Remarks Regarding Queuing Model and Packet Loss Probability for the Traffic with Self-Similar Characteristics

Mihails Kulikovs, and Ernests Petersons

Abstract—Network management techniques have long been of interest to the networking research community. The queue size plays a critical role for the network performance. The adequate size of the queue maintains Quality of Service (QoS) requirements within limited network capacity for as many users as possible. The appropriate estimation of the queuing model parameters is crucial for both initial size estimation and during the process of resource allocation. The accurate resource allocation model for the management system increases the network utilization. The present paper demonstrates the results of empirical observation of memory allocation for packet-based services.

Keywords—Queuing System, Packet Loss Probability, Measurement-Based Admission Control (MBAC), Performance evaluation, Quality of Service (QoS).

I. INTRODUCTION

NETWORK management techniques have long been of interest to the networking research community. The management of networks involves both the control of data flowing through a network and maintaining the general well-being of the network. The main reason for the network management is that resources are limited and are shared among competing users.

The second motive for the management of networks is the supply of a particular quality of resource to a user. It is a current issue because real-time multimedia applications increasingly become an indispensable part of Internet traffic. These applications include Voice over IP, audio and video streams and real-time video conferences. Network Quality of Service (QoS) may be a guarantee of a quantity of link capacity to the user.

Network management depends on reliable estimation of the current network traffic and prediction of future network traffic to plan future requirements. A number of recent empirical studies of traffic measurements from a variety of working

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packet networks have convincingly demonstrated that actual network traffic is self-similar or long-range dependent in nature (bursty over a wide range of time scales) [35], [25], [30], [7], which is in sharp contrast to common traffic modelling assumptions. This phenomena complicates trustworthy real-time traffic estimation and long-term prediction.

Moreover, many studies have shown that self-similar network traffic can have a negative impact on network performance, including queuing delays and an increase of packet loss rate [3], [8], [2]. It has been clearly shown that the performance of queuing models with self-similar inputs is radically different from the performance predicted by traditional traffic models [22], [23], [9], [1] that raises issues for the necessity of efficient queue model and allocation algorithm for a admission control management mechanism. The major measurement of the queue model is packet loss probability that mainly depends on initial buffer size of the system, traffic characteristics and allocation mechanism. The traditional queuing model mainly deals with an assured statically buffer capacity that fits to circuit-based telephony services. Over last decade telecommunication networks have changed from circuit-based telephony to packet-based broadband network services.

The present paper demonstrates the results of empirical observation of memory allocation for packet-based services.

II. MEASUREMENT-BASED ADMISSION CONTROL

Maximizing the utilisation of the network while maintaining service guarantees to network users could be an illustration of network management.

There are two main network management techniques. The first is an admission control that attempts to make the best use of the finite link capacity across a network by admitting a new flow of data into a network if the new flow can be accommodated without impacting upon the guarantees made to existing flows of data.

The second network management technique is the partitioning of transmission and buffer resources among two or more classes of traffic using a common transmission path.

Both of the mentioned above network management techniques are measurement-based or statistical service guarantees (Fig. 1). The advantages of statistical service

guarantees in the absence of strict performance bounds as deterministic service guarantees do. The deterministic service guarantee management technique uses worst-case analytical bound and it results in low network utilization because the worst-case happens rarely in real networks. In comparison to deterministic service guarantees the measurement-based admission control (MBAC) can achieve higher network utilization.

The decision algorithm of measurement-based admission control uses the *a priori* traffic characteristics only for newly arrived flows while for already existing in the system flows characteristics are measured.
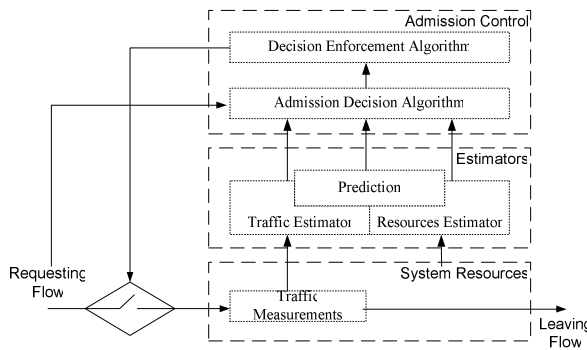

Fig. 1 Structure of MBAC

For the algorithm it is necessary to estimate characteristics of traffic measurement which are it's interarrival peak and average rates and the number of flows in the system. Also, it is needed to estimate the remaining resources in the system. When a new flow requests admission to the system, the MBAC mechanism uses the admission control algorithm to decide if this flow can be admitted. This decision is based on the inputs from the traffic and resource estimators. In addition, the decision relies on input from the requesting flow, which typically includes its quality of service requirement and its traffic description.

