APPENDIX
to
SET-VALUED PERFORMANCE APPROXIMATIONS FOR THE $GI/GI/K$ QUEUE GIVEN PARTIAL INFORMATION

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Abstract

(from the main paper) In order to understand queueing performance given only partial information about the model, we propose determining intervals of likely values of performance measures given that limited information. We illustrate this approach for the mean steady-state waiting time in the $GI/GI/K$ queue. We start by specifying the first two moments of the interarrival-time and service-time distributions, and then consider additional information about these underlying distributions, including support bounds, higher moments and Laplace transform values. As a theoretical basis, we apply extremal models yielding tight upper and lower bounds on the asymptotic decay rate of the steady-state waiting-time tail probability. We illustrate by constructing the theoretically justified intervals of values for the decay rate and the associated heuristically determined interval of values for the mean waiting times. Without extra information, the extremal models involve two-point distributions, which yield a wide range for the mean. Adding constraints on the third moment and a transform value produces three-point extremal distributions, which significantly reduce the range, yielding practical levels of accuracy.

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1 Overview of this Appendix

This appendix provides additional material expanding upon the main paper. It is divided into two parts. First, in §§2-5 we focus on the classic bounds based on the first two moments of the underlying cdf F of an interarrival time U and the cdf G of a service tims V, as in

$$(\mathbb{E}[U], \mathbb{E}[U^2], \mathbb{E}[V], \mathbb{E}[V^2]) \equiv (1, c_a^2, \rho, c_s^2) \tag{1.1}$$

taken from (1.4) of the main paper. In these sections we consider the impact of the support bounds, but not yet the Laplace transform values, which play a prominent role in our main method for generating intervals of likely values for the mean in §4 of the main paper.

In §2 we discuss the wide range of possible values of the mean $E[W]$ given only the the first two moments of F and G, without yet introducing the finite support bounds M_a for F and M_s for G. Then in §3 we elaborate on §4.1 of the main paper on how to choose the support bounds. In §4 we supplement Table 1 of the main paper by presenting additional tables studying the direct application of Theorem 3.1 of the paper, which gives bounds based on adding only support bounds to the parameters in (1.1). In §5 we relate the support bound constraints to extra third-moment constraints. In particular, we show that for appropriate choices, there is an explicit one-to-one correspondence between the third moment and the support bound. Consequently, provided that we decide to use a support bound, we can specify either the third moment or the support bound, and the other will be determined. However, our approach in this paper is to introduce support bounds that should have only negligible impact on the mean waiting time. Thus, it should not be surprising that support bounds associated with natural third moments tend to take smaller values.

In §§6-7 we present additional results related to the Laplace transform constraints in Theorem 3.2 of the main paper, which forms the basis of our main approach for generating intervals of likely values of the mean $E[W]$, as summarized in §6.1 of the main paper. In §6 we expand the study in §4.3 of the main paper, complementing Table 3 of the main paper. In §7 we present additional tables for the $M/M/1$ and $M/M/2$ model complementing Tables 4 and 7 of the main paper.

2 A Wide Range for $\mathbb{E}[W]$ Given the First Two moments

The standard way to evaluate approximations such as the heavy-traffic approximation (HTA)

$$\mathbb{E}[W] \approx \frac{\rho^2(c_a^2 + c_s^2)}{2(1-\rho)}. \tag{2.1}$$

taken from (1.2) of the main paper is to compare it to simulation estimates for specific cases. Using simulation is of course excellent if we have a specific model we want to analyze. An alternative approach to obtain a broader understanding is to look at the set of all possible values, given the partial specification by the parameter 4-tuple in (1.1) when this can be done.

A principle conclusion of this line of work is that the range of possible values for $\mathbb{E}[W]$ given the partial information in (1.1) is remarkably wide. We now illustrate by providing simple approximation formulas for the absolute and relative errors, obtained by viewing the established bounds in a revealing way. In particular, it is helpful to look at the accuracy of the upper bound (UB) separately from the lower bound (LB), and it is helpful to use the simple HTA in (2.1) as a reference.

The most familiar UB on $E[W]$ is the Kingman (1962) [8] bound,

$$E[W] \le \frac{\rho^2([c_a^2/\rho^2] + c_s^2)}{2(1-\rho)}, \tag{2.2}$$

which is known to be asymptotically correct in heavy traffic (as $\rho \to 1$). As an approximation for the UB, we use the improved (but still non-tight) Daley (1977) [4] UB

$$\mathbb{E}[W] \le \frac{\rho^2([(2-\rho)c_a^2/\rho] + c_s^2)}{2(1-\rho)}. \tag{2.3}$$

We could compute the conjectured exact tight UB using [2], but we want to produce a simple formula. We use the tight LB

$$\mathbb{E}[W(LB)] = \frac{\rho((1+c_s^2)\rho - 1)^+}{2(1-\rho)}. \tag{2.4}$$

The LB has long been known, see [12], §5.4 of [11], §V of [14], [10], Theorem 3.1 of [5] and references there. It is significant that the LB is often 0 for smaller values of ρ; indeed it occurs whenever we can have $P(V - U \le 0) = 1$, which cannot be effectively prevented by moment constraints alone. The main paper shows that a third moment and the transform constraints address this shortcoming.

Let the absolute upper error (AUE) and the relative upper error (RUE) of the heavy-traffic approximation (2.1) (HTA) be defined by the formulas

$$AUE \equiv UB - HTA \quad \text{and} \quad RUE \equiv \frac{UB - HTA}{HTA}. \tag{2.5}$$

Similarly, let the absolute lower error (ALE) and the relative lower error (RLE) of the heavy-traffic approximation (2.1) be defined by the formulas

$$ALE \equiv HTA - LB \quad \text{and} \quad RUE \equiv \frac{HTA - LB}{HTA}. \tag{2.6}$$

We subtract the smaller from the larger in each case, so that these measures of the possible errors are always positive. We use the HTA in the denominator because it produces more revealing simple formulas. (If we divided by the bound, then the RUE would decrease, but the RLE would increase.)

When ρ and $\mathbb{E}[W]$ are not too small, it seems natural to focus on the relative error; otherwise it may be better to focus on the absolute error.

Proposition 2.1 (*upper and lower errors for the mean*) *Suppose that we use the non-tight UB for the mean $E[W]$ in (2.3) and the tight LB in (2.4). For the LB, assume that $\rho > 1/(1+c_s^2)$; otherwise it must be 0. Then the upper and lower errors given the parameter four-tuple $(1, c_a^2, \rho, c_s^2)$ can be expressed as*

$$\begin{aligned}
AUE &= \rho c_a^2, \\
RUE &= \left(\frac{2(1-\rho)}{\rho}\right)\left(\frac{c_a^2}{c_a^2+c_s^2}\right) \quad or \quad \frac{1-\rho}{\rho} \quad if \quad c_a^2 = c_s^2, \\
ALE &= \left(\frac{\rho^2}{2(1-\rho)}\right)\left(c_a^2 + \frac{1-\rho}{\rho}\right) = \left(\frac{\rho^2 c_a^2}{2(1-\rho)}\right) + \frac{\rho}{2} \quad and \\
RLE &= \frac{c_a^2 + 1 - \rho}{c_a^2 + c_s^2} \quad or \quad \frac{1}{2} + \frac{1-\rho}{c_a^2} \quad if \quad c_a^2 = c_s^2.
\end{aligned} \tag{2.7}$$

Corollary 2.1 (*monotonicity as functions of the parameters*) *The relative errors RUE and RLE in (2.7) are decreasing in ρ and c_s^2 but are increasing in c_a^2.*

Corollary 2.2 (*heavy traffic and light traffic*) *The upper errors are asympotically effective in the sense that $RUE(\rho) \to 0$ as $\rho \uparrow 1$, while $AUE(\rho) \to 0$ as $\rho \downarrow 0$. In contrast, $RLE(\rho) \to c_a^2/(c_a^2 + c_s^2)$ as $\rho \uparrow 1$.*

As in Corollary 1 of [14] for the $GI/M/1$ model, which shows that the overall relative error $(UB-LB)/LB$ for the mean queue length in the $GI/M/1$ model is c_a^2, Proposition 2.1 and Corollary 2.2 dramatically show the wide range of possible values. This suggests imposing further constraints on these distributions to concentrate on realistic "typical" cases, as was done in [9] and [15] for the $GI/M/1$ model. This program was extended to phase-type distributions by [6, 7]. The main paper carries out the same program for the more general $GI/GI/1$ and $GI/GI/K$ models in a new way (by initially focusing on the asymptotic decay rate).

Now we present numerical examples, drawing on the algorithms in [2]. We include the conjectured tight upper bound and the associated upper bound formula

$$E[W] \le \frac{[2(1-\rho)\rho/(1-\delta)]c_a^2 + \rho^2 c_s^2}{2(1-\rho)}, \tag{2.8}$$

where $\delta \in (0,1)$ solves the equation

$$\delta = \exp(-(1-\delta))/\rho)). \tag{2.9}$$

from Theorem 3.2 of [2]. In the following tables we show the values of both (2.8) and the associated value of δ. We also show the maximum relative error (MRE) of (2.8) compared to the conjectured tight UB.

