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ABSTRACT

Bandwidth provisioning is generally envisaged as a viable way to support QoS in IP networks. To guarantee at the same time cost-efficient use of resources, the crucial question is: what is the minimal bandwidth provisioning required to ensure the QoS level agreed upon (for instance: the probability that the traffic supply exceeds the available bandwidth, over some predefined interval T, is below some small fixed number epsilon. This paper deals with this dimensioning problem, with as crucial novelty that the resulting guidelines are based on coarse traffic measurements. Our approach relies on a powerful `interpolation' formula that predicts QoS on relatively short time scales (say the order of 1 s), by just using large time-scale measurements (say in the order of 5 m, as in the case of the standard MRTG measurements). As a result, we find that, measuring a load rho (in Mbit/s), the required bandwidth (to meet the QoS criterion) has the form rho +alpha sqrt{rho}, where alpha depends on T and epsilon -- this expression is derived under minimal model assumptions. Apart from its simplicity, the dimensioning formula has a number of attractive features, viz. its insensitivity and robustness (as just the load rho is needed), and its transparency (the impact of changing the `QoS-parameters', i.e., T and epsilon, on alpha is explicitly given). The dimensioning rule is validated through extensive measurements obtained in several operational network environments.

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QoS-aware bandwidth provisioning for IP network links

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Abstract

Current bandwidth provisioning procedures for IP network links are mostly based on simple rules of thumb, using coarse traffic measurements made on a time scale of e.g, 5 or 15 minutes. A crucial question, however, is whether such coarse measurements give any useful insight into the capacity actually needed: QoS degradation experienced by the users may be caused by traffic rate fluctuations on a much smaller time scale. The present paper addresses this question. Our approach relies on a powerful 'interpolation' formula that predicts the bandwidth requirement on relatively short time scales (say the order of 1 sec.), *relying on coarse traffic measurements*. The QoS measure used is the probability that the traffic supply exceeds the available bandwidth, over some predefined (small) interval T, is below some small fixed number ε. As a result, we find that, measuring a load ρ (in Mbit/s), the bandwidth required to meet the QoS criterion has the form $\rho + \alpha\sqrt{\rho}$ – this expression is derived under minimal model assumptions. The impact of changing the 'QoS parameters', i.e., T and ε, on α is explicitly given. The validity of the bandwidth provisioning rule is assessed through extensive measurements performed in several operational network environments.

Key words: bandwidth provisioning • Quality of Service • traffic measurements • Gaussian traffic • M/G/∞ input

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1 Introduction

To ensure Quality of Service (QoS) in IP networks, roughly speaking three approaches seem viable. Two of these approaches, developed within the Internet Engineering Task Force (IETF), use QoS-enabling mechanisms for protecting traffic streams. The initially proposed architecture, *IntServ*, relies on per flow admission control. This approach enables stringent QoS guarantees, but suffers from the inherent scalability problems. Therefore IntServ may be applied in the edge of the network (where the number of flows is relatively low), but not likely in the core. In *DiffServ* agreements are made for *aggregates* of flows rather than micro-flows, thus solving the scalability problems. However, in addition, appropriate bandwidth provisioning is then needed, in order to actually realize the QoS requirements. The third approach to ensure QoS, which is often used in practice, is to rely *purely* on bandwidth provisioning. In particular, link capacities are chosen such that the aggregate rate of the offered traffic very rarely exceeds the link capacity (queues are just used to absorb packet-level burstiness). In this approach all traffic streams are treated in the same way, i.e., no prioritization is used.

Bandwidth provisioning has several advantages over traffic differentiation mechanisms, see also, e.g., [6]. In the first place, the complexity of the network routers can be kept relatively low, as no advanced scheduling and prioritization capabilities are needed. Secondly, traffic differentiation mechanisms require that the parameters involved are 'tuned well', in order to meet the QoS needs of the different classes – this usually requires the selection of various parameters (for instance: weights in weighted fair queueing algorithms, token bucket parameters, etc.). Bandwidth provisioning has disadvantages as well: the lack of any QoS differentiation mechanism dictates that all flows should be given the most stringent QoS requirement, thus reducing the efficiency of the network (in terms of maximum achievable utilization). However, it is expected that this effect is mitigated if there is a high degree of aggregation, even in the presence of heterogeneous QoS requirements across users, as argued in, e.g., the introduction of [6] and in [8]. Clearly, the challenge for a network operator is to provide bandwidth such that an appropriate trade-off between efficiency and QoS is achieved: Without sufficient bandwidth provisioning, the performance of the network will drop below tolerable levels, whereas by provisioning too much the performance hardly improves and is potentially already better than needed to meet the users' QoS requirements, thus leading to inefficient use of resources.

The bandwidth provisioning procedures currently used in practice are usually very crude. A common procedure is to (i) use MRTG [14] to get coarse measurement data (e.g., 5 min. intervals), (ii) determine the average traffic rate during these 5 min. intervals, and (iii) estimate the required capacity by some quantile of the 5 min. measurement data - a commonly used value is the 95% quantile. This procedure is sometimes 'refined' by focusing on certain parts of the day (for instance office hours, in the case of business customers), or by adding safety and growth margins. The main shortcoming of this approach is that it is not clear how the coarse measurement data relates to the traffic behavior at time scales relevant for QoS. More precisely, a crucial question is whether the coarse measurements give any useful information on the capacity needed: QoS degradation experienced by the users may be caused by fluctuations of the offered traffic on a much smaller time scale, e.g., seconds (file transfers, web browsing) or even less (interactive, real-time applications).

Contribution. In this paper we develop an 'interpolation' formula that predicts the bandwidth requirement on relatively short time scales (say the order of 1 sec.), *by using large time scale measurements* (e.g., in the order of 5 min.). In our approach we express QoS in terms of the probability (to be interpreted as fraction of time) that, on a predefined time scale T, the traffic supply exceeds the available bandwidth. The bandwidth C should be chosen such that this probability does not exceed some given bound ε. The time scale T and performance target ε are case-specific: they are parameters of our model, and can be chosen on the basis of the specific needs of the most demanding application involved.

