Internet's Critical Path Horizon

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Abstract. The internet is known to display a highly heterogeneous structure and complex fluctuations in its traffic dynamics. Congestion seems to be an inevitable result of users' behavior coupled with network dynamics and its effects should be minimized by choosing appropriate routing strategies. But what are the requirements of routing depth in order to optimize the traffic flow? In this paper we analyze the behavior of internet traffic with a topologically realistic spatial structure as described in a previous study (S-H. Yook et al., Proc. Natl. Acad. Sci. USA, 99 (2002) 13382). The model involves self-regulation of packet generation and different levels of routing depth. It is shown that it reproduces the relevant, key, statistical features of the internet's traffic. Moreover, we also report the existence of a critical path horizon defining a transition from poorly performing traffic to highly efficient flow. This transition is actually a direct consequence of the web's small world architecture exploited by the routing algorithm. Once routing tables reach the network diameter, the traffic experiences a sudden transition from poorly performing to highly efficient behavior. It is conjectured that routing policies might have spontaneously reached such a compromise in a distributed manner. The internet would thus be operating close to a critical path horizon.

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1 Introduction

The efficient performance of any communication network is jeopardized by congestion problems, which often show up in unpredictable ways. This seems the case, for example, of so called Internet storms [2]. Such problems were early identified in different types of engineered networks. Norbert Wiener for example mentions that "a switching service involving many stages and designed for a certain level of failure shows no obvious signs of failure until the traffic comes up to the edge of the critical point, when it goes completely into pieces, and we have a catastrophic traffic jam" [3]. These observations allow to formulate a number of key questions concerning communication nets, such as: How do critical traffic levels are reached? What is the nature of these thresholds? How appropriate routing algorithms modify this behavior? Are there optimal routing strategies?

Modeling Internet dynamics has been an active area over the last decade. The approaches include detailed simulations [4], simple statistical models and verbal models [5]. In this context, in [6] we investigated the existence of a jamming phase transition between the free phase and the congested phase in a model of network traffic over regular meshes. This phase transition depends on traffic density. It was conjectured that large-scale network traffic self-organizes near the critical point of the transition, which is linked to high network efficiency and unpredictability [7]. At the critical regime, the distribution of congestion duration lengths scales as a power-law [9][7].

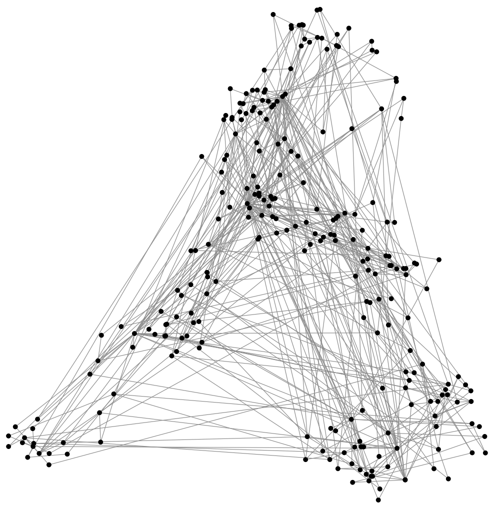

Fig. 1. Small Internet-like network (see text for generation method description). The parameters have been set to the position corresponding to Internet in the (D_f, α, σ)- phase space: M= 250, $< k >= 4$, $D_f = 1.5$, $\alpha = 1$, $\sigma = 1$.

Such a self-organized scenario is reinforced by a recent study suggesting that Internet fluctuations are a consequence of the internal dynamics of the system [10]. Against previous claims, there is mounting empirical support that network traffic heterogeneity is a consequence of collective dynamics and not because of the high variability injected by external sources.

In this paper we will show that Internet is able to route efficiently its inner flow of packets because a special combination of local routing rules and a particular network architecture. As we will see, Internet routing reaches an optimal, low-cost traffic flow as a result of a trade-off between random and deterministic routing schemes.

2 Modelling Internet's traffic

Following previous approaches [6][7] let us consider network defined on a graph Ω with M nodes (figure 1). The number of links connecting a given node with another (irrespective of their characteristics) will be indicated as k_i. The subset of closest nodes of $s_i \in \Omega$ is C_i. Only a fraction of fixed $\rho < (0, 1]$ nodes is selected as source and destination traffic endpoints (hosts). Host locations are chosen randomly. The other $(1-\rho)M$ nodes can only store and forward incoming messages (routers).