Table 1: A comparison of the unscaled bounds and approximations for the steady-state mean $E[W]$ as a function of ρ for the case $c_a^2 = 4.0$ and $c_s^2 = 4.0$

ρ	Tight LB (2.4)	HTA (2.1)	Tight UB [2]	UB Approx (2.8)	δ (2.9)	MRE	Daley (2.3)	Kingman (2.2)
0.10	0.000	0.044	0.422	0.422	0.000	0.00%	0.444	2.244
0.15	0.000	0.106	0.653	0.654	0.001	0.05%	0.706	2.406
0.20	0.000	0.200	0.904	0.906	0.007	0.19%	1.000	2.600
0.25	0.042	0.333	1.182	1.187	0.020	0.40%	1.333	2.833
0.30	0.107	0.514	1.499	1.508	0.041	0.60%	1.714	3.114
0.35	0.202	0.754	1.868	1.883	0.070	0.79%	2.154	3.454
0.40	0.333	1.067	2.304	2.326	0.107	0.94%	2.667	3.867
0.45	0.511	1.473	2.829	2.859	0.152	1.06%	3.273	4.373
0.50	0.750	2.000	3.470	3.510	0.203	1.15%	4.000	5.000
0.55	1.069	2.689	4.272	4.321	0.261	1.13%	4.889	5.789
0.60	1.500	3.600	5.295	5.352	0.324	1.07%	6.000	6.800
0.65	2.089	4.829	6.632	6.698	0.393	1.00%	7.429	8.129
0.70	2.917	6.533	8.441	8.520	0.467	0.93%	9.333	9.933
0.75	4.125	9.000	11.014	11.102	0.546	0.80%	12.000	12.500
0.80	6.000	12.800	14.917	15.017	0.629	0.67%	16.000	16.400
0.85	9.208	19.267	21.484	21.597	0.716	0.53%	22.667	22.967
0.90	15.750	32.400	34.721	34.843	0.807	0.35%	36.000	36.200
0.95	35.625	72.200	74.621	74.755	0.902	0.18%	76.000	76.100
0.98	95.550	192.080	194.557	194.702	0.960	0.07%	196.000	196.040
0.99	195.525	392.040	394.533	394.684	0.980	0.04%	396.000	396.020

Table 2: A comparison of the unscaled bounds and approximations for the steady-state mean $E[W]$ as a function of ρ for the case $c_a^2 = 4.0$ and $c_s^2 = 0.5$

ρ	Tight LB (2.4)	HTA (2.1)	Tight UB [2]	UB Approx (2.8)	δ (2.9)	MRE	Daley (2.3)	Kingman (2.2)
0.10	0.000	0.025	0.403	0.403	0.000	0.00%	0.425	2.225
0.15	0.000	0.060	0.607	0.607	0.001	0.05%	0.660	2.360
0.20	0.000	0.113	0.816	0.818	0.007	0.21%	0.913	2.513
0.25	0.000	0.188	1.036	1.041	0.020	0.45%	1.188	2.688
0.30	0.000	0.289	1.274	1.283	0.041	0.71%	1.489	2.889
0.35	0.000	0.424	1.538	1.553	0.070	0.96%	1.824	3.124
0.40	0.000	0.600	1.837	1.859	0.107	1.16%	2.200	3.400
0.45	0.000	0.828	2.184	2.214	0.152	1.35%	2.628	3.728
0.50	0.000	1.125	2.595	2.635	0.203	1.51%	3.125	4.125
0.55	0.000	1.513	3.096	3.144	0.261	1.53%	3.713	4.613
0.60	0.000	2.025	3.720	3.777	0.324	1.50%	4.425	5.225
0.65	0.000	2.716	4.519	4.586	0.393	1.45%	5.316	6.016
0.70	0.058	3.675	5.583	5.662	0.467	1.39%	6.475	7.075
0.75	0.188	5.063	7.077	7.165	0.546	1.23%	8.063	8.563
0.80	0.400	7.200	9.317	9.417	0.629	1.06%	10.400	10.800
0.85	0.779	10.838	13.055	13.168	0.716	0.86%	14.238	14.538
0.90	1.575	18.225	20.546	20.668	0.807	0.59%	21.825	22.025
0.95	4.037	40.613	43.033	43.168	0.902	0.31%	44.413	44.513
0.98	11.515	108.045	110.479	110.667	0.960	0.17%	111.965	112.005
0.99	24.008	220.523	222.971	223.167	0.980	0.09%	224.483	224.503

Table 3: A comparison of the unscaled bounds and approximations for the steady-state mean $E[W]$ as a function of ρ for the case $c_a^2 = 0.5$ and $c_s^2 = 4.0$

ρ	Tight LB (2.4)	HTA (2.1)	Tight UB [2]	UB Approx (2.8)	δ (2.9)	MRE	Daley (2.3)	Kingman (2.2)
0.10	0.000	0.025	0.072	0.072	0.000	0.00%	0.075	0.300
0.15	0.000	0.060	0.128	0.128	0.001	0.07%	0.135	0.347
0.20	0.000	0.113	0.200	0.201	0.007	0.30%	0.213	0.413
0.25	0.042	0.188	0.292	0.294	0.020	0.68%	0.313	0.500
0.30	0.107	0.289	0.409	0.414	0.041	1.08%	0.439	0.614
0.35	0.202	0.424	0.558	0.565	0.070	1.32%	0.599	0.762
0.40	0.333	0.600	0.746	0.757	0.107	1.47%	0.800	0.950
0.45	0.511	0.828	0.986	1.002	0.152	1.58%	1.053	1.191
0.50	0.750	1.125	1.289	1.314	0.203	1.91%	1.375	1.500
0.55	1.069	1.513	1.692	1.716	0.261	1.45%	1.788	1.900
0.60	1.500	2.025	2.212	2.244	0.324	1.40%	2.325	2.425
0.65	2.089	2.716	2.913	2.950	0.393	1.26%	3.041	3.129
0.70	2.917	3.675	3.875	3.923	0.467	1.23%	4.025	4.100
0.75	4.125	5.063	5.250	5.325	0.546	1.41%	5.438	5.500
0.80	6.000	7.200	7.422	7.477	0.629	0.74%	7.600	7.650
0.85	9.208	10.838	11.075	11.129	0.716	0.48%	11.263	11.300
0.90	15.750	18.225	18.470	18.530	0.807	0.32%	18.675	18.700
0.95	35.625	40.613	40.871	40.932	0.902	0.15%	41.088	41.100
0.98	95.550	108.045	108.307	108.373	0.960	0.06%	108.535	108.540
0.99	195.525	220.523	220.783	220.853	0.980	0.03%	221.018	221.020

Table 4: A comparison of the unscaled bounds and approximations for the steady-state mean $E[W]$ as a function of ρ for the case $c_a^2 = 0.5$ and $c_s^2 = 0.5$

ρ	Tight LB (2.4)	HTA (2.1)	Tight UB [2]	UB Approx (2.8)	δ (2.9)	MRE	Daley (2.3)	Kingman (2.2)
0.10	0.000	0.006	0.053	0.053	0.000	0.00%	0.056	0.281
0.15	0.000	0.013	0.082	0.082	0.001	0.11%	0.088	0.301
0.20	0.000	0.025	0.113	0.113	0.007	0.54%	0.125	0.325
0.25	0.000	0.042	0.146	0.148	0.020	1.35%	0.167	0.354
0.30	0.000	0.064	0.184	0.189	0.041	2.36%	0.214	0.389
0.35	0.000	0.094	0.228	0.235	0.070	3.16%	0.269	0.432
0.40	0.000	0.133	0.280	0.291	0.107	3.82%	0.333	0.483
0.45	0.000	0.184	0.342	0.357	0.152	4.43%	0.409	0.547
0.50	0.000	0.250	0.414	0.439	0.203	5.72%	0.500	0.625
0.55	0.000	0.336	0.515	0.540	0.261	4.62%	0.611	0.724
0.60	0.000	0.450	0.637	0.669	0.324	4.71%	0.750	0.850
0.65	0.000	0.604	0.800	0.837	0.393	4.45%	0.929	1.016
0.70	0.058	0.817	1.017	1.065	0.467	4.53%	1.167	1.242
0.75	0.188	1.125	1.312	1.388	0.546	5.42%	1.500	1.563
0.80	0.400	1.600	1.822	1.877	0.629	2.95%	2.000	2.050
0.85	0.779	2.408	2.646	2.700	0.716	1.99%	2.833	2.871
0.90	1.575	4.050	4.295	4.355	0.807	1.38%	4.500	4.525
0.95	4.037	9.025	9.284	9.344	0.902	0.65%	9.500	9.512
0.98	11.515	24.010	24.271	24.338	0.960	0.27%	24.500	24.505
0.99	24.008	49.005	49.265	49.336	0.980	0.14%	49.500	49.503

3 Elaboration on Specifying Appropriate Support Bounds

In this section we elaborate on §3.1 of the main paper, expanding upon the discussion there. As we wrote there, most applications of the $GI/GI/1$ queueing model do not have interarrival-times and service-time distributions with finite support. We introduce the support bounds M_a and M_s as a device to help expose the typical range of possible values of the simple approximations for decay rate θ_W in equations (1.5), (3.1) and (3.2) of the main paper.. We propose using values of M_a and M_s that should have negligible impact on the mean waiting time in typical cases of interest, so that the bounds with M_a and M_s give a good indication of the likely set of possible values given the partial information. (§II.5.9 of [3] provides theoretical support for this step.) Assumption 3.1 of the main paper about the critical singularity s^* of the moment generating function $\hat{g}(-s)$ is critical. We show how to construct support bounds that are typical as well ones that are conservative.

