

The impact of a heavy-tailed service-time distribution upon the M/GI/s waiting-time distribution

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By exploiting an infinite-server-model lower bound, we show that the tails of the steady-state and transient waiting-time distributions in the M/GI/s queue with unlimited waiting room and the first-come first-served discipline are bounded below by tails of Poisson distributions. As a consequence, the tail of the steady-state waiting-time distribution is bounded below by a constant times the s th power of the tail of the service-time stationary-excess distribution. We apply that bound to show that the steady-state waiting-time distribution has a heavy tail (with appropriate definition) whenever the service-time distribution does. We also establish additional results that enable us to nearly capture the full asymptotics in both light and heavy traffic. The difference between the asymptotic behavior in these two regions shows that the actual asymptotic form must be quite complicated.

Keywords: heavy-tailed distributions, subexponential distributions, tail probability asymptotics, multi-server queues, M/GI/s queue, waiting times, existence of finite moments

1. Introduction

There recently has been great interest in the performance of queues with heavy-tailed (or long-tailed) service-time distributions. Asymptotic results for the tail of the steady-state waiting-time distribution in the single-server queue with unlimited waiting room and the first-come first-served (FCFS) service discipline were first obtained by Borovkov [9, section 22], Cohen [13] and Pakes [26]. For recent extensions, see [6,22 and references therein].

The purpose of this paper is to obtain some corresponding partial results for the challenging multi-server queue, also with unlimited waiting room and the FCFS discipline. In particular, we derive a lower bound on the waiting-time tail probability in the M/GI/s model that allows us to conclude that the waiting-time distribution has a heavy-tailed distribution (with appropriate definition) whenever the service-time distribution does. This conclusion deduced from a lower bound parallels the conclusion deduced for general single-server fluid models in [12]. The bounding arguments have the appeal of quite simply determining the main qualitative behavior, even though they do not determine the full asymptotic behavior.

We also establish a second, very different, lower bound for the waiting-time tail probability in a heavy-traffic regime. Since the second lower bound leads to a much larger asymptote, it is natural to suspect that there must be a large gap between the first lower-bound asymptote and the true asymptote. However, we show that is not always the case, by showing that the first lower bound is asymptotically correct in light traffic. We also establish an upper bound that shows that the second lower bound is at least nearly correct in heavy traffic. Together, these results demonstrate that the actual asymptotic behavior must be quite complicated. We make a conjecture about the actual asymptotic behavior.

We state and discuss the main results in section 2 and provide proofs and additional details in the following sections. We conclude with a discussion of the transient waiting-time distribution. It turns out that an infinite-server lower bound also applies to the transient waiting-time distribution. That is important because steady state is approached very slowly with heavy-tailed service-time distributions. Indeed, steady state is approached so slowly that it may be preferable to use transient distributions in applications. The infinite-server lower bound is useful because it provides both a simple quantitative description of the rate of convergence to steady state and an approximation for the transient waiting-time distribution. Since these descriptions are for the infinite-server lower bound, they do not yield exact descriptions for M/G/s models, but they can serve as useful approximations when s is not too small.

We conclude this introduction by mentioning papers by Boxma et al. [10] and Korshunov [24] that came to our attention (and were evidently done) after this paper was completed. They contain asymptotic results that tend to support the conjectures here.

2. Main results

To specify the model, let G be the service-time cumulative distribution function (cdf) and let $G^c(t) \equiv 1 - G(t)$ be the associated complementary cdf (ccdf). We assume that G has finite mean m_1 . Let G_e be the stationary-excess (or equilibrium residual-lifetime) cdf associated with G , defined by

$$G_e(t) = m_1^{-1} \int_0^t G^c(u) \, du, \quad t > 0, \quad (2.1)$$

and let G_e^c be its ccdf. Let the interarrival time have finite mean λ^{-1} and let the traffic intensity be $\rho \equiv \lambda m_1/s$. To ensure model stability, we assume that $\rho < 1$. Let W be the steady-state waiting time until beginning service and let W^c be its ccdf; i.e., $W^c(t) \equiv P(W > t)$, $t \geq 0$.

The lower bound for $W^c(t)$ here is obtained by approximating the M/GI/s model by the associated infinite-server M/GI/ ∞ model. Such infinite-server models have proven very useful for approximating M_t/GI/s/r models with time-dependent Poisson arrival processes; see section 8 below and [15,25 and references therein]. It is well

known that the steady-state number of customers in the M/GI/ s model is bounded below by the steady-state number of customers in the associated M/GI/ ∞ model. Of course there is no waiting before beginning service in the M/GI/ ∞ model, but it is easy to see that the steady-state waiting time cdf $W^c(t)$ in the M/G/ s model is bounded below by the cdf $F^c(t)$ of the first passage time, starting in steady state, to a level with $s - 1$ or fewer busy servers in the M/G/ ∞ model, assuming that all future arrivals are neglected. Somewhat surprisingly, perhaps, this first-passage-time cdf F^c has a relatively simple form, being the cdf of a Poisson distribution with mean $\rho s G_e^c(t)$, where G_e^c is the cdf associated with the service-time stationary-excess cdf G_e in (2.1).

To state the result, let $\Pi^c(k; \lambda)$ be the cdf of a Poisson distribution with mean λ ; i.e., if X has the Poisson distribution, then $\Pi^c(k; \lambda) \equiv P(X > k)$. We say that f is asymptotically equivalent to g as $t \rightarrow \infty$, and write $f(t) \sim g(t)$, if $f(t)/g(t) \rightarrow 1$ as $t \rightarrow \infty$.

