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Loss probability estimation and control for OFDM/TDMA wireless systems considering multifractal traffic characteristics

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ABSTRACT

In this paper, we analyze the queueing performance in terms of loss rate of an OFDM (orthogonal frequency-division multiplexing)/TDMA (time division multiplexing access) based wireless system taking into account the multifractal behavior of the wireless traffic flows. To this end, first, we show evidences of multifractal characteristics on wireless traffic traces. These findings motivated us to propose a traffic policing and control scheme based on a multifractal envelope process in order to maintain the traffic flows well-behaved, i.e., in accordance to the desired QoS parameters. Furthermore, by assuming a multifractal traffic model, we derive a data loss probability equation for wireless traffic flows that was applied to the OFDM/TDMA based wireless system. Simulations and comparisons to other methods were carried out in order to verify the efficiency of the proposed traffic policing scheme as well as of the loss probability estimation approach.

1. Introduction

Efficient models that provide better understanding of network traffic behavior are very important in the design and optimization of communication networks. Numerous traffic models and analysis techniques have been developed for telecommunication networks [1,2]. Among them, we can include renewal models, Markov-based models, fluid models, autoregressive models, self-similar models and multifractal models [3].

Such traffic models are intended to provide ways of characterizing network traffic behavior. Moreover, once the workload is modeled, one can predict the network performance through analytical techniques or simulation. Network traffic modeling and prediction tools contribute to provide adequate decisions related to design and network management [4,5].

Self-similar and multifractal models have been receiving great attention due to their analysis and modeling performance of real network traffic [6]. These models can capture the second or higher-order temporal dependence structure of real traffic traces much better than traditional traffic models [7,8]. Compared to monofractal models, multifractal processes have in addition to long-range dependence, different scaling laws. In other words, multifractal models overcome the limitation of monofractal models, in the sense that multifractal analysis can also capture small scale characteristics such as lognormal distribution [8–10].

Some researches have revealed that multifractal models are adequate in describing different network traffic characteristics [8–11]. In fact, analyses have been performed on various real network traffic types. The examples of such traffic types are video traffic [12,13], Local Area Network (LAN) traffic [10,13], Wide Area Network (WAN) traffic [14,15] and World Wide Web (WWW) application traffic [16].

Wireless communication systems are designed to support a diverse range of services and applications [17]. In this sense, multimedia traffic, especially video traffic, is foreseen to be one of the main traffic types in wireless communication systems [3]. Due to their inner characteristics, wireless LAN traffic flows are typically affected by non-ideal channel condition underlying MAC protocol and user mobility [3,18,19]. Therefore, efficient policing and control mechanisms are required for network traffic management in wireless networks.

The most commonly discussed policing mechanism based on traffic modeling in the literature is the Leaky Bucket (LB). However, the Leaky Bucket does not work well when the traffic input process is bursty, once this kind of traffic quickly fills the bucket and the resulting overflow forces the algorithm to discard even well-behaved packet [20,21]. This situation can be observed when the incoming traffic is monofractal and multifractal [22]. A traffic regulator called Fractal Leaky Bucket (FLB) was introduced in [23] to deal with monofractal traffic. The FLB approach proved to be an efficient mechanism to police and control monofractal traffic

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sources. Aiming to develop a more accurate model, we propose a traffic policing algorithm that takes into account the multifractal properties of the network traffic, being more general than the fractal approach and adequate for real wireless network traffic as we will demonstrate.

OFDM is currently used in high-speed wireless LAN (e.g., IEEE 802.11a) and fixed broadband access systems (e.g., IEEE 802.16a). OFDM offers high speed transmission rate by transmitting data on several subcarriers at the same time and it is also robust to inter-symbol interference and frequency selective fading [24]. It seems OFDM will be widely adopted in other wireless networks in the future.

Wireless LAN traffic may exhibit singular properties related to multifractal characteristics (e.g., a structure of strong dependence among its samples with incidence of bursts at various scales) due to user behavior (statistical behavior and mobility) and due to the IEEE 802.11 MAC protocol mechanisms (i.e., mechanisms that are based on providing access to a shared medium) [3,18,19]. The IEEE 802.16 family deserves special attention due to its transmission capacity, involved long distances and other characteristics (e.g., long-range dependence in WiMAX traffic [25,26]). In this work, we show that most of the considered wireless traffic traces presents some multifractal characteristics leading us to argue that multifractal analysis can enhance the wireless traffic analysis and control. Thus, by assuming a multifractal traffic model, we derive an expression for calculating the packet loss probability of wireless traffic flows that can be applied to evaluate the queueing performance in terms of loss rate of an OFDM/TDMA based wireless system. Regarding loss rate control, we apply the proposed multifractal traffic policing algorithm to an OFDM/TDMA based wireless system, comparing its performance to other traffic model based policing approaches.

The paper is organized as follows: In Section 2, we introduce some multifractal concepts and we investigate the presence of multifractal characteristics in some wireless traffic traces. In Section 3, we discuss about traffic policing mechanisms. More specifically, on Section 3.3, we propose a novel multifractal traffic policing scheme. In Section 4, we evaluate the application of traffic policing mechanisms to the wireless system. In Section 5, we consider an analytical queueing analysis for a wavelet domain multiscale model, and we propose a loss probability equation for wireless multifractal traffic. In Section 6, we evaluate the proposed loss probability estimation approach and finally, in Section 7, we conclude.

2. Multifractal analysis

2.1. Multifractal network traffic

A wireless network traffic flow may present a structure of strong dependence among its samples with incidence of bursts at various scales as that found on wired network traffic flows [8,9]. These features can degrade network performance more than those of Gaussian traffic flows and short-range dependence [10,27].

Multifractal processes are defined by a scaling law for the statistical moments of the processes' increments over finite time intervals. This means the wireless network traffic has complex and strong dependence structures inherently, appearing very bursty and the burstiness looks similar over many scales [8,28]. Now, let us formally define the concept of a multifractal process.