Both host and routers can route only one packet at a time (the routing policy is described below). Each node s_i is provided with a finite queue of packets waiting for communication resources (free links). Queues are not allowed to store more than H packets simultaneously. New packets arriving at an already saturated queue will be simply removed from the system. This provides a very simple dissipative mechanism useful for recovering from heavy traffic congestion. If $n(s_i, t)$ is the number of packets at s_i, the total number of packets in the system will be

$$N(t) = \sum_{s_i \in \Omega} n(s_i, t) \tag{1}$$

which is the key quantity which has to be analysed here.

Any microscopic host behavior compatible with the fluid scenario must ensure a controlled injection of packets in order to not flooding the network (and thus entering the congested state). Note that in a fluid traffic regime it is unlikely that packets will be alive for an arbitrarily long time. A fluidity requirement will necessarily impose a hard constraint on the maximum time spent by a packet travelling across the network. The simplest way of ensuring fluid packet flow is to stop the sources emitting new packets when detecting local congestion, that is, when there is no empty space in the source neighborhood C_i to fill with new packets. If no self-regulation is present, it has been shown that there is a sudden and sharp jamming transition from the free to the congested state depending on the mean (system) packet generation rate $\langle \lambda \rangle$. At the critical point between the two phases the system displays optimum (global) performance. If self-regulation is allowed, it can be shown [7] that simple traffic source rules are able to self-organize the traffic network around a definite mean rate $\langle \lambda \rangle$, which scales as the quotient between the average system load $< N >$ and the averaged packet latency $\langle T \rangle$:

$$\lambda_C \approx \frac{< N >}{< T >} \tag{2}$$

where the latency is defined as the time comprised from the creation of a packet until its delivering at the destination host. The mean latency $< T >$ is averaged over all successfully released packets. Following [7] we will indicate by ξ the number of local congested neighbors:

$$\xi = \sum_{k \in C(i)} \theta \left[n(i, t) \right] \tag{3}$$

where $\theta[x] = 1$ for $x > 0$ and zero otherwise. The packet injection rate for host i is updated as follows:

$$\lambda_i(t+1) = \begin{cases} \min\{1, \lambda_i(t) + \mu\} & \xi = 0 \\ \lambda_i(t) & 0 < \xi < k_i \\ 0 & \xi = k_i \end{cases} \tag{4}$$

where μ is the so-called driving parameter. The second rule allows a particular host to stabilize around a given rate. Traffic rate increases conservatively and drops down to zero when all neighboring nodes are congested. The reader must be aware that the above rules are not intended to be a detailed model of real traffic sources. Traffic sources can not be described with an universal distribution probability. Moreover, it seems that a rich variety of distributions (exponential, bi-modal or log-normal) apply. As we will see later in the paper, it is unlikely that the variability of traffic sources will be the cause of the scaling detected in Internet traffic. Moreover, this model does not introduce any explicit correlations between sources (i.e.: like in active conversation between two hosts) so the dynamics can not be the by-product of pre-defined source correlations. Because the system is poised to criticality (the so-called fluid packet flow regime) the global dynamics emerge from the collective behavior of its components. Ultimate source details are irrelevant in this context. Moreover, although TCP is more realistic than our simplified local rules (also much more complex) our conjecture is that the large-scale dynamics will not be greatly changed by the local behavior of hosts within this fluid flow regime. This idea has been partly answered in a recent work [8] in which it has been shown that IP level traffic (packet dynamics) does not depend to any significant extent on the TCP arrival process (host behavior), supporting our view that traffic dynamics is not a consequence of detailed source (host) behavior.

