Estimation of Packet Loss Probability from Traffic Parameters for Multimedia over IP

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***Abstract*—For network service providers, assessing and monitoring network parameters according to a Service Level Agreement (SLA) as well as optimal usage of resources are important. Packet loss is one of the main factors to be monitored especially when IP networks carry multimedia applications. Measuring network parameters will be more valuable when it is accurate and online. In this paper, we investigate a method to estimate packet loss probability (*plp*) under several conditions and improve the quality of the estimation over established techniques by introducing a new formula. In this method, the estimation of the *plp* in the intermediate nodes is based on the input stochastic traffic process. Different traffic situations and node buffer sizes are simulated by NS-2 and the accuracy of the method is investigated. The simulation results show that our new formula significantly improves the quality of the *plp* estimate.**

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

I. Introduction

In telecommunications, performance is assessed in terms of quality of service (QoS). QoS is measured either in terms of technology (e.g., for ATM, cell loss, variation, etc.) [1] or at some protocol level (e.g., packet loss, delay, jitter, etc.) [2].

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 (VoIP), 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 communication 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 [3], [4]), data loss is a key issue which should be considered. If there is a possibility for online accurate measuring of the amount 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 the packet loss. Since measuring the 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) [5]-[8].

According to central limit theory, the aggregated input traffic at intermediate nodes in the network core can be described with a gaussian model [9], [10]. Based on the Large Deviation Theory (LDT) and the large buffer asymptote approach, the plp can be estimated by a stochastic process. Since the input traffic is described by a gaussian process, the latter can be identified by online measure of the mean and variance of the input traffic. In this paper, the plp is estimated by the input traffic and the information which was measured in the past. In other words, we use some online and offline measuring data for accurate online estimation and improve on earlier results. The overall architecture of measurement, estimation, and control loop to keep the quality of service/experience within the SLA bounds is shown in Fig. 1.

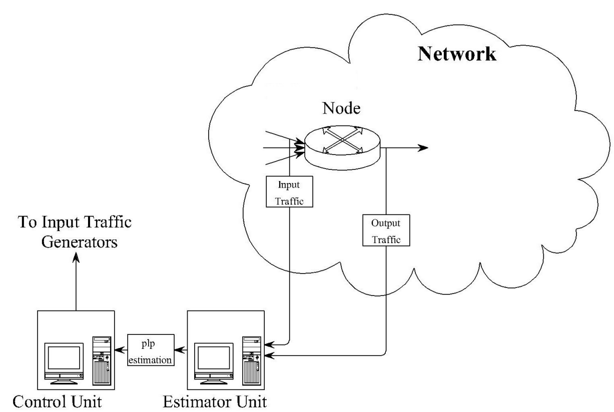

Fig. 1. Measurement, estimation, and control loop schematic.

The rest of the paper is organized as follows: Section II describes recent studies on plp estimators and introduces our improved estimator. Section III presents the testbed and our simulations. Numerical results and comparison that demonstrate the effectiveness of our new estimator are presented in Section IV. Section V concludes the paper and points to our future work.

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II. 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 [5], [11]. 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 [7], [8], [14]. In this method some important assumptions are taken as follows: 1) Measurement and estimation take place at intermediate nodes in high-speed core links of networks and 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 [9], [10]; and 2) the size of the buffer should not be large, otherwise the queue process is not exponential and the behaviour of the traffic in large buffers cannot be approximated by a logarithmically linear behaviour [12], [13], so the input traffic process cannot estimate plp.

Following the gaussian model assumption for the input traffic, the effective bandwidth in this model [15] is given by:

$$eb(\theta, t) = \mu + \frac{\theta}{2t} VarZ(t) \tag{1}$$

and

$$VarZ(t) = \sigma^2 t^{2H} \tag{2}$$

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*, *Z(t)* is the stochastic process gaussian distributed with a mean of zero, *Var* represents the second moment of *Z(t)*, σ^2 is the *variance* of the random variable, and *H* is the *Hurst* parameter.

