# RARE EVENTS OF TRANSITORY QUEUES 

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#### Abstract

We study the rare event behavior of the workload process in a transitory queue, where the arrival epochs (or 'points') of a finite number of jobs are assumed to be the ordered statistics of independent and identically distributed (i.i.d.) random variables. The service times (or 'marks') of the jobs are assumed to be i.i.d. random variables with a general distribution, that are jointly independent of the arrival epochs. Under the assumption that the service times are strictly positive, we derive the large deviations principle (LDP) satisfied by the workload process. The analysis leverages the connection between ordered statistics and self-normalized sums of exponential random variables to establish the LDP. This paper presents the first analysis of rare events in transitory queueing models, supplementing prior work that has focused on fluid and diffusion approximations.


## 1. Introduction

We explicate the rare event behavior of a 'transitory' queueing model, by proving a large deviations principle (LDP) satisfied by the workload process of the queue. A formal definition of a transitory queue follows from [16]:

Definition 1. (Transitory Queue.) Let $A(t)$ represent the cumulative traffic entering a queueing system. The queue is transitory if $A(t)$ satisfies

$$
\begin{equation*}
\lim _{t \rightarrow \infty} A(t)<\infty \text { a.s. } \tag{1.1}
\end{equation*}
$$

[^0]We consider a specific transitory queueing model where the arrival epochs (or 'points') of a finite but large number of jobs, say $n$, are 'randomly scattered' over $[0, \infty)$; that is the arrival epochs $\left(T_{1}, \ldots, T_{n}\right)$ are i.i.d., and drawn from some distribution with support in $\left[0, \infty\right.$ ). We assume that the service times (or 'marks') $\left\{\nu_{1}, \ldots, \nu_{n}\right\}$ are i.i.d., jointly independent of the arrival epochs and with $\log$ moment generating function that satisfies $\varphi(\theta)<\infty$ for $\theta \in \mathbb{R}$. We call this queueing model the $R S / G I / 1$ queue (' $R S$ ' standing for randomly scattered; this was previously dubbed the $\Delta_{(i)} / G I / 1$ queueing model in [15]).

While the i.i.d. assumption on the arrival epochs implies that this is a homogeneous model, [15] shows that the workload process displays time-dependencies in the large population fluid and diffusion scales, that mirrors those observed for 'dynamic rate' queueing models where time-dependent arrival rates are explicitly assumed. This indicates that the rare event behavior of the workload or queue length process should be atypical compared to that of time-homogeneous queueing models (such as the $G / G / 1$ queue; see [11]). Further, while the standard dynamic rate traffic model is a nonhomogeneous Poisson process that necessarily has independent increments, it is less than obvious that is a reasonable assumption for many service systems. [12, 13], for instance, highlights data analysis and simulation results in the call center context that indicate that independent increments might not be appropriate. A tractable alternative is to assume that the increments are exchangeable [1]. Lemma 10.9 in [1] implies that any traffic process over the horizon $[0,1]$ with exchangeable increments is necessarily equal in distribution to the empirical sum process

$$
\begin{equation*}
\sum_{i=1}^{N} \mathbf{1}_{\left\{T_{i} \leq t\right\}} \forall t \in[0,1], \tag{1.2}
\end{equation*}
$$

where the $\left\{T_{i}, 1 \leq i \leq N\right\}$ are independent and uniformly distributed in $[0,1]$. In [15] we defined (1.2) as the traffic count process for the $R S / G I / 1$ queue. This can be considered the canonical model of a transitory traffic process with exchangeable increments. Thus, the results in this paper can also be viewed as explicating the rare events behavior of queueing models with exchangeable increments. To the best of our knowledge this has not been reported in the literature before.

Transitory queueing models, and the $R S / G I / 1$ queue in particular, have received some recent interest in the applied probability literature, besides [15]. In forthcoming
work [14] studies large deviations and diffusion approximations to the workload process in a 'near balanced' condition on the offered load to the system. The current paper complements this by not assuming the near balanced condition. In recent work, [2] established diffusion approximations to the queue length process of the $\Delta_{(i)} / G I / 1$ queue under a uniform acceleration scaling regime, where in it is assumed that the "initial load" near time zero satisfies $\rho_{n}=1+\beta n^{-1 / 3}$. This, of course, contrasts with the population acceleration regime considered in this paper, where the offered load is accelerated by the population size at all time instances in the horizon $[0,1]$. The same authors have also considered the effect of heavy-tailed service in transitory queues in [3], and established weak limits to the scaled workload and queue length processes to reflected alpha-stable processes.

In the ensuing discussion, we will largely focus on the case that the arrival epochs are uniformly distributed with support $[0,1]$. Our first result in Theorem 3.1 establishes a large deviations result for the ordered statistics process $\left(T^{n}(t):=T_{(\lfloor n t\rfloor)} \forall t \in\right.$ $[0,1])$ and $n \geq 1$, where $T_{(j)}$ represents the $j$ th order statistic. This result parallels that in [9], where the authors derive a sample path large deviations result for the ordered statistics of i.i.d. uniform random variables. Our results deviate from this result in a couple of ways. First, we do not require a full sample path LDP, since we are interested in understanding the large deviations of the workload at a given point in time. Second, our proof technique is different and explicitly uses the connection between ordered statistics and self-normalized sums of exponential random variables. It is also important to note the result in [4], where the author uses Sanov's theorem to prove the large deviation principle for $L$-statistics, which could be leveraged to establish the LDP for the traffic process in (1.2) and, hence, the number-in-system process. The objective of our study, on the other hand, is the workload process. In Corollary 3.1 we use the contraction principle to extend this large deviations result to arrival epochs that have distribution $F$ with positive support, under the assumption that the distribution is absolutely continuous and strictly increasing. However, much of the 'heavy-lifting' for the workload LDP can be demonstrated with uniform order statistics arrival epochs, so in the remainder of the paper we do not emphasize the extension to more generally distributed arrival epochs.

In Proposition 3.1 we make use of the proof of Theorem 3.1 and the well known

Cramer's Theorem [7, Theorem 2.2.3] to derive the large deviation rate function for the offered load process $X^{n}(t):=S^{n}(t)-T^{n}(t) \forall t \in[0,1]$ and $n \geq 1$, where $S^{n}(t):=$ $\sum_{i=1}^{\lfloor n t\rfloor} \nu_{i}$ is the partial sum of the service times. Interestingly enough, the LDP (and the corresponding good rate function) shows that the most likely path to a large deviation event depends crucially on both the sample path of the offered load process up to $t$ as well as the path after $t$. This is a direct reflection of the fact that the traffic process is exchangeable and that there is long-range dependence between the inter-arrival times (which are 'spacings' between ordered statistics, and thus finitely exchangeable).

We prove the LDP for the workload process

$$
W^{n}(t):=\Gamma\left(X^{n}\right)(t)=\sup _{0 \leq s \leq t}\left(X^{n}(t)-X^{n}(s)\right)
$$

for fixed $t \in[0,1]$, by exploiting the continuity of the reflection regulator map $\Gamma(\cdot)$. However, to do so, we first establish two auxiliary results: in Proposition 4.1 we prove the exponential equivalence of the workload process and a linearly interpolated version $\tilde{X}^{n}$. Then, in Proposition 4.2 we prove the LDP satisfied by the 'partial' sample paths $\left(\tilde{X}^{n}(s), 0 \leq s \leq t\right)$ of the offered load process for fixed $t \in[0,1]$. Then, in Theorem 4.1 we establish the LDP for the workload process by applying the contraction mapping theorem with the reflection regulator map and exploiting the two propositions mentioned above. We conclude the paper with a summary and comments on future directions for this research.

### 1.1. Notation

We assume that all random elements are defined with respect to an underlying probability sample space $(\Omega, \mathcal{F}, \mathbb{P})$. We denote convergence in probability by $\xrightarrow{P}$. We denote the space $\mathcal{X}$ and topology of convergence $\mathcal{T}$ by the pair $(\mathcal{X}, \mathcal{T})$, where appropriate. In particular we note $(\mathcal{C}[0, t], \mathcal{U})$, the space of continuous functions with domain $[0, t]$, equipped with the uniform topology. We also designate $\overline{\mathcal{C}}[0, t]$ as the space of all continuous functions that are non-decreasing on the domain $[0, t] .\|\cdot\|=$ $\sup _{0 \leq s \leq 1}(\cdot)$ represents the supremum norm on $\mathcal{C}[0,1]$. Finally, we will use the following standard definitions in the ensuing results:

Definition 2. (Rate Function.) Let $\mathcal{X}$ be Hausdorff topological space. Then,

- a rate function is a lower semicontinuous mapping $I: \mathcal{X} \rightarrow[0, \infty]$; i.e., the level set $\{x \in \mathcal{X}: I(x) \leq \alpha\}$ for any $\alpha \in[0, \infty)$ is a closed subset of $\mathcal{X}$, and
- a rate function is 'good' if the level sets are also compact.

