

무선 랜 802.11b 트래픽의 두꺼운 꼬리분포 모델링

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요약

사용자가 느끼는 QoS를 최대화하면서 네트워크 대역폭의 특성을 효율적으로 활용하기 위해서는 네트워크의 패킷 손실과 대기행렬의 지연 시간을 구체적으로 예측이 필요하다. 네트워크의 자원이 충분치 않은 무선 네트워크 환경의 경우 예측은 특히 중요한 문제로 부각된다. 본 연구는 무선 네트워크의 성능 모델을 개발하는 것을 목표로 하고 있다. 실험을 위해서 실제 운영 중인 무선 네트워크 환경에서 패킷 흐름 자료를 수집하였다. 무선 환경에서의 패킷 개수 공정과 대역폭 공정은 장기 기억 특성을 갖고 있는 것으로 나타났다. 실험을 통해서 네트워크 트래픽의 주요 성능 변수들을 추출해 냈고, 대기 시간과 버퍼 오버플로우 확률에 대한 분석적 모델을 개발하였다. 프랙탈 브라운 운동 (FBM)을 이용한 대기 행렬의 꼬리 확률을 얻었고, 대기행렬의 길이 모델을 통해서 평균대기 지연을 표현하였다. 실측 데이터를 활용하여 개발한 성능 모델이 IEEE 802.11b 네트워크 트래픽의 물리적 특성을 잘 표현하고 있음을 알 수가 있다

Modeling Heavy-tailed Behavior of 802.11b Wireless LAN Traffic

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Abstract

To effectively exploit the underlying network bandwidth while maximizing user perceivable QoS, mandatory to make proper estimation on packet loss and queuing delay of the underling network. This issue is further emphasized in wireless network environment where network bandwidth is scarce resource. In this work, we focus our effort on developing performance model for wireless network. We collect packet trace from actually wireless network environment. We find that packet count process and bandwidth process in wireless environment exhibits long range property. We extract key performance parameters of the underlying network traffic. We develop an analytical model for buffer overflow probability and waiting time. We obtain the tail probability of the queueing system using Fractional Brown Motion (FBM). We represent average queuing delay from queue length model. Through our study based upon empirical data, it is found that our performance model well represent the physical characteristics of the IEEE 802.11b network traffic.

Keywords : Wireless LAN; Self-similar network traffic; Long range dependent; Fractional brown motion

1. Introduction

Over the past several decades network and

communication technology has been a significant and growing component of Internet traffic. Integrated broadband networks are expected to support various traffic types such as data, voice, image, and video. Traffic generated from these services is substantially different in its statistical characteristics, and networks are required to maintain a certain level of throughput during each session for these services. For example, real-time voice communication over computer network requires several Kbits/sec of network

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bandwidth and has to be delay sensitive. To effectively exploit the capacity of underlying network and to maximize QoS, it is mandatory to have proper performance model and use this model to allocate resource for efficient service support. The contribution of this work is twofold. First, we analyze the stochastic characteristics of wireless network traffic. We collect full packet trace from up-and-running IEEE 802.11b network. Discovery of scaling behavior in the measured teletraffic leads to model solutions that can approximate the data characteristics much better than previous techniques. Self-similar processes have been used to successfully model data, which exhibits long-range dependency in a variety of different scientific fields, including [1], geophysics [2], biology [3], telecommunication networks [4], and economics. Second, we develop performance model for packet traffic of wireless network. We apply Fractional Brownian Motion to model the incoming packet process. Our model accurately models buffer overflow and waiting time behavior of the underlying traffic.

2. Related Work

Tang and Baker[5] analyzed a 12 week trace collected from the wireless network. Their study provides a good qualitative description of how mobile users take advantage of a wireless network, although it does not give characterization of user workloads in the network. Tang and Baker [5] also characterized user behavior in a metropolitan-area network, focusing mainly on user mobility. Other studies of Queue Analysis and Multiplexing of Heavy-tailed traffic in Wireless packet networks have focused more on network performance, the asymptotic distribution of loss probability, traffic specifications, and transmission rate for wireless system [6]. Qin et. Al. aggregated the multiple input self-similar traffic sources at the Access point (AP) and

