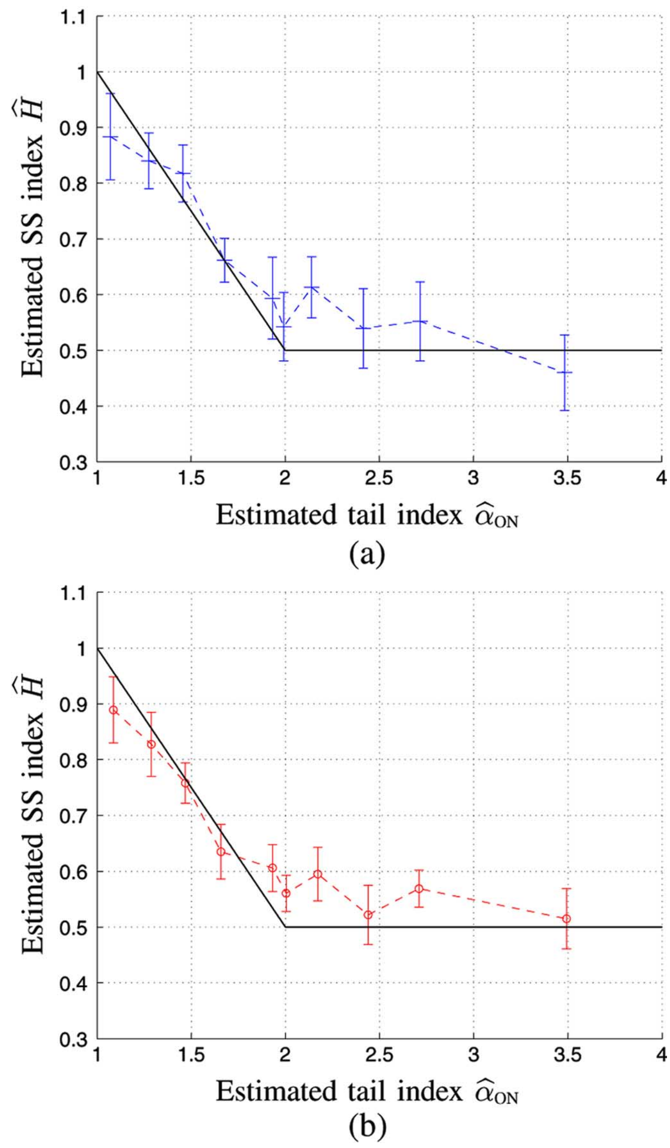

Fig. 8. Estimated self-similar index $\hat{H}$ of the aggregated traffic (aggregation interval $\Delta = 100\ \mu$s) versus estimated tail index $\hat{\alpha}_{\mathrm{ON}}$ of the corresponding flow-size distribution. Solid plots represent the theoretical model of relation (14), and dashed plots correspond to experimental results (a) with the TCP protocol and (b) with the UDP protocol.

feature that both LDs are undistinguishable in the coarse-scale domain. We conclude that when source-rate limitation precludes congestion, the protocol has no impact on the coarse scale SS.

Similarly, to inquire on the impact of the rate-limitation mechanism on the coarse scales, Fig. 7 shows typical LDs ($\alpha = 1.5$, TCP) obtained with three different rate-limitation mechanisms: PSP, HTB, and TCP window limitation. As the three LDs cannot be distinguished from one another in the coarse-scale domain, we conclude that the rate-limitation mechanism has no influence on the scaling behavior at coarse scales.

6) H versus α_{ON}: Practically, to perform an empirical validation of (14), we need to estimate the scaling parameter H and thus carefully choose the range of scales where the regression is to be performed. Although the *knee* position has been related to a measurable experimental parameter (the mean flow duration), a systematic choice of the regression range at coarse scales would certainly be hazardous. Instead, we defined for each trace an adapted regression range, based on a linearity criterion, and found that all regression ranges defined like this encompass a scale interval ($\max_\alpha \Delta_{j_1} = 20.5$ s and $\Delta_{j_{\max}} = 1310$ s), significantly extended to warrant statistically reliable SS exponent estimates.

