Stochastic Upper and Lower Bounds for General Markov Fluids

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Abstract—Promising perspectives of a hypothetical ‘Tactile Internet’, or ‘Internet at the speed of light’, whereby network latencies become imperceptible to users, have (again) triggered a broad interest to understand and mitigate Internet latencies. In this paper we revisit the queuing analysis of the versatile Markov Fluid traffic model, which was mainly investigated in the 1980-90s, yet with low accuracy. We derive upper bounds on the tail distribution of the queue size, which improve state-of-the-art results by an exponential factor $O(n^\kappa)$ in a special case, where $0 < \kappa < 1$ and $n$ is the number of multiplexed sources; additionally, we provide the first lower bounds. The underlying results are quite general in that they can be easily adapted to derive the delay distribution for SP, FIFO, and EDF scheduling. Our overall results rely on a powerful martingale methodology which was recently shown to be highly accurate.

I. INTRODUCTION

Latency/delay is a fundamental metric of communication and human perception. Not surprisingly, several recent studies reported a strong correlation between Internet latencies and the revenue of major online service providers, e.g., Google, Bing, or Amazon [39], [26], [42]; a typical cited argument is that an additional 100ms in latency would cost Amazon 1% of sales. Moreover, innovations in electronics, systems, and protocols, together with the apparent abundance of computing resources and network bandwidth, have recently sparked the hope for a major paradigm shift called ‘Tactile Internet’ [22], or ‘Internet at the speed of light’ [41]. A potential major benefit of consistently achieving negligible network latencies (e.g., sub-100ms or sub-10ms) would be the immediate opportunity for major innovations in exciting areas such as health-care (e.g., remote surgery), transportation (e.g., fully automatic driving), or entertaining.

The increasing and broadly recognized importance of network latency has recently materialized, at a large scale, into a dedicated workshop [2] and the funding of a major European Union FP-7 project [1]; a relevant outcome of such concerted efforts was a comprehensive survey on a taxonomy of latency sources and mitigating techniques [8]. While there has been much work on system solutions such as traffic engineering and replication strategies to reduce latencies [19], there has also been shown that achieved improvements reached a point of diminishing returns [31], particularly due to the dominating queuing delays (i.e., the time spent by packets in buffers, waiting to be forwarded).

As the development of system solutions to mitigate Internet latencies can strongly benefit from the fundamental/theoretical understanding of network delays, there is a need for the parallel development of related analytical tools. A similar moment occurred in the 1980-90s, when novel analytical/queueing tools emerged to especially cope with the case of non-renewal arrivals. To some extent, this goal was driven by the increasing prevalence of audio and video content, which, when viewed as stochastic processes, are subject to some form of statistical correlations. In fact, such a new characteristic of Internet traffic determined the questioning of the common and analytically convenient assumption of Poisson arrivals (at the packet level), which was convincingly shown to be largely misleading when improperly used [36]. Besides accounting for non-renewal arrivals, an additional goal of emerging analytical theories was to permit the queueing/delay analysis over a network path; such a problem is in itself extremely challenging in the case of non-Poisson arrivals, as attested by the state-of-the-art in the classical queuing theory.

A general queueing tool which can deal with non-renewal arrivals over a network path is the network calculus [7], [10]. Initially conceived by Cruz as a deterministic queueing theory [17], its main and radically new conceptual characteristic of deterministically bounding arrivals was extended in a probabilistic framework to account for not necessarily bounded arrivals. Given its wide modelling scope and also the ability to render (deterministic) worst-case measures for network queueing metrics such as end-to-end delays, the deterministic branch of network calculus has some notable practical applications, e.g., towards the certification of the Airbus A380 AFDX backbone [5]. The broad applicability of (deterministic) network calculus comes however at the price of providing bounds (i.e., not exact results), whose practical tightness in terms of efficient numerical algorithms remains an open issue in the network case [6] despite significant recent progress [3]. In turn, the stochastic branch of network calculus suffers from similar low accuracy issues, including the single-node case whereby the stochastic bounds can be loose by orders of magnitude in the case of non-renewal arrivals [14]; this drawback is exacerbated in the network case, especially under heavy-tailed arrivals [32].

In a stochastic setting, an alternative queueing tool is the theory of effective bandwidth [27] which can address a broad class of (non-renewal) arrival processes in a unified and conceivably quite elegant manner. Unlike stochastic network calculus, which yields results in terms of non-asymptotic bounds, effective bandwidth provides exact results but only
in the so-called large-buffer or many-sources asymptotic regimes [34]. Unfortunately, when fitted to practical (finite) regimes, such results are however largely inaccurate and thus practically questionable [12]; a convincing explanation is provided in [40], i.e., for more variable sources than Poisson such as most Markov-modulated processes, the underlying additivity property reveals both the elegant nature of effective bandwidth but also the conceivably conservative nature of the exact results in finite regimes.

Motivated by the need for a unified queuing tool to address non-renewal arrivals, and more importantly in terms of practically accurate results, this paper revisits the queuing analysis of the versatile class of Markov Fluid traffic models. Informally, a source is a Markov Fluid if the associated arrival process is a function of a (continuous-time) Markov process on a finite state space [28]. The seminal model is the so-called Anick/Mitra/Sondhi On-Off model, in which a source produces data (as continuous ‘fluid’) either at some positive constant or zero rates, depending on the state of a modulating Markov process [4]; for related generalizations, which are able to model larger classes of traffic patterns (e.g., video), see [43], [28]. It is worth pointing out that fluid models are the continuous approximation of their discrete counterpart, and are essentially motivated by computational reasons such as dealing with (discrete) state space explosion or various underlying granularity and sizes (e.g., modelling a large number of small packets in a short time interval) [24].