For a homogeneous network with average degree $< k >$ (and finite $< k^2 >$) it can be shown, following [7] that the time evolution of packet density $\Gamma(t) = N(t)/M$ in the limit of $H \to \infty$ is defined by the mean field equation:

$$\frac{d\Gamma}{dt} = \rho\lambda - \frac{< k >}{D} \Gamma \left(1 - \Gamma\right) \tag{5}$$

where D indicates the network diameter (also the average transient time, assuming packets jump from node to node with the same average time scale). It is not difficult to show that the equilibrium points of the previous equation are given by $\Gamma_{\pm} = [1 \pm (1 - 4\rho\lambda D / < k >)^{1/2}]/2$. For $\lambda > \lambda_c \equiv < k > /4D\rho$, the fixed points vanish and no finite density exists. In this "congested phase" the density of packets grows without bounds. For $\lambda < \lambda_c$, a finite stable density

$$\Gamma_{-} = \frac{1}{2}\left[1 - \left(1 - \frac{4\rho\lambda D}{< k >}\right)^{1/2}\right] \quad (6)$$

is observable (the other fixed point Γ_{+} is unstable). For the particular case $\rho = 1$ analysed by Fukś and Lawnizak [12], we recover their critical point $\lambda_c = 2/L$ for dynamics taking place on a square lattice, i. e. $D = L/2$. If a feedback exists between λ and γ, some finite equilibrium density Γ^* will be achieved in the previous model and thus no divergence will be allowed to occur. In this case, the mean field model indicates that a scaling relation will be observed, i. e.

$$\lambda \sim \rho^{-1} \quad (7)$$

between the (self-organized) packet release rate and the density of hosts (which is here the only relevant external parameter). Such a scaling relation was shown to occur in the previous model.

The previous mean field calculation was done by assuming that a fixed λ is beign used. The previous rules actually introduce self-regulation of injection rates by traffic. In other words, if traffic level N defines an order parameter, it will interact with a control parameter (λ), reducing it when N is large and incresing it when low. The feedback between these two key quantities results in a state dominated by fluid, but fluctuating traffic with many characteristics in common with observed Internet's dynamical patterns.

In order to explictly consider the feedback between order and control parameters, we can consider a new mean field approximation based on the previous local rules. It can be shown, asuming finite H, that the new set of equations is now:

$$\frac{d\Gamma}{dt} = \rho\lambda\left(1 - \frac{\gamma}{H}\right) - \frac{< k >}{D}\Gamma \quad (8)$$

$$\frac{d\lambda}{dt} = \mu(1 - \lambda) - \frac{\Gamma}{< k >} \quad (9)$$

for low density levels (i. e. $\Gamma \ll H$, consistently with a fluid traffic) the single fixed point (obtained from $d\Gamma/dt = d\lambda/dt = 0$) is

$$(\Gamma^*, \lambda^*) = \left(\frac{1}{\frac{<k>}{\rho D} + \frac{1}{\mu <k>}}, 1 - \frac{\Gamma^*}{< k > M}\right) \quad (10)$$

the Jacobi matrix $\mathbf{L}$ for the previous set of equations is given by

$$\mathbf{L} = \begin{pmatrix} \frac{-<k>}{D} & \rho \\ \frac{-1}{<k>} & -\mu \end{pmatrix} \quad (11)$$

The associated eigenvalues are

$$\Lambda_{\pm} = \frac{1}{2}\left[-\left(\frac{< k >}{D} + \mu\right) \pm \sqrt{\left(\frac{< k >}{D} + \mu\right)^2 - \frac{4\rho}{< k >}}\right]$$

both of them real and negative: the point attractor is globally stable. Numerical simulations of the model on a Poissonian graph (where the previous approximation would held) agree with these predicted values. Topological features are included only as averaged quantities, here mean degree $< k >$ and diameter D. However, our interest is to explore the traffic dynamics on a realistic network architecture, in order to provide the closest modeling approach under the previous rules. It has been shown that the Internet does not display the homogeneous architecture assumed by the Poissonian graphs [13]. In the next section the network's topology used in our analysis is presented. Together with an explicit definition of the routing algorithm, they will complete our model's description.

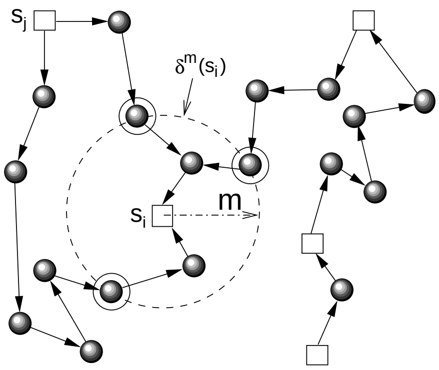

Fig. 2. Network dynamics and routing: it involves a given depth of routing m (a path horizon). A packet traveling from s_j to s_i within the $\delta^m(s_i)$ domain (of depth m) is deterministically routed along the shortest path ($d(j,i) \leq m$). The packet traverses hosts (squares) and routers (circles) indistinctly. Packets traveling outside the m-domain (i. e. for $d(j,i) > m$) have more than one path choice and perform random walks. As soon as the packet enters into the m-domain, the packet is deterministically routed along the shortest path. Here we would have $m = 2$.