Fig. 8 plots the estimates of coarse-scale SS exponents against those of the HT indices. The confidence intervals for $\hat{H}$ displayed on the graphs are supplied by the estimation procedure detailed in Section III-A2 [6], [22] (recall that the normal hypothesis underlying the estimation of these confidence intervals was successfully verified on our data). Such estimations are conducted independently for the TCP and UDP protocols.

For both protocols, estimations show a satisfactory agreement with Taqqu's theorem prediction. To the best of our knowledge, this theoretical relation between self-similarity and heavy tail had never been observed with such a satisfactory accuracy over a large and significant range of α values. For instance, and although no definitive interpretation has been proposed yet, the deviation below the theoretical relation for α close to 1 has been significantly reduced when compared to similar analysis results reported in the literature (cf., e.g., [11]).

On the contrary, the origins of the difference between the experimental and theoretical curves for α around 2 are clearly identified. As mentioned in Section V-A1, while the mean flow value is kept constant, the maximum flow size observed over a fixed period statistically decreases. This amplitude range shrinkage mechanically imposes the LD scaling interval that conveys LRD also to reduce, and thus the estimation of H to be overvalued. Another interpretation based on a bias-variance tradeoff argument, and supported by Matlab simulations, is also given in [38]. Notice, though, that when α increases, this effect balances with the natural decorrelation $(H = 0.5)$ holding beyond the maximum flow-size scale, and $\hat{H}$ stabilizes to 0.5, which also coincides with the theoretical value predicted by Taqqu's theorem.

This agreement improvement results from a number of factors. First, and in opposition to the R/S and Variance Time methods used in [11], the statistical tools for estimating H and α are chosen among the most recent and robust ones. In particular, the pioneer estimator of α is applied here for the first time to Internet data. Second, the asymptotic coarse scale nature of Taqqu's theorem is really accounted for by performing estimation in the limit of really large scales. Third, this coarse-scale behavior is observable only through really long-duration, stationary, and controlled traffic time series, which are enabled by the use of the Grid5000 platform in our case.

Additionally, our analyses do confirm that the TCP and UDP protocols do not impact this relation, at least under the congestion-avoidance conditions corresponding to our experimental setup. This is in clear agreement with the findings reported in [12] or [10] showing that TCP is not responsible for the observed self-similarity. However, despite these earlier results, a nonnegligible number of contributions debated, investigated, and argued in favor of an impact of protocols on self-similarity. Our analyses clearly show that the range of scales where protocols impact the LD is far below the characteristic timescales involved in self-similar phenomena.

As long as we actually consider coarse scales (larger than the mean duration of a flow), the only cause for self-similarity is the heavy tail in the flow-size distribution.

7) OFF Periods: To complement the experimental study of Taqqu's theorem, the experiments of series C (see Table II) were designed to assess the influence of heavy-tailed-distributed OFF periods on the coarse-scale SS exponent H. Under experimental conditions detailed in Table II, Fig. 9 displays the estimated coarse-scale SS exponents against those of the OFF periods' HT indices. Since we already demonstrated that the protocol had no influence on the scaling behavior at coarse scales, the current experiments were only performed with the TCP protocol.