Definition 3. (Large Deviations Principle (LDP).) The sequence of random elements $\left\{X_{n}, n \geq 1\right\}$ taking values in the Hausdorff topological space $\mathcal{X}$ satisfies a large deviations principle (LDP) with rate function $I: \mathcal{X} \rightarrow \mathbb{R}$ if
a) for each open set $G \subset \mathcal{X}$

$$
\liminf _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(X_{n} \in G\right) \geq-\inf _{x \in G} I(x), \text { and }
$$

b) for each closed set $F \subset \mathcal{X}$

$$
\limsup _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(X_{n} \in F\right) \leq-\inf _{x \in F} I(x)
$$

Definition 4. (Weak LDP.) The sequence of random elements $\left\{X_{n}, n \geq 1\right\}$ taking values in the Hausdorff topological space $\mathcal{X}$ satisfies a weak large deviation principle (WLDP) with rate function $I$ if
a) for each open set $G \subset \mathcal{X}$

$$
\liminf _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(X_{n} \in G\right) \geq-\inf _{x \in G} I(x), \text { and }
$$

b) for each compact set $K \subset \mathbb{R}$,

$$
\limsup _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(X_{n} \in K\right) \leq-\inf _{x \in K} I(x)
$$

Definition 5. (LD Tight.) A sequence of random elements $\left\{X_{n}, n \geq 1\right\}$ taking values in the Hausdorff topological space $\mathcal{X}$ is large deviation (LD) tight if for each $M<\infty$, there exists a compact set $K_{M}$ such that

$$
\limsup _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(X_{n} \in K_{M}^{c}\right) \leq-M
$$

## 2. Model

Let $\left\{\left(T_{(i)}, \nu_{i}\right), i=1,2, \ldots, n\right\}$ for $n \in \mathbb{N}$ represent a marked finite point process, where $\left\{T_{(i)}, i=1,2, \ldots, n\right\}$ are the epochs of the point process and $\left\{\nu_{i}, i=\right.$
$1,2, \ldots, n\}$ are the marks. We assume that the two sequences are independent of each other. $\left\{T_{(i)}, i=1,2, \ldots, n\right\}$ are the order statistics of $n$ independent and identically distributed (i.i.d.) random variables with support $[0, \infty)$ and absolutely continuous distribution $F .\left\{\nu_{i}, i=1,2, \ldots, n\right\}$ are i.i.d. random variables with support $[0, \infty)$, cumulant generating function $\varphi(\theta)<\infty$ for some $\theta \in \mathbb{R}$ and mean $\mathbb{E}\left[\nu_{1}\right]=1 / \mu$. We will also assume that $\mathbb{P}\left(\nu_{1}>0\right)=1$, for technical reasons. Let $\mathbb{D}:=\{\theta \in \mathbb{R}: \varphi(\theta)<\infty\}$ and we assume $0 \in \mathbb{D}$. In relation to the queue, $\left(T_{(j)}, \nu_{j}\right)$ represents the arrival epoch and service requirement of job $j$, and $n$ is the total arrival population. It is useful to think of the $n$ marked points, or $\left(T_{(i)}, \nu_{i}\right)$ pair, being 'scattered' over the horizon following the distribution $F$.

Let $\left\{\nu_{i}^{n}:=\nu_{i} / n, i=1,2, \ldots, n\right\}$ be a 'population accelerated' sequence of marks. Assume that $\left(T_{(0)}, \nu_{0}^{n}\right)=(0,0)$. The (accelerated) workload ahead of the $j$ th job is $W_{j}^{n}=\left(W_{j-1}^{n}+\nu_{j-1}^{n}-\left(T_{(j)}-T_{(j-1)}\right)\right)_{+}$, where $(\cdot)_{+}:=\max \{0, \cdot\}$. By unraveling the recursion, and under the assumption that the queue starts empty, it can be shown that

$$
W_{j}^{n} \stackrel{D}{=}\left(S_{j-1}^{n}-T_{(j)}\right)+\max _{0 \leq i \leq j-1}\left(-\left(S_{i}^{n}-T_{(i+1)}\right)\right)
$$

where $S_{j-1}^{n}:=\sum_{i=0}^{j-1} \nu_{i}^{n}$. We define the workload process as $\left(W^{n}(t), t \in[0,1]\right):=$ $\left(W_{\lfloor n t\rfloor}^{n}, t \in[0,1]\right)$. Using the unraveled recursion it can be argued that

$$
\begin{equation*}
W^{n}(t) \stackrel{D}{=} X^{n}(t)+\max _{0 \leq s \leq t}\left(-X^{n}(s)\right) \tag{2.1}
\end{equation*}
$$

where $X^{n}(t):=n^{-1} \sum_{i=0}^{\lfloor n t\rfloor} \nu_{i}-T_{(\lfloor n t\rfloor)}=S^{n}(t)-T^{n}(t)$ (where $\left.T_{(0)}=0\right)$ for $t \in[0,1]$ is the offered load process, under the assumption that $S_{0}^{n}=0$ (i.e., the queue starts empty). Thus, it suffices to study $\Gamma\left(X^{n}\right)(t):=X^{n}(t)+\max _{0 \leq s \leq t}\left(-X^{n}(s)\right)$, where $\Gamma: \mathcal{D}[0,1] \rightarrow \mathcal{D}[0,1]$ is the so-called Skorokhod regulator map. For future reference, we call $\left(T^{n}(t), t \in[0,1]\right):=\left(T_{(\lfloor n t\rfloor)}, t \in[0,1]\right)$ as the ordered statistics process.

We propose to study the workload process in the large population limit and, in particular, understand the rare event behavior in this limit. As a precursor to this analysis, it is useful to consider what a "normal deviation" event for this process would be. In particular, The next proposition proves a functional strong law of large numbers (FSLLN) result for the workload process, that exposes the first order behavior of the workload sample path, in the large population limit.

Proposition 2.1. The workload process $W^{n}$ satisfies

$$
W^{n} \rightarrow \bar{W}=\frac{1}{\mu} \Gamma(F-M) \text { in }(\mathcal{C}[0,1], \mathcal{U}) \text { a.s. }
$$

as $n \rightarrow \infty$, where $M(t)=\mu t$.
Proof. First assume that $\left\{0<T_{(1)} \leq \ldots \leq T_{(n)}<1\right\}$ are the ordered statistics of $n$ i.i.d. uniform random variables. Then, by [5, Lemma 5.8] it follows that the ordered statistics process satisfies $\left(T^{n}, S^{n}\right) \rightarrow\left(e, \mu^{-1} e\right)$ in $(\mathcal{C}[0,1], \mathcal{U})$ a.s. as $n \rightarrow \infty$, where $e: \mathbb{R} \rightarrow \mathbb{R}$ is the identity map, and the joint convergence follows due to the fact that the arrival epochs and service times are independent sequences. Let $\bar{X}:=\left(\mu^{-1} e-e\right)$, which is continuous by definition. Since subtraction is continuous under the uniform metric topology it follows that $X^{n} \rightarrow \bar{X}:=\mu^{-1}(e-M)$ in $(\mathcal{C}[0,1], \mathcal{U})$ a.s. as $n \rightarrow \infty$. Finally, since $\Gamma(\cdot)$ is continuous under the uniform metric, and the limit function $\Gamma(\bar{X})$ is continuous, it follows that $W^{n} \rightarrow \bar{W}$ in $(\mathcal{C}[0,1], \mathcal{U})$ a.s. as $n \rightarrow \infty$. The limit result for generally distributed arrival epochs follows by an application of the quantile transform to the arrival epochs.

From an operational perspective it is useful to understand the likelihood that the workload exceeds an abnormally large threshold. More precisely, we are interested in the likelihood that for a given $t \in[0,1] W^{n}(t)>w$, where $w \gg \bar{W}(t)$. While this is quite difficult to prove for a fixed $n$, we prove an LDP for the workload process as the population size $n$ scales to infinity, that will automatically provide an approximation to the likelihood of this event. In the ensuing exposition, we will largely focus on the analysis of a queue where the arrival epochs are modeled as the ordered statistics of i.i.d. uniform random variables on $[0,1]$. However, the results can be straightforwardly extended to a more general case where the arrival epochs have distribution $F$ (with positive support), that is absolutely continuous with respect to the uniform distribution.

Our agenda for proving the workload LDP will proceed in several steps. First, we prove an LDP for the ordered statistics process of i.i.d. uniform random variables. The proof of this result will then be used to establish an LDP for the offered load process $X^{n}(t)$. Next, we use a projective limit to establish the LDP for the sample path of the offered load process $\left(X^{n}(s), 0 \leq s \leq t\right)$, for each fixed $t \in[0,1]$. Finally, we prove an

LDP for the workload process by applying the contraction principle to the LDP for the sample path $\left(X^{n}(s), 0 \leq s \leq t\right)$, transformed through the Skorokhod regulator map $\Gamma(\cdot)$.

## 3. An LDP for the offered load

### 3.1. LDP for the ordered statistics process

As a precursor to the LDP for the offered load process we prove one for the ordered statistics process $\left(T^{n}(t), t \in[0,1]\right):=\left(T_{(\lfloor n t\rfloor)}, t \in[0,1]\right)$ by leveraging the following well-known relation between the order statistics of uniform random variables and partial sums of unit mean exponential random variables:

Proposition 3.1. Let $0<T_{(1)}<T_{(2)}<\cdots<T_{(n)}<1$ be the ordered statistics of independent and uniformly distributed random variables, and $\left\{\xi_{j}, 1 \leq j \leq n+1\right\}$ independent mean one exponential random variables. Then,

$$
\begin{equation*}
\left\{T_{(j)}, 1 \leq j \leq n\right\} \stackrel{D}{=}\left\{\frac{Z_{j}}{Z_{n+1}}, 1 \leq j \leq n\right\} \tag{3.1}
\end{equation*}
$$

where $Z_{j}:=\sum_{i=1}^{j} \xi_{i}$.
Proofs of this result can be found in [10, Lemma 8.9.1]. Now, consider the convex, continuous function $I_{t}:[0,1] \rightarrow \mathbb{R}$ indexed by $t \in[0,1]$,

$$
\begin{equation*}
I_{t}(x)=t \log \left(\frac{t}{x}\right)+(1-t) \log \left(\frac{1-t}{1-x}\right) . \tag{3.2}
\end{equation*}
$$

Figure 1 depicts (3.2) for different index values $t \in[0,1]$. In Theorem 3.1 below we show that $I_{t}$ is the good rate function of the LDP satisfied by the ordered statistics process. It is interesting to note that this function is also the rate function satisfied by a sequence of i.i.d. Bernoulli random variables with parameter $t$; see the citations in [8].

