Dynamic Bandwidth Allocation Mechanism Based on Loss Probability

Jeferson Wilian de Godoy Stênico and Lee Luan Ling

Abstract — **In this paper, we propose an analytical expression for estimating byte loss probability at a single server queue with multifractal traffic arrivals. The obtained expression is robust, stable and accurate in comparison with some existing methods in literature. Next we evaluate the potentiality of applying the proposed method in connection admission control by comparing with some other widely used admission control approaches. Finally we present a dynamic bandwidth allocation mechanism based on our multifractal based loss probability estimation method. Extensive experimental tests validate the efficiency and accuracy of the proposed loss probability estimation approach, its superior performance for admission control and link resource allocation applications with respect to some well-known approaches suggested in the literature.**

Keywords—Loss Probability, Admission Control, Dynamic Bandwidth Allocation.

I. INTRODUCTION

The research on network traffic involving the theory of fractals has intensified after the publication of the work of Leland et al [1]. Experimentally it has been found fractal properties of real traffic such as self-similarity and long-range dependence (LRD). Long-range dependence has strong influence on network performance [2], and cannot be adequately modeled by Poisson processes or, more generically, Markov models.

In contrast to the self-similar or monofractal behavior, some recent studies suggest that the measured TCP/IP and WAN ATM traffic flows exhibit a more complex scaling behavior, which is consistent with multifractals [3] [4]. Multifractal based traffic modeling is more general than the monofractal based and provides a more accurate and detailed description of network traffic series in different time scales [5].

Even taking into account the influence of the long-range dependent characteristics, the expected queuing behavior in buffer still cannot be adequately modeled without considering the multifractal nature of traffic [6]. We believe that the efficiency of an admission control mechanism as well as dynamic bandwidth allocation highly depends on the accuracy of the description of such queuing behavior what justifies the use of multifractal traffic models.

In this paper, we present a new approach for loss probability estimation in a single server link. We show how to get the estimates analytically once we assume multifractal input traffic. Based on this analytical method, we evaluate its potential applications for control admission and dynamic bandwidth allocation especially when networks traffic holds multifractal characteristics.

The paper is organized as follows: In Section II, we introduce the definition of multifractal processes, reviewing some concepts and analyze the characteristics of the second-order statistical moments. In Section III, we present the derivation of the analytical expression for the loss probability estimation in a single server queue. In Section IV, we evaluate our loss probability estimation algorithm, potentiality of the derived analytical loss probability estimates for admission control and present a new approach for dynamics bandwidth allocation. Finally in Section V we present our conclusions.

II. MULTIFRACTAL PROCESSES

Definition 1: Let $X(t)$ be the traffic rate at t. Then $W(t) = \int_0^t X(t)dt$ will be the arriving load up to t. Denote by $V(t, \Delta t) = W(t + \Delta t) - W(t)$. Assume the increment process is stationary, i.e., $V(t, \Delta t) = V(\Delta t)$. The average traffic rate is $\lambda = \lim_{\Delta t \to \infty}(V(\Delta t)/\Delta t)$. Let μ and σ^2 represent the mean the variance of $V(t)$.

Given $T > 0$, a accumulative process $W(t)$ is said to be a multifractal process at time scale T if all of the following condition are satisfied:

a) $W(t)$ has a stationary increment at time scale T, i.e., $V(t, T) = V(t)$.

b) $V(t)$ has a Pareto distribution density function with parameter α and k: $f_{v(t)} = \frac{\alpha k^\alpha}{v^{\alpha+1}}$;

c) $\mu = \lambda T$;

d) There exist an integer $M > 0$, a set $A = \{\beta_i(T): 0 < \beta_i(T) < 1, i \leq M\}$, a set $\Phi = \{\phi_i(T): 0 < \phi_i(T) < 1, i \leq M, \sum_{i=1;M} \phi_i(T) = 1\}$, and a small constant $\varepsilon > 0$ such that for any $\tau \in \{\tau: T - \varepsilon < \tau < T + \varepsilon, \tau > 0\}$ such that
$$\sigma^2 \sim \sum_{i=1}^{M} \phi_i(T) \tau^{2\beta_i(T)}. \qquad (1)$$

