Real-Time Packet Loss Probability Estimates from IP Traffic Parameters

Ahmad Vakili
Institut national de la recherche scientifique
(INRS-EMT)
Montreal, Canada
vakili@emt.inrs.ca

Jean-Charles Grégoire
Institut national de la recherche scientifique
(INRS-EMT)
Montreal, Canada
gregoire@emt.inrs.ca

***Abstract*—For network service providers, assessing and monitoring network parameters according to a Service Level Agreement and optimal usage of resources is important. Packet loss is one of the main factors to be monitored, especially when IP networks carry multimedia applications. Measuring network parameters is more valuable when it is accurate and online. In this paper, we propose an accurate approximation for packet loss probability at an intermediate high speed node with finite buffer, where a large number of sources are expected to be aggregated. In this method, based on *Large Deviation Theory*, estimation of packet loss probability at the intermediate nodes is based on the input stochastic traffic process. In accordance with *Central Limit Theorem* arguments, the input process is modelled as a general Gaussian process. Different traffic situations and node buffer sizes are simulated (with NS-2 software) and the effectiveness of the method is examined via a detailed numerical investigation. The simulation results show that our proposed method significantly improves the quality of packet loss probability estimate compared to other recently introduced estimators.**

***Keywords*—Packet loss probability, estimation, stochastic traffic process.**

I. Introduction

In telecommunications, performance is assessed in terms of quality of service (QoS). QoS, in turn, is measured either in terms of technology (e.g., for ATM, cell loss, variation, etc.) or at some protocol level (e.g., packet loss, delay, jitter, etc.) [1]–[3].

Today, increased access to Internet networks as well as broadband networks have made possible and affordable the deployment of multimedia applications such as Internet telephony, video conferencing, and IP television (IPTV) by academia, industry, and residential communities. Therefore the quality assessment of media communication systems and the parameters, which affect this quality have been an important field of study for both academia and industry for decades. Due to the interactive or online nature of media communications and the existence of applicable solutions to deduce the effect of delay and jitter (e.g., deployment of a jitter buffer at the end user node [4][5]), data loss is a key issue, which must be considered. If there is a possibility for online accurate measurement of packet loss, then the network service providers can take the appropriate action to satisfy the contractual Service Level Agreement (SLA) or to improve and troubleshoot their service without receiving end user feedback.

Packet loss often happens because of congestion. In other words, buffer overflow at the outgoing interface in intermediate network nodes causes packet loss. Since measuring packet loss ratio at the intermediate nodes in high speed networks does not seem applicable in real time, some recent research has focused on estimation of packet loss probability (plp) [1][6]–[9].

According to central limit theory, the aggregated input traffic at intermediate nodes in the network core can be described with a Gaussian model [10][11]. Based on the Large Deviation Theory (LDT) and the large buffer asymptote approach, the plp can be estimated by a stochastic process considering the probability of buffer overflow in a finite buffer system where b is the buffer size (or tail probability $\mathbb{P}\{Q > b\}$ in a infinite buffer system). Since the input traffic is described by a Gaussian process, the latter can be identified by an online measure of the mean and variance of the input traffic.

In this paper, we propose a tighter approximation of plp based on the input traffic process and the information, which was measured in the past. In other words, we use some online measures and historical data for accurate estimation and thus improve on earlier proposed estimates. Our plp estimation method can also compose with systems whose buffer size is not large enough to meet the assumptions of the large buffer asymptote approach.

Furthermore, this estimate can integrate well with a quality control architecture. Using the online estimated plp as feedback information, a control system could properly throttle the ingress traffic rate and keep the plp below some target upper bound value of packet loss in an SLA. An overall architecture of measurement, estimation, and control loop to keep the quality of service/experience within the SLA bounds is shown in Fig. 1. In this figure, the estimated plp is used as an online transducer in a control loop of packet loss.

The paper continues in Section II by reviewing prior bodies of work on measuring or estimating the packet loss probability. Section III provides some useful definitions, which are employed in this paper. In Section IV, we develop a new plp estimator. Section V presents the testbed and the simulations used to assess the quality of our estimator. Numerical results and comparison that demonstrate the effectiveness of our proposed estimator are presented in Section VI. Section VII concludes the paper and points to our future work.

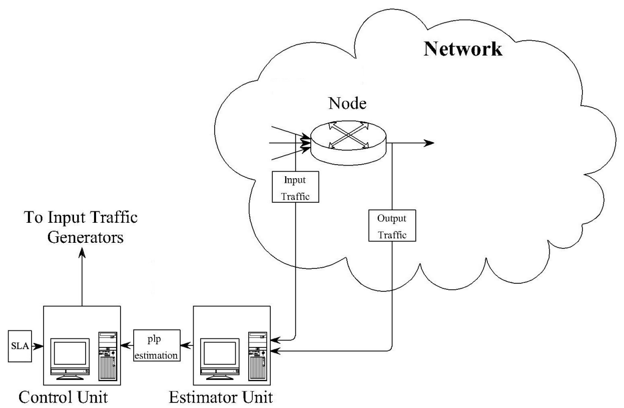


Fig. 1. Measurement, estimation, and control loop schematic.