Theorem 3.1. (LDP for the Ordered Statistics Process.) Fix $t \in[0,1]$. The ordered statistics process $T_{n}(t)$ satisfies the LDP with good rate function (3.2).

Proof. a) Let $F \subset[0,1]$ be closed. There are two cases to consider. First, if $t \in F$, then $I_{t}(F):=\inf _{x \in F} I_{t}(x)=0$, by definition. Thus, we assume that $t \notin F$. Let $x_{+}:=\inf \{x \in F: x>t\}$ and $x_{-}:=\sup \{x \in F: x<t\}$. If $\sup F<t$ then we define


Figure 1: Rate function for the ordered statistics process.
$x_{+}=1$, and if $\inf F>t$ we set $x_{-}=0$. Since $t \notin F$, there exists a connected open set $F^{c} \supseteq\left(x_{-}, x_{+}\right) \ni t$.

Now, let $0 \leq a<t$. Proposition 3.1 implies that

$$
\begin{align*}
\mathbb{P}\left(T_{(\lfloor n t\rfloor}<a\right) & =\mathbb{P}\left(\frac{Z_{\lfloor n t\rfloor}}{Z_{n+1}}<a\right) \\
& =\mathbb{P}\left(Z_{n+1-\lfloor n t\rfloor}>\frac{1-a}{a} Z_{\lfloor n t\rfloor}\right) \\
& =\int_{0}^{\infty} \mathbb{P}\left(Z_{n+1-\lfloor n t\rfloor}>\frac{(1-a) x}{a}\right) \times \mathbb{P}\left(Z_{\lfloor n t\rfloor} \in d x\right) . \tag{3.3}
\end{align*}
$$

Now, Chernoff's inequality implies that

$$
\mathbb{P}\left(Z_{n+1-\lfloor n t\rfloor}>\frac{(1-a) x}{a}\right) \leq e^{-\theta_{1} \frac{(1-a) x}{a}} E\left[e^{\theta_{1} Z_{n+1-\lfloor n t\rfloor}}\right]
$$

 for $\theta_{1}<1$. Substituting this into (3.3), we obtain

$$
\mathbb{P}\left(T_{(\lfloor n t\rfloor)}<a\right) \leq\left(1-\theta_{1}\right)^{-(n+1-\lfloor n t\rfloor)} \int_{0}^{\infty} e^{-\theta_{1} \frac{1-a}{a} x} \mathbb{P}\left(Z_{\lfloor n t\rfloor} \in d x\right)
$$

Recognize that the integral above represents the moment generating function of $Z_{\lfloor n t\rfloor}=$ $\sum_{i=1}^{\lfloor n t\rfloor} \xi_{i}$. Since $\frac{1-a}{a}>0$, if $1>\theta_{1}>\frac{a}{a-1}$ it follows that

$$
\int_{0}^{\infty} e^{-\theta_{1} \frac{1-a}{a} x} \mathbb{P}\left(Z_{\lfloor n t\rfloor} \in d x\right)=\left(1+\theta_{1} \frac{1-a}{a}\right)^{-\lfloor n t\rfloor}
$$

Putting things together, it follows that

$$
\mathbb{P}\left(T_{(\lfloor n t\rfloor)}<a\right) \leq\left(1-\theta_{1}\right)^{-(n+1-\lfloor n t\rfloor)}\left(1+\theta_{1} \frac{1-a}{a}\right)^{-\lfloor n t\rfloor}
$$

Similarly, it can be shown for any $1 \geq b>t$ that

$$
\mathbb{P}\left(T^{n}(t)>b\right) \leq\left(1-\theta_{1}\right)^{-(n+1-\lfloor n t\rfloor)}\left(1+\theta_{1} \frac{1-b}{b}\right)^{-\lfloor n t\rfloor}
$$

if $1>\theta_{1}>\frac{b}{b-1}$.
Thus, it follows that

$$
\begin{align*}
\mathbb{P}\left(T^{n}(t) \in F\right) & \leq \mathbb{P}\left(T^{n}(t) \in\left(x_{-}, x_{+}\right)^{c}\right) \\
& \leq \mathbb{P}\left(T^{n}(t) \leq x_{-}\right)+\mathbb{P}\left(T^{n}(t) \geq x_{+}\right) \\
& \leq\left(1-\theta_{1}\right)^{-(n+1-\lfloor n t\rfloor)}\left[\left(1+\theta_{1} \frac{1-x_{-}}{x_{-}}\right)^{-\lfloor n t\rfloor}+\left(1+\theta_{1} \frac{1-x_{+}}{x_{+}}\right)^{-\lfloor n t\rfloor}\right] \\
& \leq 2 \max _{x \in F}\left\{\left(1-\theta_{1}\right)^{-(n+1-\lfloor n t\rfloor)}\left(1+\theta_{1} \frac{1-x}{x}\right)^{-\lfloor n t\rfloor}\right\} \tag{3.4}
\end{align*}
$$

Now, for any $x \in[0,1]$, it can be seen that $\left(1-\theta_{1}\right)^{-(n+1-\lfloor n t\rfloor)}\left(1+\theta_{1} \frac{1-x}{x}\right)^{-\lfloor n t\rfloor}$ has a unique maximizer at $\theta_{1}^{*}=(t-x)(1-x)^{-1}$. Substituting this into (3.4), it follows that

$$
\begin{aligned}
\limsup _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(T_{n}(t) \in F\right) & \leq \max _{x \in F}\left\{-(1-t) \log \left(\frac{1-t}{1-x}\right)-t \log \left(\frac{t}{x}\right)\right\} \\
& =-\inf _{x \in F} I_{t}(x)
\end{aligned}
$$

b) Next, let $G \subset[0,1]$ be an open set, such that $t \notin G$ and $t<\inf \{G\}$. For each point $x \in G$, then there exists a $\delta>0$ (small) such that $(x-\delta, x+\delta) \subset G$. Once again appealing to Proposition 3.1, we have

$$
\begin{aligned}
\mathbb{P}\left(T^{n}(t) \in(x-\delta, x+\delta)\right)= & \mathbb{P}\left(\frac{\bar{Z}_{\lfloor n t\rfloor}}{\bar{Z}_{\lfloor n t\rfloor}+\bar{Z}_{n+1-\lfloor n t\rfloor}} \in(x-\delta, x+\delta)\right) \\
= & \int_{z_{1}=0}^{\infty} \mathbb{P}\left(\bar{Z}_{\lfloor n t\rfloor} \in d z_{1}\right) \times \\
& \mathbb{P}\left(\bar{Z}_{n+1-\lfloor n t\rfloor} \in z_{1}\left(-1+\frac{1}{x+\delta},-1+\frac{1}{x-\delta}\right)\right)
\end{aligned}
$$

where $\bar{Z}_{m(n)}:=n^{-1} Z_{m(n)}$ for $m(n) \in\{\lfloor n t\rfloor, n+1-\lfloor n t\rfloor\}$. Let $v>t>0$ implying that the right hand side (R.H.S.) above satisfies

$$
\begin{equation*}
R . H . S . \geq \mathbb{P}\left(\bar{Z}_{\lfloor n t\rfloor} \geq v\right) \mathbb{P}\left(\bar{Z}_{n+1-\lfloor n t\rfloor} \in v\left(-1+\frac{1}{x+\delta},-1+\frac{1}{x-\delta}\right)\right) \tag{3.5}
\end{equation*}
$$

Now, let $\theta_{1}>0$ and consider the partial sum of 'twisted' random variables $\left\{\xi_{1}^{\theta_{1}}, \ldots, \xi_{\lfloor n t\rfloor}^{\theta_{1}}\right\}$, $Z_{\lfloor n t\rfloor}^{\theta_{1}}=\sum_{i=1}^{\lfloor n t\rfloor} \xi_{i}^{\theta_{1}}$, where the distribution of $\xi_{1}^{\theta_{1}}$ is (by an exponential change of
measure)

$$
\frac{\mathbb{P}\left(\xi_{1}^{\theta_{1}} \in d x\right)}{\mathbb{P}\left(\xi_{1} \in d x\right)}=\frac{e^{\theta_{1} x}}{E\left[e^{\theta_{1} \xi_{1}}\right]}
$$

and, by induction,

$$
\frac{\mathbb{P}\left(Z_{\lfloor n t\rfloor}^{\theta_{1}} \in d x\right)}{\mathbb{P}\left(Z_{\lfloor n t\rfloor} \in d x\right)}=\frac{e^{\theta_{1} x}}{\left(E\left[e^{\left.\theta_{1} \xi_{1}\right]}\right)\right)^{\lfloor n t\rfloor}}
$$