3.1 Starting from a Model or Data

Starting from a specific model with unbounded U and V, we suggest choosing the support bounds M_a and M_s so that

$$P(U > M_a\mathbb{E}[U]) = P(U > M_a) = P(V > M_s\mathbb{E}[V]) = P(V > \rho M_s) = \epsilon \tag{3.1}$$

for a suitably small ϵ such as 0.001. We might take $\epsilon = 0.0001$ to be more conservative or $\epsilon = 0.01$ to narrow the range (but losing confidence in the reliability). With ample data, we would estimate the corresponding empirical complementary cdf (ccdf) of the service time, and use the same criterion in (3.1).

Example 3.1 (*the $M/M/1$ case*) As a helpful orientation, we first consider the $M/M/1$ queue with arrival rate $\lambda = 1$ and mean service time $\rho < 1$. Notice that the service-time complementary cdf (ccdf) is

$$P(V > x) = e^{-x/\rho}, \quad x \geq 0, \tag{3.2}$$

so that its decay rate $\theta_V \equiv \lim_{x\to\infty} \{-\log(P(V > x))/x\}$ is independent of x, i.e.,

$$\theta_V = -\log(P(V > x))/x = 1/\rho \quad \text{for all} \quad x. \tag{3.3}$$

while the associated waiting time ccdf is

$$P(W > x) = \rho e^{-(1-\rho)x/\rho}, \quad x \geq 0, \tag{3.4}$$

so that its decay rate is

$$\theta_W \equiv \lim_{x\to\infty} -\log(P(W > x)/x = (1-\rho)/\rho. \tag{3.5}$$

Hence, for the $M/M/1$ model we see that $\theta_W/\theta_V = 1 - \rho < 1$ which quantifies the well-known property that large waiting times ar more likely than large service times, becoming ever more so as the traffic intensity approaches 1.

Moreover, in the present light-tail case, provided that ρ is not too small, large waiting times are likely to be the result of several service times associated with a cluster of arrivals rather than one especially large service time.

For the $M/M/1$ model where U and V have exponential distributions, the target in (3.1) becomes $e^{-M} = \epsilon$. For $M_a = M_s = M = (4, 5, 6, 7, 8, 9, 10)$, the corresponding values are $\epsilon(M) = (0.0183, 0.0067, 0.0025, 0.0091, 0.0033, 0.00123, 0.00045)$. We use 7 and 9 in our experiments later.

Based on this analysis, we conduct a simulation comparison to show how the support bounds affect the decay rate θ_W of the extremal queues for the case $\rho = 0.7$ and $c_a^2 = c_s^2 = 1$ in Table 5. We implement Monte-Carlo Simulation with $N = 10^8$ and $R = 20$ to simulate the tail probability with different quantities and report 95% confidence interval length (CIL).

Table 5 shows that there is rapid convergence of $-\log(P(W > x))/x$ to the decay rate θ_W as x increases; it is not necessary to make x extraordinarily large. Notice that the estimated decay rate

Table 5: Simulation comparison of the waiting time ccdf and delay rate θ_W for two-point extremal models with $M_a = \{1 + c_a^2, 5, 10\}$ and $M_s = \{1 + c_s^2, 5, 10\}$ under $c_a^2 = c_s^2 = 1, \rho = 0.7$

$M_a = 2, M_s = 10$	$x = 10$	CIL	$x = 12$	CIL	$x = 14$	CIL	$x = 16$	CIL	$x = 18$	CIL
$P(W > x)$	2.90E-02	3.65E-05	3.54E-01	3.63E-05	8.85E-03	2.82E-05	4.83E-03	1.49E-05	2.64E-03	1.16E-05
$-\log(P(W > x))/x$	3.54E-01		3.44E-01		3.38E-01		3.33E-01		3.30E-01	
$M_a = 2, M_s = 5$	$x = 10$	CIL	$x = 12$	CIL	$x = 14$	CIL	$x = 16$	CIL	$x = 18$	CIL
$P(W > x)$	1.94E-02	3.02E-05	9.42E-03	3.04E-05	4.56E-03	1.54E-05	2.21E-03	1.20E-05	1.07E-03	8.66E-06
$-\log(P(W > x))/x$	3.94E-01		3.89E-01		3.85E-01		3.82E-01		3.80E-01	
$M_a = 2, M_s = 2$	$x = 10$	CIL	$x = 12$	CIL	$x = 14$	CIL	$x = 16$	CIL	$x = 20$	CIL
$P(W > x)$	1.31E-02	2.68E-05	5.77E-03	2.81E-05	2.51E-03	1.55E-05	1.08E-03	7.94E-06	4.58E-04	5.21E-06
$-\log(P(W > x))/x$	4.33E-01		4.30E-01		4.28E-01		4.27E-01		4.27E-01	
$M_a = 5, M_s = 2$	$x = 4$	CIL	$x = 5$	CIL	$x = 6$	CIL	$x = 7$	CIL	$x = 8$	CIL
$P(W > x)$	7.50E-02	4.46E-05	4.12E-02	3.00E-05	2.32E-02	2.20E-05	1.27E-02	1.67E-05	6.97E-03	1.47E-05
$-\log(P(W > x))/x$	6.48E-01		6.38E-01		6.28E-01		6.24E-01		6.21E-01	
$M_a = 10, M_s = 2$	$x = 4$	CIL	$x = 5$	CIL	$x = 6$	CIL	$x = 7$	CIL	$x = 8$	CIL
$P(W > x)$	2.39E-02	2.13E-05	9.98E-03	2.35E-05	4.24E-03	9.87E-06	1.73E-03	6.92E-06	7.08E-04	5.77E-06
$-\log(P(W > x))/x$	9.33E-01		9.21E-01		9.11E-01		9.08E-01		9.07E-01	

is monotone in Table 5, with the $M/M/1$ exact value $(1-\rho)/\rho = 0.3/0.7 = 0.4285$ bounded below and above by the values for $(M_a, M_s) = (2, 5)$ and $(5, 2)$ taken from the last column of Table 5.

4 Direct Application of Theorem 3.1 to the Mean $\mathbb{E}[W]$

We now elaborate on §4.1 of the main paper by providing additional results about how the extremal UB model $F_0/G_u/1$ and LB model $F_u/G_0/1$ for the decay rate from Theorem 3.1 of the main paper apply to the mean $\mathbb{E}[W]$ with $K = 1$ when we introduce the support bounds M_a and ρM_s following the prescription in §4.1 of the main paper.

This issue relates strongly to [1, 2], which studied the extremal models for $E[W]$. For the mean, there is strong evidence (but not yet a mathematical proof) that the model $F_0/G_u/1$ directly yields the UB for the mean, for both bounded and unbounded support, just as it does for the decay rate. However, the situation is different for the LB, as discussed in §2.4.1 of [2]. For unbounded support, the tight LB is given here in (2.4). It is attained by the $D/A_3/1$ model, where A_3 denotes a three-point distribution, which has all mass on multiples of the deterministic interarrival time. The D interarrival time violates the moment condition, but nevertheless is attained asymptotically. We have found that the $F_u/A_3(u)/1$ model attains the LB, where $A_3(u)$ is a natural analog of A_3

4.1 Elaborating on Table 1 of the Main Paper

Table 1 of the main paper shows how the support bounds reduce the range of the possible values of $\mathbb{E}[W]$. It reports results for the cases $(c_a, c_s^2) = (1.0, 1.0)$, $(4.0, 4.0)$, $(0.5, 0.5)$, $(4.0, 0.5)$, $(0.5, 4.0)$.

We now supplement Table 1 of the main paper by showing the UB and LB for the mean $\mathbb{E}[W]$ with the support bounds chosen to satisfy (3.1) with targets $\epsilon = 0.001$ and 0.0001 for all four cases of $c_a^2, c_s^2 \in \{0.5, 4.0\}$ for 10 values of ρ.

