An Overview of Self-Similar Traffic: Its Implications in the Network Design

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Abstract—The knowledge about the true nature of the traffic in computer networking is a key requirement in the design of such networks. The phenomenon of self-similarity is a characteristic of the traffic of current client/server packet networks in LAN/ environments dominated by network technologies such as Ethernet and the TCP/IP protocol stack. The development of networks traffic simulators, which take into account this attribute, is necessary for a more realistic description the traffic on these networks and their use in the design of resources (contention elements) and protocols of flow control and network congestion. In this scenario it is recommended do not adopt standard traffic models of the Poisson type.

Index Terms—Network Traffic, Self-similarity, Protocols, Heavy-tailed distributions, Network Resources.

I. INTRODUCTION

The recurrent use of computer networks advances with notorious growth. Network applications have multiplied, and, particularly, social networks do not stop growing up. This high-growing is mainly due to the popularization of the use of computers, mobile phones and the easy access to the Web. The transmission of data of audio and video through such networks presents demands that vary over time and requires differentiated services (high-speed data, channel band reservation and priority traffic to audio or video) generating traffic with high speed and great variability. Knowledge about the very nature and behavior of the network traffic emerges as a fundamental requirement for the design, operation and maintenance of networks, demanding the execution of several activities, among which one can highlight

• Sizing of resources: fundamental activity of design and maintenance. The dimensioning of resources aims to qualify and quantify the network components installed. Typical sizing examples are the communication channel and the allocation of contention-node buffers, such as routers and switches.
• Quality of service (QoS): maintaining the network quality of service is always a challenge and predicting the peak usage remains crucial for deciding which corrective measures can be adopted.
• Protocol Design: As a basis for network operation, the adequacy of protocols to the type of network traffic is essential. In this case, designing and implementing new policies for flow control and congestion is a key part of the process.

In this sense, the implementation of network traffic generators more closely of real networks traffic is essential to the design, operation and maintenance activities. These processes of traffic generation are based on observation of the number of requests/packets arriving at containment nodes of the network in a given time interval. A sequence of such observations represents the generated traffic. Figure 1 illustrates such a process. It illustrates the different moments in which each of the four different users place their respective requests for transmitting packets. On the right side of the figure, the arrows indicate the traffic demand generated jointly by users at the containment node. The most widely spread network traffic models (both for analysis as generation) still use Poisson processes, or more generally, Markovian processes, due to their simplicity, with consequent abridgement in the traffic model. These models were inherited of the voice traffic models of telephone networks. The main characteristics of this models are:

1) Arrivals of requests/packets are random events;
2) Arrivals of requests/packages are independent events, i.e., the arrival of one package is not determinant for another to arrive; property known as memoryless;
3) In the analysis, the counting interval is divided into sub-intervals (Δ → 0) so small that at most one or no event is observed;
4) Distribution of the number of requests/packets is proportional to the duration of the observed time interval, i.e., the arrival process follows a pre-determined rate.
5) The probability distribution for number of the arrival of packages is discrete.

The characteristics of the Poisson process can be illustrated in Figure 2 considering the users (A, B, C, D) transmitting randomly and independently only one arrival/packet request each time (in each case, time Δ → 0); the mean number of arrivals is proportional to the time of observation). Among the characteristics observed in the Poisson process, the most relevant to the traffic model based on this process is related to its memoryless property, which means that the current traffic behavior is independent of the previous traffic history. This implies in predicting that the traffic, when observed into increasing intervals of time scales (from milliseconds to minutes and even hours) tends to smooth in a few scales of observation time. In other words, the peaks rapidly dissolve with increasing time scale of observation. Statistically, this