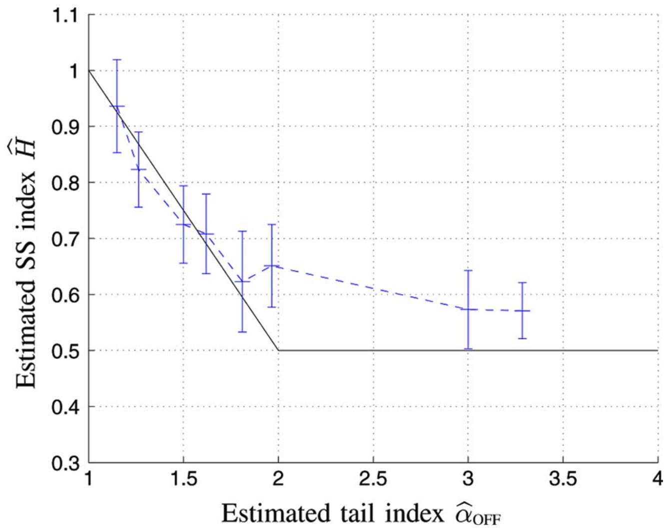

Fig. 9. Estimated self-similar index $\hat{H}$ of the aggregated traffic (aggregation interval $\Delta = 100$ μs, TCP) versus estimated tail index $\hat{\alpha}_{\mathrm{OFF}}$ of the corresponding OFF periods distribution. Solid plots represent the theoretical model of relation (14), and dashed plots correspond to experimental results.

In contrast to similar results reported in the literature (cf., e.g., (right) of [11, Fig. 5], where the estimated value of H is less than 0.7, even for $\alpha_{\mathrm{OFF}} = 1.05$), our results show a perfect match with the theoretical relation of (14). Reasons for this theoretical accord certainly have the same origins as the ones mentioned in the previous paragraph (i.e., robust estimators, long-duration stationary traces, and controlled configurations), but possibly also in the fact that we scrupulously avoided congestion and, hence, statistical alteration of the OFF periods. To the best of our knowledge, this other part of Taqqu's theorem had never been satisfactorily addressed.

Finally, let us notice that the confidence intervals displayed in Fig. 9 are significantly larger than the ones in Fig. 8. This is due to the difficulty of imposing short OFF intervals, which led us to increase the mean durations $\mu_{\mathrm{OFF}} = \mu_{\mathrm{ON}} = 2.4$ s (instead of 0.24 s). Consequently, according to the interpretation of Fig. 5, the coarse-scale regression range proportionally narrows.

B. Further Analyses of the LD

In the previous section, we focused on the coarse scales of LDs. Let us now turn to the medium and fine scales and study the influence of protocols and rate-limitation mechanisms.

1) Medium Scales: First, let us point out that while the mean flow duration gives an upper bound for the medium-scale domain, RTT (12 ms) seems to correspond to its lower bound. Therefore, this medium-scale range will be referred to as the *RTT scales*. Although no scaling behavior is visible in this medium-scale range, Fig. 6 shows a significant difference between the LDs obtained from TCP and UDP traffic. This is an expected result as RTT is the characteristic time of action of the TCP protocol.

Fig. 7 shows that there is no significant difference in this domain between the LDs corresponding to the three different rate-limitation mechanisms. The characteristic time of action of the rate limitation is the mean interpacket time. Due to the source-rate limitation at 5 Mb/s achieved with 1500-byte packets, the

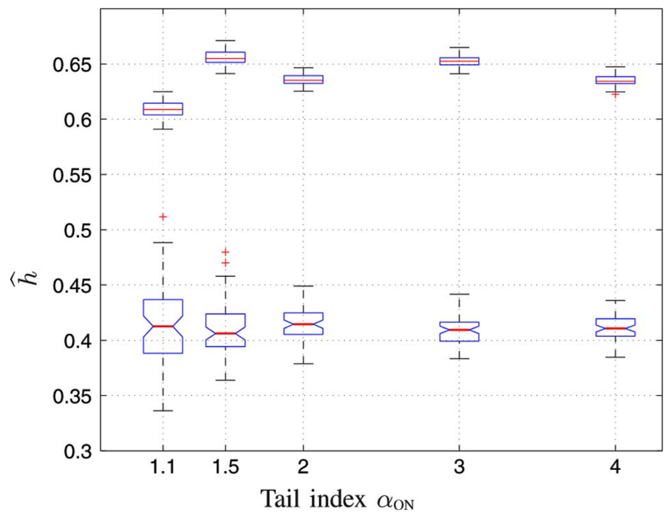

Fig. 10. Fine-scale scaling-exponent h estimates on aggregated traffic time series ($\Delta = 100\ \mu$s). For different values of the tail index α_{ON} governing the flow-size distributions, h is estimated by linear regression of log-diagrams (see Fig. 6) over the scale range [0.2–5] ms. Notched box-plots correspond to the UDP protocol, and regular box-plots to the TCP protocol.

mean interpacket time for one source is 2.4 ms. As the mean number of sources emitting simultaneously is 50, the mean interpacket time is 48 μs, which is much lower than RTT. Accordingly, the rate limitation does not impact the traffic at RTT scales.