Definition 1. A stochastic process $X(t)$ is called multifractal if it satisfies

$$E(|X(t)|^q) = c(q)t^{\tau(q)+1} \tag{1}$$

for $t \in T$ and $q \in Q$, where T and Q are intervals on the real line, and $\tau(q)$ and $c(q)$ are functions with domain Q, $\tau(q)$ is the scaling function and $c(q)$ is the moment factor of the multifractal process. Furthermore, we assume that T and Q have positive lengths, and that $0 \in T$, $[0,1] \subseteq Q$. If $\tau(q)$ is linear in q, the process $X(t)$ is called monofractal; otherwise, it is multifractal [28].

One of the most important multifractal models present in the literature was proposed by Riedi et al., namely the MWM (Multifractal Wavelet Model) [8,28]. In the MWM, a positive, stationary, long-range dependent signal $C(t)$ is represented in the wavelet domain.

Let $C^{(n)}[k]$ be a discrete-time signal that approximates $C(t)$ at resolution 2^{-n}, where n corresponds to the time scale. Using the Haar wavelet, the discrete process $C^{(n)}[k]$ takes values that correspond to the integral of $C(t)$ in the interval $[k2^{-n},(k+1)2^{-n}]$. Such processes have a natural interpretation as an increment process:

$$C^{(n)}[k] = \int_{k2^{-n}}^{(k+1)2^{-n}} C(t)\,dt = 2^{-n/2}U_{n,k} \tag{2}$$

Let $A_{j,k}$ be a random variable supported on the interval $[-1,1]$ and let us define the wavelet coefficients as

$$W_{j,k} = A_{j,k}U_{j,k}. \tag{3}$$

We can relate the shift k_j of a scaling coefficient to the shift of one of its two direct descendents k_{j+1} via $k_{j+1} = 2k_j + k'_j$, with $k'_j = 0$ corresponding to the left descendent and $k'_j = 1$ the right descendent. Fig. 1 illustrates the wavelet domain structure of the MWM. Thus, we can write the MWM wavelet and scaling coefficients as:

$$U_{j,k_j} = 2^{-j/2}U_{0,0}\prod_{i=0}^{j-1}\left[1+(-1)^{k'_i}A_{i,k_i}\right], \tag{4}$$

$$W_{j,k_j} = 2^{-j/2}A_{j,k_j}U_{0,0}\prod_{i=0}^{j-1}\left[1+(-1)^{k'_i}A_{i,k_i}\right], \tag{5}$$

It is assumed that, within each scale j, the multipliers $A_{j,k}$, $k = 0,1,\ldots,2^{j-1}$, are identically distributed according to some random variable $A_{(j)} \in [-1,1]$. Thus, we have:

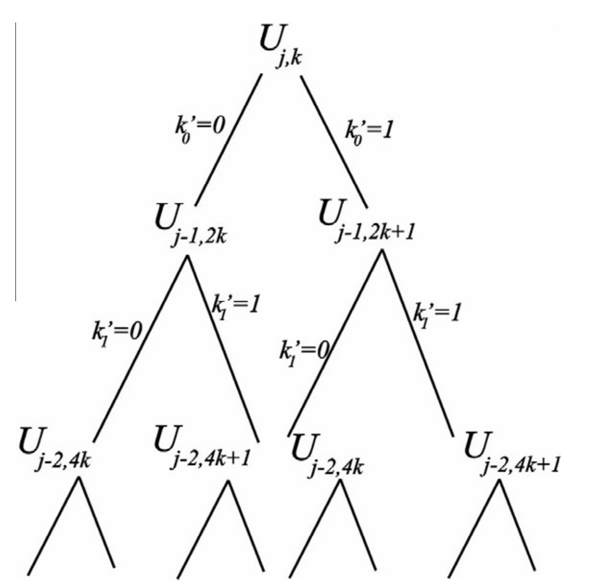

Fig. 1. Binary tree of scaling coefficients. Nodes at each horizontal level in the tree provides a constant representation of the signal with lower levels corresponding to finer resolutions [7].

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$$C^{(n)}[k] \overset{d}{=} 2^{-n} U_{0,0} \prod_{i=0}^{n-1} [1 + A_{(j)}]. \tag{6}$$

The moments of $C^{(n)}[k]$ can be readily calculated from (6) via:

$$E[C^{(n)}[k]^q] = E\left[U_{0,0}^q\right] \prod_{j=0}^{n-1} E\left[\left(\frac{1 + A_{(j)}}{2}\right)^q\right]. \tag{7}$$

2.2. Scaling function

A multifractal process as defined by Eq. (1) implies stationary condition for its increments [29,30]. Thus, the relation given in Eq. (8), presented below, can be verified for the moments of the increments, that is:

$$E[|Z^{(\Delta t)}|^q] = c(q)(\Delta t)^{\tau_0(q)}, \tag{8}$$

where $Z^{(\Delta t)}$ denotes the increment process of time sample Δt, $q > 0$ and $\tau_0(q) = \tau(q) + 1$. Then, we can rewrite (8) as:

$$E[|Z^{(m\Delta t)}|^q] = c(q)(m\Delta t)^{\tau_0(q)}, \tag{9}$$

since Eq. (8) holds for $m = 1, 2, \ldots$.

Choosing Δt as a time unit, we obtain:

$$\log E[|Z^{(m)}|^q] = \tau_0(q) \log m + \log c(q). \tag{10}$$

If the sequence of increments Z^m has scaling property, then the plot of absolute moments $E[|Z^{(m)}|^q]$ versus m on a log–log plot should be a straight line due to Eq. (10). The slope of the straight line provides the estimate of $\tau_0(q)$ and the intercept is the value for $\log c(q)$.