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means that the structure of autocorrelation, which measures the degree of dependence between current traffic and previous traffic, decays, undoes rapidly and that this traffic has short dependence interval or Short-Range Dependence (SRD).  Figure 2 shows a sequence of graphs illustrating (in a very simplified way) a traffic generated with this characteristic in three scales (1 unit of reference scale, 10 units of scale and 10,000 scale units). In the sequence of the graphs, the peaks are undoing with the increase of the scale of observation time scale. These graphics were generated by means of a Pareto probability distribution function, to be described in the sequence of this work, with parameters conveniently adjusted to illustrate the SRD characteristics. Baccelli [11] argue that until the 1990’s, modeling the traffic by traditional statistical laws was still adequate in many cases. But traffic then changed and it was necessary to understand how and why. This model started to be questioned from 1993 onwards, results from the work of Leland, Taqqu, Willinger and Wilson [2] on traffic in Ethernet LAN and followed by other works related to packet traffic, namely: Ethernet Local Network [3], Wide Area Network (WAN) [5], [6], Variable bit rate video (VBR) over Asynchronous Transmission Mode (ATM) [7], CCSN/SS7 [8] and Integrated Services Digital Network (ISDN) [9]. These works and others [10], [14] showed that, contrary to the Poisson traffic model, the actual traffic of these networks, when observed on multiple timescales, does not smooth – instead, it displays peaks across multiple scales of observation time, when compared to traffic with SRD characteristics. Statistically this means that the traffic autocorrelation structure is maintained for several time scales and the traffic presents a characteristic of long dependence interval or Long-Range Dependence (LRD) [17]. Figure 3 combines a sequence of graphs illustrating (simplified mode) traffic generated with this characteristic, a three scales (the same ones used for the graphs in Figure 2). It can be seen from the graphs that the peaks are not redo with the increasing scale of observation time. The graphs were generated by means of a distribution function of Pareto probabilities, with parameters conveniently adjusted to illustrate the LRD characteristic.

The LRD characteristic is relevant in sense that the traffic behavior, when observed through different time scales, is of great importance in the performance analysis, the flow control and network congestion, since the demand for buffers allocation in nodes of containment, latency of actuation of flow control mechanisms and congestion and, to some extent, the demand for bandwidth, depend on the sampling time scale or traffic observation. This directly implies questioning about the validity of results obtained in performance analysis and network control using Poisson-based models of traffic, that is, models with SRD characteristics used as base for the activities of network design, operation and maintenance.

II. SELF-SIMILAR TRAFFIC MODEL

Self-similarity experienced a growing explosion in publications and multiple applications in the 1990s and 2000s [2], [9], [28], [36], [49], [51]. The search for a traffic model that included the characteristics LRD led researchers in the field to associate this characteristic with the idea of “fractals” that are objects that maintains the same appearance when observed at different scales [12], [13], [22], [40]. Looking at Fig. 3 some self-similar behavior can be observed by inspection, by noting that the traffic profile remains rather the same at different time scales. This is in contrast with the traffic shown previously, in Fig. 2 which represents traffic with SRD characteristics. The processes used to describe this fractal nature of network traffic are called self-similar processes [12], [13]. These present structural similarity through a large number of observation scales, that is, the structure repeats at multiple scales and in different contexts or different dimensions (geometric, statistical or temporal) and the behavior of the process statistics, such as mean, variance and the autocorrelation function does not change with spatial or temporal scale variation (stationary processes) [16], [18], [20], [21], [22]. In this work, a brief description of self-similar traffic is made and its implications in network design investigated.

A. Model of traffic in local networks

Traffic in a local network has two components. One referring to the sources of traffic (stations and servers) which, by generating traffic in a random manner, can have their traffic modeled as a stochastic process [18]. The other component refers to the traffic itself that can be seen as an arrival of packets in a network contention element, switch or router, that can be represented as a time series, in which the application of statistical methods as aggregation, measures (mean, variance, autocorrelation) and spectral analysis, determines whether the process is self-similar. Figure 4 illustrates a process of generation traffic, in which A, B, C and D represent the sources of generating traffic in a random way, at discrete time $T$ steps ($X_n^A$, $X_n^B$, $X_n^C$, $X_n^D$). EC represents the element of contention, $X_n$ represents the incremental process and $Y_n$ represents the cumulative process, related to cumulative traffic from time zero to $n$-th interval $nT$. In this figure, the demands of each source are exemplified, in 16 consecutive time intervals ($1T$ to $16T$). The purpose of this illustration is to clarify the counting process that results in the variables of the incremental process.
Figure 2. SRD case: Representation of simulated traffic with “visual” SRD characteristic observed at intervals of: (a) 1 unit of scale (b) 10 unit of scale (c) 10,000 unit of scale. The maximum number of observations in each of the three sub-figures (axis of abscissa) is different in each case, using 900, 9,000 and 9,000,000 observations, respectively.

