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A VERIFICATION OF SELECTED PROPERTIES OF TELECOMMUNICATION TRAFFIC GENERATED BY OPNET SIMULATOR.

Erasmus exchange project work

Supervisor: Assoc. prof. dr. Andrej Košir

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Introduction

Nowadays, telecommunication has become an essential service in our daily lives. The exchange of information generates high data traffic in the networks.

Analyzing and modelling network traffic is becoming one of the biggest challenges for communication companies when planning networks and developing communication equipments are their aims.

Recent examinations of local area network traffic and wide area network traffic have challenged the commonly assumed models for network traffic, *e.g.,* the Poisson distribution. Once traffic follows a Poisson or Markovian arrival process, it would have a characteristic burst length which would tend to be smoothed by averaging over a long enough time scale. Whereas, measurements of real traffic indicate that significant traffic variance (burstiness) is present on a wide range of time scales.

Traffic that is bursty on many or all time scales can be described statistically using the notion of *self-similarity.*

The aim of the assignment is to test the selected properties of randomly generated telecommunication traffic using OPNET network simulator. These properties are stationary and self-similarity related to type of traffic sources and the number of sources. The theoretical tools include known statistical tests for stationary and procedures for Hurst parameter estimation including the test for self-similarity. The traffic analysis will be performed using SELFIS tool.

Chapter 1: Network traffic analysis

Classic models are a good approximation for telephone calls on a PSTN network [26]. Data networks designers have used them to model network traffic owing to the facilities to calculate block traffic and service level.

These models are based on Poisson processes. Poisson describe the inter-arrival times (time between files) as well as the duration of the calls with random and independent variables distributed exponentially, in other words, Poisson model doesn't have memory.

However, new studies [1, 2] have disclosed that Poisson model is not suitable to describe the bursty behavior of real traffic.

These studies confirm that models based on fractal processes represent the current traffic in a more realistic way than traditional null memory models. Besides, these studies have demonstrated fractal characteristics in several data networks such as LAN, Ethernet, ISDN, SS7 and services such as video transmission VBR, Telnet, FTP, HTTP, etc. [3].

We need to know the main characteristics of fractal traffic and its implications in order to understand the impact of this new knowledge.

1.1. Self-similarity

Self-similarity is the property we associate with one type of fractal, an object whose appearance is unchanged regardless of the scale at which it is viewed. In the case of stochastic objects like time series, self-similarity is used in the distributional sense: when viewed at varying scales, the object's correlation structure remains unchanged. As a result, such a time series exhibits bursts, extended periods above the mean, at a wide range of time scales [19].

We can understand better this definition with Figure 1; we have a representation of the packets generated in an Ethernet network per unit of time. We can see a similar statistical appearance in different scales.

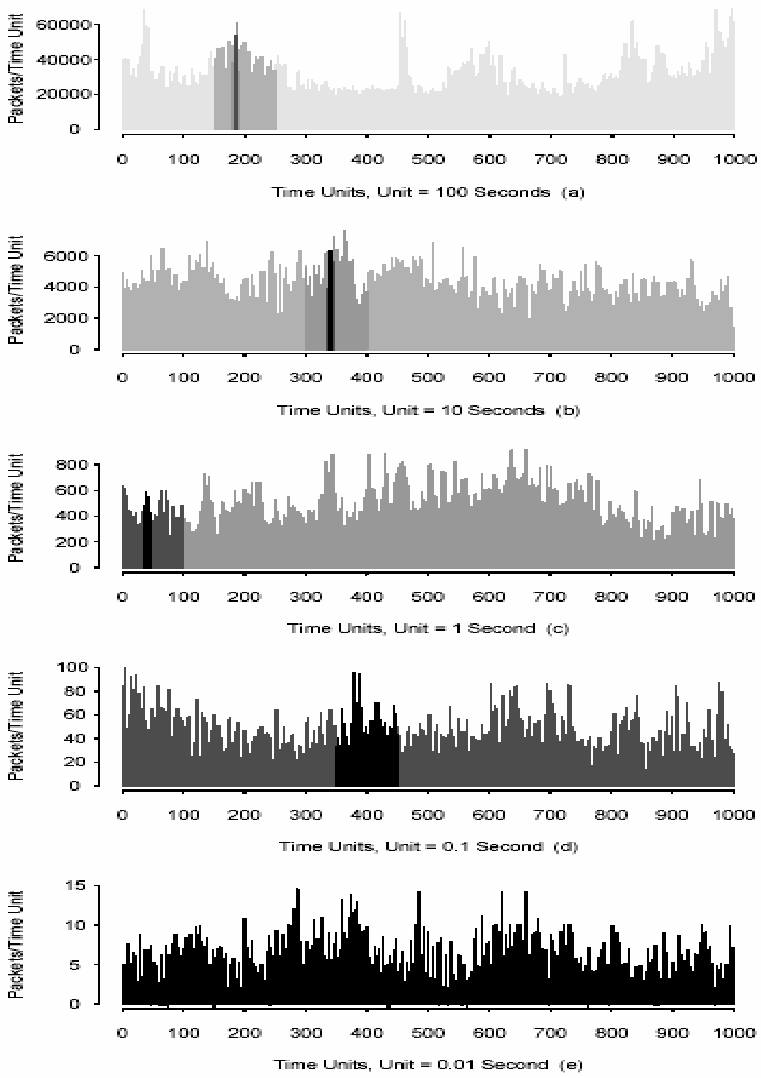


Figure 1: Ethernet trace represented in 5 different scales. [4]

1.1.1. Theoretical definition

Self-similar time series enable new aggregated series to have similar autocorrelation function to the original. That is, given a stationary time series X'= (X_t;t = 0,1,2…), we define the *m*-aggregated series

$$X^{(m)} = (X_k^{(m)} : k = 1,2,3,\ldots)$$

by adding the original series X over non-overlapping blocks of size *m*. Then, if it is self-similar, it has the same autocorrelation function

$$r(k) = E[(X_t - u)(X_{t+k} - u)]$$

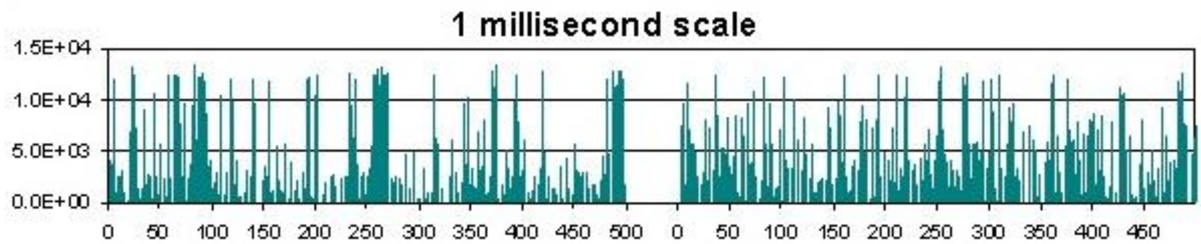
as the series $X^{(m)}$ for all m .Note that this means that the series is distributionally self-similar: the distribution of the aggregated series is the same (except for changes in scale) as that of the original.

Self-similarity manifests itself in a number of equivalent ways [15]:

1. The sample variance of aggregated processes decreases more slowly than the magnitude and is inversely proportional to the sample size.
2. The autocorrelation decay hyperbolically rather than a fast exponential, implying a non-summable autocorrelation function $\sum_k r(k) = \infty$. This infinite sum is another definition of the long-range dependence, which is why almost self-similar processes are long-range dependence.
3. If self-similar processes are examined in the frequency domain the long-range dependence phenomenon leads to the power character of the spectral density near zero. Conversely, the processes with short-range dependence can be characterized by the spectral density, having a positive and finite value at ω=0.

Finally, we can see differences between a self-similar process and a Poisson process in Figure 2. As depicted, self-similar processes do not lose the burstiness varying the scales unlike Poisson processes, which become very smooth during the aggregation process. To vary the scale means to make a zoom of the signal; in figure 2 the signal in black represents the part of the above signal.

PARETO ON/OFF PERIODS EXPONENTIAL ON/OFF PERIODS



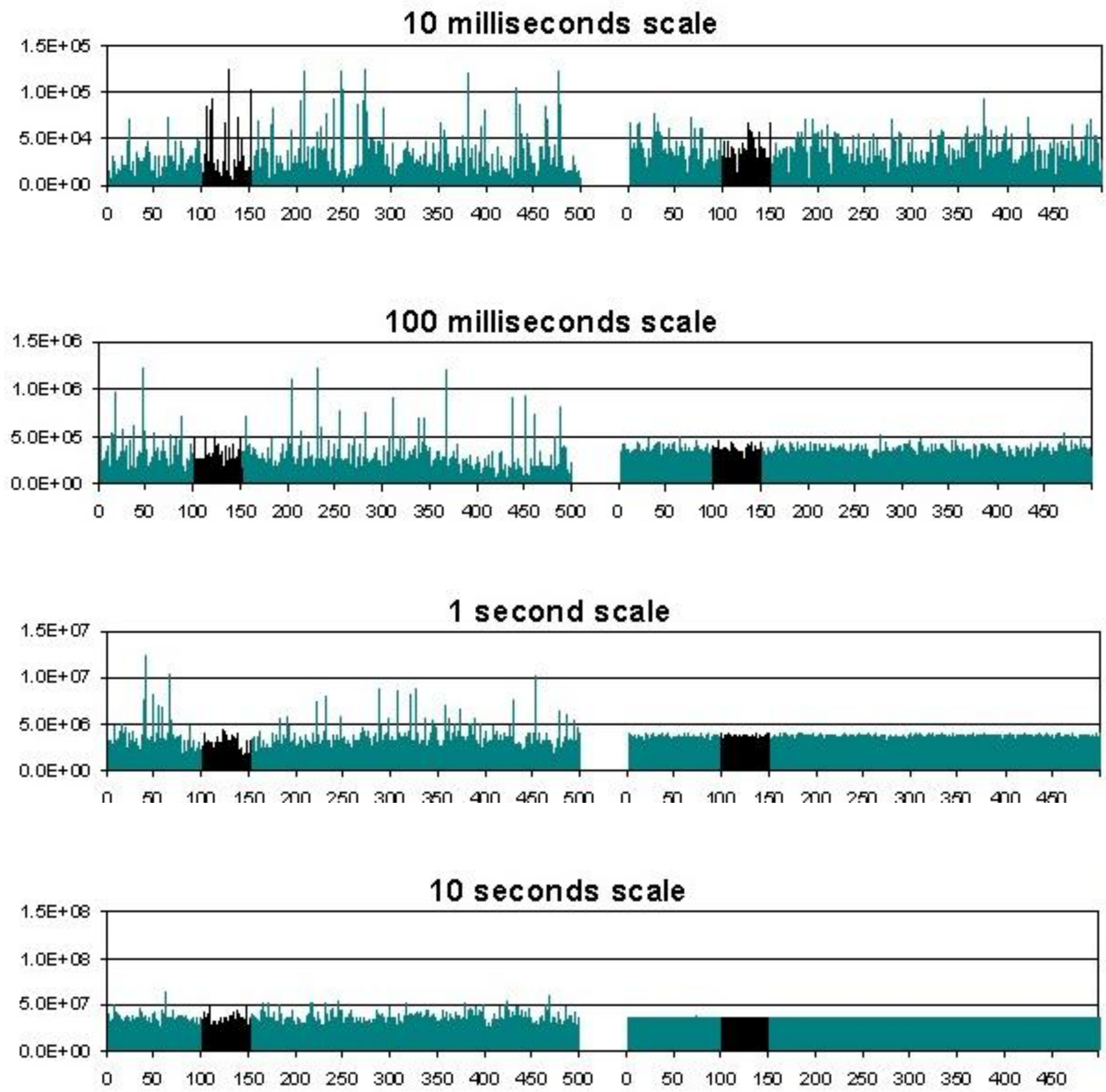


Figure 2: Comparing characteristics of heavy-tailed process (Pareto ON-OFF) with Exponential ON-OFF process varying the scale [5].

Self-similar processes are often associated with heavy-tailed distributions, which signify that we can have values far from the mean. In general, these processes can have high or infinite variance. Besides, self-similar processes and long-range dependence are related, as it will be demonstrated further down.

1.2. Hurst parameter

The most common way to define self-similarity of a process $X = (X_t, -\infty < t < \infty)$ is by means of its distribution: if $X(at) \stackrel{d}{=} a^H X(t)$ have identical finite-dimensional distributions for all $a>0$ then X is self-similar with parameter H [6].

Hurst parameter expresses the degree of the self-similarity. H takes values from 0.5 to 1. A value of 0.5 indicates the absence of self-similarity. The closer H is to 1, the greater degree of burstiness.

1.3. Long-range dependence and short-range dependence

Long-range dependence (LRD) and short-range dependence (SRD) processes are characterized by their autocorrelation functions. While the dependence between values at different times scales in SRD processes decreases rapidly, the dependence in LRD processes is much stronger. Thus, the autocorrelation function of LRD processes decays hyperbolically, defining an infinite area, unlike SRD that have exponential decaying that defines a finite area.

