A Network Calculus with Effective Bandwidth *

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Abstract

This paper establishes a link between two principal tools for the analysis of network traffic, namely, effective bandwidth and network calculus. It is shown that a general formulation of effective bandwidth can be expressed within the framework of a probabilistic version of the network calculus, where both arrivals and service are specified in terms of probabilistic bounds. By formulating well-known effective bandwidth expressions in terms of probabilistic envelope functions, the developed network calculus can be applied to a wide range of traffic types, including traffic that has self-similar characteristics. As applications, probabilistic lower bounds are presented on the service given by three different scheduling algorithms: Static Priority (SP), Earliest Deadline First (EDF), and Generalized Processor Sharing (GPS). Numerical examples show the impact of the traffic models and the scheduling algorithm on the multiplexing gain in a network.

Key Words: Network calculus, effective bandwidth, Quality-of-Service, statistical multiplexing.

1 Introduction

To exploit statistical multiplexing gain of traffic sources in a network, service provisioning requires a framework for the stochastic analysis of network traffic and commonly-used scheduling algorithms. Despite the significant advances on quantitative evaluation of network traffic, methods that can take advantage of statistical multiplexing for (nontrivial) scheduling algorithms or service allocations are available only for few special cases.

Probably the most influential framework for service provisioning is the *effective bandwidth* (see [29, 32] and references therein), which describes the minimum bandwidth required to provide an expected service for a given amount of traffic. The effective bandwidth of a flow determines a bandwidth somewhere between the average and peak rate of the flow. Effective bandwidth expressions have been derived for many traffic types including those with self-similarity [29].

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An alternative method to determine resource requirements of traffic flows in a packet network is the *network calculus*, which takes an envelope approach to describe arrivals and services in a network. Starting with Cruz's seminal work [18] the deterministic network calculus has evolved to an elegant framework for worst-case analysis, which can be used to derive upper bounds for delay and backlog for a wide variety of link scheduling algorithms (e.g., [18, 39, 36]). A strength of the deterministic network calculus is that it can be used to determine delay and backlog over multiple network nodes. Since the worst-case view of the deterministic network calculus does not reap the benefits of statistical multiplexing and generally results in an overestimation of the actual resource requirements of traffic, researchers have seeked to extend the network calculus to a probabilistic setting, e.g., [2, 7, 11, 13, 34, 40, 44, 47, 50, 52]. Probabilistic extensions of the network calculus are commonly referred to as *statistical network calculus*.

The contribution of this paper is the integration of the concept of effective bandwidth into the formalism of the statistical network calculus. As a result of this paper, it is feasible to analyze link scheduling algorithms that are not easily tractable with an effective bandwidth approach, for network traffic types that could previously not be analyzed in a network calculus context. The relationship between network calculus and effective bandwidth has been first investigated by Chang [13] (see Subsection 3.1). This paper continues to explore this relationship, and exploits recent advances in the statistical network calculus to analyze effective bandwidth in a multi-node network.

We develop a statistical network calculus where both arrivals and service are expressed in terms of probabilistic bounds. The calculus is expressed in terms of probabilistic upper bounds on arrivals (*effective envelopes* [7]) and probabilistic lower bounds on service (*effective service curves* [11]). By relating the concepts of effective envelopes and effective bandwidth, we obtain explicit bounds on delay and backlog for all traffic source characterizations for which an effective bandwidth (in the sense of [13, 29]) has been determined. The effective service curves in this paper can express the service for a wide range of scheduling algorithms.

The remaining sections are structured as follows. In Section 2, we present the statistical network calculus that is used to accommodate effective bandwidth expressions. In Section 3, we explore the relationship between effective bandwidth and effective envelopes. This enables us to construct effective envelopes for all traffic models for which effective bandwidth results are available. Specifically, we consider regulated arrivals, a memoryless On-Off traffic model, and a Fractional Brownian Motion traffic model. In Section 4, we derive probabilistic lower bounds on the service offered by the scheduling algorithms SP, EDF, and GPS, in terms of effective service curves. In Section 5, we apply the network calculus in a set of examples, and compare the multiplexing gain achievable with the traffic models and scheduling algorithms used in this paper. We present brief conclusions in Section 6.

2 Network Calculus Extensions for Effective Bandwidth

The goal of this section is to extend the state-of-the art of statistical network calculus research, so that we can view general effective bandwidth expressions in a network calculus framework. We first introduce necessary notation, and then review results from the deterministic and statistical network calculus, as needed in this paper. The main contribution of this section are the probabilistic bounds for output burstiness, backlog, delay and network service derived in Subsection 2.5.

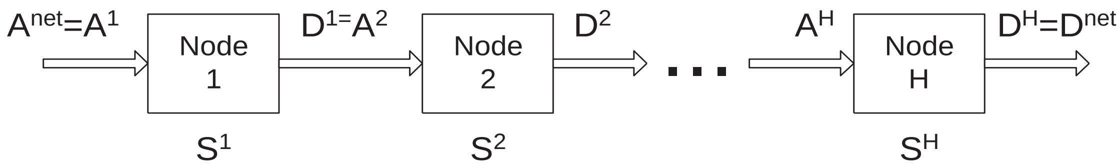


Figure 1: Traffic of a flow through a set of H nodes. The arrivals and departures from the network are given by random processes A^{net} and D^{net}. The arrivals and departures from the h-th node are described by A^h and D^h, with $A^1 = A^{net}$, $A^h = D_{h-1}$ for $h = 2, \ldots, H$, and $D^{net} = D^H$.

2.1 Notation and Definitions

We consider a discrete time model, where time slots are numbered $0, 1, 2, \ldots$. Arrivals to a network node and departures from a network node are denoted by nonnegative, nondecreasing functions $A(t)$ and $D(t)$, respectively, with $D(t) \leq A(t)$. The backlog at time t is given by $B(t) = A(t) - D(t)$, and the delay at time t is given by $W(t) = \inf\{d \geq 0 \,|\, A(t-d) \leq D(t)\}$. If $A(t)$ and $D(t)$ are represented as curves, $B(t)$ and $W(t)$, respectively, are the vertical and horizontal differences between the curves.

We use subscripts to distinguish arrivals and departures from different flows or different classes of flows, e.g., $A_i(t)$ denotes the arrivals from flow i, and $A_{\mathcal{C}}(t) = \sum_{i \in \mathcal{C}} A_i(t)$ denotes the arrivals from a collection $\mathcal{C}$ of flows. We use the same convention for the departures, the backlog, and the delay. When we are referring to a network with multiple nodes, we use superscripts to distinguish between different nodes, i.e., we use $A_i^h(t)$ to denote the arrivals to the h-th node on the route of flow i, and $A_i^{net}(t) = A_i^1(t)$ to denote the arrivals of flow i to the first node on its route. In Figure 1 we show the route of a flow that passes through H nodes, where $A^{net} = A^1$ and $D^{net} = D^H$ denote the arrivals and departures from the network, and where $A^h = D^{h-1}$ for $h = 2, \ldots, H$. To simplify notation, we drop subscripts and superscripts whenever possible. We assume that the network is started at time 0 and that all network queues are empty at this time, i.e., $A_i(0) = D_i(0) = 0$ for all i.

The min-plus algebra formulation of the network calculus [1, 8, 15], defines, for given functions f and g, the convolution operator $*$ and deconvolution operator $\oslash$ by

$$\begin{aligned} f * g(t) &= \inf_{\tau \in [0,t]} \{f(t-\tau) + g(\tau)\} \ , \\ f \oslash g(t) &= \sup_{\tau \geq 0} \{f(t+\tau) - g(\tau)\} \ . \end{aligned}$$

These operators are used to express service guarantees and performance guarantees.

2.2 Overview of Deterministic Network Calculus

In the deterministic network calculus in [1, 8, 15], service guarantees to a flow at a node are expressed in terms of *service curves*. A (minimum) service curve for a flow is a function S which specifies a lower bound on the service given to the flow such that, for all $t \geq 0$,

$$D(t) \geq A * S(t) \ . \tag{1}$$

When the arrivals are bounded by an *arrival envelope* A^*, [1] such that $A(t+\tau) - A(t) \leq A^*(\tau)$ for all $t, \tau \geq 0$, the guarantee given by the service curve in Eqn. (1) implies worst-case bounds for output burstiness, backlog and delay. According to [1, 8, 15], an envelope for the departures from a node offering a service curve S is given by $A^* \oslash S$, the backlog is bounded by $A^* \oslash S(0)$, and the delay at the node, $W(t)$, is bounded by d, if d satisfies $\sup_{\tau \geq 0}\{A^*(\tau - d) - S(\tau)\} \leq 0$.

If service curves are available at each node on the path of a flow through a network, these single-node bounds can be easily extended to end-to-end bounds. Suppose a flow is assigned a service curve S^h on the h-th node on its route ($h = 1, \ldots, H$). Then the service given by the network as a whole can be expressed in terms of a network service curve S^{net} as

$$S^{net} = S^1 * S^2 * \ldots * S^H . \tag{2}$$

With a network service curve, bounds for the output burstiness, backlog and delay for the entire network follow directly from the single-node results.

End-to-end delay bounds obtained with the network calculus are generally lower than the sum of the delay bounds at each node. For example, when the service curve at each node is given as a constant rate function, $S^h(\tau) = C\tau$ for all $h = 1, 2, \ldots, H$, we obtain $S^{net} = S^1 * S^2 * \ldots * S^H = C\tau$. Here, the end-to-end backlog and delay bounds are identical to the bounds at the first node.

At this time, the deterministic calculus has been extensively explored. Its results have led to the development of new scheduling algorithms [19, 39] and have been used to specify new network services [6, 10]. We refer to [9] for a comprehensive discussion of available results. A drawback of the deterministic network calculus is that the consideration of worst-case scenarios ignores the effects of statistical multiplexing, and, therefore, generally leads to an overestimation of the actual resource requirements of multiplexed traffic sources.

2.3 Overview of Statistical Network Calculus

The statistical network calculus extends the deterministic calculus to a probabilistic setting with the goal to exploit statistical multiplexing gain. Here, traffic arrivals and departures in the interval $[0, t]$ are viewed as random processes that satisfy certain assumptions, and the arrival and departure functions $A(t)$ and $D(t)$ represent sample paths. In this paper, we make the following assumptions on arrivals:

1. *Stationary Bounds*: For any $\tau > 0$, the arrivals A_i^{net} from any flow i to the network satisfy

$$\lim_{x \to \infty} \sup_{t \geq 0} Pr\big\{A_i^{net}(t+\tau) - A_i^{net}(t) > x\big\} = 0 .$$

2. *Independence*: The arrivals A_i^{net} and A_j^{net} from different flows $i \neq j$ are stochastically independent.

The assumptions are made only at the network entrance when traffic is arriving to the first node on its route. No such assumptions are made after traffic has entered the network. The stationary bounds are needed so that we can make statements that do not depend on specific instances of time, and that extend to the steady-state. Assuming independence of traffic sources at the network entrance allows us to exploit statistical multiplexing gain.

[1] A function E is called an *envelope* for a function f if $f(t+\tau) - f(t) \leq E(\tau)$ for all $t, \tau \geq 0$, or, equivalently, if $f(t) \leq E * f(t)$, for all $t \geq 0$.

The literature contains a number of different approaches to devise a statistical network calculus. One group of studies investigates network traffic that, in addition to the assumptions above, satisfies certain a priori assumptions on the arrival functions, such as exponentially bounded burstiness [50], linear envelope processes [13], stochastically bounded burstiness [44], general burstiness characterization [3], or stochastic domination by a given random variable [34]. Other studies assume that arrivals of individual flows at the network ingress are regulated by (deterministic) arrival envelopes A_i^*. Then, by exploiting the independence assumption of flows, they use either the Central Limit Theorem [7, 30, 31], or large deviations tools such as the Chernoff Bound [7, 23] and the Hoeffding Bound [47, 48].