Define $\Lambda_{n}\left(\theta_{1}\right):=\log \left(E\left[e^{\theta_{1} \xi_{1}}\right]\right)^{\lfloor n t\rfloor}$, and consider $\mathbb{P}\left(\bar{Z}_{\lfloor n t\rfloor}>v\right)$. From the proof of Cramér's Theorem (see [7, Chapter 2]) we have, for $\theta_{1}>0$,

$$
\frac{1}{n} \log \mathbb{P}\left(Z_{\lfloor n t\rfloor}>n v\right) \geq-\theta_{1} v-\frac{\lfloor n t\rfloor}{n} \log \left(1-\theta_{1}\right)+\frac{1}{n} \log \mathbb{P}\left(Z_{\lfloor n t\rfloor}^{\theta_{1}}>n v\right)
$$

A straightforward calculation shows that

$$
\frac{1}{n} E\left[\sum_{i=1}^{\lfloor n t\rfloor} \xi_{i}^{\theta_{1}}\right]=\frac{\lfloor n t\rfloor}{n} \frac{1}{1-\theta_{1}}
$$

Thus, we want to twist the random variables such that $\frac{t}{1-\theta_{1}}>v$, in which case $\mathbb{P}\left(Z_{\lfloor n t\rfloor}^{\theta_{1}}>n v\right) \rightarrow 1$ as $n \rightarrow \infty$ by the weak law of large numbers. It follows that

$$
\begin{equation*}
\liminf _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(\bar{Z}_{\lfloor n t\rfloor}>v\right) \geq-\theta_{1} v-t \log \left(1-\theta_{1}\right) \tag{3.6}
\end{equation*}
$$

On the other hand, consider the second probabilistic statement in (3.5),

$$
\mathbb{P}\left(\bar{Z}_{n+1-\lfloor n t\rfloor} \in v\left(-1+\frac{1}{x+\delta},-1+\frac{1}{x-\delta}\right)\right)
$$

Following a similar argument to that above, we consider the twisted random variables $\left\{\xi_{1}^{\theta_{2}}, \ldots, \xi_{n+1-\lfloor n t\rfloor}^{\theta_{2}}\right\}$, and define $\tilde{\Lambda}_{n}\left(\theta_{2}\right):=\log \left(\mathbb{E}\left[e^{\theta_{2} \xi_{1}}\right]\right)^{n+1-\lfloor n t\rfloor}=-(n+1-$ $\lfloor n t\rfloor) \log \left(1-\theta_{2}\right)$ so that $\mathbb{P}\left(\bar{Z}_{n+1-\lfloor n t\rfloor} \in v\left(-1+\frac{1}{x+\delta},-1+\frac{1}{x-\delta}\right)\right)$

$$
\begin{align*}
& =\int_{v(-1+1 /(x+\delta))}^{v(-1+1 /(x-\delta))} \mathbb{P}\left(\bar{Z}_{n+1-\lfloor n t\rfloor} \in d y\right) \\
& =\int_{v(-1+1 /(x+\delta))}^{v(-1+1 /(x-\delta))} e^{-n \theta_{2} y} \exp \left(\tilde{\Lambda}_{n}\left(\theta_{2}\right)\right) \mathbb{P}\left(\bar{Z}_{n+1-\lfloor n t\rfloor}^{\theta_{2}} \in d y\right) \\
& \geq \exp \left(-n \theta_{2} v\left(-1+\frac{1}{(x-\delta)}\right)\right) \exp \left(\tilde{\Lambda}_{n}\left(\theta_{2}\right)\right) \\
& \quad \quad \mathbb{P}\left(\bar{Z}_{n+1-\lfloor n t\rfloor}^{\theta_{2}} \in v\left(-1+\frac{1}{(x+\delta)},-1+\frac{1}{(x-\delta)}\right)\right) \tag{3.7}
\end{align*}
$$

Observe that

$$
\frac{1}{n} E\left[Z_{n+1-\lfloor n t\rfloor}^{\theta_{2}}\right]=\frac{n+1-\lfloor n t\rfloor}{n} \frac{1}{1-\theta_{2}}
$$

Thus, we should twist the random variables such that,

$$
\frac{1-t}{1-\theta_{2}} \in v\left(-1+\frac{1}{(x+\delta)},-1+\frac{1}{(x-\delta)}\right)
$$

implying that $\mathbb{P}\left(\bar{Z}_{n+1-\lfloor n t\rfloor}^{\theta_{2}} \in v\left(-1+\frac{1}{(x+\delta)},-1+\frac{1}{(x-\delta)}\right)\right) \rightarrow 1$ as $n \rightarrow \infty$ as a consequence of the weak law of large numbers. From (3.7) it follows that

$$
\begin{align*}
\liminf _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(\bar{Z}_{n+1-\lfloor n t\rfloor}\right. & \left.\in v\left(-1+\frac{1}{(x+\delta)},-1+\frac{1}{(x-\delta)}\right)\right) \\
& \geq-\theta_{2} v\left(-1+\frac{1}{x+\delta}\right)-(1-t) \log \left(1-\theta_{2}\right) \tag{3.8}
\end{align*}
$$

Using the limits in (3.8) and (3.6) it follows that for any $0<\varepsilon<\delta$,

$$
\begin{aligned}
\liminf _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(T^{n}(t)\right. & \in(x-\varepsilon, x+\varepsilon)) \\
& \geq-\theta_{1} v-t \log \left(1-\theta_{1}\right)-\theta_{2} v\left(-1+\frac{1}{x+\varepsilon}\right)-(1-t) \log \left(1-\theta_{2}\right)
\end{aligned}
$$

This is valid for any $v>t$. In particular, setting $v=x-\varepsilon$ we obtain

$$
\begin{aligned}
\liminf _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(T^{n}(t) \in(x-\varepsilon, x+\varepsilon)\right) \geq & -\theta_{1}(x-\varepsilon)-t \log \left(1-\theta_{1}\right) \\
& -\theta_{2}\left(\frac{x-\epsilon}{x+\varepsilon}\right)(1-(x+\varepsilon))-(1-t) \log \left(1-\theta_{2}\right)
\end{aligned}
$$

Now, consider the function $I\left(\theta_{1}, \theta_{2}\right):=\theta_{1}(x-\varepsilon)+t \log \left(1-\theta_{1}\right)+\theta_{2}\left(\frac{x-\varepsilon}{x+\varepsilon}\right)(1-(x+$ $\varepsilon))+(1-t) \log \left(1-\theta_{2}\right)$. For $\theta_{2}, \theta_{1}<1$, it is straightforward to see that the Hessian is positive semi definite, implying it is convex. The unique minimizer of $I\left(\theta_{1}, \theta_{2}\right)$ is

$$
\begin{gathered}
\left(\theta_{1}^{*}, \theta_{2}^{*}\right)=\left(1-t /(x-\varepsilon), 1-\left(\frac{x+\varepsilon}{x-\varepsilon}\right)\left(\frac{1-t}{1-(x+\varepsilon)}\right)\right) . \text { Letting } \epsilon \rightarrow 0, \text { it follows that } \\
I\left(\theta_{1}^{*}, \theta_{2}^{*}\right)=t \log \left(\frac{t}{x}\right)+(1-t) \log \left(\frac{1-t}{1-x}\right)=I_{t}(x)
\end{gathered}
$$

Thus, we have

$$
\begin{equation*}
\liminf _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(T^{n}(t) \in(x-\delta, x+\delta)\right) \geq-I_{t}(x) \tag{3.9}
\end{equation*}
$$

Next, it follows by definition that, for small enough $\delta>0$,

$$
\frac{1}{n} \log \mathbb{P}\left(T^{n}(t) \in G\right) \geq \sup _{x \in G} \frac{1}{n} \log \mathbb{P}\left(T^{n}(t) \in(x-\delta, x+\delta)\right)
$$

implying that

$$
\liminf _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(T^{n}(t) \in G\right) \geq-\inf _{x \in G} I_{t}(x)
$$

On the other hand, if $t>\sup \{G\}$, we will now consider a $v>1-t>0$ in the lower bounding argument used in (3.5). Since the remaining arguments are identical to the previous steps, we will not repeat them. This proves the LD lower bound.

Finally, observe that the rate function $I_{t}$ is continuous and convex. Consider the level set $L(c)=\left\{x \in[0,1]: I_{t}(x) \leq c\right\}$, for $c>0$. Let $\left\{x_{n}, n \geq 1\right\}$ be a sequence points in the set $L(c)$ such that $x_{n} \rightarrow x^{*} \in(0,1)$ as $n \rightarrow \infty$. Since $I_{t}$ is continuous, it follows that $I_{t}\left(x_{n}\right) \rightarrow I_{t}\left(x^{*}\right)$ as $n \rightarrow \infty$. Suppose $I_{t}\left(x^{*}\right)>c$, then the only way this can happen is if there is a singularity at $x^{*}$. However, this contradicts the fact that $I_{t}$ is continuous on the domain $(0,1)$, implying that $x^{*} \in L(c)$. Therefore, it is the case that $L(c)$ is closed. Furthermore, this level set is bounded (by definition), implying that it is compact. Thus, $I_{t}$ is a good rate function as well.