2) Fine Scales: ***TCP and UDP impact on fine-scales scaling***. Fig. 6 shows a good scaling behavior at fine scales, with a scaling index that seems to be different for UDP and TCP.

To analyze in more detail the fine-scales scaling exponent, every 8-h trace corresponding to a particular value of α (see experimental conditions of experiment A in Table II) is chopped into 66 short-length segments of duration $T = 100$ s each. The resulting time series are then analyzed independently, and a fine-scales scaling exponent h is estimated. Based on these 66 values of $\hat{h}$, box-plots are displayed in Fig. 10 for each theoretical value of α. The values for TCP remain roughly constant around $h \simeq 0.63$. Likewise for UDP, h does not seem to depend on α, but stands around 0.4, a significantly smaller value than that for TCP.

Smaller than RTT, these fine scales correspond to the *packet scales*. Clearly then, the scaling index at these scales is sensitive to the packet-sending mechanism. When using UDP, packets are emitted individually, separated by an interpacket interval (2.4 ms) imposed by iperf to maintain the rate limitation (5 Mb/s). Therefore, UDP traffic is constantly and erratically varying. When using TCP, packets are sent by bursts containing up to five packets. Thus, TCP traffic is bursty but also sparse, with "long" periods without packets. We believe that this packet-sending scheme difference, in close relationship with our experimental condition (source-rate limitation used to avoid congestion), is solely responsible for the observed difference between TCP and UDP on the local regularity.

Bandwidth limitation's impact on fine-scales scaling. Fig. 7 shows that the scaling index at fine scales is approximately the same with TCP and HTB limitation, but it is very different with PSP limitation. This difference can again be explained by the packet-sending mechanism. When using HTB limitation, packets are sent by bursts in the same way as with TCP limitation. This explains why the local regularity observed with HTB is the same as the one observed with TCP window limitation. On the contrary, when using PSP, packets are sent individually, in the same way as with UDP. Then, at fine scale, the scaling index observed with PSP is lower than the one observed with TCP limitation, as was the one observed with UDP.

VI. Conclusion and Perspectives

In this paper, we experimentally demonstrated that the traffic generated on a real network platform conforms to the theoretical bond between the file-size distribution and the self-similar nature of instantaneous throughput measured at the link level. This work is based on an innovative combination of three important factors: the use of accurate estimation tools, a deeper analysis of Taqqu's theorem applicability conditions, and the use of a large-scale reconfigurable experimental facility. The wavelet-based estimation procedure for H is known as a state-of-the-art tool, among the most reliable and robust ones (with respect to nonstationarities). Here, it has been used with the utmost care. Regarding the α index, its estimation uses a procedure that was shown to outperform most standard techniques and that had never been used in the context of Internet data. The essential asymptotic nature of Taqqu's theorem has been better accounted for by conducting estimations of the self-similarity parameter at really coarse scales (coarse meaning scales that lie far beyond the system dynamics). This asymptotic limit requires producing particularly long-term traffic under stationary and well-controlled conditions. The nationwide and fully reconfigurable Grid5000 instrument enables generation, control, and monitoring of a large number of finely controlled transfer sessions with real transport-protocol stacks, end-host mechanisms, and network equipments and links. Given such realistic and long traces, we have been able to demonstrate experimentally, and with an accuracy never achieved with real data or with simulations, that Taqqu's theorem and the relation between self-similarity and heavy-tailedness effectively holds. In particular, we significantly ameliorated the coherence between theoretical and experimental values at the transition point $\alpha = 2$. This is a particularly delicate case, for it mixes difficulties of different kinds regarding the estimation of indices H and α. Pursuing our empirical certification of Taqqu's relation, we rigorously demonstrated that when the distribution of the OFF periods has an heavier tail than that of the flow size's, it prevails at imposing long-range dependency to the aggregated traffic. As it is elegantly tackled in [39] and [40], we believe that a precise statistical characterization of idle times is an important factor for traffic modeling. In this direction, we are currently exploiting the flexibility of our original Grid5000 testbed to study how the response of protocol mechanisms to congestion creates new OFF periods and how these OFF periods impact the traffic's self-similarity properties.