calculated the H parameter by using three method Rescaled (R/S), Variance-time plots and Periodogram-based for estimating of the self-similar wireless LAN traffic. They used the OPNET simulator and compared real data traffic with the simulation data [7]. Chen et. al. calculated the loss probabilities in a finite size partitioned buffer system. The input is modeled as a fractional Brownian motion (FBM) process included J [8] classes of traffic with different packet loss requirements. Heuristic expressions of the loss probabilities for all the J classes are derived, and validated by computer simulations [8]. Zhifei et. al. represented in real-time multimedia applications, the delay is an important performance metric as well as packet loss probability (PLP). Based on their statistical characteristics and with the PLP and the delay considered, a computationally simple approximate expression for the equivalent bandwidth of the multimedia applications, has been proposed for real-time bandwidth estimation and management [9]. Yunhua et. al. represented the bandwidth allocation bounds and admission control of a self-similar traffic input queue system with FBM process are investigated. The analytic formulas about resource allocation are obtained with the overflow probability of queuing system [10]. Yunhua et. al. analyzed the self-similar phenomenon in network traffic. The modeling of self-similar traffic and its impact to the performance of network queue system is also designed. The character of long-range dependence in network traffic, the delay and jitter of queue system can be influenced greatly, which is different from that of Markov model in a long time and must considered in network design [11]. Mayor et. al. introduced a new traffic model based on a fractional Brownian motion envelope process. They show that this characterization can be used to predict queuing dynamics. They derive new framework for computing delay bounds in

ATM networks based on this traffic model [12]. Whereas our study focuses on small time scale statistical characteristics, like estimating the tail probability based on an approximation using FBM tail probability, the average queuing buffer waiting time using the Little's law, and buffer length with FBM queueing. In our case, we calculated the theoretical channel capacity by using Norros question [13] and Dependency between variance coefficient and buffer size. The paper is organized as follows. In Section 2 we discuss related work and Section 3 explain long range dependent properties and Fractional Brown Motion. Section 4 shows measurement, in Section 5 the traffic analysis for FBM with a section on long range dependent property, Tail probability analysis and estimates the buffer overflow probability. In section 6 we presented the average waiting time and in section 7 for conclusion.

3. Synopsis: Long Range Dependence and Fractional Brownian Motion

3.1 Long-range Dependence

Long-range dependence is defined in terms of the behavior of the autocovariance $C(\tau)$ of a stationary process as τ increases. For many processes, the autocovariance rapidly decays with τ . For the Poisson increment process with increment L and mean λ , the autocovariance for values of $\tau > L$ is in [14, 17], $C(\tau) = R(\tau) - \lambda^2 = \lambda^2 - \lambda^2$. In general, a short-range dependent process satisfies the condition that its autocovariance decays exponentially: $C(k) \sim a^{|k|}$ as $|k| \rightarrow \infty$, $0 < a < 1$.

The types of data traffic models typically considered in the literature or in the papers employ only short-range dependent processes.

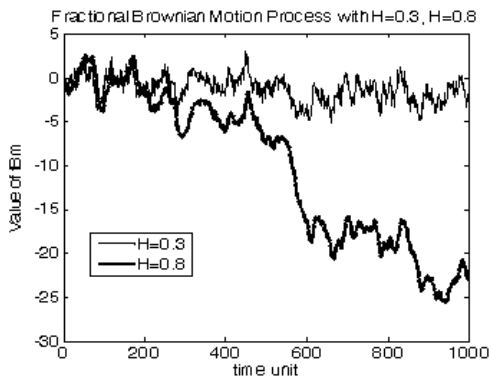
Using the equality $\sum_{k=0}^{\infty} x^k = \frac{1}{1-x}$, $|x| < 1$ we can observe that $\sum_K C(K)$ for a short-range dependent process is finite. In contrast, a long-range dependent process has a hyperbolically decaying autocovariance: $C(K) \sim |k|^{-\beta}$ as $|k| \rightarrow \infty$, $0 < \beta < 1$ where β is the same parameter defined earlier and is related to the Hurst parameter as $H = 1 - \frac{\beta}{2}$. In this case, $\sum_K C(K) = \infty$. The variances of the aggregated self-similar processes $X^{(m)}$, $m \geq 1$, decrease more slowly than the reciprocal of the non-overlapping batch size m . This property is given by in [18] : $Var[X^{(m)}] \rightarrow cm^{-\beta}$ when $m \rightarrow \infty$, c is a constant and $0 < \beta < 1$. If $\beta = 1$ in this case that processes such as Poisson processes in [18] proved that $H = 1 - \frac{\beta}{2}$ [18]. Variance time function become is [19]: $Var[X_n^{(m)}] = \sigma^2 m^{-2(1-H)}$ where $\sigma^2 = \lambda a \tau^{2H}$, λ and a are incoming rate and variance [18].