Now, suppose that $\left\{\tilde{T}_{(i)}, i \leq n\right\}$ are the ordered statistics of random variables with distribution $F$ (assumed to have positive support) that is absolutely continuous with respect to the Lebesgue measure, and strictly increasing. Define

$$
\begin{equation*}
\tilde{I}_{t}(y):=\inf _{x \in[0,1]: F^{-1}(x)=y} I_{t}(x) . \tag{3.10}
\end{equation*}
$$

The following corollary establishes an LDP for the corresponding order statistics process.

Corollary 3.1. Fix $t \in[0,1]$. Then, the ordered statistics process corresponding to $\left\{\tilde{T}_{(i)}, i \leq n\right\}$ satisfies the LDP with good rate function $\tilde{I}_{t}$.

Since $F^{-1}$ maps $[0,1]$ to $[0, \infty)$, which are Hausdorff spaces, the proof is a simple application of the contraction principle [18, (2.12)]. For the remainder of the paper, however, we will operate under the assumption that the arrival epochs are i.i.d. uniform random variables. The analysis below can be straightforwardly extended to the more general case where the distribution is absolutely continuous with respect to the Lebesgue measure.

### 3.2. LDP for the offered load

Next, recall that $\left\{\nu_{i}, i \geq 1\right\}$ is a sequence of i.i.d. random variables with cumulant generating function $\varphi(\theta)=\log \mathbb{E}\left[e^{\theta \nu_{1}}\right]<\infty$ for some $\theta \in \mathbb{R}$. The next theorem shows that the service process $\left(S^{n}(t), t \in[0,1]\right)$ satisfies the LDP.

Lemma 3.1. (Cramér's Theorem [7].) Fix $t \in[0,1]$. Then, the sequence of random variables $\left\{S^{n}(t), n \geq 1\right\}$ satisfies the LDP with good rate function $\Lambda_{t}^{*}(x):=$ $\sup _{\theta \in \mathbb{R}}\{\lambda x-t \varphi(\theta)\}$.

Note that we specifically assume that $0 \in \mathbb{D}$, since [7, Lemma 2.2.5] shows that if $\mathbb{D}=\{0\}$, then $\Lambda_{t}^{*}(x)$ equals zero for all $x$. [7, Lemma 2.2.20] proves that the rate function is good if the interior condition is satisfied. We now establish an LDP for the offered load process $\left(X^{n}(t)=S^{n}(t)-T^{n}(t), t \geq 0\right)$ by leveraging Theorem 3.1 and Lemma 3.1.

Proposition 3.1. Fix $t \in[0,1]$, and let $\mathcal{X}:=[0,1] \times[0, \infty)$. Then, the sequence of random variables $\left\{X^{n}(t), n \geq 1\right\}$ satisfies the LDP with good rate function $J_{t}(y)=$ $\inf _{\left\{x \in \mathcal{X}: x_{1}=x_{2}+y\right\}} I_{t}\left(x_{1}\right)+\Lambda_{t}^{*}\left(x_{2}\right)$ for $y \in \mathbb{R}$.

Proof. [18, Lemma 2.6] implies that $\left\{S^{n}(t), n \geq 1\right\}$ and $\left\{T^{n}(t), n \geq 1\right\}$ are LD tight (as defined in Definition 5). By [18, Corollary 2.9] it follows that $\left(S^{n}(t), T^{n}(t)\right), n \geq 1$ satisfy the LDP with good rate function $\tilde{I}_{t}\left(x_{1}, x_{2}\right)=I_{t}\left(x_{1}\right)+\Lambda_{t}^{*}\left(x_{2}\right)$. Now, since subtraction is trivially continuous on the topology of pointwise convergence, it follows that $\left\{X^{n}(t)=S^{n}(t)-T^{n}(t), n \geq 1\right\}$ satisfies the LDP with rate function $J_{t}$ as a consequence of the contraction principle (see [18, (2.12)]).

As an example of the rate function, suppose the service times are exponentially distributed with mean 1. Then, we have

$$
J_{t}(y)=\inf _{x \in[0,1]}\left\{t \log \left(\frac{t}{x}\right)+(1-t) \log \left(\frac{1-t}{1-x}\right)+t \log \left(\frac{t}{x-y}\right)+(x-y-t)\right\}
$$

Some (tedious) algebra shows that $J_{t}(y)$ is strictly convex, and thus has a unique minimizer, which is the solution to the cubic equation

$$
x^{3}-y x^{2}-2 t x+t y=0
$$

Unfortunately, the sole real solution to this cubic equation has a complicated form, which we do not present, but can be found by using a symbolic solver.

## 4. An LDP for the Workload

Recall that $W^{n}(t)=\Gamma\left(X^{n}\right)(t)=\sup _{0 \leq s \leq t}\left(X^{n}(t)-X^{n}(s)\right)$. The key difficulty in establishing the LDP for $W^{n}(t)$ is the fact that while $\Gamma$ is continuous on the
space $(\mathcal{D}[0,1], \mathcal{U})$, the latter is not a Polish space. Therefore, it is not possible to directly apply the contraction principle to $\Gamma$ to establish the LDP. Consider, instead, the continuous process $\left(\tilde{W}^{n}(t), t \in[0,1]\right)$, formed by linearly interpolating between the jump levels of $W^{n}$; equivalently, $\tilde{W}^{n}=\Gamma\left(\tilde{X}^{n}\right)$, where $\tilde{X}^{n}$ is the linearly interpolated version of the offered load. We first show that $\left(\tilde{W}^{n}(t), t \in[0,1]\right)$ is asymptotically exponentially equivalent to $\left(W^{n}(t), t \in[0,1]\right)$. Next, we prove that, for each fixed $t \in[0,1],\left(\tilde{X}^{n}(s), s \in[0, t]\right)$ satisfies the LDP, via a projective limit. This enables us to prove that $\tilde{W}^{n}(t)$ satisfies the LDP by invoking the contraction principle with $\Gamma$ and using the fact that $(\mathcal{C}[0, t], \mathcal{U})$ is a Polish space. Finally, by [7, Theorem 4.2.13] the exponential equivalence of the processes implies that $W^{n}(t)$ satisfies the LDP with the same rate function.

### 4.1. Exponential Equivalence

We define the linearly interpolated service time process as

$$
\tilde{S}^{n}(t):=S^{n}(t)+\left(t-\frac{\lfloor n t\rfloor}{n}\right) \nu_{\lfloor n t\rfloor+1}
$$

and the linearly interpolated arrival epoch process as

$$
\tilde{T}^{n}(t):=T^{n}(t)+\left(t-\frac{\lfloor n t\rfloor}{n}\right)\left(T_{(\lfloor n t\rfloor+1)}-T_{(\lfloor n t\rfloor)}\right) .
$$

Define $\Delta_{n, t}:=T_{(\lfloor n t\rfloor+1)}-T_{(\lfloor n t\rfloor)}$ and note that these are spacings of ordered statistics. The process $\tilde{X}^{n}=\tilde{S}^{n}-\tilde{T}^{n} \in \mathcal{C}[0,1]$ can now be used to define the interpolated workload process $\tilde{W}^{n}=\Gamma\left(\tilde{X}^{n}\right) \in \mathcal{C}[0,1]$. Recall that $\|\cdot\|$ is the supremum norm on $\mathcal{C}[0,1]$.

Proposition 4.1. The processes $\tilde{W}^{n}$ and $W^{n}$ are exponentially equivalent. That is, for any $\delta>0$

$$
\limsup _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(\left\|\tilde{W}^{n}-W^{n}\right\|>\delta\right)=-\infty
$$

Proof. First, observe that for each $t \in[0,1)$

$$
\begin{aligned}
\left|S^{n}(t)-\tilde{S}^{n}(t)\right| & \leq\left|\left(t-\frac{\lfloor n t\rfloor}{n}\right) \nu_{\lfloor n t\rfloor+1}\right| \\
& \leq \frac{\nu_{\lfloor n t\rfloor+1}}{n}
\end{aligned}
$$

and $S^{n}(1)=\tilde{S}^{n}(1)$ by definition. Similarly,

$$
\left|T^{n}(t)-\tilde{T}^{n}(t)\right| \leq\left(t-\frac{\lfloor n t\rfloor}{n}\right)\left(T_{(\lfloor n t\rfloor+1)}-T_{(\lfloor n t\rfloor)}\right)=\frac{n t-\lfloor n t\rfloor}{n} \Delta_{n, t} \forall t \in[0,1)
$$

and $T^{n}(1)=\tilde{T}^{n}(1)$. Now, let $\left\{E_{1}, \ldots, E_{n+1}\right\}$ be a collection of independent unit mean exponential random variables, and define $Z_{n+1}:=\sum_{i=1}^{n+1} E_{i}$. Recall (from [6, pp. 134-136], for instance) that the spacings of the uniform ordered statistics are equal in distribution to the ratio $\Delta_{n, t} \stackrel{D}{=} \frac{E_{1}}{Z_{n+1}}$. It follows that

$$
\begin{aligned}
\left\|X^{n}-\tilde{X}^{n}\right\| & \leq\left\|S^{n}-\tilde{S}^{n}\right\|+\left\|T^{n}-\tilde{T}^{n}\right\| \\
& \leq\left\|\frac{\nu_{\lfloor n t\rfloor+1}}{n}\right\|+\left\|\left(\frac{n t-\lfloor n t\rfloor}{n}\right) \Delta_{n, t}\right\|
\end{aligned}
$$