Based on the classical assumption for input traffic, the H parameter is set to 0.5 [7]. So the effective bandwidth can be simplified into:

$$eb(\theta, t) = \mu + \frac{\theta}{2}\sigma^2 \tag{3}$$

In [16], Chang has proven that plp can be calculated by the following equation based on LDT:

$$ln(P_{loss}) = -\theta^* b - ln(\mu\theta^*) \tag{4}$$

where θ^* is the solution for

$$\lim_{t \to \infty} eb(\theta, t) = c \tag{5}$$

and *c* is the finite value (i.e., the bandwidth). By solving (3) and (5) and replacing θ^* in (4), P_{loss} can be obtained from:

$$ln(P_{loss}) = -\frac{2(c-\mu)}{\sigma^2} - ln\left(\frac{2\mu(c-\mu)}{\sigma^2}\right) \tag{6}$$

In line with other similar studies [7], [8], we change the base of the logarithm function from e to 10. Thus, (6) can be replaced by:

$$log(P_{loss}) = -\frac{2(c-\mu)}{\sigma^2} log(e) - log\left(\frac{2\mu(c-\mu)}{\sigma^2}\right) \tag{7}$$

Replacing μ and σ with their measurement value $\bar{\mu}(k)$ and $\bar{\sigma}(k)$ changes (7) to the following equation:

$$\begin{aligned} log(P_{loss}) = &-\frac{2(c-\bar{\mu}(k))}{\bar{\sigma}^2(k)} log(e) \\ &-log\left(\frac{2\bar{\mu}(k)(c-\bar{\mu}(k))}{\bar{\sigma}^2(k)}\right) \end{aligned} \tag{8}$$

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

$$\bar{\mu}(k) = \frac{1}{N}\sum_{i=0}^{N-1} \bar{\alpha}(k-i) \tag{9}$$

and

$$\bar{\sigma}^2(k) = \frac{1}{N-1}\sum_{i=0}^{N-1} [\bar{\alpha}(k-i) - \bar{\mu}(k)]^2 \tag{10}$$

where $\bar{\alpha}(k)$ 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 the formulas above, and $plp(k)$ denotes the logarithm of real packet loss probability during the time slot $[k, k+1)$ which can be expressed by:

$$plp(k) = log\left(\frac{l(k)}{\alpha(k)}\right) \tag{11}$$

where $l(k)$ is the number of lost packets during the time slot $[k, k+1)$ and $\alpha(k)$ 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 (8). Zhang et al. introduce in [8] a Reactive Estimator (re) which is constructed as:

$$re(k) = epl(k) + \frac{1}{n}\sum_{l=1}^{n}[plp(k-l) - re(k-l)] \tag{12}$$

where $epl(k)$ and $plp(k)$ are calculated via (8) and (11), respectively. This estimator uses the measured $\{plp(k-l), l = 1, 2, ..., n\}$ data for reducing the error between re and plp.

A careful examination of (12) reveals that the error will be decreased to the amount of difference between re and plp, whereas the error is really the difference between epl and plp. We therefore present a new, improved estimator, cre, defined as:

$$\begin{aligned} cre(k) = &\ epl(k) \\ &+\frac{1}{n}\sum_{l=1}^{n}[plp(k-l-m) - epl(k-l-m)] \end{aligned} \tag{13}$$

where m is the number of interval periods after which the data of plp is available from (11).

With this new estimator, the required time for measuring and calculating the plp is represented by m in (13), 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. Therefore, the duration of time interval is independent from measurement and calculation speed of plp, whereas in former estimator (re) the minimum duration of time interval was equal or greater than the required time for measuring and calculating plp (it is assumed in (12) that the measured plp is available after one interval time). In other words, m in (13) makes the new estimator flexible about duration of measuring time interval.