Two significant approaches for the provision of QoS in the networks are the following. The INTSERV proposal [29], offering per-flow guarantees and the alternative, DIFFSERV [18], that does not use explicit admission control and instead relies on the classification of flows to be admitted to the network.

Currently the DIFFSERV approach is seen as more practical than INTSERV. However, determining the amount of resource that ought to be committed for each class of traffic continues to be an ongoing challenge of the DIFFSERV approach. Hybrid approaches that use attractive aspects of both INTSERV and DIFFSERV have been introduced in [34].

III. BACKGROUND

A. Self-Similar Traffic

Self-similar processes are emerging as a powerful mathematical representation of a great variety of physical phenomena. Self-similarity has been discovered, analyzed and exploited in many frameworks, especially in the field of traffic modelling in broadband networks [13].

Recently, it was revealed that there is a relationship between the self-similar property of network traffic and the heavy tail distribution of duration time of Internet connections, which makes self-similar processes a popular tool for modelling Internet traffic flows [24].

Suppose $X(t)$ is a second order stationary stochastic process and fx and γx its spectrum and autocorrelation function respectively. The process $X(t)$ is said to be Long Range Dependent (LRD) if either, for some constant c_f,

$$f_x(\upsilon) \sim c_f |\upsilon|^{-\alpha} \text{ as } |\upsilon| \to 0, \text{ where } \alpha \in (0,1), \qquad (1)$$

Or if, for a different constant c_γ,

$$\gamma x(k) \sim c_\gamma |k|^{-(1-\alpha)} \text{ as } |k| \to \infty, \text{ where } \alpha \in (0,1). \qquad (2)$$

The process is called long-range dependant because $\gamma x(k)$ goes to zero so slow, as $k \to \infty$ that $\sum_k \gamma x(k) = \infty$. A process $Y(t)$ is said to be self-similar with so called self-similarity Hurst parameter H if and only if

$$c^{-H} Y(ct) = Y(t) \text{ for all } c > 0 \qquad (3)$$

There is close connection between LRD and self-similar process (Shu-Gang Liu; Pei-Jin Wang; Lin-Jie Qu, 2005). The increment of any finite variance self-similar process is long-range dependent, as long as $\frac{1}{2} < H < 1$, with H and α related through H=(α+1)/2. A value of H=0.5 indicates the lack of self-similarity that corresponds to Poisson data flows, whereas large values for H (close to 1.0) indicate a large degree of long-range dependence in the process.

B. Traffic Models Used in the Study

In the study originally suggested by Mandelbrot [20] approach was applied for traffic with self-similar behaviour and predefined H parameter generation. The author shows that the superposition of many strictly alternating independent and identically distributed (i.i.d) *ON-OFF* sources, each of which exhibits a phenomenon called the "Noah Effect" results in self-similar aggregate traffic. A strict alternation of *ON- OFF-* periods is used in the present research work.

The results of [20] identify the Noah Effect as the essential point of departure from traditional to self-similar traffic modelling. The Noah Effect for an individual *ON-OFF* source model results in *ON-* and *OFF-*periods, i.e. "train lengths" and "intertrain distances" that can be very large with no negligible probability. In other words, the Noah Effect guarantees that each *ON-OFF* source individually exhibits characteristics that cover a wide range of time scales.

In traditional traffic modelling, in the framework of *ON-OFF* source models, uses finite variance distributions for the *ON-* and *OFF-*periods (e.g. exponential distribution).