The accumulated values for the demand correspond to a sum with 11 terms: \(1+2+0+1+0+2+0+1+1+0+2 = 10\) (column \(Y_{nT}\)). For the sake of simplicity, one can assume normalized instants setting \(T = 1\). The random traffic of generating sources can be modeled by a probability distribution that, for the current networks should be able to capture the high variability in traffic network. The most appropriate distribution is the Pareto distribution of the long tail (heavy-tailed) \[5\], \[6\].

Figure 3. LRD case: Representation of simulated traffic with “visual” LRD characteristic observed at intervals of: (a) 1 unit of scale (b) 10 unit of scale (c) 10,000 unit of scale. The maximum number of observations in each of the three sub-figures (axis of abscissa) is different in each case, using 900, 9,000 and 9,000,000 observations, respectively. Nevertheless, the overall traffic profile does not change substantially.

B. Characterization of Self-Similar Processes

A self-similar process that captures the LRD-nature is characterized by a single parameter, called Hurst parameter \((H)\) \[19\], \[2\], \[23\] in a range \(0.5 \leq H < 1\), being the process classified with a low degree of self-similarity when \(H\) is close to 0.5 and with high degrees of self-similarity when it is close to 1. The value of \(H\) can be estimated from three different approaches. (i) Time domain analysis based on R/S statistics \[3\], \[24\], (ii) Analysis of variances of the aggregate process \(\{Y_{mn}\}n\), in which \(m\) is the aggregation level \(m \in Z^+\) \[3\] and (iii) domain analysis frequency (periodogram) \[24\].

Rescaled adjusted range statistics (or R/S method) is a graphical method for estimating hurst parameter of self-similar network traffic \[45\], \[46\]. An aggregate traffic stream is a
collection of flows that are grouped together for common treatment between two points in a network. All aggregate packets are subject to the same traffic management policies. The value of $H$ is related to the slope measurement of line in a $\log \times \log$-chart. In this work both methods (Aggregate Variance and R/S) are used owing to their implementation simplicity, with a good level of precision.

For the aggregate variance approach, the parameter $H$ is measured by $H = 1 - \beta/2$, in which $\beta$ is the slope of the graph line $\log(\text{Variance}_\text{Aggregate}) \times \log(m)$. The graph of Figure 5 represents the application of the method of Variance Aggregate to evaluate the degree of self-similarity of a set of data collected by Bellcore Morris Research and Engineering Center (MER). The series corresponds to traffic values one hour of normal use of an Ethernet network, collected in units of time of 10 milliseconds, resulting in a sample of size $n = 360,000$. The values of the series represent the number of packets per unit of time. These data were first analyzed in [2], [3]. The result obtained for the value of the parameter $H$ was $H = 0.8$, while the value obtained in this work was from $H = 0.8$, the inclination being estimated at 0.39 for the interval between cut-off points 1.0 and 4.0.

For the R/S method the parameter $H$ is measured directly as the slope of the line in the graph $\log(\text{R}(n)/\text{S}(n)) \times \log(n)$. Figure 6 represents the application of the method R/S to evaluate the degree of self-similarity for the same set of data from the previous scenario. The estimate obtained for parameter $H$ was $H = 0.81$, which is perfectly in line with the range of typical values expected for a traffic of LRD-nature.

C. Model for Self-Similar Traffic Generation

Among the models for self-similar traffic generation, one can cite the Fractional Brownian Motion (FBM), the Fractional Gaussian Noise (FGN) and the On/Off model. The focus is a model that captures the essential elements of a local network, namely independent sources generating traffic that is aggregated in a medium shared by that sources. In this case, the On/Off model is the most suitable.