II. Previous work

In our observations, earlier research on measuring and modelling the packet loss would generally either increase the burden of probe packets' bit rate to the available bandwidth [6][12][13] or not provide real time information [14]–[16]. For example, [14] and [15] have characterized loss traces by identifying mathematical models. Yin Zhang et al. in [17] and [18] have analyzed the stationarity of the loss process on the Internet paths and studied its predictability. Although these studies are undoubtedly useful to understand the general loss characteristics, they cannot be used in real time performance estimation and consequently online control systems.

To obtain real time network performance information such as available bandwidth, delay, and loss, various probing techniques have been recently used by researchers. For instance, [15], [19], and [20] have employed packet pair and packet train techniques, respectively, to measure bottleneck bandwidth. He et al. in [21] have used probing method to explore end-to-end traffic by exploiting the long range dependence nature of Internet traffic. The authors of [12] and [13] have measured the loss rate on individual links by end-to-end multicast/unicast probes and different inference techniques. Further, Tao and Guérin in [6] have used a probing method to construct a Hidden Markov Model (HMM) [22] to capture the main characteristics of loss process such as loss length distribution, loss distance, etc. The disadvantage of these methods is to increase the burden of probe packets' bit rate to the available bandwidth when better accuracy is required.

To cope with the shortcomings of the aforementioned methods, many researchers have tried to link the input process to the loss probability at intermediate nodes. Behavior of the FIFO scheduler fed by many on-off sources was investigated by Anick et al. in [23]. Elvalid et al. and Stern et al. in [24] and [25], respectively, extended Anick's work by presenting a simple approximation of the loss for a very large buffer size system whose input can be modelled with Markov Modulated Rate Processes (MMRP). Their mathematical models are derived from large deviation theory (LDT).

Studies, which estimate loss probability based on input traffic process generally fall into one of the following methodological categories given their underlying assumptions:

- *Large buffer asymptote*: In this approach, the intermediate node's buffer size is assumed to be large. The value of overflow and consequently loss attained in the case of small buffer size is extrapolated using the large buffer asymptote. Chang in [26] and the references therein review this topic comprehensively. Zhang and Ionescu in [8][9][27][28] have extended this research to estimate the loss probability.
- *Large number of sources asymptotic*: This method is based on the homogeneity of n identical sources that feed the intermediate node's input buffer. Likhanov and Mazumdar in [29] used this methodology to estimate the loss probability.
- *Aggregate traffic approximation*: This approach is used to reduce the computational complexity of input traffic model estimation. It is employed when an intermediate high-speed node's input traffic consists of a large number of individual user traffic flows with unique characteristics, in which case the large number of sources asymptotic method is not applicable [30]. The main justification for a packet loss probability estimation based on aggregate traffic approximation is the Bahadur-Rao Theorem, which computes the asymptotic tail distribution of the sum of n identically non-lattice random variables when $n \to \infty$ [31].

In this paper, we use *large buffer asymptote* approach for online packet loss estimation. Our work revisits Zhang and Ionescu's research [8][9][27][28] (i.e., recent work on this topic); we will review their method and explain how we overcome its shortcomings at the end of Section IV.

III. Definitions

The input traffic model and packet loss probability are explained in this section. All the definitions are related to a high speed intermediate node in which the received packets are served with First In First Out (FIFO) scheduling.

A. Input traffic model

According to the Central Limit Theorem (CLT), the aggregated traffic at an intermediate link in a high-speed network can be well approximated by a Gaussian process [32][33][34]. Moreover, characterizing the input process of a large number of sources with the traditional Markovian models seems infeasible. Therefore, in our study the input process λ_n is characterized by a Gaussian process and presented by

$$\lambda(t) = \mu t + \sigma Z(t), \tag{1}$$

where μ and σ^2 are the mean and variance of arrival rate (i.e., $\lambda(t)$), respectively. $Z(t)$ is a centered Gaussian process when $Var\{Z(t)\} = 1$ [35].

B. Packet loss probability

The packet loss probability, P_{loss}, is defined as the long term ratio of the number of lost packets to the number of input packets. It is expressed by the following formula:

$$P_{loss} = \lim_{N\to\infty} \frac{\sum_{k=1}^{N}(q_{k-1}+\lambda_k - c - b)^+}{\sum_{k=1}^{N}\lambda_k} = \frac{\mathbb{E}[l_k]}{\mathbb{E}[\lambda_k]}, \quad (2)$$

where $(x)^+$ denotes $max\{x,0\}$, b is buffer size, c is output link capacity, and q_k and l denote the number of packets that occupy the buffer in the time interval $[k, k+1)$ and the number of lost packets, respectively. $\mathbb{E}[x]$ is the expected value of variable x.

The packet loss ratio, $plr(k)$, is defined as the short term ratio of the amount of packets lost to the amount of input packet. It is expressed by the following formula:

$$plr(k) = \frac{l(k)}{\lambda(k)}, \quad (3)$$

where $l(k)$ is the number of lost packets during the time slot $[k, k+1)$ and $\lambda(k)$ is the number of packets that arrive during the time slot $[k, k+1)$.