3.2 Fractional Brownian Motion

Fractional Brown motion is a model which is used for modeling self-similar processes[14]. The model itself was introduced by Mandelbrot and Van Ness [15]. Let $B_H(t)$ be a self-similar process with stationary increments. We define the increments as: $Y(t) = B_t(t) - B_H(t-1)$ where $Y(t)$ is a Gaussian process. The set $B_H(t)$ is called Fractional Brownian Motion and $Y(t)$ is called Fractional Gaussian Motion. The definition given by Mandelbrot for Fractional Brownian Motion is given by [15]:

$$B_H(t) = \frac{1}{\Gamma\left(H + \frac{1}{2}\right)} \int_{-\infty}^0 \left[(t-s)^{H-\frac{1}{2}} - (-s)^{H-\frac{1}{2}} \right] dB + \int_0^t (t-s)^{H-\frac{1}{2}} dB \tag{Eq 1}$$

where Γ is the Gamma distribution. The Fractional Brownian Motion is a continuous time Gaussian process, when Hurst parameter is bounded between zero and one, $0 < H < 1$. (Fig. 1) shows the Fractional Brownian Motion process with $H=0.3$ and $H=0.8$. It shows that when value of Fractional Brownian Motion changes slowly, it becomes more dependent on Hurst parameter.



(Figure 1) Fractional Brown Motion $H=0.3$ and $H=0.8$

4. Data Study

4.1 Measurement Setup

(Fig. 2) shows the network configuration and connection used in this study. To cover

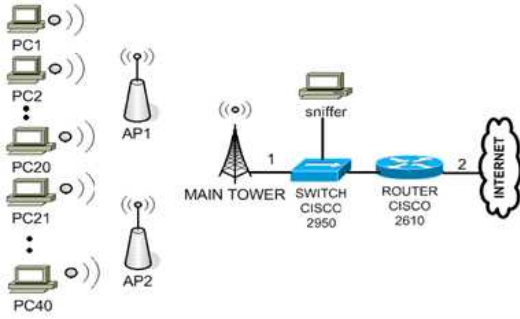
wider geographical area, it is more cost effective to use wireless network than to use wired network technology. Particularly, in a sparsely populated country like Mongolia, wireless network is preferred communication medium. In a wireless network there is one six-sector antenna system where each sector antenna approximately covers 60° degree angle and adjacent sector antennas slightly overlaps with each other. 40 wireless clients are connected to 2 Access Point of the provider. Routing of all connections, and also the control and management of throughput (Traffic Shaping, QoS) are carried out with a router. Each wireless client has throughput ranging from 64 up to 512 kbps. We use packet sniffer to collect the packet trace[16]. Sniffer is connected to the network so as to record traffic going through Point “1” and simultaneously through Point “2” in (Fig. 2). Please note that the point of “1” receiving traffic information sharing among wireless customers, and with it the traffic flow of information between customers and Internet. After a point “2” is only the latest of them. All packages are recorded down to the file with tcpdump format. More than 12.7 million packets were collected in this study. Of these, 70 percent were used to construct the TCP datagram.

4.2 The Characteristics of Realizations

Packet was collected from March, 18th, 2005 (Wednesday) at 10:00 to March, 18th at 17:00.

<Table >1 Traffic data sets description

Data sets	File description	Protocol layer
eth.dat	Aggregate traffic, captured at point 1	2(Ethernet)
eth.src	Upstream traffic, captured at point 2.	2(Ethernet)
eth.dst	Downstream traffic, captured at point 2.	2(Ethernet)
tcp.dat	TCP traffic, captured at point 2	4(TCP)



(Figure 2) The Wireless network configuration

The duration is 7 hours, short description is given in <table 1>.

Data are presented with two columns in ASCII-format: the first column contains time labels (in sec.), and the second column contains the size of the Ethernet-frame in bytes, or the size of a field of data of an IP-packet in case of a TCP-packet.