The Noah Effect can be well described using distributions with infinite variance [20]. Mathematically, to obtain the Noah Effect we use *heavy-tailed* distributions with infinite variance (e.g., Pareto), and the parameter α describes the "heaviness" of the tail of such a distribution and gives a measure of the intensity of the Noah Effect.
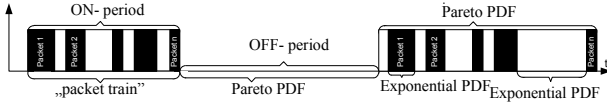

Fig. 2 On-Off Traffic Model

For the traffic modeling (Fig. 2) the "train lengths" and "intertrain distances" are Pareto PDF distributed, while for the interarrival packets within the "packet train" (batch) distributions with finite variance have been chosen.

IV. QUEUING SYSTEM

A. Queue Model

In the current study a multi-input channel open form queue model with finite number of customers is used and it is depicted in Fig. 3. An open model is characterized by customers that enter the system from outside, receive service, and leave the system and is correlated to modern interconnection systems.

This model could be used for multi-service network modelling where traffic of different customers or traffic of the different services share network resources, e.g bandwidth and buffer size. In the Fig. 3 circles λ_i, where $i \in 1..n$ correspond to traffic sources with interarrival rate λ_i, circle μ_0 correspond to server with respective service rate, the rectangle K corresponds to the buffer with size K shared by traffic sources.
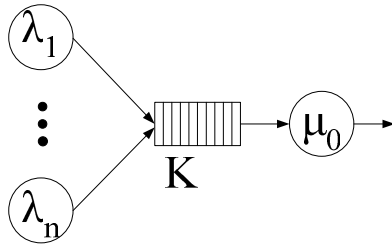

Fig. 3 Queue Model

Traditional open single-channel queuing system models are well-known and analytically proved [12]. Open systems with infinite number of customers can be reasonably approximated by such models as explained by Buzen and Goldberg[17]. Although, multi-input channel systems are not as widely presented and lack analytical expression. Hence, the simulation of such models is useful for future examination.

B. Resource Allocation

The buffer size plays a critical role for the network performance. The adequate size of the buffer maintains Quality of Service (QoS) requirements within limited network capacity for as many users as possible. Calculation of the buffer size according to an accurate queuing model should be used to get some benefits.

The appropriate estimation of the queuing model parameters is crucial for both initial size estimation and during the process of resource allocation. The underestimation of the buffer size will cause high rate of the packet loss and dangerous consequence will be the lost packets retransmission and network overload.

Since the admission control establishes the connection only in case there are enough resources, decision algorithm should use fast methods based on traffic parameters of the new arrival data flow for queuing model parameters estimation. Since classical queuing models do not suit modern packet switched networks the other models have to be used.

Next, a queuing model suitable for self-similar traffic input where interarrival time defined by Pareto distribution is described. The lack of closed-form expression for their Laplace transform for most of heavy-tailed distributions forces the development of numerical techniques to analyze queuing systems with self-similar type of traffic. In the present study the size of the buffer was chosen according to R. Rodriguez [28]. The author shows the analytical expression for the derivative of the Laplace transform of the Pareto PDF and uses it with a purpose to calculate the asymptotic packet loss probability.

According to R. Rodriguez [28], the loss probability $P_{K_{LOSS}}$ of the GI/M/1/K theorem by Choi, B. Kim & I.Wee [4] can be written in closed form as following:

$$P_{Loss}^K = \left(1 - \frac{\alpha(\alpha-1)}{\rho} M^{\frac{\alpha}{2}-1} e^{M/2}\right) \times$$

$$\left[\sqrt{M} W_{-\frac{\alpha+1}{2},-\frac{\alpha}{2}}(M) - W_{-\frac{\alpha}{2},\frac{1-\alpha}{2}}(M)\right]\sigma^K \qquad (4)$$

where $\sigma = \alpha M^{\frac{\alpha-1}{2}} e^{M/2} W_{-\frac{(\alpha+1)}{2},-\frac{\alpha}{2}}(M)$ - Laplace transform of the interarrival time, $M = \frac{(\alpha-1)(1-\sigma)}{\rho}$, $W_{\eta,\xi}(\phi)$ - Whittaker's function, $\rho = \frac{\lambda}{\mu}$ - utilization and λ – interarrival rate, μ - service rate.