With such arrival assumptions, probabilistic backlog and delay bounds for a single node have been derived for FIFO schedulers with a fixed service rate. Some studies [13, 50, 44] also derive probabilistic bounds for the output of a node, which can then be iterated to yield end-to-end bounds. However, end-to-end bounds obtained in this fashion degrade rapidly with the number of nodes. Other studies consider more complex scheduling algorithms [48, 7, 40] for a single node. There are a few results available for end-to-end statistical guarantees, generally for special arrival or service models [42, 43, 41].

A different set of studies attempts to express a statistical network calculus using the min-plus algebra formulation with convolution and deconvolution operators [2, 11]. The challenge in this approach is to construct a probabilistic network service curve that can be expressed as the convolution of per-node service curves, analogous to Eqn. (2). In [11] it was shown that a network service curve in the statistical network calculus can be constructed if the service curve satisfies additional properties. In [2], a probabilistic network service curve is derived under the assumption that each node drops traffic that locally violates a given delay guarantee. The results in [11] and [2] do not make any assumptions on arrivals and hold for all sample paths of the arrivals. The current state of the statistical network calculus has shown that expressions for backlog, delay, and output bounds at a single node carry over from the deterministic network calculus to a statistical framework. However, a network service curve requires to make significant additional assumptions. At present, finding suitable assumptions that permit a formulation of a network service curve as in Eqn. (2), without restricting the applicability of the framework, is an open research problem.

We next describe the probabilistic framework used in this paper. We follow the framework for a statistical calculus presented in [7] and [11]. For traffic arrivals, we use a probabilistic measure called *effective envelopes* [7]. An effective envelope for an arrival process A is defined as a non-negative function $\mathcal{G}$ such that for all t and τ

$$Pr\Big\{A(t+\tau) - A(t) \leq \mathcal{G}^{\varepsilon}(\tau)\Big\} > 1 - \varepsilon \; . \tag{3}$$

Simply put, an effective envelope provides a stationary bound for an arrival process. Effective envelopes can be obtained for individual flows, as well as for multiplexed arrivals (see Section 3 below). To characterize the available service to a flow or a collection of flows we use *effective service curves* [11] which can be seen as a probabilistic measure of the available service. Given an arrival process A, an effective service curve is a non-negative function $\mathcal{S}^{\varepsilon}$ that satisfies for all $t \geq 0$,

$$Pr\Big\{D(t) \geq A * \mathcal{S}^{\varepsilon}(t)\Big\} \geq 1 - \varepsilon \; . \tag{4}$$

By letting $\varepsilon \to 0$ in Eqs. (3) and (4), we recover the arrival envelopes and service curves of the deterministic calculus with probability one.

2.4 What Makes Statistical Network Calculus Hard?

To illustrate that the statistical network calculus is not a straightforward extension of the deterministic network calculus, we want to mention two technical difficulties encountered when extending the calculus to a probabilistic setting. The first appears when estimating the tail distribution for the backlog or the envelope of the output traffic at a node. In the case of the backlog, the expression takes the form

$$Pr\Big\{B(t) > y\Big\} = Pr\Big\{\sup_{\tau \geq 0}\{A(t-\tau,t) - S(\tau)\} > y\Big\} , \tag{5}$$

where we have used $A(t-\tau,t)$ to denote $A(t) - A(t-\tau)$. The difficulty relates to the evaluation of the right hand side of the equation. Note that in Eqn. (5), the arrivals are random but service is deterministic; a probabilistic view of service causes no additional complications here. In [7] and [16], the above expression is approximated by

$$Pr\Big\{\sup_{\tau \geq 0}\{A(t-\tau,t) - S(\tau)\} > y\Big\} \approx \sup_{\tau \geq 0} Pr\Big\{A(t-\tau,t) - S(\tau) > y\Big\} , \tag{6}$$

by using an argument from extreme-value value theory [12]. The approximation can be justified in some situations, for instance when traffic is described by a Gaussian process. However, in general the right hand side is only a lower bound for the left hand side. In [3], the right hand side of Eqn. (5) is controlled by assuming the existence of a probabilistic bound for the entire arrival sample path. Another way to deal with Eqn. (5) is to use Boole's inequality, which yields

$$Pr\Big\{\sup_{\tau \geq 0}\{A(t-\tau,t) - S(\tau) > y\}\Big\} \leq \sum_{\tau=0}^{\infty} Pr\Big\{A(t-\tau,t) - S(\tau) > y\Big\} . \tag{7}$$

where the sum is replaced by an integral in a continuous time domain. This can yield a useful bound if one has available a tail estimate on the distribution of $A(t-\tau,t) - S(\tau)$, or if there exists a maximum relevant time scale, say T_{max}, such that $Pr\{A(t-\tau,t) - S(\tau) > y\} = 0$ for $\tau > T_{max}$ and the sum contains only finitely many terms.

The second difficulty arises in the derivation of a probabilistic version of a network service curve. This issue was pointed out in [11] for a network as shown in Figure 1, with $H = 2$ nodes, and is repeated here. An effective service curve $\mathcal{S}^{2,\varepsilon}$ in the sense of Eqn. (4) at the second node guarantees that, for any given time t, the departures from this node are with high probability bounded below by

$$D^2(t) \geq A^2 * \mathcal{S}^{2,\varepsilon}(t) = \inf_{\tau \in [0,t]} \big\{A^2(t-\tau) + \mathcal{S}^{2,\varepsilon}(\tau)\big\} . \tag{8}$$

Suppose that the infimum in Eqn. (8) is assumed at some value $\hat{\tau} \leq t$. Since the departures from the first node are random, even if the arrivals to the first node satisfy the deterministic bound A^*, $\hat{\tau}$ is a random variable. An effective service curve $\mathcal{S}^{1,\varepsilon}$ at the first node guarantees that for any arbitrary but fixed time x, the arrivals $A^2(x) = D^1(x)$ to the second node are with high probability bounded below by

$$D^1(x) \geq A^1 * \mathcal{S}^{1,\varepsilon}(x) . \tag{9}$$

Since $\hat{\tau}$ is a random variable, we cannot simply evaluate Eqn. (9) for $x = t - \hat{\tau}$ and use the resulting bound in Eqn. (8). Furthermore, there is, a priori, no time-independent bound on the distribution of $\hat{\tau}$. This is different in the deterministic calculus, where deterministic service curves make guarantees that hold for all values of x. This problem can also be resolved if a time scale bound T_{max} is available, which limits the range over which the infimum is taken as follows:

$$A^2 * \mathcal{S}^{2,\varepsilon}(t) = \inf_{\tau \in [0, T_{max}]} \left\{ A^2(t-\tau) + \mathcal{S}^{2,\varepsilon}(\tau) \right\} .$$

2.5 Network Calculus for Probabilistically Bounded Arrivals and Service

We next improve the state-of-the-art of statistical network calculus analysis, by presenting a network calculus in the min-plus algebra formulation where both arrivals and service are described in terms of probabilistic bounds.

As we pointed out in the previous subsection, the difficulties of the statistical network calculus can be dealt with by assuming appropriate time scale limits. The assumption made in this paper is that the node offers a service curve $\mathcal{S}^{\varepsilon_s}$ which satisfies the additional requirement that there exists a time scale T such that for all $t \geq 0$,

$$Pr\Big\{ D(t) \geq \inf_{\tau \leq T} \left\{ A(t-\tau) + \mathcal{S}^{\varepsilon}(\tau) \right\} \Big\} \geq 1 - \varepsilon \, . \tag{10}$$

Thus T bounds the range of the convolution in Eqn. (4). This assumption solves both problems discussed in the previous subsection. In general, the value of T depends on the arrival process as well as on the service curve. In a workconserving scheduler, such a bound can be established in terms of a probabilistic bound of the busy period, or from a priori backlog or delay bounds. This will be addressed in Subsection 2.6.

The following theorem establishes statistical bounds for delay and backlog in terms of min-plus algebra operations on effective envelopes and effective service curves. Note that we distinguish two violation probabilities: ε_g is the probability that arrivals violate the effective envelope, and ε_s is the probability that the service violates the effective service curve or the condition in Eqn. (10).

Theorem 1 *Assume that $\mathcal{G}^{\varepsilon_g}$ is an effective envelope for the arrivals A to a node, and that $\mathcal{S}^{\varepsilon_s}$ is an effective service curve satisfying Eqn. (10) with some $T < \infty$. Define ε to be*

$$\varepsilon = \varepsilon_s + T \varepsilon_g \, . \tag{11}$$

Then the following hold:

1. **Output Traffic Envelope:** *The function $\mathcal{G}^{\varepsilon_g} \oslash \mathcal{S}^{\varepsilon_s}$ is an effective envelope for the output traffic from the node.*

2. **Backlog Bound:** *$\mathcal{G}^{\varepsilon_g} \oslash \mathcal{S}^{\varepsilon_s}(0)$ is a probabilistic bound on the backlog, in the sense that, for all $t \geq 0$, $Pr\Big\{ B(t) \leq \mathcal{G}^{\varepsilon_g} \oslash \mathcal{S}^{\varepsilon_s}(0) \Big\} \geq 1 - \varepsilon$.*

3. **Delay Bound:** *If $d \geq 0$ satisfies $\sup_{\tau \leq T} \Big\{ \mathcal{G}^{\varepsilon_g}(\tau - d) - \mathcal{S}^{\varepsilon_s}(\tau) \Big\} \leq 0$, then d is a probabilistic delay bound, in the sense that, for all $t \geq 0$, $Pr\Big\{ W(t) \leq d \Big\} \geq 1 - \varepsilon$.*

By setting $\varepsilon_s = \varepsilon_g = 0$, we recover the corresponding statements of the deterministic network calculus from Subsection 2.3 as presented in [1, 8, 14]. Similarly, when only $\varepsilon_g = 0$, the time scale bound T disappears from Eqn. (11) and one can take $T \to \infty$. Thus, the statistical calculus from [11], which deals with deterministic arrivals (where $\varepsilon_g = 0$) and effective service curves $\mathcal{S}^{\varepsilon_s}$, is also recovered by the above theorem.

Proof. First, we prove that $\mathcal{G}^{\varepsilon_g} \oslash \mathcal{S}^{\varepsilon_s}$ is an effective envelope for the output traffic. Fix $t, \tau \geq 0$.

$$Pr\Big\{D(t+\tau) - D(t) \leq \mathcal{G}^{\varepsilon_g} \oslash \mathcal{S}^{\varepsilon_s}(\tau)\Big\} \geq Pr\Big\{D(t+\tau) - D(t) \leq \sup_{x \leq T}\{\mathcal{G}^{\varepsilon_g}(\tau + x) - \mathcal{S}^{\varepsilon_s}(x)\}\Big\} \tag{12}$$

$$\geq Pr\left\{\exists x \leq T : \begin{pmatrix} A(t+\tau) - A(t-x) \leq \mathcal{G}^{\varepsilon_g}(\tau + x) \\ \text{and } D(t) \geq A(t-x) + \mathcal{S}^{\varepsilon_s}(x) \end{pmatrix}\right\} \tag{13}$$

$$\geq Pr\left\{\begin{array}{l} \forall x_1 \leq T : \; A(t+\tau) - A(t-x_1) \leq \mathcal{G}^{\varepsilon_g}(\tau + x_1) \\ \text{and } \exists x_2 \leq T : \; D(t) \geq A(t-x_2) + \mathcal{S}^{\varepsilon_s}(x_2) \end{array}\right\} \tag{14}$$

$$\geq 1 - \Big(\varepsilon_s + T\varepsilon_g\Big). \tag{15}$$

In Eqn. (12), we have expanded the deconvolution operator and reduced the range of the supremum, i.e., by assuming that the supremum is achieved for a value $x \leq T$. In Eqn. (13), we replaced $D(t+\tau)$ by $A(t+\tau)$. Further, by adding the condition that $D(t) \geq A(t-x) + \mathcal{S}^{\varepsilon_s}(x)$ we were able to replace $D(t)$ by $A(t-x) + \mathcal{S}^{\varepsilon_s}(x)$. The inequality holds since adding the condition and the replacements restrict the event. In Eqn. (14) we further restricted the event, by demanding that the first condition in Eqn. (13) holds for all values of x. To obtain Eqn. (15), we applied the assumption in Eqn. (10), and used the definition of $\mathcal{G}^{\varepsilon_g}$. We added the violation probabilities of the two events using Boole's inequality. The factor T in front of ε_g appears since we added the violation probabilities over all values of x_1.