The expression (1) means there exists a probability measure for set A, and $\beta_i(T)$ occurs with probability $\phi_i(T)$. The continuous version of (1) is

$$\sigma^2 \sim \int_{-\infty}^{+\infty} f_{A(T)}(\beta) \tau^{2\beta} d\beta \qquad (2)$$

where $f_{A(T)}$ denotes the probability density function of the scaling exponents $\beta(T)$. This applies when infinitely many scaling exponents exist. Notice that the description of symbol "~" in (2) has the following interpretation: $x(p) \sim y(p)$ means $\lim_{u \to p}(x(u)/y(u)) = c$, where $0 < c < \infty$ is a constant.

A. *Second-Order Moments of the Multi-Scaling processes*

For simplicity, we assume that the scaling exponents $\beta(T)$ at time scale T of a traffic process follow a normal distribution $N(\tilde{\alpha}, \tilde{\sigma}^2)$ with mean $\tilde{\alpha}$ and variance $\tilde{\sigma}^2$. Here we omit the subscript T for $\tilde{\alpha}$ and $\tilde{\sigma}^2$.Therefore, the variance of the distribution σ^2 of the traffic process at time scale T can be represented as:

$$\sigma^2 \sim \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\tilde{\sigma}} exp\left[-\frac{(\alpha - \tilde{\alpha})^2}{2\tilde{\sigma}^2}\right] T^{2\alpha} d\alpha \qquad (3)$$

Jeferson Wilian de Godoy Stênico and Lee Luan Ling, Department of Communication, School of Electrical and Computer Engineering, State University of Campinas – Unicamp, Brazil: E-mails: {jeferson, lee}@decom.fee.unicamp.br

Let $z = T^{2\alpha}$, then $\alpha = ln(z)/(2ln(T))$ and $d\alpha/dz = dz/(2ln(T)z)$. Then Equations (3) becomes

$$\sigma^2 \sim \int_0^\infty z \frac{1}{\sqrt{2\pi}(2ln(T)\tilde{\sigma})z} exp\left[-\frac{\left(ln(z)-(2ln(T)\tilde{\alpha})\right)^2}{2(2ln(T)\tilde{\sigma})^2}\right] dz \quad (4)$$

The right hand side of Equation (4) shows that σ^2 simply has a lognormal distribution $L(\omega, \theta)$ with parameters $\omega = 2ln(T)\tilde{\alpha}$ and $\theta = (2ln(T)\tilde{\sigma})^2$. For the lognormal representation given by (4), a simple calculation can show that the mean μ and variance σ^2 of the distribution of the multi-scaling increment traffic process at time scale T are related to ω and θ as:

$$\mu = exp(\varpi + \theta^2/2) \quad (5)$$

and

$$\sigma^2 = exp(2\varpi + \theta^2)[exp(\theta^2) + 1] \quad (6)$$

Therefore,

$$\omega = ln(\mu) - \frac{1}{2} ln\left(\frac{\sigma^2}{\mu^2} + 1\right) \quad (7)$$

and

$$\theta = \sqrt{ln\left(\frac{\sigma^2}{\mu^2+1}\right)} \quad (8)$$

Under the lognormal distribution, it can be that shown immediately that

$$\sigma^2 \sim exp[2ln(T)\tilde{\alpha} + 2(ln(T)\tilde{\sigma})^2] = T^{2\tilde{\alpha}} T^{2\tilde{\sigma} ln(T)} \quad (9)$$

III. Loss Probability Estimation

We now present the equation used to estimate the loss probability on a server considering multifractal traffic.