Kim and Shroff in [32] showed that the plp in a buffer of size x can be well approximately mapped from the tail probability in the infinite buffer system. Tail probability also called the *overflow probability* $\mathbb{P}\{Q > x\}$ is expressed as

$$\mathbb{P}\{Q > x\} = \lim_{N\to\infty} \frac{1}{N}\sum_{k=1}^{N} I(Q_k > x), \quad (4)$$

where $I(A)$ is an identification function, which is equal to 1 if A is true and equal to 0 otherwise, and Q is the dynamic queue size. Although $\mathbb{P}\{Q > x\}$ is averaged by time and plp is averaged by the input, [32] shows the following relationship between $\mathbb{P}\{Q > x\}$ and plp:

$$P_{loss}(x) = \alpha\mathbb{P}\{Q > x\}, \quad (5)$$

where α is constant and equal to $P_{loss}(0)/\mathbb{P}\{Q > 0\}$ and $P_{loss}(0)$ denotes the packet loss probability in a bufferless system.

C. Effective bandwidth

The *effective bandwidth* of arrival traffic process $A(t)$ is defined as

$$\omega(\theta, t) = \frac{1}{\theta t} ln\mathbb{E}[e^{\theta A(t)}] \quad 0 < \theta, t < \infty, \quad (6)$$

where θ and t are system parameters determined by the channel capacity and buffer size, the QoS requirement, and the characteristics of the multiplexed sources [36]. Based on Gärtner-Ellis theorem [37][38], $\omega(\theta,\infty)$ exists when the input traffic is Gaussian. So,

$$\omega(\theta^*, \infty) = \lim_{t\to\infty} \frac{1}{\theta^* t} ln\mathbb{E}[e^{\theta^* A(t)}] = c, \quad (7)$$

where c is link capacity. Glynn and Whitt in [39][40] have proved that overflow probability can be related to θ^*, which is calculated from (7) as following

$$\lim_{x\to\infty} \frac{1}{x} ln\mathbb{P}\{Q > x\} = -\theta^*. \quad (8)$$

IV. Packet Loss Probability Estimator

There are several approaches to estimate packet loss probability. Sending probe packets periodically through the path and processing the returned signals for predicting the performance of path (e.g., packet loss ratio, delay, etc.) is one of the recent methods for estimating the plp [6][41]. The disadvantage of this method is to increase the burden of probe packets' bit rate to the available bandwidth when greater accuracy is requested.

Estimation of plp based on stochastic input traffic process is another approach in this field [8][9][42]. In this method some important assumptions are made as follows: 1) Measurement and estimation take place at intermediate nodes in high-speed network core links, therefore the input traffic is a mix of a large number of individual traffics and thus the Gaussian process model is considered to represent the stochastic input traffic process [10][11]; and 2) the size of the buffer should be large, otherwise the queue process is not exponential and the behaviour of the traffic in small buffers cannot be approximated by a logarithmically linear behavior [43][44][26], so the input traffic process cannot estimate plp.

Following the Gaussian model assumption for the input traffic, the effective bandwidth in this model [36] is given by:

$$\omega(\theta, t) = \mu + \frac{\theta}{2}\sigma^2 t^{(2H-1)} VarZ(t), \quad (9)$$

where θ is the *space* parameter, t is the *time* parameter, which corresponds to the most probable duration of the buffer congestion period prior to overflow, μ is defined as the *traffic mean*, *Var* represents the second moment of *Z(t)*, which is equal to 1 (see (1)), σ^2 is the *variance* of the input traffic random variable, and *H* is the *Hurst* parameter.

The Hurst parameter H shows the degree of self-similarity in the traffic. $H = 0.5$ corresponds to a well behaved Gaussian traffic while any value larger than 0.5 indicates a self-similar traffic source. Based on the classical assumption for input traffic [42][45], the H parameter is set to 0.5. So the effective bandwidth is finite, independent of time, and can be simplified into:

$$\omega(\theta, t) = \mu + \frac{\theta}{2}\sigma^2. \quad (10)$$

Further, if μ and σ exist, effective bandwidth, in case of $t\to\infty$, is equal to link capacity (see (7)). Therefore,

$$\omega(\theta^*, \infty) = \mu + \frac{\theta^*}{2}\sigma^2 = c. \quad (11)$$

Based on our second assumption of large buffer asymptotic approach for packet loss estimation, the overflow probability for the large buffer size can be approximated by a logarithmically behavior as follow [39][40]:

$$\exists\kappa \in \mathbb{R}^+, \mathbb{P}\{Q > x\} = \kappa e^{-\theta^* x}, \quad (12)$$

where θ^* is the solution of (11). Note that such an approximation in (12) is more precise when the buffer size x is large [26]. Therefore, $\mathbb{P}\{Q = x\}$ can be defined by

$$\mathbb{P}\{Q = x\} = \kappa(e^{\theta^*} - 1)e^{-\theta^* x}. \tag{13}$$

To estimate the packet loss probability, $\mathbb{E}[l_k]$ of (2) is defined as follows (recall that b is buffer size):

$$\mathbb{E}[l_k] = \int_b^\infty (x - b)\mathbb{P}\{Q = x\}\, dx. \tag{14}$$

From (13) and (14), we have

$$\mathbb{E}[l_k] = \kappa(e^{\theta^*} - 1)\frac{e^{-\theta^* b}}{{\theta^*}^2}, \tag{15}$$

where θ^* calculated from (11) is

$$\theta^* = 2\frac{c - \mu}{\sigma^2}. \tag{16}$$

Solving (11) in θ^* and replacing in (15) define P_{loss} by the following equation:

$$P_{loss} = \frac{\mathbb{E}[l_k]}{\mathbb{E}[\lambda_k]} = \kappa(e^{2\frac{(c-\mu)}{\sigma^2}} - 1)\frac{e^{-2b\frac{(c-\mu)}{\sigma^2}}}{4\mu\frac{(c-\mu)^2}{\sigma^4}}. \tag{17}$$