In this paper we generalize existing stochastic upper bounds, available for the specific On-Off process [14], to the case of general Markov fluids. The obtained stochastic (upper) bound on the steady-state queue size distribution is shown to be tighter than the existing state-of-the-art result from [35] by a reversible Markov process

\[ Q = \sup_{k,n} \langle A_k(t) \rangle \]

where \( Q \) is the steady-state queue size distribution for a single process or the delay distribution in the case of scheduling. The general queueing model is depicted in Figure 1. Given a continuous time model, \( A_1(t) \) and \( A_2(t) \) are two (cumulative) Markov fluid processes served at some constant rate \( C > 0 \) with corresponding departure processes \( D_1(t) \) and \( D_2(t) \), respectively. Each process \( A_k(t) \), \( k = 1, 2 \), is modulated by a reversible Markov process \( Z_k(t) \) with \( n_k + 1 \) states, generator

\[ Q_k = (q_{k,i,j})_{i,j=0,...,n_k} \]

and increment process \( A_k(s) = r_k Z_k(s) \) \( \forall s \geq 0 \). We remark that if \( Z_k(t) \) was not reversible, then one could consider as input the corresponding reversed process. The reversibility property enables expressing Reich’s equation for the steady-state queue size as

\[ Q = \sup_{t \geq 0} \{ A_1(t) + A_2(t) - Ct \} \]

For each arrival process \( A_k(t) \) we consider the generalized eigenvalue problem

\[ Q_k h_k = -\gamma_k u_k h_k, \quad k = 1, 2, \]

where \( Q_k \) are the underlying generators, \( \gamma_k \) are the eigenvalues, \( u_k \) are the right eigenvectors, \( h_k \) are diagonal matrices with \( (u_k,0, u_k,1, \ldots, u_k,n_k) \) on the diagonal, and where

\[ u_k,j = r_k,j - C_k \]

are the instantaneous queueing drifts for \( j = 0, 1, \ldots, n_k \). Here, \( C_1 \) and \( C_2 \) are positive values such that \( C_1 + C_2 = C \), and can be regarded as the per-class/flow allocated capacity. Assuming the per-class stability conditions

\[ \sum_{j=0}^{n_k} \pi_{k,j} u_{k,j} < 0, \quad k = 1, 2, \]

we provide the most critical component of latency, i.e., its tail (e.g., the 95\%-percentile) and not its average; in fact, the importance of the tail to the development of the much desired and anticipated ‘latency tail-tolerant’ systems has been convincingly exposed in a recent Google study [19].

The remainder of the paper is organized as follows: In §II we present a general tool to analyze Markov fluids in an infinte buffer queuing model. This tool is subsequently applied to derive upper and lower bounds on the queue size distribution (§III), and to the (per-flow) delay bounds in a scheduled system (§IV). In §V we provide a collateral but important result, i.e., the first analytical construction for the space-parameter in the classical effective bandwidth approximation. Finally in §VI we summarize the paper.

II. A GENERAL QUEUING RESULT

In this section we first derive a general queuing result which can be instantiated to several scenarios, e.g., the queue size distribution for a single process or the delay distribution in the case of scheduling.

The general queueing model is depicted in Figure 1. Given a continuous time model, \( A_1(t) \) and \( A_2(t) \) are two (cumulative) Markov fluid processes served at some constant rate \( C > 0 \) with corresponding departure processes \( D_1(t) \) and \( D_2(t) \), respectively. Each process \( A_k(t), k = 1, 2 \), is modulated by a reversible Markov process \( Z_k(t) \) with \( n_k + 1 \) states, generator

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\[ \sum_{j=0}^{n_k} \pi_{k,j} u_{k,j} < 0, \quad k = 1, 2, \]
Lemma 5.1 from [35] guarantees the existence of real generalized eigenvalues \( \gamma_k \) (as the ones with the biggest negative real parts) and also of the generalized eigenvectors 

\[
\mathbf{h}_k = (h_{k,0}, h_{k,1}, \ldots, h_{k,n_k})^T
\]

with positive coordinates. Thus, \( \gamma_k > 0 \) for \( k = 1, 2 \).

We now present a general result which will be used throughout the paper.

**Lemma 1.** Consider the single-node queueing scenario from Figure 1 and the solutions for the generalized eigenvalue problems from Eq. (1). Then for all \( 0 \leq u \leq t \) and \( \sigma \geq 0 \)

\[
\mathbb{P}
\left\{ \sup_{0 \leq s \leq t - u} \left\{ A_1(s, t - u) + A_2(s, t) - C(t - s) \right\} > \sigma \right\}
\]

\[
\leq \inf_{0 \leq \gamma \leq \min\gamma_k} \inf_{C_1, C_2 = C} \kappa e^{-\gamma(C_1 u + \sigma)} ,
\]

where

\[
\kappa = \sum_{i,j} \pi_{i,1} \pi_{2,j} \frac{h_{i,1} h_{2,j}}{\min(h_{i,1}, h_{i,2})} \geq 0 ,
\]

whereas the condition \( C_1 + C_2 = C \) is subject to the stability conditions from Eq. (2).