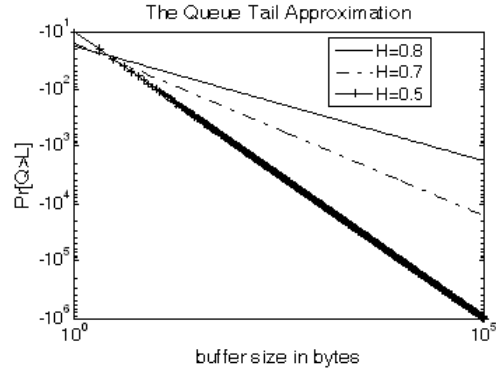
5. Characteristics of Traffic

5.1 Buffer overflow Probability Approximation Analysis

We analyze the tail probability of a given queuing system with finite queue. We assume that incoming traffic follows FBM (Fractional Brownian Motion). Fractional Brownian motion is one of the most widely known model for self-similar process [13]. Let us briefly explain fractional Brownian motion. FBM process, $A(t)$, is defined as in Eq. 2.

$$A(t) = mt + \sqrt{m\alpha} Z_H(t), t \in R \quad \text{Eq. 2}$$

where m and α denotes average and variance of arrival process. $Z_H(t)$ is Gaussian process with zero mean and variance of $Var[Z_H(t)] = |t|^{2H}$. H denotes Hurst parameter and satisfies $H \in [0.5, 1]$. Fractional Brownian Motion traffic is modeled by the three parameters $FBM(m, \alpha, H)$. Norros et. Al.



(Figure 3) The queue tail approximation with the queue length L for $m=5$ and fixed H established a relationship between queue length and overflow probability especially when incoming traffic bears long range dependent property (Eq. 3) [13].

$$\begin{aligned} \ln(\Pr[Q > L]) = & \\ & - \frac{1}{2m\alpha(1-H)^2} \left(\frac{C(1-\rho)(1-H)}{H} \right)^{2H} L^{2(1-H)} \end{aligned} \quad \text{Eq. 3}$$

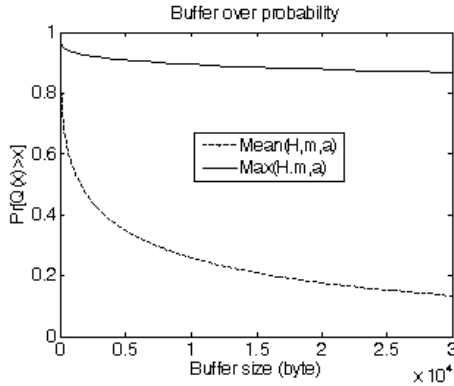
where the buffer size L , the service rate C and the traffic parameters m , α and H for the boundary values [6].

The analysis of a single queue construction with FBM at the input was presented for the first time in [13], where it was shown that the queue length distribution can be approximated by Weibull distribution. (Fig. 3) shows the function of the queue tail approximation with the queue size in log-log scale for fixed H and m .

The observed plot linearity illustrates the probability decay in accordance with the Weibull law. The approximation tail probability is follows:

$$P(Q > x) \approx \exp(-\gamma^* x^{2(1-H)}) \quad \text{Eq. 4}$$

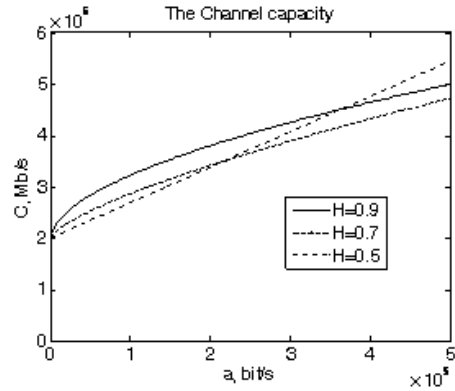
where $x \rightarrow \infty$, $\rho = m/c$, and $\gamma = \frac{1}{2m\alpha(1-H)^2} \left(\frac{C(1-\rho)(1-H)}{H} \right)^{2H}$ is the offered load. If the observed traffic, that is, the traffic