Applying the natural logarithm (ln) to (17), we derive the following estimator:

$$\begin{aligned}\ln(P_{loss}) = \ln(e^{2\frac{(c-\mu)}{\sigma^2}} - 1) - 2b\frac{(c-\mu)}{\sigma^2} \\ -\ln\left(4\mu\frac{(c-\mu)^2}{\sigma^4}\right) + \ln(\kappa).\end{aligned} \tag{18}$$

In line with other similar studies [8][9], we change the base of the logarithm function from e to 10. Thus, (18) can be replaced by:

$$\begin{aligned}\log(P_{loss}) = \log(e^{2\frac{(c-\mu)}{\sigma^2}} - 1) - 2b\frac{c-\mu}{\sigma^2}\log(e) \\ -\log\left(4\mu\frac{(c-\mu)^2}{\sigma^4}\right) + \log(\kappa).\end{aligned} \tag{19}$$

Replacing μ and σ with their measurement value $\bar{\mu}(k)$ and $\bar{\sigma}(k)$ changes (19) into the following equation:

$$\begin{aligned}\log(P_{loss}) = \log(e^{2\frac{(c-\bar{\mu}(k))}{\bar{\sigma}^2(k)}} - 1) - 2b\frac{c-\bar{\mu}(k)}{\bar{\sigma}^2(k)}\log(e) \\ -\log\left(4\bar{\mu}(k)\frac{(c-\bar{\mu}(k))^2}{\bar{\sigma}^4(k)}\right) + \kappa',\end{aligned} \tag{20}$$

where $\kappa' = \log(\kappa)$ and $\bar{\mu}(k)$ and $\bar{\sigma}(k)$ are defined as:

$$\bar{\mu}(k) = \frac{1}{N}\sum_{i=0}^{N-1}\bar{\lambda}(k-i), \tag{21}$$

and

$$\bar{\sigma}^2(k) = \frac{1}{N-1}\sum_{i=0}^{N-1}\left[\bar{\lambda}(k-i) - \bar{\mu}(k)\right]^2, \tag{22}$$

where $\bar{\lambda}(k)$ is the measured input packet rate in the kth time interval and N is the number of time intervals for calculating the average of the mean and variance of the packet rate.

In the rest of the paper let $epl(k)$ denote the $\log(P_{loss})$, which is estimated by

$$\begin{aligned}epl(k) = \log(e^{2\frac{(c-\bar{\mu}(k))}{\bar{\sigma}^2(k)}} - 1) - 2b\frac{c-\bar{\mu}(k)}{\bar{\sigma}^2(k)}\log(e) \\ -\log\left(4\bar{\mu}(k)\frac{(c-\bar{\mu}(k))^2}{\bar{\sigma}^4(k)}\right),\end{aligned} \tag{23}$$

and let $plp(k)$ denote the logarithm of real packet loss probability during the time slot $[k, k+1)$, which can be expressed by:

$$plp(k) = \log\left(\frac{l(k)}{\lambda(k)}\right), \tag{24}$$

where $l(k)$ is the number of packets lost during the time slot $[k, k+1)$ and $\lambda(k)$ is the number of packets that arrive during the time slot $[k, k+1)$.

Some estimation errors are expected due to the assumption made for the stochastic traffic process and the simplifications and approximations employed in (23) (e.g., κ' is eliminated from (20)). Numerical results in the next section show that estimating the plp with (23) completely follows the variation of plp, although there is an almost constant offset between the real plp value and epl, which is best explained from ignoring the constant κ' in (20).

To eliminate this difference it is proposed to use the offline measured plp and compare it with the estimated one to obtain the offset. We therefore present an improved estimator, iep, defined as:

$$\begin{aligned}iep(k) = epl(k) \\ +\frac{1}{n}\sum_{l=1}^{n}\left[plp(k-l-m) - epl(k-l-m)\right],\end{aligned} \tag{25}$$

where m is the number of interval periods after which the data of plp is available and $epl(k)$ and $plp(k)$ are calculated via (23) and (24), respectively.

With this improved estimator, the required time for measuring and calculating the plp is represented by m in (25), where the mean of errors between epl and plp during a moving window (i.e., n time intervals) in the past (i.e., m time intervals ago) is added to epl to estimate the new plp. Note that the duration of the time interval is independent from the measurement and calculation speed of plp. In other words, the estimator depends on m, in (25), only for the duration of the measuring time interval.

As we have mentioned in Section II, Zhang and Ionescu [8][27][28] also have proposed a packet loss probability estimator based on LDT and buffer asymptote approach. Their estimator describes packet loss probability by:

$$epl' = \log(P_{loss}) = -2b\frac{c-\mu}{\sigma^2}\log(e) - \log\left(2\mu\frac{(c-\mu)}{\sigma^2}\right). \tag{26}$$

To cope with their estimator's error, they have introduced a Reactive Estimator (re) [9], which is defined as:

$$re(k) = epl'(k) + \frac{1}{n}\sum_{l=1}^{n}\left[plp(k-l) - re(k-l)\right], \tag{27}$$

where epl' is packet loss probability estimated by (26).

A careful examination of (27) reveals that the error re attempts to correct will decrease to the amount of difference between re and plp, whereas the error really is the difference between epl' and plp.