Proposition 1: Let $T > 0$, $W(t)$ be an accumulative multifractal process at time scale T, with a stationary increment at time scale T and with Pareto distribution . The loss probability for a single server with rate C and buffer size q is given by the following expressions:

$$P_{steady}(t) = \left(1 - \frac{\lambda}{C}\right) \int_0^\infty \frac{\left(aexp(bt)\right)\left((\lambda t) - \left(aexp(bt)\right)^{-1}(\lambda t)\right)^{aexp(bt)}}{(Ct + q)^{aexp(bt)+1}} dt \quad (10)$$

or

$$P_{steady}(t) = \left(1 - \frac{\lambda}{C}\right) \int_0^\infty \frac{(aexp(bt)+2)\left((\lambda t)\left(\frac{aexp(bt)+1}{aexp(bt)+2}\right)\right)^{aexp(bt)+2}}{(Ct+q)^{aexp(bt)+3}} dt \quad (11)$$

Proof: We assume that the single queue is stable with buffer capacity sufficient to accommodate eventual traffic transient bursts. Then, the balance equation for queue occupation is $Q(t_0) + V(t - t_0) = Q(t) + O(t - t_0)$, where $Q(t)$ is the queue length at time t, $V(t - t_0) = W(t) - W(t - t_0)$ is the cumulative traffic load over the period $[t, t_0]$, and $O(t - t_0)$ denotes the traffic load leaving on (t_0, t). Let $O(t) = C(t - I(t))$, where C is the constant service rate and $I(t)$ denotes the total server idle time of up to t. Assume $V(0) = 0$ and $Q(0) = 0$, then $Q(t) = max(V(t) - O(t), 0)$ or $Q(t) = max(Y(t) + \Delta t, 0)$, where $Y(t) = V(t) - Ct$ and $\Delta t = CI(t)$.

Applying the law of total probability, the loss probability in queue can be calculated as:

$$P_{loss} = P(Y(t) > q) + P\left(Y(t) \leq q < Y(t) + \Delta(t)\right) \quad (12)$$

The first term $P(Y(t) > q)$ in (12) is called the absolute loss probability (P_{abs}) and the second term $P\left(Y(t) \leq q \leq \Delta(t)\right)$ the opportunistic loss probability (P_{opp}). Assuming $Q(T)$ stationary, letting $\rho = 1 - \eta = 1 - \lambda/C$ and using the result derived by Benes [7 (Chapter 2)], the second term (P_{opp}) can be written as:

$$P_{opp}(t) = P\left(Y(t) \leq q < Y(t) + \Delta(t)\right)$$
$$= \rho \int_0^t f_{V(u)}(v)|_{v=Cu+q} du \quad (13)$$

Also, the absolute loss probability (P_{abs}) can be written as an integral:

$$P_{abs}(t) = P(Y(t) > q) = P(V(t) > Ct + q)$$
$$= \int_{Ct+q}^\infty f_{V(u)}(v) dv \quad (14)$$

Thus, the fully characterized queuing behavior of eventually any traffic type in term of information loss is given by:

$$P_{loss}(t) = \int_{Ct+q}^\infty f_{V(t)}(v) dPv + \rho \int_0^t f_{V(u)}(v)|_{v=Cu+q} du \quad (15)$$

For multifractal traffic process $V(t)$ with a Pareto distribution $f_{V(t)}(x) = \frac{\alpha k^\alpha}{x^{\alpha+1}}$ for $x > k$, the mean μ and variance σ^2 are related to the distribution parameters, k and α, as $\mu = \frac{\alpha k}{\alpha - 1}$ and $\sigma^2 = \left(\frac{k}{\alpha-1}\right)^2 \left(\frac{\alpha}{\alpha-2}\right)$, respectively. In other words, the mean and variance values can be numerically estimated directly from given input network traffic flows. Thus:

$$\alpha = \frac{\mu^2}{\sigma^2} \quad (16)$$

and

$$k = \mu - \frac{\sigma^2 \mu}{\mu^2} \quad (17)$$

or

$$\alpha = \frac{\mu^2}{\sigma^2} + 2 \quad (18)$$

and

$$k = \frac{\mu^3 + \sigma^2 \mu}{\mu^2 + 2\sigma^2} \quad (19)$$

Therefore, the first term on the right side of Eq. (14) can be further detailedly expressed as:

$$P_{abs}(t) = \int_{Ct+q}^\infty f_{V(t)}(v) dv = \left(\frac{k}{x}\right)^\alpha \text{ para } x \geq k \quad (20)$$