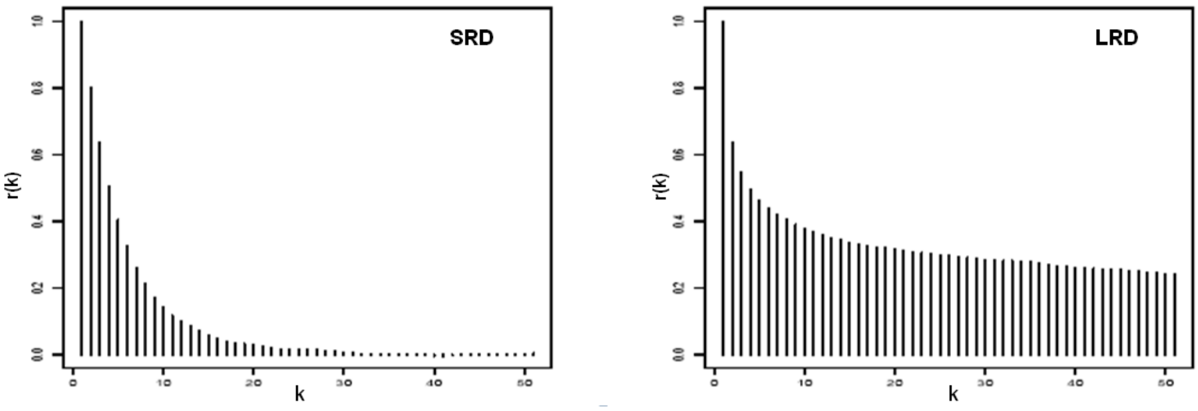


Figure 3: SRD autocorrelation function, left picture, shows exponential decaying and finite area in opposite of the right picture that LRD autocorrelation function shows hyperbolically decaying and infinite area [9].

The LRD means that small values of the autocorrelation function have important effects in high scales because the signal energy is more powerful at low frequency. Processes when Hurst parameter is closer to 1, exhibits more self-similar characteristics and stronger LRD as shown in figure 4.

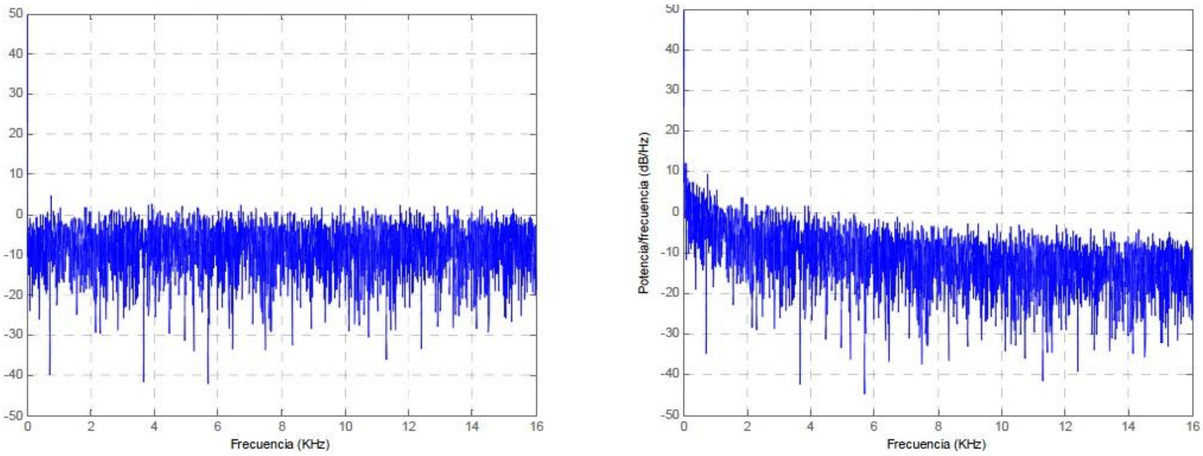


Figure 4: Spectral power density: left, process with H=0.5 (SRD) and right, process with H=0.9 (LRD) [7].

As we can see, the process with H = 0.5 has a uniform spectral power density while the process with H=0.9 shows a higher power at low frequencies.

1.4. Testing the long-range dependence

We are not able to make out if the autocorrelation function exhibits short or long range dependence. Therefore, we need tools to verify the behavior. SELFIS implements an intuitive approach for the detection and validation of long-range dependence known as Bucket shuffling [8].

Bucket shuffling [8] is based on decoupling short-range from long-range correlations in a series to infer the existence of long-range dependence. This is achieved through shuffling and the examination of the autocorrelation function.
We will test the following process with two bucket shuffling to understand this technique properly. This is explained in the following figure.

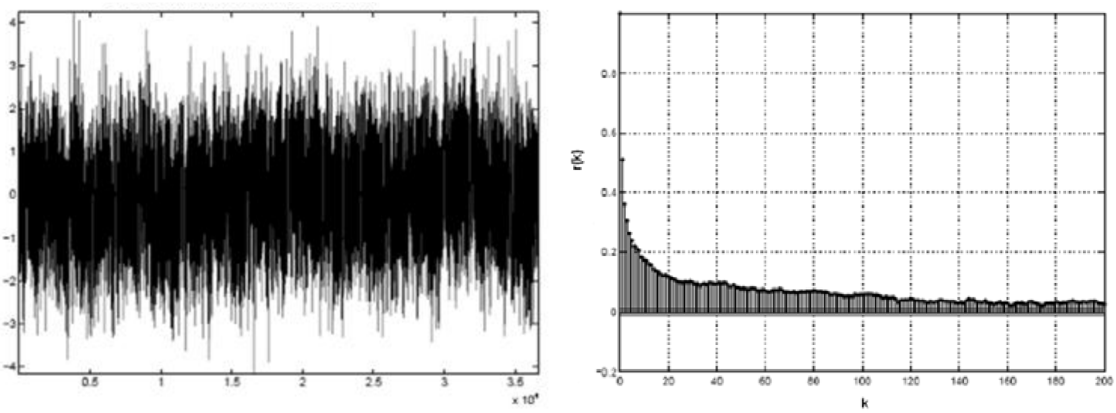


Figure 5: Process with H=0.8 and its autocorrelation function [8].

Specifically, the time series is divided in buckets of length *b*. Then two levels of shuffling can be applied:

- External Shuffling

The order of buckets is shuffled whereas the contents of buckets remain intact. This can be achieved by creating a new ordered series consisting of bucket ids. Each bucket is given incrementally an id, starting from the beginning of the time series. Then, we replace each bucket contents after the bucket-id series is shuffled. External shuffling results from preserving the time-series correlations up to the bucket length. Long range correlations are distorted because of the shuffling. Thus, the autocorrelation function should not exhibit significant correlations beyond the bucket size.

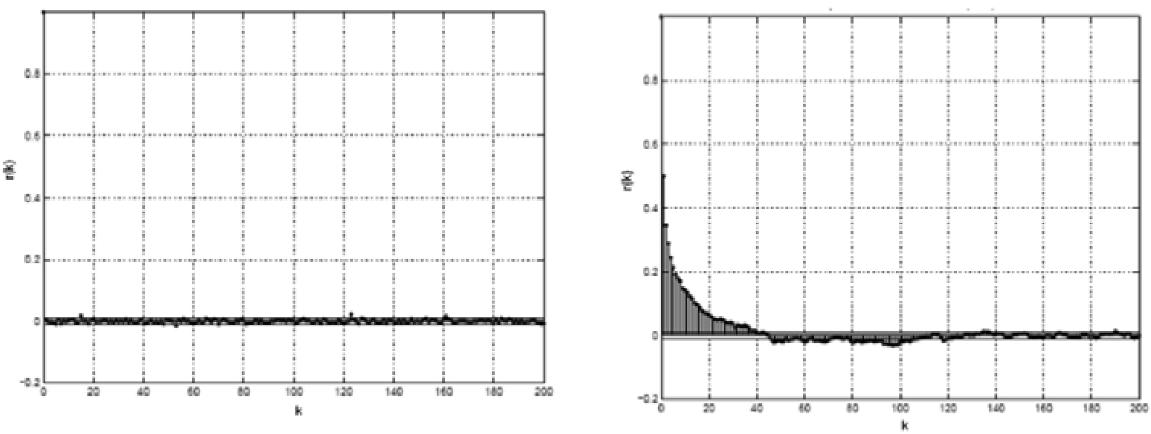


Figure 6: External shuffling method done at the previous process. (»bucket« = 1 left), (»bucket« = 50 right) [8].

- Internal Shuffling

The order of bucket remains the same as that of the original signal whereas the contents of each bucket are shuffled. As a result, short range correlations are distorted, whereas long-range correlations remain relatively unaltered. Hence, if the original signal has long-memory, the autocorrelation function of the internal-shuffled series should still show power-law behaviour.

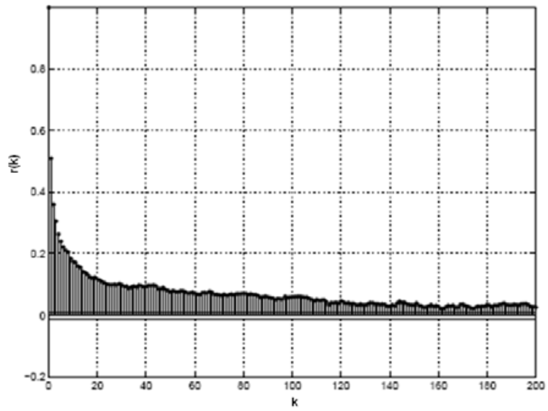


Figure 7: Internal shuffling has done in the previous process. (»bucket« = 50) [8].

1.5. Heavy-tailed distributions

Self-similar processes are modelled by heavy-tailed distributions. These distributions can be used to characterise the probability density function of stochastic processes. Two important stochastic processes for describing self-similar traffic are the size packet and the inter-arrival time.

Heavy-tailed distributions are defined as:

$$P[X \geq x] \sim x^{-\alpha}, \quad \text{as } x \to \infty, \quad 0 < \alpha < 2.$$

Some researchers have demonstrated that the easiest way to generate self-similar traffic is modelling both processes with heavy-tailed distributions as Weibull or Pareto [9].

1.5.1. Pareto distribution

The simplest heavy-tailed distribution is Pareto. The probability and distribution functions are:

$$f(x) = F(x) = 0 \ , \quad (x < k)$$

$$f(x) = \left(\frac{\alpha}{k}\right)\left(\frac{k}{x}\right)^{\alpha+1} \quad F(x) = 1 - \left(\frac{k}{x}\right)^{\alpha}, \quad (x > k; \alpha > 0)$$

and the mean value is:

$$E[X] = \frac{\alpha k}{(\alpha - 1)} \quad , \quad (\alpha > 1)$$

Where *α* is a shape parameter and *k* is a local parameter which represents the minimum possible positive values of the variable *x.* Depending the value of *α*, the main value and the variance could be infinite or finite.

When *α* ≤ 2, the variance of the distribution is infinite.

When *α* ≤ 1, the mean value is infinite as well.

Furthermore, theoretical Hurst parameter we can get by $H = (3 - \alpha) / 2$, where α is the shape parameter of Pareto distribution [24].

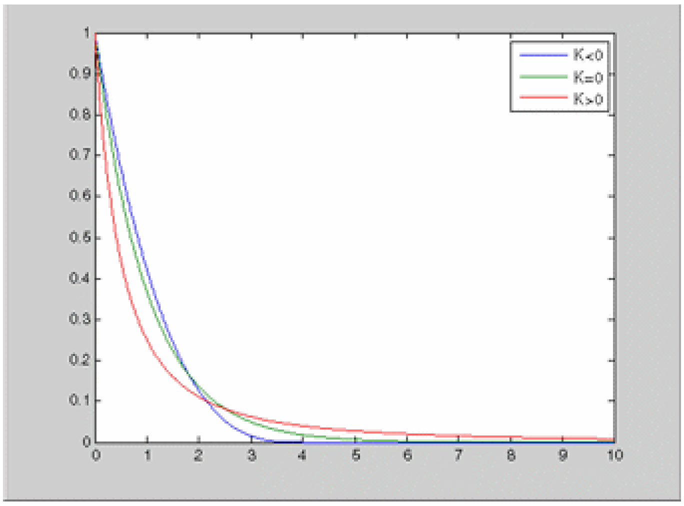


Figure 8: Example of Pareto distribution with different K values [10].

1.5.2. Weibull distribution

Weibull distribution, like Pareto distribution, is also one of the basic heavy-tailed distributions. The probability function is:

$$f(T) = \frac{\beta}{\eta}\left(\frac{T-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{T-\gamma}{\eta}\right)^{\beta}}$$

$$f(T) \geq 0,\ T \geq 0 \text{ or } \gamma,\ \beta > 0,\ \eta > 0,\ -\infty < \gamma < \infty$$

The following figure shows the effect of different values of the shape parameter, β, on the shape of the probability density function [pdf]. One can see that the shape of the pdf can take on a variety of forms based on the value of β.