To investigate the accuracy and applicability of the re and epl estimators and to compare their performance with that of our proposed estimator, cre, 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, which will be discussed in detail in Sections III and IV.

III. Simulation Testbed

The NS-2 software [17] is used to simulate the network. The network topology which is simulated is shown in Fig. 2.

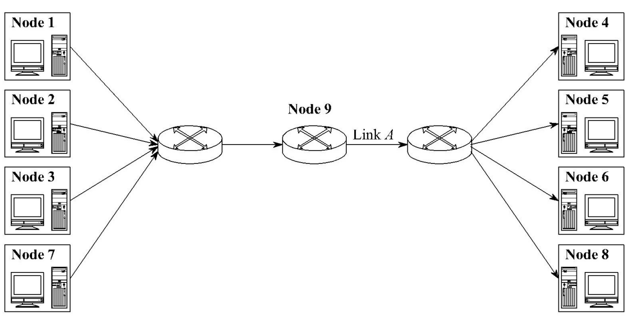


Fig. 2. Testbed topology.

An MPEG2 traffic flow is generated by node 1 and the RTP protocol is deployed for transferring video data to node 4. Node 2 generates the voice traffic flow which is coded by G.729. 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 [18]. The protocol deployed for communications between nodes 3 and 6 is TCP. Since the background traffic is TCP-based traffic, 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 packet loss probability. 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 buffer of node 9 from 5 packets to 100 packets to examine different router configurations. The bandwidth of link A, to generate different amounts of packet loss, varies between 8 Mbps to 10 Mbps. With these settings loss takes place only in node 9. When the bandwidth of link A is set to 10 Mbps and nodes 7 and 8 do not generate any traffic, the packet loss probability will be about 0.1 percent and when the bandwidth is decreased to 8 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 considerable. 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 loss packet ratio for media communications. In the next section the numerical values of the different estimators in these situations will be examined.

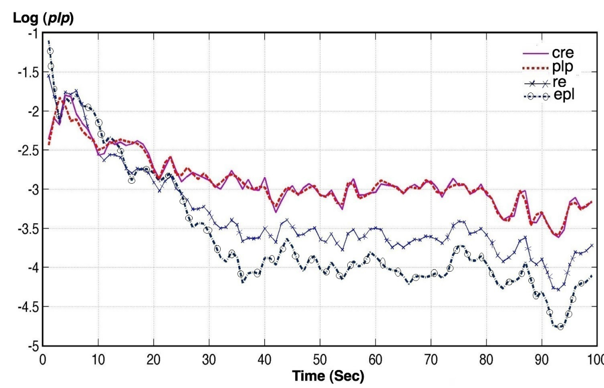


Fig. 3. Measurement and estimation of packet loss probability when plp is about -3.

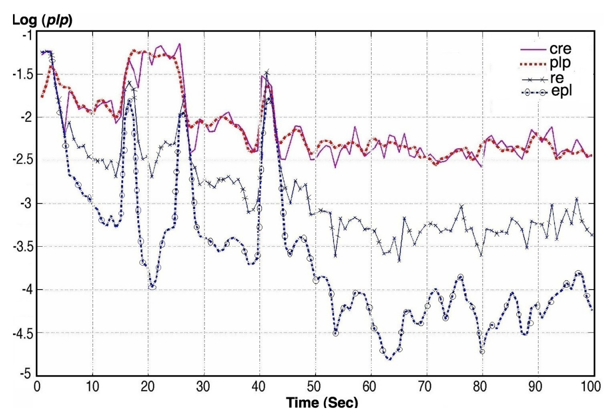
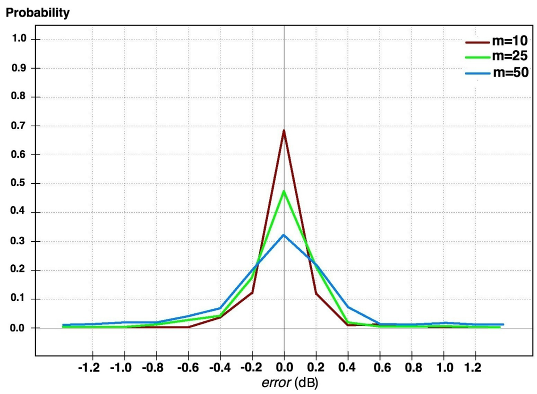