Table 6: Evaluation of $\mathbb{E}[W]$ for $F_u/G_0/1$ and $F_0/G_u/1$ with (M_a, M_s) for $c_a^2 = c_s^2 = 4$

ρ	Tight LB	$M_a = 39.9$	$M_a = 31.1$	HTA	$M_s = 31.1$	$M_s = 39.3$	Tight UB
0.10	0.000	0.000	0.000	0.044	0.401	0.402	0.422
0.20	0.000	0.026	0.033	0.200	0.867	0.873	0.904
0.30	0.107	0.172	0.186	0.514	1.453	1.463	1.499
0.40	0.333	0.458	0.498	1.067	2.254	2.265	2.304
0.50	0.750	1.013	1.097	2.000	3.419	3.430	3.470
0.60	1.500	2.079	2.282	3.600	5.239	5.251	5.295
0.70	2.917	4.303	4.748	6.533	8.384	8.394	8.441
0.80	6.000	9.829	10.697	12.800	14.856	14.865	14.917
0.90	15.750	28.924	30.239	32.400	34.658	34.671	34.721
0.95	35.625	68.695	70.106	72.200	74.553	74.568	74.621

Table 7: Evaluation of $\mathbb{E}[W]$ for $F_u/G_0/1$ and $F_0/G_u/1$ with (M_a, M_s) for $c_a^2 = c_s^2 = 0.5$

ρ	Tight LB	$M_a = 4.5$	$M_a = 3.5$	HTA	$M_s = 3.5$	$M_s = 3.5$	Tight UB
0.10	0.000	0.000	0.000	0.006	0.050	0.050	0.053
0.20	0.000	0.000	0.000	0.025	0.101	0.101	0.113
0.30	0.000	0.000	0.000	0.064	0.159	0.163	0.184
0.40	0.000	0.000	0.000	0.133	0.243	0.255	0.280
0.50	0.000	0.000	0.000	0.250	0.377	0.388	0.414
0.60	0.000	0.076	0.164	0.450	0.588	0.601	0.637
0.70	0.058	0.410	0.530	0.817	0.966	0.982	1.017
0.80	0.400	1.167	1.311	1.600	1.760	1.774	1.822
0.90	1.575	3.613	3.771	4.050	4.207	4.229	4.295
0.95	4.037	8.596	8.735	9.025	9.185	9.220	9.284

Table 8: Evaluation of $\mathbb{E}[W]$ for $F_u/G_0/1$ and $F_0/G_u/1$ with (M_a, M_s) for $c_a^2 = 4, c_s^2 = 0.5$

ρ	Tight LB	$M_a = 39.9$	$M_a = 31.1$	HTA	$M_s = 3.5$	$M_s = 4.5$	Tight UB
0.10	0.000	0.000	0.000	0.025	0.400	0.400	0.403
0.20	0.000	0.000	0.000	0.113	0.805	0.806	0.816
0.30	0.000	0.000	0.000	0.289	1.253	1.254	1.274
0.40	0.000	0.000	0.000	0.600	1.806	1.808	1.837
0.50	0.000	0.000	0.000	1.125	2.556	2.559	2.595
0.60	0.000	0.005	0.065	2.025	3.669	3.675	3.720
0.70	0.058	0.342	0.450	3.675	5.524	5.533	5.583
0.80	0.400	1.268	1.798	7.200	9.250	9.261	9.317
0.90	1.575	9.075	11.988	18.225	20.469	20.486	20.546
0.95	4.037	32.083	34.934	40.613	42.955	42.970	43.033

Table 9: Evaluation of $\mathbb{E}[W]$ for $F_u/G_0/1$ and $F_0/G_u/1$ with (M_a, M_s) for $c_a^2 = 0.5, c_s^2 = 4.0$

ρ	Tight LB	$M_a = 4.5$	$M_a = 3.5$	HTA	$M_s = 31.1$	$M_s = 39.9$	Tight UB
0.10	0.000	0.000	0.000	0.025	0.064	0.065	0.072
0.20	0.000	0.034	0.046	0.113	0.184	0.188	0.200
0.30	0.107	0.179	0.192	0.289	0.388	0.393	0.409
0.40	0.333	0.462	0.487	0.600	0.720	0.726	0.746
0.50	0.750	0.957	0.988	1.125	1.263	1.270	1.289
0.60	1.500	1.841	1.869	2.025	2.176	2.186	2.212
0.70	2.917	3.464	3.494	3.675	3.841	3.851	3.875
0.80	6.000	6.973	6.985	7.200	7.374	7.379	7.422
0.90	15.750	17.973	17.993	18.225	18.408	18.427	18.470
0.95	35.625	40.183	40.322	40.613	40.811	40.826	40.871

Table 1 of the main paper and Tables 6-9 above show that the support bounds reduce the range of possible value in all cases. The tables also show that the cases differ dramatically. Just as in Corollaries 2.1 and 2.2, we see that the relative errors are remarkably small for $(c_a^2, c_s^2) = (0.5, 4.0)$, but remarkably large for $(c_a^2, c_s^2) = (4.0, 0.5)$, even with the support bounds.

5 Relating Third Moments to Support Bounds

So far, we have obtained a reduced range of possible values of $\mathbb{E}[W]$, by introducing the support bounds M_a and ρM_s in addition to the model parameters $(1, c_a^2, \rho, c_s^2)$. We can then apply Theorem 3.1 of the main paper. In §3 we chose M_a and M_s so that the approximate tail probability was suitably small, as in (3.1). To cover typical distributions, we used the approximate tail probabilities based on the decay rates of typical distributions.

An alternative way is to exploit third moments. For third moments, we might also specify candidate values by looking at candidate distributions with the given parameters $(1, c_a^2, \rho, c_s^2)$. Indeed that was done in §5.1 of [13], and we use the same prescription here. For $c_a^2 \geq 1$, based on the H_2 distribution with balanced means as before, $m_{3,a} = 3c_a^2(1 + c_a^2)$. For $c_a^2 \leq 1$, based on the E_k distribution, let $m_{3,a} = (2c_a^2 + 1)(c_a^2 + 1)$.

We apply these "typical" third moments to go with $(1, c_a^2, \rho, c_s^2)$ by relating the third moments to the support bounds M associated with F_u and G_u. We observe that the third moment of F_u is

$$m_3^U = \frac{c_a^2 M_a^3}{c_a^2 + (M_a - 1)^2} + \frac{(M_a - 1 - c_a^2)^3}{(M_a - 1)(c_a^2 + (M_a - 1)^2)}, \tag{5.1}$$

while the third moment of F_0 is

$$m_3^L = \frac{c_a^2 (1 + c_a^2)^3}{c_a^2 + c_a^4}. \tag{5.2}$$

Now observe that the third moment in (5.1) is a strictly increasing function of M_a, so that we can invert it to obtain M_a as a function of m_3, getting

$$M_a = \frac{-1 - c_a^2 + m_3^U + \sqrt{1 + 6c_a^2 + 9c_a^2 + 4c_a^3 - 2m_3^U - 6c_a^2 m_3^U + (m_3^U)^2}}{2c_a^2}. \tag{5.3}$$

Hence, given typical values of m_3 associated with any parameter 4-tuple $(1, c_a^2, \rho, c_s^2)$, we can construct a corresponding support bound M_a^* for which we can determine the range of possible mean values. With this approach, we obtain $M_a^* = 13.081$ for $c_a^2 = 4$, $M_a^* = 3.414$ for $c_a^2 = 1$ and $M_a^* = 2.366$ for $c_a^2 = 0.5$. We note that these values are substantially smaller than the values determined in §3. Table 10 presents the numerical ranges of third moment as a function of c^2 and M.

Table 10: Reasonable ranges in third moment relating to reasonable setting of bounded support

M	5.25	6.75	7.00	9.00	17.5	22.5	m_3^L
$c^2 = 0.5$	4.566	5.332	5.458	6.469	10.735	13.238	2.25
$c^2 = 1$	8.015	9.576	9.833	11.875	20.439	25.454	4.000
$c^2 = 4$	26.235	33.217	34.333	43.000	78.030	98.256	25.000

We again applied simulation to study the performance of the extremal queues based on the third moments in addition to the basic model parameters in (1.1). As a first step, we use the support bounds that come from the third moments via (5.3). Based on Theorem 3.1 of the main paper, the candidate UB and LB models for the mean $E[W]$, based on the reverse order for θ_W, are $F_0/G_u/1$ and $F_u/G_0/1$. As shown in [2], there is strong evidence that $F_0/G_u/1$ actually yields the tight UB for the mean $E[W]$, but it known that $F_u/G_0/1$ is not actually the tight LB for $E[W]$, although it is close. It is conjectured that the LB for $E[W]$ is attained by a special three-point distribution, denoted by $A_3(u)$. Table 11 compares the resulting LB and UB extremal queues to the HTA in (2.1). We include results for both the $F_u/A_3(u)/1$ and $F_u/G_0/1$ candidate LB models.