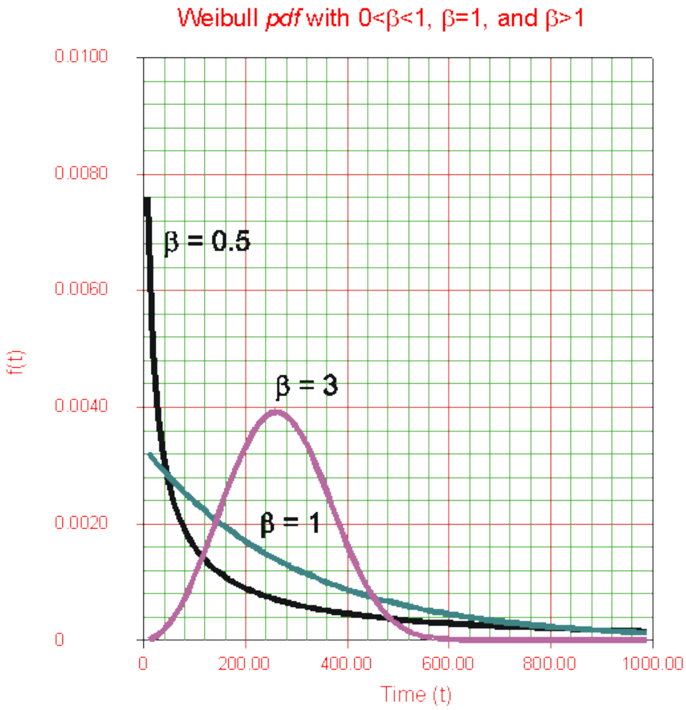


Figure 9: Example of Weibull distribution with different values [18].

Another characteristic of the distribution, where the value of β has a distinct effect, is the failure rate. The failure rate is the frequency that the traffic generated fails within specified time frame. The following plot shows the effect of the value of β on the Weibull failure rate.

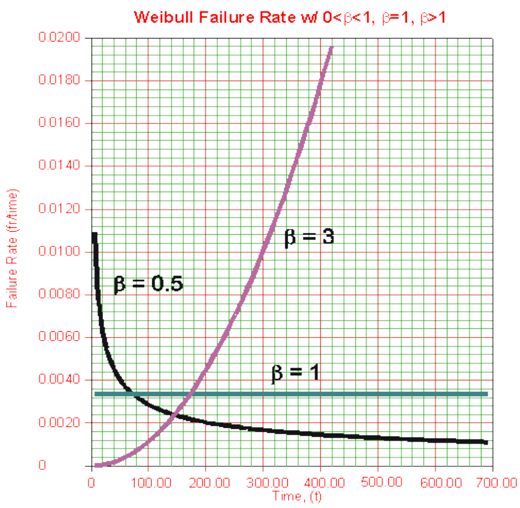


Figure 10: Example of the effect of the value of β on the Weibull failure rate [18].

This is one of the most important aspects of the effect of β on the Weibull distribution. As the plot indicates, Weibull distributions with β < 1 have a failure rate that decreases with time. Weibull distributions with β close to or equal to 1 have a fairly constant failure rate, indicative of useful life or random failures. Weibull distributions with β > 1 have a failure rate that increases with time.

1.6. Self-similarity network performance impact.

Long-range dependence of traffic has effect in queues traffic and networks elements behaviours such as multiplexors, routers, etc. Modern traffic cannot be predicted with models based on Poisson arrivals [11].

Queues following the new model decrease sub-exponentially (heavy-tailed) unlike the Poisson model where the tail decreases exponentially. This means that increasing buffers capacity to reduce the packet loss is not useful, because a small decrease in losses causes an increase in delay packets.

Figure 11 corresponds to several queue sizes against channel utilization of Poisson (M/M/1 and M/D/1 model) and self-similar traffic. The latter, as we can see, has bigger impact in queues than Poisson because the queue size goes to infinite quickly. Besides, as shown, the higher self-similarity has a bigger impact.

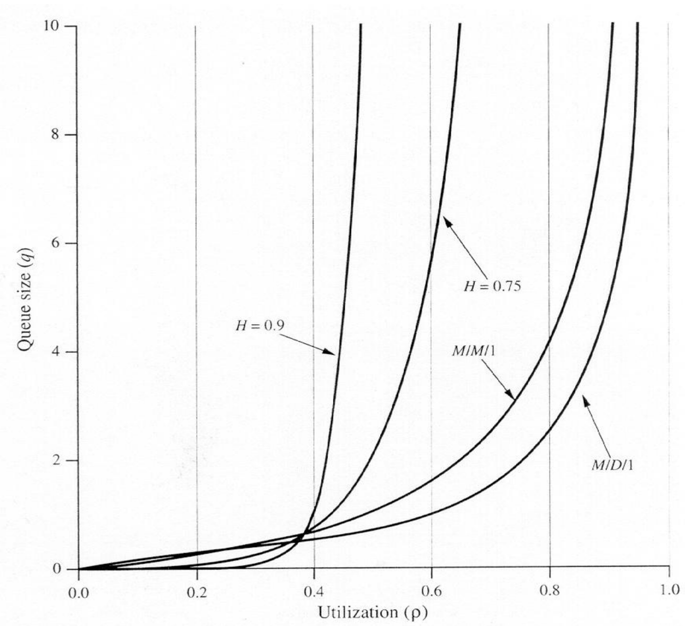


Figure 11: Comparing size queues between Poisson and self-similar traffic [11].

We have studied the impact of self-similar traffic in queues, delays, etc on network performance. To view please refer chapter4, section4.

1.7. Examples of self-similar traffic

We are daily sending and receiving network information. These data traffic have self-similarity properties. Below, we have several examples of self-similar traffic:

- Ethernet traffic

Ethernet traffic (send and received traffic measured as packets/s or bits/s) is self-similar traffic with common H values between 0.7 and 0.9 and Pareto distributions with 1.2 [12].

- WWW traffic

The browser traffic (send and received traffic measured as packets/s or bits/s) is also a self-similar traffic. The density distributions can be modelled with Pareto distribution between 1.16 and 1.5 values [12].

- TCP, FTP and TELNET traffic

When TCP traffic has quite elevated losses, the congestion control mechanism generates OFF periods displaying heavy-tailed distributions over long-range scales ,self-similarity can be observed depend on round trip time (RTT) and the number of simultaneous TCP sessions [27]. Application on TCP as FTP and TELNET shows self-similar features [13].

- VBR video

Digital video, as H.26x and MPEG, has hyperbolically decreasing autocorrelation function and can be modelled by heavy-tailed distributions [14].

Chapter 2: Hurst Parameter estimators

Hurst parameter is a measure of self-similarity. While the Hurst parameter is mathematically perfectly well defined, measuring it is problematic [28]. There are several methods to estimate the Hurst parameter each providing a different value. All estimators are vulnerable to trend of the periodicity in the data and other corruption sources. Many estimators assume specific functional forms for the underlying model and perform poorly if this is misspecified when taking into account that the problems with real-life data are worse than those faced when measuring artificial data.
This is why we do not have a criterion to determine which method gives us the best result.

The R/S parameter, the aggregated variance and the periodogram are well-known techniques, which have been used for a long time in measurements of the Hurst parameter. The local Whittle and wavelet techniques are new techniques which generally fare well in comparative studies.

In this thesis we have used the SELFIS tool to estimate the Hurst parameter [8].

There are many estimators that are used to estimate the value of the Hurst parameter. Below, we are going to explain all the methods implemented in SELFIS. However, in this thesis we have only used some of the methods. An example will be provided at the end of this chapter.

2.1. Absolute value method

H is estimated by the slope when an aggregated series $X^{(m)}$ is defined, using different block sizes m. The log-log plot of the aggregation level versus the absolute first moment of the aggregated series $X^{(m)}$ should be a straight line with a slope of H-1, if the data is long-range dependent.

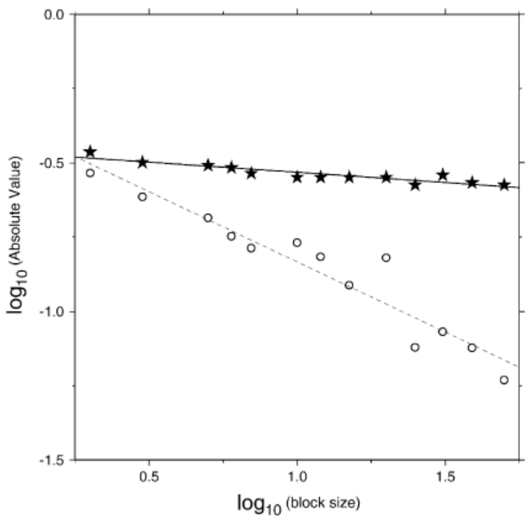


Figure 12: The absolute method applied (stars: actual sequence, circles: randomly sequence slope of -0.5) [29].

2.2. Variance method

The variance estimator is a graphical method based on properties of slowly decreasing variance where we plot on a log-log plot the sample variance versus the block size of each aggregation. If the series is self-similar with long-range dependence, then the plot is a line with slope β greater than -1. The estimation of H is given by H = 1 + β / 2.

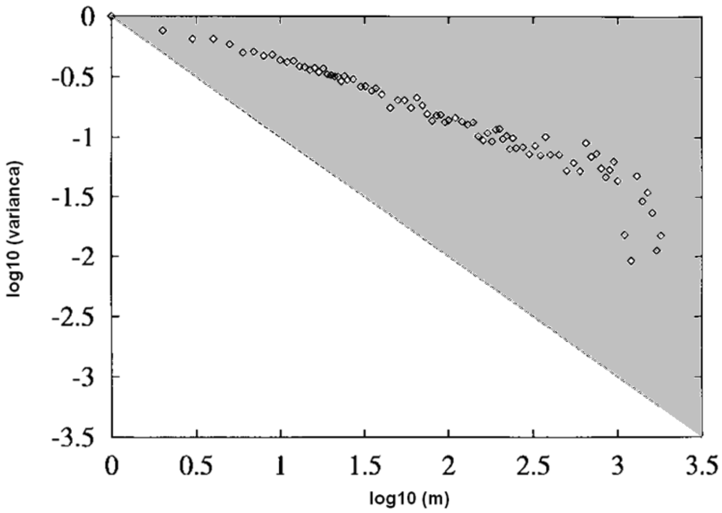


Figure 13: Example of variance method [9].

2.3. R/S method

This method uses the rescaled range statistic. The R/S statistic is the range of partial sums of deviations of a time-series from its mean, rescaled by its standard deviation. A log-log plot of the R/S statistic versus the number of points of the aggregated series should be a straight line with the slope being an estimation of the Hurst exponent.

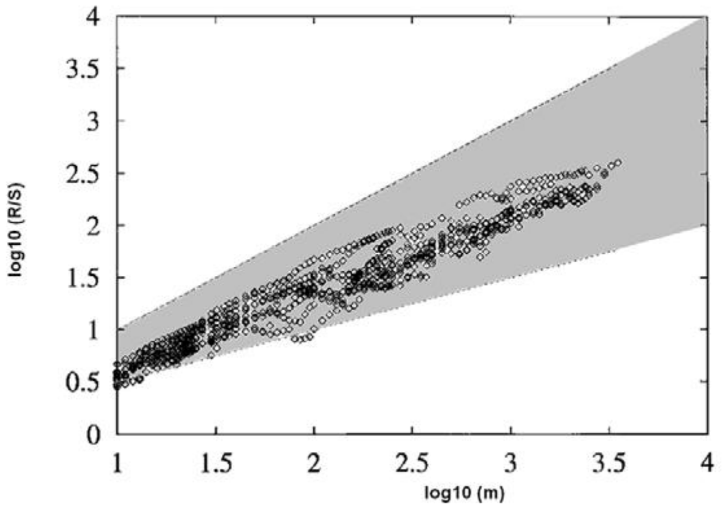


Figure 14: Example of R/S method [9].

2.4. Periodogram method.

The estimation of H is given by the slope of the spectral density of a time series versus the logarithm of the frequencies. The periodogram is given by

$$I(\nu) = \frac{1}{2\pi N} \left| \sum_{j=1}^{N} X(j) e^{ij\nu} \right|^2$$

where *v* is the frequency, N is the length of the time series and X is the actual time series.