(Figure 4) Buffer overflow probability with different values of H and variance coefficient

extracted traffic data with 1 sec can be approximated $H = 0.82$, $m = 0.22 \text{ Mbps}$, and $\alpha = 1.0 \cdot 10^7 (\text{bit}/\text{sec})^2$. Thus, tail probability can be calculated with Eq. 4. In previous studies, we analyzed dependency for parameters of variance and Hurst parameter. In this case, we calculated the time scale and then find the maximum values for variance and Hurst parameter in 1 sec interval which follows: $H_{\text{max}} = 0.89$, $m_{\text{max}} = 1 \text{ Mbps}$, and $\alpha = 3.5 \cdot 10^7 (\text{bit}/\text{sec})^2$. Consequently, the different values of H and variance coefficient result in different shapes of Buffer overflow probability for the same buffer size. These enables to use FBM to model real-traffic traces. Hence, an optimal representation of buffer overflow probability under a certain criterion is desirable and optimal approximation is well worth discussing. Let θ be the maximum set containing H parameter and variance coefficient for FBM of self-similar process of eth.dat, eth.src, eth.dst, and tcp.dat.

Let χ the mean a set containing H parameter and variance coefficient for FBM of self-similar process of eth.dat, eth.src, eth.dst, tcp.dat. Then, $\theta \cup \chi$ is the set containing maximum value of Buffer overflow probability $\max \Pr\{Q(x) > x\}$. Construct a



(Figure 5) The channel capacity with $m=2\text{Mb/s}$ and $L=1\text{Mb}$

$\max \Pr\{Q(x) > x\}$ containing all $\Pr\{Q(x) > x\}$ [13] for data sets, including the eth.dat, eth.src, eth.dst, and tcp.dat. This approximation estimates tail probability by taking the maximum value of all tail probabilities for all parameter sets. This approximation given by Eq. 4 is shown in(Fig. 4). In this case, the approximation is larger than the mean values of H, m (mean input rate), α (mean input variance coefficient in time interval 1 sec).

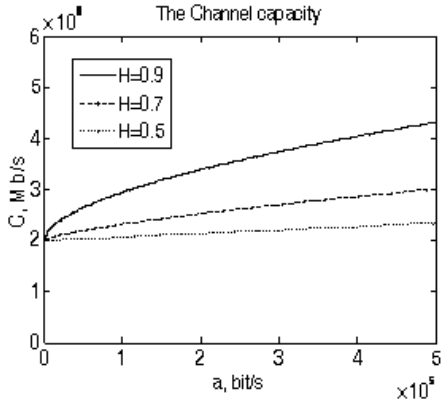
5.2 Channel Characteristic Analysis

Assuming the probability $\Pr(Q > L) = \epsilon$ and $\rho = m/c$, it is possible to solve [13] with respect to C and to find that the QoS is achieved approximately when

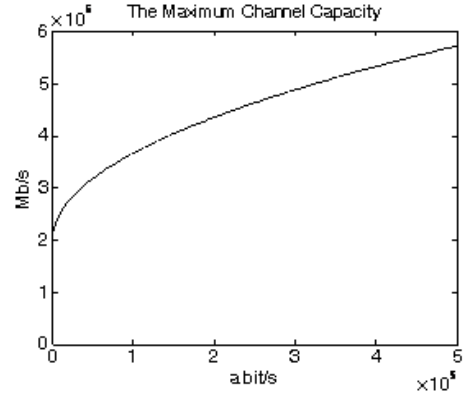
$$C = m + \left\{ H^H (1-H)^{1-H} \sqrt{-2 \ln(\epsilon)} \right\}^{1/H} \alpha^{\frac{1}{2H}} L^{-\frac{-(1-H)}{H}} m^{\frac{1}{2H}} \tag{Eq. 5}$$

For a practical application of Eq. 5 as the formula giving the channel size, it is of interest to examine its sensitivity to α and H.

(Fig. 5) and (Fig 6) show the channel characteristics with different values of α and H for $m = 2 \text{ Mb/s}$, $\epsilon = 10^{-3}$ and for two buffer sizes $L=1\text{Mb}$ and $L=10\text{Mb}$ respectively. In this case, it can be seen that when the buffer is small, the requirements to the channel are less



(Figure 6) The channel capacity with $m=2\text{Mb/s}$ and $L=10\text{Mb}$



(Figure 7) The maximum channel capacity

dependent on H than when the buffer is large.