Following up the controversial discussion about the relationship between transport protocols and self-similarity, raised after and despite Crovella *et al.*'s meaningful contributions [3] (see discussion in [12], among others), our observations confirm that in loss-free situations, protocols, bitrate mechanisms, or packet- and flow-level controls do not impact the observed long-range dependency. Our analyses show that this is so because the ranges of scales (segmented according to the RTT and to the mean flow duration) related to self-similarity are far coarser than those (fine and medium scale) associated to such mechanisms. As a natural sequel to the present work, we now plan to confront these results to more actual situations involved in real network applications. In particular, we will generate long-term stationary traces under various congestion and aggregation levels, with heterogeneous source rates, involving different source protocols, mixing variable RTTs, including several bottlenecks and buffer capacities, and run with variants of the high-speed transport protocols. A precise study of self-similarity's impact on buffer utilization, queueing delays, and dynamics would certainly be worth investigating as well. In our opinion, though, the present study involving idealized conditions builds the definitive support to get new insights on the relevance of Taqqu's relation regarding actual applications. Should the values of H and α, estimated on actual Internet traffic traces, not follow the theoretical law, this mismatch would likely be explained by application- or user-specific arguments. Eventually, such an understanding will help researchers to design the future transport and network-control protocols.

Acknowledgment

The authors would like to thank the anonymous referees for their thorough review of the work. Their thoughtful remarks and suggestions helped to considerably improve the paper. They also thank AIST, T. Kudoh, Y. Kodama, A. Cedeyn, and M. Imbert for their precious help.

References

[1] V. Paxson and S. Floyd, "Wide area traffic: The failure of Poisson modeling," in *Proc. ACM SIGCOMM*, 1994, pp. 257–268.

[2] W. E. Leland, M. S. Taqqu, W. Willinger, and D. V. Wilson, "On the self-similar nature of ethernet traffic (extended version)," *IEEE/ACM Trans. Netw.*, vol. 2, no. 1, pp. 1–15, Feb. 1994.

[3] M. E. Crovella and A. Bestavros, "Self-similarity in World Wide Web traffic: Evidence and possible causes," *IEEE/ACM Trans. Netw.*, vol. 5, no. 6, pp. 835–846, Dec. 1997.

[4] T. Karagiannis, M. Molle, and M. Faloutsos, "Long-range dependence—Ten years of Internet traffic modeling," *IEEE Internet Comput.*, vol. 8, no. 5, pp. 57–64, Sep. 2004.

[5] P. Abry, R. Baraniuk, P. Flandrin, R. Riedi, and D. Veitch, "Multiscale nature of network traffic," *IEEE Signal Process. Mag.*, vol. 19, no. 3, pp. 28–46, May 2002.

[6] P. Abry, P. Flandrin, M. S. Taqqu, and D. Veitch, "Wavelets for the analysis, estimation and synthesis of scaling data," in *Self-Similar Network Traffic and Performance Evaluation*, K. Park and W. Willinger, Eds. New York: Wiley, 2000.

[7] M. S. Taqqu, W. Willinger, and R. Sherman, "Proof of a fundamental result in self-similar traffic modeling," *Comput. Commun. Rev.*, vol. 27, no. 2, pp. 5–23, 1997.

[8] W. Willinger, M. S. Taqqu, R. Sherman, and D. V. Wilson, "Self-similarity through high-variability: Statistical analysis of ethernet lan traffic at the source level," *IEEE/ACM Trans. Netw.*, vol. 5, no. 1, pp. 71–86, Feb. 1997.

[9] P. Doukhan, G. Oppenheim, and M. S. Taqqu, *Long-Range Dependence: Theory and Applications*. Boston, MA: Birkhäuser, 2003.