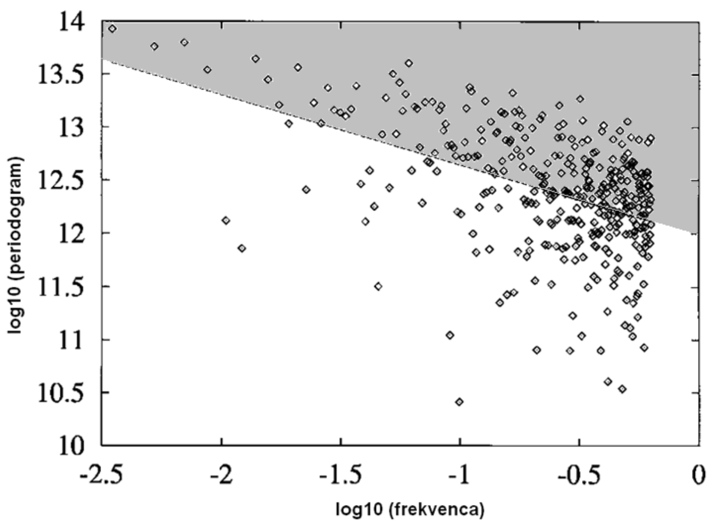


Figure 15: Example of periodogram [9].

2.5. Whittle estimator

The method is based on the minimization of a likelihood function, which is applied to the Periodogram of the time series. It gives an estimation of H and produces the confidence interval. It does not produce a graphical output.

2.6. Variance of Residuals

A log-log plot of the aggregation level versus the average of the variance of the residuals of the series. The graph should be a straight line with slope of H/2.

2.7. Abry-Veitch

Wavelets are used to estimate the Hurst value. The energy of the series in various scales is studied to calculate the Hurst parameter. This method is the most comprehensive and robust method for determining the scaling behaviour of traffic traces [20].

2.8. Example

We are going to calculate the Hurst parameter of the following process by different methods with SELFIS.

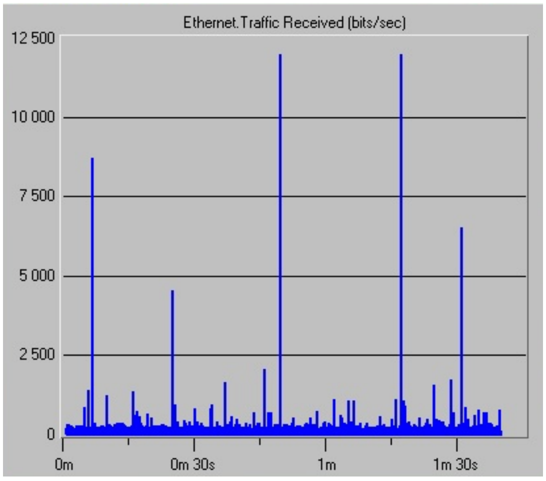


Figure 16: Discrete stochastic process used as an example. The theoretical Hurst value is 0.7.

The next table shows each method with its Hurst Parameter estimated. The evaluation was carried out using SELFIS.

	Variance method	R/S method	Residual variance	Periodogram method	Whittle estimator	Arby-Veitch
Hurst parameter	0.806	0.825	1.116	0.810	0.686	0.656

Table 1: Hurst values

As we expected, we have different values of the Hurst parameter. I really do not understand why sometimes we obtain values bigger than 1. Even though, we have studied some data traffic trying to find out an answer for this misunderstood results and we can conclude that:

- Periodicity in LRD data affects the estimation.
- SELFIS is not able to estimate non-stationary series.

Chapter 3: OPNET Modeler

OPNET Modeler [21] is the industry's leading network development software firstly introduced in 1986 by the MIT graduate. OPNET allows you to design and study communication networks, devices, protocols, and applications. The modeler is used by world's most prestigious technology organizations to accelerate the R&D process. Some of the customers are prestigious institutions including Pentagon, MIT, UIC, and many others. OPNET'S object-oriented modelling approach and graphical user interface enable relatively easy way of developing models from the actual world network, hardware devices, and protocols [30]. The modeler supports all major network types and technologies, allowing to design and test various scenarios with reasonable certainty of the output results.

The application area includes:

- Network planning (both LAN and/or WAN), analysis of performance and problems prior to actual implementation.
- Wireless and Satellite communication schemes and protocols.
- Microwave and Fiber-optic based on Network Management.
- Protocol Development and management.
- Routing algorithm evaluation for routers, switches, and other connecting devices.

OPNET models are composed of three primary model layers: the process layer, the node layer and the network layer. The former represents the lowest layer. The architectural structure is not strictly aligned with the OSI model; although both are totally compatible [22].

The Open Systems Interconnection model (OSI model) is a product of the Open Systems Interconnection effort at the International Organization for Standardization. The model is a way of sub-dividing a communication system into smaller parts called layers [23].

In the following table we can see the OPNET architecture:

Network Models	Network and sub-networks
Node Models	Individual nodes and stations
Process Models	State transmission diagram (STD) that defines a node

Table 2: OPNET architecture.

Like many other researchers we have used OPNET simulator to investigate on self-similar network traffic.

3.1. Generating self-similar traffic with OPNET

Prior of further analysis, let us state that all the traffic generated by OPNET is previous to fragmentation, i.e. we are going to model the file size to generate Ethernet or IP traffic. Then, OPNET will fragment the file in to packets.

OPNET modeller can generate self-similar data traffic in the following ways:

- Raw Packet Generator

The Raw Packet Generator (RPG) is a traffic model specific of OPNET that generates self-similar traffic.

- ON-OFF processes

This method is based on superposition of many independent ON/OFF sources, this is a model where the ON and OFF periods strictly alternate and are independent from one another [31]. There is no need for these periods to have the same distribution but in order to produce self-similar traffic we have to use heavy-tailed distributions with infinite variance as Pareto or Weibull distributions.

- Traffic aggregation

OPNET modeller includes stations that allow us to create specific traffic as FTP, HTTP, mail services, etc.

We have designed a LAN with 20 computers sharing printers, email server and local files. The users also run several online applications. We want to test the main features of the traffic obtained by several applications running at the same time [17]. For the study refer to chapter 4, section 1.

- External file

OPNET modeller allows us to use external traffic in Ethernet stations created by other applications as Matlab. OPNET permits to import traffic saved as a text file. This traffic has to be files before IP fragmentation. Therefore, traffic data from protocols analyzer as Wireshark are not compatible because this traffic is already fragmented.

We will not prove this method during the development of this thesis.

3.2. RPG model features

As stated before the Raw Packet Generator model is a traffic source model used to generate self-similar traffic. An RPG module can be used over the IP and Ethernet layers of the standard models.

Two workstation node models and one Ethernet station node model support self-similar traffic.

- The ppp_rpg_wkstn models a self-similar traffic source running over an IP stack with a serial interface.
- The Ethernet_rpg_wkstn models a self-similar traffic source running over an IP stack that supports an underlying Ethernet interface.
- The Ethernet_rpg_station models an Ethernet station where the RPG module resides directly over the MAC layer.

All of the RPG nodes have a “RPG Traffic Generation Parameters” attribute that is used to specify the characteristics of the self-similar traffic. A source can generate self-similar traffic using one or more arrival processes. To use more than one arrival process, specify each process in a separate row of the RPG Traffic Generation Parameters Table.

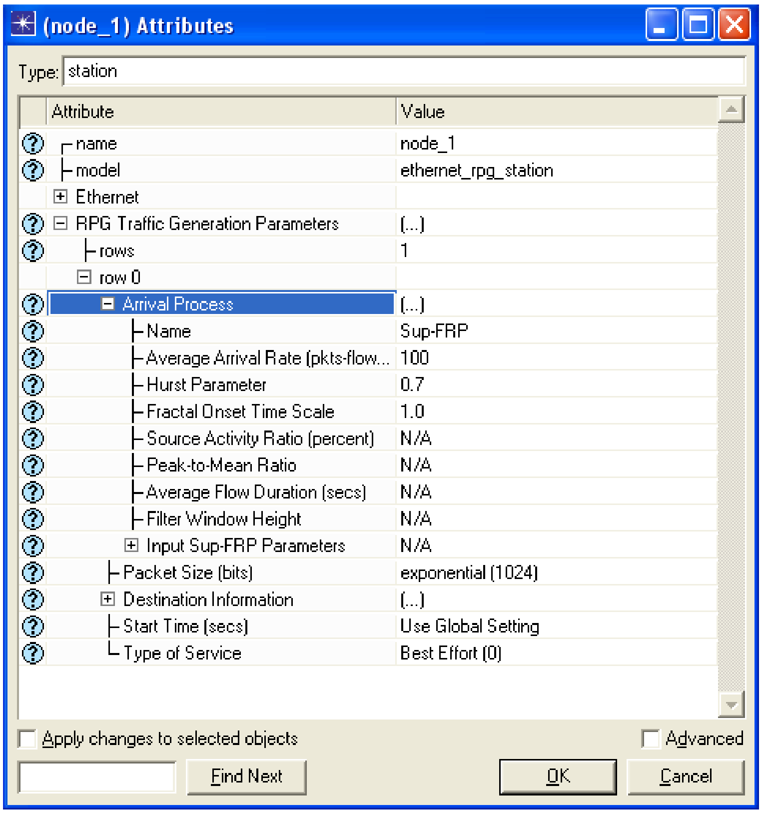


Figure 17: Example of RPG configuration.

The main RPG Process sub-attributes are described below:

- Average Arrival Rate

Defines the average arrival rate for the aggregate traffic that is generated by all sources of the arrival process. The unit is in packets/sec for ON-OFF processes.

- Hurst Parameter

Defines the Hurst characteristic of the self similar traffic source. The Hurst characteristic determines the shape parameter for the Pareto distribution.

- Fractal Onset time Scale

The fractal onset time scale is used with the Hurst characteristic to determine the location parameter for the Pareto distribution.

- Source activity ratio

  Defines the percentage of the time that at least one of the independent ON-OFF traffic sources is active.

- Peak-to-mean ratio

  Defines the ratio of peak traffic over the mean traffic rate, which is defined in the Average Arrival Rate attribute.

- Packet size

  The packet size is specified using a probability density function (PDF). Varying the packet size or the average arrival rate will modify the amount of traffic generated by the self-similar traffic source.

- Destination information

  This attribute is used to specify the destination node of the traffic generated by the arrival process. The Destination Name is specified using either the node's name, its IP Address, or its MAC address.

The Ethernet RPG station, ethernet_rpg_station, can send self-similar traffic to another Ethernet RPG station only; it cannot send self-similar traffic to RPG workstations that use the ppp_rpg_wkstn or ethernet_rpg_wkstn node models. Similarly, RPG workstations, ppp_rpg_wkstn and ethernet_rpg_wkstn, can send self-similar traffic only to other RPG workstations (but not ethernet RPG stations).

The flow-based arrival processes allow you to send all of the generated traffic to either one node or several different nodes. If all of the traffic generated by the arrival process is destined for only one node, use the default value of 100 for the % Traffic attribute. To distribute the generated traffic to several different nodes, specify each destination in a separate row of the Destination Information Table.

- Start Time

This attribute is used to specify when the arrival process starts generating traffic. The default value of Use Global Setting sets all of the arrival processes (for every node in the network) to begin traffic generation at the time specified in the RPG Start Time simulation attribute.

Note: This section, 3.2, have been extracted of RPG model tutorial of Opnet. For more information refer to [21].

In chapter 4, section 2 we have analysed the RPG model. We have studied the RPG model to see how this model really works and how to acquire the desired self-similar traffic. To test it, we have designed a simple scenario and have varied different parameters.

3.3. ON / OFF processes

As we have already explained, the aggregation of individual ON-OFF sources also allows the explanation of self-similarity observed in traffic networks.

The time spent during the ON state (*ton*) and during the OFF state (*toff*) is modelled by heavy-tailed distribution. When a large number of these sources are aggregated it results self-similar traffic.

This theory can be explained by OPNET with IP stations. IP stations, unlike the RPG model, were not designed to generate self-similar traffic, but modelling two stochastic processes (inter-arrival time and packet-size process) with the right parameters, let us get self-similar traffic.

If we chose Pareto distribution for packet size (example: $k = 26$, $\alpha = 1$) and Weibull distribution (example: $k = 0,0002$, $\alpha = 0,005$), then generated traffic must be self similar [9].

- Inter-arrival time packet

Packet inter-arrival time means time between »files« not between generated packets. The time between files is defined by Weibull distribution with the adequate parameters.

- Packet-size

Packet-size does not mean the »packet« size in OPNET, but size before fragmentation. It is just like »file« or »data« size.

Example: If you chose the constant distribution for packet-size process 3000B, such IP station will generate two packets (2*1500B if MTU size is 1500B).

Note that: MTU (maximum transmission unit) is the size in bytes of the largest protocol data unit that the layer can pass onwards.

The size of packets is modelled by Pareto distribution.

