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A Tight Upper Bound Approximation of Loss Ratio in High-Speed Networks Based on Self-Similar Traffic

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***Abstract*— High-speed communication network technologies such as MPLS, ATM, DiffServ, etc can support multiple classes of traffic with different Quality of Service (QoS) requirements and diverse traffic characteristics. A main QoS requirement is Packet/Cell Loss Ratio (PLR/CLR). We need a real-time expression for calculating the loss ratio in these networks where statistical multiplexing is an important factor. In this paper, according to the fact that the real data traffic in high-speed networks in several cases shows a self-similar (fractal) behavior, we first, present a PLR simulation based on the self-similar traffic. Then, we have found a tight linear PLR approximation that can be calculated in real-time. At the end we have proposed a linear piece-wise approximation method to cover the whole practical range of the PLR in a finite buffer system.**

I. Introduction

Nowadays high-speed communication networks have concerned a lot of attention because they are expected to support a wide variety of services such as voice and video, and providing a guaranteed Quality of Service (QOS). Due to the huge link capacity of these networks, hundred even thousand of network applications and traffic classes are likely to be served by a network multiplexer.

To facilitate the coexistence of the multiple traffic classes, each type of these network technologies uses a specified mechanism e.g., ATM networks use virtual path (VP) and virtual circuits (VCs). These techniques simplify the traffic control, resource management and call establishment.

As the loss ratio is a main QoS requirement, we are interested in finding an accurate practical expression for the Packet/Cell Loss Ratio (PLR/CLR), which can be used in Call Admission Control (CAC) mechanism and routing algorithm of high-speed networks. The essential issue of CAC is exact estimation of network performance through real-time calculations.

To find an accurate loss expression we have to use a proper traffic model that captures the statistical characteristics of the actual traffic. This model will be used to predict queuing performance, delays and buffer dimensions [2].

Extensive data studies indicate that traffic in high-speed communication networks has Long-Range Dependency (LRD) and heavy-tailed (impulsive) characteristics which cannot be sufficiently represented by traditional models such as Markovian, but instead can be more accurately matched by self-similar models. These traffic features have a deteriorating impact on the network performance [2], [3]. Also when a large number of sources are multiplexed, characterizing the input process with Markovian models results in computational infeasibility problems.

In this work we have built an accurate numerical (simulation) model for a finite buffer system which is fed by the self-similar input. Second, we have proposed a tight linear approximation for the PLR in the mentioned networks that can be calculated in real-time. Then, we have improved our approximation model by applying a piece-wise linear approximation method to cover the practical range of PLR in a finite buffer.

The remainder of this paper is organized as follows:

Section Π gives an introduction to the proper traffic model of sources and the self-similarity phenomena with related distribution function. Loss probability concept and existing CLR/PLR expressions based on self-similar traffic are introduced in section Ш. In section IV we have proposed an accurate numerical model for finding Packet Loss Probability in a finite buffer system. The event processing and generating models are also given in this section and then, we propose a real-time upper bound expression for PLR based on a linear approximation in section V. In section VI, we extend our model to a piece-wise linear approximation model in the whole practical range of PLR and finally section VΠ contains the main conclusions and related discussions.

II. Traffic Model

A single traffic resource has a variable bit rate bounded by the maximum bit rate of its physical attachment. In order to characterize the effective bit rate or equivalent capacity of a connection we need to select an appropriate model to specify its characteristics in terms of known parameters or metrics.

Several studies of the real traffic data, mainly at the Bellcore [4] and EMU [5] have shown that the high-speed communication network traffics have LRD and heavy-tailed characteristics that have serious effects on Packet Loss issue. In the following we introduce the proper model to generate such traffics.

A. An Introduction to Self-Similarity

The self-similarity concept implies that a process is indistinguishable from its scaled versions obtained by averaging the original process within different observation time scales. Missing this property makes some other popular traffic model such as Poisson trace give over-optimized evaluation of network performances [6].