Table 11: Range of mean waiting times after including typical third moments: balanced models

	$c_a^2 = 4, c_s^2 = 0.5, M_a = 13.1, M_s = 2.37$				$c_a^2 = 4, c_s^2 = 4, M_a = 13.1, M_s = 13.1$			
ρ	$\mathbb{E}[W(F_u, A_3(u))]$	$\mathbb{E}[W(F_u, G_0)]$	HTA	$\mathbb{E}[W(F_u, G_0)]$	$\mathbb{E}[W(F_u, A_3(u))]$	$\mathbb{E}[W(F_0, G_u)]$	HTA	$\mathbb{E}[W(F_0, G_u)]$
0.50	0.040	0.154	1.125	2.552	0.917	1.856	2.000	3.336
0.60	0.174	0.737	2.025	3.663	1.750	3.622	3.600	5.148
0.70	1.213	2.577	3.675	5.515	3.886	6.768	6.533	8.289
0.80	5.799	6.572	7.200	9.235	10.591	13.263	12.800	14.758
0.90	17.447	17.988	18.225	20.451	30.510	33.004	32.400	34.555
	$c_a^2 = 0.5, c_s^2 = 0.5, M_a = 2.37, M_s = 2.37$				$c_a^2 = 0.5, c_s^2 = 4, M_a = 2.37, M_s = 13.1$			
ρ	$\mathbb{E}[W(F_u, A_3(u))]$	$\mathbb{E}[W(F_u, G_0)]$	HTA	$\mathbb{E}[W(F_u, G_0)]$	$\mathbb{E}[W(F_u, A_3(u))]$	$\mathbb{E}[W(F_0, G_u)]$	HTA	$\mathbb{E}[W(F_0, G_u)]$
0.50	0.058	0.131	0.250	0.348	0.933	1.015	1.125	1.216
0.60	0.200	0.353	0.450	0.550	1.775	1.886	2.025	2.124
0.70	0.537	0.725	0.817	0.924	3.385	3.516	3.675	3.780
0.80	1.336	1.496	1.600	1.714	6.884	7.019	7.200	7.311
0.90	3.749	3.935	4.050	4.169	17.899	17.994	18.225	18.340

From Table 11, we see that

$$\mathbb{E}[W(F_u, A_3(u))] \leq \mathbb{E}[W(F_u, G_0)] \leq \mathbb{E}[W(F_0, G_u)]$$

in all cases. In addition,

$$\mathbb{E}[W(F_u, G_0)] \leq HTA \leq \mathbb{E}[W(F_0, G_u)]$$

in all cases except $(c_a^2, c_s^2) = (4.0, 4.0)$. In that case, the smaller values of M than produced by (3.1) makes it important to use the better LB model $(F_u/A_3(u))$.

Most important, we see that our range of possible values of the mean $\mathbb{E}[W]$ is reduced subtantially by adding the additional parameters (M_a, M_s) obtained from $(m_{a,3}, m_{s,3})$. To illustrate, note that the range in the case $(\rho, c_a^2, c_s^2) = (0.8, 4, 4)$ is reduced from $[6.000, 14.917]$ to $[10.593, 14.758]$. The change is obviously much greater for F than for G.

6 The Impact of the Laplace Transform Constraints

We now elaborate on §4.2 of the main paper, which investigates the application of Theorem 3.2 in the main paper to obtain practically useful shorter intervals of likely values for the mean $E[W]$ by exploiting values of the Laplace transform $\hat{f}(s)$ and the moment generating function (mgf) $\hat{g}(-s)$. Recall that the Laplace transform is defined as

$$\hat{f}(s) \equiv \int_0^\infty e^{-st}\, dF(t) = E[e^{-sU}], \quad s \geq 0 \tag{6.1}$$

When we look at $\hat{g}(-s)$, it corresponds to the mgf, i.e.,

$$\hat{g}(-s) \equiv \int_0^\infty e^{st}\, dG(t) = E[e^{sV}], \quad s \geq 0. \tag{6.2}$$

We now show how a direct application of Theorem 3.2 in the main paper reduces the range. In this section we avoid issues involving the singularity s^* in Assumption 3.1 of the main paper, by primarily considering case (ii) in (2.14) of Theorem 3.2 in the main paper, in which

$$\mu_s < \theta_W < \mu_a, \tag{6.3}$$

which we achieve by following (3.6) of the main paper, i.e.,

$$\mu_s \equiv \theta_W / R \quad \text{and} \quad \mu_a \equiv R\theta_W \tag{6.4}$$

for suitable R. We begin by considering a range of R.

6.1 The Impact of Truncation

We initially truncate the basic models by M_a, M_s because Theorem 3.2 of the main paper only applies to models with bounded support. In the implementation, we do not want to $\mu_s > s^*$. Thus, if we are considering one of the cases with $\mu_s \geq \theta_W$, then we first check to see if $R\theta_W > s^*$ for our largest value of R, which we take to be $R = 20$. If it is, then we create alternative values of μ_s in the interval (θ_W, s^*). In particular, we use

$$\mu_s \equiv \theta_W + \left(\frac{R}{25}\right)(s^* - \theta_W), \quad 1 \leq k \leq 4, \tag{6.5}$$

so that the values of R remain in $\{5, 10, 15, 20\}$, but all values are within (θ_W, s^*).

Table 12 shows a careful comparison between parameters under truncation or not.

Table 12: A numerical comparison of truncated and original Laplace transform values for $E_2/H_2/1$ ($\theta_W = 0.1527$) and $M/M/1$ ($\theta_W = 0.4286$)

	$E_2/H_2/1$	Truncated	Original	Truncated	Original	$M/M/1$	Truncated	Original	Truncated	Original
	$R_a = R_s$	$\hat{f}(s)$	$\hat{f}(s)$	$\hat{g}(-s)$	$\hat{g}(-s)$	$R_a = R_s$	$\hat{f}(s)$	$\hat{f}(s)$	$\hat{g}(-s)$	$\hat{g}(-s)$
$\mu_a, \mu_s \geq \theta_W$	1	0.8630	0.8632	1.1568	1.1585	1	0.6998	0.7000	1.4293	1.4286
	5	0.5229	0.5238	1.4582	1.5498	5	0.3180	0.3182	4.9983	4.9779
	10	0.3205	0.3216	1.4582	1.5498	10	0.1890	0.1892	4.9983	4.9779
	20	0.1558	0.1566	1.4582	1.5498	20	0.1044	0.1045	4.9983	4.9779
$\mu_a, \mu_s \leq \theta_W$	1	0.8630	0.8632	1.1568	1.1585	1	0.6998	0.7000	1.4293	1.4286
	5	0.9701	0.9701	1.0226	1.0226	5	0.9210	0.9210	1.0639	1.0638
	10	0.9849	0.9849	1.0110	1.0110	10	0.9589	0.9589	1.0310	1.0309
	20	0.9924	0.9924	1.0054	1.0054	20	0.9790	0.9790	1.0152	1.0152

Additionally, the first three moments with and without truncation are close, i.e, $s_2 = 2.44, s_3 = 20.191$ for the truncated model and $s_2 = 2.45, 20.58$ for the original model for $E_2/H_2/1$. Since difference between parameters are negligible, it may suffice to apply the original $m_{a,2}, m_{a,3}$ instead of $m''_{a,2}, m''_{a,3}$ for reducing computation complexity. In other word, we could ignore the truncation effect and simply apply Theorem 3.2 of the main paper using parameters of the basic models without truncation.

6.2 The Parameter Pair (R_a, R_s)

However, we also report results exploring a more general two-parameter range, using (R_a, R_s) with R_a applying to F and R_s applying to G. In summary, we proceed as follows: Given an initially specified decay rate θ_W, the range vector (R_a, R_s) with $R_s \leq 1 \leq R_a$ and the specified parameters $(1, c_a^2, m_{a,3}, \mu_a, M_a)$ partially characterizing F and $(1, c_s^2, m_{s,3}, \mu_s, M_s)$ partially characterizing G, where $\mu_s \equiv \theta_W/R_s \leq \theta_W < R_a\theta_W$, we identify the set of possible performance measures in two steps.

In the first step, we can determine the extremal distributions F_L, G_L, F_U, G_U by solving n equations in n unknowns for the appropriate n. In the second step, we simulate $\mathbb{E}[W(F_L, G_L)]$ and $\mathbb{E}[W(F_U, G_U)]$ by Monte-Carlo simulation and obtain decay rates by solving equation (6) of the main paper for the LB and UB models F_L/G_L and F_U/G_U.

We now illustrate the results.

6.3 The $H_2/H_2/1$ Model with $c_a^2 = c_s^2 = 4.0$

We use UB (LB) to refer to the minimum (maximum) decay rate, which yields our estimate of the UB (LB) for $E[W]$. Table 13 shows estimates of the UB and LB for the decay rate θ_W and the mean $\mathbb{E}[W]$ in the case $c_a^2 = c_s^2 = 4$ and $\rho = 0.7$ for a range of R_a and R_s varying from 1 to 20, based on the first three moments and LT transforms from model $H_2/H_2/1$ with balanced means, which has exact mean $\mathbb{E}[W(H_2, H_2)] = 6.608$ and exact decay rate $\theta_W = 0.1064$. (See Table 2 of the main paper.)

As indicated above, here we allow R_a and R_s to differ, but we still require that $\mu_s \equiv \theta_W/R_s$ and $\mu_a \equiv R_a\theta$ for $R_a \geq 1$ and $R_s \geq 1$.

Table 13: The improved LB and UB based on information of $H_2/H_2/1$

$c_a^2 = c_s^2 = 4,\ \rho = 0.7,\ \theta_W = 0.1064$ and exact $\mathbb{E}[W(H_2, H_2)] = 6.608$											
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
θ_W (UB)	1	0.106	0.105	0.104	0.104	$\mathbb{E}[W]$ (UB)	1	6.292	6.197	6.175	6.708
	5	0.106	0.105	0.104	0.103		5	6.329	6.275	6.163	6.684
	10	0.106	0.105	0.104	0.103		10	6.336	6.278	6.155	6.688
	20	0.100	0.099	0.099	0.098		20	6.884	7.047	7.134	7.225
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
θ_W (LB)	1	0.106	0.107	0.108	0.108	$\mathbb{E}[W]$ (LB)	1	6.667	6.516	6.465	6.410
	5	0.107	0.108	0.108	0.108		5	6.692	6.485	6.443	6.387
	10	0.107	0.108	0.108	0.108		10	6.693	6.474	6.448	6.386
	20	0.109	0.110	0.110	0.110		20	6.866	6.664	6.532	6.420

Consistent with part (d) of Theorem 3.2 in the main paper, Table 13 show that the UB decay rate θ_W is monotone decreasing in R_a and R_s, while the LB decay rate is monotone increasing. Moreover, recall we utilize information from the exact queueing models where F and G have unbounded support, so that we do not expect perfect consistency. On the other hand, there is less order in the corresponding values of $E[W]$. Nevertheless, from Table 13, we conclude that a reasonable range of $E[W]$ can be generated by $R_a = R_s = 20$.