3 Network topology

In previous analyses [6] [7] the topology of the graph was chosen to be a lattice. Although this might seem a limited topological arrangement, it has been successfully tested on real hardware and the presence of a phase transition fully confirmed [14]. Moreover, mesh connected topologies may be the most efficient solution at the limit of very large parallel computer architectures [15][16].

Regular lattices fail to describe Internet topology. Remarkably, Internet displays a scale-free architecture [13]. The origins and causes of this topology have been the subject of most discussion and controversy. It has been show that most existing Internet generators fall in a very different region of the phase space where real Internet is located [1]. This phase space is defined by (D_f, σ, α), where every parameter defines a major force shaping a different aspect of the large-scale Internet topology. Note that this model does not define all detailed correlations observed in

Internet and/or the precise functional form of Internet's path length and degree distribution (i.e.: the exact exponent of the scale-free distribution). This is a minimal set of universal parameters that any realistic Internet model must satisfy and it is a very good approximation to the large-scale topology.

The spatial distribution of Internet nodes is not random. It has been noticed a strong correlation between fractal distribution of cities and Internet nodes. The measured fractal dimension is $D_f = 1.5$. When generating the Internet-like network, the position of nodes is obtained by sampling a Rayleigh-Lévy dust of the same fractal dimension. The likelihood of placing a link between two nodes s_i and s_j depends both on the (euclidean) link length w_{ij} and linear preferential attachment:

$$\Pi(k_j, d_{ij}) \approx \frac{k_j^\alpha}{w_{ij}^\sigma}$$

Note that longer links cost more and thus will be selected with less probability. Traditional topology generators based on Waxman model [17] wrongly assume exponential decay instead of linear cost decay. On the other side, there is empirical evidence that highly connected nodes will be linked with higher probability. Increasing α will favor linking to nodes with higher degree, while a higher σ will penalize longer links. From real measurements [1], it has been identified the position of Internet at $D_f = 1.5$, $\sigma = 1$ and $\alpha = 1$. Here, all numerical simulations have been performed using this topological arrangement (figure 1).

4 Path horizon and routing tables

An important ingredient when modeling network dynamics is to describe the paths followed by packets towards their destinations, that is, the routing policy. By properly defining this routing algorithm, we will complete our model's definition.

Real routing protocols do not drive packets at random. Instead, they try to route packets along the most efficient routes (i.e: minimize distance or latency). At the same time, it is unrealistic to assume that all packets follow optimal paths because the large amount of global information replicated at every single node. Clearly, the paths traced by packets in real networks are properly characterized as a trade-off between random diffusion and optimal routing. This is reflected in the real Internet by its two-level routing organization. Nodes are grouped in so-called Autonomous Systems (AS) and different routing rules apply at each level. Intra-AS routing is based on shortest path routing but inter-AS routing does not cleary follow any minimization criteria.

A simple way to explore the cost/efficiency trade-off is by introducing a parameter defining the visibility scope of the node (depth of routing parameter m or node domain diameter), that is, a sphere $\Gamma^{(m)}(s_i)$ of radius m centered at every node $s_i \in \Omega$ (figure 1). We allow every node to known every other node at a distance of m hops or less

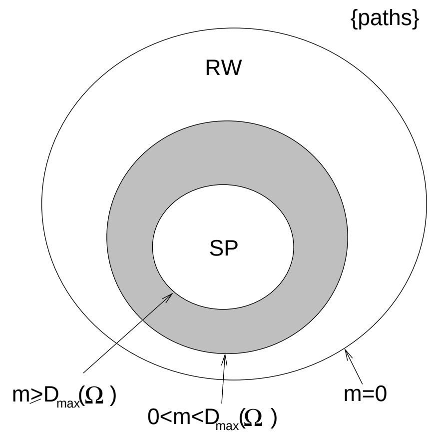

Fig. 3. Hierarchy of path sets defined by the routing policy. Every routing scheme explores a fraction of network paths (a subset of the entire path set $P(\Omega)$). Pure random walk strategy (m=0) visits all available paths, even shortest paths. In fact, random walk travel more frequently along those shortests paths. The more restrictive set is associated to pure shortest path routing ($m \geq [\langle d \rangle]$), which chooses a small fraction of all possible routes on the network.