Theorem 1. In the M/GI/ s model, for all ρ , $0 < \rho < 1$, and $t > 0$,

$$W^c(t) \geq F^c(t) \equiv \Pi^c(s - 1; \rho s G_e^c(t)) \equiv e^{-\rho s G_e^c(t)} \sum_{m=s}^{\infty} \frac{(\rho s G_e^c(t))^m}{m!}, \quad (2.2)$$

where

$$F^c(t) \sim \frac{(\rho s)^s}{s!} G_e^c(t)^s \quad \text{as } t \rightarrow \infty, \quad (2.3)$$

$$F^c(t) \sim \frac{e^{\rho s G_e^c(t)} (e \rho G_e^c(t))^s}{(1 - \rho G_e^c(t)) \sqrt{2\pi s}} \quad \text{as } s \rightarrow \infty, \quad (2.4)$$

and

$$F^c(t) \sim \frac{(e \rho G_e^c(t))^s}{\sqrt{2\pi s}} \quad \text{as } s \rightarrow \infty \text{ and then } t \rightarrow \infty. \quad (2.5)$$

Remark. Note that we can also establish the same lower bound asymptote in (2.3) by keeping only the term corresponding to $m = s$ in (2.2). Then

$$W^c(t) \geq F^c(t) \geq H_1^c(t) \equiv e^{-\rho s G_e^c(t)} \frac{(\rho s G_e^c(t))^s}{s!} \sim \frac{(\rho s)^s}{s!} G_e^c(t)^s \quad (2.6)$$

as $t \rightarrow \infty$. Also note that

$$W^c(t) \geq H_1^c(t) \geq A G_e^c(t)^s \quad \text{for } A = \frac{e^{-\rho s} (\rho s)^s}{s!}. \quad (2.7)$$

Our primary goal is to apply this lower bound F^c in theorem 1 to deduce that in the M/G/ s model the waiting-time cdf W^c inherits a heavy-tail property from the service-time cdf G^c , with appropriate definitions. However, we also point out that the lower bound may serve as a useful reference point and sometimes even a useful approximation, because it is remarkably tractable, because it applies for all t

and because the M/G/s model with a heavy-tailed service-time distribution is very difficult to analyze. A heavy-tailed service-time distribution also makes it difficult to accurately estimate the waiting-time distribution with simulation; see [4].

One approach to carrying out numerical calculations with a heavy-tailed service-time distribution is to first approximate the heavy-tailed distribution by a hyperexponential distribution as in [17], or a more general phase-type distribution as in [5], and then solve the resulting M/H_k/s or M/PH/s queue, using algorithms such as in [7,28,29]. Of course, those approximations fail to capture the asymptotics as $t \rightarrow \infty$, but the approximations can be good for arbitrarily large t . For the GI/GI/1 queue, the calculations can be done directly as in [1].

Since F^c in (2.2) has a Poisson distribution, it can be computed. The normal approximation

$$\Pi^c(s-1, \rho s G_e^c(t)) \approx \Phi^c\left(\frac{s-0.5-\rho s G_e^c(t)}{\sqrt{\rho s G_e^c(t)}}\right) \quad (2.8)$$

should be a good approximation for $F^c(t)$ if the argument

$$\alpha(s, t) \equiv \frac{s-0.5-\rho s G_e^c(t)}{\sqrt{\rho s G_e^c(t)}} \quad (2.9)$$

is not too large.

It is significant that both the lower-bound cdfs F^c in (2.2) and H_1^c in (2.6) are asymptotically exact in light traffic.

Theorem 2. In the setting of theorem 1,

$$\lim_{\lambda \rightarrow 0} \frac{W^c(t)}{H_1^c(t)} = \lim_{\lambda \rightarrow 0} \frac{W^c(t)}{F^c(t)} = 1 \quad \text{for each } t > 0$$

for H_1^c in (2.6) and F^c in (2.3).

The basis for theorem 2 is a light-traffic result proved by Burman and Smith [11], which was reviewed Whitt in [35, section 2].

The tractable infinite-server lower bound can be a useful reference point, but it can grossly underestimate the true tail probabilities at higher traffic intensities, as we demonstrate by establishing a second lower bound for higher traffic intensities.

Theorem 3. In the M/GI/s model, if $1 - s^{-1} < \rho < 1$, then

$$W^c(t) \geq H_2^c(t) \equiv p G_e^c(t) p_1(t) p_2(t), \quad (2.10)$$

where p , $p_1(t)$ and $p_2(t)$ are positive probabilities with $p_i(t) \rightarrow 1$ as $t \rightarrow \infty$ for $i = 1, 2$, so that

$$H_2^c(t) \sim p G_e^c(t) \quad \text{as } t \rightarrow \infty. \quad (2.11)$$

Notice that (2.11) differs significantly from (2.3) and (2.7) when $s > 1$, because $G_e^c(t)$ appears on the right in (2.11) instead of $G_e^c(t)^s$.

We also apply an increasing-convex-order upper bound by Wolff [36] to show that this second lower-bound asymptote in theorem 3 is close to the true asymptote in this heavy-traffic regime. To state the result, we make a definition. We say that a cdf G is *subexponential* and belongs to class \mathcal{S} if

$$(G * G)^c(t) \sim 2G^c(t) \quad \text{as } t \rightarrow \infty, \tag{2.12}$$

where $(G * G)^c$ is the ccdf of the two-fold convolution of G with itself. The subexponential distributions are a large subclass of the heavy-tailed distributions; see [19].