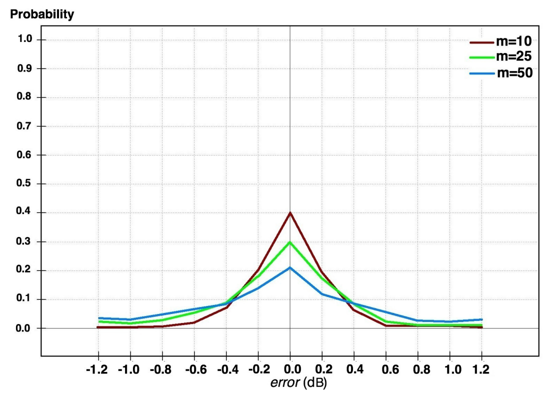
Fig. 4. Measurement and estimation of packet loss probability when plp is about -2.

IV. Numerical Results Analysis

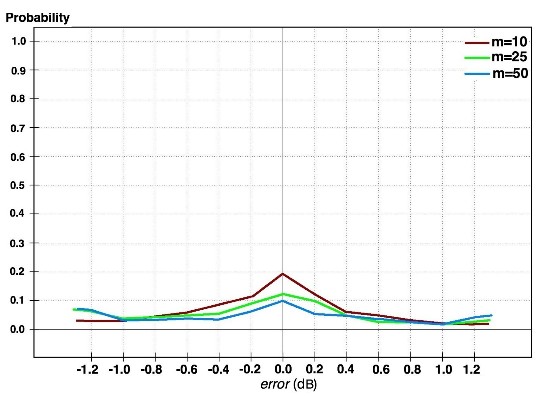
First, all the mentioned estimators (i.e., epl, re, and cre) are evaluated in a situation where the bandwidth of link A is 10 Mbps and there is no traffic coming from nodes 7 and 8.



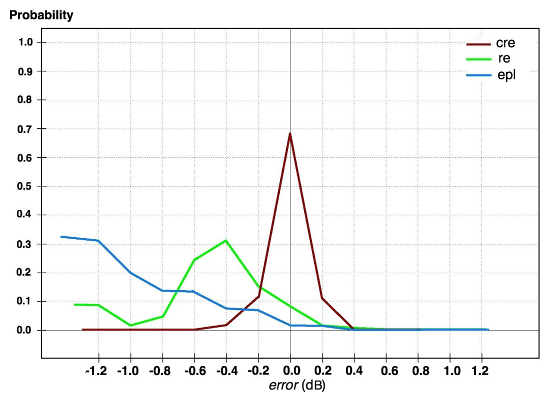
(a) PDF of $error$ for different m when buffer size is 5.



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



(c) PDF of $error$ for different m when buffer size is 100.



(d) PDF of $error$ for different estimators when buffer size is 5 and m=10.

Fig. 5. The comparison of PDF of $error$ for different conditions.

As shown in Fig. 3, the measured plp is around -3 (packet loss probability $\simeq 10^{-3}$). The accuracy of proposed estimator (cre) to estimate the plp compared to other estimators is demonstrated in this figure. With this amount of loss, although there is an offset between the plp, re, and epl, but re and epl follow the variations of plp and it can be seen as some soundness of the use of re and epl as the packet loss probability estimator but with a considerable error. In all experiences the time interval is 20 ms. In Fig. 3 cre is calculated according to (13) where m is 50. It means cre uses plp data measured one second before.