To elaborate further, Table 14 shows the explicit numerical values of the three-point extremal distributions F_L, G_L and F_U, G_U obtained in the case $c_a^2 = c_s^2 = 4, \rho = 0.7$ with $R = R_a = R_s \in \{1, 5, 10, 20\}$, supporting Table 13.

Table 14: Numerical examples of extremal distributions

$R_a = R_s = 1$		F			G		$R_a = R_s = 5$		F			G	
$F_L/G_L/1$	q_1	q_2	q_3	p_1	p_2	p_3	$F_L/G_L/1$	q_1	q_2	q_3	p_1	p_2	p_3
	0.620	0.370	1.04E-02	0.677	0.317	6.08E-03		0.526	0.459	1.57E-02	0.656	0.336	7.69E-03
	y_1	y_2	y_3	x_1	x_2	x_3		y_1	y_2	y_3	x_1	x_2	x_3
	0	2.21	17.6	0	1.93	14.4		0.0	1.65	15.5	0	1.78	13.4
$F_U/G_U/1$	q_1	q_2	q_3	p_1	p_2	p_3	$F_U/G_U/1$	q_1	q_2	q_3	p_1	p_2	p_3
	0.956	0.0433	2.88E-04	0.965	0.0345	1.73E-04		0.936	0.0639	4.30E-04	0.963	0.0370	2.12E-04
	y_1	y_2	y_3	x_1	x_2	x_3		y_1	y_2	y_3	x_1	x_2	x_3
	0.587	9.86	39.9	0.440	7.86	27.9		0.505	7.99	39.9	0.431	7.54	27.9
$R_a = R_s = 10$		F			G		$R_a = R_s = 20$		F			G	
$F_L/G_L/1$	q_1	q_2	q_3	p_1	p_2	p_3	$F_L/G_L/1$	q_1	q_2	q_3	p_1	p_2	p_3
	0.451	0.530	1.87E-02	0.654	0.338	7.88E-03		0.358	0.621	2.14E-02	0.653	0.339	7.97E-03
	y_1	y_2	y_3	x_1	x_2	x_3		y_1	y_2	y_3	x_1	x_2	x_3
	0.0	1.37	14.6	0	1.76	13.4		0	1.13	14.0	0	1.75	13.3
$F_U/G_U/1$	q_1	q_2	q_3	p_1	p_2	p_3	$F_U/G_U/1$	q_1	q_2	q_3	p_1	p_2	p_3
	0.917	0.0828	5.02E-04	0.962	0.0374	2.17E-04		0.891	0.108	5.62E-04	0.962	0.0376	2.20E-04
	y_1	y_2	y_3	x_1	x_2	x_3		y_1	y_2	y_3	x_1	x_2	x_3
	0.439	6.97	39.9	0.430	7.50	27.9		0.360	6.08	39.9	0.429	7.48	27.9

Next, Figure 1 plots the extremal Laplace transforms $\hat{f}(s)$ and $1/\hat{g}(-s)$ for UB (LHS) and LB (RHS) for the case $c_a^2 = c_s^2 = 4$ and $\rho = 0.7$. The curves intersect at the decay rate θ_W. The decay rate for $R_a = R_s = 1$ is 0.106, while for $R = R_a = R_s = 20$ it is 0.098 for the UB and 0.110 for the LB.

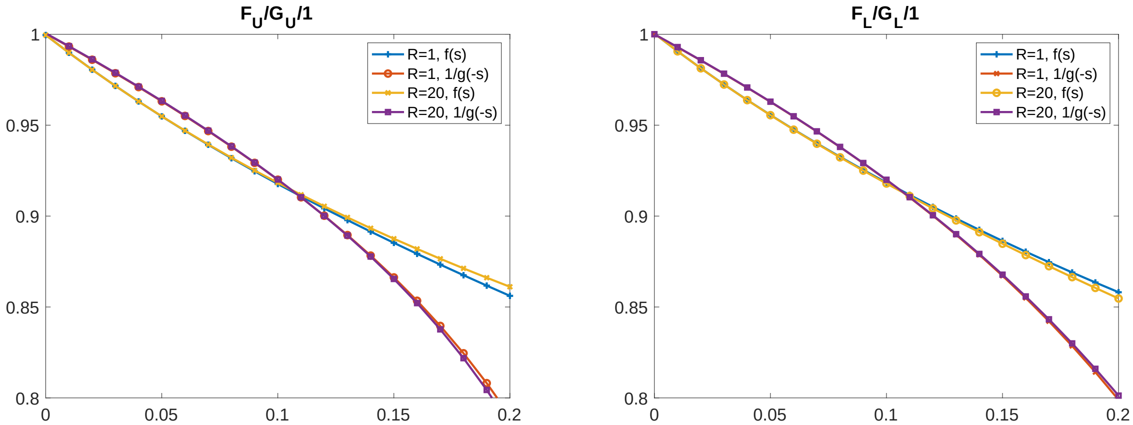

Figure 1: Display of $\hat{f}(s)$ and $1/\hat{g}(-s)$ for UB (LHS) and LB (RHS) for the case $c_a^2 = c_s^2 = 4$ and $\rho = 0.7$: the decay rate for $R = 1$ is 0.106 and for $R = 20$ in UB is 0.098 and in LB is 0.110

Next Tables 15 and 16 show the estimated extremal values of θ_W and $E[W]$ as a function of $R_a, R_s \in \{1, 5, 10, 20\}$ based on simulation for $\rho = 0.5, 0.9$ for this same case $(c_a^2, c_s^2) = (4, 4)$.

Table 15: The improved LB and UB based on information of $H_2/H_2/1$ with $\rho = 0.5$

$c_a^2 = c_s^2 = 4$, $\rho = 0.5$, $\theta_W = 0.2444$, $E[W] = 2.02$											
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
θ_W (UB)	1	0.244	0.235	0.231	0.227	$\mathbb{E}[W]$ (UB)	1	1.97	2.32	2.48	2.60
	5	0.239	0.231	0.227	0.224		5	1.95	2.02	1.97	2.20
	10	0.239	0.230	0.227	0.224		10	1.96	2.03	1.98	2.20
	20	0.238	0.230	0.227	0.224		20	1.96	2.03	1.99	2.21
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
θ_W (LB)	1	0.244	0.251	0.253	0.255	$\mathbb{E}[W]$ (LB)	1	2.09	1.87	1.81	1.75
	5	0.250	0.258	0.261	0.263		5	2.12	1.83	1.80	1.75
	10	0.251	0.258	0.261	0.263		10	2.12	1.84	1.80	1.75
	20	0.251	0.259	0.261	0.264		20	2.12	1.85	1.80	1.75

Table 16: The improved LB and UB based on information of $H_2/H_2/1$ for $\rho = 0.9$

$c_a^2 = c_s^2 = 4,\ \rho = 0.9,\ \theta_W = 0.0278, E[W] = 32.6$											
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
θ_W (UB)	1	0.0278	0.0277	0.0277	0.0277	$\mathbb{E}[W]$ (UB)	1	32.9	31.4	31.7	32.1
	5	0.0278	0.0277	0.0277	0.0277		5	32.8	31.8	31.5	32.1
	10	0.0278	0.0277	0.0277	0.0277		10	32.8	31.7	31.6	32.2
	20	0.0278	0.0277	0.0277	0.0277		20	33.0	31.6	31.5	32.2
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
θ_W (LB)	1	0.0278	0.0278	0.0278	0.0278	$\mathbb{E}[W]$ (LB)	1	32.8	32.6	32.7	33.2
	5	0.0278	0.0278	0.0278	0.0278		5	32.8	32.7	32.9	33.4
	10	0.0278	0.0278	0.0278	0.0278		10	32.7	32.8	32.7	33.4
	20	0.0278	0.0278	0.0278	0.0278		20	32.7	32.9	32.9	32.4

6.4 The $H_2/E_2/1$ Model with $c_a^2 = 4.0, c_s^2 = 0.5$

Next, Tables 17-19 show corresponding results for the case $c_a^2 = 4, c_s^2 = 0.5$, based on the first third moments and LT transform values from the model $H_2/E_2/1$, again using H_2 with balanced means. The exact values for the original $H_2/E_2/1$ model are given in Table 2 of the main paper. The exact values for $\rho = 0.7$ are $\mathbb{E}[W(H_2, E_2)] = 3.368$ and exact decay rate $\theta_W = 0.2602$.