Now, consider the measure of the event $\left\{\left\|X^{n}-\tilde{X}^{n}\right\|>2 \delta\right\}$, and use the inequality above to obtain:

$$
\begin{align*}
\mathbb{P}\left(\left\|X^{n}-\tilde{X}^{n}\right\|>2 \delta\right) & \leq \mathbb{P}\left(\left\|\frac{\nu_{\lfloor n t\rfloor+1}}{n}\right\|+\left\|\left(\frac{n t-\lfloor n t\rfloor}{n}\right) \Delta_{n, t}\right\|>2 \delta\right) \\
& \leq \mathbb{P}\left(\left\|\frac{\nu_{\lfloor n t\rfloor+1}}{n}\right\|>\delta\right)+\mathbb{P}\left(\left\|\left(\frac{n t-\lfloor n t\rfloor}{n}\right) \Delta_{n, t}\right\|>\delta\right) \\
& \leq n \mathbb{P}\left(\nu_{1}>n \delta\right)+n \mathbb{P}\left(\Delta_{n, 1}>n \delta\right) \tag{4.1}
\end{align*}
$$

where $\mathbb{P}\left(\left\|\nu_{\lfloor n t\rfloor+1}\right\|>n \delta\right)=\mathbb{P}\left(\left(\sup _{0 \leq t<1} \nu_{\lfloor n t\rfloor+1}>n \delta\right)=\mathbb{P}\left(\cup_{m=1}^{n}\left\{\nu_{i}>n \delta\right\}\right) \leq n \mathbb{P}\left(\nu_{1}>\right.\right.$ $n \delta)$ follows from the union bound and the fact that the service times are assumed i.i.d. Similarly, since $\Delta_{n, t} \stackrel{D}{=} E_{1} / Z_{n+1}$ and $n^{-1}>n^{-1}(n t-\lfloor n t\rfloor)$ for all $t \in[0,1]$ and $n \geq 1$, we obtain the bound on $\Delta_{n, t}$ by similar arguments. Note that we have abused notation slightly in (4.1) and re-used $\Delta_{n, m}=T_{(m)}-T_{(m-1)}$ for $m \in\{1, \ldots, n\}$ with the understanding that $T_{(0)}=0$.

Using Chernoff's inequality to obtain

$$
\mathbb{P}\left(\nu_{1}>n \delta\right) \leq e^{-n \delta \theta_{1}} e^{\varphi\left(\theta_{1}\right)}
$$

so that

$$
\begin{equation*}
\limsup _{n \rightarrow \infty} \frac{1}{n} \log \left(n \mathbb{P}\left(\nu_{1}>n \delta\right)\right) \leq-\theta_{1} \delta \tag{4.2}
\end{equation*}
$$

for all $\theta \in \mathbb{R}$. On the other hand, we have

$$
\begin{aligned}
\mathbb{P}\left(\Delta_{n, 1}>n \delta\right) & =\mathbb{P}\left(E_{1}(1-n \delta)>n \delta Z_{n}\right) \\
& =\int_{0}^{\infty} \mathbb{P}\left(E_{1}>x \frac{n \delta}{1-n \delta}\right) \mathbb{P}\left(Z_{n} \in d x\right)
\end{aligned}
$$

using the fact that $\left\{E_{i}, 1 \leq i \leq n\right\}$ are i.i.d. Again, using Chernoff's inequality, the
right hand side (R.H.S.) satisfies

$$
\begin{aligned}
\text { R.H.S. } & \leq \frac{1}{1-\theta_{2}} \int_{0}^{\infty} \exp \left(-\theta_{2} x \frac{n \delta}{1-n \delta}\right) \mathbb{P}\left(Z_{n} \in d x\right) \forall \theta_{2}<1 \\
& =\frac{1}{1-\theta_{2}}\left(\frac{1-n \delta}{1-n \delta\left(1-\theta_{2}\right)}\right)^{n}
\end{aligned}
$$

It follows that $\limsup _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(\Delta_{n, 1}>n \delta\right)$

$$
\begin{aligned}
& \leq \limsup _{n \rightarrow \infty} \frac{\log \left(1-\theta_{2}\right)}{n}+\limsup _{n \rightarrow \infty} \log \left(\frac{1-n \delta}{1-n \delta\left(1-\theta_{2}\right)}\right) \\
& =-\log \left(1-\theta_{2}\right)
\end{aligned}
$$

and so

$$
\begin{equation*}
\limsup _{n \rightarrow \infty} \frac{1}{n} \log \left(n \mathbb{P}\left(\Delta_{n, 1}>n \delta\right)\right) \leq-\log \left(1-\theta_{2}\right) \forall \theta_{2}<1 \tag{4.3}
\end{equation*}
$$

Now, (4.1), (4.2) and (4.3), together with the principle of the largest term ([7, Lemma 1.2.15]), imply

$$
\limsup _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(\left\|X^{n}-\tilde{X}^{n}\right\|\right) \leq \max \left\{-\theta_{1} \delta,-\log \left(1-\theta_{2}\right)\right\}
$$

Since $\theta_{1} \in \mathbb{R}$ and $\theta_{2} \in(-\infty, 1)$, by letting $\theta_{1} \rightarrow \infty$ and $\theta_{2} \rightarrow-\infty$ simultaneously, it follows that

$$
\begin{equation*}
\limsup _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(\left\|X^{n}-\tilde{X}^{n}\right\|>2 \delta\right)=-\infty \tag{4.4}
\end{equation*}
$$

Finally, using the fact that the map $\Gamma$ is Lipschitz in $\left(\mathcal{D}, J_{1}\right)$ (see [20, Theorem 13.5.1]) we have

$$
\mathbb{P}\left(\left\|W^{n}-\tilde{W}^{n}\right\|>4 \delta\right) \leq \mathbb{P}\left(\left\|X^{n}-\tilde{X}^{n}\right\|>2 \delta\right)
$$

and thus

$$
\begin{equation*}
\limsup _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}\left(\left\|W^{n}-\tilde{W}^{n}\right\|>4 \delta\right)=-\infty \tag{4.5}
\end{equation*}
$$

Since $\delta>0$ is arbitrary, the theorem is proved.

### 4.2. Sample path LDP for the offered load

First, we prove an LDP for the increments of the offered load process. Fix $t \in[0,1]$, and consider an arbitrary $d$-partition of $[0, t], j:=\left\{0 \leq t_{1}<t_{2}<\cdots<t_{d} \leq t\right\}$, so that the increments are $\boldsymbol{\Delta}_{n}^{X}(j)=\boldsymbol{\Delta}_{n}^{S}(j)-\boldsymbol{\Delta}_{n}^{T}(j)$, where

$$
\begin{equation*}
\Delta_{n}^{T}(j):=\left(T^{n}\left(t_{1}\right), T^{n}\left(t_{2}\right)-T^{n}\left(t_{1}\right), \ldots, T^{n}(t)-T^{n}\left(t_{d}\right)\right) \tag{4.6}
\end{equation*}
$$

and

$$
\boldsymbol{\Delta}_{n}^{S}(j)=\left(S^{n}\left(t_{1}\right), S^{n}\left(t_{2}\right)-S^{n}\left(t_{1}\right), \ldots, S^{n}(t)-S^{n}\left(t_{d}\right)\right)
$$

Now, using representation (3.1), it follows that

$$
\Delta_{n}^{T}(j) \stackrel{D}{=} \frac{1}{Z_{n+1}}\left(Z_{\left\lfloor n t_{1}\right\rfloor}, Z_{\left\lfloor n t_{2}\right\rfloor}-Z_{\left\lfloor n t_{1}\right\rfloor}, \ldots, Z_{\lfloor n t\rfloor}-Z_{\left\lfloor n t_{d}\right\rfloor}\right)
$$

A straightforward calculation shows that the cumulant generating function of the $(d+$ 1)-dimensional random vector $\mathbb{Z}_{n}:=\left(Z_{\left\lfloor n t_{1}\right\rfloor}, \ldots, Z_{\lfloor n t\rfloor}-Z_{\left\lfloor n t_{d}\right\rfloor}, Z_{n+1}\right)$ satisfies

$$
\begin{equation*}
\lim _{n \rightarrow \infty} \frac{1}{n} \log \mathbb{E}\left[\exp \left(\left\langle\lambda, \mathbb{Z}_{n}\right\rangle\right)\right]=\Lambda(\lambda) \text { for } \lambda \in \mathbb{R}^{d+1} \tag{4.7}
\end{equation*}
$$

where

$$
\Lambda_{j}(\lambda):= \begin{cases}-\sum_{i=1}^{d}\left(t_{i}-t_{i-1}\right) \log \left(1-\lambda_{i}-\lambda_{d+1}\right)-(1-t) \log \left(1-\lambda_{d+1}\right), & \lambda \in \mathbb{D}_{\Lambda} \\ +\infty, & \lambda \notin \mathbb{D}_{\Lambda}\end{cases}
$$

and $\mathbb{D}_{\Lambda}:=\left\{\lambda \in \mathbb{R}^{d+1}: \max _{1 \leq i \leq d} \lambda_{i}+\lambda_{d+1}<1\right.$, and $\left.\lambda_{d+1}<1\right\}$; note, $t_{0}:=0$. We also define the function

$$
\begin{aligned}
\Lambda_{j}^{*}(\mathbf{x}):=\sup _{\lambda \in \mathbb{D}_{\Lambda}} \sum_{i=1}^{d}\left(\lambda_{i}+\lambda_{d+1}\right) x_{i} & +\left(t_{i}-t_{i-1}\right) \log \left(1-\lambda_{i}-\lambda_{d+1}\right) \\
& +\lambda_{d+1} x_{d+1}+(1-t) \log \left(1-\lambda_{d+1}\right)
\end{aligned}
$$

Now, define the continuous function $\Phi: \mathbb{R}^{d+1} \rightarrow \mathbb{R}^{d}$ as $\Phi(\mathbf{x})=\left(x_{1}, \ldots, x_{d}\right) / \sum_{i=1}^{d+1} x_{i}$. We can now state the LDP for the increments $\boldsymbol{\Delta}_{n}^{T}(j)$.