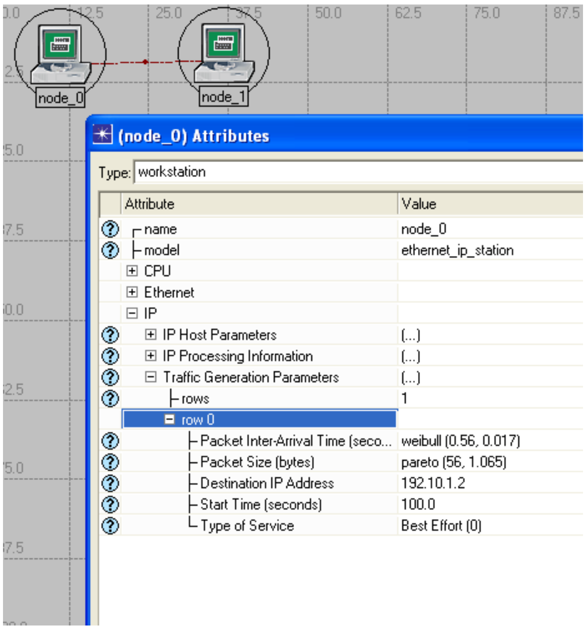


Figure 18: Examples of IP station configuration

In chapter 4, section 3 we have modelled IP station with heavy-tailed distribution and study the self-similarity of the traffic generated.

Chapter 4: OPNET simulations

We have developed four different case studies to test in OPNET, based on the theoretical features that we have explained in the previous chapters.

For the beginning, we used a real scenario to study the self-similarity of Ethernet and Internet traffic. The Ethernet traffic is generated by several aggregation sources while Internet traffic is generated by user requests to online applications.

Thereafter, we analyze how to generate self-similar traffic with the RPG model (cf. Chapter 3, section 2). The main goal is to understand how the model works to get the traffic we wish. We have used some alternates features of the model and compared their different Hurst parameters. Besides, we have studied the simulation complexity of this model. By that, we mean the number of events, the time of simulation and the memory that OPNET needs to simulate the scenario.

Furthermore, we demonstrate how self-similar traffic modelling IP station with heavy-tailed distributions is generated. Our goals in this case study are to test the dependence on self-similarity of generated flow from Pareto distribution parameter α in ON/OFF periods and from a given number of ON/OFF sources.

In the last project, we want to prove the importance of knowing the network traffic. Specially, for design network devices, modelling networks and to provide a good quality service. Therefore, we have designed a scenario with self-similar and exponential stations to demonstrate the consequence of using a bad traffic model.

4.1. Case study 1: Testing Ethernet and Internet traffic

Firstly, we wanted to know the behaviour of Ethernet and Internet traffic. We have used a real scenario to test the main features of both traffics.

4.1.1. Simulation Environment

The company's LAN [17] has 20 user PCs sharing three printers and also run locally served applications like intranet E-mail and database access. The users run different online applications including E-mail, web browsing, video streaming, and FTP.

Our goal is to study the self-similarity of the Ethernet and Internet traffic.

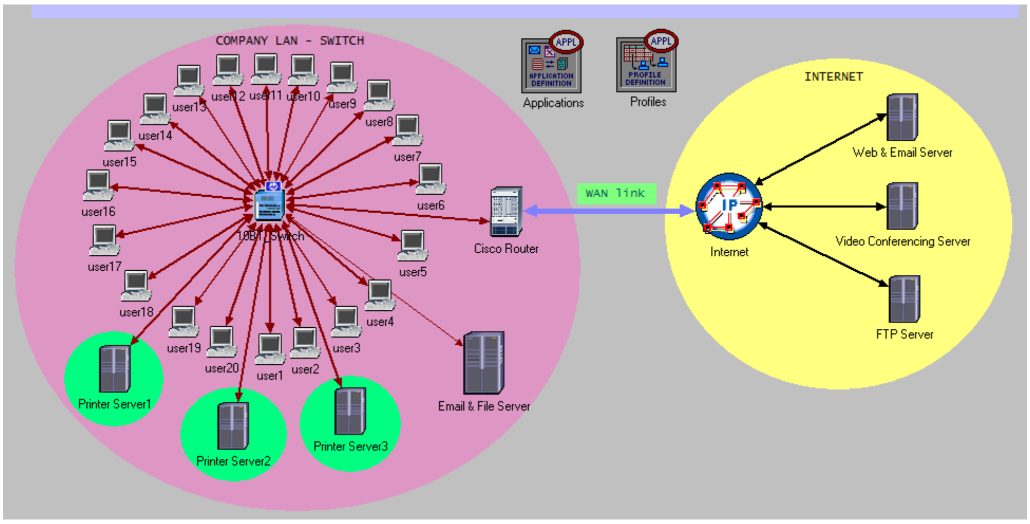


Figure 19: Case study 1 scenario

4.1.2. Generation traces

Traffic generated in Intranet and Internet network was previously configured by [17]. We have not modified its features because we considered that there are enough services running and are properly configured for our goal.

On one hand, self-similarity of Ethernet traffic was checked by studying the throughput from Cisco router to Internet which is the same as from switch to Cisco router. On the other hand, self-similarity of Internet traffic was tested getting traffic from Internet to Cisco router.

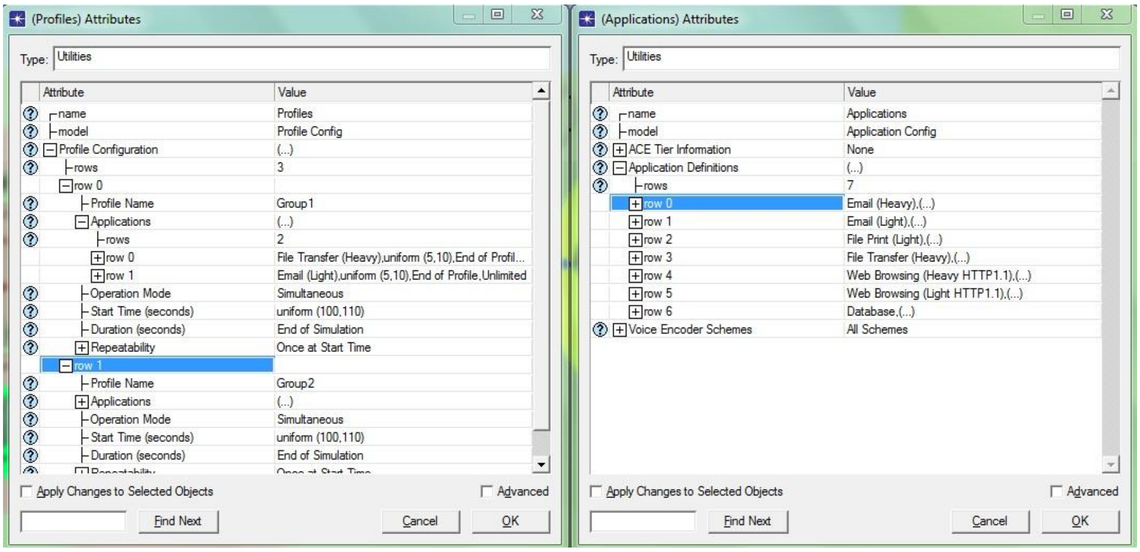


Figure 20: Case study 1, applications and profiles attributes.

4.1.3. Traffic Analysis

We have simulated the scenario, during one hour and have acquired 5000 samples of traffic.

Firstly, we are going to study Ethernet traffic.

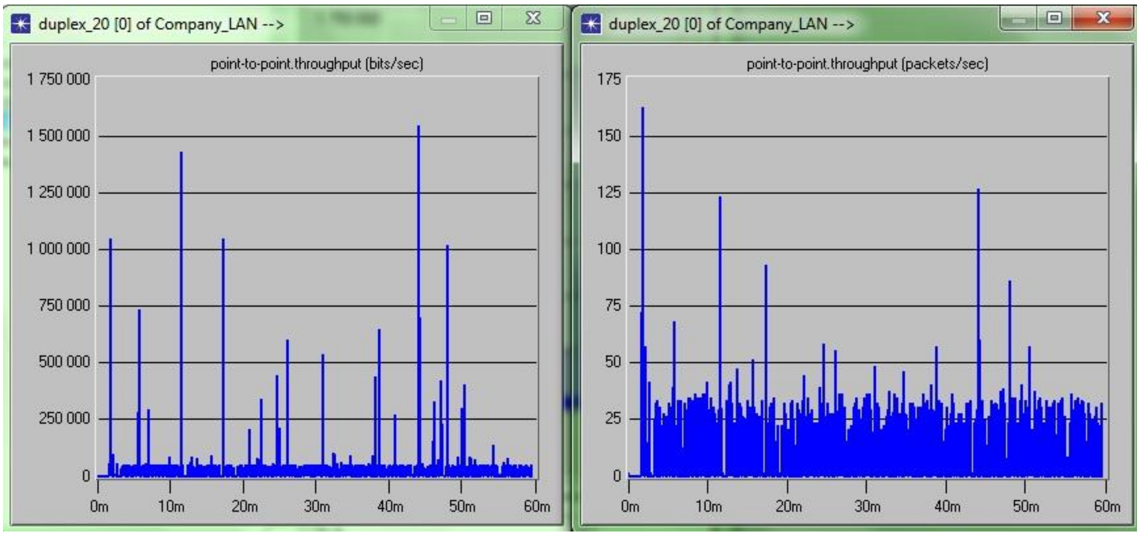


Figure 21: Ethernet traffic (switch to Cisco router).

As we can see in the above figure Ethernet traffic exhibits self-similar behaviours. The several applications running generate burst traffic. Then, the next step is to check the Hurst Parameter and long-range dependence of autocorrelation function with SELFIS tool.

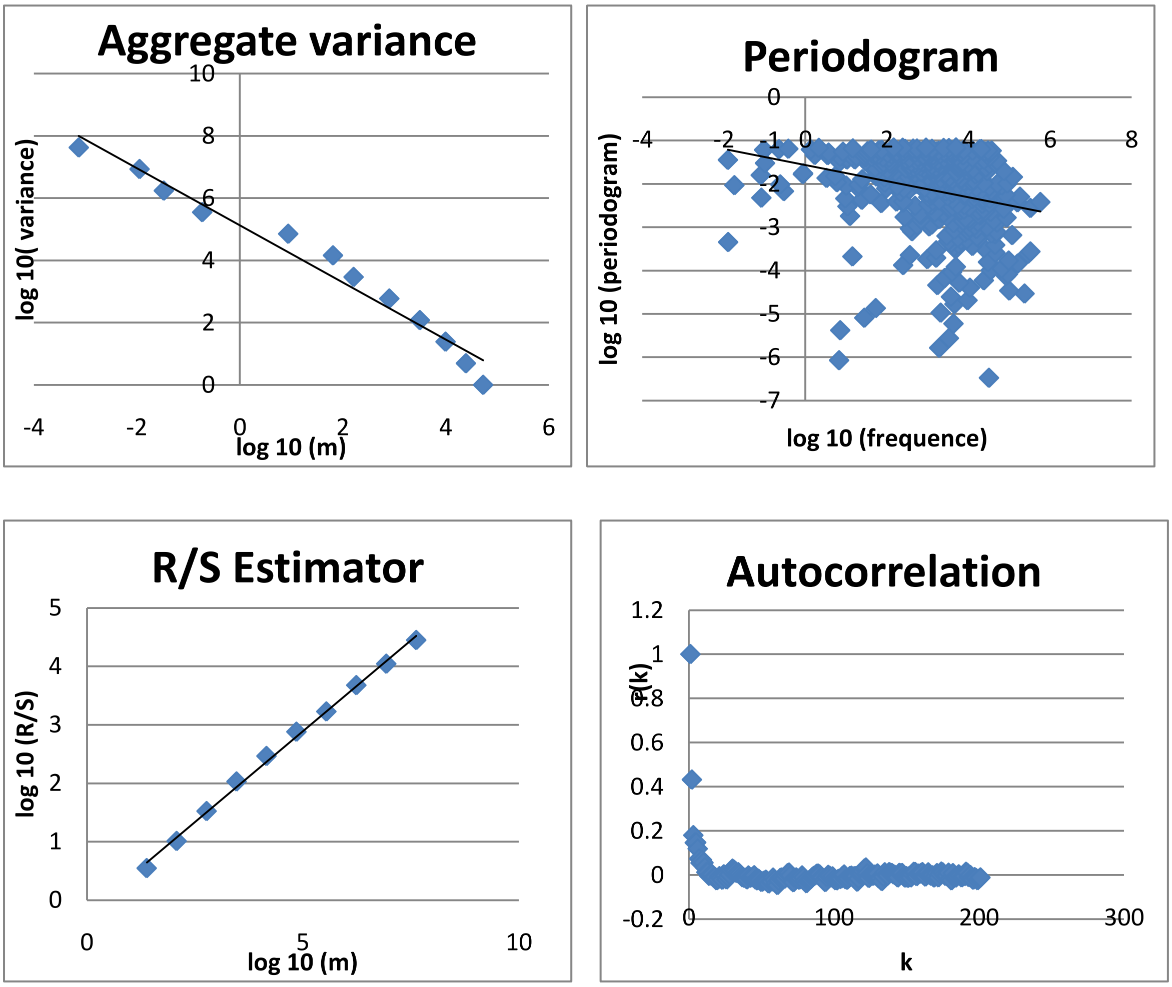


Figure 22: Linear regression of three estimators and autocorrelation function.