The scaling function plot for a self-similar trace is shown in Fig. 2. We can observe that the scaling function plot for this trace shows a linear relationship between $\tau_0(q)$ and q, which is fully consistent to the monofractal scaling behavior. In contrast, the $\tau_0(q)$ function for some wireless traffic traces (Fig. 2), for example, the USC_06spring_trace collected from USC (University of Southern California) WLAN traffic traces [32], show characteristics of a non-linear mapping, i.e., a concave shape that are inconsistent to monofractal behavior, suggesting a multifractal structure for these wireless traces [30]. Fig. 2 also shows similar results for the wireless traffic trace called ISF_wifidog, available at [33].

2.3. Multifractal spectrum

In contrast to other traffic models, multifractal processes contain a multiplicity of Hölder local exponents within any finite interval [8]. The Hölder exponents describe the local scale characteristics in a process at a given point in time. The Hölder exponent concept is related to the uniqueness of a local process, i.e., the process is characterized by its smoothness (number of bursts) at a certain time instant [34]. The exponents' distribution can be represented by this normalized density called multifractal spectrum. In other words, the multifractal spectrum describes the fractal dimension of the set of moments which has a local exponent [35].

The multifractal spectrum $f(\alpha)$ of a process $X(t)$ can be seen as the Legendre transform of $\tau(q)$ (scaling function defined earlier) by the relation:

$$f(\alpha) = \min_q (q(\alpha) - \tau(q)). \tag{11}$$

The cases where the spectrum $f(\alpha)$ is defined to only one point, resulting in a single Hölder exponent, are classified as monofractal. For multifractal processes, the spectrum has a parabolic concave $f(\alpha) \leqslant \alpha(t)$, for all $\alpha(t)$ and $f(\alpha) \leqslant f(\alpha_0)$ for all $\alpha(t)$, where $f(\alpha_0)$ is the maximum value of $f(\alpha)$ [8,29].

Fig. 3 presents the Legendre spectrum for a wireless traffic trace present in the USC_06spring_trace packet [32] and also for a monofractal traffic trace (dec-pkt-2) obtained from the internet traffic archive [31]. Note we verified that the considered wireless traffic trace also presents this multifractal characteristic, i.e., a wide Legendre spectrum. A wide set of Hölder values is an evidence of 'multifractality' [36,37]. Similar results were obtained for other wireless traffic traces.

2.4. Multiscale diagram

The wavelet partition function is defined as [7]:

$$S_j(q) = E|W_{j,k}|^q. \tag{12}$$

For certain multifractal processes the partition function scales asymptotically $j \to \infty$ as:

$$\log_2 S_j(q) \sim q \cdot k + j\alpha_q. \tag{13}$$

Thus, the slope of $\log_2 S_j(q)$ against j provides an estimate of α_q.

Aiming to consider one more way to verify whether a multifractal behavior is present on real wireless traffic traces, we considered the following two quantities: $\zeta_q = \alpha_q - q/2$ and $h_q = \zeta_q/q$ [37]. For monofractal processes, e.g. fBm (fractional Brownian motion) [36] and fGn (fractional Gaussian noise) [36], we have $\zeta_q = qH$ and $h_q = H$, where H is the so-called Hurst parameter [1]. Thus, a straight line ζ_q plot or a constant h_q plot characterizes monofractal

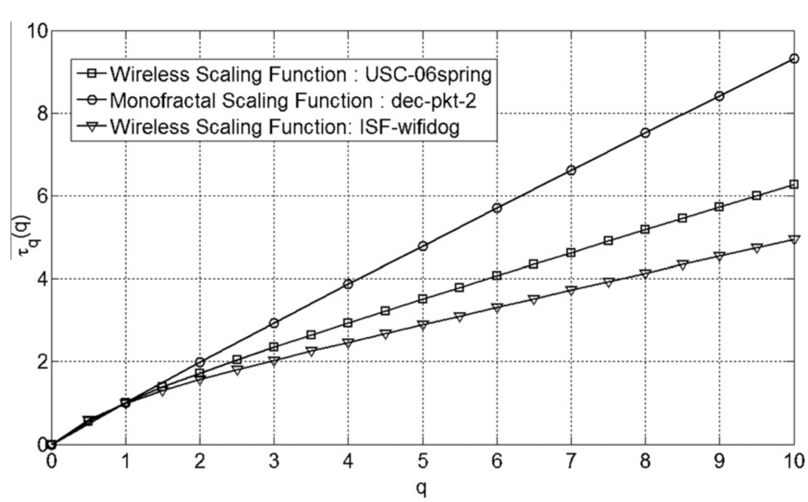

Fig. 2. The scaling function plots for a monofractal traffic trace (dec-pkt-2, available at [31]) and for the wireless traffic traces USC_06spring_trace [32] and ISF_wifidog [33].

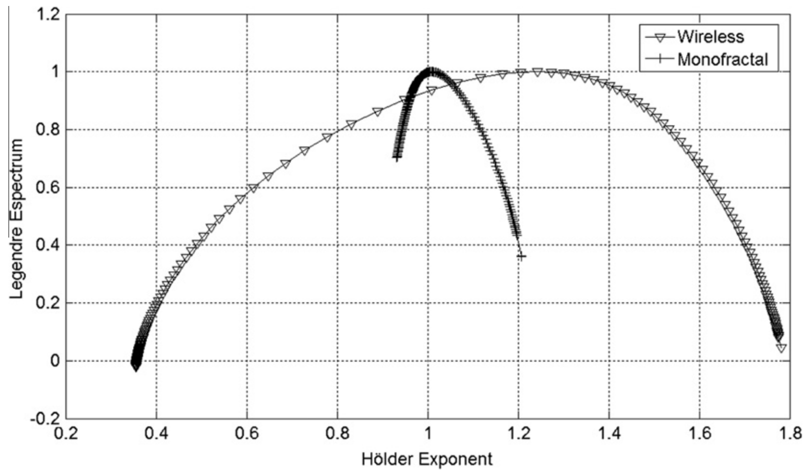

Fig. 3. Comparison of wireless and monofractal traffic spectra plots.

processes, while a non-linear ζ_q plot or a non-constant h_q plot characterizes multifractal processes [37].