Theorem 4. In an M/GI/s model with $\rho < 1$ and service-time cdf G , if $G_e \in \mathcal{S}$, then

$$\liminf_{t \rightarrow \infty} \frac{P(W > t)}{G_e^c(t)} \leq \frac{\rho}{1 - \rho}. \tag{2.13}$$

We now focus on the asymptotic behavior as $t \rightarrow \infty$. For the special case $s = 1$, the lower-bound asymptote in (2.3) and (2.6) underestimates the known limit in the heavy-tailed case (when $G_e^c \in \mathcal{S}$) only by the constant factor $(1 - \rho)^{-1}$. Thus, for $s = 1$ the bound is sharp in the sense that is asymptotically correct in light traffic.

We are able to apply theorem 1 to deduce that the waiting-time ccdf is heavy tailed whenever the service-time ccdf is, with appropriate definitions. For that purpose, we introduce a new definition of a heavy-tailed distribution. Recall that a ccdf H^c is stochastically greater than or equal to another ccdf G^c if $H^c(t) \geq G^c(t)$ for all t . A ccdf G^c on $[0, \infty)$ is said to belong to the class \mathcal{L} if $G^c(t) > 0$ for all $t > 0$ and

$$G^c(t - u) \sim G^c(t) \quad \text{as } t \rightarrow \infty \quad \text{for all } u > 0. \tag{2.14}$$

A ccdf H^c is *heavy tailed*, and we write $H^c \in \mathcal{H}$, if there is a ccdf $G^c \in \mathcal{L}$ such that

$$H^c(t) \geq G^c(t) \quad \text{for all } t.$$

It is known that $\mathcal{S} \subseteq \mathcal{L}$, so that $\mathcal{S} \subseteq \mathcal{H}$. An important subset of \mathcal{S} is the set \mathcal{P} of power-tail ccdfs; $G^c \in \mathcal{P}$ if

$$G^c(t) \sim \beta t^{-\alpha}, \quad \text{as } t \rightarrow \infty, \tag{2.15}$$

where α and β are positive constants.

The standard heavy-tail notions embody regularity properties for asymptotics as well as relatively large probabilities of large values. Hence, if G has a heavy tail by one of the standard definitions and if H is stochastically larger than G , i.e., if $H^c(t) \geq G^c(t)$ for all t , then it does *not* follow that H too has a heavy tail by the same definition. Hence, there is motivation for our introduction of the class \mathcal{H} .

Here is our main result.

Theorem 5. For an M/GI/ s model with $\rho < 1$ and service-time cdf G^c , if $G^c \in \mathcal{H}$, then $W^c \in \mathcal{H}$.

It is intuitively clear that having more servers reduces the impact of a heavy-tailed service-time distribution, but that is not shown in theorem 5. We now obtain a result for a smaller class of heavy-tailed distributions that reveals this property. For that purpose, we say that a cdf G^c on $[0, \infty)$ is regularly varying of index α , and write $G^c \in \mathcal{R}(\alpha)$, if $G^c(t) > 0$ for all $t > 0$ and

$$G^c(ut) \sim u^\alpha G^c(t) \quad \text{as } t \rightarrow \infty \quad (2.16)$$

for all $u > 0$; see [8]. Paralleling the class \mathcal{H} defined above, we define a class $\mathcal{T}(-\alpha)$. A cdf H^c is said to be dominated by a regularly varying tail of index $-\alpha$, and we write $H^c \in \mathcal{T}(-\alpha)$, if there exists a cdf G^c in $\mathcal{R}(-\alpha)$ such that

$$H^c(t) \geq G^c(t) \quad \text{for all } t.$$

Theorem 6. For an M/GI/ s models with $\rho < 1$ and service-time cdf G^c , if $G^c \in \mathcal{T}(-\alpha)$ for $\alpha > 1$, then $W^c \in \mathcal{T}(-s(\alpha - 1))$.

Unfortunately, we have been unable to determine the full asymptotic behavior of $W^c(t)$ as $t \rightarrow \infty$, but theorems 1, 3 and 4 lead us to make a conjecture about the true asymptotic form.

Conjecture. In the stable M/GI/ s model with service-time cdf G , if $G_e \in \mathcal{S}$, where G_e^c is the service-time stationary-excess cdf in (2.1), and if

$$s - k < \rho s < s - k + 1 \quad \text{for some } k, \quad 1 \leq k \leq s, \quad (2.17)$$

then

$$W^c(t) \sim \gamma G_e^c(\eta t)^k \quad \text{as } t \rightarrow \infty, \quad (2.18)$$

where γ and η are positive constants (as functions of t).

As indicated above, for $s = 1$, (2.18) is known to hold with $\gamma = \rho/(1 - \rho)$, $\eta = 1$ and $k = 1$. For $s > 1$, conjecture (2.18) is consistent with theorems 1, 3 and 4. Here is some additional intuition behind (2.18) and (2.17) for $s > 1$: First, by (2.17), k is the minimum number of servers that can be removed (occupied by exceptionally long service times), so that the temporary traffic intensity without these servers exceeds 1, causing the workload to grow at positive rate. Second, the completed service times of the customers at k servers at an arbitrary time in steady state should be approximately distributed as k i.i.d. random variables with cdf G_e . (For example, that would be the case if the s servers were continuously busy; assuming that the cdf G is nonlattice.) Thus, the probability that there are k customers present who have all been in service for at least time ηt should be of order $\gamma G_e^c(\eta t)^k$ for constants γ and η . The scaling

constant η in (2.18) is introduced because the workload grows at rate $\delta \equiv \rho s - (s - k)$ during this period of length ηt , so that the waiting time should be of order t for appropriate choice of the constant η .

If the conjecture is correct, then it seems evident that the asymptotic behavior will be quite complicated when the traffic intensity is at a boundary point, i.e., when $\rho s = s - k$ for some k , $1 \leq k \leq s - 1$. When (2.17) does hold, we also make the stronger conjecture that (2.18) holds for the more general GI/GI/ s model with a nonlattice interarrival-time distribution. (That is consistent with the known GI/GI/1 result.)