A mathematical description of self-similarity can be concluded as follow:

Assume an increment process X_i *(i=1, 2 ...)* and another process $X_j^{(m)}$ *(j=1, 2…)* which is obtained by aggregating the values in non-overlapped blocks of size *m* in X_i, i.e.,

$$X_j^{(m)} = \frac{1}{m}\left(X_{jm-m+1} + X_{jm-m+2} + \dots + X_{jm}\right) \quad (1)$$

The process X_i is said self-similar if

$$X_j^{(m)} \overset{dis}{\sim} m^{h-1} X_i \quad (2)$$

The symbol $\overset{dis}{\sim}$ denotes equality in distribution and the similarity between the distribution of $X_j^{(m)}$ and the distribution of X_i decays by a power law, i.e., factor m^{h-1}. In a more understandable way, this implies:

$$Var(X_j^{(m)}) = m^{2h-2} Var(X_i) \quad (3)$$

Where Var (.) denotes the variance of a process. Here *m* $(m \geq 1)$ is the scale parameter, whereas *h* $(0.5 < h \leq 1)$ is the Hurst parameter which is used to measure the burstiness of a process.

The LRD implies a non-summable autocorrelation function (ACF) of the process. It has been proved when $0.5<h<1$, the ACF of X_i is not summable [4].

B. Generating Self-Similar Traffic

The self-similarity is resulted from high probability for very large values that cannot be neglected. This can be understood as that a large packet burst makes the averaged value in a large observation time scale differentiated from its contemporaries. Therefore, when the large values occur so often that their effect cannot be neglected the variance of the trace decays very slow while the observation scale increases, i.e., exhibiting self-similarity. Therefore, to model self-similar trace we need some distribution with heavy-tailed Probability Density Function (PDF).

In practice we usually choose Pareto distribution to model heavy-tailed traffic trains [4]. The PDF of Pareto distribution is presented as:

$$\rho(x) = \frac{\alpha\beta^{\alpha}}{x^{\alpha+1}} \quad x \geq \beta \quad (4)$$

Where α is the shape parameter and β is the minimum value of *x*. When $1< \alpha$, this distribution has finite mean whereas when $\alpha <2$ it has infinite variance. Therefore, to model self-similar traffics we need $1< \alpha<2$, [6].

There are three different promising self-similar traffic generator based on different modeling approaches [5]:

- **Fractional Brownian traffic**, (Norros, 1993)
- **Superposed *on-off* sources**, (Mandelbrot, 1994)
- **Chaotic maps**,(Erramiili and Singh; 1994, 1999)

In this paper we consider the superposed *on-off* sources which cover the self-similarity and LRD characteristics of the network traffic. In this model each source independently and asynchronously alternates between the *on* and *off* states. Such source in an *on* period transmits at the peak rate and in an *off* period does not generate any traffic. The duration of the *on* and *off* periods are Pareto distributed for each source [4]. Moreover, the sources are mutually independent.

III. Loss Probability and Related Works

Loss probability (P_{loss}) in a finite buffer system is defined as the long-term ratio of the amount of fluid lost to the amount of fluid fed [7] or the probability of buffer overflow. It is a function of the traffic characteristics of the sources and the available network resources. P_{loss} is an important QoS measurement factor in communication networks as it can be used in CAC mechanisms and routing algorithms of high-speed communication networks.

There are two approximation models for the Cell Loss Probability in ATM multiplexers, fed by self-similar traffics in [3], [8].

In the first work, the self-similar process is modeled as a fractional Brownian motion which is proper to specify the connectionless traffics. This model is based on the theory of large deviation.

The second model is based on the Rational Approximation (RA), which can be used for connection oriented data traffic and estimating the small Cell Loss Probabilities. In the considered model sessions occur according to a Poisson process and each session has a Pareto distributed life time.

In reference [7] a loss approximation method is presented for the finite buffer systems that can be occupied in high-speed networks, where a large number of sources are expected to be multiplexed. The author has shown the accuracy of the proposed expression trough the simulation results by using different input traffic models, including self-similar Gaussian processes.