Since 10^{-3} can be negligible for loss packet ratio in media communication, we change the network conditions to increase the loss ratio and then re–evaluate the accuracy of estimators. To achieve this situation, the bandwidth of the link A is decreased to 8 Mbps. Fig. 4 shows the results of this experience: during the time periods of $[15, 25]$ and $[40, 41]$, nodes 7 and 8 add network traffic and bring the loss ratio close to 7 percent ($log(plp) = -1.5$). As Fig. 4 shows, the effect of simplification and approximation in (7) and (12) on the operation of epl and re methods for the bigger loss ratio is more apparent.

As mentioned before, buffer size affects the plp and the accuracy of estimators [12], [13]. The bigger the buffer size, the lesser plp and the accuracy of estimation. The effect of buffer size on estimation methods, re and epl, has been examined in [7] and [19] respectively. Beside the size of buffer, m, in (13), also affects the accuracy of cre estimation and it is determined by the speed of measuring and processing packet loss. We define the $error$ as the difference between estimated and measured plp, and study this parameter in different configurations to shows the effect of the network situation on estimation accuracy. Fig. 5 shows the probability density function of $error$ when buffer size is 5, 20, and 100 packet and m is 10, 25, and 50 ($m = 50$ means using a plp measured 1 s before), and the effect of the buffer size on estimation. Considering the effect of buffer size on estimation derived from (8), it appears that the accuracy of estimation (cre) will improve if the role of the measured plp is increased. Therefore, (13) is changed to:

$$cre(k) = p \times epl(k) + \frac{1}{n}\sum_{l=1}^{n}[plp(k-l-m) - p \times epl(k-l-m)] \quad (14)$$

where p is the proportional coefficient and is less than 1. To increase the importance of the second term in (13), n is increased from 3, which is recommended in [8], to 10 and to decrease the effect of first part, p is set to $\frac{2}{3}$. For an smaller

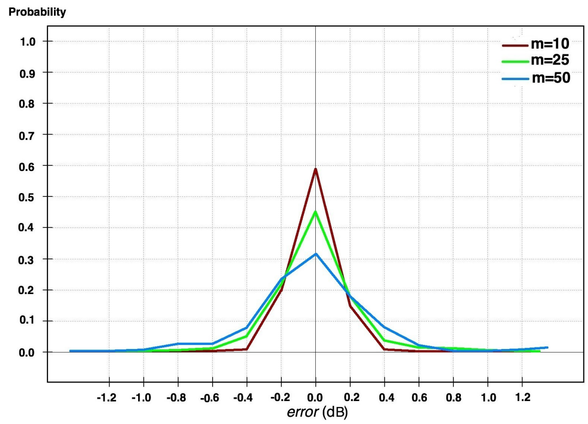


Fig. 6. PDF of $error$ for estimator which uses (14) when buffer size is 100.

p, when a considerable variation happens to plp (e.g., at 40 s in Fig. 4), the estimator (cre) cannot follow the plp properly and the $error$ will be significant.

Fig. 6 shows the $error$ when buffer size is 100 and (14) is used for estimation. Comparing Fig. 6 and Fig. 5c, the effectiveness of the changes in estimation is clear.

To conclude, the advantages of proposed estimator compared to other estimators are: 1) increasing the accuracy of estimation by using the measured parameters properly, 2) being flexible about duration of measuring time interval, and 3) estimating the plp reasonably accurately in case of large buffer.

V. 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 action 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 plp estimation. By changing the way we use the measurement of output traffic of the node in which loss happens, we have introduced a new formula which significantly improves the quality of the estimate. To study the accuracy of the estimates, we have used the NS-2 simulator and real input 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 can be possible to estimate the end user's perception, aka the Quality of Experience (QoE). 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 QoE measurement.

References

[1] D. McDysan, *QoS & Traffic Management in IP & ATM Networks*, McGraw-Hill, 2000.