[10] L. Guo, M. Crovella, and I. Matta, "Corrections to 'How does TCP generate pseudo-self-similarity?'," *Comput. Commun. Rev.*, vol. 32, no. 2, p. 30, Apr. 2002.

[11] K. Park, G. Kim, and M. Crovella, "On the relationship between file sizes, transport protocols, and self-similar network traffic," in *Proc. IEEE ICNP*, Washington, DC, 1996, p. 171.

[12] D. R. Figueiredo, B. Liu, A. Feldmann, V. Misra, D. Towsley, and W. Willinger, "On TCP and self-similar traffic," *Perform. Eval.*, vol. 61, no. 2–3, pp. 129–141, 2005.

[13] R. Bolze, F. Cappello, E. Caron, M. Daydé, F. Desprez, E. Jeannot, Y. Jégou, S. Lanteri, J. Leduc, N. Melab, G. Mornet, R. Namyst, P. Primet, B. Quetier, O. Richard, E.-G. Talbi, and I. Touche, "Grid'5000: A large scale and highly reconfigurable experimental grid testbed.," *Int. J. High Perform. Comput. Appl.*, vol. 20, no. 4, pp. 481–494, Nov. 2006.

[14] K. Park and W. Willinger, *Self-Similar Network Traffic and Performance Evaluation*. New York: Wiley, 2000.

[15] P. Barford, J. Kline, D. Plonka, and A. Ron, "A signal analysis of network traffic anomalies," in *Proc. SIGCOMM Internet Meas. Workshop*, Marseille, France, Nov. 2002, pp. 71–82.

[16] B. White, J. Lepreau, L. Stoller, R. Ricci, S. Guruprasad, M. Newbold, M. Hibler, C. Barb, and A. Joglekar, "An integrated experimental environment for distributed systems and networks," *Oper. Syst. Rev.*, vol. 36, no. SI, pp. 255–270, 2002.

[17] D. G. Andersen, H. Balakrishnan, M. F. Kaashoek, and R. Morris, "Resilient overlay networks," in *Proc. 18th ACM SOSP*, Oct. 2001, pp. 131–145.

[18] A. Bavier, M. Bowman, B. Chun, D. Culler, S. Karlin, L. Peterson, T. Roscoe, T. Spalink, and M. Wawrzoniak, "Operating system support for planetary-scale network services," in *Proc. 1st Symp. Netw. Syst. Design Implement.*, Mar. 2004, p. 19.

[19] A. B. Downey, "Evidence for long-tailed distributions in the internet," in *Proc. SIGCOMM Internet Meas. Workshop*, New York, 2001, pp. 229–241.

[20] C. Barakat, P. Thiran, G. Iannaccone, C. Diot, and P. Owezarski, "A flow-based model for internet backbone traffic," in *Proc. SIGCOMM Internet Meas. Workshop*, New York, 2002, pp. 35–47.

[21] N. Hohn, D. Veitch, and P. Abry, "Cluster processes, a natural language for network traffic," *IEEE Trans. Signal Process*, vol. 51, no. 8, pp. 2229–2244, Oct. 2003, Special Issue on Signal Processing in Networking.

[22] P. Abry, P. Gonçalves, and P. Flandrin, "Wavelets, spectrum analysis and $1/f$ processes," in *Lecture Notes in Statistics: Wavelets and Statistics*, A. Antoniadis and G. Oppenheim, Eds., 1995, vol. 103, pp. 15–29.

[23] S. Mallat, *A Wavelet Tour of Signal Processing*. New York: Academic, 1999.

[24] R. J. Adler, R. E. Feldman, and M. S. Taqqu, *A Practical Guide to Heavy Tails*. New York: Chapman & Hall, 1998.

[25] J. H. McCulloch, "Measuring tail thickness to estimate the stable index alpha: A critique," *Amer. Stat. Assoc.*, vol. 15, pp. 74–81, 1997.