We thus claim that our proposed estimator, iep, does a better job at tracking plp. To investigate the accuracy and applicability of the aforementioned estimators and to compare their performance with that of our estimator, we propose to conduct simulations. In these simulations, the effects of different configurations of network traffic and packet loss ratio on estimators' performance are examined, and then will be discussed in detail in Sections V and VI.

V. Simulation Testbed

The NS-2 software [46] is used to simulate the network. The network topology, which is simulated is shown in Fig. 2.

An MPEG2 traffic flow is generated by node 1 and the Real-time Transport Protocol (RTP) is deployed for transferring video data to node 4. Node 2 generates the voice traffic flow, which is coded by G.729 [47]. This data is transferred to node 5. Node 3 and node 6 are designed to generate the common Internet traffic flow for background traffic and make the aggregated traffic situation closer to the Gaussian distributed traffic for stochastic input traffic process. The Tmix module in NS-2 is utilized in node 3 and 6 in order to generate realistic Internet network traffic [48]. The protocol deployed for communications between nodes 3 and 6 is TCP. Since the background traffic is TCP-based, congestion (i.e., buffer overflow and loss) affects traffic flows, which leads to a situation similar to that of a real Internet network traffic. Nodes 7 and 8 generate the on-off traffic to randomly increase the probability of packet loss. Measurement of the input and output traffics is performed at node 9. Since the focus is on node 9, the bandwidth of all links except link A is set to 100 Mbps and the buffer size of all nodes except node 9 is set to 500 packets. We vary the size of the node 9 buffer from 5 packets to 100 packets to examine different router configurations. To generate different amounts of packet loss, the bandwidth of link A varies between 7.4 Mbps and 7.8 Mbps. With these settings loss takes place only in node 9. When the bandwidth of link A is set to 7.8 Mbps and nodes 7 and 8 do not generate any traffic, the packet loss probability is about 0.1 percent and when the bandwidth is decreased to 7.4 Mbps, the packet loss probability in node 9 increases to about 1 percent, which is closer to the amount where effect of loss on media communication quality becomes annoyingly noticeable. By turning on the traffic of nodes 7 and 8 at some short periods of time, the packet loss probability reaches 7 percent, which is an unacceptable amount of packet loss for media communications. In the next section the numerical values of the different estimators in these situations will be examined.

VI. Numerical Results Analysis

This section presents the experimental results of the evaluation of the performance of the proposed estimator for the different types of traffic generated in the simulation testbed. The accuracy of the loss probability predicted by our proposed estimator is compared to that of a couple of other recent estimators.

A. Input traffic

The crucial assumption in estimating loss probability based on input traffic process is the Gaussian behavior of the aggregated input traffic. Therefore, the verification of this statement (i.e., the aggregated input traffic process is a Gaussian process) is the first test, which should be performed. So, the received times of all packets for aggregated traffic are measured, while node 1 generates MPEG2 traffic flow, a voice traffic is generated by node 2, and node 3 sends an approximate common Internet traffic mix through the core of testbed.

In this paper the graphical technique is used for normality testing, although, the Chi-Square test [49] could also be used to verify the assumption of Gaussian behavior of input traffic in our simulations. Fig. 3, which shows the instantaneous input traffic bit rate and the distribution of input traffic visually, verifies that in our simulations the aggregated traffic in core link can be approximated by Gaussian traffic and consequently, the main assumption of proposed estimator is met.

B. Individual flow loss

To satisfy the SLA and to take the appropriate action on each flow's source, a control system needs to be aware of the packet loss probability of each flow. However, only the aggregated traffic loss probability can be estimated by the proposed estimator.

The simulation results show that the loss ratio of each flow (e.g., MPEG2 flow) is very close to loss ratio of the aggregated traffic. Therefore, it can be concluded that the estimated loss probability of aggregated traffic can be used as the individual probability of packet loss. Fig. 4 verifies this statement by showing that the measured MPEG2 flow's packet loss ratio is very close to the packet loss ratio of aggregated traffic in node 9.

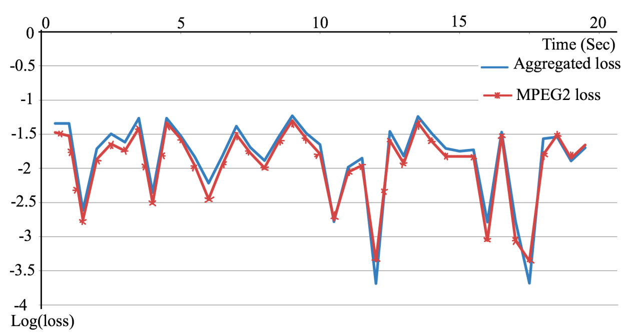


Fig. 4. Comparison of the MPEG2 loss ratio with the aggregated traffic loss ratio.