Here is how the rest of this paper is organized: We establish the two lower bounds in theorems 1 and 3 in sections 3 and 4. We then discuss heavy-tailed distributions and prove theorem 5 in section 5. We prove theorem 4 establishing the upper bound in section 6. We discuss the existence of finite moments in section 7. In particular, the lower-bound asymptote in (2.3) leads us to conjecture that, for $s > 1$, unlike for $s = 1$, the existence of the mean EW or other higher waiting-time moment EW^r depends upon more than the traffic intensity and the existence of service-time moments. Finally, we discuss a lower bound for the transient waiting-time distribution in section 8.

3. The infinite-server lower bound

In this section we prove theorem 1. We start by considering a general A/A/ s model with unlimited waiting room, the FCFS discipline and arbitrary arrival and service processes. It is easy to see that, for each sample path of arrival times and service times, the remaining service times of all customers in the system at any time are bounded below by the remaining service times in the corresponding A/A/ ∞ system with the same arrival times and service times but infinitely many servers. Thus the waiting time for any arrival (or potential arrival) at any time t in the A/A/ s system is bounded below by the first passage time to the state of $s - 1$ or fewer busy servers in the A/A/ ∞ system starting at time t , with future arrivals shut off.

As a consequence, if steady-state distributions exist, then the steady-state waiting-time distribution in the A/A/ s model is bounded below, in the sense of stochastic order, by the steady-state first passage time to level $s - 1$ or below in the A/A/ ∞ model; i.e.,

$$W^c(t) \geq F^c(t) \quad \text{for all } t, \quad (3.1)$$

where F^c is the ccdf of the steady-state first passage time to $s - 1$ or fewer busy servers in the A/A/ ∞ model, assuming that future arrivals are neglected.

We are able to usefully exploit the ordering (3.1) for the M/GI/ s model, because there is a convenient exact characterization of the cdf F in the associated M/GI/ ∞ model. In particular, for the M/GI/ ∞ model, it is known that the steady-state number of busy servers has a Poisson distribution with mean ρs , independent of the service-time cdf G beyond its mean. Moreover, conditional on there being n busy servers in steady state, the n residual service times are distributed as n i.i.d. random variables

with the service-time stationary-excess cdf G_e ; see [31, p. 161]. (This M/GI/ ∞ property is also applied in [14,21].)

Moreover, it is elementary to see that the ccdf F^c in (3.1) is the tail of a Poisson distribution, because each of the Poisson random number of customers initially in the system at time 0 is still there t time units later with probability $G_e^c(t)$, independent of the other customers. Hence, we have an independent thinning of the original Poisson population, which is again Poisson. The associated analytic derivation is

$$\begin{aligned}
 F^c(t) &= \sum_{n=s}^{\infty} \frac{e^{-\rho s} (\rho s)^n}{n!} \sum_{k=s}^n \binom{n}{k} G_e^c(t)^k G_e(t)^{n-k} \\
 &= \frac{e^{-\rho s} (\rho s)^s}{s!} \sum_{n=0}^{\infty} \frac{(\rho s)^n}{(s+n)!} \sum_{l=0}^n \binom{s+n}{s+l} G_e^c(t)^{s+l} G_e(t)^{n-l} \\
 &= \frac{e^{-\rho s} (\rho s)^s}{s!} \sum_{l=0}^{\infty} \frac{(\rho s G_e^c(t))^l}{(s+l)!} \sum_{n=l}^{\infty} \frac{(\rho s G_e(t))^{n-l}}{(n-l)!} \\
 &= e^{-s\rho G_e^c(t)} \sum_{n=s}^{\infty} \frac{(\rho s G_e^c(t))^n}{n!} = \Pi^c(s-1; \rho s G_e^c(t)). \tag{3.2}
 \end{aligned}$$

It thus remains to establish the asymptotic relations for this special Poisson distribution, which of course is classic. First, recall that the ccdf of a Poisson distribution can always be expressed as the cdf of an Erlang distribution, using the familiar inverse relation between partial sums of nonnegative random variables and counting processes. Equivalently, we can express F^c in terms of special functions. In particular,

$$\begin{aligned}
 F^c(t) &= \frac{\gamma(s, \rho s G_e^c(t))}{\Gamma(s)} = e^{-\rho s G_e^c(t)} \frac{(\rho s G_e^c(t))^s}{s!} M(1, s+1, \rho s G_e^c(t)) \\
 &\sim \frac{(\rho s G_e^c(t))^s}{s!} \quad \text{as } t \rightarrow \infty, \tag{3.3}
 \end{aligned}$$

where γ is the incomplete gamma function, Γ is the gamma function and M is the confluent hypergeometric function, which satisfies $M(1, s+1, 0) = 1$; see [3, 6.5.2, 6.5.12, 13.1.2 and 13.5.5]. As noted in the remark, we can get the same asymptote as $t \rightarrow \infty$ by keeping only the terms with $G_e^c(t)^s$ in (3.2), i.e.,

$$\begin{aligned}
 F^c(t) &\geq H_1^c(t) \equiv \sum_{n=s}^{\infty} \frac{e^{-\rho s} (\rho s)^n}{n!} \binom{n}{s} G_e^c(t)^s G_e(t)^{n-s} \\
 &= \frac{(\rho s)^s e^{-\rho s} G_e^c(t)^s}{s!} \sum_{n=s}^{\infty} \frac{(\rho s)^{n-s}}{(n-s)!} G_e(t)^{n-s} \\
 &= \frac{(\rho s)^s}{s!} e^{-\rho s G_e^c(t)} G_e^c(t)^s \sim \frac{(\rho s)^s}{s!} G_e^c(t)^s \quad \text{as } t \rightarrow \infty. \tag{3.4}
 \end{aligned}$$

Moreover, from [3, 13.1.2], it follows that for any x

$$M(1, 1 + s, \rho s x) \rightarrow 1 + \rho x + (\rho x)^2 + \dots = (1 - \rho x)^{-1}, \quad (3.5)$$

so that

$$F^c(t) \sim \frac{e^{-\rho s G_e^c(t)}}{(1 - \rho G_e^c(t))} \frac{(\rho s G_e^c(t))^s}{s!} \quad \text{as } s \rightarrow \infty. \quad (3.6)$$

Applying Stirling's formula to (3.6), we obtain (2.4).