Another possibility for $P_{K_{LOSS}}$ estimation can be derived using the approximation method described in [36]. It is possible to derive the geometric parameter from the numerically approximated Laplace transform of Pareto distribution [5]:

$$\sigma = \frac{1}{N}\sum_{k=1}^{N}\exp\left(\frac{(1-\sigma)}{\rho}(1-\alpha)\left(\left[\frac{N}{k-0.5}\right]^{1/\alpha}-1\right)\right) \quad (5)$$

$P_{Loss}^{K} = \left(\frac{1-\sigma}{1-\sigma^{K+1}}\right)^{a}\sigma^{K}$, where α parameter is added for

reflecting the effect of the shape parameter and is selected by setting the asymptotic loss probability:

$$a = \lim_{K\to\infty}\frac{\log(1+\mu A'(\mu-\mu\sigma)}{\log\left(\frac{1-\sigma}{1-\sigma^{K+1}}\right)} = \frac{\log(1+\mu A'(\mu-\mu\sigma))}{\log(1-\sigma)} \quad (6)$$

where A' is a differentiate of the Laplace transform of the interarrival time.

Both of the mentioned methods give quite similar results concerning $P_{K_{LOSS}}$ loss probability. On the other side, the method presented by Kih [36] is much easier implemented and gives suitable results with smaller computing expenses that produces smaller system overheads.

The Fig. 4 presents the relation between Hurst parameter, buffer size and packet loss probability for different utilization of the queuing system evaluated by R. Rodriguez [25]. He shows that the closed-form mathematical expressions for the performance measures in Pareto/M/1/K queuing system give appropriate results.
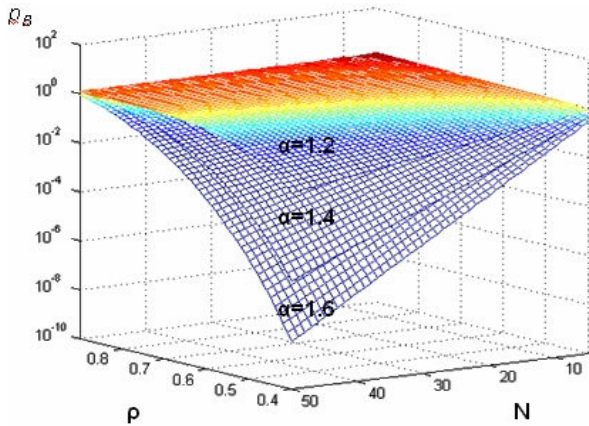

Fig. 4 Relation between utilization, buffer size and packet loss probability for Hurst parameter H=0.9 (a), 0.8(b), 0.7(c) (α=1.2;1.4;1.6)

It is commonly considered that a linear increase in buffer sizes will produce nearly exponential decreases in packet loss, and that an increase in buffer size will result in a proportional increase in the effective use of transmission capacity. As it can be seen in the Fig. 4 (self-similar traffic), these assumptions do not hold. The decrease in packet loss with buffer size is far less than expected, and as it can be seen, the buffer requirements begin to explode at lower levels of utilization for higher degrees of long-range dependence (higher values of H).

V. SIMULATION

As it was mentioned above, the lack of analytical expressions for multi-input channel queuing model forces the researchers to use the simulation environment for the study of such models.

The real network traffic is based on the aggregation and superposition of ON-OFF sources, where activity (ON) and inactivity (OFF) periods follow a heavy tailed PDF. This approach could allow an immediate use of widespread network simulation tools, such as the software family from OPNET depicted in Fig. 5.
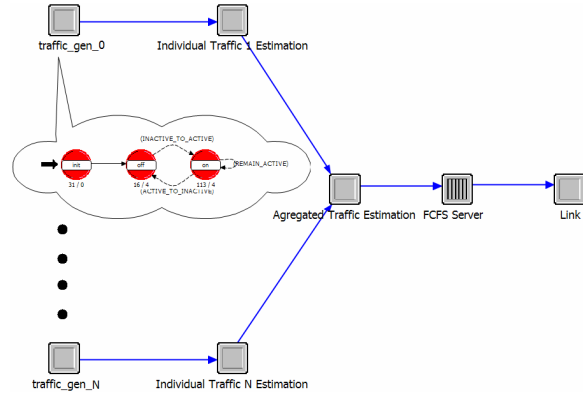