The proof of the backlog bound proceeds along the same lines. We estimate

$$Pr\Big\{B(t) \leq \mathcal{G}^{\varepsilon_g} \oslash \mathcal{S}^{\varepsilon_s}(0)\Big\} = Pr\Big\{A(t) \leq D(t) + \mathcal{G}^{\varepsilon_g} \oslash \mathcal{S}^{\varepsilon_s}(0)\Big\} \tag{16}$$

$$\geq Pr\left\{\exists x \leq T : \begin{pmatrix} A(t) \leq A(t-x) + \mathcal{S}^{\varepsilon_s}(x) + \mathcal{G}^{\varepsilon_g} \oslash \mathcal{S}^{\varepsilon_s}(0) \\ \text{and } D(t) \geq A(t-x) + \mathcal{S}^{\varepsilon_s}(x) \end{pmatrix}\right\} \tag{17}$$

$$\geq Pr\left\{\begin{array}{l} \forall x_1 \leq T : \; A(t) - A(t-x_1) \leq \mathcal{G}^{\varepsilon_g}(x_1) \\ \text{and } \exists x_2 \leq T : \; D(t) \geq A(t-x_2) + \mathcal{S}^{\varepsilon_s}(x_2) \end{array}\right\} \tag{18}$$

$$\geq 1 - \Big(\varepsilon_s + T\varepsilon_g\Big). \tag{19}$$

In Eqn. (16), we have used the definition of the backlog $B(t)$. The arguments made in Eqs. (17)–(19) are analogous to those used in Eqs. (13)–(15).

Finally, we prove the delay bound. If d satisfies $\sup_{\tau \leq T}\{\mathcal{G}^{\varepsilon_g}(\tau - d) - \mathcal{S}^{\varepsilon_s}(\tau)\} \leq 0$, then

$$Pr\Big\{W(t) \leq d\Big\} = Pr\Big\{A(t-d) \leq D(t)\Big\} \tag{20}$$

$$\geq Pr\left\{\exists x \leq T : \begin{pmatrix} A(t-d) \leq A(t-x) + \mathcal{S}^{\varepsilon_s}(x) \\ \text{and } D(t) \geq A(t-x) + \mathcal{S}^{\varepsilon_s}(x) \end{pmatrix}\right\} \tag{21}$$

$$\geq Pr\left\{\begin{array}{l} \forall x_1 \leq T : \; A(t-d) - A(t-x_1) \leq \mathcal{G}^{\varepsilon_g}([x_1 - d]_+) \\ \text{and } \exists x_2 \leq T : \; D(t) \geq A(t-x_2) + \mathcal{S}^{\varepsilon_s}(x_2) \end{array}\right\} \tag{22}$$

$$\geq 1 - \Big(\varepsilon_s + T\varepsilon_g\Big). \tag{23}$$

In Eqn. (20), we have used the definition of the delay $W(t)$, and in Eqn. (21), we have used the assumption on d. The remaining steps apply the same arguments as the proofs of the output bound and the backlog bound. $\square$

Next we derive an expression for a probabilistic version of a network service curve, which expresses the service given by the network as a whole as a convolution of the service at each node. Consider the path of a flow through a network, as illustrated in Figure 1. At each node, the arrivals are allotted an effective service curve, where $\mathcal{S}^{h,\varepsilon_s}$ denotes the effective service curve at node h. Similar to Eqn. (10), we assume that each node satisfies

$$Pr\Big\{D^h(t) \geq \inf_{\tau \leq T^h} \{A^h(t-\tau) + \mathcal{S}^{h,\varepsilon_s}(\tau)\}\Big\} \geq 1 - \varepsilon_s \tag{24}$$

for some numbers $T^1, \ldots T^H < \infty$. For notational convenience, we assume that the violation probabilities ε_s are identical at each node. This assumption is easily relaxed.

Theorem 2 Effective Network Service Curve. *Assume that the service offered at each node $h = 1, \ldots, H$ on the path of a flow through a network is given by a service curve $\mathcal{S}^{h,\varepsilon_s}$ satisfying Eqn. (24). Then an effective network service curve $\mathcal{S}^{net,\varepsilon}$ for the flow is given by*

$$\mathcal{S}^{net,\varepsilon} = \mathcal{S}^{1,\varepsilon_s} * \mathcal{S}^{2,\varepsilon_s} * \ldots * \mathcal{S}^{H,\varepsilon_s} , \tag{25}$$

with violation probability bounded above by

$$\varepsilon = \varepsilon_s \sum_{h=1}^{H} \Big(1 + (h-1)T^h\Big) . \tag{26}$$

The convolution expression in Eqn. (25) has the same form as the corresponding expression in a deterministic setting seen in Eqn. (2), and the deterministic statement is recovered with probability one by letting $\varepsilon \to 0$. On the other hand, the violation probability ε in Eqn. (26) increases at each hop by $\varepsilon_s T^h$. Clearly, it is important to control the time scale bound T^h.

Proof. We start the proof with a deterministic argument for a sample path. Fix $t \geq 0$, and suppose that, for a particular sample path, we have

$$\begin{cases} \forall \tau \leq \sum_{k=h+1}^{H} T^k : \; D^h(t-\tau) \geq \inf_{x_h \leq T^h} \{A^h(t-\tau-x_h) + \mathcal{S}^{h,\varepsilon_s}(x_h)\} , & \text{if } h < H, \\ D^H(t) \geq \inf_{x_H \leq T^H} \{A^H(t-x_H) + \mathcal{S}^{H,\varepsilon_s}(x_H)\} , & \text{if } h = H . \end{cases} \tag{27}$$

Since the arrivals at each node are given by the departures from the previous node, that is, $A^h = D^{h-1}$ for $h = 2, \ldots, H$, we see by repeatedly inserting the first line of Eqn. (27) into the second line of Eqn. (27) that

$$D^H(t) \geq \inf_{x_h \leq T^h,\, h=1,\ldots,H} \Big\{A^h(t - (x_h + \ldots + x_H)) + \sum_{k=h}^{H} \mathcal{S}^{k,\varepsilon_s}(x_k)\Big\} . \tag{28}$$

Setting $h = 1$ in Eqn. (28), and using the definitions of A^{net}, D^{net}, and $\mathcal{S}^{net,\varepsilon}$, we obtain

$$D^{net}(t) \geq \inf_{x_h \leq T^h,\, h=1,\ldots H} \Big\{A^{net}(t - (x_1 + \cdots + x_H)) + \mathcal{S}^{net,\varepsilon}(x_1 + \cdots + x_H)\Big\} . \tag{29}$$

Thus, we have shown that Eqn. (27) implies

$$D^{net}(t) \geq A^{net} * \mathcal{S}^{net,\varepsilon}(t). \tag{30}$$

We conclude proof of the theorem by

$$\begin{aligned} Pr\Big\{D^{net}(t) \geq A^{net} * \mathcal{S}^{net,\varepsilon}(t)\Big\} \quad &\geq \quad Pr\Big\{ \text{ Eqn. (27) holds } \Big\} & (31) \\ &\geq \quad 1 - \varepsilon_s \cdot \sum_{h=1}^{H} \Big(1 + \sum_{k=h+1}^{H} T^k\Big) . & (32) \end{aligned}$$

In Eqn. (31) we have used that Eqn. (27) implies Eqn. (30). In Eqn. (32), we have applied Eqn. (24) and added the violation probabilities of Eqn. (27) over all possible values of $h = 1, \ldots, H$. Exchanging the order of summation completes the proof. $\square$

2.6 Busy Period Analysis

We now turn to the question of estimating the time scale T which appears in Theorems 1 and 2. For workconserving schedulers, this time scale can be bounded by the length of the busy period of the scheduler at time t. More precisely, let $A_{\mathcal{C}}(t)$, $D_{\mathcal{C}}(t)$, and $B_{\mathcal{C}}(t)$ denote the aggregate arrivals, the departures, and the backlog of a set $\mathcal{C}$ of flows arriving at a scheduler. By definition, the busy period for a given time $t \geq 0$ is the maximal time interval containing t during which the backlog from the flows in $\mathcal{C}$ remains positive. The beginning of the busy period of t is the last idle time before t, given by

$$\underline{t} = \max\{\tau \leq t : \ B_{\mathcal{C}}(\tau) = 0\} \ . \tag{33}$$

Our assumption that the queues are empty at time $t = 0$ guarantees that $0 \leq \underline{t} \leq t$.

The following lemma establishes a busy period bound for an output link that operates at a constant rate C. The bounds are expressed in terms of probabilistic arrival bounds that are related to the effective envelopes defined in Eqn. (3).

Lemma 1 *Consider a work-conserving scheduler with constant rate C. Fix $\varepsilon > 0$, and assume that there exists a function $\overline{\mathcal{G}}^{\varepsilon}_{\mathcal{C}}$ such that for all $t, \tau \geq 0$.*

$$\sum_{\tau=0}^{\infty} Pr\Big\{A_{\mathcal{C}}(t+\tau) - A_{\mathcal{C}}(t) > \overline{\mathcal{G}}^{\varepsilon}_{\mathcal{C}}(\tau)\Big\} \leq \varepsilon \ . \tag{34}$$

Set

$$T = \sup\left\{\tau \mid \overline{\mathcal{G}}^{\varepsilon}_{\mathcal{C}}(\tau) > C\tau\right\} . \tag{35}$$

Then T is a probabilistic bound on the busy period which satisfies

$$Pr\Big\{t - \underline{t} \leq T\Big\} \geq 1 - \varepsilon \ . \tag{36}$$

Since a workconserving scheduler satisfies $D_C(t) \geq A_{\mathcal{C}}(\underline{t}) + C(t - \underline{t})$ by definition, Eqn. (36) implies the desired time scale bound in Eqn. (10).

Proof. Since $B_{\mathcal{C}}(\tau) > 0$ for $\underline{t} < \tau \leq t$, we have by definition of the workconserving scheduler that $D_{\mathcal{C}}(t) - D_{\mathcal{C}}(\underline{t}) \geq C(t - \underline{t})$. Since $D_{\mathcal{C}}(t) < A_{\mathcal{C}}(t)$, and $D_{\mathcal{C}}(\underline{t}) = A_{\mathcal{C}}(\underline{t})$ by definition of $\underline{t}$, this implies $A_{\mathcal{C}}(t) - A_{\mathcal{C}}(\underline{t}) > C(t - \underline{t})$. It follows that

$$Pr\Big\{t - \underline{t} > T\Big\} \leq Pr\Big\{\exists \tau > T : \ A_{\mathcal{C}}(t) - A_{\mathcal{C}}(t - \tau) > C\tau\Big\} \ . \tag{37}$$

Let now T be given by Eqn. (35). Then

$$\begin{aligned} Pr\Big\{t - \underline{t} > T\Big\} &\leq \sum_{\tau=T+1}^{\infty} Pr\Big\{A_{\mathcal{C}}(t) - A_{\mathcal{C}}(t-\tau) > C\tau\Big\} && (38) \\ &\leq \sum_{\tau=0}^{\infty} Pr\left\{A_{\mathcal{C}}(t) - A_{\mathcal{C}}(t-\tau) > \overline{\mathcal{G}}^{\varepsilon}_{\mathcal{C}}(\tau)\right\} && (39) \\ &\leq \varepsilon \ . && (40) \end{aligned}$$

In Eqn. (38), we have applied Boole's inequality to Eqn. (37). In Eqn. (39), we have use the assumption on T, and in the last third step, we have replaced t with $t-\tau$ and used the assumption on $\overline{\mathcal{G}}^{\varepsilon}_{\mathcal{C}}$. $\square$

The lemma is easily extended from constant-rate workconserving servers to output links that offer a (deterministic) *strict service curve*, which is a nonnegative function $S(\tau)$ such that for every $t_2 \geq t_1 \geq 0$ and every sample path, $D_{\mathcal{C}}(t_2) - D_{\mathcal{C}}(t_1) \geq S(t_2 - t_1)$ whenever $B_{\mathcal{C}}(t) > 0$ for $t \in [t_1, t_2]$. This includes, in particular, *latency-rate service curves* [45] with $S(t) = K(t-L)$ for a rate K and a latency L.