Our approach relies on minimal modeling assumptions. Notably, we assume that the underlying traffic model is Gaussian – empirical evidence for this assumption can be found in e.g., [6,10]. For the special case of peak-rate constrained traffic (peak rate r), we can use M/G/∞ type of input processes, leading to an elegant, explicit formula for the required bandwidth; M/G/∞ corresponds to a flow arrival process that is Poisson with rate λ and flow durations that are i.i.d. as some random variable D (with $\delta := \mathbb{E}D$). We find that, measuring a load $\rho \equiv \lambda\delta r$ (in Mbit/s), the required bandwidth (to meet the QoS criterion) has the form $\rho + \alpha\sqrt{\rho}$. Apart from its simplicity, this bandwidth provisioning formula has a number of attractive features. In the first place it is *transparent*, in that the impact of changing the 'QoS parameters' (that is, T and ε) on α is explicitly given. Secondly, the provisioning rule is to some extent *insensitive*: α does not depend on λ, but just on characteristics of the flow duration D and the peak rate r. This property enables a simple estimate of the additionally required bandwidth if in a future scenario traffic growth is mainly due to a change in λ (e.g., due to growth of the number of subscribers). Furthermore, the analytical expression for α provides valuable insight into the impact of essential changes in D and r. Our bandwidth provisioning rule $\rho + \alpha\sqrt{\rho}$ has been empirically investigated through the analysis of extensive traffic measurements in various network environments with different aggregation levels, user populations, etc.

Literature. There is a vast body of literature on bandwidth provisioning, see for instance [17]. With respect to traffic modeling, it was empirically shown that Poisson packet arrivals do not accurately capture the dependencies present in network traffic [16]. Gaussian approximations do incorporate these dependencies; their use was advocated in several papers, e.g., [1,6,10,13]. The use of flow level traffic models, like the M/G/∞ model (in which flows arrive according to a Poisson process), is justified in, e.g., [2,3,15]. In [15] it is pointed out that the M/G/∞ traffic model is extremely flexible, in that it allows all types of dependence structures: by choosing the flow durations Pareto-type one can construct long-range dependent traffic, whereas exponential-type flows lead to short-range dependent traffic.

The study by Fraleigh *et al.* [6] is related to ours, in that it uses bandwidth provisioning based on traffic measurements to deliver QoS. An important difference, however, is that in their case the performance metric is packet delay (rather than our link rate exceedance criterion). Also, in [6] measurements are used to fit the Gaussian model, and subsequently this model is used to estimate the bandwidth needed; this is an essential difference with our work, where our objective is to minimize the required measurement input/effort and bandwidth provisioning is done on the basis of only coarse measurements. Another closely related paper is [5], where several bandwidth provisioning rules are empirically validated.

Organization. The remainder of this paper is organized as follows. In Section 2 we describe in detail the objectives of this study and the proposed modeling approach; next, we provide the analysis leading to our bandwidth provisioning rule. Numerical results of our modeling and analysis are presented and discussed in Section 3. In Section 4, the bandwidth provisioning rule is assessed through extensive measurements performed in several operational network environments. Finally, conclusions and topics for further research are given in Section 5.

2 Objectives, modeling and analysis

The typical network environment we focus on in this paper corresponds to an IP network with a considerable number of users generating mostly TCP traffic (from e.g. web browsing). Then the main objective of bandwidth provisioning is to take care that the links are more or less 'transparent' to the users, in that the users should not (or almost never) perceive any degradation of their QoS due to a lack of bandwidth. Clearly, this objective will be achieved when the link rate is chosen such that only during a small fraction of time ε the aggregate rate of the offered traffic (measured on a sufficiently small time scale T) exceeds the link rate. The values to be chosen for the QoS parameters T and ε typically depend on the specific needs of the application(s) involved.

Clearly, the more interactive the application, the smaller T and ε should be chosen.

In more formal terms our objective can be stated as follows: The fraction ('probability') of sample intervals of length T in which the aggregate offered traffic exceeds the available link capacity C should be below ε, for prespecified values of T and ε. In other words:

$$\Pr(A(T) \geq CT) \leq \varepsilon, \tag{1}$$

where $A(T)$ denotes the amount of traffic generated in an arbitrary interval of length T. For provisioning purposes, the crucial question is: for given T and ε, find the *minimally* required bandwidth $C(T, \varepsilon)$ to meet the target.

In the remainder of this section we derive explicit, tractable expressions for our target probability (1), i.e., $p(C, T) := \Pr(A(T) \geq CT)$; we do this for a given traffic input process $\{A(t), t \geq 0\}$. Once we have an expression for $p(C, T)$, we can find the minimal C required to make sure that this probability is kept below ε. We thus find the required bandwidth $C(T, \varepsilon)$ – it is expected that this function decreases in both T and ε (as increasing T or ε makes the service requirement less stringent).

2.1 General traffic

Based on the classical Markov inequality $\Pr(X \geq a) \leq (\mathrm{E}X)/a$ for non-negative random variables X, we have, by putting $X = \exp(\theta A(T))$, for $\theta \geq 0$, the upper bound

$$\Pr(A(T) \geq CT) = \Pr\left(e^{\theta A(T)} \geq e^{\theta CT}\right) \leq \mathrm{E}e^{\theta A(T) - \theta CT}.$$

Because this holds for *all* non-negative θ, we can choose the *tightest* upper bound:

$$\Pr(A(T) \geq CT) \leq \min_{\theta \geq 0} \left(\mathrm{E}e^{\theta A(T) - \theta CT}\right). \tag{2}$$

This bound, also known as the *Chernoff bound*, is usually quite tight, but unfortunately rather implicit, as it involves both the computation of the moment generating function $\mathrm{E}\exp(\theta A(T))$ and an optimization over θ.