$P_{abs}(t) \to 0$ for $t \to \infty$, then the loss probability under stationary states is:,

$$P_{steady}(t) = \lim_{t\to\infty} P_{loss}(t) = \rho \sup_{t>0} \left\{\int_0^t f_{V(u)}(v)|_{v=Cu+q} du\right\} \quad (21)$$

or

$$P_{steady}(t) = \left(1 - \frac{\lambda}{C}\right) \int_0^\infty \frac{\alpha k^\alpha}{x^{\alpha+1}}|_{x=Cu+q} du \quad (22)$$

Note that for multifractal traffic series the variables α and k can be calculated using equations (16) and (17) or (18) and (19), respectively. Substituting the relations given by the equations (16) and (17) into (22), the loss probability can be estimated by:

$$P_{steady}(t) = \left(1 - \frac{\lambda}{c}\right) \int_0^\infty \frac{\left(\frac{\mu^2}{\sigma^2}\right)\left(\mu - \frac{\sigma^2 \mu}{\mu^2}\right)^{\frac{\mu^2}{\sigma^2}}}{(Ct+q)^{\frac{\mu^2}{\sigma^2}+1}} dt \qquad (23)$$

Again, now substituting the relations given by the equations (18) and (19) into (22), the loss probability can be estimated by:

$$P_{steady}(t) = \left(1 - \frac{\lambda}{c}\right) \int_0^\infty \frac{\left(\frac{\mu^2}{\sigma^2}+2\right)\left(\frac{\mu^3+\sigma^2\mu}{\mu^2+\sigma^2}\right)^{\frac{\mu^2}{\sigma^2}+2}}{(Ct+q)^{\frac{\mu^2}{\sigma^2}+3}} dt \qquad (24)$$

where $\mu = \lambda T$ and $\sigma^2 = T^{2\tilde{\alpha}} T^{2\tilde{\sigma} ln(T)}$.

Using an exponential function of the form $aexp(bT)$ to characterize the relation between the square mean and the variance under time scale $\left(\frac{\mu^2}{\sigma^2} \cong aexp(bx)\right)$, we get the expressions for the loss probability on a server considering multifractal traffic input.

$$P_{steady}(t) = \left(1 - \frac{\lambda}{C}\right) \int_0^\infty \frac{(aexp(bt))\left((\lambda t) - (aexp(bt))^{-1}(\lambda t)\right)^{aexp(bt)}}{(Ct + q)^{aexp(bt)+1}} dt$$

or

$$P_{steady}(t) = \left(1 - \frac{\lambda}{c}\right) \int_0^\infty \frac{(aexp(bt)+2)\left((\lambda t)\left(\frac{aexp(bt)+1}{aexp(bt)+2}\right)\right)^{aexp(bt)+2}}{(Ct+q)^{aexp(bt)+3}} dt \square$$

IV. EXPERIMENTAL INVESTIGATIONS

In this section we evaluate our approach for loss probability estimation, present our method for traffic admission control and dynamic resource allocation.

Figure 1 shows how the loss probability changes in terms of buffer size for two loss probability estimation equation given by (10) and (11) for traffic lbl-tcp-3 [8], considering server capacity equals 1 x 10^{-5} *Bytes/s*. Clearly, two loss probability curves are very close. Thus, for this work we adopt Eq. (10) thereafter.

A. Loss Probability Estimation

In experimental test we use Simpson's numerical method for solving the proposed expression to calculate the loss probability. For this, we used in simulation TCP/IP traffic trace named (lbl_pkt-5-10, dec-pkt-1-40, lbl-pkt-5). The traffic used in this study were taken from [8], the lbl-pkt-5-10 traffic trace corresponds to lbl-pkt-5 at an aggregation scale 10 milliseconds. Similarly, the dec-pkt-1-40 traffic trace comes of dec-pkt-1 at aggregation scale of 40 milliseconds. Table I summarizes the queuing system configuration (server capacity and buffer size) of the single server queue used in the simulation.