In order to verify whether the traces exhibit multifractal scaling at small time scales, we perform the multifractal analysis using the code from [38]. We plot the estimates of ζ_q and h_q at small time scales for self-similar traffic traces and for wireless traffic traces. The result for self-similar traffic traces reveal that ζ_q is linear in q and h_q is nearly constant, a typical characteristic of monofractal processes, as can be observed in Fig. 4, where the vertical bars represent the confidence intervals. On the other hand, we claim that the wireless traffic trace [32] tends to be multifractal, since ζ_q is not linear in q and h_q is far away from being constant as depicted by Fig. 5. Similar results to that shown in Fig. 5 were obtained for other wireless traffic traces, e.g., the ISF_wifidog traffic trace, available at [33].

3. Traffic policing mechanisms based on network traffic modeling

In this section, we briefly describe some traffic modeling based policing algorithms.

3.1. Leaky Bucket traffic regulator

The traditional Leaky Bucket (LB) can be interpreted as a sequential test to analyze the behavior of an incoming traffic flow [39]. In this test, the packets are submitted to a traffic behavior analysis to determine which action will be taken in accordance to the Service Level Agreement (SLA).

The LB algorithm is composed of a bucket possessing capacity of S bytes or packets that can be stored, sending them to the network at a constant rate ρ [39].

3.2. Fractal Leaky Bucket traffic regulator

Fractal Leaky Bucket (FLB) is a policing mechanism that was introduced in [23]. The FLB is based on the concept of fBm (fractional Brownian motion) modeling of packet traffic process. It has been verified that the FLB accurately polices monofractal traffic flow with average $\bar{a}$, standard deviation σ and Hurst parameter H [40]. The Hurst parameter (H) represents the degree of self-similarity of the traffic process [41].

Let X_n ($n = 1,2,3,\ldots$) be the process of packet arrivals. That is, X_n represents the cumulative number of packets that arrive at the buffer of the Leaky Bucket algorithm during a time interval Δ. The maximum amount of work accepted (envelope process) by the FLB algorithm is:

$$\widehat{L}_{FLB}(t) = \bar{a}t + \kappa\sigma t^H + S, \tag{14}$$

where S is a variable analogous to the bucket size in the LB algorithm. H is the Hurst parameter, t is the time instant, $\bar{a}$ is the mean value of the input traffic, σ is the standard deviation of the input

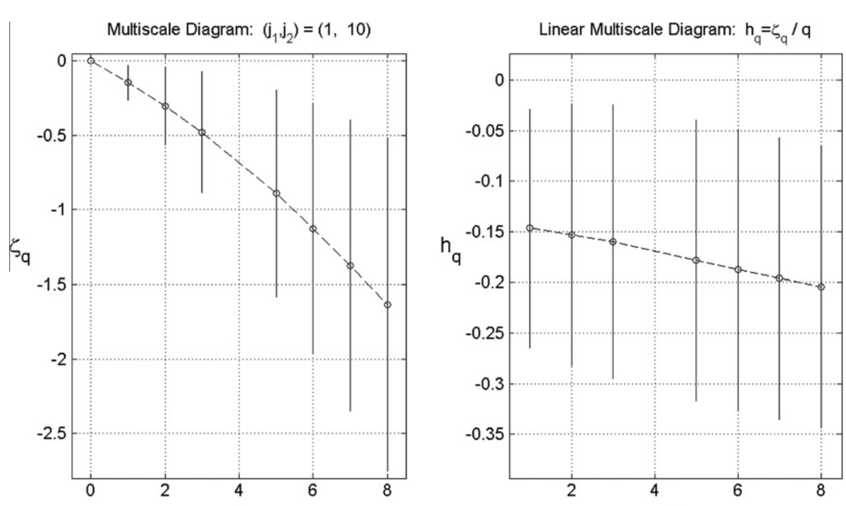

Fig. 4. The multiscale diagram for a monofractal traffic trace called dec-pkt-2 from DEC (digital equipment corporation) [31].

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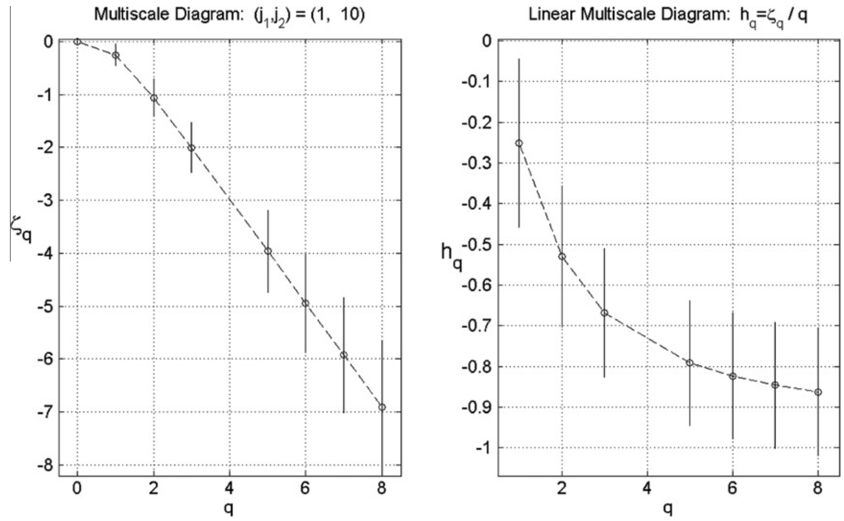

Fig. 5. The multiscale diagram for a wireless traffic trace called USC_06spring_trace packet [32].

traffic. The constant κ is related to the probability ϵ that the real cumulative process would exceed the envelope process and can be given by the following expression [23].

$$\kappa = \sqrt{-2\ln\epsilon}. \tag{15}$$

One can observe that the FLB envelope process has higher values than the envelope process of the real traffic without policing, as we will show. This causes the network traffic to be weakly policed, i.e., packets marked as badly-behaved can travel through the network without being dropped.