Now, noting that $C(T, \epsilon)$ should be the smallest number C such that the right hand side of (2) is smaller than ε, it is easily derived that:

$$C(T, \varepsilon) = \min_{\theta \geq 0} \frac{\log \mathrm{E}e^{\theta A(T)} - \log \varepsilon}{\theta T}. \tag{3}$$

2.2 Explicit formula for Gaussian traffic

Assuming that $A(T)$ contains the contributions of many individual users, it is justified (based on the Central Limit Theorem) to assume that $A(T)$ is *Gaussian* if T is not too small, see e.g., [6,10]. In other words $A(T) \sim \text{Norm}(\rho T, v(T))$, for some load ρ (in Mbit/s), and variance $v(T)$ (in Mbit^2). For this Gaussian case we now show that we can determine the right hand side of (3) explicitly.

The first step is to compute the moment generating function involved (this is done by isolating the square):

$$\mathbb{E}e^{\theta A(T)} = \exp\left(\theta\rho T + \frac{1}{2}\theta^2 v(T)\right).$$

The calculation of the minimum in (3) is now straightforward:

$$C(T,\varepsilon) = \rho + \min_{\theta\geq 0}\left(\frac{\frac{1}{2}\theta v(T)}{T} - \frac{\log\varepsilon}{\theta T}\right) = \rho + \frac{1}{T}\sqrt{(-2\log\varepsilon)\cdot v(T)}. \quad (4)$$

We remark that expression (4) is of the same spirit as the effective bandwidth formula derived in [7]. Obviously, given the values of ρ and $v(T)$, $C(T,\varepsilon)$ can also be calculated by numerical inversion of the Normal distribution $\text{Norm}(\rho T, v(T))$.

Hence, suppose we are able to estimate the load ρ and the variance $v(T)$ on the 'advertised' time scale T, we have found a straightforward provisioning rule. The load can be easily estimated by using coarse measurements, but for estimating $v(T)$ measurements on the time scale T are required. In the next subsection, we focus on the special case of M/G/∞ input; in that (still quite general) case the expressions simplify further.

As $v(T)$ cannot increase faster than quadratically (in fact, a quadratic function $v(T)$ corresponds to perfect positive correlation), $\sqrt{v(T)}/T$ is decreasing in T, and hence also the function $C(T,\varepsilon)$ – the longer T, the easier it is to meet the QoS requirement. Also, the higher ε, the easier it is to meet the requirement, which is reflected by the fact that the function decreases in ε.

2.3 M/G/∞ *traffic*

Whereas the above provisioning formula holds for general traffic arrival processes, we now focus on an important sub-class: M/G/∞ input. In this traffic model, jobs arrive according to a Poisson process with rate λ, and stay in the system during a period that is distributed as the random variable D (i.i.d.).

While in the system they generate traffic at rate r. Hence, $\rho = \lambda\delta r$, with $\delta = \mathbb{E}D$. Notice that the M/G/∞ traffic model is particularly appropriate in scenarios in which a peak-rate limitation is imposed, see also [1,15]. As we will see later, by choosing D appropriately, it covers a broad range of correlation structures.

Denote by f_X and F_X the density and the distribution function, respectively, of the random variable X. Let D^r be the residual distribution of D, i.e., $1 - F_D(x) = \delta f_{D^r}(x)$. As was derived in [11,12], for M/G/∞ input,

$$\begin{aligned}v(T) = &\lambda r^2\delta\left(\int_0^T x^2 f_{D^r}(x)\mathrm{d}x + T^2(1-F_{D^r}(T))\right)\\&+\lambda r^2\int_0^T\int_u^T (x-u)^2 f_D(x-u)\mathrm{d}x\mathrm{d}u\\&+\lambda r^2\int_0^T (T-u)^2(1-F_D(T-u))\mathrm{d}u.\end{aligned}$$

This can be simplified further to

$$\lambda r^2\left(2T\int_0^T x(1-F_D(x))\mathrm{d}x - \delta\int_0^T x^2 f_{D^r}(x)\mathrm{d}x + \delta T^2(1-F_{D^r}(T))\right). \quad (5)$$

Hence, cf. (4), the required bandwidth $C(T,\varepsilon)$ can be expressed as:

$$C(T,\varepsilon) = \rho + \alpha\sqrt{\rho}, \quad (6)$$

where α depends exclusively on the distribution of the flow duration D and peak rate r (and QoS requirements T and ϵ), but does *not* depend on the flow arrival rate λ. Now we evaluate (5) for different distributions D, covering both the long-range dependent and short-range dependent case.

2.3.1 *Exponential flow durations*

For exponentially distributed flow lengths D, the variance $v(T)$ reads

$$v(T) = 2\rho\delta^2 r(e^{-T/\delta} - 1 + T/\delta),$$

such that

$$\alpha = \left(\frac{T}{\delta}\right)^{-1}\sqrt{(-2\log\varepsilon)\cdot 2r(e^{-T/\delta} - 1 + T/\delta)}.$$

Observe that $v(T)$ is, for T large, linear, corresponding to short-range dependent input. Also observe, that α depends on T only through the ratio T/δ.

2.3.2 Pareto flow durations

For Pareto-distributed flow lengths D, i.e., obeying $F_D(x) = 1 - ((b/(x+b))^a$ and $\delta = b/(a-1)$ (where $a > 1$ and $b > 0$), substantial calculus gives (assume for ease $a \neq 2$, $a \neq 3$)

$$v(T) = \frac{2\rho r}{(3-a)(2-a)} \cdot (b^{a-1}\left(T+b\right)^{3-a} - (3-a)bT - b^2\Big) ;$$

$$\alpha = \frac{1}{T}\sqrt{(-2\log\varepsilon)\cdot\frac{2r}{(3-a)(2-a)}\cdot(b^{a-1}(T+b)^{3-a} - (3-a)bT - b^2)}.$$

If $a < 2$, $v(T)$ grows 'superlinearly' for large T (in fact, it grows as T^{3-a}), corresponding to long-range dependent input; for $a > 2$, we see that $v(T)$ is essentially linear, cf. [4].