TABLE I. QUEUING SYSTEM CONFIGURATION

Traffic Trace	Server Capacity (Bytes/s)	Buffer Size (Bytes)
lbl_pkt_5	5.6 x 10^4	3 x 10^5
lbl_pkt_5_10	1.3 x 10^4	3 x 10^4
dec_pkt_1_40	12 x 10^5	3 x 10^5

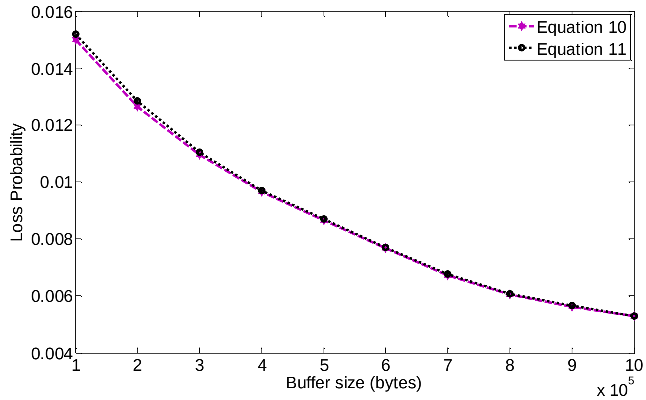

Fig.1. Differences between Equations 10 and 11

Table II compares the loss probability estimates (in number of bytes) for these traffic traces feeding a single server queue scheme defined in Table I, under the following methodologies, namely:

- Simulations: by simulations;
- The Duffield: by Duffield's method [9];
- Lognormal: the proposed exponential approach for variance with normal distribution and traffic having lognormal distribution;[10]
- MSQ: Multiscale Queue [6]
- CDTSQ: Critical Dyadic Time-Scale Queue [6].
- Proposed: our approach proposed in this paper.

Notice that Duffield method provides a lower bound of loss probability $P(Q > b)$ for self-similar processes. "Lognormal", "MSQ" and "CDTSQ" are three multifractal analyses for network traffic with long-range dependence [6]. Clearly the proposed analytical method provides the most faithful estimate among them, as illustrated by Table II. Our proposed approach in this work can be viewed as an alternative and improved version for the Lognormal method proposed in [10].

TABLE II. LOSS PROBABILITY ESTIMATES

Traffic Trace	lbl_pkt_5	lbl_pkt_5_10	dec_pkt_1_40
Simulation	4.76×10^{-4}	4.89×10^{-4}	4.08×10^{-5}
Duffield	4.02×10^{-30}	1.29×10^{-19}	8.09×10^{-15}
Lognormal	1.49×10^{-4}	1.87×10^{-4}	4.32×10^{-5}
MSQ	7.22×10^{-8}	4.28×10^{-7}	1.20×10^{-7}
CDTSQ	1.72×10^{-8}	1.80×10^{-7}	7.20×10^{-8}
Proposed	2.20×10^{-4}	4.18×10^{-4}	4.19×10^{-5}

Figure 2 compare how loss probability estimates vary in function of buffer size, for the dec_pkt_1_40 traces. Again, the proposed approach provides considerably better performances.

B. Admission Control for Multifractal Network Traffic

In this section we evaluate the potential application of the proposed loss probability estimation method and compare its performance to some widely used admission control algorithms, taking into account the characteristics of multifractal modeled traffic traces.

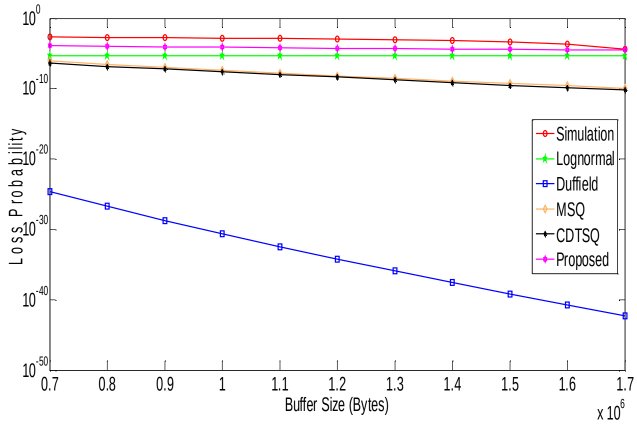

Fig. 2. Loss Probability versus Size of Buffer for the traffic trace dec_pkt_1_40.