Let us make several observations about the two inﬁmum operators. The parameter \( \gamma \) in the outer inﬁmum reconciles the different burstiness of the two not necessarily homogeneous ﬂows \( A_1(t) \) and \( A_2(t) \), loosely expressed through the exponential decay factor. The extreme optimal value \( \gamma = \min \{ \gamma_1, \gamma_2 \} \) is attained when \( \sigma \to \infty \); in turn, a numerical optimization after \( \gamma \) is necessary in ﬁnite regimes of \( \sigma \). In turn, due to the implicit expression of \( \kappa \) in terms of the (generalized) eigenvectors from Eq. (1), which depend on \( C_1 \) and \( C_2 \), the values for the inner inﬁmum are subject to further numerical optimizations.

Lemma 1 generalizes a result from [14] (see Theorem 1 therein) to the case of general and not necessarily homogeneous Markov ﬂuid processes. The theorem also generalizes a result from [35] (see Proposition 5.1 therein), restricted to \( A_3(t) = 0 \), and also the seminal result from Kingman [29] to the non-renewal case. We point out that the key beneﬁt of our generalization result is that it can lend itself to per-ﬂow delay bounds in a scheduling scenario (see §IV).

**Proof.** Fix \( u \geq 0 \) and \( \sigma \geq 0 \). Since the two arrival processes are reversible, we can rewrite the probability from Eq. (3), by shifting the time origin, as

\[
\mathbb{P}
\left\{ \sup_{t > u} \{ A_1(u, t) + A_2(u, t) - C(t - u) \} \geq \sigma \right\}
\]

\[
= \mathbb{P}
\left\{ \sup_{t > u} \{ A_1(u, t) + A_2(u, t) - C(t - u) \} + A_2(u) - C_2 u > C_1 u + \sigma \right\} .
\]

Let the following stopping time

\[
T := \inf \left\{ t > u : A_1(u, t) + A_2(u, t) - C(t - u) + A_2(u) - C_2 u > C_1 u + \sigma \right\} .
\]

In the rest of the proof we shall bound \( \mathbb{P}(T < \infty) \), which is exactly the target probability from Eq. (4).

Let \( P_{i,j} \) denote the underlying probability measure conditioned on \( Z_1(u) = i \) and \( Z_2(0) = j \), for \( 0 \leq i \leq n_1 \) and \( 0 \leq j \leq n_2 \). Next we deﬁne the following two processes

\[
\bar{M}_{1,t} := \frac{h_{1,1} Z_1(t)}{h_{1,1}} e^{\int_{1}^{u} \frac{Q_{1,1}}{h_{1,1}}(x) dx} \forall t \geq u \text{ and } \bar{M}_{2,t} := \frac{h_{2,2} Z_2(t)}{h_{2,2}} e^{\int_{1}^{u} \frac{Q_{2,2}}{h_{2,2}}(x) dx} \forall t \geq 0 .
\]

\( M_1(t) \) and \( M_2(t) \) are martingales with respect to (wrt) \( P_{i,j} \) and the natural ﬁltration (see [21], p. 175). Considering the solution of the generalized eigenvalue problem from Eq. (1), we can rewrite

\[
\bar{M}_{1,t} = \frac{h_{1,1} Z_1(t)}{h_{1,1}} e^{\gamma \int_{1}^{u} u(t) \pi_{1,1}(t) dx} \forall t \geq u \text{ and } \bar{M}_{2,t} = \frac{h_{2,2} Z_2(t)}{h_{2,2}} e^{\gamma \int_{1}^{u} u(t) \pi_{2,2}(t) dx} \forall t \geq 0 .
\]

For \( 0 \leq \gamma \leq \min \{ \gamma_1, \gamma_2 \} \) we consider the transformations

\[
M_{1,k} := \bar{M}_{k,t}^{1/\kappa} \quad k = 1, 2 .
\]

Denoting by \( F_{k,s} \) the natural ﬁltrations of \( M_{k,t} \), we can write for \( 0 \leq s \leq t \)

\[
E[M_{k,t} | F_{k,s}] = E\left[ M_{k,t}^{1/\kappa} | F_{k,s} \right] \leq E\left[ M_{k,t} | F_{k,s} \right]^{1/\kappa} \leq M_{k,s}^{1/\kappa} = M_{k,s} \cdot
\]

where the ﬁrst line is due to Jensen’s inequlity (applied to the concave function \( x \mapsto x^{1/\kappa} \) for \( x \geq 0 \)) and the second inequality is due to the martingale property of \( M_{k,t} \). Therefore, the new processes \( M_{k,t} \) are also martingales; we point out that their construction is motivated by the need of having the same decay rate, i.e., \( \gamma \), in the corresponding exponentials.