2.3.3 Discussion on the M/G/∞ input model

1. If T is small (i.e., small compared to δ), then α becomes insensitive in the flow duration D. This can be seen as follows. From (5) it can be derived that $v(T)/T^2 \to \rho r$ if $T \downarrow 0$. Then (4) yields $C(T,\varepsilon) \approx \rho + \sqrt{(-2\log\varepsilon)\cdot\rho r}$, exclusively depending on ρ, for T small.

   This result can be derived differently, by noting that for $T \downarrow 0$, the performance criterion boils down to requiring that the number of active users does not exceed C/r. It is well-known that the number of active users has a Poisson distribution with mean $\lambda\delta$; this explains the insensitivity.
2. The case of exponential flow lengths can be easily extended to, e.g., *hyperexponentially* distributed flows. This can be done by considering the hyperexponential case as a situation with multiple flow types feeding independently into the link (each type has its own exponential flow length distribution) and noting that the variance of the total traffic is equal to the sum of the variances of the traffic generated by each of the different exponential flow types.
3. The above approach assumes that traffic arrives as 'fluid', during a flow's 'life time': traffic is generated at a constant rate r. It is perhaps more realistic to assume that traffic arrives in packets (of size s) generated according to a Poisson process with rate γ, where γs is equal to r. Denoting the above, fluid-based, variance function by $v_{\rm f}(T \mid r)$, and the packet-based variance function by $v_{\rm p}(T \mid \gamma, s)$, it can be verified that

   $$v_{\rm p}(T \mid \gamma, s) = v_{\rm f}(T \mid r) + \rho s T, \tag{7}$$

   irrespective of the flow duration distribution. Importantly, $C(T,\varepsilon) = \rho + \alpha\sqrt{\rho}$ remains valid (for an α that does not depend on λ).

Table 1
Default parameter settings for the numerical results.

TRAFFIC MODEL			QOS PARAMETERS		
δ	1	sec	T	1	sec
distr. of D	exp.		ε	0.01	-
ρ	10	Mbit/s			
model	fluid				
FLUID MODEL			PACKET-LEVEL MODEL		
r	1	Mbit/s	γ	83.3	Packet/s
			s	1500	Bytes

3 Numerical results

This section presents numerical results obtained by using the analytical model of Section 2. The goal is to illustrate a few key features of our bandwidth provisioning formula. We use the traffic parameters and QOS parameters displayed in Table 1, unless specified otherwise.

Experiment 1: Fluid model vs. packet-level model

Figure 1 shows the required capacity obtained by the packet-level and fluid model as a function of T, for various mean flow durations δ. It is seen that for large values of the time scale T, both models obtain the same required capacity. This can be understood by looking at the extra term $\rho s T$ of (7), which influence on $C(T,\varepsilon)$ becomes negligible for increasing T, cf. (4).

For $T \downarrow 0$ the required capacity obtained by the packet-level model behaves like $C(T,\varepsilon) \sim \rho + \sqrt{\rho s}\frac{1}{\sqrt{T}}\sqrt{-2\log\varepsilon}$ and hence $C(T,\varepsilon) \uparrow \infty$ as $T \downarrow 0$, whereas the required capacity of the fluid model converges to $\rho + \sqrt{(-2\log\varepsilon)\cdot \rho r}$, as was already argued in Section 2.3.3.

The fast increase in the required capacity in the packet-level model for a decreasing time scale T was also observed in e.g., [6]. Note that, in fact, the required capacity is not influenced by the *absolute value* of T, but rather by the *ratio* of T/δ. The right graph of Figure 1 shows the same results as the left graph, but now on a linear axis and only for $T \in [0,1]$.

In the remainder of this section we restrict ourselves to the flow-level model, as we will focus on situations with values of $T/\delta > 0.1$ for which the required capacity is almost identical in both models.

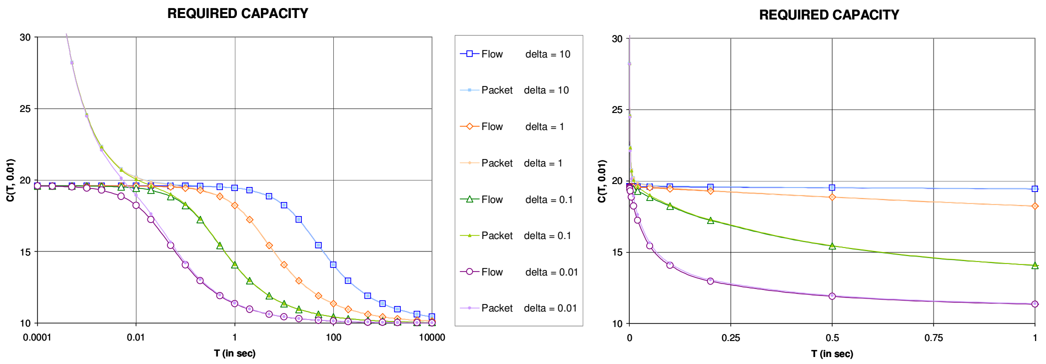

Fig. 1. Comparison of the required capacity for the flow-level and packet-level model as a function of the time scale T. Left: logarithmic axis. Right: linear axis.

Experiment 2: Impact of the flow duration distribution

Next we investigate the impact of the flow duration distribution on the required capacity. Figure 2 contains four graphs with results for hyperexponentially distributed flow durations D. Each graph shows, for a particular value of the mean flow size δ, the required capacity as a function of the offered load ρ, for different coefficients of variation (CoV) of D. These graphs show that the required capacity is almost insensitive to the CoV for the long ($\delta = 10$ sec.) and short flow durations ($\delta = 0.01$ sec.). For the other cases ($\delta \in \{0.1, 1\}$ sec.) the required capacity is somewhat more sensitive to the CoV. The graphs show that for hyperexponentially distributed flow durations *less* capacity is required if the CoV increases.