Inserting Lemma 1 into Theorem 1 immediately provides bounds on output, delay, and backlog for a single node in terms of the arrivals and the available service at that node. Using Lemma 1 for a probabilistic network service curve is less straightforward. The difficulty is that Theorem 2 requires bounds on the time scales T^h at each node $h = 1, \ldots, H$ on the path of a flow. In principle, such arrival bounds can be obtained by iterating the input-output relation of Theorem 1. However, this approach leads to bounds on the violation probabilities that grow exponentially in the number of nodes.

In our numerical examples, we use Lemma 1 to obtain time scale bounds for each node. We first choose a function $\overline{\mathcal{G}}^{net,\varepsilon}_{\mathcal{C}}$ for the arrivals to the network satisfying

$$Pr\big(A^{net}_{\mathcal{C}}(t+\tau) - A^{net}_{\mathcal{C}}(t) > \overline{\mathcal{G}}^{net,\varepsilon}_{\mathcal{C}}\tau\big) \leq \frac{2\varepsilon}{\pi(1+\tau^2)}\,. \tag{41}$$

This formula is analogous to the definition of the effective envelope in Eqn. (3), with ε replaced by $(2\varepsilon)/(\pi(1+\tau^2))$. Since $\sum_\tau (1+\tau^2)^{-1} \leq \pi/2$, this definition of $\overline{\mathcal{G}}^{net,\varepsilon}_{\mathcal{C}}$ satisfies Eqn. (34), and the time scale bound at the ingress node is provided by Lemma 1. To obtain the time scale bounds T^h at downstream nodes, we assume that any packet whose delay at a node exceeds a certain delay threshold d^* is dropped. Under this assumption, the arrivals to the h-th node are bounded in terms of the arrivals to the ingress node by

$$A^h_{\mathcal{C}}(t) - A^h_{\mathcal{C}}(t-\tau) \leq A^{net}_{\mathcal{C}}(t) - A^{net}_{\mathcal{C}}(t-\tau-(h-1)d^*)\,.$$

It follows that

$$\sum_{\tau=0}^{\infty} Pr\big\{A^h_{\mathcal{C}}(t) - A^h_{\mathcal{C}}(t-\tau) > \overline{\mathcal{G}}^{net,\varepsilon}_{\mathcal{C}}(\tau+(h-1)d^*)\big\} \leq \varepsilon\,, \tag{42}$$

and we can apply Lemma 1 with

$$\overline{\mathcal{G}}^{h,\varepsilon}_{\mathcal{C}}(\tau) = \overline{\mathcal{G}}^{net,\varepsilon}_{\mathcal{C}}(\tau+(h-1)d^*). \tag{43}$$

Finally, we use Theorems 1 and 2 to verify that d^* is large enough so that the loss rate due to this dropping policy is a small fraction of the traffic rate. Even though these choices are clearly very conservative, leading to rather loose bounds on T^h, the numerical results on backlog and delay are satisfactory.

The above assumption on an a priori delay threshold d^* is analogous to an assumption in [3] that all traffic exceeding a certain delay bound is dropped. Bounds for T^h can also be obtained from a priori bounds on the backlog, e.g., as done in [47]. Such bounds on the backlog naturally result from finite buffer sizes in a network. Alternatively, a priori bounds on delay, backlog, and the length of busy periods can be obtained from the deterministic calculus. Generally, it suffices to derive loose bounds on T^h, because the violation probabilities provided in Eqn. (11) and Eqn. (26) depend only linearly on T, while effective envelopes $\mathcal{G}$, and consequently the time scale bound T, typically deteriorates very slowly as $\varepsilon \to 0$.

In summary, as is done in the related literature, we address the general problem of determining time scale bounds in a general multi-node setting by relying on external assumptions. The challenge to formulate a multi-node calculus that does not require separate verification of a priori bounds remains open.

3 Effective Envelopes and Effective Bandwidth

In this section, we reconcile two methods for probabilistic traffic characterization, effective envelopes and effective bandwidth, and explore the relationship between them. The effective bandwidth, which has been extensively studied, is motivated by the rate functions that appear in the theory of large deviations. Effective bandwidth expressions have been derived for numerous source traffic models with applications in computer networks. We refer to [15, 29, 32] for a detailed discussion. By providing a link between effective bandwidth and effective envelopes, the results in this section make effective bandwidth results applicable to the network calculus.

In this paper we use the general definition from [29], which defines the *effective bandwidth* of an arrival process A as

$$\alpha(s,\tau) = \sup_{t\geq 0} \left\{ \frac{1}{s\tau} \log E[e^{s(A(t+\tau)-A(t))}) \right\} , \qquad s,\tau \in (0,\infty) . \tag{44}$$

The parameter τ is called the time parameter and indicates the length of a time interval. The parameter s is called the space parameter and contains information about the distribution of the arrivals. Generally, the effective bandwidth of a traffic flow varies between the mean and peak rates of the traffic and provides a link between the traffic characteristics of a flow and the resources in terms of bandwidth and buffer size necessary to support a required level of service. Near $s = 0$, the effective bandwidth is dominated by the mean rate of the traffic, while near $s = \infty$, it is primarily influenced by the peak rate of the traffic. Thus, the space parameter s can be seen as relating to a violation probability ε (see Lemma 2).

3.1 Overview of Effective Bandwidth

The notion of effective bandwidth emerged in the early 1990s in [25, 26, 27, 28] as a method to characterize and exploit the statistical multiplexing gain of traffic flows and, thereby, increase the utilization of network resources. The effective bandwidth of a traffic flow can be related to the minimum bandwidth needed to satisfy service guarantees for that flow. Then, one can verify that a link with capacity C is able to provide the required service to N traffic flows by testing if $\sum_{i=1}^{N} \alpha_i < C$, where α_i is the effective bandwidth of the i-th flow for suitable choices of s and τ.

Early work on effective bandwidth focused on Markov modulated fluid flow and on-off traffic models [25, 26, 28]. By relating the effective bandwidth concept to the theory of large deviations in [13, 20, 49], the effective bandwidth theory could be extended to a wide range of network traffic models including general Markovian and self-similar traffic models [20, 21]. The theory has also been generalized from FIFO scheduling algorithm to non-FIFO scheduling algorithms such as Static Priority (SP) [4, 5, 22, 33] and Generalized Processor Sharing (GPS) [46, 51], and has become an elegant and powerful framework with many applications.

A crucial result in the effective bandwidth theory concerns the large buffer asymptotics for links with FIFO scheduling. The result states that $\sum_{i=1}^{N} \alpha_i(s) < C$ if and only if $Pr\big(B > x\big) \sim e^{-sx}$ as $x \to \infty$, where $\alpha_i(s) = \lim_{\tau\to\infty} \alpha_i(s,\tau)$ and B is the steady-state backlog of the traffic. In other words, as long as the effective bandwidth of a set of flows is below the capacity of the link, the probability of a packet loss due to a buffer overflow decays exponentially fast as a function of the buffer size. This frequently cited result, however, is an asymptotic approximation for large buffer sizes and may either overestimate or underestimate the actual backlog behavior by several orders of magnitude, especially if arriving traffic is bursty [17]. Furthermore, in the asymptotic regime, the bandwidth requirements given by the effective bandwidth are additive, and, hence, do not reflect the gains due to statistical multiplexing [17].

The asymptotic bounds from the effective bandwidth literature are not directly applicable in a network calculus context. Instead, when we insert effective bandwidth expressions in the network calculus we need to work explicitly with finite buffer sizes. Such non-asymptotic bounds have been presented by Chang [13, 15] for a class of linear envelope processes with parameters $\big(\sigma(s), \rho(s)\big)$, characterized by

$$\frac{1}{s} \log\big(e^{sA(t,t+\tau)}\big) \leq \sigma(s) + \rho(s)\tau \ . \tag{45}$$

If $\rho(s) < C$ for these processes, Chang [13] bounds the tail probability of the backlog behavior by $Pr\big(B > x\big) \leq \beta(s) e^{-sx}$, where the constant $\beta(s)$ is explicitly given as $\beta(s) = e^{s\tau(s)}\big(1 - e^{s(\rho(s)-C)}\big)^{-1}$. Chang relates these and other results on envelope processes to draw analogies to the deterministic network calculus [18]. Chang [13] also shows that the output at a link with FIFO scheduling is again a linear envelope processes. In principle, this property can be iteratively applied to obtain delay and backlog bounds for a network with multiple nodes. In practice, however, the bounds obtained with such an iterative procedure deteriorate quickly (exponentially) in the number of nodes. (Closely related results, without referring to effective bandwidth, are obtained by Yaron and Sidi for the class of exponentially bounded burstiness [50]).

The motivation for our work is to further develop the relationship between effective bandwidth and the network calculus. Our results, all expressed as explicit (non-asymptotic) bounds, extend the relationships established by Chang in several directions. First, we do not restrict ourselves to a specific class of arrival models, but consider all arrival models for which effective bandwidth expressions are available. For example, we consider FBM traffic which has been used to model self-similar characteristics of network traffic, but which cannot be characterized by a linear envelope process. Second, using the network calculus from Section 2, our results can be related to a (effective) network service curve which yields end-to-end backlog and delay bounds over multiple nodes. Lastly, we will (in Section 4) consider a number of commonly used scheduling algorithms, which are more complex than FIFO scheduling used predominantly in the effective bandwidth literature.

3.2 Relating Effective Bandwidth and Effective Envelopes

The choice of the term 'effective envelope' as introduced in [7] suggests a connection to the notion of effective bandwidth, but without making that connection explicit. The following lemma establishes a formal relationship between the two concepts, and thus, links the effective bandwidth theory to the statistical network calculus.

Lemma 2 *Given an arrival process A with effective bandwidth $\alpha(s,\tau)$, an effective envelope is given by*

$$\mathcal{G}^{\varepsilon}(\tau) \quad = \quad \inf_{s>0} \Big\{ \tau\alpha(s,\tau) - \frac{\log \varepsilon}{s} \Big\} \ . \tag{46}$$

Conversely, if, for each $\varepsilon \in (0,1)$, the function $\mathcal{G}^{\varepsilon}$ is an effective envelope for the arrival process, then its effective bandwidth is bounded by

$$\alpha(s,\tau) \quad \leq \quad \frac{1}{s\tau} \log\left(\int_0^1 e^{s\mathcal{G}^{\varepsilon}(\tau)} d\varepsilon \right) \ . \tag{47}$$

We emphasize that the effective envelope is a more general concept than effective bandwidth, in the sense that each effective bandwidth expression can be immediately expressed in terms of an effective envelope, whereas there may not be an effective bandwidth corresponding to a given effective envelope. As another way to see the generality of the effective envelope, even when the effective bandwidth $\alpha(s,\tau)$ is infinite for some values of s and τ, and the corresponding construction in Lemma 2 is not applicable, it may be feasible to specify an effective envelope $\mathcal{G}^{\varepsilon}(\tau)$ according to Eqn. (3), which is finite for all values of ε and τ.