3.3. Multifractal Arrival Policing Mechanism traffic regulator

The multifractal characteristics encountered in wireless traffic traces motivated us to investigate traffic policing mechanisms that consider such characteristics [42–44].

We argue that network traffic presenting more complex properties (e.g. multifractal characteristics) will not be accurately described by monofractal or simpler models. Our proposal consists of a more general and sophisticated policing algorithm, namely Multifractal Arrival Policing Mechanism (MAPM) that is based on multifractal modeling.

In order to develop our policing algorithm, we start from the concept known as Multifractal Bounded Arrival Process (MFBAP) [40]. The envelope process MFBAP is able to represent the accumulated traffic of a multifractal process without assuming a particular marginal distribution. The MFBAP envelope process is given by the following equations [46]:

$$\widehat{L}_{MFBAP}(t) = \bar{a}t + \kappa\sigma\widehat{C}(t), \tag{16}$$

$$\widehat{C}(t) = t^{H(t)}, \tag{17}$$

where $H(t)$ represents the Hölder exponent [45] and the other parameters were already defined earlier.

By considering the MFBAP envelope process, we propose the following algorithm to police network traffic:

Algorithm 1. MAPM algorithm

Step (1) Compute $\bar{a}$ as the average of input traffic (X_n) and Δ the time interval of the traffic. After that calculate E_n using:

$$E_n = \max\{0, E_{n-1} + X_n - \bar{a}\Delta\}. \tag{18}$$

Step (2) Set the value of S close to the average of the input traffic, compute κ using (15) and estimate $H(t)$ using the FracLab software [47]. Next, obtain K_n by the following equation:

$$K_n = \begin{cases} S, & E_n = 0, \\ \kappa\sigma\Delta^{H(n)}\left[n^{H(n)} - (n-1)^{H(n)}\right] + K_{n-1}. \end{cases} \tag{19}$$

Step (3) Compute σ using the standard deviation of the X_n and calculate J_n by:

$$J_n = \begin{cases} 0, & E_n \leqslant K_n, \\ X_n - \bar{a}\Delta - \kappa\sigma\Delta^{H(n)}\left[n^{H(n)} - (n-1)^{H(n)}\right]. \end{cases} \tag{20}$$

The J_n sequence represents the number of packets marked as low priority or discarded. It is straightforward to notice that En is a test sequence, K_n is an adaptive decision threshold for E_n and J_n is the control applied to the incoming random sequence X_n.

Fig. 6 shows the envelope processes for the USC 2005 summer wireless traffic trace [32] obtained after the application of the traffic policing algorithms considered in this work. The closer the envelope process of the traffic policing algorithm to that of the traffic without policing, the more efficient can be the algorithm. That is, the algorithm is able to police traffic achieving the same QoS parameters but with a less packet discarding. The envelope process produced by the MAPM policing algorithm proved to be closer to that of the traffic without policing than the FLB and LB algorithms.

4. Traffic policing applied to the OFDM/TDMA based OFDM/TDMA wireless system

In the considered simplified OFDM/TDMA wireless system, data traffic for each user is buffered into a separate queue and the buffer size is finite. We consider a scenario such as that described in [48] presenting characteristics of TDMA-based multiple access with round-robin scheduling as shown in Fig. 7.

The round robin scheduler allocates resources to each process/queue in a quantum. If the process of allocating resources to a queue does not end after a quantum, there is preemption, and the queue enters in vacation mode, waiting for another chance to be served. If the process ends before a quantum, the server is released from that queue and the next queue is served. In both cases, after the release of the current queue, a new process is chosen in the next queue.

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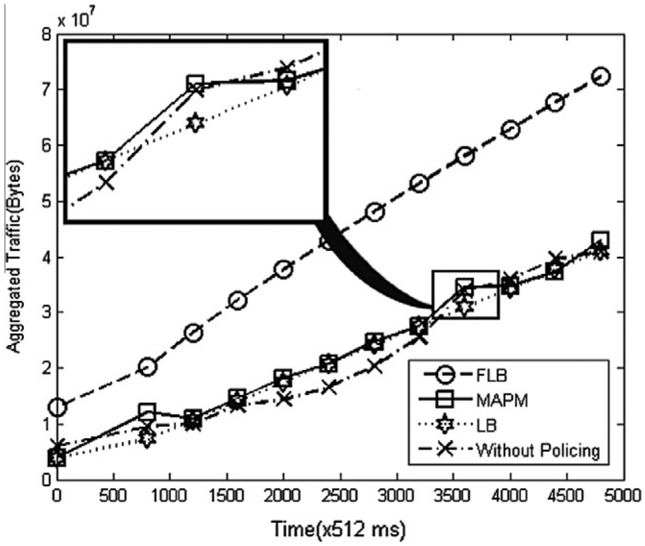

Fig. 6. Envelope process obtained with the LB, FLB and MAPM.

We also assume that the channel state information (i.e., signal-to-noise ratio (SNR)) is available at the transmitter system, and the total transmission bandwidth is B. Then, each subcarrier has a bandwidth of $\Delta f = B/M$ Hz.

By using adaptive modulation and coding (AMC), the maximum number of bits per symbol (per Hz), denoted by $C_{m,n}(t)$ that subcarrier m of a user n can transmit per time unit during time slot t can be expressed as a function of the SNR and the target bit error rate (BER). Although, there are several approximations for this function (e.g., [34]), all of them are upper bounded by the following capacity expression [43]:

$$C_{m,n}(t) = \left\lfloor \log_2\left(1 + \frac{-1.5}{\ln(5P_{ber})}\gamma_{m,n}(t)\right)\right\rfloor, \quad (21)$$

where P_{ber} is the target bit error rate (BER) and $\gamma_{m,n}(t)$ is the instantaneous SNR at time slot t for subcarriers m corresponding to user n, assumed to be a random variable whose probability distribution is given by:

$$p_\gamma(\gamma_{m,n}) = \frac{1}{\bar{\gamma}_{m,n}} \exp\left(-\frac{\gamma_{m,n}}{\bar{\gamma}_{m,n}}\right), \quad (22)$$

where $\bar{\gamma}_{m,n}(t)$ is the time-invariant average SNR of subcarrier m for user n.