Next we invoke a result from [11] (stating that the product of two independent martingales is also a martingale) and the Optional Switching Theorem ([25], p. 488), and obtain that the process

\[
M_t := \begin{cases} M_{1,t} M_{2,t} & t \leq u \\ M_{1,t} & t > u \end{cases}
\]

is also a martingale (note that \( M_{1,u} = 1 \) by deﬁnition). It can be explicitly written as

\[
M_t = \begin{cases} \left( \frac{h_{2,2} Z_2(t)}{h_{2,2}} e^{\gamma (A_2(t) - C_2 u)} \right)^{1/\kappa} & t \leq u \\ \left( \frac{h_{1,1} Z_1(t)}{h_{1,1}} e^{\gamma (A_1(t) + A_2(t) - C(t - u))} \right)^{1/\kappa} & t > u \end{cases}
\]
Referring now to the stopping time $T$ from Eq. (5), which may be unbounded, we construct the bounded stopping times $T \wedge \nu$ for all $\nu \in \mathbb{N}$. For these times, the Optional Sampling Theorem (see, e.g., [25], p. 489) yields

$$E_{i,j}[M_0] = E_{i,j}[M_{T \wedge \nu}] ,$$

for all $\nu \in N$, where the expectations are taken wrt the underlying probability measures $\mathbb{P}_{i,j}$. Moreover, from the definition of $T$ as an infimum over a set, it holds for $\nu \geq 0$ that

$$(u_1, x(T) + u_2, y(T)) I_{T \leq \nu} \geq 0 ,$$

where $I_{\nu}$ denotes the indicator function. Using now that $E_{i,j}[M_0] = 1$ we obtain for $\nu > u$

$$1 \geq E_{i,j}[M_{T \wedge \nu}(T \leq \nu)] \geq \min \left( \frac{h_1}{h_2}, \frac{h_2}{h_3} \right) e^{\gamma (C_{1,\nu} + \sigma)} \mathbb{P}_{i,j}(T \leq \nu) ,$$

where the ‘min’ operator is taken over the set $\{(l_1, l_2) : u_1, l_1 + u_2, l_2 \geq 0\}$ according to Eq. (6).

Finally, by deconditioning on $i$ and $j$ (recall that $Z_1(u)$ and $Z_2(0)$ are in steady-state by construction) we obtain

$$\mathbb{P}(T \leq \nu) \leq ke^{-\gamma (C_{1,\nu} + \sigma)} .$$

Letting $\nu \to \infty$ completes the proof.

\[\square\]

III. QUEUE SIZE DISTRIBUTION: UPPER AND LOWER BOUNDS

Here we apply Lemma 1 to derive upper bounds on the steady-state queue size distribution, and then provide the corresponding lower bounds.

A. Upper Bounds

Consider a server with constant rate $C > 0$ serving a Markov fluid process $A(t)$ which is modulated by a reversible Markov process $Z(t)$ with $n+1$ states, generator $Q = (q_{i,j})_{i,j=0,...,n}$, equilibrium distribution $\pi = (\pi_0, ..., \pi_n)$, arrival rates $r = (r_0, ..., r_n)$, and increment process $a(s) = r Z(s)$ for all $s \geq 0$. The steady-state queue size is

$$Q = \sup_{t \geq 0} \{A_1(t) + A_2(t) - C t\} ,$$

and the steady-state virtual delay is defined via

$$\{W(t) \geq d\} = \{A_1(t - d) + A_2(t - d) \geq D_1(t)\} \leq \left\{\sum_{t \geq 0} (A_1(t) + A_2(t) - C t) \geq C d\right\} .$$

Let the generalized eigenvalue problem

$$Q \mathbf{h} = -\gamma \mathbf{h} ,$$

where $\mathbf{h}$ is a diagonal matrix with $(u_0, u_1, ..., u_n)$ on the diagonal, and where

$$u_j = r_j - C$$

are the instantaneous queueing drifts for $j = 0, 1, ..., n$. Assume further the stability condition

$$\sum_{j=0}^{n} \pi_j u_j < 0 .$$

As mentioned earlier, there exists a real generalized eigenvalue $-\gamma < 0$, and the corresponding eigenvector

$$\mathbf{h} = (h_0, h_1, ..., h_n)^T$$

with positive coordinates.

An immediate consequence of Lemma 1, instantiated with $A_2(t) := 0$ and $u := 0$, is the following:

**Corollary 2. (Queue Size Distribution: Upper Bound)** Consider the previous queueing system with a single Markov fluid $A(t)$ served at rate $C$. Then the stationary queue size distribution $Q$ and waiting time distribution $W(t)$ satisfy for all $\sigma, t \geq 0$

$$\mathbb{P}(Q \geq \sigma) \leq \frac{\sum_{i \geq h_{1,i} \geq 0} \pi_i h_i}{\min_{i \geq h_{1,i} \geq 0} h_i} e^{-\gamma \sigma} ,$$

$$\mathbb{P}(W(t) \geq d) \leq \frac{\sum_{i \geq h_{1,i} \geq 0} \pi_i h_i}{\min_{i \geq h_{1,i} \geq 0} h_i} e^{-\gamma C d} ,$$

where $\gamma$ and $\mathbf{h} = (h_0, h_1, ..., h_n)^T$ are the solutions of the generalized eigenvalue problem from Eq. (7).

Let us next compare this bound with the state-of-the-art bound from [35], i.e.,

$$\mathbb{P}(Q \geq \sigma) \leq \frac{\sum_{i \geq h_{1,i} \geq 0} \pi_i h_i}{\min_{i \geq h_{1,i} \geq 0} h_i} e^{-\gamma \sigma} ,$$

$$\mathbb{P}(W(t) \geq d) \leq \frac{\sum_{i \geq h_{1,i} \geq 0} \pi_i h_i}{\min_{i \geq h_{1,i} \geq 0} h_i} e^{-\gamma C d} .$$

Clearly, our bound is tighter due to the additional constraint on the ‘min’ operator from Eq. (8).