C. Estimator performance

First, to evaluate that if the epl from (23) follows the plp variation with an almost constant offset, a situation has been

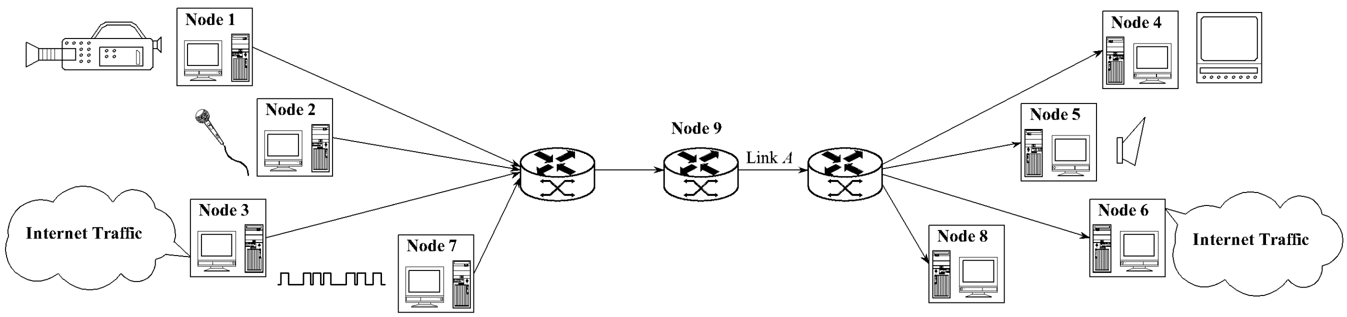
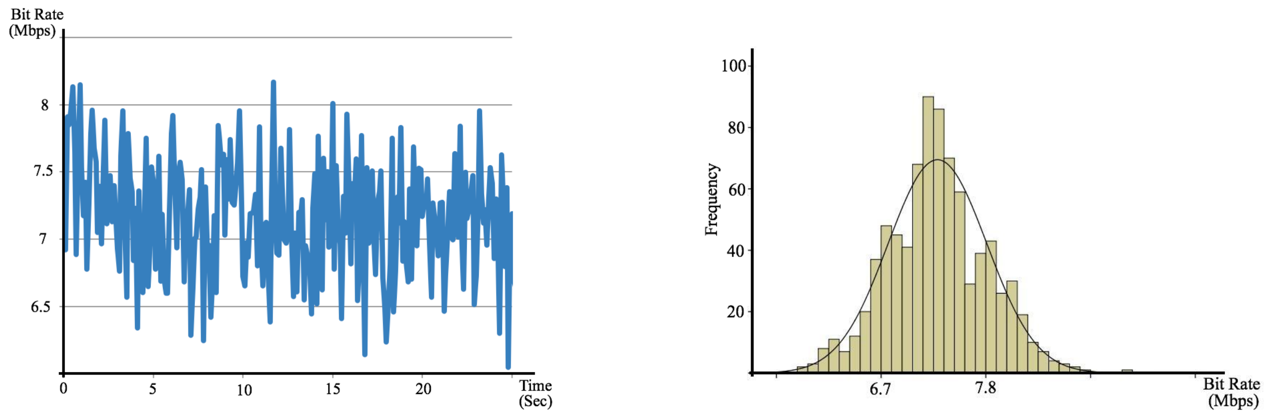


Fig. 2. Testbed topology.



(a) Instantaneous input traffic bit rate.

(b) Histogram of input traffic distribution.

Fig. 3. Aggregated input traffic characteristics in network core.

investigated in which the bandwidth of link A was 7.4 Mbps and there was no traffic coming from nodes 7 and 8. As shown in Fig. 5, although there is an offset between plp and epl, epl follows the variation of plp thoroughly and this can be seen as a clear sign of soundness of the use of epl as the main part of proposed estimator.

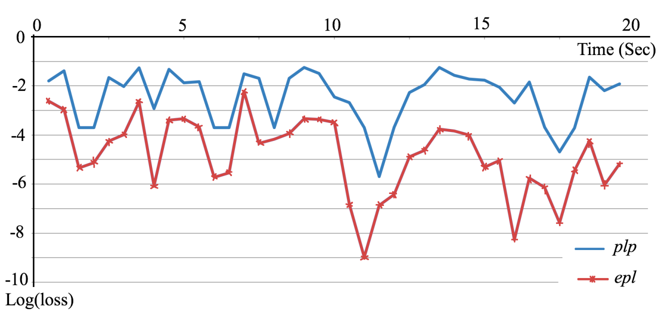


Fig. 5. Comparison of plp (measured loss) and epl (estimated loss with offset).

Next, all the mentioned estimators (i.e., epl', re, and our proposed estimator, iep) are evaluated and their performance compared in different situations.

Fig. 6 shows the performance of the different estimators in a situation where the bandwidth of link A is 7.8 Mbps and there is no traffic coming from nodes 7 and 8. The accuracy of proposed estimator (iep) to estimate the plp compared to the other estimators is demonstrated in this figure.

In all experiences the time interval is 100 ms. In Fig. 6 iep is calculated according to (25) where m is 5. This means that iep uses plp data measured up to 500 ms earlier.

Since the amount of loss in the former example might be negligible for media communications, we change the network conditions to increase the loss ratio and then re–evaluate the accuracy of estimators. To achieve this situation, the buffer size of node 9 is decreased to 10 packets. Fig. 7 shows the results of this experience: during the time periods of $[10, 15]$, nodes 7 and 8 add network traffic and bring the loss ratio close to 7 percent ($log(plp) = -1.5$). As Fig. 7 shows, the effect of simplification and approximation in (26) and (27) on the operation of epl' and re methods is more apparent at this larger loss ratio.

Tables I and II summarize the statistics for the different estimators with varying loss ratio. In all comparisons the error is defined as the difference between estimated and measured plp.