D'Apice *et al*. [9] proposed a Poison-Pareto model as a self-similar process to properly define the network traffic characteristics and determine the Packet Loss Ratio in telecommunication networks. In this work sessions arrive according to a Poisson process and the length of each session is Pareto distributed. It is shown here that the Packet Loss Probability is a function of the buffer size.

IV. Simulations Analysis

In this section an accurate numerical model for obtaining the loss ratio through simulation will be introduced.

In the simulation we consider a finite buffer with the capacity of *x* (Mbits), the FIFO queuing with self-similar arrival traffic and superposed *on-off* sources such that *on* and *off* periods are Pareto distributed with respective mean of 1(s) and $\frac{\alpha_{off}\,\beta_{off}}{\alpha_{off}-1}$ (s).

The source bit rate is zero during the *off* period and *r* (Mbps) in the *on* periods. The link capacity is *c* (Mbps) and we have a finite buffer of size *x*, receiving the traffic from *l*, *on-off* sources and discharging at the constant rate of *c*. The fraction of time the source is active is defined by *ρ*, and *f* represents the ratio of the link capacity to the source peak rate (*f=c/r*). As mentioned before *h* shows the burstiness of the traffic (Hurst parameter).

The objective is to find the buffer overflow probability (the loss probability). A discrete event simulation is built in C++ to obtain the P_{loss} for different value of l, x, f, h and ρ.

The simulation is done at the packet level and the results of the simulations are accurate with a confidence interval of $P_{loss} \pm 10^{-10}$ and confidence level of 99.9%. In the following, we will explain the event processing and generating model, which is used in this numerical model.

A. Event Processing Model

We model the finite-buffer case as a discrete event system. Such system is described by its state variables. A transition in the state variables occurs only as a result of an event. A transition in the state of a source from *on* to *off* or vice versa is described by an event. Each traffic source is represented by a chain of events triggered by an initial random seed event. The events are processed in chronological order.

B. Event Generating Model

The system maintains a Future Events List (FEL). For each source upon completion of an event, the next event in the chain is scheduled and stored in the FEL. In the presence of the l, *on-off* sources, the FEL contains l events at each time. Each event can be of the two *on*-to-*off* and, *off*-to-*on* types, which depends on the current state of the source. The event inter-arrival times are generated using an array of Pareto random numbers.

V. Linear Approximation

In this section we develop an accurate computationally efficient upper bound expression for the real-time calculation of the P_{loss} as a function of different network parameters such as l, x, h, f and ρ. This expression can be used in CAC mechanism of high-speed networks. Usually the desired Packet/Cell Loss Probability is considered in the range of 10^{-6} to 10^{-9} [1]. We have however, considered the range of 10^{-3} to 10^{-9} for P_{loss} to cover a wide range of parameters. Our objective is to find a numerically efficient expression for P_{loss} in this range with high accuracy.

Fig.1 shows PN_{loss} (the simulation results) for different values of ρ as a function of l. It can be seen that the logarithm of PN_{loss} in the range of 10^{-3} to 10^{-7} is a linear function of l.

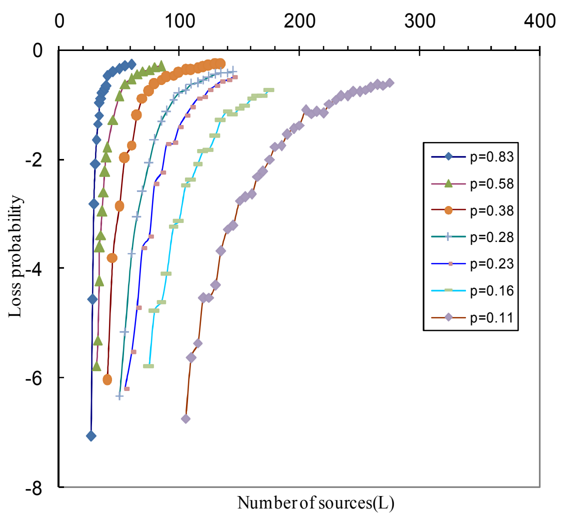

Fig.1. Log PN_{loss} as a function of l for different values of ρ, f=25, x=24, h=0.85.