As we can see in the autocorrelation function (right-down picture figure 22), Ethernet traffic have long-range dependence [12] and Hurst parameter bigger than 0.5 except in Aggregate variance method, as shown in the next table.

	Aggregate variance	R/S	Periodogram	Whittle estimator
Hurst Parameter	0.472	0.622	0.677	0.783

Table 3: Hurst values of Ethernet traffic

Secondly, we are going to study Internet traffic.

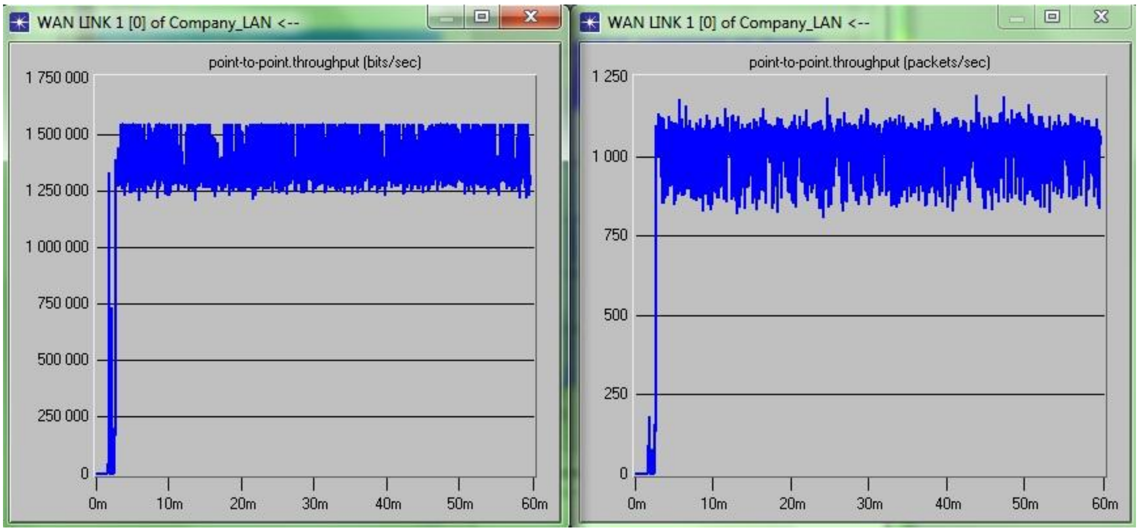


Figure 23: Internet traffic (Wan to Cisco router).

The autocorrelation function and the Hurst parameter are described below.

	Aggregate variance	**R/S**	**Periodogram**	**Whittle estimator**
Hurst Parameter	0.978	0.164	1.464	0.998

Table 4: Hurst values.

From the values of Hurst Parameter we can predict that there is no self-similar traffic or, simply, the SELFIS fails to estimate the Hurst value because of the particular characteristics of the traffic.

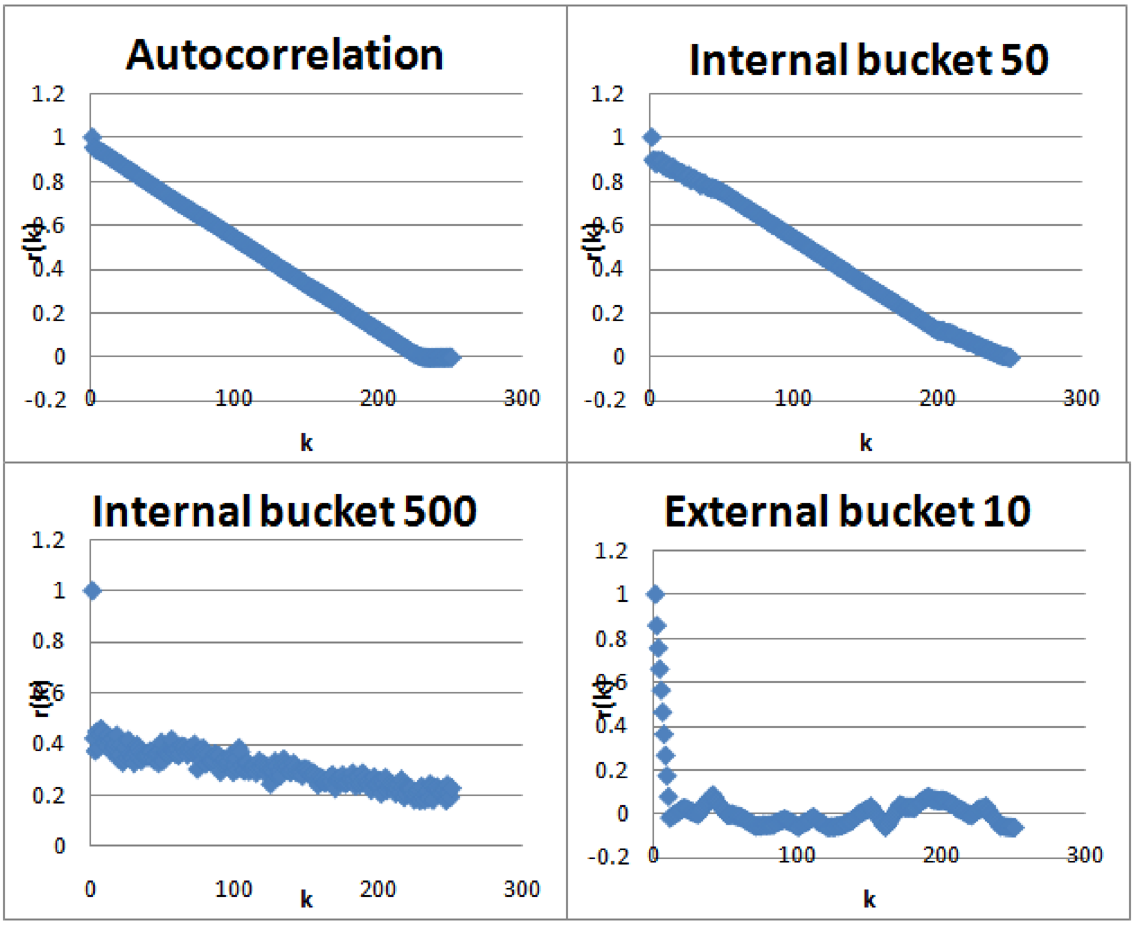


Figure 24: Up-left autocorrelation function, up-right autocorrelation function after internal bucket size 50, down-left autocorrelation function after internal bucket size 500, down-right autocorrelation function after external bucket size 10.

As opposed to the Hurst parameter results, the autocorrelation function has long-range dependence as we can see up-left in figure 24. Moreover, testing the LRD with SELFIS, doing an internal bucket of 50 and 500, the autocorrelation function keep exhibiting LRD. Doing an External bucket of 10, as we can see down-right, in figure 24, the autocorrelation function is SRD as we can expect.

4.1.4. Conclusions

The results demonstrate that, on one hand, Ethernet traffic has self-similarity properties. On the other hand, Internet traffic results diverge with [8] because it shows LRD and Hurst parameter lowers than 0.5. This ambiguity prevents us from a clear conclusion.

4.2. Case study 2: RPG simulation

The Raw Packet Generator offers various traffic generation methods based on Fractal Point Processes (FPP): sup-FRP, PowON-PowOFF, PowOn-ExpOFF, ExpON-PowOFF, etc. The implementation of these FPPs is based on a paper by B.Ryu and S.Lowen. Theoretical background and implementation details can be found in [16].

In this case study we have used the *PowON-PowOFF* method. The aim is to find a model with the right input parameters able to approach the measured network traffic.

4.2.1. Simulation Environment

The model is based on a superposition of ON/OFF sources of which both the ON-times and the OFF-times have a heavy-tailed distribution.
This model has only four parameters: the average arrival rate, the Hurst parameter, the Fractal Onset Time Scale (FOTS) and the source activity ratio [32].

Taking into account that this model allows us to generate self-similar traffic just with one source, we have used a simple configuration one server - one client.

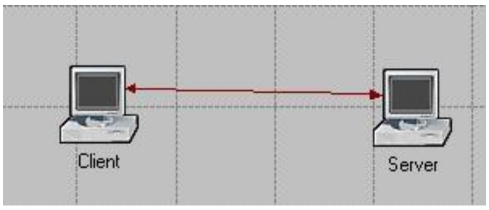
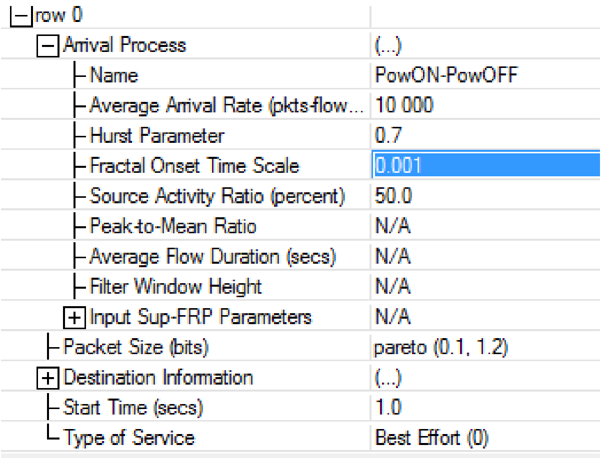


Figure 25: Case study 2 scenario

4.2.2. Generation traces

One important decision at this point was choosing the proper distribution and values for “the packet size” parameter. We have modelled “the packet size” with Pareto distribution of values k=10 and α =1,2. The values are chosen arbitrarily but are representative of an Ethernet realistic traffic [12]. The link bandwidth is high enough to avoid saturation.



row 0	
Arrival Process	(...)
Name	PowON-PowOFF
Average Arrival Rate (pkts-flow...	10 000
Hurst Parameter	0.7
Fractal Onset Time Scale	0.001
Source Activity Ratio (percent)	50.0
Peak-to-Mean Ratio	N/A
Average Flow Duration (secs)	N/A
Filter Window Height	N/A
Input Sup-FRP Parameters	N/A
Packet Size (bits)	pareto (0.1, 1.2)
Destination Information	(...)
Start Time (secs)	1.0
Type of Service	Best Effort (0)

Figure 26: Configuring the arrival process of the RPG model.

We have tested this scenario nine different times varying the main features: Changing the source activity to 50%, 75% and 90%, and by altering the FOTS to 0.0001, 0.001 and 0.01 sec respectively. The Hurst parameter is 0.7 and average of arrival time are 10.000 packets/sec.

Table 5 gives an overview of the different configurations.

	Fractal Onset Time Scale	Source Activity Ratio
Trace 1	0.0001	50%
Trace 2	0.0001	75%
Trace 3	0.0001	90%
Trace 4	0.001	50%
Trace 5	0.001	75%
Trace 6	0.001	90%
Trace 7	0.01	50%
Trace 8	0.01	75%
Trace 9	0.01	90%

Table 5: Different PowON-PowOFF traces configurations

The collection method for the "Traffic Received (bit/s)" statistic was changed from "sample" to "all values". This enabled the timestamps of individual events to be recorded.

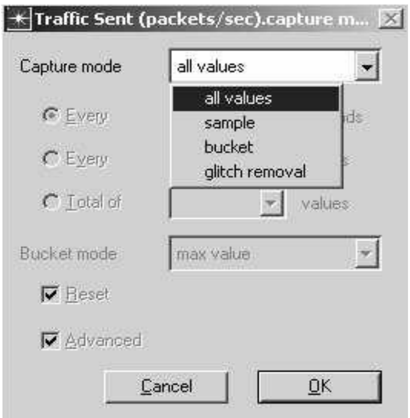


Figure 27: OPNET traffic capture configuration.

This statistic could be exported by choosing the "Export Graph Data to Spreadsheet". SELFIS is used to check the above mentioned characteristic of generated traces.

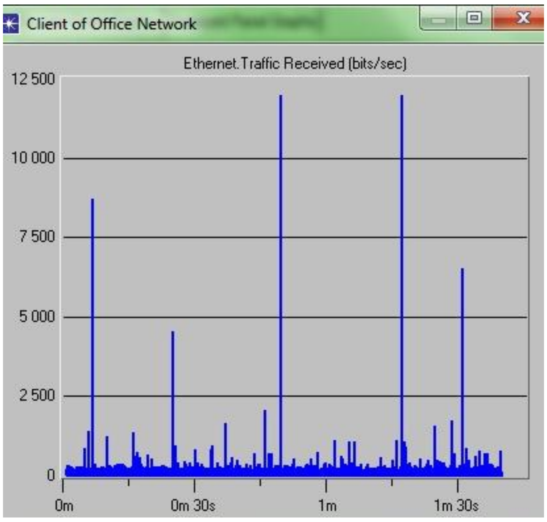


Figure 28: Example of Ethernet traffic (bits/s) generated by RPG model.

We have got from each trace the mean and the Hurst parameter estimation for three different methods: Aggregation variance estimator, variance of residuals and Abry-Veitch estimator. Besides, we have studied the simulation complexity.

The traffic should have an average arrival rate of 10,000 packets/sec and the Hurst parameter of 0.7.