Fig. 5 Simulation Environment

The analysis of self-similarity undertaken in this paper involves the simulation of aggregation of ON-OFF traffic sources, traffic measurement and estimation of the Hurst parameter. The numbers of traffic sources used in different scenarios were 1, 2, 5, 10, 20, 30, 50 and 100.

The traffic generated by sources is independent and identically distributed. The average aggregate rate Λ of the s sources was set to create 0.5, 0.7 and 0.9 network utilization for each scenario with defined Hurst parameter. The queue size for each scenario was estimated by R. Rodriguez [25] method.

In the paper the following approach is used. The total intensity generated by all sources is the constant value through all scenarios and does not depend on the source number. It means that the traffic intensity of each source is in inverse ratio to the number of sources. During the activity periods (ON), each source sends data at a rate of Λ/n, where n is the number of sources. While the number of sources increases the intensity of each individual source decreases and vice verse.

In our ON-OFF model, the number of sources is fixed for each scenario, while each source sends several bursts with random duration. The destination does not send any reply to these requests. A traffic estimator was connected to the network to record the information of individual and aggregated traffic.

A. Results and Analysis

The results gained during the simulation, show two important empirical observations. The first is that characteristics of the traffic do not depend on the number of sources that is in consistency to the results of previous works [27], [26]. While number of sources increasing, for all shape parameters, there are no significant changes in the estimated Hurst parameter.

Another significant observation is related to packet loss rate and can be denoted as following: if the above mentioned requirement about individual source interarrival rate is met, the packet loss probability tends to decrease while number of the individual sources increases. This statement is represented graphically in Fig. 6 - Fig. 11.
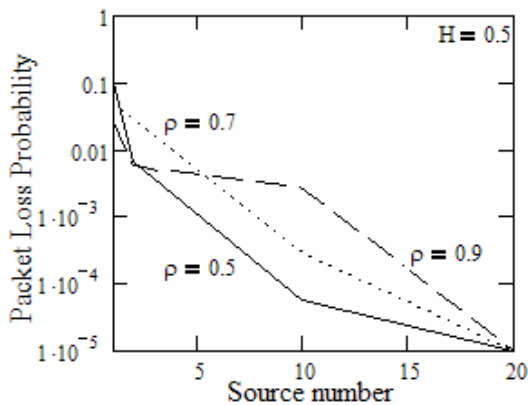

Fig. 6 Packet Loss Probability dependence on the ON-OFF source number for different utilization and H=0.5

The Fig. 6 - Fig. 8 indicate results corresponding to scenarios, where for the each scenario the Hurst parameter is a constant value, while utilization varies. The value of the Hurst parameter defined by distribution of the ON-OFF model and utilization defined by interarrival rate within the ON state.
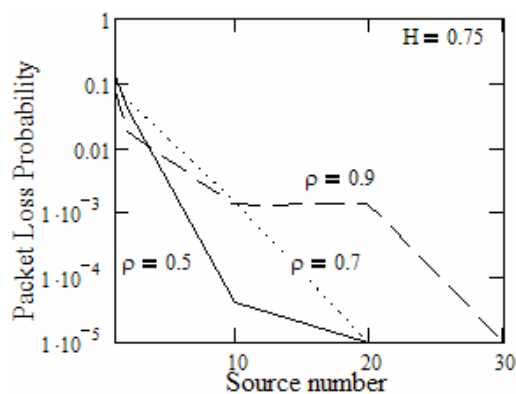

Fig. 7 Packet Loss Probability dependence on the ON-OFF source number for different utilization and H=0.75

The Fig. 9 - Fig. 11 indicate results corresponding to scenarios, where for each scenario the utilization parameter is

a constant value, while Hurst parameter varies.