TABLE I
The End Points of 27 Lines Which Estimate PLR in A Wide Range of x, f, p and h

x	f	p	h	X_1	Y_1	X_2	Y_2
24	25	0.11	0.85	114	3.56e-6	218	2.47e-2
		0.5	0.85	32	7.61e-7	50	5.23e-2
		0.83	0.85	27	1.43e-5	30	2.27e-2
	50	0.11	0.85	260	3.24e-6	440	1.03e-1
		0.5	0.85	76	5.88e-6	110	1.39e-1
		0.83	0.85	54	5.71e-6	70	1.47e-1
	100	0.11	0.85	590	4.09e-5	850	6.21e-2
		0.5	0.85	162	2.27e-7	230	1.70e-1
		0.83	0.85	110	3.75e-7	130	5.14e-2
48	25	0.11	0.85	120	1.71e-6	240	1.03e-1
		0.5	0.85	27	2.39e-6	35	1.63e-1
		0.83	0.85	27	4.23e-6	35	1.44e-1
	50	0.11	0.85	250	6.78e-6	470	1.36e-1
		0.5	0.85	78	4.94e-6	100	1.41e-2
		0.83	0.85	55	1.19e-6	68	1.41e-1
	100	0.11	0.85	170	3.65e-7	280	1.70e-2
		0.5	0.85	162	3.25e-7	200	2.48e-2
		0.83	0.85	112	9.68e-6	138	1.03e-1
96	25	0.11	0.85	130	2.67e-6	210	2.27e-2
		0.5	0.85	36	2.83e-7	54	1.23e-1
		0.83	0.85	27	2.74e-7	33	1.12e-1
	50	0.11	0.85	259	1.45e-7	410	3.46e-2
		0.5	0.85	79	9.04e-6	100	2.99e-2
		0.83	0.85	55	4.56e-6	70	1.00e-1
	100	0.11	0.85	480	7.78e-7	890	1.37e-1
		0.5	0.85	163	3.26e-7	210	1.07e-1
		0.83	0.85	112	2.94e-6	140	1.26e-1

We, therefore, use a linear approximation to obtain an expression for P_{loss}. The slope of the log (P_{loss}) is a function of the f, x, h and ρ. Let us define ψ as follows:

$$Log\,(p_{loss}) = \psi(l, f, x, \rho, h)$$
and
$$\partial\psi(l, f, x, \rho, h)/\partial l = f(l, f, x, \rho, h) \qquad (5)$$

Considering that ψ is a linear function of l. Table I shows the end points of 27 lines ,which estimate ψ *for* x of 24, 48 and 96, f of 25, 50 and 100, and ρ of 0.11, 0.5 and 0.83 and h of 0.85.

Our linear approximate model heavily depends on the ranges of the parameters (x, f, h *and* ρ) used in simulation. Therefore, it is very important that the values of the parameters cover the whole practical ranges concerning the high-speed network technologies.

In this approximation a wide range of traffic patterns from nearly burst (ρ=0.11) to nearly consistent bit rate (ρ=0.83) is considered. Additionally, we have considered the range of x (the buffer capacity) up to 96 Mbits, because a bigger buffer size leads to a higher delay [1].

These ranges are considered wide enough to achieve a general expression, which is valid in all ranges of the f, h, ρ, x and l. We need to find a line, in which the end points ((x_1, y_1) and (x_2, y_2)) are the functions of f, h, ρ and x and these parametric end points must be fitted to all of 27 end points ((x_1, y_1) and (x_2, y_2)) listed in Table I.