4.2.3. Traces analysis

Table 6 summarize the measured statistics.

	Mean (packets/s)	Aggregate estimator	Variance of residuals	Abry-Veitch Estimator	Average Hurst Parameter	Relative error Average
Trace 1	9808	0.683	0.712	0.674	0.69	1.48%
Trace 2	9845	0.738	0.769	0.771	0.76	-8.48%
Trace 3	9763	0.646	0.663	0.741	0.68	2.38%
Trace 4	9817	0.669	0.81	0.626	0.70	-0.24%
Trace 5	9832	0.717	0.794	0.839	0.78	-11.90%
Trace 6	9790	0.689	0.755	0.822	0.76	-7.90%
Trace 7	9620	0.796	0.962	0.66	0.81	-15.14%
Trace 8	9563	0.802	0.967	0.703	0.82	-17.71%
Trace 9	9595	0.784	0.949	0.664	0.80	-14.14%

Table 6: measured mean, Hurst Parameter estimations and relative error.

The mean is very well fitted for all traces but the deviation from the mean value will become smaller if the simulation time is increased.

Trace 4 is the only one able to accurately fit the Hurst parameter, as can be read from Table 6. Others configurations generate traffic of which the burstiness is not high enough.

4.2.4. Simulation complexity

Tables 7 give an overview of the number of events, the simulation time and the memory that is needed to generate the traces.

	Number of events	Simulation Time (sec)	Memory usage (Mb)
Trace 1	22698455	54	6.4
Trace 2	23239712	56	6.4
Trace 3	22703584	56	6.4
Trace 4	31826386	69	6.4
Trace 5	28140960	65	6.4
Trace 6	26535750	61	6.4
Trace 7	33982593	55	6.4

Trace 8	25327255	45	6.4
Trace 9	21918929	42	6.4

Table 7: Simulation complexity

Varying the parameters of the built-in RPG models, it clearly influences the number of events and the simulation time that is needed. Reducing the source activity ratio increases the number of events. The simulation time changes more or less proportionally in most cases. Although simulation with Fots equal 0.001, it takes more time than the others. As for the memory usage, it remains rather constant.

4.2.5. Conclusions

The main conclusion is a complex relation between the input parameters and the produced traffic. We can conclude again that it is important to check the RPG output when you need an accurate self-similar source, because in some cases, large deviations from the expected Hurst parameter can be noticed.

A good approximation of the measured traffic could be found in our case study by lower source activity ratio and FOTS 0.0001 or 0.001.

Unfortunately we cannot choose the variance [33]. We are forced to vary the other parameters in order to examine their impact on the variance of the generated trace. As we have said, it is not evident to obtain a traffic source with predefined characteristics.

Finally, we want to advise that RPG model cannot be used independently without protocol, must be supported by IP or MAC protocol, i.e, our network has to follow the OSI model.

4.3. Case study 3: IP station simulation

In this experiment, self-similar traffic is generated by aggregated multiplexing ON/OFF sources. In fact, this kind of models generated self-similar traffic by multiplexing ON/OFF sources with heavy-tailed distribution.

Every ON/OFF data source alternates between ON and OFF, emitting packets at constant rate when ON and suspending when OFF. The time intervals of ON and OFF are respectively independent and coincide with heavy-tailed distributions [34].

OPNET allows us to configure ON/OFF sources with IP stations. Our goals in this case study are to test the dependence of self-similarity on generated flow from both a Pareto distribution parameter α in ON/OFF periods and from a given number of ON/OFF sources [34]. Furthermore, we are going to study the simulation complexity.

4.3.1. Simulation environment

To study both objectives mentioned above, we built two different scenarios.

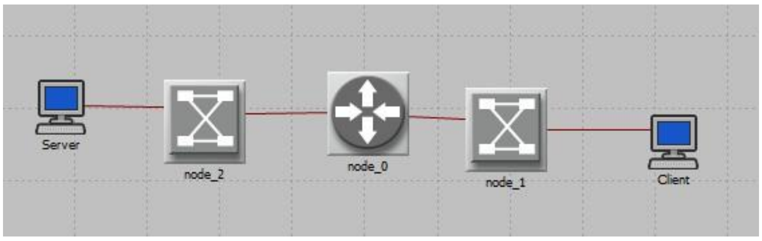


Figure 29: Case study 3: Scenario 1

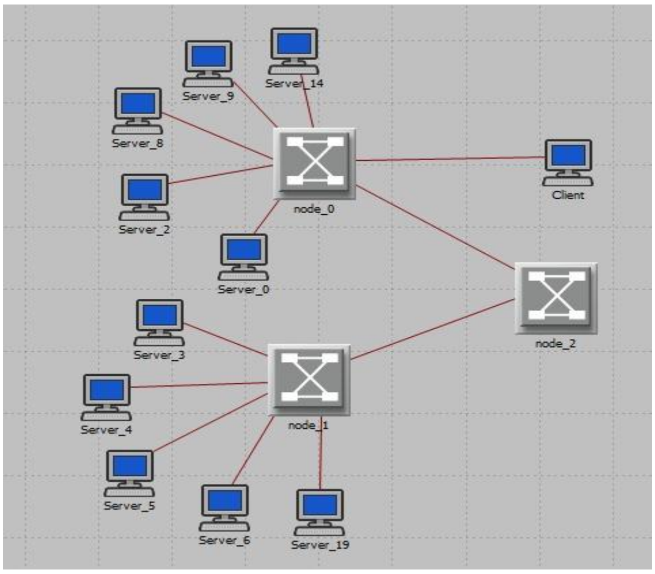


Figure 30: Case study 3: Scenario 2

4.3.2. Generation traces

Server's configurations in both scenarios are the following:

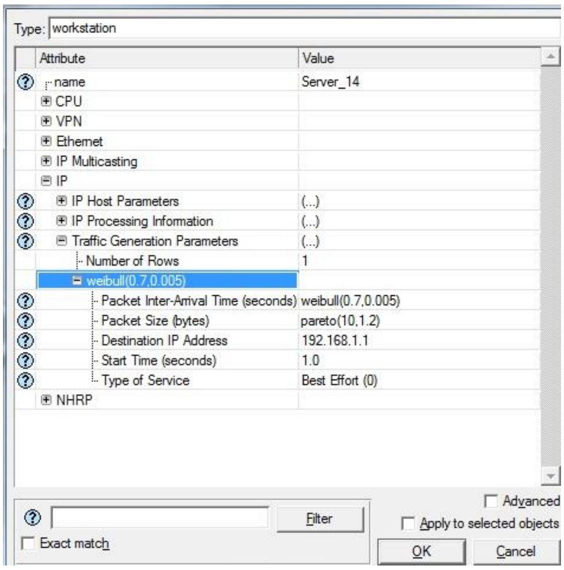


Figure 31: Servers configuration.

Firstly, we are going to study the effect on self-similarity, by varying the α parameter in Pareto distribution. We are going to use only one server sending to one client in scenario 1. Whereas in scenario 2, we are going to use two servers, each one connected to the different switches sending information to the only client.

Scenario 1 and 2	ON /OFF Period parameter
Trace 1	Pareto(10,0.8)
Trace 2	Pareto(10,1)
Trace 3	Pareto(10,1.2)
Trace 4	Pareto(10,1.4)
Trace 5	Pareto(10,1.6)
Trace 6	Pareto(10,1.8)

Table 8: Pareto distribution values to test it.

Secondly, we are going to study the effect on self-similarity with the aggregation of multiple sources (N= 1,5,10,20,30 and 40).

4.3.3. Traces analysis

Table 9 and 10 summarize the results of scenario 1 and 2 varying the α parameter.

Scenario1	ON /OFF Period parameter	Aggregate estimator	R/S estimator	Periodogram estimator	Whittle estimator	Average H value	Theoretical H value
Trace 1	Pareto(10,0.8)	0.203	0.496	0.416	0.514	0.41	
Trace 2	Pareto(10,1)	0.558	0.498	0.454	0.5	0.50	
Trace 3	Pareto(10,1.2)	0.555	0.508	0.425	0.502	0.50	0.90
Trace 4	Pareto(10,1.4)	0.601	0.527	0.476	0.509	0.53	0.80
Trace 5	Pareto(10,1.6)	0.573	0.55	0.541	0.538	0.55	0.70
Trace 6	Pareto(10,1.8)	0.64	0.528	0.805	0.561	0.63	0.60

Table 9: Scenario 1 simulation testing Pareto distribution

Scenario2 (2 sources)	ON /OFF Period parameter	Aggregate estimator	R/S estimator	Periodogram estimator	Whittle estimator	Average
Trace 1	Pareto(10,0.8)	0.459	0.485	0.315	0.502	0.44
Trace 2	Pareto(10,1)	0.397	0.426	0.786	0.514	0.53
Trace 3	Pareto(10,1.2)	0.458	0.419	0.75	0.537	0.54
Trace 4	Pareto(10,1.4)	0.489	0.278	0.77	0.582	0.53
Trace 5	Pareto(10,1.6)	0.613	0.253	0.89	0.71	0.62
Trace 6	Pareto(10,1.8)	0.627	0.241	1.069	0.789	0.68

Table 10: Scenario 2 simulation testing Pareto distribution

Table 9 and 10 show completely opposite results, as we expected. Theory specify that self-similarity is dependent on characteristics of the ON/OFF periods, and with α closer to 1, traffic becomes more self-similar than with α values greater than 1. In our results, traces with higher α are more self-similar.

Next tables summarize the second simulation.

Source Number	ON /OFF Period parameter	Aggregate estimator	R/S estimator	Periodogram estimator	Whittle estimator	Average
5	Pareto(10,1.6)	0.736	0.372	1.192	0.696	0.75
10	Pareto(10,1.6)	0.725	0.342	1.213	0.792	0.77
20	Pareto(10,1.6)	0.757	0.304	1.29	0.82	0.79
30	Pareto(10,1.6)	0.741	0.264	1.424	0.884	0.83
40	Pareto(10,1.6)	0.744	0.245	1.4	0.967	0.84

Table 11: Scenario 1 simulation testing number of sources.

Source Number	ON /OFF Period parameter	Aggregate estimator	R/S estimator	Periodogram estimator	Whittle estimator	Average
6	Pareto(10,1.6)	0.434	0.467	0.407	0.5	0.45
10	Pareto(10,1.6)	0.416	0.434	0.517	0.5	0.47
16	Pareto(10,1.6)	0.496	0.449	0.513	0.5	0.49
20	Pareto(10,1.6)	0.505	0.428	0.557	0.505	0.50
24	Pareto(10,1.6)	0.493	0.464	0.52	0.534	0.50

Table 12: Scenario 2 simulation testing number of sources.

Table 11 and 12 verified the relationship between self-similarity degrees and the number of ON/OFF sources. When ON/OFF sources increases, H increases too. From the above tables, we can conclude that there is a minimal dependence of self-similarity on different numbers of ON/OFF sources.

4.3.4. Simulation complexity

Table 13 and 14 summarize the simulation complexity results.

	Scenario 1			Scenario 2		
	Number of events	Simulation Time (sec)	Memory usage	Number of events	Simulation Time (sec)	Memory usage (Mb)
Trace 1	1820964	41	16	51225039	95	28

Trace 2	1526663	36	16	27095140	52	14
Trace 3	1036246	26	15	22761396	44	12
Trace 4	977283	23	14.5	21888215	42	11.5
Trace 5	972656	22	14.5	21533638	42	11
Trace 6	960310	22	14	21468369	41	11

Table 13: Scenario 1 and 2 simulation testing simulation complexity varying Pareto distribution

Source Number	Number of events	Simulation Time (sec)	Memory usage (Mb)
5	4879458	11	15
10	10080567	22	16
20	22138917	46	18
30	35195022	71	20
40	47873560	97	22

Source Number	Number of events	Simulation Time (sec)	Memory usage (Mb)
6	10314299	17	13
10	23500301	34	13
16	52908343	71	14
20	78329728	100	14
24	109461000	136	15

Table 14: Scenario 1 and 2 simulation complexity to different sources.

As we can see in table 13, Pareto distribution with α parameter closer to 1 requires more events, simulation time and memory usage.

Table 14 demonstrates that the number of events, the simulation time needed and the memory usage grow if we increase the number of sources.

4.3.5. Conclusion

As shown previously, on one hand the Hurst value of self-similar traffic produced by this method is unstable and is different from the theory. On the other hand, increases the number of sources do not have a big impact in the self-similarity of the traffic.

OPNET needs more time, memory and events to simulate the scenario if we increase the sources and also if the α parameter of Pareto distribution is closer to 1.

4.4. Case study 4: Self-similarity network performance impact

Since the discovery of the self-similar nature of data traffic, it is clear that the Poisson model is no longer suitable to accurately describe the bursty behaviour of real traffic.

This scenario demonstrates the bursty of self-similar traffic and compares the Ethernet utilization, queue and delay time between self-similar and classical models.