The observed result illustrates the well-known fact that it is very difficult to fill a large buffer by short-range dependent traffic. The obtained results show that the queue length distribution with FBM arrival process has much slower of autocorrelation decay than in the exponential case in (Fig. 3). At first we define that an overflow occurs whenever the arrival rate (m) exceeds the service rate (C). In this case, the upper bound of channel capacity as follows [10]:

$$\begin{aligned} \epsilon &= \Pr(X(t) > b) \leq \Pr(\sqrt{am} Z_H(1) + m > c) \\ &= \Pr\left(Z_H(1) > \frac{C-m}{\sqrt{am}}\right) \\ &= \Phi\left(\frac{C-m}{\sqrt{am}}\right) \\ &= e^{-\frac{(C-m)^2}{2am}} \end{aligned} \tag{Eq. 6}$$

We find the upper bound channel capacity for large buffers and see in (Fig. 7) [10]:

$$C \leq m + \sqrt{-2am \ln(\epsilon)} \tag{Eq. 7}$$

All of previous analysis, there are the parameters a and H to more dependent on the QoS.

5.3 Average Waiting Time for FBM Process

The FBM process is a Gaussian based approximation process. Possible approach consists of a waiting time approximation method using the Little's law and Norris queuing theory[13]. Average waiting time is as follows: $E(w) = \frac{1}{m} E(n)$; $m = \rho * C$, where m -input rate, ρ -utilization, C -service rate, and $E(n)$ - average length of buffer for FBM. The queuing buffer for FBM traffic and service rate C is defined as follows[13]

$$\Pr(Q > x) \geq \max_{t > 0} \Phi\left(\frac{(C-m)t+x}{t^H \sqrt{ma}}\right) \tag{Eq. 8}$$

where $\Phi(*)$ is the standard Gaussian distribution. The time t satisfying Eq. 8 is given by:

$$t = \frac{Hx}{(1-H)(C-m)} \tag{Eq. 9}$$

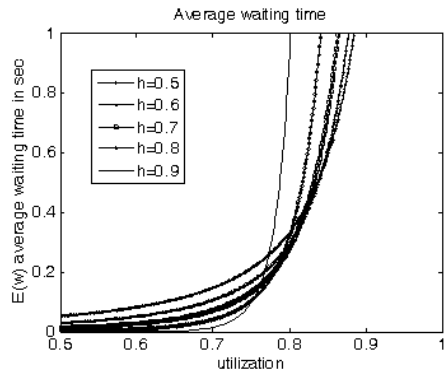
Mayor et. al. [12] find t that maximum equation is busy period for the queuing system:

$$t = \left(\frac{\sqrt{-2\ln(\epsilon)}}{C-m} * a * H\right)^{\frac{1}{1-H}} \tag{Eq. 10}$$

We can derived the maximum queuing length

$$B_{max} = \frac{C(1-H)(1-\rho)}{H} \left[\frac{\sqrt{-2\ln(\epsilon)}}{C(1-\rho)} aH\right]^{\frac{1}{1-H}} \tag{Eq. 11}$$

Average waiting time of buffer length is as follows for FBM process:



(Figure 8) Average waiting time with different values of H

$$E(w) = \frac{(1-\rho)(1-H)}{\rho H} \left(\frac{\sqrt{-2\ln(\epsilon)}}{C(1-\rho)} - aH \right)^{\frac{1}{1-H}}$$

Eq. 12

(Fig. 8) shows that for big H-parameters a much higher waiting time is required with the same utilization and keeping the QoS requirements. If utilization is more than 0.5 we can see more dependency on the Hurst parameter in (Fig. 8). In high channel capacity, H parameter in waiting time is very clear. It shows that traffic is long range dependent process in (Fig. 8).

6. Conclusion

We have analyzed a wireless traffic model with a finite buffer and a constant loss probability and estimated the channel capacity with dependent from Hurst parameter and variance in 1 sec time interval. We have derived exact analytical results which have dependent parameters of buffer overflow probability and waiting time. The problem of buffer storage size, belonging to the general limited length queuing problem, is important in buffer length, Hurst parameter. Both the mean information loss and waiting time play a critical role in the over a QoS of network traffic, so that a joint investigation of their effect should be a power tool for the actual design. The results,

however, seem to be applicable to more general input distribution FGM (Fractional Gaussian Motion), where an equation analogous to Eq. 4, and 8 may hold.

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