We attempt to find a linear approximation in the range of 10^{-3} to10^{-9} for the PLR. In all of these cases 4.09×10^{-5} is an upper bound for y_1 and 1.7×10^{-1} is an upper bound for y_2. We can therefore, write:

$$y_1 = Ln(4.09\times10^{-5}) = -10.1$$
$$y_2 = Ln(1.7\times10^{-1}) = -1.7 \qquad (6)$$

Due to the fact that the above fixed values are considered for y_1 and y_2 only x_1 and x_2 must be determined as functions of the network and traffic parameters. In Table I, we have several sample points of two multiple parameters functions ((x_1, y_1) and (x_2, y_2)). Now, we want to fit two curves to these sample points so that the Mean Square Error (MSE) becomes minimum.

We have considered that these functions can be estimated as expression (7):

$$x(f,x,\rho,h) = k_1 f + k_2 x + k_3 \rho + k_4 h + k_5 fx + \dots + k_i fx\rho h + \dots + k_n \frac{fx}{\rho h} \qquad (7)$$

We use a new extended of the Least Mean Square Error (LMSE) method, to be used for estimating the coefficients of the multiple parameter expression (7) numerically [1]. In this approach, we have developed an algorithm to find the best coefficients of a full free multiple parameter function by minimizing the Mean (or sum) Square Error for all the sample points.

We ran this algorithm for the sample points of Table I, and the following expressions were found. It should be noted that some of the coefficients are zero (or nearly zero).

$$\begin{aligned} x_1 &= f(0.16+0.3h)+\frac{1}{\rho}(0.5f+0.6h) \\ x_2 &= f\left(0.4+0.5h+\frac{4}{x}\right)+\frac{1}{\rho}(0.7f+1.3h) \end{aligned} \qquad (8)$$

The linear estimation can be written as:

$$\ln(P_{lin\_loss}) = \frac{y_2(x_1-l)+y_1(l-x_2)}{x_1-x_2} \qquad (9)$$

By substituting for x_1, x_2, y_1 and y_2 in the above expression we can write:

$$P_{lin\_loss} = e^{\frac{8.4l-f(3.4+7.6h-\frac{40.4}{x})-\frac{1}{\rho}(11h+9.2f)}{f(\frac{4}{x}+0.24+0.2h)+\frac{1}{\rho}(0.7h+0.2f)}} \qquad l < x_2 \qquad (10)$$

Figs. 2(a, b) demonstrate the accuracy of expression (10) in the practical range of operation. It should be noted that PN_{loss} is considered as the actual value of the PLR.

VI. PIECE-WISE LINEAR APPROXIMATION

For the purpose of generality, we develop a piece-wise linear approximation model for the whole range of PLR in a finite buffer system. This model consists of tree line segments. Based on the results in Fig. 1, we considered these segments as follows (see Table II).

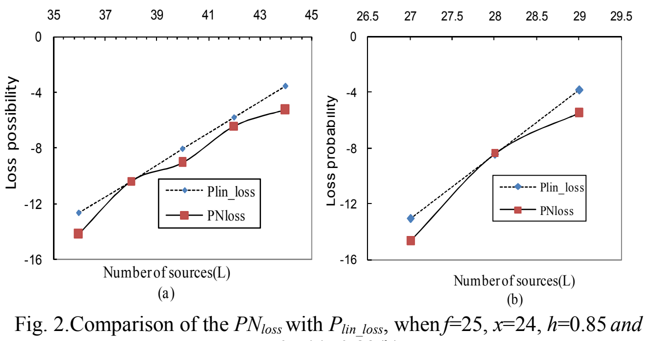

Fig. 2.Comparison of the PN_{loss} with P_{lin_loss}, when f=25, x=24, h=0.85 *and* ρ= 0.5(a), 0.83(b).