An additional supplemental investigation was executed for Poisson data flow, where interarrival rate is exponentially distributed. The analysis reveals that if the same requirement to aggregated interarrival rate is fulfilled, the packet loss rate tends to increase with individual sources number increasing.
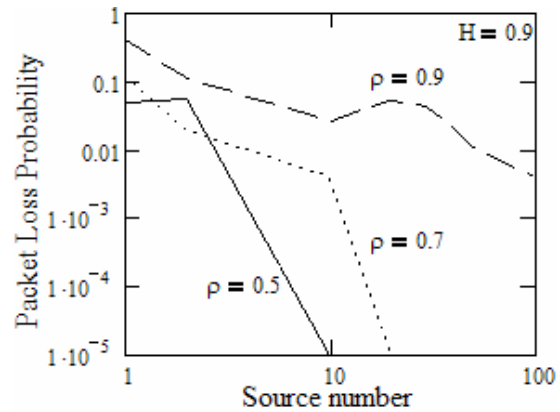

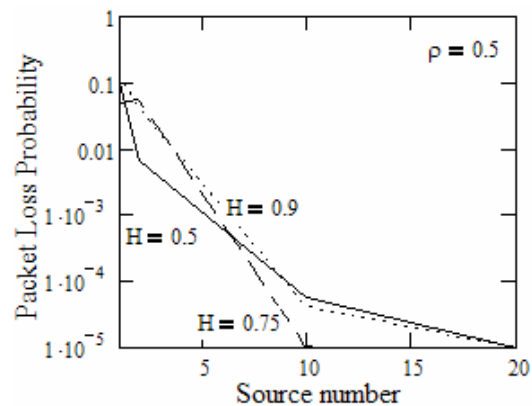Fig. 8 Packet Loss Probability dependence on the ON-OFF source number for different utilization and H=0.9

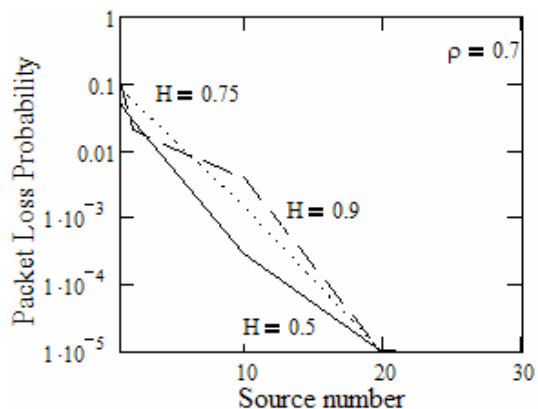Fig. 9 Packet Loss Probability dependence on the ON-OFF source number for different Hurst parameter and ρ=0.5

Fig. 10 Packet Loss Probability dependence on the ON-OFF source number for different Hurst parameter and ρ=0.7

This phenomenon can be partially explained taken into account traditional model M/M/1/K. It ease to prove that for the N independent and identically distributed sources with interarrival rate Λ/N the larger buffer size is required than for one source with interarrival rate: Λ.
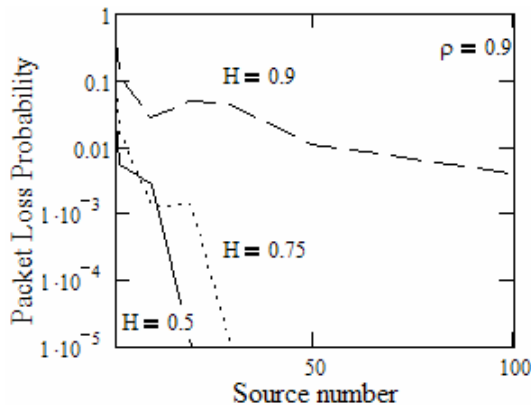

Fig. 11 Packet Loss Probability dependence on the ON-OFF source number for different Hurst parameter and ρ=0.9

These findings are valuable because they are related to admission control algorithm and allow to achieve higher network utilization. The results suggest that admitting connections with low utilization and thus the packet loss rate would be smaller. In the case of new flow arrival, the admission condition would be satisfied and additional flows k can be admitted. Thus, the aggregated flow of $N+k$ with individual packet arrival rate Λ/N, where k is additional admitted sources number, would be higher than flow of individual source with Λ arrival rate with the same packet loss probability value.