It should also be noticed that the required capacity for $T = 0$, also shown in Figure 2, corresponds to the often used $M/G/\infty$ bandwidth provisioning approach, cf. the discussion in Section 2.3.3 and the discussion on Experiment 1. The numerical results show that particularly for short flow durations significantly less capacity is required than suggested by the classical $M/G/\infty$ approach; for longer flows this effect is less pronounced.

Experiment 3: Impact of QoS parameter ε

Figure 3 shows the required capacity as a function of the QoS requirement ε, which specifies the fraction of intervals in which the offered traffic may exceed the link capacity. A larger value of ε means relaxing the QoS requirement, and hence less capacity is needed. Obviously, for $\varepsilon \to 1$ the required capacity converges to the long term average load $\rho = 10$. For $\varepsilon \downarrow 0$ the required capacity increases rapidly to infinity (according to $\sqrt{-2\log\varepsilon}$).

Experiment 4: Impact of the CoV of the flow duration distribution

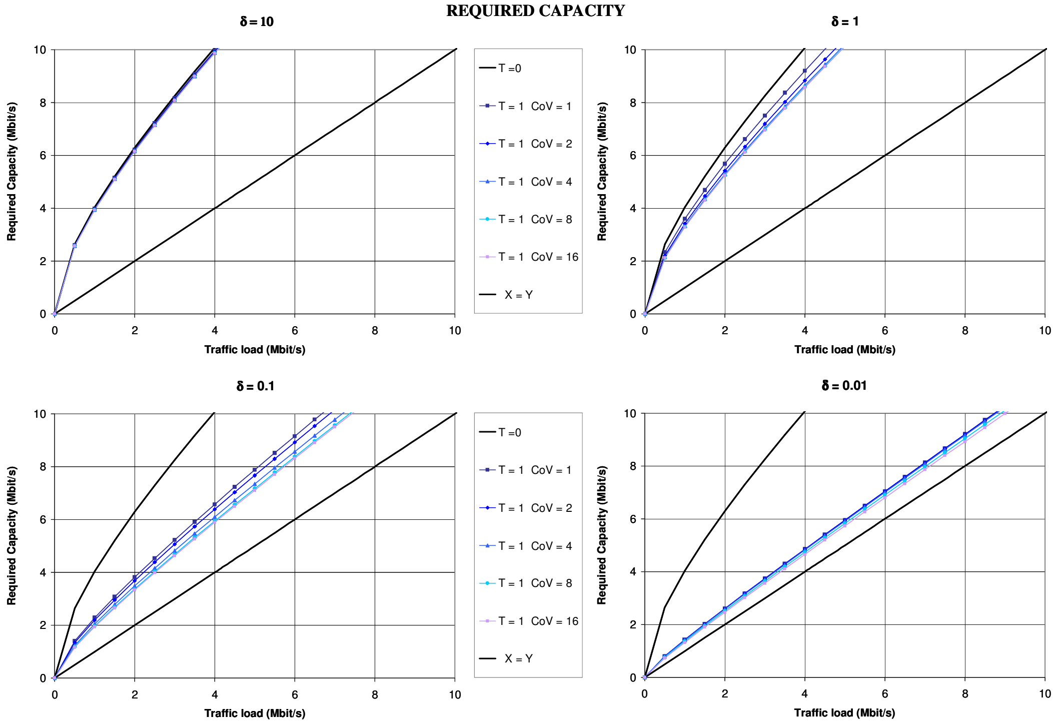

Fig. 2. Required capacity for hyper-exponential flow durations with different means and CoVs.

To investigate the impact of the flow duration characteristics, we computed the required capacity for exponential, hyperexponential, and Pareto distributed flow durations with different CoV values, see the left panel of Figure 4. The graph shows that the required capacity is almost insensitive to the flow duration distribution. The left graph also confirms the earlier observations that the capacity is almost insensitive to the CoV of the flow duration distribution. Note, that for hyperexponentially distributed flow durations the required capacity slightly decreases for increasing CoV, while for Pareto distributed flow durations the required capacity slightly increases for increasing CoV.

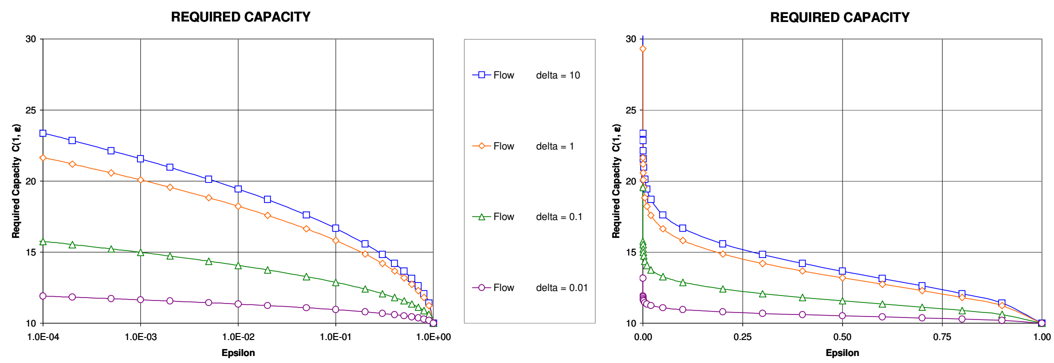

Fig. 3. Comparison of the required capacity for the flow-level and packet-level model as a function of the QoS requirement T. Left: logarithmic axis. Right: linear axis.