Proof. To prove the first statement, fix $t, \tau \geq 0$. By the Chernoff bound [38],[2] we have for any x and any $s \geq 0$

$$\begin{aligned} Pr\Big\{ A(t+\tau) - A(t) \geq x \Big\} &\leq e^{-sx} E\left[e^{s(A(t+\tau)-A(t))} \right] && (48) \\ &\leq e^{s(-x+\tau\alpha(s,\tau))} \, . && (49) \end{aligned}$$

Setting the right hand side equal to ε and solving for x, we see that, for any choice of $s > 0$, the function

$$x^{\varepsilon,s}(\tau) = \tau\alpha(s,\tau) - \frac{\log \varepsilon}{s} \tag{50}$$

is an effective envelope for A, with violation probability bounded by ε. (The superscripts are added to show the dependence of x on ε and s.) Minimizing over s proves the claim.

For the second statement, fix $t, \tau \geq 0$, and let

$$F^{t,\tau}(x) = Pr\big\{ A(t+\tau) - A(t) \leq x \big\} \tag{51}$$

be the distribution function of $A(t+\tau) - A(t)$. For any $s > 0$, we can write the moment-generating function of $A(t+\tau) - A(t)$ in the form

$$E\left[e^{s(A(t+\tau)-A(t))} \right] = \int_0^{\infty} e^{sx} dF^{t,\tau}(x) \, . \tag{52}$$

By using a suitable approximation, we may assume without loss of generality that $F^{t,\tau}$ is continuous and strictly increasing for $x \geq 0$. Let $G^{t,\tau}$ be the inverse function of $1 - F^{t,\tau}$. Since

$$Pr\left\{ A(t+\tau) - A(t) > G^{t,\tau}(\varepsilon) \right\} = \varepsilon \, , \tag{53}$$

we must have $G^{t,\tau}(\varepsilon) \geq \mathcal{G}^{\varepsilon}(\tau)$ by the definition of the effective envelope. Performing the change of variables $1 - F^{t,\tau}(x) = \varepsilon$, i.e., $x = G^{t,\tau}(\varepsilon)$ in the integral, we obtain

$$E\left[e^{s\big(A(t+\tau)-A(t)\big)} \right] = \int_0^1 e^{sG^{t,\tau}(\varepsilon)} d\varepsilon \leq \int_0^1 e^{s\mathcal{G}^{\varepsilon}(\tau)} d\varepsilon \, . \tag{54}$$

It follows that

$$\alpha(s,\tau) \leq \frac{1}{s\tau} \int_0^1 e^{s\mathcal{G}^{\varepsilon}(\tau)} d\varepsilon \, , \tag{55}$$

as claimed. □

With this lemma we can construct an effective envelope for a traffic class if its effective bandwidth is known. Since many effective bandwidth formulas have been provided in the literature (e.g., [15, 29]), Lemma 2 provides a useful tool to apply the presented network calculus to a wide range of traffic models. We next use the lemma to obtain effective envelopes for regulated arrivals, memoryless on-off traffic, and FBM.

[2] For a random variable X, the Chernoff bound is given by $Pr\Big\{ X \geq x \Big\} < e^{-sx} E\left[e^{sX} \right]$.

3.3 Regulated Arrivals

We refer to arrivals that are bounded by an arrival envelope A^* (see Subsection 2.3) as regulated arrivals. The regulated arrival model is a suitable description when the amount of traffic that enters the network is limited at the network ingress, e.g., by a leaky bucket. More formally, let A^* be a nondecreasing, nonnegative, subadditive function. We say that an arrival process A is *regulated by* A^* if

$$\forall t, \tau \geq 0 : \quad A(t+\tau) - A(t) \leq A^*(\tau) \tag{56}$$

holds for every sample path. The peak rate and the average rate of regulated traffic, denoted by P and ρ, are defined as

$$P = A^*(1) \, , \quad \rho = \lim_{t \to \infty} \frac{A^*(t)}{t} \, . \tag{57}$$

Consider a collection $\mathcal{C}$ of flows, where A_i^*, P_i and ρ_i are the arrival envelope, the peak rate, and the average rate of flow i. Clearly, the aggregate of the flows $A_\mathcal{C}$ is bounded by $A_\mathcal{C}^* = \sum_{i \in \mathcal{C}} A_i^*$, with peak and average rates of $P_\mathcal{C} = \sum_{i \in \mathcal{C}} P_i$ and $\rho_\mathcal{C} = \sum_{i \in \mathcal{C}} \rho_i$. We assume that each flow $i \in \mathcal{C}$ satisfies the stationary bound

$$E\big[A_i(t+\tau) - A_i(t)\big] \leq \rho_i \tau \, , \tag{58}$$

and that the arrivals from different flows are independent. The effective bandwidth for such a collection of flows $A_\mathcal{C}$ satisfies [29]

$$\alpha_\mathcal{C}(s,t) \leq \frac{1}{st} \sum_{i \in \mathcal{C}} \log \left(1 + \frac{\rho_i t}{A_i^*(t)} (e^{sA_i^*(t)} - 1) \right) \, . \tag{59}$$

By Lemma 2, the corresponding effective envelope is given by

$$\mathcal{G}_\mathcal{C}^\varepsilon(t) \ = \ \inf_{s>0} \Big\{ \sum_{i \in \mathcal{C}} \frac{1}{s} \log \Big(1 + \frac{\rho_i t}{A_i^*(t)} \big(e^{sA_i^*(t)} - 1 \big) \Big) - \frac{\log \varepsilon}{s} \Big\} \, . \tag{60}$$

This effective envelope satisfies

$$\rho_\mathcal{C} t \leq \mathcal{G}_\mathcal{C}^\varepsilon(t) \leq A_\mathcal{C}^*(t) \tag{61}$$

for all $t \geq 0$.

3.4 Memoryless On-Off traffic

On-Off traffic models are frequently used to model the behavior of (unregulated) compressed voice sources. We consider a variant of On-Off traffic with independent increments. As illustrated in Figure 2, we describe an On-Off traffic source as a two-state memoryless process. In the ‘On’ state, traffic is produced at the peak rate P, and in the ‘Off’ state, no traffic is produced, with an overall average traffic rate $\rho < P$. For a collection $\mathcal{C}$ of independent flows with peak rates P_i and average rates ρ_i ($i \in \mathcal{C}$), the effective bandwidth for the aggregate traffic of the flows in $\mathcal{C}$ is given by [15]

$$\alpha_\mathcal{C}(s,t) = \frac{1}{s} \sum_{i \in \mathcal{C}} \log \left(1 + \frac{\rho_i}{P_i} \big(e^{P_i s} - 1 \big) \right) \, . \tag{62}$$

Lemma 2 gives the corresponding effective envelope as

$$\mathcal{G}_\mathcal{C}^\varepsilon(t) \ = \ \inf_{s>0} \Big\{ \frac{t}{s} \sum_{i \in \mathcal{C}} \log \Big(1 + \frac{\rho_i}{P_i} \big(e^{P_i s} - 1 \big) \Big) - \frac{\log \varepsilon}{s} \Big\} \, . \tag{63}$$

(t)

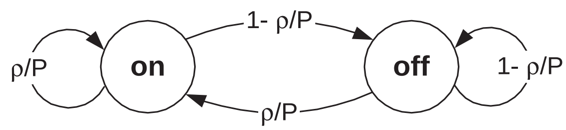


Figure 2: On-Off Transition Model.

3.5 Fractional Brownian Motion (FBM) traffic

As pointed out in [37], the self-similarity properties of measured traffic data can sometimes be modeled by processes of the form

$$A(t) = \rho t + \beta Z_t \ , \tag{64}$$

where Z_t is a normalized fractional Brownian motion with Hurst parameter $H > \frac{1}{2}$, $\rho > 0$ is the mean traffic rate, and β^2 is the variance of $A(1)$. By definition, $\{Z_t\}_{t\in\mathbb{R}}$ is a Gaussian process with stationary increments which is characterized by its starting point $Z_0 = 0$, expected values $E[Z_t] = 0$, and variances $E[Z_t^2] = |t|^{2H}$ for all t.

Following [37], we will refer to Eqn. (64) as the *Fractional Brownian Motion (FBM)* traffic model. Note that the sum of the arrivals from a collection $\mathcal{C}$ of independent FBM sources with common Hurst parameter is again of type FBM. where the mean traffic rate is given by $\rho_\mathcal{C} = \sum_{i\in\mathcal{C}} \rho_i$, and the variance β^2 is given by $\beta_\mathcal{C}^2 = \sum_{i\in\mathcal{C}} \beta_i^2$. FBM traffic is of interest because the statistical analysis of actual network traffic has shown to be self-similar, that is, traffic exhibits long range dependence [24].

We remark that the FBM model is an idealization that fails to capture certain basic properties of actual traffic. Most notably, even though the average rate is positive, increments can be negative, and there is positive probability that a sample path fails to be nondecreasing, or even nonnegative. Furthermore, fractional Brownian traffic is defined for continuous time, while we consider here discrete-time arrival processes. We note that the estimates below hold for all (discrete-time) arrival processes that have nonnegative increments, and whose moment generating function is bounded by the moment generating function of fractional Brownian traffic.

The effective bandwidth for fractional Brownian traffic has been derived as [29]

$$\alpha_\mathcal{C}(s,t) = \rho_\mathcal{C} + \frac{1}{2}\beta_\mathcal{C}^2 s t^{2H-1} \ . \tag{65}$$

By Lemma 2, this results in an effective envelope of

$$\mathcal{G}_\mathcal{C}^\varepsilon(t) \quad = \quad \rho_\mathcal{C} t + \sqrt{-2\log\varepsilon}\,\beta_\mathcal{C} t^H \ . \tag{66}$$

4 Effective Service Curves for Scheduling Algorithms

We next present probabilistic lower bounds on the service guaranteed to a class of flows in terms of effective service curves. We derive effective service curves at a node for a set of well-known scheduling algorithms.

From here on, we assume that each flow belongs to one of Q classes. We denote the arrivals from all flows in class q by A_q, and the arrivals to the collection $\mathcal{C}$ of all flows in all classes $q = 1,\ldots,Q$ by $A_\mathcal{C}$. We make similar conventions for departures and backlogs. We use $\mathcal{G}_q^{\varepsilon_g}$ to denote an effective envelope for the arrivals from class q. We consider a workconserving link with rate C, and three scheduling algorithms:

Static Priorities (SP), Earliest Deadline First (EDF), and Generalized Processor Sharing (GPS). We begin with a brief description of the three schedulers.

1. In an SP scheduler, every class is assigned a priority index, where a lower priority index indicates a higher priority. An SP scheduler selects for transmission the earliest arrival from the highest priority class with a nonzero backlog.

2. In an EDF scheduler, every class q is associated with a delay index d_q. A class-q packet arriving at t is assigned the deadline $t + d_q$, and the EDF scheduler always selects the packet with the smallest deadline for service. Note that, in a probabilistic context, actual delays may violate the delay index, and deadlines can become negative.

3. In a GPS scheduler, every class q is assigned a weight index ϕ_q and is guaranteed to receive at least a share $\frac{\phi_q}{\sum_p \phi_p}$ of the available capacity. If any class uses less than its share, the extra bandwidth is proportionally shared by all other classes.

For these schedulers, we now present effective service curves for each traffic class q. The effective service curves consider the 'leftover' bandwidth which is not used by other traffic classes $p \neq q$. A similar construction was used in the *statistical service envelopes* from [40]. A major difference between statistical service envelopes and our effective service curves is that the latter are non-random functions. This makes the analysis of effective service curves more tractable. In [35] such leftover service curves where used to derive lower bounds on the service for an individual flow when the scheduling algorithms are not known.