Table 17: The improved LB and UB based on information of $H_2/E_2/1$

$c_a^2 = 4, c_s^2 = 0.5,\ \rho = 0.7,\ \theta_w = 0.2602$ and exact $\mathbb{E}[W(H_2, E_2)] = 3.368$											
	$R_s \backslash R_a$	1	5	10	20	$R_s \backslash R_a$	1	5	10	20	
θ_W (UB)	1	0.260	0.228	0.218	0.210	$\mathbb{E}[W]$ (UB)	1	3.438	3.920	4.091	4.265
	5	0.260	0.228	0.218	0.210		5	3.436	3.925	4.093	4.265
	10	0.260	0.228	0.217	0.210		10	3.436	3.993	4.194	4.335
	20	0.260	0.228	0.217	0.210		20	3.441	3.993	4.197	4.341
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
θ_W (LB)	1	0.260	0.291	0.306	0.321	$\mathbb{E}[W]$ (LB)	1	3.343	2.951	2.782	2.638
	5	0.260	0.291	0.306	0.321		5	3.345	2.950	2.789	2.641
	10	0.260	0.292	0.307	0.321		10	3.345	2.965	2.815	2.692
	20	0.260	0.292	0.307	0.321		20	3.345	2.966	2.815	2.692

Table 18: The improved LB and UB based on information of $H_2/E_2/1$ for $\rho = 0.5$

$c_a^2 = 4, c_s^2 = 0.5,\ \theta_w = 0.8260, \rho = 0.5$											
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
	1	0.826	0.531	0.484	0.456	$\mathbb{E}[W]$ (UB)	1	0.93	1.53	1.72	1.84
	5	0.826	0.531	0.484	0.456		5	0.93	1.53	1.72	1.84
θ_W (UB)	10	0.826	0.531	0.484	0.456		10	0.93	1.54	1.72	1.84
	20	0.814	0.530	0.483	0.456		20	0.89	1.60	1.77	1.88
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
	1	0.826	1.21	1.44	1.64	$\mathbb{E}[W]$ (LB)	1	0.860	0.498	0.381	0.305
	5	0.827	1.22	1.45	1.66		5	0.856	0.499	0.384	0.309
θ_W (LB)	10	0.827	1.22	1.45	1.66		10	0.854	0.495	0.386	0.307
	20	0.831	1.24	1.49	1.74		20	0.856	0.507	0.399	0.325

Table 19: The improved LB and UB based on information of $H_2/E_2/1$ for $\rho = 0.9$

$c_a^2 = 4, c_s^2 = 0.5,\ \theta_w = 0.0537, \rho = 0.9$											
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
delay rate (UB)	1	0.0537	0.0534	0.0531	0.0529	EW (UB)	1	18.0	18.1	18.2	18.3
	5	0.0537	0.0534	0.0531	0.0529		5	18.1	18.2	18.3	18.4
	10	0.0537	0.0534	0.0531	0.0529		10	18.1	18.2	18.3	18.4
	20	0.0537	0.0534	0.0531	0.0529		20	18.1	18.2	18.3	18.4
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
delay rate (LB)	1	0.0537	0.0539	0.0540	0.0541	EW (LB)	1	18.0	17.9	17.9	17.8
	5	0.0537	0.0539	0.0540	0.0541		5	18.0	17.9	17.9	17.8
	10	0.0537	0.0539	0.0540	0.0541		10	18.0	17.9	17.9	17.9
	20	0.0537	0.0539	0.0540	0.0541		20	18.0	17.9	17.9	17.9

Again, consistent with part (d) of Theorem 3.2 in the main paper, these tables show that the UB decay rate θ_W is monotone decreasing in R, while the LB decay rate is monotone increasing. Recall that we utilize information from the exact queueing models where F and G have unbounded support, so that we do not expect perfect consistency.

Next, Table 20 presents the extremal decay rates that go with the associated mean values $E[W]$ in Table 5 of the main paper. We obtain the rates here by solving the key equation (1.6) of the main paper for the original E_2 and H_2 distributions, so there is good numerical precision, but there is a minor difference from the truncated model, which explains the lack of precise order in a few cases.

Table 20: The decay rates for all basic models under $\rho = 0.7$

$E_2/H_2/1$	$R_s \backslash R_a$	5	10	20	$H_2/E_2/1$	$R_s \backslash R_a$	5	10	20
$\mu_s \leq \theta_W \leq \mu_a$	UB	0.150	0.150	0.149	$\mu_s \leq \theta_W \leq \mu_a$	UB	0.228	0.217	0.210
	LB	0.156	0.156	0.164		LB	0.291	0.307	0.321
	$R_s \backslash R_a$	5	10	20		$R_s \backslash R_a$	5	10	20
$\mu_s \geq \theta_W \geq \mu_a$	UB	0.151	0.150	0.143	$\mu_s \geq \theta_W \geq \mu_a$	UB	0.246	0.243	0.242
	LB	0.153	0.153	0.150		LB	0.283	0.286	0.288
	$R_s \backslash R_a$	5	10	20		$R_s \backslash R_a$	5	10	20
$\mu_s, \mu_a \leq \theta_W$	UB	0.150	0.149	0.149	$\mu_s, \mu_a \leq \theta_W$	UB	0.246	0.243	0.242
	LB	0.156	0.156	0.164		LB	0.283	0.287	0.289
	$R_s \backslash R_a$	5	10	20		$R_s \backslash R_a$	5	10	20
$\mu_s, \mu_a \geq \theta_W$	UB	0.151	0.150	0.143	$\mu_s, \mu_a \geq \theta_W$	UB	0.228	0.218	0.210
	LB	0.153	0.154	0.150		LB	0.291	0.306	0.320
$E_2/E_2/1$	$R_s \backslash R_a$	5	10	20	$H_2/H_2/1$	$R_s \backslash R_a$	5	10	20
$\mu_s \leq \theta_W \leq \mu_a$	UB	0.842	0.833	0.825	$\mu_s \leq \theta_W \leq \mu_a$	UB	0.105	0.104	0.098
	LB	0.880	0.889	0.893		LB	0.108	0.108	0.110
	$R_s \backslash R_a$	5	10	20		$R_s \backslash R_a$	5	10	20
$\mu_s \geq \theta_W \geq \mu_a$	UB	0.847	0.841	0.825	$\mu_s \geq \theta_W \geq \mu_a$	UB	0.106	0.105	0.103
	LB	0.861	0.859	0.842		LB	0.107	0.107	0.108
	$R_s \backslash R_a$	5	10	20		$R_s \backslash R_a$	5	10	20
$\mu_s, \mu_a \leq \theta_W$	UB	0.849	0.848	0.848	$\mu_s, \mu_a \leq \theta_W$	UB	0.106	0.105	0.100
	LB	0.866	0.867	0.867		LB	0.107	0.107	0.111
	$R_s \backslash R_a$	5	10	20		$R_s \backslash R_a$	5	10	20
$\mu_s, \mu_a \geq \theta_W$	UB	0.839	0.826	0.805	$\mu_s, \mu_a \geq \theta_W$	UB	0.105	0.104	0.101
	LB	0.874	0.880	0.863		LB	0.107	0.108	0.108

Remark 6.1 In general, we cannot claim that the bounds for θ_W yield bounds for $\mathbb{E}[W]$, so the connection is heuristic. From equation (3.205) in §II.5.11 of [3], it follows that for the $K_2/GI/1$ model that $\mathbb{E}[W] = A + \theta_W^{-1}$, where A is a constant that depends on the parameters in (1.1) and F within K_2, but not otherwise on G. As a consequence, for fixed F, $\mathbb{E}[W]$ is a strictly decreasing function of θ_W for given first two moments.

6.5 The Possibility of Using Heavy-Traffic Approximations

Tables 21 and 22 show (contrast) the improved LB and UB for the mean $E[W]$ starting with the exact decay rates of the base models and the approximation in (3.5) of the main paper. These show that we could also work with the HT approximations.

Table 21: The improved LB and UB for $GI/GI/1$ Queues under Exact Decay Rates

$\rho = 0.5$	$c_a^2 = c_s^2 = 0.5$			$\rho = 0.7$	$c_a^2 = c_s^2 = 0.5$			$\rho = 0.9$	$c_a^2 = c_s^2 = 0.5$		
	5	10	20		5	10	20		5	10	20
UB	0.200	0.204	0.222	UB	0.720	0.719	0.734	UB	3.91	3.92	3.89
LB	0.153	0.145	0.143	LB	0.649	0.625	0.642	LB	3.82	3.94	3.92
$\rho = 0.5$	$c_a^2 = c_s^2 = 4$			$\rho = 0.7$	$c_a^2 = c_s^2 = 4$			$\rho = 0.9$	$c_a^2 = c_s^2 = 4$		
	5	10	20		5	10	20		5	10	20
UB	2.02	1.98	2.21	UB	6.28	6.16	7.23	UB	31.8	31.6	32.2
LB	1.83	1.80	1.75	LB	6.49	6.45	6.42	LB	32.7	32.7	32.4
$\rho = 0.5$	$c_a^2 = 4, c_s^2 = 0.5$			$\rho = 0.7$	$c_a^2 = 4, c_s^2 = 0.5$			$\rho = 0.9$	$c_a^2 = 4, c_s^2 = 0.5$		
	5	10	20		5	10	20		5	10	20
UB	1.53	1.72	1.88	UB	3.92	4.19	4.34	UB	18.2	18.3	18.4
LB	0.499	0.386	0.325	LB	2.95	2.82	2.69	LB	17.9	17.9	17.9