VI. Conclusions and Future Work

The immediate implication of this study is the demonstration of the packet loss probability dependence on the number of traffic sources.

These findings are important as they argue against the idea that bursty traffic always drastically impact network performance. The investigation has shown that together with the principles of admission control the network performance for group arriving traffic can be radically increased.

As the future work, we intend to find out analytical relation between utilization, the number of sources and the shape parameter of the Pareto PDF. The mentioned above analytical model together with fast Hurst parameter estimator provide an accurate model for the efficient measurement-based admission control.

References

[1] A. Erramilli, O. Narayan, and W. Willinger. (1996). Experimental queueing analysis with long-range dependent traffic. IEEE/ACM Trans. Networking, vol. 4 , pp. 209–223.

[2] Addie, R.G., Neame, T.D. & Zukerman, M. (2002, October). Performance Evaluation of a Queue Fed by a Poisson Pareto Burst Process. Computer Networks, Vol. 40, Nº 3 , pp. 377-397.

[3] Beran, J. (1994). Statistics for Long-Memory Processes. New York: Chapman & Hall/CRC, 1 ed.

[4] B. D. Choi, B. Kim, and I.Wee, "Asymptotic behavior of loss probability in GI/M/1/K Queue as K tends to infinity, Queueing Systems, vol. 36, pp. 437–442, 2000.

[5] Carl M. Harris, Percy H. Brill , Martin J. Fischer "Internet-Type Queues with Power-Tailed Interarrival Times and Computational Methods for their Analysis", INFORMS Journal on Computing, 2000

[6] Chengyu Zhu and Oliver W. W. Yang, "A Comparison of Active Queue Management Algorithms Using the OPNET Modeler", IEEE Communications Magazine • June 2002

[7] Crovella, M. E. & Bestravos, A. (1997, December). Self-Similarity in World Wide Web Traffic: Evidence and Possible Causes. IEEE Trans. Networking, 5(6).

[8] Downey, A. B. (2001, November). Evidence for Long-Tailed Distributions in the Internet. ACM SIGCOMM IMW 2001.

[9] Duffield, N. G. (Preprint, 1994.). Economies of scale in queues with sources having power-law large deviation scalings.

[10] F. Ferreira (speaker) and A. Pacheco, "Analysis of Pareto -Type/M/s/c finite buffer queues.", Second Workshop on New Trends in Modelling, Quantitative Methods and Measurements, Aveiro, Portugal, 24/11/2005 – 25/11/2005.

[11] Gordon, J., "Pareto Process as a Model of Self-Similar Packet Traffic", Global Telecommunications Conference, 1995. GLOBECOM '95., IEEE.

[12] G. Bolch, S. Greiner, H. Meer, K S. Trivide, "Queueing Networks and Markov Chains Modeling and Perfomance Evaluation with Computer Science Applications", 2nd Edition Wiley-Interscience 2006

[13] Guanghui He, Yuan Gao I Jennifer H Hou, Kihong Park. (2004, August). A Case for Exploiting Self-Similarity of Network Traffic in TCP Congestion Control. The International Journal of Computer and Telecommunications Networking Volume 45, Issue 6 , pp. p. 743 – 766.

[14] Hengky Susanto Byung-Guk Kim, „Examining Self-Similarity Network Traffic intervals".

[15] Ilkka Norros, On the use of fractional Brownian motion in the theory of connectionless networks (1995).

[16] Jeong, H.-D. J., McNickle, D. & Pawlikowski., K. "Fast Self-Similar Teletraffic Generation Based on FGN and Wavelets". IEEE ICON'99, Sept. 1999

[17] J. P. Buzen, "A Queueing Network Model of MVS," ACM Computing Surveys, Vol. 10, No. 3, Sept. 1978,pp. 319-331.