Lemma 4.1. Let $j:=\left\{0 \leq t_{1}<t_{1}<\cdots<t_{d} \leq t\right\}$ be an arbitrary partition of $[0, t]$. Then the increments of the ordered statistics process, $\Delta_{n}^{T}(j)$, satisfy the LDP with good rate function $\hat{\Lambda}_{j}(\mathbf{y})=\inf _{\mathbf{x} \in \mathbb{R}^{d+1}: \Phi(\mathbf{x})=\mathbf{y}} \Lambda_{j}^{*}(\mathbf{x})$ for all $\mathbf{y} \in(0,1]^{d}$. Furthermore,

$$
\hat{\Lambda}_{j}(\mathbf{y})=\sum_{i=1}^{d}\left(t_{i}-t_{i-1}\right) \log \left(\frac{t_{i}-t_{i-1}}{y_{i}}\right)+(1-t) \log \left(\frac{1-t}{1-\sum_{l=1}^{d} y_{l}}\right)
$$

Proof. Equation (4.7) implies that the sufficient conditions of the Gartner-Ellis Theorem [7, Theorem 2.3.6] are satisfied, so that $\mathbb{Z}_{n}$ satisfies the LDP with rate function $\Lambda_{j}^{*}$. Equivalently, the random vector $\left(Z_{\left\lfloor n t_{1}\right\rfloor}, Z_{\left\lfloor n t_{1}\right\rfloor}-Z_{\left\lfloor n t_{2}\right\rfloor}, \ldots, Z_{\lfloor n t\rfloor}-Z_{\left\lfloor n t_{d}\right\rfloor}, Z_{n+1}-\right.$ $\left.Z_{\lfloor n t\rfloor}\right)$ satisfies the LDP with good rate function $\Lambda_{j}^{*}$. Now, since $\mathbb{R}^{d+1}$ and $\mathbb{R}^{d}$ are Polish spaces, the contraction principle applied to the map $\Phi$ yields the LDP. Finally, it is
straightforward to check that the Hessian of $\Lambda_{j}^{*}(\mathbf{x})$ is positive semi-definite, implying that the latter is convex. It can now be seen that the minimizer $\mathrm{x}^{*}$ is such that $\sum_{j=1}^{d+1} x_{j}^{*}=1$ and $x_{i}^{*}=y_{i}$, for a given $\mathbf{y} \in(0,1]^{d}$. The final expression for $\hat{\Lambda}_{j}(\mathbf{y})$ follows.

As a sanity check, we show that if $d=1$ the rate function $\hat{\Lambda}_{j}(\mathbf{y})$ is precisely the rate function $I_{t}$ in (3.2).

Corollary 4.1. Let $j=\left\{0 \leq t_{1} \leq t\right\}$ and $d=1$, then the rate function is

$$
\hat{\Lambda}_{j}(y)=t_{1} \log \left(\frac{t_{1}}{y}\right)+\left(1-t_{1}\right) \log \left(\frac{1-t_{1}}{1-y}\right), \forall y \in(0,1) .
$$

Proof. Since $d=1$, by definition we have for all $\mathbf{x} \in \mathbb{R}^{2}$

$$
\Lambda_{j}^{*}(\mathbf{x})=\left(\lambda_{1}+\lambda_{2}\right) x_{1}+t_{1} \log \left(1-\lambda_{1}-\lambda_{2}\right)+\lambda_{2} x_{2}+\left(1-t_{1}\right) \log \left(1-\lambda_{2}\right) .
$$

Substituting the unique maximizer $\left(\lambda_{1}^{*}, \lambda_{2}^{*}\right)=\left(\frac{1-t_{1}}{x_{2}}-\frac{t_{1}}{x_{1}}, 1-\frac{1-t_{1}}{x_{2}}\right)$, it follows that

$$
\Lambda_{j}^{*}(\mathbf{x})=\left(x_{1}+x_{2}-1\right)+t_{1} \log \left(\frac{t_{1}}{x_{1}}\right)+\left(1-t_{1}\right) \log \left(\frac{1-t_{1}}{x_{2}}\right) .
$$

Finally, using the fact that $\mathbf{x}^{*}=\arg \inf \left\{\Lambda^{*}(\mathbf{x})\right\}$ satisfies $x_{1}^{*}+x_{2}^{*}=1$, the corollary is proved.

As an aside, note that this result shows that Theorem 3.1 could also be established as a corollary of Lemma 4.1. However, while the proof is straightforward, it is also somewhat 'opaque': the proof of Theorem 3.1 explicitly demonstrates how the longrange dependence inherent in the order statistics process affects the LDP and is, we believe, more clarifying as a consequence. Next, we use this result to prove a sample path LDP for the ordered statistics process ( $\tilde{T}^{n}(s), s \in[0, t]$ ) (for each fixed $t)$ in the topology of pointwise convergence on the space $\mathcal{C}[0, t]$. Observe that the exponential equivalence of $\tilde{T}^{n}$ and $T^{n}$ implies that the increments of $\tilde{T}^{n}$ satisfy the LDP in Lemma 4.1.

Let $\mathcal{J}_{t}$ be the space of all possible finite partitions of $[0, t]$. Note that for each partition $j=\left\{0 \leq t_{1}<t_{1}<\cdots<t_{d} \leq t\right\} \in \mathcal{J}_{t}$, the increments take values in the space $[0,1]^{d}$ which is Hausdorff. Thus, we can appeal to the Dawson-Gartner theorem [7, Theorem 4.6.1] to establish the LDP for the sample path ( $\left.\tilde{T}^{n}(s), s \in[0, t]\right)$ via a projective limit. Let $p_{j}: \mathcal{C}[0, t] \rightarrow \mathbb{R}^{|j|}$ be the canonical projections of the
coordinate maps, and $\mathcal{X}$ be space of all functions in $\mathcal{C}[0, t]$ equipped with the topology of pointwise convergence. Recall that any non-decreasing continuous function $\phi \in$ $\overline{\mathcal{C}}[0, t]$ is of bounded variation, so that $\phi=\phi^{(a)}+\phi^{(s)}$ by the Lebesgue decomposition theorem; here, $\phi^{(a)}$ is the absolutely continuous component and the $\phi^{(s)}$ is the singular component of $\phi$. Recall, too, that a singular component has derivative that satisfies $\dot{\phi}^{(s)}(t)=0$ a.e. $t$.

Lemma 4.2. Fixt $\in[0,1]$. Then the sequence of sample paths $\left\{\left(\tilde{T}^{n}(s), s \in[0, t]\right), n \geq\right.$ 1) satisfies the LDP with good rate function

$$
\hat{\Lambda}_{t}(\phi)=-\int_{0}^{t} \log \left(\dot{\phi}^{(a)}(s)\right) d s+(1-t) \log \left(\frac{1-t}{1-\phi(t)}\right) \quad \forall \phi \in \overline{\mathcal{C}}[0, t] .
$$

Proof. The proof largely follows that of [7, Lemma 5.1.8]. There are two steps to establishing this result. First, we must show that the space $\mathcal{X}$ coincides with the projective limit $\tilde{\mathcal{X}}$ of $\left\{\mathcal{Y}_{j}=\mathbb{R}^{|j|}, j \in \mathcal{J}_{t}\right\}$. This, however, follows immediately from the proof of [7, Lemma 5.1.8]. Second, we must argue that

$$
\tilde{\Lambda}_{t}(\phi):=\sup _{0 \leq t_{1}<\ldots<t_{k} \leq t} \sum_{l=1}^{k}\left(t_{l}-t_{l-1}\right) \log \left(\frac{t_{l}-t_{l-1}}{\phi\left(t_{l}\right)-\phi\left(t_{l-1}\right)}\right)+(1-t) \log \left(\frac{1-t}{1-\phi(t)}\right)
$$

is equal to $\hat{\Lambda}_{t}(\phi)$. Without loss of generality, assume that $t_{k}=t$. Recall that $\phi$ has bounded variation, implying that $\phi^{(a)}(t)=\int_{0}^{t} \dot{\phi}(s) d s$ or, equivalently, $\dot{\phi}^{(a)}(s)=\dot{\phi}(s)$ a.e. $s \in[0, t]$. Since $\log (\cdot)$ is concave, Jensen's inequality implies that

$$
\begin{aligned}
\sum_{l=1}^{k}\left(t_{l}-t_{l-1}\right) \log \left(\frac{\phi\left(t_{l}\right)-\phi\left(t_{l-1}\right)}{t_{l}-t_{l-1}}\right) & =\sum_{l=1}^{k}\left(t_{l}-t_{l-1}\right) \log \left(\frac{\int_{t_{l}}^{t_{l-1}} \dot{\phi}(r) d r}{t_{l}-t_{l-1}}\right) \\
& \geq \sum_{l=1}^{k} \int_{t_{l}}^{t_{l-1}} \log (\dot{\phi}(r)) d r \\
& =\int_{0}^{t} \log \left(\dot{\phi}^{(a)}(r)\right) d r,
\end{aligned}
$$