4. The minimal-stability lower bound

In this section we prove theorem 3, which holds under the condition that (2.17) holds for $k = 1$, i.e., $1 - s^{-1} < \rho < 1$. Following Scheller-Wolf and Sigman [27], we refer to this case as the minimal-stability case.

In order to consider the virtual waiting time of a potential arrival at time 0 in steady state, we look at the system at time $-Bt$, which is also in steady state. By the Poisson-Arrivals-See-Time-Averages (PASTA) property, see [37], the waiting time of an actual arrival has the same distribution.

We assume that the servers are numbered and that new arrivals and waiting customers are always assigned to the lowest-numbered free server. We then focus on server number 1. Server 1 experiences an alternating series of idle and busy periods, with the busy periods made up of a succession of service times. (Since we have a Poisson arrival process, the empty state is a regeneration point for the model; e.g., see [32].) If we look at this server at an arbitrary time in steady-state, which we have set as $-Bt$, with probability p , $0 < p < 1$, this server is busy and, conditional on this server being busy, the remaining service time exceeds Bt with probability $G_e^c(Bt)$, where G_e is the service-time stationary excess cdf. (See [20] for more on this property.)

Let $A(t, u)$ count the Poisson number of arrivals in the interval $(t, u]$ and let V_k denote the k th service time. By the Poisson, i.i.d. and finite-mean assumptions, we have the laws of large numbers (LLNs)

$$u^{-1}A(t, t + u) \rightarrow \lambda \quad \text{w.p. 1} \quad \text{as } u \rightarrow \infty \quad (4.1)$$

and

$$n^{-1}(V_1 + \dots + V_n) \rightarrow m_1 \equiv EV_1 \quad \text{w.p. 1} \quad \text{as } n \rightarrow \infty. \quad (4.2)$$

Because the arrival process is assumed to be Poisson, the arrival process after time $-Bt$ is independent of the remaining service time observed for the customer being served by server 1 at time $-Bt$. By (4.1), for any $\varepsilon > 0$,

$$P(A(-Bt, 0) > \lambda B((1 - \varepsilon)t)) \rightarrow 1 \quad \text{as } t \rightarrow \infty. \quad (4.3)$$

Given n arrivals in $(-Bt, 0]$, the waiting time of an arrival at time 0 is bounded below by the case in which all of these n arrivals occur together at time $-Bt$. Since

server 1 is occupied during $(-Bt, 0]$, work is cleared by at most rate $s - 1$ during $(-Bt, 0]$ and then afterwards at rate s . The waiting time of the potential customer at time 0 will exceed t if the sum of the $(n - s + 1)$ smallest of the n service times exceed $(s - 1)Bt + t$. (All but $s - 1$ of the original customers in the system at time $-Bt$ must have been served.) This sum in turn is greater than or equal to the overall sum, say S_n , minus $(s - 1)$ times the maximum M_n .

Combining these features, we obtain

$$P(W > t) \geq H_2^c(t) \equiv pG_e^c(Bt)P(A(-Bt, 0) > \lambda B(1 - \varepsilon)t) \\ \times P(S_n - (s - 1)M_n > (s - 1)Bt + st), \quad (4.4)$$

where $n = \lfloor \lambda B(1 - \varepsilon)t \rfloor$.

However, $n^{-1}M_n \rightarrow 0$ as $n \rightarrow \infty$ by lemma 7 below and $n^{-1}S_n \rightarrow m_1$ as $n \rightarrow \infty$ by (4.2), so that, for any $\varepsilon > 0$,

$$P(S_n - (s - 1)M_n > m_1(1 - \varepsilon)n) \rightarrow 1 \quad \text{as } n \rightarrow \infty. \quad (4.5)$$

Hence, in order to show that

$$H_2^c(t) \sim pG_e^c(Bt) \quad \text{as } t \rightarrow \infty \quad (4.6)$$

for $H_2^c(t)$ in (4.4), it suffices to choose B suitably large and ε suitably small so that

$$\lambda B(1 - \varepsilon)^2 m_1 > (s - 1)B + s \quad (4.7)$$

or, equivalently,

$$B(\rho s(1 - \varepsilon)^2 - (s - 1)) > s. \quad (4.8)$$

However, by (2.17), we can achieve (4.8); in particular, by choosing ε suitably small, B can be any number larger than s/δ , where $\delta \equiv \rho s - (s - 1) > 0$.

One would expect that this argument also extends to cover the more general GI/GI/ s , G/GI/ s and G/G/ s models, exploiting assumed LLNs as in (4.1) and (4.2), but there is some dependence, conditioning on the state of server 1 at time $-Bt$, that needs to be controlled.

We need the following to complete the proof above.

Lemma 7. If $EV_1 = m_1 < \infty$, then $n^{-1}M_n \Rightarrow 0$ as $n \rightarrow \infty$.