TABLE II
The Line Segments of the Piece-Wise Linear Approximation Method

Line segment	Ln of PLR in the first end point	Ln of PLR in the second end point
Line segment of 1	y_1=LN(4.09×10^{-5})	y_2=LN(1.7×10^{-1})
Line segment of 2	y_2=LN(1.7×10^{-1})	y_3=LN(6.2×10^{-1})
Line segment of 3	y_3=LN(6.2×10^{-1})	y_4=LN(9.1×10^{-1})

Fig. 1 shows that the logarithm of PN_{loss} in each of the above ranges is a linear function of *l*. Just like the mentioned linear approximation method, here we have found again the following upper bound values based on the Table Ш.

$$\begin{aligned} y_3 &= Ln(6.2\times10^{-1}) = -0.47 \\ y_4 &= Ln(9.1\times10^{-1}) = -0.09 \end{aligned} \qquad (11)$$

Also, we have found following expressions based on the Table Ш, which are approximations of x_3 and x_4:

$$\begin{aligned} x_3 &= \frac{1}{\rho}(0.16x+0.8f+2.8h)+\frac{1}{x}(2.8f+1.1h+1.9\rho)+0.8\frac{f}{h} \\ x_4 &= \frac{1}{\rho}(0.6x+4.9f+5.5h)+\frac{1}{x}(5.7f+5.5h)+4.5\frac{f}{h}+7\frac{h}{f} \end{aligned} \qquad (12)$$

We can now find PLR expressions for line segments 2 and 3, based on the above linear approximation. For example for the segment 2 we have:

$$\ln(P_{lin\_loss}) = \frac{y_3(x_2-l)+y_2(l-x_3)}{x_2-x_3} \qquad (13)$$

After replacing x_2 and x_3 by their approximations and y_2 and y_3 by their values, we have:

$$P_{lin\_loss} = e^{\left(\frac{1.23l+f(0.18+0.23h-\frac{1.27}{h})-\frac{1}{\rho}(0.26x+4.1h+0.94f)-\frac{1}{x}(3.1\rho+1.8h+2.8f)}{\frac{1}{x}(1.9\rho+1.1h-1.2f)+f(\frac{0.8}{h}-0.5h-0.4)+\frac{1}{\rho}(1.5h+0.1f)}\right)} \quad x2 \le l < x3 \qquad (14)$$

Repeating this process for the last segment, the following piece-wise linear approximation of the PLR is obtained:

$$P_{Piece\_wise\_loss} = \begin{cases} e^{\left(\frac{8.4l-f(3.4+7.6h-\frac{40.4}{x})-\frac{1}{\rho}(11h+9.2f)}{f(\frac{4}{x}+0.2h+0.24)+\frac{1}{\rho}(0.7h+0.2f)}\right)} & l < x2 \\ e^{\left(\frac{1.23l+f(0.18+0.23h-\frac{1.27}{h})-\frac{1}{\rho}(0.26x+4.1h+0.94f)-\frac{1}{x}(3.1\rho+1.8h+2.8f)}{\frac{1}{x}(1.9\rho+1.1h-1.2f)+f(\frac{0.8}{h}-0.5h-0.4)+\frac{1}{\rho}(1.5h+0.1f)}\right)} & x_2 \le l < x_3 \\ e^{\left(\frac{0.38l-\frac{1}{\rho}(0.2x+2h+1.8f)-\frac{1}{x}(2h+2.1f)-0.26\frac{h}{f}-1.7\frac{f}{h}}{-\frac{1}{\rho}(0.03x+0.24h+0.36f)-\frac{1}{x}(0.17\rho+0.39h+0.33f)-0.6\frac{h}{f}}\right)} & x_3 \le l \end{cases} \qquad (15)$$