but no more. No information will be stored about nodes outside the node domain. This idea is indicated in figure 2, where a given target node s_i is shown at the center of its m-sphere. When a foreign node $s_j \in \Omega - \Gamma^{(m)}(s_i)$ send a packet towards s_i, while moving in the outside of the sphere it performs as a random walk. Once the packet hits the boundary of the sphere, $\partial\Gamma^{(m)}(s_i)$, it is routed along the shortest path [19].

5 Efficiency and network's exploration

The depth of routing parameter m induces a hierarchy of path subsets over the entire set of available network paths (see figure 3). The random $m = 0$ and deterministic $m = M$ routing represent the most general and restrictive subsets, respectively. Increasing m will progressively reduce the randomness at routing decisions. Here, we find a nested collection of subsets corresponding to the intermediate situations $0 < m < M$. The relative size of each subset can be approximated by measuring the fraction of nodes F visited by packets:

$$F = \frac{1}{M} \sum_{i=1}^{M} \theta \left[A_i \right] \qquad (12)$$

where A_i is the probability of visiting the node s_i. This term depends both on the network dynamics and the geometrical situation of the node within the network. Considerable effort has been devoted to characterize the likelihood of visiting a node in a purely static fashion. In this context, two relevant centrality (or 'load' [20][21]) measures are Random Walk Centrality [22] and Betweenness Centrality [23] which certainly represent the two extremes

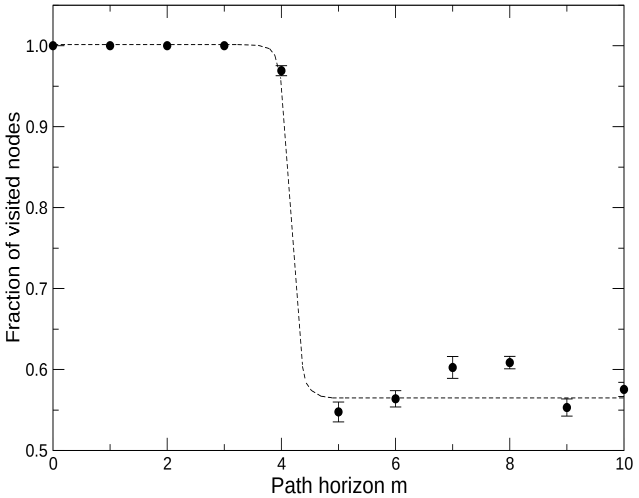

Fig. 4. The fraction of visited nodes depends on the amount of order defined by the depth of routing parameter. Determinism sharply constraints the routing paths. Every point was obtained averaging over an ensemble of four different networks and every single network was simulated in five different host configurations. Network parameters: M = 512, $< k >= 4$, $\rho = 0.1$, $\mu = 0.01$, H = 10, $D_f = 1.5$, $\sigma = 1$, $\alpha = 1$ and $T = 7 \times 10^5$ steps.

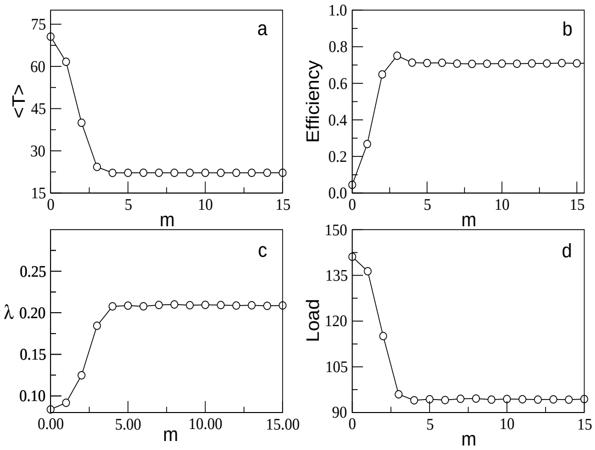

Fig. 5. Exploring the network traffic dependency on depth of routing parameter (m). The lines connect the points for illustrating purposes only. (A) Mean latency is considerably reduced when enough system information is given to individual nodes. Most packets are forwarded along the minimum number of hops. (B) Global throughput is optimal at the critical point when path horizon is about the network diameter. (C) Mean packet rate also drops down at intermediate value. (D) Mean workload also experiences sudden transition from heavy to light load. Network parameters: M=250, $< k >= 4$, $D_f = 1.5$, $\sigma = 1$, $\alpha = 1$. Simulation parameters: $\rho = 0.1$, $\mu = 0.01$, H = 10, $T = 10^5$ steps. The shape of these plots does not depend on network size, that is, the optimal point is always found at $m = [\langle d \rangle]$.