Table 22: The improved LB and UB for $GI/GI/1$ Queues under Approximate Decay Rates

$\rho = 0.5$	$c_a^2 = c_s^2 = 0.5$			$\rho = 0.7$	$c_a^2 = c_s^2 = 0.5$			$\rho = 0.9$	$c_a^2 = c_s^2 = 0.5$		
	5	10	20		5	10	20		5	10	20
UB	0.220	0.238	0.247	UB	0.721	0.720	0.734	UB	3.87	3.93	3.92
LB	0.153	0.145	0.143	LB	0.649	0.625	0.642	LB	3.82	3.94	3.92
$\rho = 0.5$	$c_a^2 = c_s^2 = 4$			$\rho = 0.7$	$c_a^2 = c_s^2 = 4$			$\rho = 0.9$	$c_a^2 = c_s^2 = 4$		
	5	10	20		5	10	20		5	10	20
UB	2.02	1.98	2.19	UB	6.27	6.15	6.70	UB	31.8	33.0	33.1
LB	1.84	1.80	1.75	LB	6.48	6.45	6.42	LB	32.7	32.5	32.5
$\rho = 0.5$	$c_a^2 = 4, c_s^2 = 0.5$			$\rho = 0.7$	$c_a^2 = 4, c_s^2 = 0.5$			$\rho = 0.9$	$c_a^2 = 4, c_s^2 = 0.5$		
	5	10	20		5	10	20		5	10	20
UB	1.35	1.62	1.78	UB	3.84	4.11	4.28	UB	18.2	18.3	18.4
LB	0.629	0.494	0.390	LB	3.01	2.88	2.74	LB	17.9	17.9	17.9

7 More on the $M/M/K$ Model

In this section we present results for $M/M/1$ and $M/M/2$ complementing Table 4 and 7 of the main paper. As above in this appendix, we use the parameter pair (R_a, R_s).

7.1 Results for $M/M/1$

We start by presenting results for the $M/M/1$ model that complement Table 4 of the main paper. First, Table 23 shows results for $M/M/1$ model using case (ii) of (2.14) in Theorem 3.2 in the main paper.

Table 23: The Decay Rates and Set-valued Approximations of $M/M/1$ under Different μ_a, μ_s in case (ii) of of (2.14) in Theorem 3.2

$c_a^2 = c_s^2 = 1,\ \theta_w = 0.4286, \rho = 0.7,\ \mathbb{E}[W(M,M)] = 1.63,\ \mu_s \le \theta_W \le \mu_a$											
	$R_s\backslash R_a$	1	5	10	20		$R_s\backslash R_a$	1	5	10	20
θ_W (UB)	1	0.429	0.423	0.419	0.416	$\mathbb{E}[W]$ (UB)	1	1.60	1.56	1.62	1.69
	5	0.427	0.421	0.418	0.415		5	1.61	1.59	1.61	1.68
	10	0.427	0.421	0.418	0.415		10	1.61	1.61	1.62	1.68
	20	0.427	0.421	0.418	0.415		20	1.61	1.58	1.60	1.68
	$R_s\backslash R_a$	1	5	10	20		$R_s\backslash R_a$	1	5	10	20
θ_W (LB)	1	0.429	0.433	0.435	0.437	$\mathbb{E}[W]$ (LB)	1	1.60	1.51	1.55	1.57
	5	0.430	0.434	0.437	0.438		5	1.61	1.53	1.54	1.56
	10	0.430	0.434	0.437	0.439		10	1.61	1.53	1.56	1.56
	20	0.436	0.441	0.444	0.446		20	1.68	1.65	1.63	1.61

Next, Table 24 shows results for $M/M/1$ model using case (i) of (30) in Theorem 6 of the main paper with $\mu_a, \mu_s \le \theta_W$.

Table 24: The Decay Rates and Set-valued Approximations of $M/M/1$ under Different μ_a, μ_s in case (i) of of (2.14) in Theorem 3.2

$c_a^2 = c_s^2 = 1,\ \theta_w = 0.4286, \rho = 0.7, \mathbb{E}[W(M,M)] = 1.63$											
	$R_s\backslash R_a$	1	5	10	20		$R_s\backslash R_a$	1	5	10	20
$\theta_W(F_L, G_U)$	1	0.429	0.427	0.427	0.427	UB	1	1.67	1.67	1.68	1.67
	5	0.427	0.426	0.425	0.425		5	1.66	1.67	1.68	1.68
	10	0.427	0.426	0.425	0.425		10	1.66	1.67	1.68	1.68
	20	0.427	0.425	0.425	0.425		20	1.66	1.67	1.67	1.67
	$R_s\backslash R_a$	1	5	10	20		$R_s\backslash R_a$	1	5	10	20
$\theta_W(F_U, G_L)$	1	0.429	0.430	0.431	0.431	LB	1	1.66	1.65	1.65	1.65
	5	0.430	0.432	0.432	0.432		5	1.66	1.65	1.65	1.65
	10	0.430	0.432	0.432	0.432		10	1.66	1.65	1.65	1.65
	20	0.437	0.439	0.439	0.439		20	1.55	1.56	1.56	1.56

Table 25 shows results for $M/M/1$ model using case (iii) of of (2.14) in Theorem 3.2 in the main paper with $\mu_a, \mu_s \ge \theta_W$.

Table 25: The Decay Rates and Set-valued Approximations of $M/M/1$ under Different μ_a, μ_s in case (iii) of (2.14) in Theorem 3.2

$c_a^2 = c_s^2 = 1,\ \theta_w = 0.4286, \rho = 0.7, \mathbb{E}[W(M,M)] = 1.63$											
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
$\theta_W(F_U, G_L)$	1	0.429	0.423	0.419	0.416	UB	1	1.67	1.71	1.72	1.73
	5	0.422	0.417	0.413	0.411		5	1.68	1.71	1.72	1.71
	10	0.422	0.417	0.413	0.411		10	1.68	1.71	1.72	1.71
	20	0.422	0.417	0.413	0.411		20	1.68	1.71	1.72	1.71
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
$\theta_W(F_L, G_U)$	1	0.429	0.433	0.435	0.437	LB	1	1.67	1.65	1.63	1.62
	5	0.429	0.433	0.435	0.437		5	1.67	1.65	1.64	1.62
	10	0.429	0.433	0.435	0.437		10	1.67	1.65	1.64	1.62
	20	0.429	0.433	0.435	0.437		20	1.67	1.65	1.63	1.62

7.2 Corresponding Results for $M/M/2$

Tables 26 and 27 present corresponding results for the $M/M/2$ model in cases (ii) and (iii) of (2.14) in Theorem 3.2 of the main paper.

Table 26: The Set-valued Approximations for $M/M/2$ in case (ii): $\mu_s \le \theta_W \le \mu_a$

$c_a^2 = c_s^2 = 1,\ \theta_w = 0.4286, \rho = 0.7,\ \mathbb{E}[W(M,M)] = 1.35,\ \mu_s \le \theta_W \le \mu_a$											
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
θ_W (UB)	1	0.429	0.424	0.420	0.417	$\mathbb{E}[W]$ (UB)	1	1.31	1.34	1.40	1.42
	5	0.428	0.422	0.418	0.416		5	1.30	1.34	1.39	1.42
	10	0.427	0.421	0.418	0.415		10	1.30	1.34	1.39	1.41
	20	0.427	0.421	0.418	0.415		20	1.30	1.34	1.39	1.41
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
θ_W (LB)	1	0.426	0.430	0.432	0.434	$\mathbb{E}[W]$ (LB)	1	1.33	1.32	1.33	1.34
	5	0.430	0.434	0.436	0.438		5	1.34	1.30	1.31	1.33
	10	0.430	0.434	0.437	0.438		10	1.34	1.30	1.31	1.32
	20	0.430	0.434	0.437	0.439		20	1.34	1.30	1.31	1.33

Table 27: The improved LB and UB based on information of $M/M/2$ $(\mu_a, \mu_s \geq \theta_W)$

$c_a^2 = c_s^2 = 1$, $\theta_w = 0.4286, \rho = 0.7$											
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
$\theta_W(F_U, G_L)$	1	0.426	0.420	0.417	0.414	UB	1	1.40	1.40	1.39	1.37
	5	0.422	0.417	0.413	0.411		5	1.40	1.41	1.38	1.34
	10	0.422	0.417	0.413	0.411		10	1.41	1.41	1.38	1.34
	20	0.422	0.417	0.413	0.411		20	1.40	1.40	1.38	1.34
	$R_s \backslash R_a$	1	5	10	20		$R_s \backslash R_a$	1	5	10	20
$\theta_W(F_L, G_U)$	1	0.429	0.432	0.434	0.437	LB	1	1.35	1.32	1.27	1.25
	5	0.429	0.433	0.435	0.437		5	1.35	1.32	1.29	1.26
	10	0.429	0.433	0.435	0.437		10	1.36	1.31	1.28	1.26
	20	0.429	0.433	0.435	0.437		20	1.36	1.31	1.29	1.26

Tables 26 and 27 show that the method for producing approximate intervals of likely values for the mean $E[W]$ remains effective for $K = 2$.

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