TABLE III

Values of x_3, x_4, y_3 and y_4 in a Wide Range of x, f, h and ρ

X	f	p	h	X_3	Y_3	X_4	Y_4
24	25	0.11	0.85	360	4.6e-1	1800	9.0e-1
		0.5	0.85	80	3.9e-1	520	9.1e-1
		0.83	0.85	60	5.6e-1	290	9.0e-1
	50	0.11	0.85	700	4.4e-1	3000	9.0e-1
		0.5	0.85	200	5.2e-1	960	9.0e-1
		0.83	0.85	150	6.2e-1	640	9.0e-1
	100	0.11	0.85	1400	4.5e-1	5000	9.0e-1
		0.5	0.85	450	5.7e-1	2000	9.0e-1
		0.83	0.85	260	5.4e-1	1100	9.0e-1
48	25	0.11	0.85	360	4.6e-1	1800	9.0e-1
		0.5	0.85	60	5.0e-1	500	9.0e-1
		0.83	0.85	55	4.6e-1	300	9.0e-1
	50	0.11	0.85	880	5.5e-1	3360	9.0e-1
		0.5	0.85	140	3.1e-1	940	9.0e-1
		0.83	0.85	112	4.7e-1	600	9.0e-1
	100	0.11	0.85	440	4.1e-1	5200	9.0e-1
		0.5	0.85	280	3.3e-1	2000	9.0e-1
		0.83	0.85	220	4.5e-1	1200	9.0e-1
96	25	0.11	0.85	360	4.6e-1	1800	9.0e-1
		0.5	0.85	110	5.6e-1	500	9.0e-1
		0.83	0.85	68	5.6e-1	320	9.0e-1
	50	0.11	0.85	650	3.9e-1	3300	9.0e-1
		0.5	0.85	160	3.9e-1	920	9.0e-1
		0.83	0.85	140	5.7e-1	600	9.0e-1
	100	0.11	0.85	1300	4.2e-1	5000	9.0e-1
		0.5	0.85	450	5.7e-1	2000	9.0e-1
		0.83	0.85	260	5.5e-1	1200	9.0e-1

Where x_1 to x_4 are defined by the following expressions:

$$x_1 = (0.16 + 0.3h)f + \frac{1}{\rho}(0.5f + 0.6h) \quad (16)$$

$$x_2 = (0.5 + 0.4h + \frac{4}{x})f + \frac{1}{\rho}(0.7f + 1.3h)$$

$$x_3 = \frac{1}{x}(1.9\rho + 2.8f + 1.1h)f + \frac{1}{\rho}(0.16x + 0.8f + 2.8h) + 0.8\frac{f}{h}$$

$$x_3 = \frac{1}{x}(5.7f + 5.5h)f + \frac{1}{\rho}(0.6x + 4.9f + 5.5h) + 4.5\frac{f}{h} + 7\frac{h}{f}$$

Fig.3 illustrate the accuracy of the discussed piece-wise linear approximation technique. Here it can be observed that the proposed model is a tight upper bound approximation that covers a wide range of PLR.

VII. CONCLUSION

In this paper we discuss the Packet Loss Ratio as an important factor of Quality of Service (QoS) requirements in high-speed networks. We first, present an accurate numerical simulation to model a finite buffer system and the loss issues in such system. By considering the self-similar characteristics of the real network traffic in many cases, we used a self-similar process as the input traffic model in our simulations. Second, to decrease the computational complexity of calculating the loss ratio, we proposed a tight linear PLR approximation expression, based on exact modeling of system behavior in the finite buffer case. This expression can be computed in real-time.

Finally we improved our model to a piece-wise approximation that covers the practical range of PLR in this system. We have verified the accuracy of our proposed models through simulation results.

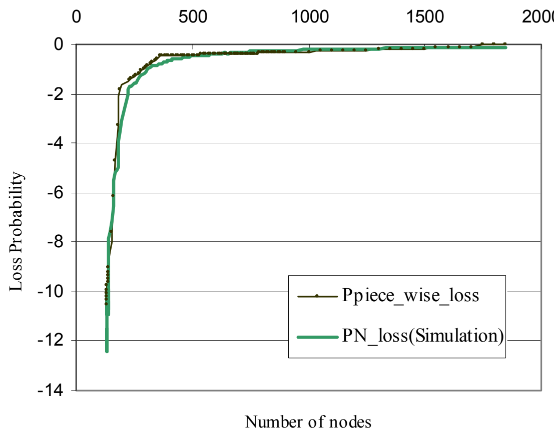

Fig. 3.Comparison of the PN_{loss} with $P_{piece\_wise\_loss}$, when f=25, x=96, h=0.85 *and* ρ= 0.11.

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