The method consist of calculating the loss probability of input traffic data estimates at connections through Equation 10 or 11 and then making decision of acceptance or rejection of requested connections based on the computed analytical loss probability

The proposed admission control algorithm works as follows:

- Given a traffic trace, calculate the statistical parameters, including (mean and variance);
- We find the coefficients a and b of the exponential function used in the approximation of the relation between the square mean and the variance under time scale;
- We fixed the server setting to be used (the Server Capacity (C) and Buffer Size (q));
- We execute the Simpson method for calculating the loss probability given by Equation 10 or 11;
- Then, we do the multiplexing of the initial series with another series of traffic with the same amount of samples and rerun the algorithm;
- We multiplex a new traffic trace with others and run the algorithm for the loss probability to the value of be equal to 1;

In our simulations, different types of traffic traces were used, including TCP / IP traffic, video traffic and synthetic multifractal traffic. For the two experiments show in this paper, some synthetic traffic traces were generated by using FRACLAB [11], a Matlab toolbox. Each synthetic traffic trace holds 16,384 packet samples.

Table III shows the settings of the connection configuration adopted for each performed experiment. In each experiment, we varied the input traffic flow by aggregating a number of traffic traces. The main purpose of this manipulation is to determine the degree of quality of service, in terms of the loss probability, a connection can be granted to a traffic flow obtained from aggregating a number of distinct individual traffic traces. The number of traffic series involved in the aggregation varies from 1 to 10.

Figures 3 and 4 are related to the following traffic traces, respectively: synthetic fBm, synthetic multifractal. The figures show the amount of aggregate series versus the loss probability. In order to verify the validity of the proposed method, we perform experimental tests in a comparison with three other methods in the literature ("MVA", "Virtual Loss" and "Lognormal" strategies). The MVA model is an admission control algorithm based on maximum variance approaches, assuming that traffic has Gaussian characteristics [12]. Loss Virtual describe in [13] is an admission control strategy based on ratio of excess traffic and traffic load (see [13] for detail). Lognormal describe in [10] used an exponential approximation to model the second-order moment and assumes that the input traffic has a lognormal distribution.

TABLE III INPUT TRAFFIC TYPE AND QUEUING SYSTEM CONFIGURATION

Traffic Trace	Server Capacity (Bytes/s)	Buffer Size (Bytes)
Synthetic Multifractal	1×10^4	4×10^4
Synthetic fBm	2×10^4	4×10^4

Each figure shows how the loss probability changes in function of number of aggregated traffic series; that is, number of traffic series (i) denotes that the input traffic flow at queue was obtained from aggregating i traffic traces, which in most cases they are distinct. Remarkably the loss probabilities estimated from the proposed calculation faithfully follow to those obtained from the simulation, considerably much more than those obtained from applying the MVA, Virtual Loss and Lognormal methods. Mostly important, this result is observed for both experiments that involved different types of traffic data.

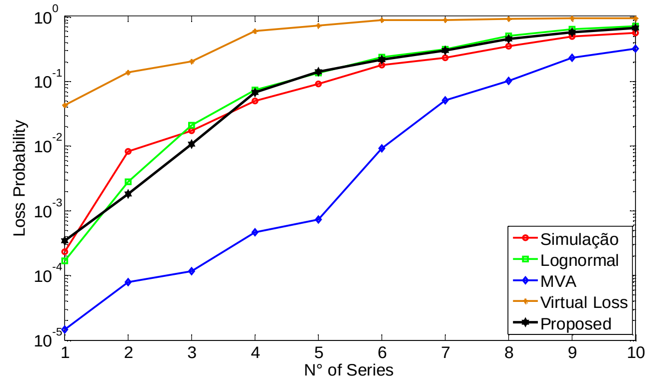

Fig. 3. Performance comparison for aggregated synthetic monofractal (fBm) traffic traces with varying long range dependences.