Proof. Note that

$$P(M_n \leq nx) = G(nx)^n = \left(1 - \frac{nG^c(nx)}{n}\right)^n.$$

However, since $EV_1 < \infty$, $G^c(x)$ is integrable, which implies that $nG^c(nx) \rightarrow 0$ as $n \rightarrow \infty$. Since $(1 - n^{-1}c_n)^n \rightarrow e^{-c}$ as $n \rightarrow \infty$ if $c_n \rightarrow c$, $P(M_n \leq nx) \rightarrow e^0 = 1$. \square

5. Properties of heavy-tailed distributions

We now elaborate on the heavy-tail property and prove theorems 5 and 6. In addition to the classes of cdfs G^c on $[0, \infty)$ with $G^c(t) > 0$ for all t defined in section 2, we define two more. We say that $G^c \in \mathcal{S}^*$ if G has finite mean m_1 and

$$\int_0^t G^c(t-u)G^c(u) du \sim 2m_1G^c(t) \quad \text{as } t \rightarrow \infty. \tag{5.1}$$

We say that $G^c \in \mathcal{C}_3$, i.e., class III according to [1], if for all $\varepsilon > 0$

$$\int_0^\infty e^{\varepsilon t} dG(t) = \infty. \tag{5.2}$$

The following orderings are known or easy to establish.

Proposition 8. The classes are ordered by

$$\mathcal{S}^* \subseteq \mathcal{S} \subseteq \mathcal{L} \subseteq \mathcal{H} \subseteq \mathcal{C}_3 \quad \text{and} \quad \mathcal{R}(-\alpha) \subseteq \mathcal{T}(-\alpha) \subseteq \mathcal{H}.$$

For $\alpha > 1$, $\mathcal{R}(-\alpha) \subseteq \mathcal{S}^*$. For $\alpha > 0$, $\mathcal{R}(-\alpha) \subseteq \mathcal{S}$.

We now consider how properties of G induce corresponding properties in its stationary-excess cdf G_e .

Proposition 9. Let G have finite mean.

- (i) If $G \in \mathcal{R}(-\alpha)$ for $\alpha \geq 1$, then $G_e \in \mathcal{R}(-(\alpha - 1))$.
- (ii) If $G \in \mathcal{S}^*$, then $G_e \in \mathcal{S}$.
- (iii) If $G \in \mathcal{L}$, then $G_e \in \mathcal{L}$.
- (iv) If $G \in \mathcal{H}$, then $G_e \in \mathcal{H}$.
- (v) If $G^c \in \mathcal{T}(-\alpha)$ for $\alpha \geq 1$, then $G_e^c \in \mathcal{T}(-(\alpha - 1))$.
- (vi) If $G \in \mathcal{C}_3$, then $G_e \in \mathcal{C}_3$.

Proof. (i) See [18, VIII.9]. The case $\alpha = 1$ follows from the fact that if $L(t)$ is slowly varying and $L(t)/t$ is integrable, then $\int_x^\infty (L(u)/u) du$ is slowly varying.

(ii) See [23].

(iii) Write

$$G_e^c(t-u) = m_1^{-1} \int_t^\infty G^c(v-u) dv$$

and recall that integration preserves tail equivalence; see [16, p. 17].

(iv) Suppose that $G^c(t) \geq H^c(t)$ for all $t \geq 0$ where $H \in \mathcal{L}$. By (iii), $H_e^c \in \mathcal{L}$, but

$$G_e^c(t) = \frac{1}{m_1(G)} \int_t^\infty G^c(u) du \geq \frac{1}{m_1(G)} \int_t^\infty H^c(u) du \geq \frac{m_1(H)}{m_1(G)} H_e^c(t), \tag{5.3}$$

where $m_1(G) \geq m_1(H)$, so that the right side of (5.3) can itself be regarded as a lower bound cdf in \mathcal{L} .

(v) Use part (i) and the proof of (iv).

(vi) See [2, lemma 3.2]. □

For our application to theorems 5 and 6, it is also important to consider how the properties apply to the cdf $G_1^c(t)G_2^c(t)$ associated with the minimum of two independent random variables with cdf's G_1^c and G_2^c . The following is immediate.

Proposition 10. Let G_1^c and G_2^c be two cdf's on $[0, \infty)$ with $G_i^c(t) > 0$ for all $t > 0$ and let $G^c(t) = G_1^c(t)G_2^c(t)$.

(i) If $G_i \in \mathcal{R}(-\alpha_i)$ for $\alpha_i > 0$ and $i = 1, 2$, then $G \in \mathcal{R}(-(\alpha_1 + \alpha_2))$.

(ii) If $G_i^c \in \mathcal{L}$ for $i = 1, 2$, then $G^c \in \mathcal{L}$.

(iii) If $G_i^c \in \mathcal{H}$ for $i = 1, 2$, then $G^c \in \mathcal{H}$.

(iv) If $G_i^c \in \mathcal{T}(-\alpha_i)$ for $\alpha_i \geq 0$ and $i = 1, 2$, then $G^c \in \mathcal{T}(-(\alpha_1 + \alpha_2))$.

We are motivated to introduce the class \mathcal{H} because the standard heavy-tail notions embody regularity properties for asymptotics as well as large tails.