[26] P. Gonçalves and R. Riedi, "Diverging moments and parameter estimation," *J. Amer. Stat. Asso.*, vol. 100, no. 472, pp. 1382–1393, Dec. 2005.

[27] "Iperf, NLANR/DAST project," [Online]. Available: http://dast.nlanr.net/Projects/Iperf/

[28] Y. Kodama, T. Kudoh, T. Takano, H. Sato, O. Tatebe, and S. Sekiguchi, "GNET-1: Gigabit ethernet network testbed," in *Proc. IEEE Int. Conf. Cluster 2004*, San Diego, CA, Sep. 20–23, 2003.

[29] "Ipsumdump," [Online]. Available: http://www.cs.ucla.edu/~kohler/ipsumdump/

[30] N. Duffield, C. Lund, and M. Thorup, "Estimating flow distributions from sampled flow statistics," *IEEE/ACM Trans. Netw.*, vol. 13, no. 5, pp. 933–946, Oct. 2005.

[31] M. E. Crovella, M. S. Taqqu, and A. Bestavros, "Heavy-tailed probability distributions in the World Wide Web," in *A Practical Guide To Heavy Tails*, R. J. Adler, R. E. Feldman, and M. S. Taqqu, Eds. New York: Chapman & Hall, 1998, ch. 1, pp. 3–26.

[32] S. I. Resnick, H. Dress, and L. De Haan, "How to make a hill plot," OR & IE University, 1998.

[33] S. Soudan, R. Guillier, and P. V.-B. Primet, "End-host based mechanisms for implementing flow scheduling in Gridnetworks," in *Proc. GridNets*, Oct. 2007, Article no. 1.

[34] "Iproute2, the Linux Foundation," [Online]. Available: http://www.linuxfoundation.org/en/Net:Iproute2/

[35] R. Takano, T. Kudoh, Y. Kodama, M. Matsuda, H. Tezuka, and Y. Ishikawa, "Design and evaluation of precise software pacing mechanisms for fast long-distance networks," PFLDnet, Lyon, France, 2005.

[36] "Hierachical token bucket packet scheduler," [Online]. Available: http://luxik.cdi.cz/~devik/qos/htb/

[37] M. Roughan, J. Yates, and D. Veitch, “The mystery of the missing scales: Pitfalls in the use of fractal renewal processes to simulate LRD processes,” in *Proc. ASA-IMS Conf. Appl. Heavy Tailed Distrib. Econ., Eng., Stat.*, Washington, DC, Jun. 1999.

[38] P. Abry, P. Borgnat, F. Ricciato, A. Scherrer, and D. Veitch, “Revisiting an old friend: On the observability of the relation between long range dependence and heavy tail,” *Telecommun. Syst.*, 2009, Special Issue on Traffic Modeling, Its Computations and Applications, to be published.

[39] L. Guo, M. Crovella, and I. Matta, “How does TCP generate pseudo-self-similarity?,” in *Proc. MASCOTS*, Washington, DC, 2001, p. 215.

[40] D. R. Figueiredo, B. Liu, V. Misra, and D. Towsley, “On the autocorrelation structure of TCP traffic,” *Comput. Netw.*, vol. 40, no. 3, pp. 339–361, 2002.

Patrick Loiseau received the Professeur-Agrégé de Sciences-Physiques degree, the M.S. degree in physics, and the Ph.D. degree in computer science from École Normale Supérieure de Lyon, Lyon, France, in 2005, 2006, and 2009, respectively.

He is currently working as a Post-Doctoral Fellow with INRIA Paris-Rocquencourt, Le Chesnay, France. His main research interests are in statistical analysis and modeling of network traffic with application to the quality of service. This includes, in particular, wavelet-based analysis of scaling phenomena, long-range dependent and multifractal models, large deviations for Markov models, and queuing theory with correlated input processes. He is also interested in statistical estimation methods.

Paulo Gonçalves (M’08) received the M.S. and Ph.D. degrees in signal processing from Institut National Polytechnique de Grenoble (INPG), Grenoble, France, in 1990 and 1993, respectively, and graduated from the Signal Processing Department of CPE Lyon, Villeurbanne, France, in 1993.