The simulations of the traffic policing algorithms applied to the considered OFDM/TDMA system show that the number of packets discarded by the LB and FLB policing algorithms is higher than that of the MAPM algorithm.

That is, we argue that the FLB overestimate the traffic envelope once its envelope process is not tight to that of the traffic trace without policing algorithm.

When the incoming traffic envelope is higher than that established by the policing algorithm, the traffic is considered badly-behaved and is discarded (punished). In order to quantify the punishment degree of each traffic policing algorithm, we estimate the probability (P_d) of a packet be considered bad-behaved or dropped for some wireless traffic traces [24]. Compared to other policing algorithms, the MAPM algorithm presented some important characteristics: an envelope process as precise as that of real traffic and more policed packets (more packets marked as badly-behaved or discarded) than the monofractal FLB approach and the LB algorithm, as can be seen by Fig. 8.

Fig. 9 shows the mean buffer utilization versus the incoming traffic rate for all the considered policing algorithms. The MAPM policing algorithm achieved a slightly larger mean buffer utilization than the LB algorithm due to a less packet dropping for traffic shaping.

We also verify the relation between the mean loss rate (P_b) and the buffer size for all users in the OFDM/TDMA system after the user traffic being policed and be inserted into the system (Fig. 10). The MAPM algorithm provides the lowest mean loss rate among the considered policing algorithms. The simulation results emphasize that a traffic policing algorithm based on a more adequate model can provide better quality of service parameters in general even with a less packet dropping for traffic shaping, i.e., through a less severe policing algorithm. For bursty traffic, the LB algorithm could not be efficient, as we verified. We considered the buffer size started in zero (0) bytes, with increments of 1×10^6 until the limit of 10×10^6 bytes.

This fact was already pointed out in other works involving multifractal traffic [39,49].

5. Loss probability estimation for wireless network traffic

Let L_i be a discrete-time random process, where $i \in \mathbb{Z}$. The traffic load represented by this process is the input of a single server queue with constant link capacity c and finite buffer. Also let Q_i be the queue size at time instant i. Then, we can denote K_r, the aggregate traffic arriving between time instants $-r+1$ and 0, as:

$$K_r := \sum_{i=-r+1}^{0} L_i. \quad (23)$$

Next, we refer to K_r as representing the data at timescale r. Setting $K_0 = 0$, using Lindley's equation [50] and assuming the queue was empty at some time in the past, we have [1]:

$$Q_0 = \sup_{r\in\mathbb{N}}(K_r - rc). \quad (24)$$

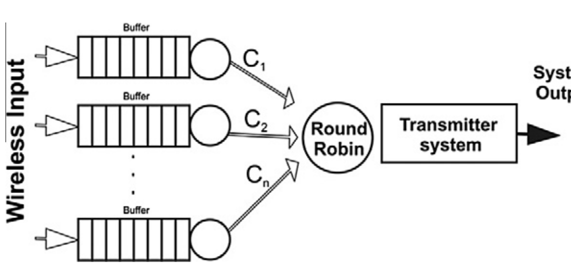

Fig. 7. OFDM/TDMA system model with round robin scheduling.

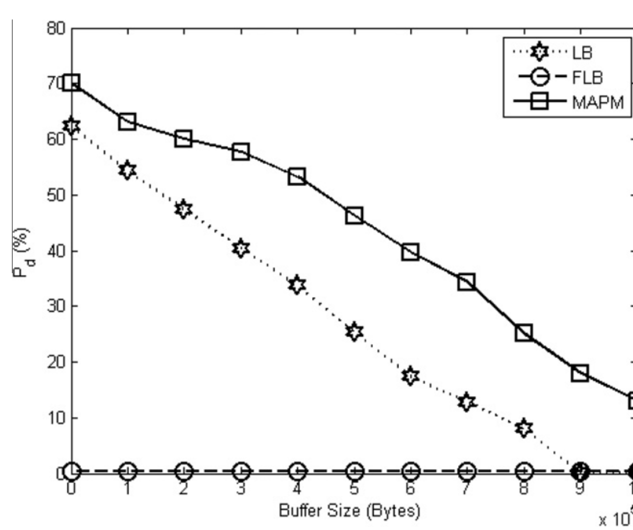

Fig. 8. Probability of packet dropping x buffer size (USC_06spring).

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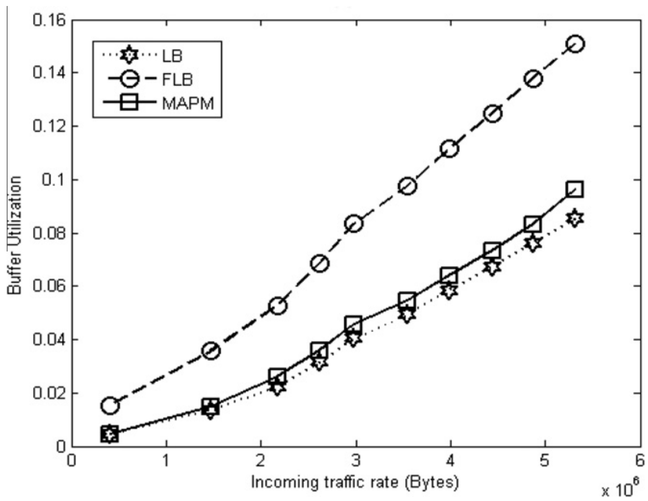

Fig. 9. Mean buffer utilization x incoming traffic rate (USC_06spring).