Lemma 3 *Consider the arrivals from Q classes to a workconserving server with capacity C. For each class $q = 1, \ldots, Q$, let $\mathcal{G}_q^{\varepsilon_g}$ be an effective envelope for the arrivals A_q from flows in class q. Let T be a busy period bound for the aggregate $A_\mathcal{C}$ that satisfies Eqn. (36) with some $\varepsilon_b < 1$. Assume the scheduling algorithm employed at the server is either SP, EDF, or GPS. In the case of GPS, assume additionally that the functions $\mathcal{G}_p^{\varepsilon_p}$ are concave. Define functions $\mathcal{S}_q^{\varepsilon_s}$ as follows:*[3]

1. **SP:** $$\mathcal{S}_q^{\varepsilon_s}(t) = \Big[Ct - \sum_{p<q} \mathcal{G}_p^{\varepsilon_g}(t)\Big]_+ , \quad \varepsilon_s = \varepsilon_b + (q-1)T\varepsilon_g \; . \tag{67}$$

2. **EDF:** $$\mathcal{S}_q^{\varepsilon_s}(t) = \Big[Ct - \sum_{p \neq q} \mathcal{G}_p^{\varepsilon_g}(t - [d_p - d_q]_+)\Big]_+ , \quad \varepsilon_s = \varepsilon_b + (Q-1)T\varepsilon_g \; . \tag{68}$$

3. **GPS:** $$\mathcal{S}_q^{\varepsilon_s}(t) = \lambda_q\Big(Ct + \sum_{p \neq q} \Big[\lambda_p Ct - \mathcal{G}_p^{\varepsilon_g}(t)\Big]_+\Big) , \quad \varepsilon_s = \varepsilon_b + (Q-1)T\varepsilon_g \; , \tag{69}$$

where $\lambda_p = \phi_p / \sum \phi_r$ is the guaranteed share of class p.

Then, in each case $\mathcal{S}_q^{\varepsilon_s}$ is an effective service curve for class q, satisfying

$$Pr\Big\{D_q(t) \geq \inf_{\tau \leq T} \{A_q(t-\tau) + \mathcal{S}_q^{\varepsilon_s}(\tau)\}\Big\} \geq 1 - \varepsilon_s \; . \tag{70}$$

By setting all violation probabilities ε_b, $\varepsilon_g = 0$ in Lemma 3, we can recover a deterministic (worst-case) statement on the lower bound of the service seen by a service class. The assumption that the scheduler is workconserving is used to establish that the service curves $\mathcal{S}_q^{\varepsilon_s}$ is nonnegative. The lemma easily extends to

[3]We use the notation $[x]_+ = \max(x, 0)$ to denote the positive part of x.

servers offering a *strict* deterministic service curve S, which need not be constant-rate (see the remark after Lemma 1). In that case, the term Ct should be replaced by $S(t)$ in the conclusions in Eqs. (67)–(69). Given a service curve S satisfying only Eqn. (1), the leftover service curve for class q in the case of an SP scheduler is given by $S(t) - \sum_{p<q} \mathcal{G}_p^{\varepsilon_g}(t)$, which is likely to be negative for small values of t. The corresponding formulas hold for EDF and GPS schedulers.

The formulas in Eqs. (67)–(69) do not fully characterize the service available to class q for the three schedulers. Rather, they represent lower bounds on the leftover capacity that is left by other classes. Among the three scheduling algorithms, Eqn. (67) describes the performance of an SP scheduler rather closely. Eqn. (69) for the GPS scheduler is not the best possible description, but improves on the minimal guaranteed rate $\lambda_q C$. On the other hand, Eqn. (68) does not entirely reflect the properties of the EDF scheduler. For example, in the limit where $d_p \approx d_q$ for all classes $p \neq q$, Eqn. (68) approaches the service guarantees of an SP scheduler for the lowest priority class, while the actual EDF scheduler approaches FIFO.

Proof. We show that Eqn. (70) holds separately for each of the scheduling algorithms.

1. SP scheduling: Denote the arrivals from flows of priority at least q by $A_{\leq q}$, and the arrivals from flows of priority higher than q by $A_{<q}$, and correspondingly for departures and backlogs. Fix $t \geq 0$, and let

$$\underline{t}_{\leq q} = \max\big\{x \leq t : \ B_{\leq q}(x) = 0\big\} \tag{71}$$

be the beginning of the busy period containing t from the perspective of class q. If the class-q backlog $B_q(t) = 0$, there is nothing to show. If $B_q(t) > 0$, then we have by the properties of the SP scheduler that

$$\begin{aligned} D_q(t) &= D_q(\underline{t}_{\leq q}) + \big(D_{\leq q}(t) - D_{\leq q}(\underline{t}_{\leq q})\big) - \big(D_{<q}(t) - D_{<q}(\underline{t}_{\leq q})\big) & (72)\\ &\geq A_q(\underline{t}_{\leq q}) + \Big[C(t - \underline{t}_{\leq q}) - \big(A_{<q}(t) - A_{<q}(\underline{t}_{\leq q})\big)\Big]_+ . & (73) \end{aligned}$$

In Eqn. (73), we have used that $D_p(\underline{t}_{\leq q}) = A_p(\underline{t}_{\leq q})$ for all $p \leq q$, that $D(t) - D(\underline{t}_{\leq q}) \geq C(t - \underline{t}_{\leq q})$ by the properties of the workconserving server, and that $D_p(t) \leq A_p(t)$ for all p. It follows that

$$\begin{aligned} &Pr\Big\{D_q(t) \geq \inf_{\tau \leq T}\big(A_q(t-\tau) + \mathcal{S}_q^{\varepsilon_s}(\tau)\big)\Big\} \\ &\quad \geq Pr\Big\{t - \underline{t}_{\leq q} \leq T \text{ and } D_q(t) \geq A_q(\underline{t}_{\leq q}) + \Big[C(t - \underline{t}_{\leq q}) - \sum_{p<q} \mathcal{G}_p^{\varepsilon_g}(t - \underline{t}_{\leq q})\Big]_+\Big\} & (74)\\ &\quad \geq Pr\Big\{t - \underline{t}_{\leq q} \leq T \text{ and } A_{<q}(t) - A_{<q}(\underline{t}_{\leq q}) \leq \sum_{p<q} \mathcal{G}_p^{\varepsilon_g}(t - \underline{t}_{\leq q})\Big\} & (75)\\ &\quad \geq Pr\Big\{t - \underline{t} \leq T \text{ and } \forall p < q, \ \forall \tau \leq T : \ A_p(t) - A_p(t-\tau) \leq \mathcal{G}_p^{\varepsilon_g}(\tau)\Big\} & (76)\\ &\quad \geq 1 - \Big(\varepsilon_b + (q-1)T\varepsilon_g\Big) , & (77) \end{aligned}$$

where $\underline{t}$ is the beginning of the busy period of the server. In Eqn. (74), we have set $\tau = t - \underline{t}_{\leq q}$ and inserted the definition of $\mathcal{S}_q^{\varepsilon_s}$, and in Eqn. (75), we have used Eqn. (73). In Eqn. (76), we have restricted the event and used that $\underline{t} \leq \underline{t}_{\leq q}$, and in the last line, we have applied the definitions of T and $\mathcal{G}_p^{\varepsilon_g}$. This proves the claim for SP.

2. EDF scheduling: Fix $t \geq 0$, and let $\underline{t}$ be the beginning of the busy period containing time t. If $B_q(t) > 0$, then according to the EDF scheduling algorithm, class-p packets which arrive after $t + d_q - d_p$ will not be served by time t. Since the server is workconserving, this implies

$$
\begin{aligned}
D_q(t) &= D_q(\underline{t}) + \big(D_{\mathcal{C}}(t) - D_{\mathcal{C}}(\underline{t})\big) - \sum_{p\neq q}\big(D_p(t) - D_p(\underline{t})\big) && (78)\\
&\geq A_q(\underline{t}) + \Big[C(t-\underline{t}) - \sum_{p\neq q}\big(A_p(t-(d_p-d_q)_+) - A_p(\underline{t})\big)\Big]_+ . && (79)
\end{aligned}
$$

We argue as in Eqs. (74)-(77) that

$$
\begin{aligned}
&Pr\Big\{D_q(t) \geq \inf_{\tau\leq T}\Big(A_q(t-\tau) + \mathcal{S}_q^{\varepsilon_s}(\tau)\Big)\Big\}\\
&\geq Pr\Big\{t-\underline{t}\leq T \text{ and } \forall p\neq q,\ \forall\tau\leq T:\ A_p(t) - A_p(t-\tau) \leq \mathcal{G}_p^{\varepsilon_g}(\tau)\Big\} && (80)\\
&\geq 1 - \Big(\varepsilon_b + (Q-1)T\varepsilon_g\Big) . && (81)
\end{aligned}
$$

3. GPS scheduling: For $t \geq 0$, let

$$\underline{t}_p = \max\big\{x \leq t:\ B_p(x) = 0\big\} \tag{82}$$

be the beginning of the busy period of t with respect to class p. Clearly,

$$B_p(t) = A_p(t) - D_p(t) \leq A_p(t) - A_p(\underline{t}_p) - \lambda_p C(t-\underline{t}_p) \tag{83}$$

by the properties of the GPS scheduler. For $t \geq 0$ and $p \neq q$, let

$$\underline{t}_{qp} = \max\big\{x \leq \underline{t}_q:\ B_p(x) = 0\big\} , \tag{84}$$

then Eqn. (83) with t replaced by $\underline{t}_q$ and $\underline{t}_p$ replaced by $\underline{t}_{pq}$ implies that

$$
\begin{aligned}
D_p(t) - D_p(\underline{t}_q) &\leq A_p(t) - A_p(\underline{t}_q) + B_p(\underline{t}_q) && (85)\\
&\leq A_p(t) - A_p(\underline{t}_{qp}) - \lambda_p C(\underline{t}_q - \underline{t}_{qp}) . && (86)
\end{aligned}
$$

It follows that

$$
\begin{aligned}
D_q(t) - D_q(\underline{t}_q) &\geq \lambda_q\Big(C(t-\underline{t}_q) + \sum_{p\neq q}\big[\lambda_p C(t-\underline{t}_q) - D_p(t) + D_p(\underline{t}_q)\big]_+\Big) && (87)\\
&\geq \lambda_q\Big(C(t-\underline{t}_q) + \sum_{p\neq q}\big[\lambda_p C(t-\underline{t}_{qp}) - A_p(t) + A_p(\underline{t}_{qp})\big]_+\Big) . && (88)
\end{aligned}
$$

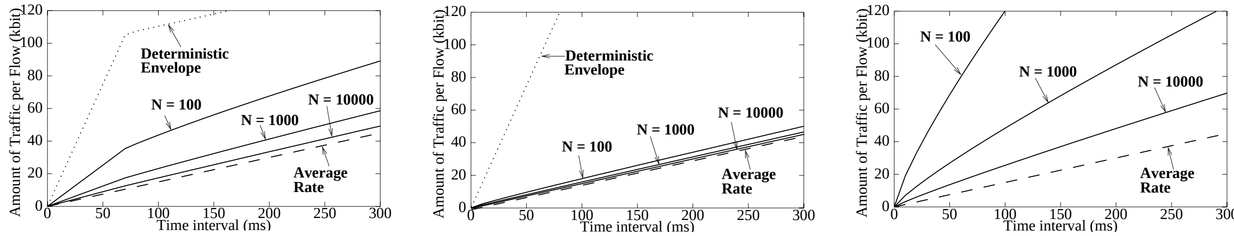
Fix $t \geq 0$, let $\underline{t}$ be the beginning of the busy period containing time t, and assume for the moment that

$$t - \underline{t} \leq T \text{ and } \forall p \neq q, \forall\tau\leq T:\ A_p(t) - A_p(t-\tau) \leq \mathcal{G}_p^{\varepsilon_g}(\tau) . \tag{89}$$

Since $\underline{t} \leq \underline{t}_{qp} \leq \underline{t}_q$, it follows with by Eqn. (88) that

$$
\begin{aligned}
D_q(t) &\geq D_q(\underline{t}_q) + \lambda_q\Big(C(t-\underline{t}_q) + \sum_{p\neq q}\big[\lambda_p C(t-\underline{t}_{qp}) - A_p(t) + A_p(\underline{t}_{qp})\big]_+\Big) && (90)\\
&\geq A_q(\underline{t}_q) + \lambda_q\Big(C(t-\underline{t}_q) + \sum_{p\neq q}\big[\lambda_p C(t-\underline{t}_{qp}) - \mathcal{G}_p^{\varepsilon_g}(t-\underline{t}_{pq})\big]_+\Big) . && (91)
\end{aligned}
$$

(t)



(a) (P, σ, ρ) Regulated. (b) On-Off. (c) FBM.