Example. To illustrate, we give an example of a cdf in \mathcal{H} but not in \mathcal{L} . First, the cdf

$$G^c(t) = e^{-\int_1^t z^{-1} dz}, \quad t > 1, \quad (5.4)$$

is in \mathcal{L} . Let

$$\alpha(t) = 2^n, \quad 2^n \leq t < 2^{n+1}$$

for $n \geq 0$. Since $\alpha(t) \leq t$ for all $t > 0$, we have the ordering

$$H^c(t) \equiv G^c(\alpha(t)) \geq G^c(t) \quad \text{for all } t > 0.$$

Hence, the cdf H^c is in \mathcal{H} . However, H^c is not in \mathcal{L} , because

$$\begin{aligned} 1 &= \liminf_{t \rightarrow \infty} \frac{H^c(t-u)}{H^c(t)} < \limsup_{t \rightarrow \infty} \frac{H^c(t-u)}{H^c(t)} = \limsup_{n \rightarrow \infty} e^{+\int_{2^n}^{2^{n+1}} z^{-1} dz} \\ &= \exp(\ln(2^{n+1}) - \ln(2^n)) = 2. \end{aligned} \quad (5.5)$$

Proof of theorem 5. Now we prove theorem 5, using theorem 1. Suppose that $G^c \in \mathcal{H}$. Then there exists $H^c \in \mathcal{L}$ such that $G^c(t) \geq H^c(t)$ for all t . That ordering implies that a steady-state waiting time in the system with service-time cdf H , say $W(H)$, exists and, in addition, by making a sample path comparison, as in [34, theorem 4],

$$P(W(G) > t) \geq P(W(H) > t) \quad \text{for all } t. \quad (5.6)$$

Now, considering the M/GI/ s system with service-time cdf H , we first have $H_e \in \mathcal{L}$ by proposition 9(iii). Then by (2.3) and proposition 10(ii), it follows that $F^c(H) \in \mathcal{L}$ too, for F^c defined in (2.2). (If $G_1^c \in \mathcal{L}$ and $G_1^c \sim G_2^c$, then $G_2^c \in \mathcal{L}$.) Thus, by (2.2), $W^c(H) \in \mathcal{H}$. Finally, by (5.6), $W^c(G) \in \mathcal{H}$, as claimed. \square

Proof of theorem 6. Let H^c be a ccdf in $\mathcal{R}(-\alpha)$ with $G^c(t) \geq H^c(t)$ for all $t > 0$. Just as in the proof of theorem 5, (5.6) holds. By proposition 9(i), $H_e \in \mathcal{R}(-(\alpha - 1))$. Then, by (2.3) and proposition 10(i), $F^c(H) \in \mathcal{R}(-s(\alpha - 1))$ for F^c in (2.2). (If $G_1^c \in \mathcal{R}(-\alpha)$ and $G_1^c \sim G_2^c$, then $G_2^c \in \mathcal{R}(-\alpha)$.) Hence, first, $W^c(H) \in \mathcal{T}(-s(\alpha - 1))$ by (2.2) and, second, $W^c(G) \in \mathcal{T}(-s(\alpha - 1))$ by (5.6). \square

6. Upper bounds

In this section we prove theorem 4. The proof is based on a stochastic comparison between multi-server and single-server queues. Given a GI/GI/ s model, let W_1 be the steady-state waiting time in the associated single-server queue obtained by assigning successive arrivals cyclically to the s servers, i.e., the GI/GI/1 system in which the interarrival-time distribution is the s -fold convolution of the interarrival-time in the original s -server system. Wolff [36] showed that W is bounded above by W_1 in increasing convex stochastic order, i.e.,

$$Ef(W) \leq Ef(W_1) \tag{6.1}$$

for all nondecreasing convex real-valued functions f or, equivalently (see [30, p. 9]),

$$\int_t^\infty P(W > u) du \leq \int_t^\infty P(W_1 > u) du \quad \text{for all } t. \tag{6.2}$$

However, the ordering cannot be extended to ordinary stochastic order, i.e., (6.1) need not hold for all nondecreasing f or, equivalently, we need *not* have

$$P(W > t) \leq P(W_1 > t) \quad \text{for all } t; \tag{6.3}$$

see [33]. Nevertheless, we can apply (6.2) to deduce that

$$\liminf_{t \rightarrow \infty} \frac{P(W > t)}{P(W_1 > t)} \leq 1. \tag{6.4}$$

When G_e is subexponential, we have

$$\lim_{t \rightarrow \infty} \frac{P(W_1 > t)}{G_e^c(t)} = \frac{\rho}{1 - \rho}. \tag{6.5}$$

Hence, we can combine (6.4) and (6.5) to obtain theorem 4.

Scheller-Wolf and Sigman [27] have established conditions for W to have finite moments that also support the conjecture when $s = 2$ and $\rho < 1/2$. They show that (i) $EW < \infty$ if $EV^{3/2} < \infty$ and (ii) $EW^2 < \infty$ if $EV^2 < \infty$. We can apply

Chebychev's inequality to convert finite moments into tail-probability upper bounds; i.e., if $EW^r < \infty$, then

$$P(W > t) \leq \frac{EW^r}{t^r}. \quad (6.6)$$

To illustrate, suppose that $s = 2$ and $G^c(t) \sim At^{-(\varepsilon+3/2)}$ for small positive ε . The infinite-server lower bound yields

$$W^c(t) \geq F^c(t) \sim A_1 G_\varepsilon^c(t)^2 \sim A_2 t^{-(1+2\varepsilon)}, \quad (6.7)$$

while $EV^{3/2} < \infty$, so that $EW < \infty$ by Scheller-Wolf and Sigman [27], and

$$P(W > t) \leq \frac{EW}{t}. \quad (6.8)$$

Inequalities (6.7) and (6.8) show that the exponents in the two power-tail bounding cdfs differ by only 2ε , where ε was arbitrary.

7. Moments

Bounds on the waiting-time tail probabilities allow us to determine whether moments are finite or not. For this purpose, recall that a nonnegative random variable V with cdf G satisfies $EV^r < \infty$ if and only if $t^{r-1}G^c(t)$ is integrable over $(0, \infty)$; see [18, p. 151].