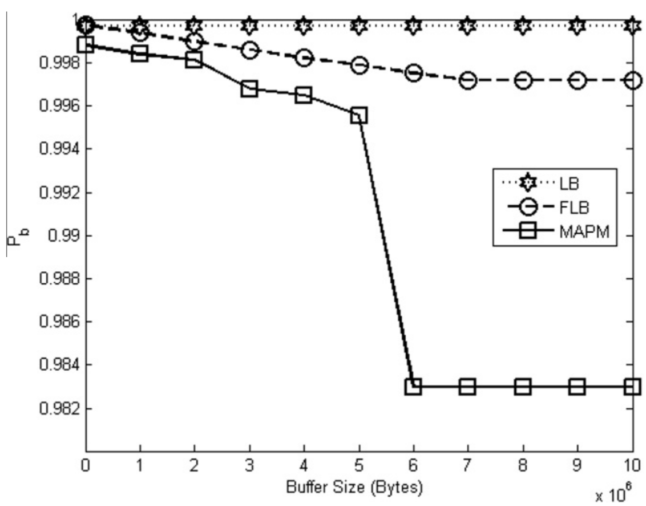

Fig. 10. Loss rate *x* buffer size (USC 06spring trace).

Note that (23) provides a direct link between the queue size Q and the aggregate of the traffic arrival process K_r at multiple time scales r. We also state the system studied here will be limited to the steady-state scenario, where $Q_0 = 0$ when $t = 0$.

Tree based wavelet domain models such as the MWM provide explicit and simple formulas of K_r for dyadic time scales (i.e., $r = 2^m$). For such processes the following approximation is valid [7]:

$$P[Q < b] \approx \prod_{i=0}^{n} P[K_{2^i} < b + c2^i]. \tag{25}$$

This approach of loss probability computing is known as MSQ (Multiscale Queueing), which provides a queueing formula for tree-based wavelet domain models. Another approach, similar to MSQ, is called CDTSQ (Critical Dyadic Time-Scale Queue) which takes into account only the traffic distributions at dyadic time scales instead of all time scales [7].

5.1. Loss probability for multifractal wireless network traffic

Initially, we consider a simple queueing model: a single server queue in continuous time where the service discipline for the offered work is FIFO (First In, First Out), the queue has finite buffer and the constant service rate is c.

Let $X(t)$ be the input arrival process to the queue and $A(t)$ be the accumulated amount of work that arrives to the queue model in the interval $[0,t)$. The so called workload process $W(t)$ is the total amount of work stored in the buffer in the time interval $[0,t)$, i.e.,

$$W(t) = A(t) - ct. \tag{26}$$

Our interest, in order to estimate loss probability, is the current buffer queueing length, denoted by Q. This is the queue length in the equilibrium state of the queue when the system has been running for a long time and the initial queue length has no influence. If this state of the system does exist, i.e., stationarity and ergodicity of the workload process hold, and the stability condition for the system is also satisfied, so using the *Lindley's equation* [50], we have:

$$Q = \sup_{t \geqslant 0} W(t), \tag{27}$$

where $W(0)$ is assumed to be 0.

As we are considering a finite buffer size b, an important measurement of a queueing model is the loss probability. Mathematically, we have:

$$P(T) = \sum_{t=0}^{T} \max(Q(t) - c, 0), \tag{28}$$

where $Q(0)$ is also assumed to be 0, P is the amount of loss and T is the considered time period.

For dyadic time scales 2^m, the amount of traffic is also related to K_{2^m}, defined previously, where $m \in (0, \ldots, n)$ and n is the number of scales considered. Then, we define the loss probability of the queueing model immediately after the time period T as:

$$P(Q > b) = P(T)/A(T). \tag{29}$$

Now, we can enunciate the following proposition regarding loss probability as defined in (29) for multifractal traffic.

Proposition 1. *Let $X(t)$ be a multifractal process whose multipliers $A_{(j)}$ of the corresponding wavelet domain multifractal model possess a symmetric probability distribution, b is the buffer size and c is the server capacity. The loss probability for this server is given by:*

$$P(Q > b) \approx 1 - \prod_{i=0}^{n} \left[1 - \frac{E[U_{0,0}] \prod_{j=0}^{n-1} E\left(\frac{1+A_{(j)}}{2}\right)}{(b + c2^i)} \right]. \tag{30}$$

Proof. Let X be a non-negative random variable and a a possible value that X can assume. Then, Markov's Inequality states that [51]:

$$P\{X \geqslant a\} \leqslant \frac{E[X]}{a}. \tag{31}$$

We can easily note that:

$$P\{X < a\} > 1 - \frac{E[X]}{a}. \tag{32}$$

In addition, inequality (32) can be rewritten for a dyadic process K_r as:

$$P[K_{2^i} < b + c2^i] > 1 - \frac{E[K_{2^i}]}{b + c2^i}. \tag{33}$$

This result can be reintroduced into Eq. (25) to produce:

$$P[Q < b] \approx \prod_{i=0}^{n} \left[1 - \frac{E[K_{2^i}]}{b + c2^i} \right]. \tag{34}$$

By substituting Eq. (7), into (34), we have:

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$$P(Q < b) \approx \prod_{i=0}^{n}\left[1 - \frac{E[U_{0,0}]\prod_{j=0}^{n-1}E\left(\frac{1+A_{(j)}}{2}\right)}{(b + c2^{i})}\right]. \quad (35)$$

Alternatively, we obtain the desired loss probability equation:

$$P(Q > b) \approx 1 - \prod_{i=0}^{n}\left[1 - \frac{E[U_{0,0}]\prod_{j=0}^{n-1}E\left(\frac{1+A_{(j)}}{2}\right)}{(b + c2^{i})}\right]. \quad (36)$$

Eq. (36) provides a direct relationship between the queue size Q and the traffic arrival process K_r at multiple time scales r. That is, the traffic behavior represented by the $A_{(j)}$ multipliers influence the loss probability value for a given queue. The accuracy of the approximation is also experimentally investigated by us. □

6. Evaluation of the proposed loss probability estimation approach

In this section, we apply the proposed loss probability estimation in the same wireless system considered in Fig. 7.