of our hierarchy of path subsets. Anyway, the correlation of these measurements with dynamic centrality A_i is weak, to say the least.

In figure 4 the numerically measured $F(m)$ for a finite range of m values is shown. This fraction equals 1 for random routing $0 \leq m < [\langle d \rangle]$, where $\langle d \rangle$ is the averaged shortest path length and $[x]$ denotes the integer part of x. Random routing does not discard any network node. A sharp transition takes place from this point $[\langle d \rangle] < m \leq M$ and a large fraction of network nodes (about 45 percent) are never visited by deterministic routing. This severly restricts the diversity of routes and yields a load-insensitive system [24]. The system requires a certain degree of noise in order to avoid sending packets through already collapsed nodes while it is enabled to choose less optimal but free routes. Note that depth of routing parameter m defines an order parameter because quantifies the degree of order existing in the system. The existence of an order parameter confirms the critical nature of Internet traffic.

Numerical simulations have shown that flow is maximized at the order-disorder transition point $m = [\langle d \rangle]$. This can be observed in network throughput reaching a maximum at this point (see figure 5). Throughput is defined by the quotient of the number of successfully released packets and the sum of all packets generated during the simulation. In the next section, we will show that several real statistics can be reproduced by the system dynamics poised to criticality.

6 Average stretch

The average stretch s measures the efficiency of routing by comparing the number of hops h traversed by a packet to the shortest path distance d between source and destination:

$$s = \frac{h}{d}$$

Compact routing schemes minimize the average stretch while maintaining the size of routing tables small [25]. Reducing the average strech will progressively raise up the memory requirements at each router. Assuming Thorup-Zwick (TZ) compact routing scheme [26], the average stretch can be expressed as a function of the distance distribution and the graph size M only: $\langle s \rangle = f(\langle d \rangle, \sigma_d)$ [27]. This TZ scheme ensures a nearly optimal lower memory upper bound for $\langle s \rangle = 3$ in generic networks. For scale-free networks, TZ achieves lower bounds. In particular, for the Internet interdomain graph (Autonomous Systems) with degree distribution exponent $\gamma \approx 2.1$ and $M = 10^4$, the TZ average stretch $\langle s \rangle \approx 1.14$[27]. Also, the average number of entries in the routing tables is approximately 52. It turns out that $\langle s \rangle (\langle d \rangle, \sigma_d)$ surface has unique minimums. Strikingly, the points corresponding to Internet distance distribution are very close to them [27]. This suggests that Internet topology is shaped by some hidden optimization