The On/Off model considers $N$ independent sources of traffic $X_i(t)$, $i \in \mathbb{N}$, where each source is a 0/1 renewal-renewal process with i.i.d periods $On$ and i.i.d periods $Off$. This means that $X_i(t)$ assumes values 1 ($On$) and 0 ($Off$) alternating and non-overlapping time intervals called periods $On$ and $Off$, respectively. Here, $X_i(t) = 1$ is interpreted as being a packet transmission. Therefore a period $On$ can be seen as constituting a packet train [4,5]. Three of these sources and their aggregations are shown in Figure 7. Since $S_N(t)$ is the process that represents the traffic aggregated at time $t$ (similar to the process $X_{nT}$ shown in Figure 4) so that: $S_N(t) = \sum_{i=1}^{N} X_i(t)$. Let us also consider the cumulative process $Y_N(T\tau)$ such that $Y_N(T\tau) = \int_0^{T\tau} \sum_{i=1}^{N} X_i(s)ds$ where $T > 0$ is a scale factor that is explicitly incorporated. Therefore, $Y_N(T\tau)$ measures the total traffic up to time $T\tau$.

Let us now consider the time distribution of $On$ and $Off$ periods. Let $\tau_{on}$ be the random variable that describes the
duration of the On and \( \tau_{\text{off}} \) Off periods. If the distribution of \( \tau_{\text{on}} \) is a heavy-tailed one, \( N \) and \( T \) are sufficiently large, then \( Y_N(Tt) \) behaves asymptotically as a FBM process \([41],[42],[43],[44],[47],[48],[49],[50],[52],[53],[54],[55]\), being \( H = (3 - \beta)/2 \), where \( \beta \) is a parameter of the long tail distribution. That is, for generate self-similar traffic and LDR is necessary \( \beta \) in the interval \( 1 < \beta < 2 \). In the case of Pareto distribution, briefly mentioned in Section II.A, it shows a long tail in this support \([\alpha, \infty)\) and its density function probability can be written as \( f_X(x) = \left(\frac{\beta}{\alpha}\right) \left(\frac{x}{a}\right)^{\beta-1} \).

Figure 8 shows the Pareto distribution for the following parameters: Figure 8(a) \( \alpha = 1, \beta = 1.1 \). In Figure 8(b) \( \alpha = 1, \beta = 1.9 \). It is observed that the more the parameter \( \beta \) approaches 2, the distribution becomes short-tailed, approaching the exponential distribution, and leads to a process SRD, i.e., a Poisson-like process.

Different heavy tail distributions can be used to adjust the traffic model. A method for generating a large number of such distributions from known probability distributions was introduced [4]. Studying a specific network traffic scenario, an investigation would be interesting modifying the type of distribution in order to result in a better adherence to the actual data.

D. Self-Similar Traffic Generator Implementation of the On/Off Model

Consider the scenario shown in Figure 9. Here, \( N \) independent sources of traffic transmit according to the model On/Off, on a lossless channel, in which the traffic is added. The traffic sources are shown as closed boxes, which are associated with a transmission time that follows a long-tail distribution. In this case, it is assumed that each source has a Pareto-distributed traffic with the same parameters \( \alpha \) and \( \beta \) for times On and Off, and with constant transmission rate. Based on the On/Off model described in the scenario of Figure 9 the following pseudocode was implemented for the generation of aggregate traffic \( Y_N(Tt) \).

The procedure Initializing_sources (\( N \)): it randomly generates the initial on/off state of each source. The random generation is done by a normal distribution \( \sim N(0,1) \), where

```plaintext
Traffic_generator_On_Off(N,T)
    Initializing_sources(N)
    for each sampling T
        Y_N(Tt) ← 0
        for each source(1 ...N)
            X_i(Tt) ← 0
            rate_fx ← etc
            X_i(Tt) ← source(rate_fx,T)
            Y_N(Tt) ← Y_N(Tt) + X_i(Tt)
        end_for_each_source
    end_for_each_sampling
end_Traffic_generator_On_Off
```
0 (Off state) is assigned to the negative values generated by \( \sim N(0, 1) \) and 1 (state On) to the positive values generated by \( \sim N(0, 1) \).

The procedure \( \text{source}(\text{rate}\_tx, T) \) returns the amount of packet transmitted from each traffic source at each sampling time \( T \) and uses the Pareto distribution for the generation of times in the On/Off states over the sampling time \( T \).