The configuration of the simulation parameters was set according to [48] as follows. For the specified OFDM/TDMA system, a scenario with 128 subcarriers (i.e., $M = 128$) and total bandwidth B of 1.920 MHz was considered. The number of users, and consequently the number of queues was set to be 5. The length of a time slot is set to be 10 ms and the packet size is assumed to be 256 bits.

The bandwidth of each subcarrier Δf is 15 kHz. We assume a Rayleigh fast fading channel that is a commonly used model for wireless communications [52–54]. In order to capture the effect of frequency selective fading, the average SNR for each subcarrier is chosen from a distribution given by Eq. (22) with mean 15 dB and variance of 2 dB. That is, the instantaneous SNR $\gamma_{m,n}(t)$ is assumed to be an exponential process whose values are introduced in Eq. (21) in order to compute the capacity $C_{m,n}(t)$. When assuming a Rayleigh fast fading channel, the variable SNR is considered to be an exponential process [48,55]. The target BER was set to be 10^{-6} and the maximum modulation level to be 5 (i.e., $C = 5$).

We compare the performance of the proposed multifractal loss probability equation to those of the MSQ and the CDTSQ methods [7]. These methods (MSQ and the CDTSQ) estimate $P(Q > b)$, i.e., the probability of the queue size exceeds b for a constant service rate, where it is considered that the queue is fed by MWM multifractal traffic type.

Figs. 11 and 12 show the loss probability in terms of buffer size. The results were collected from the considered scenario and the simulation was repeated several times. The queue and the wireless network user related to Fig. 11 are different to those of the Fig. 12.

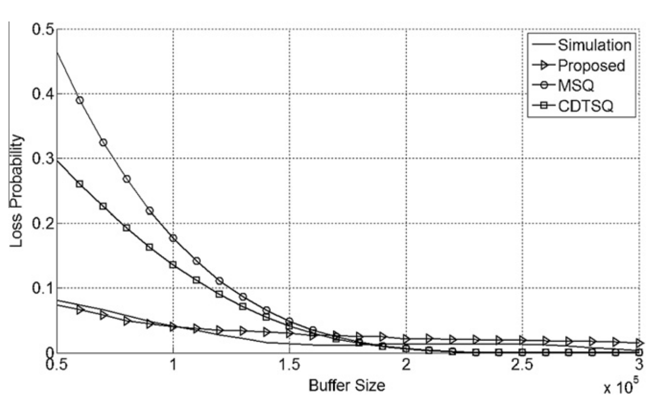

Fig. 11. Comparison of the loss probability in function of buffer size for the USC_06spring_trace.

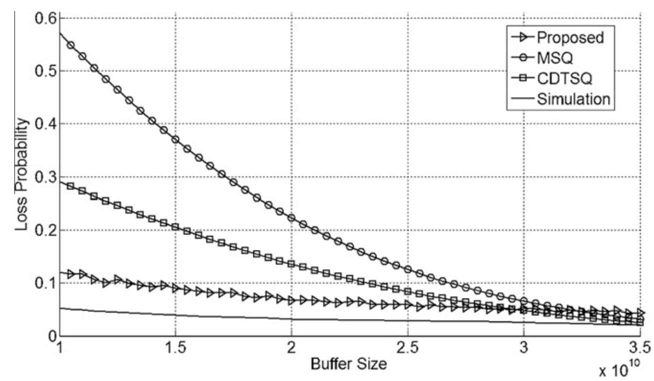

Fig. 12. Comparison of the loss probability in function of buffer size for the ISF_wifidog trace.

More precisely, Fig. 11 represents the loss probability considering as input traffic the USC_06spring_trace [32], captured in the first queue of the system (top to the bottom in Fig. 7), and Fig. 12 represents the loss probability for the ISF_wifidog trace [33] as input traffic, observed in the second queue of the system.

It can be observed that the proposed equation provides more precise values than the other considered methods. We also observed that the other methods present results close to those of the simulations only when the buffer size is greatly increased. On the other hand, we emphasize that the proposed equation is also capable of capturing the multifractal behavior of real traffic traces in the queueing system for a larger buffer size interval.

7. Conclusion

The characteristics of traffic flows especially in wireless networks, as long-range dependence and bursts at multiple scales make traffic modeling a difficult and challenging task. In this paper, we first showed that the multifractal analysis is suitable to characterize the wireless network traffic.

In order to evaluate loss probability in wireless networks, we considered a simplified scenario operating under an OFDM/TDMA scheme, where a round robin scheduling controls the data transmission.

Traffic policing schemes are strongly related to loss probability in communication networks once we apply these schemes to control the data loss rate. For the considered wireless traffic traces (traffic collected at University of Southern California available in [32]), the multifractal MAPM policing algorithm showed to be more efficient in general than the fractal FLB and the LB algorithms. Among the policing algorithms, we verified a better performance to the MAPM than those of the LB and FLB algorithms. In fact, the MAPM envelopes are closer to the traffic envelope processes without policing than the other considered envelopes, while providing the lowest probability of packet dropping. From our analysis, we conclude that the proposed policing algorithm is able to efficiently police real traffic data, even presenting multifractal characteristics.

By considering multifractal characteristics, we also obtained an analytical expression to determine the loss probability for wireless traffic traces applied to an OFDM/TDMA wireless scenario. Comparisons to other loss probability equations showed that in general more precise results were obtained for the proposed equation.

Nevertheless, the simulated scenario could be more accurate by also considering Doppler effects, which we left for future work. Another future consideration is to adapt the wireless scenario to more specific specifications of some wireless technologies such as Wi-Fi,

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WiMAX and LTE. Furthermore, in future works, we will apply the loss probability equation to forecast the loss rate of the traffic policing algorithms as well as to control traffic flows in order to provide QoS parameters.

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