Figure 3: **Example 1:** Per-flow effective envelopes $\mathcal{G}_N^{\varepsilon}(t)/N$ for Type-1 flows (with $\varepsilon = 10^{-9}$).

Since $\mathcal{G}_p^{\varepsilon_g}$ is concave, the function $\left[\lambda C t - \mathcal{G}_p^{\varepsilon_g}(t)\right]_+$ is nondecreasing in t. Replacing $t - \underline{t}_{pq}$ with the smaller value $t - \underline{t}_q$ in Eqn. (91) and using the definition of $\mathcal{S}_q^{\varepsilon}$ yields

$$D_q(t) \geq A_q(\underline{t}_q) + \mathcal{S}_q^{\varepsilon}(t - \underline{t}_q) \; . \tag{92}$$

Finally, we estimate

$$\begin{aligned} Pr\Big\{ D_q(t) \geq \inf_{\tau \leq T} \Big(A_q(t-\tau) + \mathcal{S}_q^{\varepsilon}(\tau) \Big) \Big\} &\geq Pr\Big\{ t - \underline{t}_q \leq T \text{ and Eqn. (92) holds} \Big\} && (93) \\ &\geq Pr\Big\{ \text{Eqn. (89) holds} \Big\} && (94) \\ &\geq 1 - \Big(\varepsilon_b + (Q-1) T \varepsilon_g \Big) \; . && (95) \end{aligned}$$

This completes the proof. □

5 Numerical Examples

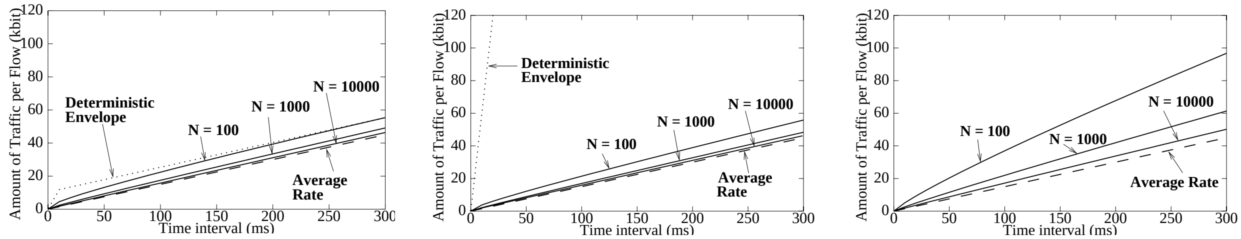
In this section, we present numerical examples to illustrate the multiplexing gain for the different traffic models (Regulated, On-Off, Fractional Brownian Motion) and scheduling algorithms (SP, EDF, GPS) considered in this paper.

	REGULATED TRAFFIC			ON-OFF TRAFFIC		FBM TRAFFIC		
Type	P (Mbps)	ρ (Mbps)	σ σ (bits)	P (Mbps)	ρ (Mbps)	ρ (Mbps)	β (Mbps)	H
1	1.5	0.15	95400	1.5	0.15	0.15	4.5	0.78
2	6.0	0.15	10345	6.0	0.15	0.15	0.94	0.78

Table 1: Source Traffic Parameters.

For each of the three traffic models, we consider two types of flows. The parameters are given in Table 1. Since we are working in a discrete time domain, we need to select a time unit, which we set to 1 ms. For regulated traffic, we select a peak-rate constrained leaky bucket with arrival envelope $A^*(t) = \min\left(Pt\,, \sigma + \rho t\right)$, with parameters as in [7]. The parameters of the other traffic sources are selected to match the average rate ($\rho = 0.15$ Mbps). For FBM traffic, we set the Hurst parameter to $H = 0.78$ as suggested in [37], and select $\beta = 4.5$.

(t)



(a) (P, σ, ρ) Regulated. (b) On-Off. (c) FBM.

Figure 4: **Example 1:** Per-flow effective envelopes $\mathcal{G}_N^{\varepsilon}(t)/N$ for Type-2 flows (with $\varepsilon = 10^{-9}$).

5.1 Example 1: Comparison of Effective Envelopes

In the first example, we evaluate the effective envelopes for Regulated traffic, On-Off traffic, and FBM traffic. We evaluate the effective envelope normalized by the number of flows as $\mathcal{G}_N^{\varepsilon}(t)/N$, where $\mathcal{G}_N^{\varepsilon}(t)$ is the effective envelope for N homogeneous flows. Figures 3 and 4 show the per flow effective envelopes with $\varepsilon = 10^{-9}$ for Type-1 and Type-2 flows, respectively. For comparison, we also include the average rate of the sources. For regulated traffic we also include the deterministic envelopes $\min(Pt\,, \sigma + \rho t)$, and for On-Off traffic we include the peak rate.

We make the following observations. The effective envelopes capture a significant amount of statistical multiplexing gain for each of the considered traffic types, the multiplexing gain increases sharply with the number of flows N. The effective envelope for FBM traffic is larger than for the other source models. This is due to our selection of the parameters H and β.

5.2 Example 2: Number of Admissible Flows

Next we consider three scheduling algorithms (SP, EDF, and GPS) and multiplex Type-1 and Type-2 flows on a link with 100 Mbps capacity. The evaluation focuses on the service given to flows from Type 1. We assume that Type-1 flows must satisfy a probabilistic delay bound of 100 ms. Given a certain number of Type-2 flows on the 100 Mbps link, we determine the maximum number of Type-1 flows that can be added to the link without violating their probabilistic delay bounds using the results from Lemma 3. Such an admission control decision is greedy, in the sense that it entirely ignores the delay requirements of other flow types. For example, using Lemma 3 for admission control of Type-1 flows ignores the delay requirements of Type-2 flows.

The parameters of the scheduling algorithms are the priority indices for SP, the delay indices for EDF, and the weights for GPS. For SP, Type-1 flows have a higher priority index, and, therefore, a lower priority, than Type-2 flows. For EDF, the delay index of Type-1 flows is $d_1 = 100$ ms and that of Type-2 flows is $d_2 = 10$ ms. For GPS, we set the weights to $\phi_1 = 0.25$ and $\phi_2 = 0.75$. As in the previous examples, we consider three traffic models: regulated traffic, On-Off traffic, and FBM traffic. The source traffic parameters are as shown in Table 1. For comparison, we also include the number of flows that can be accommodated on the link with an average rate allocation and a peak rate allocation.

Figure 5 depicts the number of Type-1 flows that can be admitted without violating the probabilistic delay bounds, as a function of the number of Type-2 flows already in the system. We observe that the choice

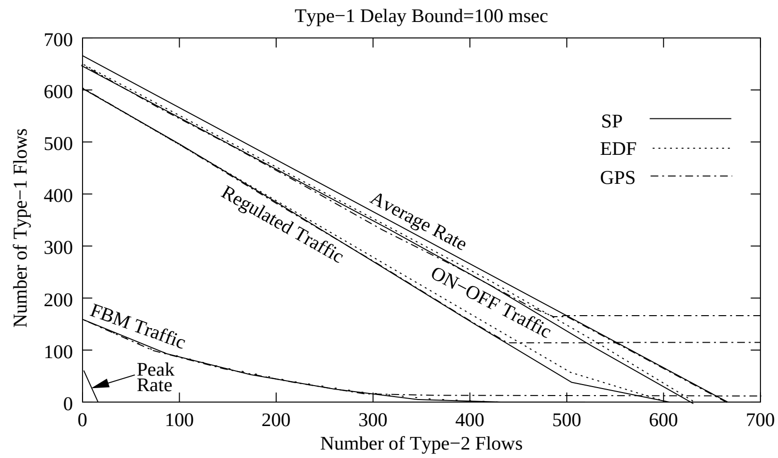


Figure 5: **Example 2:** Number of admissible Type-1 flows as a function of the number of Type-2 flows (C = 100 Mbps) for different schedulers and traffic models with $\varepsilon = 10^{-6}$, $d_1 = 100$ ms, $\phi_1 = 0.25$, $\phi_2 = 0.75$.

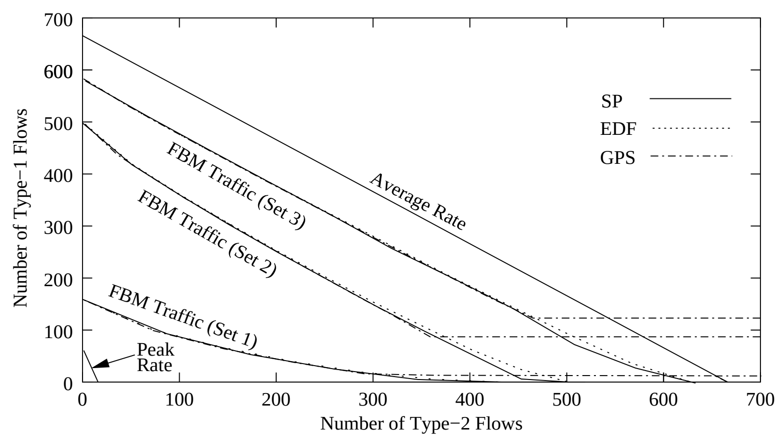


Figure 6: **Example 2:** Number of admissible Type-1 flows as a function of the number of Type-2 flows (C = 100 Mbps) for FBM traffic with different choices of β with $\varepsilon = 10^{-6}$, $d_1 = 100$ ms, $\phi_1 = 0.25$, $\phi_2 = 0.75$.

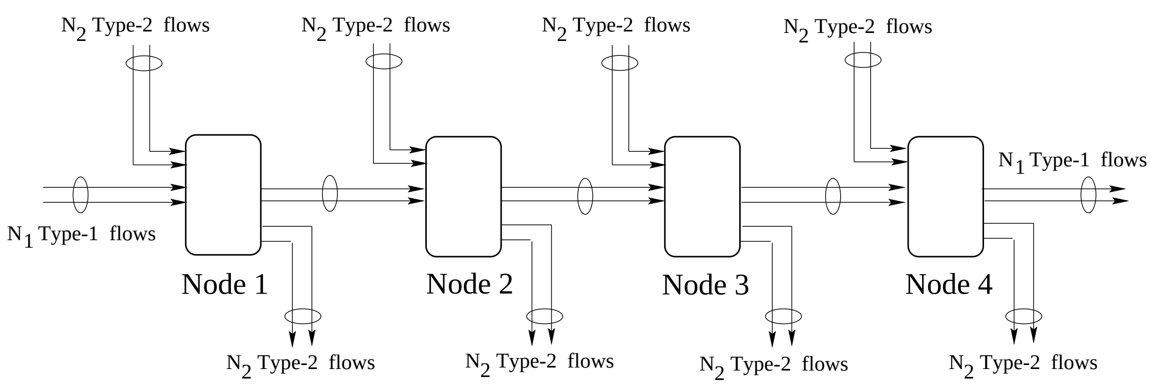


Figure 7: **Example 3:** A network with four nodes and with cross traffic.

of the traffic model has a significant impact on the number of admitted Type-1 flows. The number of Type-1 flows that can be admitted with FBM traffic is much smaller than with the other traffic models. We also observe in the figure, that the selection of the scheduling algorithm has only a limited impact. Given a traffic model, the number of admitted Type-1 flows is similar for all scheduling algorithms, with one notable exception: for GPS, the minimum number of Type-1 flows admitted is independent of the number of Type-2 flows. This is due to the rate guarantee provided by GPS, which guarantee a minimum number of Type-1 flows: 114 flows for regulated traffic, 165 for On-Off traffic, and 12 for FBM traffic.