To give an explicit order of the improvement, consider the classical scenario when the process $A(t)$ is a superposition of $n$ Markov-modulated On-Off processes (see Figure 2). Each sub-process is modulated by a Markov process with two states, denoted by ‘On’ and ‘Off’, and which communicate at rates $\lambda$ and $\mu$. While in the ‘On’ state, each sub-process generates ‘fluid’ at some constant rate $P$. To avoid trivial situations we assume that $nP > C$ and that the utilization factor $\rho = \frac{nP}{C}$ satisfies the stability condition $\rho < 1$. 

![Fig. 2. A superposition of $n$ On-Off processes](image)
A key advantage of the chosen multiplexed On-Off model is that it lends itself to an explicit solution for the generalized eigenvalue problem from Eq. (7), i.e.,

$$
\begin{align}
\gamma &= \frac{n\lambda + (1-\rho)}{\bar{n} - C} \\
\bar{h}_i &= e^{-\gamma \theta_i}, \quad i = 0, 1, \ldots, n ,
\end{align}
$$

where $\theta = \log \frac{\lambda + \rho}{\lambda - \rho}$ (see also [35]). Thus, an explicit bound in Corollary 2 is

$$
\mathbb{P} (Q \geq \sigma) \leq \kappa^n e^{-\gamma \sigma}
$$

where $\kappa = \rho \left( \frac{\mu - \rho}{\lambda + \rho} \right)^{\frac{1}{\gamma - 1}}$ and $p = \frac{\mu}{\lambda + \rho}$ is the steady-state probability for an On-Off process in the ‘On’ state. As it was shown in [14] that $0 < \kappa < 1$, whereas the prefactor from Eqs. (10) and (11) is clearly greater than 1, it follows that the improvement of our bound from Corollary 2 relative to the one from Eq. (10) and (11) is of the order $O (\kappa^n)$ (in the specific case of a superposition of On-Off processes).

The technical explanation for this drastic improvement can be found in the proof of Lemma 1. More specifically, the key observation resides in Eq. (6): in the current case of a single fluid $A(t)$, the equation ‘says’ that there must be a non-negative drift $a(Z(T)) - C$ when the stopping time $T$ is attained; although seemingly elementary, this observation does have the reported drastic impact on the bounds. We point out that this observation is reminiscent of the works in [9], [35].

**B. Lower Bounds**

We now provide the matching lower bounds for the upper bounds from Corollary 2. Consider the same scenario from § III-A with a single Markov fluid $A(t)$ served at rate $C > 0$.

**Corollary 3. (Queue Size Distribution: Lower Bound)**
The stationary queue size distribution $Q$ and waiting time distribution $W(t)$ satisfy for all $\sigma, t \geq 0$

$$
\begin{align}
\mathbb{P} (Q \geq \sigma) &\geq \sum_{\max_i u_i \geq 0 \subset h_i} \pi_i h_i e^{-\gamma \sigma} , \\
\mathbb{P} (W(t) \geq d) &\geq \sum_{\max_i u_i \geq 0 \subset h_i} \pi_i h_i e^{-\gamma C d} ,
\end{align}
$$

where $\gamma$ and $h = (h_0, h_1, \ldots, h_n)^T$ are the solutions of the generalized eigenvalue problem from Eq. (7).

Remarkably, the only difference to the corresponding upper bound is that the factor $\min_i u_i \geq 0$ from Eq. (8) is now replaced by $\max_i u_i \geq 0$. In particular, in a scenario where the set $\{u_i \mid u_i \geq 0\}$ only consists of a single element, upper and lower bounds coincide and hence, Eqs. (8) and (14) (as well as Eqs. (9) and (15)) provide exact results. The proof of Corollary 3 is similar to that of Lemma 1, but it uses an additional stopping time following an idea from [38] to derive bounds in the GI/GI/1 (renewal) queue:

**Proof.** Fix $\sigma \geq 0$. The queue size distribution can be written as

$$
\mathbb{P} (Q \geq \sigma) = \mathbb{P} \left( \sup_{t \geq 0} (A(t) - Ct) \geq \sigma \right).
$$

As in the proof of Lemma 1, let $\mathbb{P}_i$ denote the underlying probability measure conditioned on $Z(0) = i$ for $0 \leq i \leq n$ (recall that $Z(t)$ is the underlying modulating Markov process of $A(t)$). Again, the process

$$
M_t := h Z(t) - \int_0^t h \left( \frac{\lambda Z(s)+\sigma}{\lambda Z(s)+\gamma} \right) ds \quad \forall t \geq 0
$$

is a martingale wrt $\mathbb{P}_i$ and the natural filtration. Considering the solution of the generalized eigenvalue problem from Eq. (7), we have $\forall t \geq 0$

$$
M_t = \frac{h Z(t)}{h_i} e^{\gamma \sum_i u_i (A(t)-Ct)}
$$

Let us now define the stopping time

$$
T = \inf \{ t \geq 0 \mid A(t) - Ct \geq \sigma \}
$$

which is the equivalent of the one from Eq. (5), in the current context with a single fluid. Define further a second stopping time for some $y > 0$:

$$
T_y = \min \{ T, \inf \{ t \geq 0 \mid A(t) - Ct \leq -y \} \}
$$

as the first hitting time of the boundary of the interval $[-y, \sigma]$. Since $T_y$ is a finite stopping time, relative to the natural filtration $\mathcal{F}_t$, it follows from the Optional Stopping Theorem that the process $(M_{T_y \wedge t})_t$ is a martingale, which is bounded and hence uniformly integrable. Since $M_{T_y \wedge t} \to M_{T_y}$ a.s. and in $L^1$, we can further write

$$
E_i [M_0] = E_i [M_{T_y \wedge 0}] = E_i [M_{T_y}]
$$

$$
= E_i [M_{T_y} \mid A(T_y) \geq CT_y + \sigma] P_i (A(T_y) \geq CT_y + \sigma)
$$

$$
+ E_i [M_{T_y} \mid A(T_y) \leq CT_y - y] P_i (A(T_y) \leq CT_y - y) ,
$$

where the expectations are taken wrt $\mathbb{P}_i$.

To deal with the first term we first observe that

$$
\{ A(T_y) \geq CT_y + \sigma \} \Rightarrow \{ T_y = T \} .
$$

Because the process $A(t)$ is continuous it follows that the ‘hitting’ condition from Eq. (17) is attained with equality, i.e.,

$$
A(T_y) = CT_y + \sigma .
$$

Moreover, since $\gamma > 0$, we can bound the conditional expectations from Eq. (18) as follows

$$
1 \leq E_i [M_0] \leq \sup_{u_i \geq 0} \frac{h_i}{h_i} e^{\gamma \sigma} P_i (A(T_y) \geq CT_y + \sigma)
$$

$$
+ \sup_{u_i \geq 0} \frac{h_i}{h_i} e^{-\gamma y} .
$$

Letting $y \to \infty$ the second term vanishes and thus

$$
1 \leq \sup_{u_i \geq 0} \frac{h_i}{h_i} e^{\gamma \sigma} P_i (T < \infty) .
$$

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By recalling that \( \{ T < \infty \} \) is the same (a.s.) with the event from Eq. (16), and finally deconditioning on \( i \) (i.e., \( \mathbb{P}(T < \infty) = \sum_i \pi_i \mathbb{P}(T < \infty) \)), the proof for the queue size \( Q \) is complete.

The proof for the waiting time \( W(t) \) is entirely analogous.

For an explicit lower bound, consider again the case when \( A(t) \) is the superposed process from Figure 2. Denoting \( p = \frac{1}{1+p} \), the equilibrium distribution \( \pi \) of \( Z(t) \) has the components \( \pi_i = (\frac{n}{i}) p^i (1-p)^{n-i} \) for \( i = 0, 1, \ldots, n \). Recalling the explicit solution of the underlying generalization eigenvalue problem from Eq. (12), the prefactor of the exponential bound from Eq. (14) becomes after elementary calculations

\[
\sum_{i=0}^{n} \binom{n}{i} p^i (1-p)^{n-i} e^\theta(n-i) = e^{\theta n} (pe^{-\theta} + 1 - p)^n = \rho^n,
\]

where \( \rho = \frac{n^\theta}{C} \) is the utilization factor. The explicit lower bound is thus

\[
\mathbb{P}(Q \geq \sigma) \geq \rho^\sigma e^{-\gamma \sigma},
\]

which has the same analytical structure as the corresponding upper bound from Eq. (13), except for the constant in the prefactor (i.e., \( \rho \) vs. \( \kappa \), both belonging to \((0, 1)\)).

C. Evaluation

In order to numerically validate the bounds given in Corollaries 2 and 3, we consider the simulation scenario as in Figure 3: A 3-state Markov process alternates with rates \( \lambda_{i,j} \) between one inactive and two active states. In the active states, fluid is generated with rates \( P \) and \( 2P \), respectively; in the inactive state no fluid is generated.

Figure 4 shows the CCDF of the aggregate delay distribution for a scenario with \( n = 2, 5, 10 \) such Markov processes being multiplexed. The parameters are \( \lambda_{i,j} = 1 \) (for all \( i,j \)), \( P = 1 \), and \( C > 0 \) is scaled such that for the link utilization holds \( \rho = 0.75 \) (Figure 4a) and \( \rho = 0.9 \) (Figure 4b), respectively.

By the symmetry of the transition rates, the Markov process is reversible. The analytical results are shown as coloured areas between the upper and lower bounds from Eqs. (9) and (15), the simulations are displayed as single points.

To gain insight into the impact of multiplexing, we refer to Figure 5: For different violation probabilities \( \varepsilon = 10^{-2}, 10^{-4}, 10^{-6} \), the delay is given in dependency of the number of multiplexed sources \( n \). Again, the link utilization is \( \rho = 0.75 \) (Figure 5a) and \( \rho = 0.9 \) (Figure 5b) and the bounds from Eqs. (9) and (15) are shown as coloured areas; in addition, the state-of-the-art (upper) bounds from Eqs. 10 and 11 are displayed as lines. One immediately sees that the beneficial effect of multiplexing (multiplexing gain) manifests itself in an exponential decay of the corresponding delay. Although this effect is also captured by the state-of-the-art bounds, they are too large by a factor of at least three times the width of the newly obtained interval, revealing their large inaccuracy.