As mentioned before, the buffer size affects the plp and the accuracy of estimators [43][44]. The larger the buffer size, the lesser plp and the better the accuracy of the estimation. The

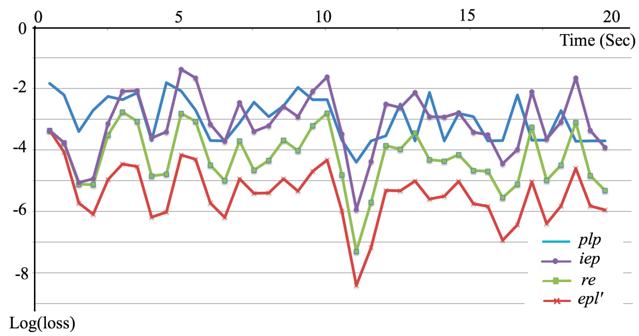


Fig. 6. Measurement and estimation of packet loss probability when plp is about -2.5.

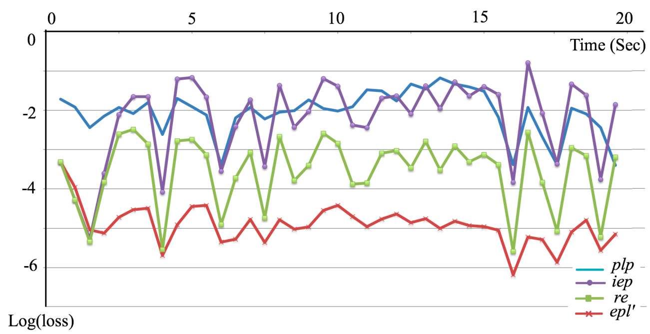


Fig. 7. Measurement and estimation of packet loss probability when plp is about -1.5.

effect of buffer size on estimation methods re and epl' has been examined in [8] and [27], respectively. The value of m, in (25), also affects the accuracy of iep estimation.

To examine the accuracy of the proposed estimator in different configurations (i.e., buffer size and m), we introduce a new variable, $error$. Given that the errors of logarithmic variables (plp's) are not easily comparable, $error$ is defined as follows to make it more sensible to small variations:

$$error = 10^{estimation} - 10^{plp}. \quad (28)$$

Fig. 8 shows the probability density function of $error$ when buffer size is 10, 30, and 100 packets, and m is 5, 10, and 20 ($m = 10$ means using a plp measured 1 s before), and the effect of buffer size on estimation. Fig. 8-(a),(b), and (c) show that our proposed estimator has better performance in the case of a larger buffer. Note that a larger buffer size causes more latency, which is not suitable particularly for multimedia transmission; hence, it should be set carefully. However, in our simulations, the buffer size of 100 packets causes only a 15 ms delay, which could be even lower in real high speed intermediate networks.

It can be also shown by Fig. 8 that the offline measuring speed affects the accuracy of our proposed estimator: the faster the measurement, the more accurate the estimation.

Further considering the effect of buffer size on estimations derived from (23), it appears that the accuracy of estimation

TABLE I
STATISTICS SYNOPSIS ON LOSS PROBABILITY ESTIMATION FOR DIFFERENT ESTIMATORS WHEN plp IS ABOUT -2.5.

Estimator	Error* Mean	Error Variance	Error Min	Error Max
iep	0.16	0.77	0.016	2.24
epl'	2.47	0.60	0.88	4.22
re	1.27	0.70	0.25	2.98

Error* is equal to difference between estimations (iep, epl', and re) and plp.

TABLE II
STATISTICS SYNOPSIS ON LOSS PROBABILITY ESTIMATION FOR DIFFERENT ESTIMATORS WHEN plp IS ABOUT -1.5.

Estimator	Error Mean	Error Variance	Error Min	Error Max
iep	0.19	0.45	0.016	2.8
epl'	2.86	0.50	1.59	3.8
re	1.49	0.24	0.20	2.93

(iep) will improve if the role of the measured plp is increased. Therefore, (25) is changed to:

$$iep(k) = p \times epl(k) + \frac{1}{n}\sum_{l=1}^{n}[plp(k-l-m) - p \times epl(k-l-m)], \quad (29)$$

where p is the proportional coefficient and is less than 1. To increase the importance of the second term in (29), n is increased from 3, which is recommended in [9], to 10 and to decrease the effect of first part, p is set to $\frac{2}{3}$. For a smaller p, when a considerable variation happens to plp, the estimator (iep) cannot follow the plp properly and the value of $error$ will be significant.

Fig. 9 shows the value of $error$ when buffer size is 10 and (29) is used for estimation. Comparing Fig. 9 and Fig. 8(a), the effectiveness of the changes in estimation is clear.

To conclude, the advantages of our proposed estimator are: 1) an increase in the accuracy of estimation by using the measured parameters properly, 2) flexibility on the duration of measuring time interval, and 3) an estimate of plp reasonably accurate in the case of a small buffer.