While working toward the Ph.D. degree, he was with ÉNS Lyon, Lyon, France. From 1994 to 1996, he was a Post-Doctoral Fellow with Rice University, Houston, TX. Since 1996, he has been an Associate Researcher with INRIA, first with FRACTALES from 1996 to 1999), then with IS2 from 2000 to 2003, and now with the team RESO at the Parallel Computing Laboratory (LIP), ÉNS Lyon. From 2003 to 2005, he was on leave at IST Lisbon, Lisbon, Portugal. His research interests are in multiscale analysis and wavelet-based statistical inference. His principal application is in metrology and deals with grid-traffic statistical characterization and modeling for protocol quality assessment and control.

Guillaume Dewaele was born in Hazebrouck, France, in 1978. He received the Professeur-Agrégé de Sciences Physiques degree, the Master’s degree in physics, and the Ph.D. degree in numerical simulation and computer vision from École Normale Supérieure (ÉNS) de Lyon, Lyon, France, in 2000, 2001, and 2005, respectively.

Since November 2005, he has been an Agregé Préparateur (Lecturer) with the Laboratoire de Physique, ÉNS Lyon. His research interests are in signal and image processing, numerical simulations, and Internet traffic measurement and modeling for anomaly-detection and identification purposes.

Pierre Borgnat (M’06) was born in Poissy, France, in 1974. He received the Professeur-Agrégé de Sciences Physiques degree, the M.Sc. degree in physics, and the Ph.D. degree in physics and signal processing from École Normale Supérieure (ÉNS) de Lyon, Lyon, France, in 1997, 1999, and 2002, respectively.

From 2003 to 2004, he spent one year with the Signal and Image Processing group of the IRS, IST, Lisbon, Portugal. Since October 2004, he has been a full-time CNRS Researcher with the Laboratoire de Physique, ÉNS Lyon. His research interests are in statistical signal processing of nonstationary processes (time-frequency representations, time deformations, stationarity tests) and scaling phenomena (timescale, wavelets) for complex systems (turbulence, networks, etc.). He is also working on Internet-traffic measurements and modeling, especially for security enforcement based on measurements.

Patrice Abry (SM’07) was born in Bourg-en-Bresse, France, in 1966. He received the Professeur-Agrégé de Sciences Physiques degree and the Ph.D. degree in physics and signal processing from École Normale Supérieure de Lyon, Lyon, France, in 1989 and 1994, respectively.

Since October 1995, he has been a permanent CNRS Researcher with the Laboratoire de Physique of École Normale Supérieure de Lyon. He is the author of *Ondelettes et Turbulences* (Paris, France: Diderot, 1997). His current research interests include the wavelet-based analysis and modeling of scaling phenomena, of hydrodynamic turbulence and computer network teletraffic.

Dr. Abry received the AFCET-MESR-CNRS prize for best Ph.D. in signal processing for the years 1993-1994. He has been a member of the SPS-SPTM committee since 2004.

Pascale Vicat-Blanc Primet received the M.Sc. and Engineer diploma and the Ph.D. degree in computer science from INSA de Lyon, Villeurbanne, France, in 1984 and 1988, respectively, and the Habilitation à Diriger les Recherches degree from Université de Lyon, Lyon, France, in 2002.

She has been a Senior Researcher with the National Institute of Research in Computer Science (INRIA) since 2005. Since 2002, she has been leading the INRIA RESO team (22 researchers and engineers) within the LIP laboratory of École Normale Superieure de Lyon, Lyon, France. Since the beginning of 2008, she has also led the “Semantic Networking” research team of the INRIA-Bell Labs common laboratory. She is a member of the scientifical committee of Grid5000’s/ALADDIN—French Computer Science Grid initiative. She has published more than 80 papers in international journals and conferences in networking and grid computing. Her research interests include high-speed and high-performance networks, Internet protocols’ design and architecture, quality of service, network and traffic measurement, network programmability and virtualization, and grid networking.

Dr. Vicat-Blanc Primet is a Member of the IEEE.