First notice that our minimal-stability lower bound in theorem 3 allows us to deduce that $EW^r = \infty$ whenever $EV^{r+1} = \infty$ and $k = 1$ in (2.17), which is one side of an equivalence established by Scheller-Wolf and Sigman [27].

Next we assume that the service-time cdf G^c has a power tail, i.e., (2.15) holds. Then $EV^r = \infty$ for $r > 0$ if and only if $\alpha \leq r$, where α is the exponent of the power tail. Hence we can apply the infinite-server lower bound theorem 1 to deduce the following.

Theorem 11. Suppose that the service-time cdf G^c has a power tail as in (2.15).

- (i) If $EV^r = \infty$ for $r > 0$, then $EW^{s(r-1)} = \infty$.
- (ii) When $s = 2$, $EV^{3/2} < \infty$ if and only if $EW < \infty$.
- (iii) When $s = 2$, $EV^2 < \infty$ if and only if $EW^2 < \infty$.

Proof. (i) Since G^c has a power tail with exponent α , G_ε^c and the cdf H_2^c in (2.10), which is a lower bound for $W^c(t)$, have power tails with exponents $\alpha - 1$ and $s(\alpha - 1)$, respectively. If $EV^r = \infty$, then the exponent α of the power tail of G^c must satisfy $\alpha \leq r$. Since $\alpha \leq r$, $s(\alpha - 1) \leq s(r - 1)$, so that we must have $EW^{s(r-1)} = \infty$.

(ii) and (iii) Apply part (i) together with upper bounds of [27, proposition 4.1]. \square

We now point out that our infinite-server lower bound does *not* support part (i) of theorem 11 in general, i.e., without the power-tail condition. Suppose that the service-time cdf satisfies

$$G^c(t) \sim \frac{A}{t^\alpha(\log t)^\beta} \quad \text{as } t \rightarrow \infty, \tag{7.1}$$

so that $EV^\alpha < \infty$ if and only if $\beta > 1$. Let $\beta = 3/4$, so that $EV^\alpha = \infty$. It is easy to see that

$$G_e^c(t) \sim \frac{A'}{t^{\alpha-1}(\log t)^\beta} \quad \text{as } t \rightarrow \infty, \tag{7.2}$$

so that

$$H_1^c(t) \sim \frac{A''}{t^{s(\alpha-1)}(\log t)^{s\beta}} \quad \text{as } t \rightarrow \infty \tag{7.3}$$

for H_1^c in (2.6), which implies that

$$\int_0^\infty t^{s(\alpha-1)} dH_1(t) < \infty \quad \text{for all } s \geq 2, \tag{7.4}$$

making it impossible to deduce that $EW^{s(\alpha-1)} = \infty$. We conjecture that $EW^{s(\alpha-1)} < \infty$ in this example, but that is yet to be proved because H_1 in (7.4) is only a lower bound.

8. The transient waiting-time distribution

An infinite-server lower bound also applies with time-dependent non-Poisson arrival processes. As a special case, it applies to the transient distribution in the M/GI/s model.

Of course the transient waiting-time distribution depends on the initial conditions. To have a relatively simple description, we assume that the M/G/s system starts off empty at time 0. We are then interested in the time-dependent waiting-time cdf. Let $W(t)$ be the waiting time before beginning service for a customer arriving at time t . (Since the arrival process is Poisson, the distribution is unaffected by the presence of an arrival at time t ; i.e., the virtual and actual waiting-time distributions coincide.) Let $W^c(u; t) \equiv P(W(t) > u)$ be the transient cdf at time t . Then, paralleling (2.2), we have

$$W^c(u; t) \geq F^c(u; t) \quad \text{for all } u > 0, \tag{8.1}$$

where $F^c(\cdot; t)$ is the cdf of the first passage time to $s - 1$ or fewer busy servers in the infinite-server model, starting off with the transient M/G/ ∞ distribution at time t and neglecting all subsequent arrivals. As a consequence, we have the following result.

Theorem 12. In the M/G/s model starting out empty at time 0, for all positive λ , u and t ,

$$W^c(u; t) \geq F^c(u; t) = \Pi(s-1; \lambda m_1 [G_e^c(u) - G_e^c(t+u)]), \quad (8.2)$$

where

$$F^c(u; t) \sim \frac{(\lambda m_1)^s}{s!} [G_e^c(u) - G_e^c(t+u)]^s \quad \text{as } u \rightarrow \infty. \quad (8.3)$$

Proof. The number $N(t)$ of customers in the M/G/ ∞ model at time t has a Poisson distribution with mean

$$EN(t) = \lambda m_1 G_e(t), \quad (8.4)$$

where λ is the arrival rate, m_1 is the mean service time and G_e is the service-time stationary-excess cdf in (2.1); see [15, (20), p. 740]. Moreover, the number of customers arriving in $[0, t]$ that are still present at time u has a Poisson distribution with mean

$$EN(t, u) = \lambda \int_0^t G^c(u+s) ds = \lambda \int_u^{u+t} G^c(s) ds = \lambda m_1 [G_e^c(u) - G_e^c(t+u)] \quad (8.5)$$

by the Poisson-random measure argument in the proof of Eick et al. [15, theorem 1]. \square

From theorem 12, we can see the approach to steady state as $t \rightarrow \infty$. From (8.4) we see that $EN(t)$ approaches the steady-state mean $EN(\infty) = \lambda m_1$. Moreover, we obtain an explicit expression for the rate of convergence:

$$\frac{EN(\infty) - EN(t)}{EN(\infty)} = G_e^c(t), \quad t > 0. \quad (8.6)$$

So, for heavy-tailed cdfs G^c , the convergence of $EN(t)$ to $EN(\infty)$ is relatively slow.

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