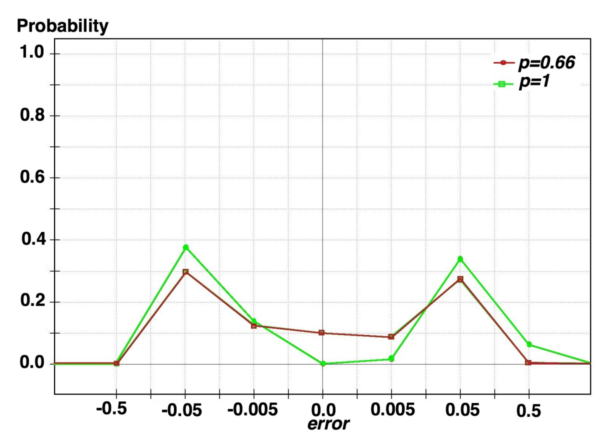
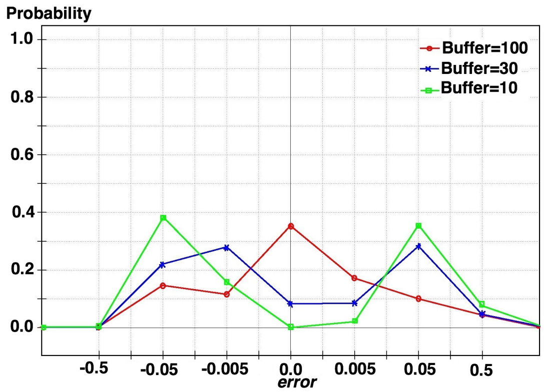
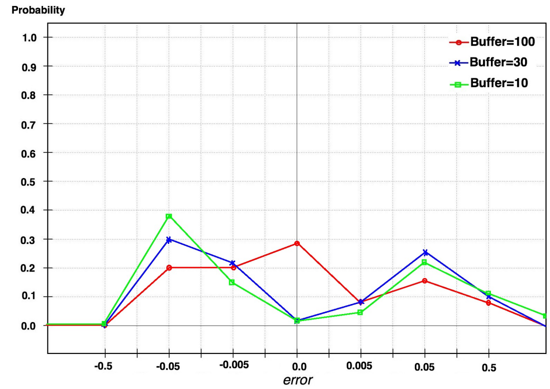


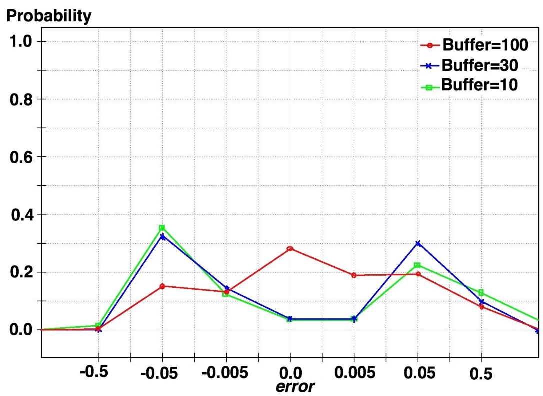
Fig. 9. PDF of $error$ for estimator, which uses (29) when buffer size is 10.



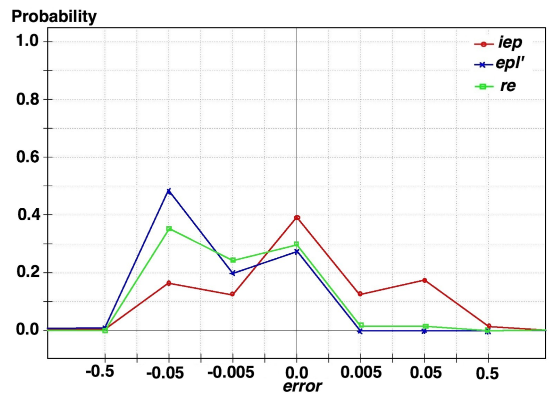
(a) PDF of $error$ for different buffer size when m is 5.



(b) PDF of $error$ for different buffer size when m is 10.



(c) PDF of $error$ for different buffer size when m is 20.



(d) PDF of $error$ for different estimators when buffer size is 100, m=5, and there is no random traffic.

Fig. 8. The comparison of PDF of $error$ for different conditions.

VII. Conclusion

One of the most important issues in multimedia quality of experience is packet loss, which has an especially critical role in interactive communications. Accurate online network-based measurements of loss are necessary to give service providers the means to estimate the quality received by a user and to give them an opportunity to take remedial actions to satisfy the contractual SLA. Increased use of multimedia communications in the Internet has led to a renewed interest in the measure and estimation of loss, in the form of the plp, in modern communication networks. More specifically, recent studies have focused on estimation of the plp by measurement of input traffic based on LDT and the large buffer asymptote. In this paper, we have reviewed the theory behind the finite buffer overflow probability (tail probability in infinite buffer) estimation. Based on *central limit theory*, by modelling the input traffic of an intermediate high speed node as a Gaussian process, we have introduced a new approximation for plp. Combining this online approximation with the offline output traffic measurement, we have proposed an accurate plp estimator, which significantly improves the quality of the estimate compared to the recent proposed plp estimators [27][28], which have used similar theoretical basis.

To study the accuracy of the estimates, we have used the NS-2 simulator with the input traffic, which is very similar to the Internet traffic at the measurement node. Overall, the simulation results demonstrate the effect of different configurations, such as buffer size, on the estimates. The analysis of the results shows the improvement of accuracy in plp estimation achieved by our new calculation method.

For future research, we plan to investigate how it is possible to estimate the end user's perception, aka the Quality of Perception (QoP), based on the effect of loss. Along this line of research, we plan to study the methods of estimation of other network parameters (e.g., delay and jitter) to utilize them as the input of QoP measurement.

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