We emphasize again that the low multiplexing gain of FBM traffic is a result of our choice of parameters H and β. To illustrate this point, we present results for FBM traffic with different parameters, shown in Table 2. We consider three different sets of parameters. In Set 1, we use the same parameters as in Example 1. For Set 2, we select β so that the variance of FBM traffic is matched with the variance of regulated sources at a time scale corresponding to the delay bounds. This is 100 ms for Type-1 traffic and 10 ms for Type-2 traffic. For Set 3, we match the variance of FBM traffic at a time scale of 1000 ms, which is comparable to the longest busy period observed in these experiments. The results for the number of flows that can be admitted, shown in Figure 5, illustrate the dependency of the results on the parameter selection. For Set 3, FBM traffic exhibits a similar multiplexing gain as On-Off traffic.

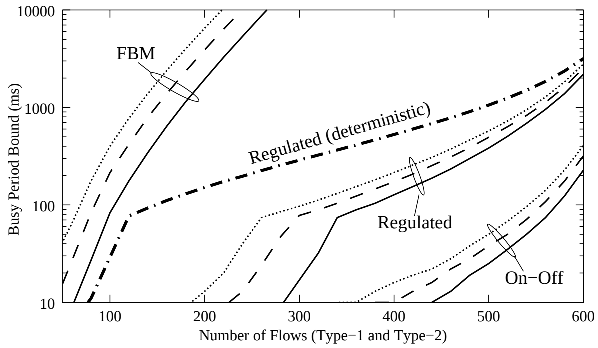
	SET 1	SET 2	SET 3
Type	β (Mbps)	β (Mbps)	β (Mbps)
1	4.5	1.04	0.40
2	0.94	0.65	.13

Table 2: Parameters for FBM traffic.

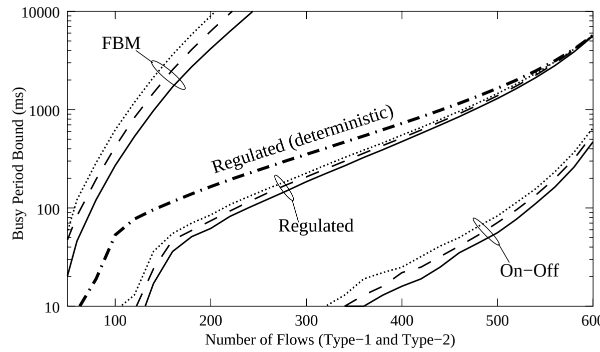
5.3 Example 3: Multiple Nodes with Cross Traffic.

In this example, we consider a network with four nodes, as shown in Figure 7. We assume that all links have the same capacity of $C = 100$ Mbps. There are N_1 Type-1 flows that pass through all four nodes. At each node, there is cross traffic from N_2 Type-2 flows. We assume $N_1 = N_2$.

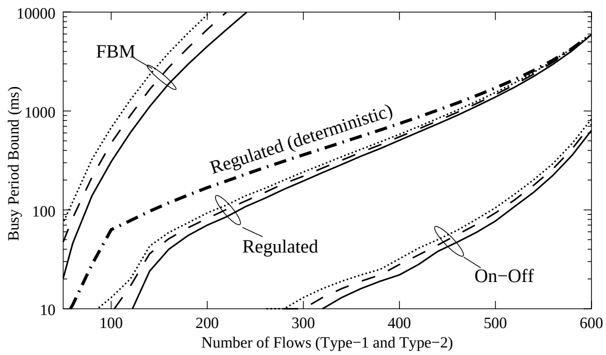
First, we demonstrate how our bounds of the busy period grow as the number of flows increases and how the busy period varies at different nodes. We calculate the probabilistic busy period bounds at each node for violation probabilities $\varepsilon = 10^{-3}, 10^{-6}, 10^{-9}$ using the approach outlined in Subsection 2.6 with the number of classes $Q = 2$. We use the formula for the effective envelope given in Eqn. (46), with ε replaced by $\varepsilon/(\pi(1+\tau^2))$ to construct for each class $q = 1, 2$ a function $\overline{\mathcal{G}}_q^{net,\varepsilon/2}$ satisfying $Pr\left\{A^{net}(t) - A^{net}(t-\tau) > \overline{\mathcal{G}}_q^{net,\varepsilon/2}(\tau)\right\} \leq \varepsilon/(\pi(1+\tau^2))$, as required in Eqn. (41). At the h-th node on the route of the through flows, we set $\overline{\mathcal{G}}_1^{h,\varepsilon/2}(\tau) = \overline{\mathcal{G}}_1^{et,\varepsilon/2}(\tau + (h-1)d^*)$, as given in Eqn. (43). For regulated traffic, we choose the threshold d^* comparable to the worst-case delay bound experienced by the Type-1 traffic at Node 1, as provided by the deterministic calculus. For On-Off and FBM traffic, we choose d^* comparable to the delay bound of Type-1 traffic at Node 1, as provided by Theorem 1 with $\varepsilon = 10^{-15}$. We assume that any packet experiencing a delay exceeding d^* per node is dropped before entering the next node. Since all nodes are ingress nodes for the Type-2 flows, we can use the same bound $\overline{\mathcal{G}}_2^{h,\varepsilon/2}(\tau) = \overline{\mathcal{G}}_2^{net,\varepsilon/2}(\tau)$ for the Type-2 flows at each node, where $\overline{\mathcal{G}}^{\varepsilon/2}$ is the function computed above. We then apply Lemma 1,



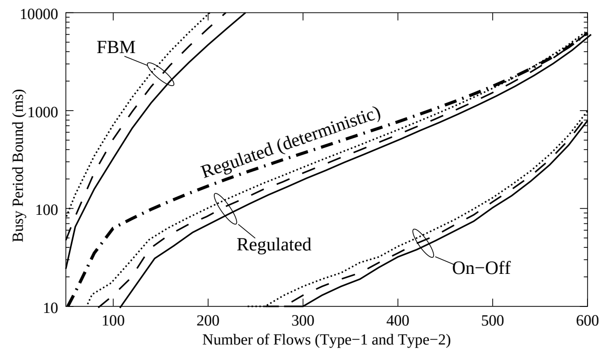
(a) Node 1.



(b) Node 2.



(c) Node 3.



(d) Node 4.

Figure 8: **Example 3:** Probabilistic Busy Period Bounds for $\varepsilon = 10^{-3}$ (solid line), $\varepsilon = 10^{-6}$ (dashed line), and $\varepsilon = 10^{-9}$ (dotted line). The x-axis corresponds to $N_1 + N_2$, the number of Type-1 and Type-2 flows, where we assume $N_1 = N_2$. The thick dotted-dashed line is a deterministic busy period bound for regulated traffic.

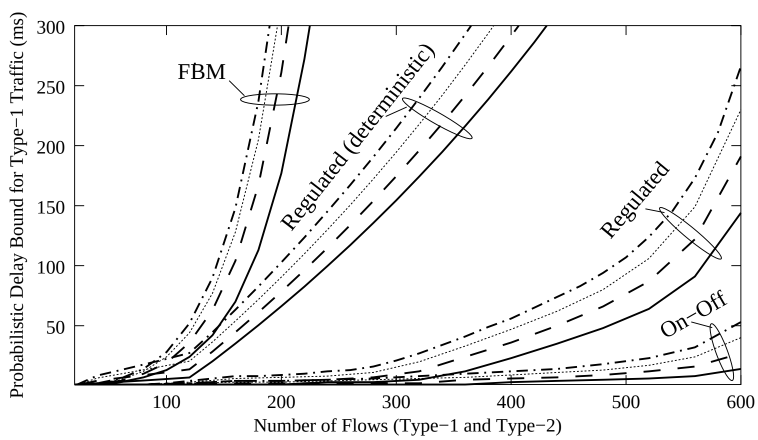


Figure 9: **Example 3:** Probabilistic bounds for the total queueing delay experienced by Type-1 traffic when leaving Node 1 (solid line), Node 2 (dashed line), Node 3 (dotted line), and Node 4 (dotted-dashed line) with violation probability $\varepsilon = 10^{-6}$. The x-axis corresponds to $N_1 + N_2$, the number of Type-1 and Type-2 flows, where we assume $N_1 = N_2$.

with $\overline{\mathcal{G}}_{\mathcal{C}}^{h,\varepsilon} = \overline{\mathcal{G}}_1^{h,\varepsilon/2} + \overline{\mathcal{G}}_2^{1,\varepsilon/2}$ to obtain bounds on the busy periods T^h at each node. Finally, we use Theorems 1 and 2 to check that the loss rate due to the dropping threshold never exceeds a fraction of 10^{-15} of the traffic rate.

Figure 8 shows the probabilistic busy period bounds at each node for the three different traffic models, where the number of flows is varied from 60 to 600. Note that 600 flows corresponds to a utilization of 90%. As a reference point, we also plot the exact value for the worst-case busy period of the regulated traffic (plotted as thick dotted-dashed line). While regulated traffic permits to determine the worst-case busy period, such deterministic bounds are not available for On-Off and FBM traffic. We observe that the probabilistic busy period bounds for downstream nodes are larger than that for upstream nodes and that the probabilistic busy period bounds for FBM traffic are significantly larger than those for Regulated or On-Off traffic at each node.

Next, we exhibit the queueing delay experienced by Type-1 traffic in the network described in Figure 7. For the SP scheduling algorithm, as in Example 2, Type-1 flows have a higher priority index, and, therefore, a lower priority, than Type-2 flows. Figure 9 depicts the probabilistic bounds of the total queueing delay experienced by Type-1 traffic when leaving Node h, $h = 1, 2, 3, 4$, with the violation probability 10^{-6} in the network with SP scheduling. The total queueing delay experienced by Type-1 traffic when leaving Node h includes the queueing delay experienced by Type-1 traffic at Node h, Node $h - 1$, and down to Node 1. As expected, the probabilistic bounds for the total queueing delay experienced by Type-1 traffic increase when the path traveled by Type-1 traffic increases. As a reference point, we also plot the worst case queueing delay experienced by Regulated traffic. From Figure 9, for Regulated traffic, we observe that the probabilistic bounds for the total queueing delay are dramatically smaller than the worst case queueing delay. Note that the probabilistic bounds for FBM traffic are larger than those for Regulated or On-Off traffic. For EDF and GPS scheduling algorithms, the end-to-end delay bounds experienced by Type-1 traffic in the same network with the violation probability 10^{-6} are similar to those in Figure 9 and omitted.

6 Conclusions

We have presented a statistical network calculus for determining delays and backlog where both arrivals and service are described in terms of probabilistic bounds. We presented bounds on the queueing behavior in terms of the min-plus algebra, and integrated the concept of effective bandwidth into the envelope-based approach of the statistical network calculus. We derived backlog and delay bounds for several traffic models (regulated, On-Off, FBM), and scheduling algorithms (SP, EDF, GPS). An important assumption for the derived calculus is the existence of a time-scale bound at each node that decorrelates arrivals and departures. For a single node, such a bound can often be obtained from an estimate on the busy period. For multiple nodes, as seen in Example 3, we require additional assumptions, e.g., that traffic exceeding a maximum delay be dropped. While such an assumption can often be justified, a goal of future work is to determine when and how to dispense with such assumptions.

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