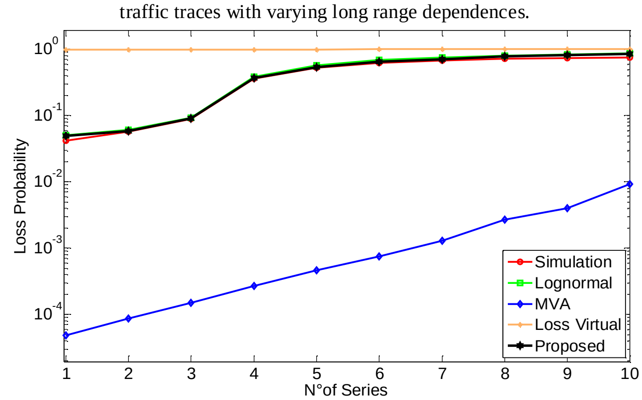

Fig. 4. Performance comparison for aggregated synthetic Multifractal traffic traces with varying statistical characteristics

C. *Dynamic Bandwidth Allocation*

The dynamic bandwidth allocation mechanism proposed here consists of determining the necessary bandwidth through the expression (10), which relates the QoS in terms of loss probability in function of transmission rate. In other words, for transmitting the traffic data on the time window (W_{n+1}) we make use of traffic information derived from the traffic data of the previous time window (W_n) such that the predefined connection QoS can be satisfied. Notice that it may happen that two adjacent windows overlap.

For comparison purposes, we also implemented: (a) a Virtual Loss [13] based dynamic resource allocation mechanism; (b) a numerical algorithm that determines precisely the minimum bandwidth for transmitting traffic data for each window and (c) the lognormal [10] based dynamic resource allocation mechanism. (d) The proposed dynamic resource allocation mechanism. Figure 5 shows the necessary transmission rate for transmitting a video traffic (Jurassic) [14] with 750 samples on each time window. Also included in Figure 5 the following additional information: (e) the average traffic rate (for each window); (f) the peak traffic rate (for each window). Similarly, Figure 6 compares the different dynamic resource allocation mechanism for Internet traffic BC_pAug89 [8].

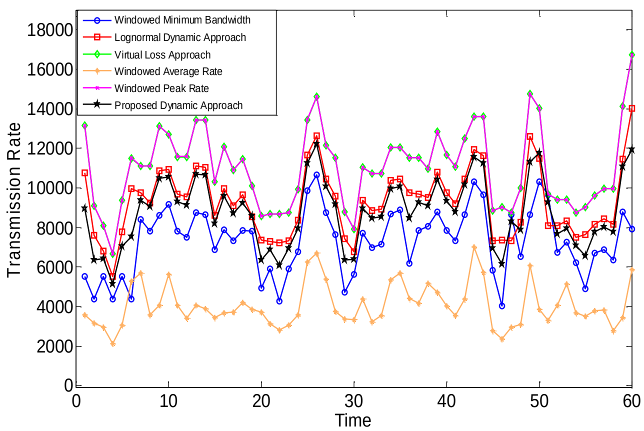

Fig. 5. Comparison among transmission rates estimated from different dynamic allocation strategies for an video traffic trace (Jurassic).

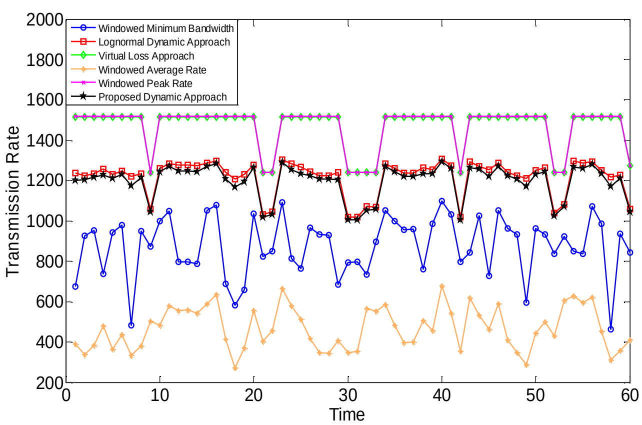

Fig. 6. Comparison among transmission rates estimated from different dynamic allocation strategies for an Internet traffic trace (BC_pAug89).