### E. Implementation Results of the On/Off model

For a closer result of the reference model \( H = (3 - \beta)/2 \), several combinations of number of sources \( (N) \), time of sampling \( (T) \) and several seeds for the generation of random numbers were experimented. The best result is described in Figure 10, which shows the relationship between \( \beta \) and \( H \), which is close to what was expected. The generated traffic had the assessment of its degree of self-similarity evaluated by the methods of aggregate variance and R/S.

![Figure 10. Plot of the Hurst parameter \( H \) as a function of the \( \beta \) parameter, for the time-scale \( T = 1 \) unit and several ensemble of sources \( (N) \). For the aggregate variance, the value of \( \beta \) can be estimated by the slope of the straight line of the plot \( \log(\text{VarianceAggregate}(m)) \times \log(m) \), where \( m \) is the aggregation level adopted.](image)

In an Ethernet local area network model, the stations make requests to the server at short time intervals \( \tau_{on} \) and spend a long time \( \tau_{off} \) without transmitting, while the server has opposite behavior. In this scenario times \( \tau_{on} \) of customer sources have short tail \( \beta = 1.9 \) and the times \( \tau_{off} \) long tail \( \beta = 1.1. \) To the server source, consider \( \tau_{on} \) with long tail, \( \beta = 1.1 \) and \( \tau_{off} \) short tail with \( \beta = 1.9 \).

Figure 11 shows the scenario described in the previous paragraph. Figure 12 shows the influence of the number of On/Off sources (as described in the previous paragraph) on the Hurst parameter. These results are in agreement with the traffic generation for a self-similar model described in [30], which suggests that traffic in a Ethernet network may have a self-similar behavior, in the case with degree of self-similarity around 0.85.

As a remark, Figure 12 suggests that in a network of client and server packages with On-Off time characteristics similar to those considered, the traffic may have an auto-similar behavior, in the case, with a degree of self-similarity around 0.85. If these results are compared to those obtained in measurements made on Ethernet LAN in [2] (\( H = 0.80 \)) and modeling and traffic generation On/Off [49] (\( H = 0.90 \)), and our results can be considered as satisfactory.

### F. Implications of self-similarity on network performance

The performance of a network is directly related to the performance of the R/S containment elements (Router/Switch). Figure 13 illustrates a typical containment element, in this case, the routing element [20]. This element presents two processes, one of arrival and one of service. Figure 14 illustrates the context of this contention element in a network. Several scenarios of arrival self-similar and Poisson service were simulated. The simulation results are shown in Figure 15, allocation of buffers as a function of degree of self-similarity of the traffic generated by the sources, and the Figure 16, allocation of buffers to avoid packet loss due to variation of the degree of self-similarity. It can be observed in Figure 15 that the allocation of buffers grows abruptly when the degree of self-similarity increases, the same occurs with packet loss in Figure 16. Buffers limitation lead to discard of packets and network degradation.

It is observed in Figure 15 that the allocation of buffers grows abruptly when the degree of self-similarity increases, the same occurs with packet loss in Figure 16. Buffers
limitation lead to discard of packets and degradation of the network.

The strategy for reducing packet loss based on increasing buffers seems to lead to an excessive increase in queue size and consequent packet send delay. The strategy of increasing the service rate with the increase of the output bandwidth seems to be more suitable because it reduces packet loss and maintains the queue size small, thus reducing the delay in the packet dispatch. However, this strategy may lead to under utilization or waste of the channel band, due to the variable characteristic of self-similar traffic.

III. CONCLUSIONS

Self-similarity in the traffic of computer networks is not at all an up-to-the-minute discovery and neither is the work in this area, even though today’s networks are dominated by fiber optic technology, Ethernet and TCP/IP stack protocols, which reinforce the phenomenon. However, a few researchers and network designers insist on using the Poisson processes to generate the traffic model, which, as argued in this paper, does not reflect nor approximate the actual behavior of the present-day networks, often leading to the incorrect dimensioning of resources (mainly of contention elements and channel bandwidth). In this tutorial, the need for adoption of models that take into account the self-similarity present in traffic is emphasised. Heavy-tailed distributions are nice tools to build a suitable model. By studying a specific network traffic scenario, an investigation would be interesting by modifying the heavy-tailed distribution so as to result in better adherence to the data.

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