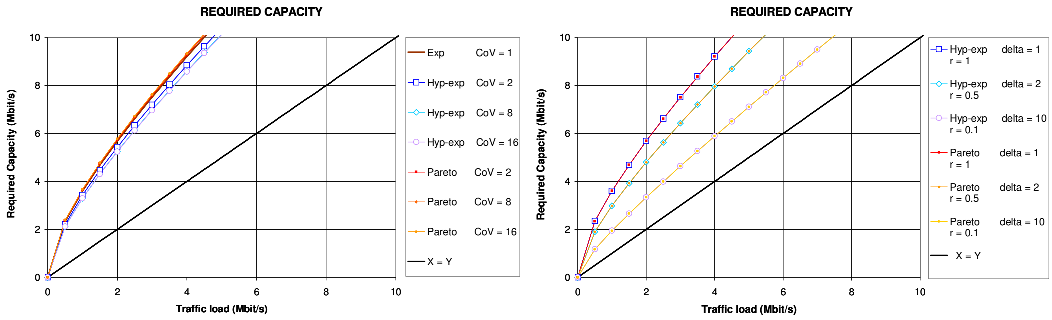

Fig. 4. Left: required capacity for different flow duration distribution and CoVs. Right: required capacity for different access rates.

Experiment 5: Impact of the access rate

Finally, the right panel of Figure 4 studies the effect of the access rate r on the required capacity. Three values of the access rate r and the mean flow duration δ are chosen such that the mean flow size $\delta \cdot r$ remains constant. As expected, the required capacity increases considerably when r becomes larger (i.e. the traffic burstiness grows). The results in this graph for hyperexponential and Pareto flow sizes confirm the conclusions from Experiments 2 and 4 that the required capacity is almost insensitive to the flow duration distribution.

4 Experimental verification & bandwidth provisioning

In this section we will analyze measurement results obtained in operational network environments in order to validate the modeling approach and bandwidth provisioning rule presented in Section 2. In particular, we will investigate the relation between measured traffic load values $\hat{\rho}$ during 5 min. periods (long enough to assume stationarity) and the traffic fluctuations at a 1 sec. time scale within these periods.

Clearly, if (A) our $M/G/\infty$ traffic modeling assumptions of Section 2.3 apply *and* if (B) differences in the load ρ are caused by changes in the flow arrival rate λ (i.e. the flow size characteristics remain unchanged during the measurement period), then as a function of ρ, for given (T, ε), the required bandwidth C_ρ should satisfy

$$C_\rho = \rho + \alpha\sqrt{\rho}, \qquad (8)$$

for some fixed value of α. To assess the validity of this relation, we have carried out measurements in three different network environments: (i) a national IP network providing Internet access to residential ADSL users, (ii) a college network, and (iii) a campus network.

In the ADSL network environment the main assumptions made in Section 2.3

in order to justify use of the M/G/∞ traffic model seem to be satisfied, i.e. the flow peak rates are limited due to the ADSL access rates (which are relatively small compared to the network link rates) and the traffic flows behave more or less independently of each other (the IP network links are generously provisioned and, hence, there hardly is any interaction among the flows). The other network environments have essentially different characteristics. In particular, in the college and campus network the ratio of the access rate and link rate is relatively large, which, obviously, may lead to violation of our traffic modeling assumptions.

The measurement scenarios and results will be described and discussed in more detail in the following subsections.

4.1 ADSL *network environment*

We first focus on the ADSL network environment with residential users, see Figure 5. An ADSL connection consists of an ADSL modem on both sides of the local loop between the subscriber and the local exchange. On the local exchange side, up to 500 modems are contained in Digital Subscriber Line Access Multiplexers (DSLAM).

The DSLAMs are connected to the core IP infrastructure by means of optical STM-1 (155 Mbit/s) links. The aggregated traffic of all the ADSL subscribers of a certain Internet Service Provider (ISP) is carried over a high-capacity link between the core infrastructure and the ISP. Depending on the size of the ISP, this can vary between a single STM-1 link and multiple Gigabit Ethernet links. At the time of the measurements, none of the network links were saturated, and hence the traffic was not affected by any shortage of capacity in the ADSL network.

We choose the sample size $T = 1$ sec., motivated by the fact that this can be assumed to be the time scale that is most relevant for the Quality of Service perception of end-users of typical applications like web browsing. Elementary transactions, such as retrieving single web pages, are normally completed in intervals roughly in the order of 1 sec. If the network performance is seriously degraded during one or several seconds, then this will affect the quality as perceived by the users.

The method that was chosen to measure the traffic at the 1 sec. time scale was to use the internal traffic counters (interface MIBs) of the DSLAMs. These counters keep track of the accumulated number of bytes that are transported on each port in each direction. In this experiment, the counters for the STM-1 ports in the downstream direction (toward the subscribers) were used. The counters were read-out using SNMP.

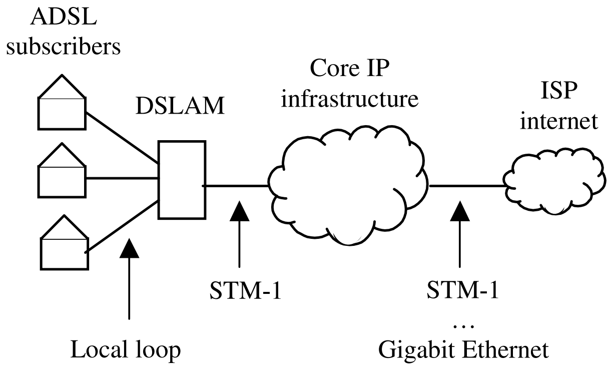

Fig. 5. Overview of ADSL infrastructure

The measurements were done during several evenings (between 5 PM and 11 PM), as this is the busiest period of the day for ADSL traffic. The measurements were performed on a large number of DSLAMs, in locations ranging from small villages to major cities.

Time was split into 5 minute chunks, over which the load ρ is determined for each STM-1 link. In addition, for each 5 min. period, the 99% quantile of the 1 sec. measurements was determined. This quantile was assumed to indicate the minimum capacity C that is needed to fulfill the QoS requirement $\Pr(A(T) \geq CT) \leq \varepsilon$, with $\varepsilon = 1\%$ and $T = 1$ sec.