4.4.1. Simulation Environment

In the network model, self-similar stations communicate with each other, as exponential stations. Consecutively, the traffic that flows over hub1 is purely self-similar traffic and the traffic that flows over hub2 is only non-self-similar traffic [21].

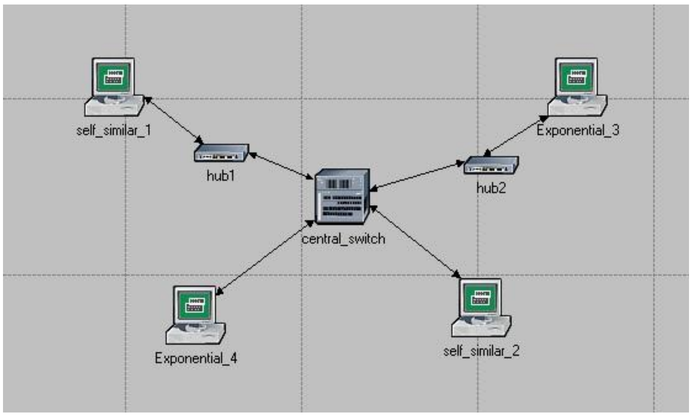
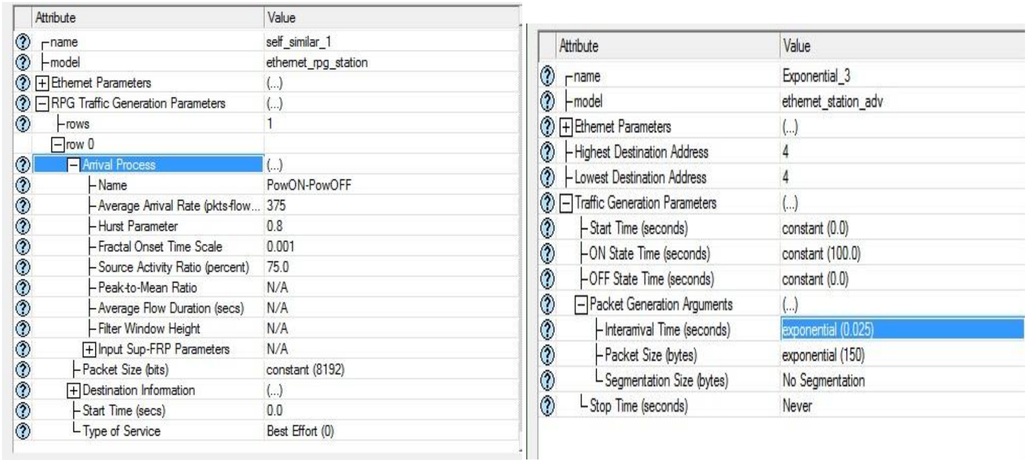


Figure 32: Self-similar and exponential stations connected by a switch and a Hub [21].

4.4.2. Generation traffic

Traffic generated in Intranet and Internet network was previously configured by [21]. We have not modified its features because are properly set for our goal.



Attribute	Value
name	self_similar_1
model	ethernet_rpg_station
Ethernet Parameters	(...)
RPG Traffic Generation Parameters	(...)
rows	1
row 0	
Arrival Process	(...)
Name	PowON-PowOFF
Average Arrival Rate (pkts-flow...	375
Hurst Parameter	0.8
Fractal Onset Time Scale	0.001
Source Activity Ratio (percent)	75.0
Peak-to-Mean Ratio	N/A
Average Flow Duration (secs)	N/A
Filter Window Height	N/A
Input Sup-FRP Parameters	N/A
Packet Size (bits)	constant (8192)
Destination Information	(...)
Start Time (secs)	0.0
Type of Service	Best Effort (0)

Attribute	Value
name	Exponential_3
model	ethernet_station_adv
Ethernet Parameters	(...)
Highest Destination Address	4
Lowest Destination Address	4
Traffic Generation Parameters	(...)
Start Time (seconds)	constant (0.0)
ON State Time (seconds)	constant (100.0)
OFF State Time (seconds)	constant (0.0)
Packet Generation Arguments	(...)
Interarrival Time (seconds)	exponential (0.025)
Packet Size (bytes)	exponential (150)
Segmentation Size (bytes)	No Segmentation
Stop Time (seconds)	Never

Figure 33: configuration of the stations.

4.4.3. Traffic analysis

As shown on the figure 34, while the average utilization of two hubs is more or less closer in a long simulation time, the fluctuation of the utilization of the self-similar hub is much wider. This indicates the burstiness of the self-similar traffic versus non-self-similar traffic.

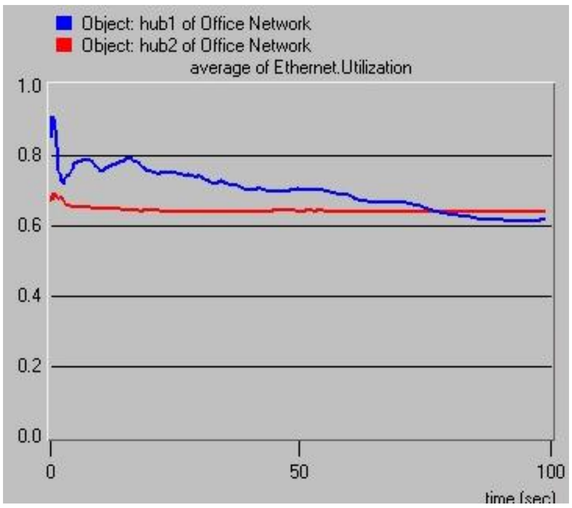


Figure 34: Comparing Ethernet utilization average of both hubs.

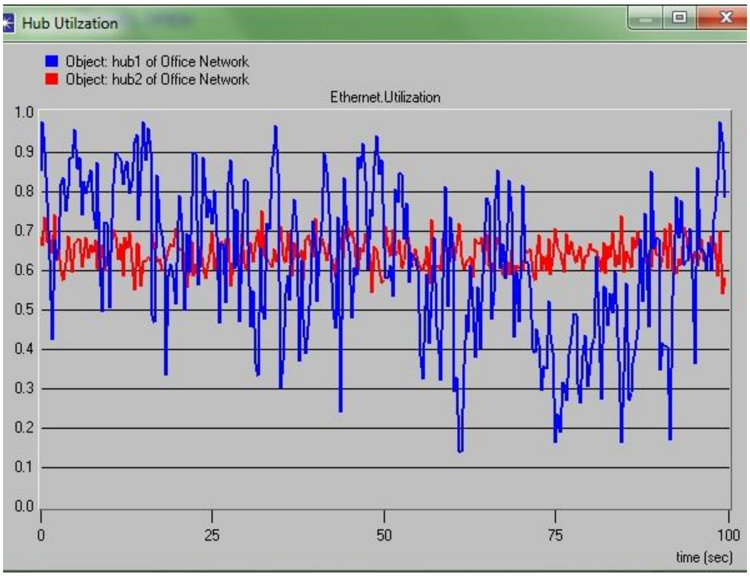


Figure 35: Comparing Ethernet utilization of both hubs.

We will demonstrate how these traffic peaks impact on queues.

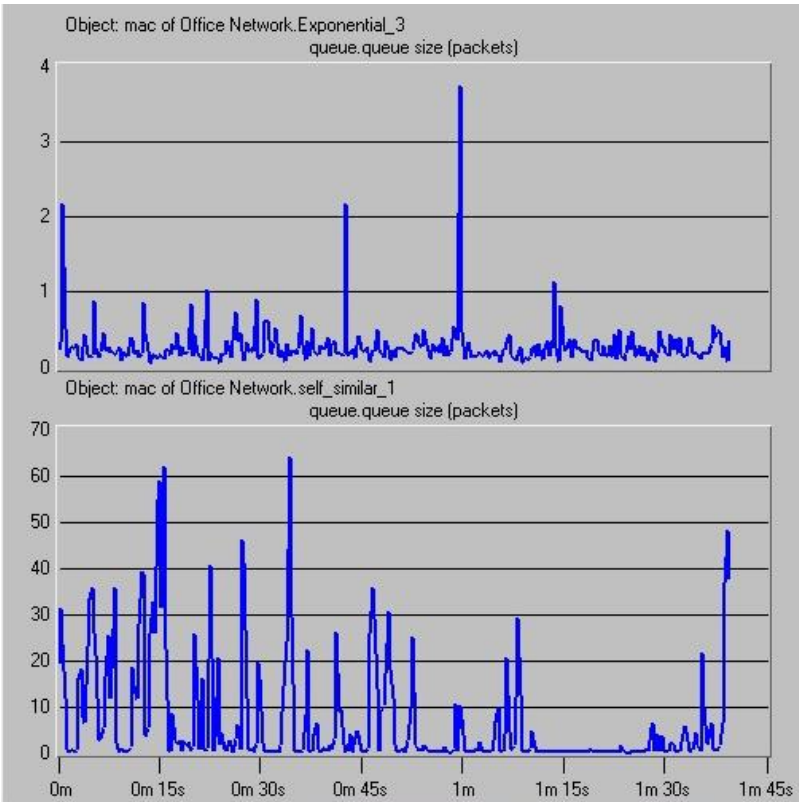


Figure 36: Comparing queue size packets.

The queue size of self-similar station fluctuates significantly reaching values over 60 packets for many times, while the other queue size is relatively much smoother barely getting close to 4 packets. These high values may result, as we said before, packet delays or losses.

For example, if the switch queue memory can only save 40 packets and the packet arrival rate is greater than the transmission capacity of the switch we are going to lose packets which will influence the service quality.

This result also has relation with delay time in the network. Higher average queue size cause higher average queue delay for the packets it transmits.

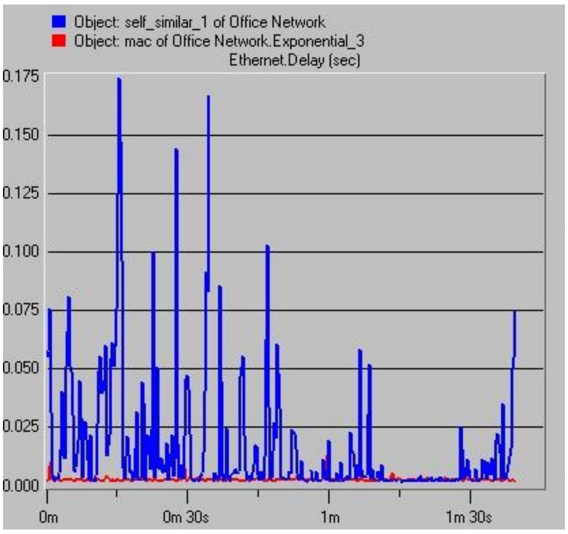


Figure 37: Comparing Ethernet delay.

4.4.4. Conclusion

This case leads us to conclude that when we study the network traffic on a wide range of time scales, peaks appear in the traffic load. This peak behaviour is very harmful: queues not able to handle the large amounts of traffic induce large packet delays or losses. Especially multimedia applications are very sensitive to these Quality of Service (QoS) characteristics.

Accurate traffic models are needed to predict realistic packet delay and loss values in simulations. This is a fundamental requirement to dimension data networks optimally. Poor traffic models can result in a severe underestimation of packet delay and loss.

5. Final conclusion and further work

The aim of this thesis was to test self-similarity property in telecommunication network using OPNET network simulator.

First of all, we demonstrated the self-similarity of Ethernet traffic as well as the SRD features of Internet traffic. Moreover, in order to have a better understanding of our objective we exhibited the impact of burstiness traffic in network performance (chapter 4, section 4). Burst traffic is very damaging for guaranteeing services quality in networks due to the need of accurate traffic models to predict realistic packet delay and loss values in simulations.

The traffic model specific of OPNET that generates self-similar traffic, RPG, has a complex relation between the input parameters and the produced traffic. In our case study a good approximation of the measured traffic could be found by lower source activity ratio and FOTS of 0.0001 or 0.001.

A drawback of the model would be the impossibility of alternating the value of the variance. We are forced to modify other parameters in order to examine their impact on the variance of the generated trace. As we have said, it is not evident to obtain a traffic source with predefined characteristics and thus it is advised to check the RPG output when an accurate self-similar source is needed. Recommendation for further development would be to re-program RPG stations to allow the user to choose the variance accordingly.

Moreover, IP station modelled with heavy-tailed distributions generate unstable Hurst parameter and differs from the theory. By increasing the number of sources, it is observed that it does not have a big impact on the self-similarity of the traffic. This model can be further improved testing the self-similar characteristic of a traffic generated by different values of Pareto distribution in each ON and OFF periods. Besides, we suggest using different estimators such as MATLAB implementation or SELQOS [25] to test the Hurst parameter and LRD.

In conclusion, let us emphasize that our models have difficulties to accurately fit the Hurst parameter. Besides, the models prevent us from generating traffic with an arbitrary combination of average arrival rate, variance and Hurst parameter. The RPG model makes use of parameters which cannot easily be measured in real-life traffic traces; thus making the parameterization of these models very complex.

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