V. Conclusion

In this paper we present a new approach for calculating the loss probability for network traffic traces that have multifractal characteristics.

Initially, we address the definition concerning multifractal processes, assuming the processes have Pareto distribution. Using the queueing theory and some multifractal properties we are able to derive an expression to estimate the loss probability of the data in connections.

We compare the performance of the proposed approach with some other relevant approaches (e.g., monofractal based methods, Lognormal, MSQ and CDTSQ using real traffic traces.

Further, through the equation proposed was possible to propose an admission control scheme, which can be applied to various contexts of networks to ensure that flows meet loss requirements. Finally we present a dynamic bandwidth allocation mechanism based on our multifractal based loss probability.

The experimental results showed that the proposed estimation of loss probability is simple and accurate and we observed that the results obtained by admission control scheme proposed scheme as well dynamic bandwidth allocation mechanism is more robust and efficient in different situations compared to several existing methods in the literature.

References

[1] Leland, W.; Taqqu, M.; Willinger, W.; Wilson, D. On The Self-Similar Nature of Ethernet Traffic (extended version), IEEE/ACM Transactions on Networking, v.2,n.1, pp 1-15, Feb 1994.

[2] Norros, I. A Storage Model with Self-Similar Input, Queueing Systems, 16, pp.387-396, 1994.

[3] Feldmann, A.; Gilbert, A.; Willinger, W.; Kurtz, T. G. The Changing Nature of Network Traffic: Scaling Phenomena. ACM Computer Communication Review, v.28, p.5-29. Group, Tech.1 Rep.Disas-STP-93-30. 1998.

[4] Riedi, R. H.; Véhel, J. L. Multifractal Properties of TCP Traffic: A Numerical Study. Technical Report 3129, INRIA Rocquencourt, March 1997.[14]

[5] Taqqu, M. S.; Teverovsky, V.; Willinger, W. Is Network Traffic Self-Similar or Multifractal?, Fractals, vol. 5, pp. 63-74, 1997.

[6] Ribeiro, V. J.; Riedi, R. H.; Crouse, M. S.; Baraniuk, R. G. Multiscale Queueing Analysis of Long-Range-Dependent Network Traffic. IEEE INFOCOM 2000, pp. 1026-1035.,Tel Aviv, Israel.

[7] Benes, V. General Stochastic Processes in Theory of Queues.Reading, MA: Addison Wesley,1963.

[8] http://ita.ee.lbl.gov/html/traces.html. (Retrieved: April, 2013).

[9] Duffield, N.G.; O'Connell, N. Large Deviations and Overflow Probabilities for the General Singles-Server Queue, with Applications. Dublin Institute for Advanced Studies-applied Probability.

[10] Stenico, J.W.G; Lee.L.L. A Multifractal Based Dynamic Bandwidth Allocation Approach for Network Traffic Flows, IEEE ICC2010 – International Conference on Communications 23-27 may 2010 – Cape Town, South Africa.

[11] http://fraclab.saclay.inria.fr/ (Retrieved: April, 2013).

[12] Knightly, E.; Shroff, N. Admission Control for Statistical QoS: Theory and Practice. IEEE Network, 13(2), pp. 20–29, 1999.

[13] Murase, T.; Suzuki, H.; Sato, S.; Takeuchi, T. A Call Admission Control Scheme for ATM Networks Using a Simple Quality Estimate. IEEE JSAC, vol. 9, n°9, pp.1461-1470, December 1991.

[14] http://www.cs.columbia.edu/~hgs/internet/traces.html (Retrieved: April, 2013).