The left graph in Figure 6 results from measurements on 11 STM-1 links at various locations. Each location is represented by a distinct color. For orientation purposes, the dotted line shows the unity ($y = x$) relation. It is remarkable how the 99% quantiles almost form a solid curve. We fitted a function $\rho + \alpha\sqrt{\rho}$, such that roughly 95% of the 99% quantiles are lower or equal to this function. The reason for fitting an upper bound, instead of finding the function that gives the minimum least square deviation, is that eventually we intend to use this function for capacity planning: then it is better to *over*estimate the required bandwidth than to underestimate it. The graph shows an extremely nice fit for the function $C = \rho + 1.0\sqrt{\rho}$ (with C and ρ expressed in Mbit/s).

At the time of the measurements, the busiest STM-1's did not carry more traffic than 20 Mbit/s during the busiest hours, so we could not verify that the found upper bound also holds for higher traffic volumes. To overcome this problem at least partly, we synthesized artificial traffic measurements by taking the superposition of the traffic measured on several (unrelated) STM-1's. The right graph of Figure 6 shows the results of this experiment. As expected on theoretical grounds, the fitted function $C_\rho = \rho + 1.0\sqrt{\rho}$ remains valid.

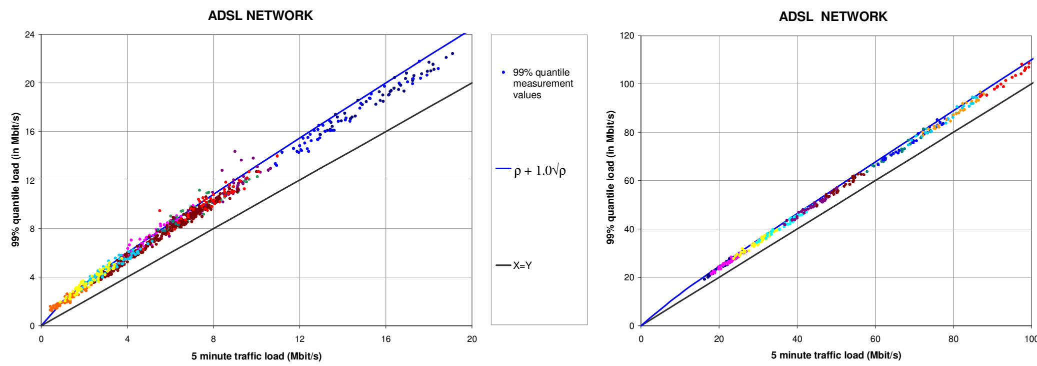

Fig. 6. Left: 99% maximum 1 sec. traffic as function of 5 min. traffic mean. Right: synthesized traffic measurements for higher traffic volumes.

4.2 College and campus network

We have performed similar experiments in two other network environments, viz. a college network and a campus network, with essentially different characteristics than the ADSL network. In particular, in these alternative network environments the ratio of the access rate and link rate is relatively small, and, hence, one would expect that the M/G/∞ modeling assumption underlying the analysis in Section 2 is not valid anymore. The question is whether or up to what extent the bandwidth requirement formula (6) still applies.

In the first scenario, we have measured a 1 Gbit/s link connecting a college network to the Internet. This link is shared by about 1000 students and teachers, each having a 100 Mbit/s FastEthernet connection (a ratio of 1:10). In the second scenario, we have measured a 300 Mbit/s (trunked) link connecting an university campus (residential) network to the Internet. This link is shared by some 2000 students, each of them having a 100 Mbit/s connection (a ratio of 1:3). Thus, theoretically, it takes only 10 or 3 users, respectively, to saturate the observed network links.

The left graph of Figure 7 shows the measurement results for the college network. As expected, the cloud of 99% quantiles of the 1 sec. traffic rate samples within 5 min. intervals does not form such a nice 'curve' as in the previous (ADSL) scenario, but the typical square-root behavior can still be recognized.

For the university campus network, the 'peak versus average load' is plotted in the right graph of Figure 7. Note that the traffic in both directions has been aggregated during the measurements, which explains that the link load as plotted in the graph is sometimes higher than the link capacity (which is one-way). Although the number of measurements available for the campus

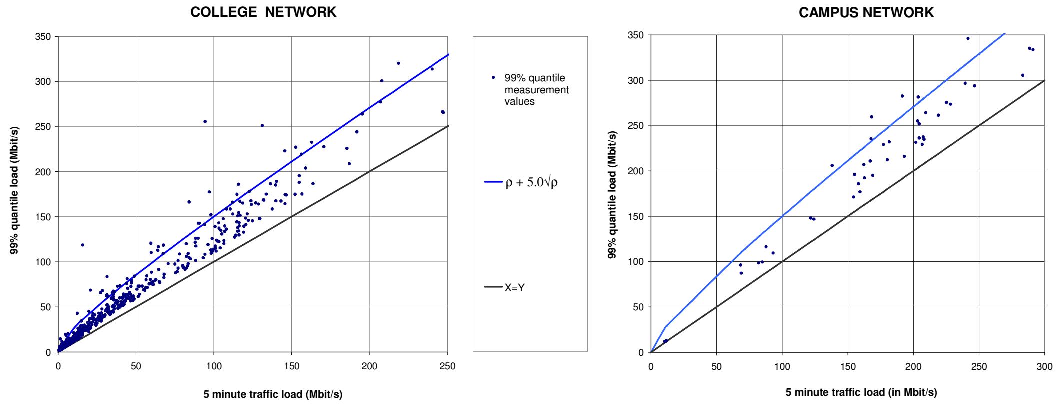

Fig. 7. 99% maximum 1 sec. traffic as function of 5 min. traffic mean. Left: college network. Right: campus residential network.

network is relatively low, we conclude from the graph that the relation between the average link loads and the 99% quantiles of 1 sec. samples shows a similar behavior as in the college network.