[2] W. C. Hardy, *VoIP Service Quality: Measuring and Evaluation Packet-Switched Voice*, McGraw-Hill, 2003.

[3] B. Oklander and M. Sidi, "Jitter buffer analysis", Proc. of 17th IEEE International Conference on Computer Communications and Networks, pp. 1–6, August 2008.

[4] H. Hata, "Playout buffering algorithm using of random walk in VoIP", Proc. of IEEE International Symposium on Communications and Information Technology, pp. 457–460, October 2004.

[5] S. Tao and R. Guerin, "On-line estimation of internet path performance: an application perspective", Proc. of 23rd IEEE Conference on Computer Communications, Vol. 3, pp. 1774–1785, March 2004.

[6] R. Serral-Gracia, A. Cabellos-Aparicio, and J. Domingo-Pascual, "Packet loss estimation using distributed adaptive sampling", Proc. of IEEE Workshop on End-to-End Monitoring Techniques and Services, pp. 124–131, April 2008.

[7] D. Zhang and D. Ionescu, "A new method for measuring packet loss probability using a Kalman filter", IEEE Transaction on Instrumentation and Measurement, Vol. 58, No. 2, pp. 488–499, February 2009.

[8] D. Zhang and D. Ionescu, "Reactive estimation of packet loss probability for IP-based video services", IEEE Transaction on Broadcasting, Vol. 55, No. 2, pp. 375–385, June 2009.

[9] R. van de Meent and M. Mandjes, "Evaluation of user-oriented and black-box traffic models for link provisioning", Proc. of the 1st EuroNGI Conference on Next Generation Internet Networks Traffic, pp. 380–387, April 2005.

[10] J. Kilpi and I. Norros, "Testing the Gaussian approximation of aggregate traffic", Proc. of the 2nd ACM SIGCOMM Workshop on Internet Measurement, pp. 49–61, November 2002.

[11] S. Tao, K. Xu, A. Estepa, T.F.L. Gao, R. Guerin, J. Kurose, D. Towsley, and Z.L. Zhang, "Improving VoIP quality through path switching", Proc. of 24th IEEE Conference on Computer Communications, Vol. 4, pp. 2268–2278, March 2005.

[12] D. P. Heyman and T. V. Lakshman, "What are the implications of long-range dependence for VBR-video traffic engineering?", IEEE/ACM Transactions on Networking, Vol. 4, No. 3, pp. 301–317, June 1996.

[13] B. K. Ryu and A. Elwalid, "The importance of long-range dependence of VBR video traffic in ATM traffic engineering: myths and realities", Proc. of ACM SIGCOMM Conference on Applications, Technologies, Architectures, and Protocols for Computer Communications, pp. 3–14, August 1996.

[14] C. Lambiri, D. Ionescu, and V. Groza, "A new method for the estimation and measurement of traffic packet loss for virtual private networks services", Proc. of the 21st IEEE Conference on Instrumentation and Measurement Technology, Vol. 1, pp. 401–406, May 2004.

[15] F. Kelly, *Notes on effective bandwidths*, in Stochastic Networks: Theory and Applications, Oxford University Press, pp. 141–168, 1996.

[16] C. Chang, *Performance Guarantees In Communication Networks*, New York: Springer-Verlag, 2000.

[17] UC Berkeley, LBL, USC/ISI, and Xerox PARC, *Network Simulator NS-2*, http://www.isi.edu/nsnam/ns, [Accessed: 6 May 2011].

[18] M.C. Weigle, P. Adurthi, F. Hernandez-Campos, K. Jeffay, and F.D. Smith, "Tmix: A tool for generating realistic application workloads in NS-2", ACM SIGCOMM Computer Communication Review, Vol 36, No 3, pp. 67–76, July 2006.

[19] D. Zhang and D. Ionescu, "On packet loss estimation for virtual private networks services", Proc. of 13th IEEE Conference on Computer Communications and Networks, pp. 175–180, October 2004.

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