IV. PER-FLOW DELAY DISTRIBUTION UNDER SCHEDULING

Clearly, the formulation from Lemma 1 is cumbersome, especially due to the apparently obscure parameter \( u \). It has however the key advantage that it can be broadly applied to obtain per-flow/class bounds in the general queueing scenario from Figure 1, besides the previous results on the queue size distribution. We will derive in particular bounds on the virtual delay \( W_i(t) \) of the tagged flow \( A_i(t) \), under three scheduling policies: FIFO, SP, and EDF. While the derivations resemble those from [14], we present the generalized results (i.e., holding for general Markov fluids) for the sake of completeness.

First, we describe a common step to the derivations of all the three cases. In a scheduled scenario, the departure process \( D_1(t) \) of the tagged flow has the representation

\[
D_1(t) \geq A_1 * S_1(t) := \inf_{0 \leq x \leq t} \{ A_1(s) + S_1(s, t) \},
\]

where \( S_1(t) \) is the service process, encoding information about the cross flow \( A_2(t) \) and the specific scheduling policy, and where ‘*’ is a \((min, +)\) convolution operator [10].

Using the equivalence of events

\[
\{ W_i(t) \geq d \} = \{ A_1(t - d) \geq D_1(t) \},
\]

we can bound the distribution of \( W_i(t) \) as

\[
\mathbb{P}(W_i(t) \geq d) \leq \mathbb{P}(A_1(t - d) \geq A_1 * S_1(t)).
\]

The three delay bounds (i.e., for FIFO, SP, and EDF) can be then obtained by plugging in the service process for the corresponding scheduling policy, and by choosing a suitable value for the parameter \( u \) in Lemma 1.

A. FIFO

Under this policy, the fluid from the sources \( A_1(t) \) and \( A_2(t) \) is processed in the order of the respective arrival times. The service process of the tagged flow is [18]

\[
S_1(s, t) = [C(t - s) - A_2(s, t - x)]_+ I_{t-x > x},
\]
for some fixed $x \geq 0$, independent of $s$ and $t$. Eq. (21) continues as follows
\[ P(W_1(t) \geq d) \leq P\left( \sup_{0 \leq s < t - d} \{A_1(s, t - d) - A_2(s, t - x)\} \geq 0 \right). \]
Note that we could restrict the range of $s$ from $[0, t]$ to $[0, t - d)$, using the positivity of the $\left[ \cdot \right]$ operator and the monotonicity of $A_1(s, t)$. By making the choice $x := d$, it follows that
\[ P(W_1(t) \geq d) \leq P\left( \sup_{0 \leq s < t - d} \{A_1(s, t - d) - A_2(s, t - d) - C(t - s)\} \geq 0 \right). \]

Further applying Lemma 1 with $u := 0$ and $\sigma := Cd$ yields:

**Corollary 4. (Per-Flow Delay Distribution: FIFO)**

Under FIFO scheduling, the delay of flow $A_1(t)$ satisfies for all $d \geq 0$
\[ P(W_1(t) \geq d) \leq \kappa e^{-\gamma Cd}, \tag{23} \]
where $\kappa$ and $\gamma$ are given in Lemma 1.

**B. SP**

Under this policy, fluid from $A_1(t)$ is only served when there is no unprocessed fluid from $A_2(t)$. A service process for the low-priority tagged flow is given by [10]
\[ S_1(s, t) = C(t - s) - A_2(s, t), \]
such that Eq. (21) continues as follows:
\[ P(W_1(t) \geq d) \leq P\left( \sup_{0 \leq s < t - d} \{A_1(s, t - d) - A_2(s, t - C(t - s))\} \geq 0 \right). \]
Recalling the arbitrary split $C_1 + C_2 = C$, Lemma 1 yields (with $u := d$ and $\sigma := 0$):

**Corollary 5. (Per-Flow Delay Distribution: SP)**

Under SP scheduling, the delay of flow $A_1(t)$ satisfies for all $d \geq 0$
\[ P(W_1(t) \geq d) \leq \kappa e^{-\gamma C_1 d}, \tag{24} \]
where $\kappa$ and $\gamma$ are given in Lemma 1.

**C. EDF**

An EDF server associates the relative deadlines $d_1^*$ and $d_2^*$ to the fluids of $A_1(t)$ and $A_2(t)$, respectively. All fluids are served in the order of their remaining deadlines, even when they are negative. A service process for the tagged flow $A_1(t)$ is given by [33]
\[ S_1(s, t) = \left[ C(t - s) - A_2(s, t - \min\{x, y\}) \right]_+ I_{t-s \geq x}. \tag{25} \]
for some $x > 0$ and where $y := d_1^* - d_2^*$.

For the sake of brevity, we only consider the case $y \geq 0$. Setting $x := d$ as for the FIFO case, Eq. (21) continues to
\[ P(W_1(t) \geq d) \leq P\left( \sup_{0 \leq s < t-d} \{A_1(s, t-d) + A_2(s, t-d - \min\{d, y\}) - C(t-s)\} \geq 0 \right). \]
By changing the variable $t \leftarrow t + d - \min\{d, y\}$ we get
\[ P(W_1(t) \geq d) \leq P\left( \sup_{0 \leq s < t-\min\{d, y\}} \{A_1(s, t - \min\{d, y\}) + A_2(s, t) - C(t-s)\} \geq 0 \right). \]

We can now apply Lemma 1 with $u := \min\{d, y\}$ (note that both $d$ and $y$ are positive) and $\sigma := C(d - \min\{d, y\})$, and finally obtain:

**Corollary 6. (Per-Flow Delay Distribution: EDF)**

Under EDF scheduling with $y := d_1^* - d_2^* \geq 0$, the delay of flow $A_1(t)$ satisfies for all $d \geq 0$
\[ P(W_1(t) \geq d) \leq \kappa e^{-\gamma C_2 \min\{d_1^*-d_2^*, d\}} e^{-\gamma Cd}, \]
where $\kappa$ and $\gamma$ are given in Lemma 1.
V. AN ANALYTICAL CONSTRUCTION FOR THE SPACE-PARAMETER IN THE EFFECTIVE BANDWIDTH APPROXIMATION

As a collateral result, we now give the first analytical construction for the space-parameter in the effective bandwidth approximation, which was proposed in the 1980–90s as a fundamental technique for traffic engineering. For an arrival process $A(t)$, the effective bandwidth of $A(t)$ is defined for some $\theta > 0$ as [27]

$$\alpha(\theta, t) := \frac{1}{\theta} \log E [e^{\theta A(t)}].$$

Let

$$\alpha_\theta := \lim_{t \to \infty} \alpha(\theta, t)$$

and $\theta^*$ be the solution of

$$\alpha_\theta = C,$$

where $C$ is the rate at which $A(t)$ is served at a stable queue. The effective bandwidth approximation states that the steady-state queue size distribution satisfies

$$P(Q > \sigma) \sim \kappa e^{-\theta^* \sigma},$$

where $\kappa$ is the asymptotic constant, $\theta^*$ is the asymptotic decay rate, and $f(x) \sim g(x)$ means that $f(x)/g(x) \to 1$ as $x \to \infty$ (see [12], [15]).

The space-parameter of the effective bandwidth approximation is generally the parameter $\theta$ in the expression of $\alpha(\theta, t)$, and more particularly $\theta^*$, which was shown to play a fundamental role in traffic engineering; unfortunately, the construction of $\theta^*$ is based on either numerical search or simulations [15]. To the best of our knowledge, the next result provides the first analytical construction of $\theta^*$ (in the case of Markov fluids).

**Lemma 7. (Space-Parameter Construction)** For the previous queueing scenario it holds

$$\theta^* = \gamma,$$

where $\gamma$ was defined in Corollary 2 (as the solution of the generalized eigenvalue problem from Eq. (7)).

**Proof.** From the construction of $\gamma$ we have that

$$(Q + \gamma u) h = 0.$$  

(28)

Let the diagonal matrix $V$ with $(r_1^\gamma, r_2^\gamma, \ldots, r_n^\gamma)$ on the diagonal, and construct the matrix

$$Q_\gamma := Q + V.$$  

Then it holds that

$$Q_\gamma x = \alpha_\gamma \gamma I x$$  

(29)

where $\alpha_\gamma \gamma$ is the spectral radius of $Q_\gamma$ and $x$ is the corresponding (positive) eigenvector (see [28]).

Let us now observe that

$$Q + \gamma u = Q_\delta - C \gamma I.$$  

Combining with Eqs. (28) and (29) we obtain that

$$0 = (Q_\gamma - \alpha_\gamma \gamma I) x = (Q_\gamma - C \gamma I) h.$$  

Therefore, $C \gamma$ is an eigenvalue for the eigenvalue problem from Eq. (29) and thus

$$\alpha_\gamma \geq C,$$

since by construction $\alpha_\gamma \gamma$ is the corresponding spectral radius.

To show the converse, i.e., $\alpha_\gamma \leq C$, consider the exact asymptotic decay of the distribution of the queue occupancy (of $A(t)$ when fed at a queue with capacity $C$), i.e.,

$$\lim_{\sigma \to \infty} \frac{1}{\sigma} \log P(Q > \sigma) = -\theta^*,$$

(30)

where $\alpha_\theta = C$ (see [27]). In other words, $\theta^*$ is the exact asymptotic decay rate. As Corollary 2 predicts $\gamma$ as a decay rate, in terms of an upper bound, it follows that $\gamma \leq \theta^*$. Finally, since $\alpha_\theta$ is increasing in $\theta$ (see [10], p. 241), it follows that

$$\alpha_\gamma \leq \alpha_\theta = C,$$

completing the proof. Alternatively, one can invoke the lower bound from Corollary 3. Note that a more direct proof can be

![Fig. 5. Comparison of upper/lower bounds from Eqs. (9), (15) (depicted as shaded areas) on the $e$-quantiles of the delay with state-of-the-art upper bound from Eq. (11) (depicted as lines), for $\varepsilon = 10^{-2}, 10^{-4}, 10^{-6}$.](image-url)
VI. CONCLUSIONS

In this paper we have advanced the queueing analysis of the versatile class of general Markov fluids. In particular, we have improved the state-of-the-art upper bounds on the queue size distribution by an exponential factor in the special case of Markov modulated On-Off sources. We have further provided the first matching lower bounds, and also the first bounds on the per-flow delay distribution under FIFO, SP, and EDF scheduling.

An attractive feature of our stochastic bounds is that they are obtained using a powerful martingale methodology, which essentially invokes Kolmogorov-Doob inequality arguments, and which was shown to render accurate stochastic bounds. An alternative and arguably more powerful technique based on integral equations was provided by Kingman [30] in the case of renewals and a discrete-time setting; its extension to the non-renewal case can in principle provide clues for further improving the current upper/lower bounds.

REFERENCES