From the above results it is concluded that, as expected, for these alternative scenarios our model developed in Section 2 does clearly not apply as well as for the ADSL scenario. Indeed, it may be expected that this is caused by the high access link speed, which leads to a possibly high variability in the rate at which traffic is generated by the users in the alternative scenarios (while the M/G/∞ model assumes that sources generate traffic at a fixed rate). Apparently, under these highly variable traffic conditions the 5 min. average traffic rate does not provide sufficient information to estimate the traffic behavior on much smaller time scales (i.e. more detailed information than just ρ is needed), and, consequently, other underlying traffic models should be applied.

4.3 Bandwidth provisioning procedure

Our formula (6) for the required bandwidth $C(T, \varepsilon)$, can be used to develop bandwidth provisioning procedures. Obviously, a first step in this procedure is to verify whether the main M/G/∞ modeling assumptions are satisfied in the network environment under consideration, such that formula (6) can indeed be applied. A next step is then to find ρ and α. Clearly, ρ can be estimated through coarse traffic measurements, as it is just the average load; α, however, contains (detailed) traffic characteristics on time scale T (viz., the variance $v(T)$). In particular, cf. Section 2.3, α depends on the flow peak rate r and on the parameters of the flow duration D (for instance: δ for exponential flows; a and b for Pareto flows); but α does *not* depend on the flow arrival rate λ.

Now, under the hypothesis that fluctuations in the load ρ are due to fluctuations in the flow arrival rate λ, whereas the characteristics of the flow duration D and the peak rate r remain constant, we propose the following bandwidth provisioning procedure.

Provisioning procedure.

1. Perform one detailed measurement at time scale T, yielding an estimate of α;
2. Perform coarse measurements (e.g., every 5 min, by using the MRTG tool [14], or on an even more infrequent basis) to estimate ρ, and use provisioning rule $\rho + \alpha\sqrt{\rho}$.

The estimate of α has to be updated after a certain period (perhaps in the order of months). This should correspond to the time at which it is expected that the 'nature' of the use of resources changes (due to e.g., new applications, etc.).

The measurement period of 5 min. mentioned above for estimating the load ρ is motivated by the fact that this is the time scale on which measurements in an operational network can be (and are) performed on a routine basis. A higher frequency would be desirable, but this would put a high load on processing capacity of routers, transport capacity of management links, etc., particularly if there are many routers and ports involved. On the other hand, measurements performed on lower frequencies (for instance 1 to several hours) are too coarse, as traffic is not likely to be stationary over such long periods. Therefore, 5 min. will usually be a suitable trade-off, as this is feasible to measure, and at the same time a reasonable period during which the traffic can still be assumed stationary.

5 Concluding remarks & further research

In this paper we have developed a method for predicting fluctuations of the offered traffic on relatively short time scales (say in the order of 1 sec.) by just using standard, coarse traffic measurements (typically in the order of 5 min.). This result has been used to derive a formula for the minimally required link bandwidth $C(T,\varepsilon)$, such that the aggregate traffic rate (measured on a time scale T) exceeds the link rate only during a small fraction ε of time. In particular, for the situation that the traffic is generated by peak rate constrained flows that arrive according to a Poisson process and remain active for some random time D (i.e. M/G/∞ input traffic) the resulting bandwidth provisioning rule is of the form $C(T,\varepsilon) = \rho + \alpha\sqrt{\rho}$, where ρ denotes the average traffic rate measured on, e.g., a 5 min. time scale, and the factor α is independent of the flow arrival rate. Note that this property suggests a simple estimate for the additional bandwidth to be supplied when a foreseen growth of ρ is mainly due to a larger flow arrival rate (e.g. an increase of the number of subscribers) while the other traffic parameters remain unchanged.

The explicit expression of α shows the impact of the flow size, peak rate and other traffic and system parameters on the required link bandwidth. In particular, $0 \leq \alpha \leq \sqrt{(-2\log\varepsilon)r}$ depending mainly on the ratio of the time scale of interest T and the mean flow duration. Extensive numerical results show that $C(T,\varepsilon)$ is quite insensitive to the flow size distribution (apart from its mean value).

The above provisioning rule has been empirically validated through the analysis of extensive traffic measurements in three practical scenarios: (i) an IP network connecting private and small business ADSL users to the Internet, (ii) a college network and (iii) a campus network. A particularly good correspondence with our theoretical results was found from the measurements in the IP network scenario, where the flow rates are bounded by relatively small ADSL access rates. The measurement results for the other scenarios showed, as expected, less good correspondence: the M/G/∞ modeling assumptions are not really satisfied there; in particular the flow rates may be strongly variable due to the relatively high access rates (compared to the network link rates) in these scenarios. It remains for further research whether other underlying traffic models could be used to improve the results for network environments like the college and campus network. An attractive alternative traffic model is the fractional Brownian motion (fBm) model, as used in e.g., [6].

Another topic for further research is the investigation of the validity of the stationarity assumption in our modeling approach. In particular, up to which time scale $\hat{t}$ can the traffic arrival process be assumed stationary? It is clear that the estimates of the average rate ρ should be measured at a time scale smaller than $\hat{t}$. It should also be investigated in more detail under which conditions (and to what extent) the Gaussian traffic assumption is valid, cf. Section 2.2.

As a last topic for further research we mention the QoS criterion used in this paper, i.e., the fraction of time ε that the aggregate offered traffic rate (measured at time scale T) is restricted by the link rate. In particular, we could obtain more insight in the relation between this QoS criterion, which we used as link bandwidth provisioning objective, and the actual QoS that the users are offered. E.g., up to what extent does this criterion actually determine the *duration* of a congestion period (this will depend on the traffic characteristics, in particular the flow-level dynamics)? What are appropriate choices of T and ε for different (TCP) application types (file downloading, interactive web browsing, etc.)?

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