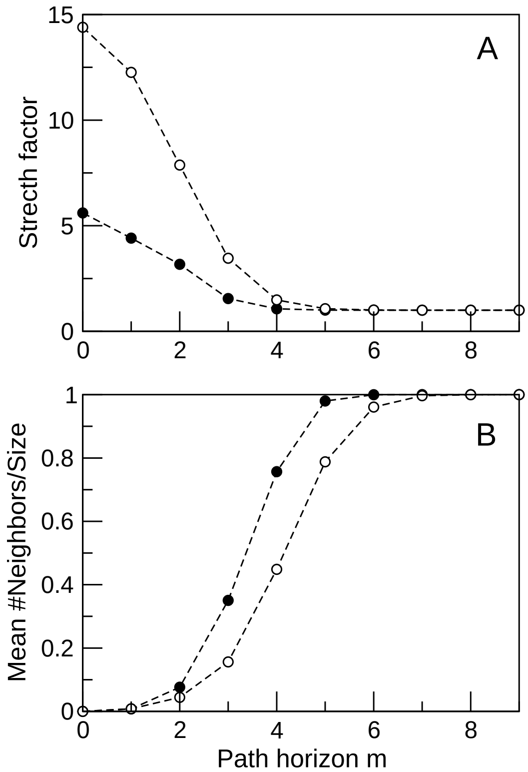

Fig. 6. (A) Average stretch (B) Average fraction of nodes inside m-domain is an estimation of the amount of information required by each node. Here open circles correspond to the Internet's nodel. For comparison, the simulation has been repeated in a poissonian network of same size and mean degree (filled circles). Network parameters: $M = 500$, $< k >= 4$, $D_f = 1.5$, $\sigma = 1$, $\alpha = 1$. Simulation parameters: $\rho = 0.1$, $\mu = 0.01, H = 10, T = 5\times10^4$ timesteps. Measurement window = 200. The distributions were obtained from an statistical ensemble of three networks, every network simulated three times with hosts located at different configurations.

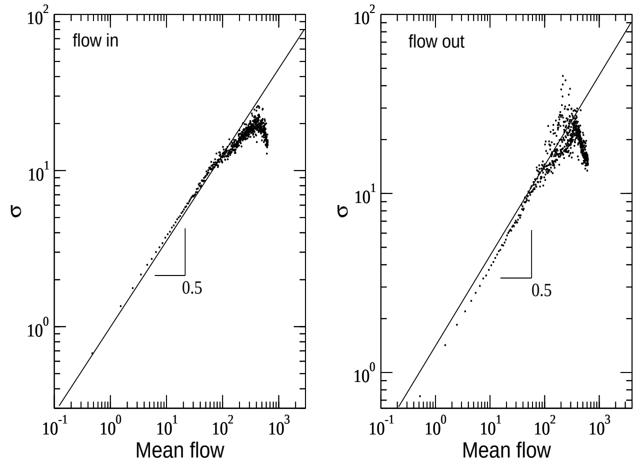

Fig. 7. The relationship between fluctuations and the average incoming node flux (a similar distribution holds for average outgoing router flux). The plot shows that both quantities are related by a power law of exponent 1/2, which is consistent with the measurements from Internet routers. Network parameters: M=500, $< k >= 4$, $D_f = 1.5$, $\sigma = 1$, $\alpha = 1$. Simulation parameters: $\rho = 0.1$, $\mu = 0.01$, H = 10, T = 10000 steps. Measurement window = 200. The distributions were obtained from an statistical ensemble of 10 networks, every network simulated 5 times with hosts located at 5 different configurations.

criteria. Anyway, TZ scheme is not a realistic Internet interdomain routing scheme because assumes that global topology view is available. We have numerically measured the average stretch and the average fraction of neighbours at distance m for our routing scheme (see figure 6). Note that the critical path horizon $m = [\langle d\rangle]$ is very close to the minimum average stretch.

7 Network fluctuations and performance

In order to test the goodness of the model presented here, it is interesting to compare some real Internet statistics with their respective model measurements. In particular, those measurements will be collected for the model at the critical path horizon, that is, when $m = [\langle d\rangle]$.

When understanding the competition between a network's internal collective dynamics (i.e: Internet traffic) and external environmental changes (i.e: traffic sources or host behaviour), it is useful to study the relationship between the mean flux and the size of fluctuations around the average [10]. Previous explanations of ocurrence of self-similarity in traffic networks are based on the superposition of many and high-variable (infinite variance) sources [11]. This point of view discards the effects of the system's collective dynamics and considers that Internet is an externally driven system. Real data shows that Internet dynamics can not be simply reduced to the behaviour of traffic sources.

Let us define the incoming (outgoing) flux f_i as the amount of packets received (forwarded) at router s_i during a given and fixed period of time. For every router, compare the average flux $\langle f_i\rangle$ with the dispersion σ_i around the mean. It has been noticed that for several real systems the following scaling relation holds:

$$\sigma \approx \langle f\rangle^{\alpha}$$

where α is an exponent which can take the values of 1/2 and 1 [10]. This suggests that real systems can be classified in two main classes depending on the value of this exponent. The relevant exponent in this context is $\alpha = 1/2$, which has been observed in daily traffic measurements at 374 geographically distinct Internet routers [10]. Systems exhibiting the 1/2 exponent are representative of endogeneous dynamics, that is, determined by the system's internal collective fluctuations. Moreover, measurements on our model reproduce the same exponent (see figure 7).