[18] K. Nichols, V. Jacobson, and L. Zhang. "A Two-bit Differentiated Services Architecture for the Internet", RFC 2638, IETF, July 1999. (pp 23, 25, 102, 213)

[19] Leonard Klienrock, "Queuing System", A Wiley-Interscience Publication, John Wiley & Sons, 1979

[20] Mandelbrot B.B., "Long-Run Linearity, Locally Gaussian Processes, H-Spectra and Infinite Variances", International Economic Review, Vol.10, pp. 82-113, 1969.

[21] M. S. Taqqu, "A bibliographical guide to self-similar processes and long-range dependence," in Dependence in Probability and Statistics, E. Eberlein and M. S. Taqqu, Eds. Boston, MA: Birkh¨auser, 1986, pp. 137–162.

[22] N. G. Duffield and N. O'Connell. (1995). Large deviations and overflow probabilities for the general single-server queue, with applications. in Math, Proc. Cambridge Philos. Soc. , pp. 363–375.

[23] Norros, I. (1994). A storage model with self-similar input. Queueing Syst., vol. 16 , pp. 387–396.

[24] Park, J. and Park, C, Robust estimation of the Hurst parameter and selection of an onset scaling //Under revision, 2007, Web available: ttp://www.maths.lancs.ac.uk/~parkj1/paper/robusth_Dec07.pdf

[25] Park, K. Kim, G. & Crovella, M.E. (1997, November). On the Effect of Traffic Self-similarity on Network Performance. SPIE International Conference on Performance and Control of Network Systems.

[26] P. Leys, J. Potemans1, B. Van den Broeck, J. Theunis, E. Van Lil, A. Van de Capelle, "Use of the Raw Packet Generator in OPNET", OPNETWORK, (Washington, DC, 2001).

[27] P.Ulanovs, E.Petersons, "Modeling Methods of Self-Similar Traffic for Network Performance Evaluation", Scientific Proceedings of RTU. Series 7. Telecommunications and Electronics, 2002.

[28] Ramon M. Rodrıguez-Dagnino, "Some Remarks Regarding Asymptotic Packet Loss in the Pareto/M/1/K Queueing System, IEEE Communications Letters, VOL. 9, NO. 10, October 2005.

[29] R. Braden, L. Zhang, S. Berson, S. Herzog, and S. Jamin. "Resource ReSerVation Protocol (RSVP) — Version 1 Functional Specification", RFC 2205, IETF, September 1997. (pp 23, 24, 85, 124, 160, 210).

[30] Sahinoglu, Z. & Tekinay, Sirin. (1999, January). On Multimedia Networks: Self-Similar Traffic and Network Performance. IEEE Comm. Mag., 37(1).

[31] Saralees Nadarajah and Samuel Kotz, „On the Laplace Transform of the Pareto Distribution", Queuing Systems, Volume 54, Number 4, December 2006.

[32] Stenio Fernandes, Carlos Kamienski & Djamel Sadok, "Accuracy and Computational Efficiency on the Fractal Traffic Generation".

[33] Walter Willinger, Murad S. Taqqu, Robert Sherman, and Daniel V. Wilson , "Self-Similarity Through High-Variability: Statistical Analysis of Ethernet LAN Traffic at the Source Level", IEEE/ACM Transactions on Networking, VOL. 5, NO. 1, February 1997.

[34] W. E. Leland, M. S. Taqqu, W. Willinger, and D. V. Wilson, "On the Self-similar nature of Ethernet traffic (extended version)," IEEE/ACM Trans. Networking, vol. 2, pp. 1–15, 1994.

[35] Willinger, W., Taqqu, M.S., Sherman, R. & Wilson, D.V. (1997). Self-Similarity Through High-Variability: Statistical Analisys of Ethernet LAN Traffic at the Source Level. IEEE Trans. Networking, 5(1) , pp. 71-86.

[36] Younsuk Koh and Kiseon Kim, "Loss Probability Behavior of Pareto/M/1/K Queue", IEEE Communications Letters, Vol. 7, No. 1, January 2003.

[37] Y. Bernet, R. Yavatkar, P. Ford, F. Baker, and L. Zhang. A Framework for End-to-End QoS Combining RSVP/Intserv and Differentiated Services, March 1998. Internet Draft: draft-bernet-intdiff-00.txt. (p 25).