A measure of Internet end-to-end performance is the normalized latency time τ [28] defined as the quotient between latency time L (measured as Round-Trip-Time) and geographical distance w:

$$\tau = \frac{L}{w}$$

There are several factors governing τ. First, propagation rate is finite. There is a minimum delay because packets can not move faster than speed of light. Second, the number of nodes traversed departs from the minimum found along the geodesic path from node to destination. And third, packets spent some time at every intermmediate node because queueing delays. Define $\tau_{min} = L_{min}/w$ as the normalized latency without taking into acount queue delays and $\tau_{av} = L_{av}/w$ as the normalized latency while considering all factors affecting packet latency.

Their probability distributions have been measured from two years of PingER [29] data and follow power-law scaling with stable exponents of about -3.0 for τ_{min} and -2.5 for τ_{av} [28]. Numerical simulations on the model poised to criticality reproduced the power-law $P(\tau_{av})$ probability distribution. The exponent of the distribution is about -2.45, which is very close to real observations (see figure 8). The previous results seems to be quite robust and independent of most model parameters changes. An interesting thing to note is that current model cannot reproduce the existing correlation between τ_{min} and τ_{av} and geographical distance w reported by previous studies [28]. The reason might be that propagation rate is (unrealistically) assumed to be infinite in the model. It might be that this factor has little influence in shaping the τ_{av} probability distribution. Moreover, it is worth noting that any deviation of the order parameter from the critical regime resulted in an exponential distribution for τ_{av}, reinforcing the view of an optimally efficient and self-organized Internet.

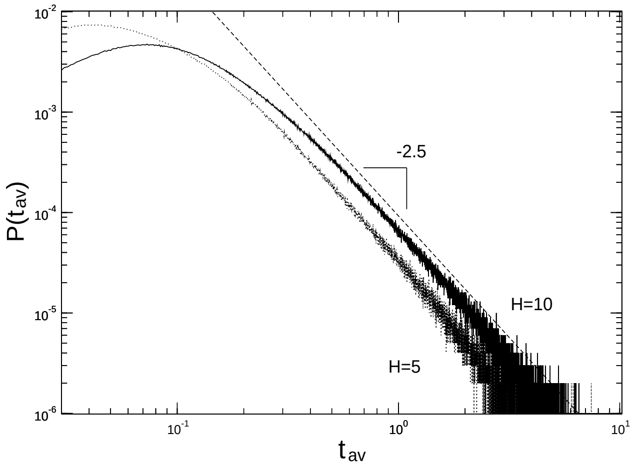

Fig. 8. Normalized latency τ_{av} distributions at the critical point $m = [\langle d \rangle]$ follows power law of exponent ~ -2.45 and fits very well the real measurements (see text). Here, we plot the distributions for $H = 5$ (shaded line) and $H = 10$ (continuous line) showing that the long tail does not depend on the maximum queue size. Any deviation from $m = \langle d \rangle$ results in an exponential distribution, deviating from real observations. Network parameters: $M = 1000$, $< k >= 4$, $D_f = 1.5$, $\sigma = 1$, $\alpha = 1$. Simulation parameters: $\rho = 0.1$, $\mu = 0.01$, $H = 5, 10$ and $T = 5 \times 10^5$ steps. The distributions were obtained from an statistical ensemble of 10 different networks and every network was simulated five times with different host arragements.

8 Discussion

In this paper we have shown that a simple model of traffic dynamics incorporating the appropriate Internet's network topology is able to recover several statistical features of real traffic. More important, we have seen that the routing algorithms can take advantage of the small-world structure of the web by reaching a critical path horizon close to the network's average path length. In doing so, a highly efficient system is reached at low cost: routing strategies only need to consider a small depth. Once the m parameter reaches the network's diameter, no further information is required to properly reach the target. A full-system deterministic routing strategy is actually unnecesary and would be too costly. Instead, the constraints imposed by network's architecture allow to exploit the implicit information defined by the small-world architecture.

It might be that Internet evolves in a way that throughput or global performance is maximized. This trend is constrained within the limits of available communication resources. Inside this regime, Internet is shaped in order to provide better response. This is reflected in the optimal and lower average stretch observed in real Internet, which is close to global minimum [26]. This suggest hat some hidden optimization is at work. Clearly, an unresponsive system will be no good. How a distributed collection of designers were able to define this globally efficient infrastructure is a question that deserves attention.

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