so that $\tilde{\Lambda}_{t}(\phi) \leq \hat{\Lambda}_{t}(\phi)$.
Next, define

$$
\phi_{n}(r)=n\left(\phi^{(a)}\left(\frac{[n r]+1}{n}\right)-\phi^{(a)}\left(\frac{[n r]}{n}\right)\right)+n\left(\phi^{(s)}\left(\frac{[n r]+1}{n}\right)-\phi^{(s)}\left(\frac{[n r]}{n}\right)\right),
$$

and observe that

$$
\lim _{n \rightarrow \infty} \phi_{n}(r)=\dot{\phi}^{(a)}(r) \text { a.e. } r \in[0, t],
$$

since $n\left(\phi^{(a)}\left(\frac{[n r]+1}{n}\right)-\phi^{(a)}\left(\frac{[n r]}{n}\right)\right) \rightarrow \dot{\phi}^{(a)}(r)$ and $n\left(\phi^{(s)}\left(\frac{[n r]+1}{n}\right)-\phi^{(s)}\left(\frac{[n r]}{n}\right)\right) \rightarrow$ $\dot{\phi}^{(s)}(r)=0$ a.e. $r \in[0, t]$ as $n \rightarrow \infty$. Now, consider the uniform partition $0=t_{0}<t_{1}<$ $\ldots<t_{n}=t$ of $[0, t]$, where $t_{l}=t l / n$, so that $\liminf _{n \rightarrow \infty} \sum_{l=1}^{n} \frac{1}{n} \log \left(n\left(\phi\left(t_{l}\right)-\phi\left(t_{l-1}\right)\right)\right)$

$$
=\liminf _{n \rightarrow \infty} \sum_{l=1}^{n} \frac{1}{n} \log \left(n\left(\phi^{(a)}\left(t_{l}\right)-\phi^{(a)}\left(t_{l-1}\right)\right)+n\left(\phi^{(s)}\left(t_{l}\right)-\phi^{(s)}\left(t_{l-1}\right)\right)\right)
$$

$$
=\liminf _{n \rightarrow \infty} \int_{0}^{t} \log \left(\phi_{n}(r)\right) d r
$$

$$
\geq \int_{0}^{t} \liminf _{n \rightarrow \infty} \log \left(\phi_{n}(r)\right) d r
$$

$$
=\int_{0}^{t} \log \left(\dot{\phi}^{(a)}(r)\right) d r
$$

where the inequality follows from Fatou's Lemma and the last equality is a consequence of the continuity of $\log (\cdot)$. Now, by definition,

$$
\tilde{\Lambda}_{t}(\phi) \geq \liminf _{n \rightarrow \infty}-\sum_{l=1}^{n} \frac{1}{n} \log \left(n\left(\phi\left(t_{l}\right)-\phi\left(t_{l-1}\right)\right)\right)+(1-t) \log \left(\frac{1-t}{1-\phi(t)}\right)
$$

implying that

$$
\tilde{\Lambda}_{t}(\phi) \geq-\int_{0}^{t} \log \left(\dot{\phi}^{(a)}(r)\right) d r+(1-t) \log \left(\frac{1-t}{1-\phi(t)}\right)=\hat{\Lambda}_{t}(\phi)
$$

For the service process, we consider the following result implied by [19]. As noted in [9], the form of Mogulskii's theorem presented in [7, Theorem 5.1.2] does not cover the case of exponentially distributed service times, thus we appeal to the generalization proved in [19]. Note that [19] proves the result in the $M_{1}$ topology on the space $\mathcal{D}[0, t]$ which implies convergence pointwise as required here.

Lemma 4.3. Fix $t \in[0,1]$. Then the sequence of sample paths $\left\{\left(\tilde{S}^{n}(s), s \in[0, t]\right)\right\}$ satisfies the LDP with good rate function, for each $\psi \in \overline{\mathcal{C}}[0, t]$,

$$
\hat{I}_{t}(\psi)=\int_{0}^{t} \Lambda^{*}\left(\dot{\psi}^{(a)}(s)\right) d s+\psi^{(s)}(t)
$$

These two results now imply the LDP for the sequence of sample paths $\left\{\left(\tilde{X}^{n}(s), s \in\right.\right.$ $[0, t])\}$.

Proposition 4.2. Fix $t \in[0,1]$. Then the sequence of sample paths $\left\{\left(\tilde{X}^{n}(s)\right.\right.$, $s \in$ $[0, t])\}$ satisfies the LDP with good rate function, for $\psi \in \mathcal{C}[0, t]$,

$$
\hat{J}_{t}(\psi)=\inf _{\substack{\phi \in \overline{\mathcal{C}}[0, t] \\ \dot{\phi}(s)-\dot{\psi}(s) \geq 0, s \in[0, t]}} \hat{\Lambda}_{t}(\phi)+\hat{I}_{t}(\phi-\psi)
$$

Proof. The independence of $\left(\tilde{T}^{n}(s), s \in[0, t]\right)$ and $\left(\tilde{S}^{n}(s), s \in[0, t]\right)$ for each $n \geq 1$ implies that they jointly satisfy the LDP with good rate function $\hat{\Lambda}_{t}(f)+\hat{I}_{t}(g)$ as a consequence of $[18$, Corollary 2.9], and where $(f, g) \in \overline{\mathcal{C}}[0, t] \times \overline{\mathcal{C}}[0, t]$. Since subtraction is continuous on the Polish space $\mathcal{C}[0, t]$ equipped with the topology of pointwise convergence, applying the contraction principle along with Lemma 4.1 and [7, Lemma 5.1.8] completes the proof.

As an illustration of the result, suppose that the service times are exponentially distributed with mean 1. Define the function

$$
\begin{aligned}
\check{J}_{t}(\phi, \psi):=\int_{0}^{t}\left(\log \left(\dot{\phi}^{(a)}(s)\right)\right. & \left.+s \log \left(\frac{\dot{\phi}^{(a)}(s)-\dot{\psi}^{(a)}(s)}{s}\right)\right) d s \\
& -\left(\phi^{(s)}(t)-\psi^{(s)}(t)-\frac{t^{2}}{2}+(1-t) \log \left(\frac{1-t}{1-\phi(t)}\right)\right)
\end{aligned}
$$

Then, the rate function for the offered load sample path is

$$
\begin{equation*}
\hat{J}_{t}(\psi)=\inf _{\substack{\phi \in \overline{\mathcal{C}}[0, t] \\ \dot{\phi}(t)-\dot{\psi}(s) \geq 0, s \in[0, t]}}-\check{J}_{t}(\phi, \psi) \tag{4.8}
\end{equation*}
$$

We now establish the LDP for the workload process at a fixed $t \in[0,1]$.

Theorem 4.1. Fix $t \in[0,1]$. Then, the sequence of random variables $\left\{W^{n}(t), n \geq 1\right\}$ satisfy the LDP with good rate function $\tilde{J}_{t}(y)=\inf _{\{\phi \in \mathcal{X}: y=\Gamma(\phi)(t)\}} \hat{J}_{t}(\phi)$ for all $y \in \mathbb{R}$.

Proof. Recall that $\Gamma: \mathcal{C}[0, t] \rightarrow \mathcal{C}[0, t]$ is continuous. Furthermore, $\mathcal{C}[0, t]$ (under the topology of pointwise convergence) and $\mathbb{R}$ are Hausdorff spaces. Therefore, the conditions of the contraction principle [7, Theorem 4.2.1] are satisfied. Thus, it follows that $\left\{\tilde{W}^{n}(t), n \geq 1\right\}$ satisfies the LDP with the rate function $\tilde{J}_{t}$. Finally, the exponential equivalence proved in Proposition 4.1 implies that $\left\{W^{n}(t), n \geq 1\right\}$ satisfies the LDP with rate function $\tilde{J}_{t}$, thus completing the proof.

### 4.3. Effective Bandwidths

As noted in Section 2, our primary motivation for studying the large deviation principle is to model the likelihood that the workload at any point in time $t \in[0,1]$ exceeds a large threshold. This is also related to the fact that most queueing models in practice have finite-sized buffers, and so understanding the likelihood that the workload exceeds the buffer capacity is crucial from a system operation perspective. More precisely, if $w \in[0, \infty)$ is the buffer capacity, we are interested in probability of the event $\left\{W^{n}(t)>w\right\}$. Theorem 4.1 implies that

$$
\mathbb{P}\left(W^{n}(t)>w\right) \leq \exp \left(-n \tilde{J}_{t}((w, \infty))\right)
$$

where $\tilde{J}_{t}((w, \infty))=\inf _{y \in(w, \infty)} \tilde{J}_{t}(y)$. A reasonable performance measure to consider in this model is to find the 'critical time-scale' at which the large exceedance occurs with probability at most $p$. That is, we would like to find

$$
t^{*}:=\inf \left\{t>0 \mid \exp \left(-n \tilde{J}_{t}((w, \infty))\right) \leq p\right\}
$$

Consider the inequality $\tilde{J}_{t}((w, \infty)) \geq-\frac{1}{n} \log p$. Using the definition of rate function, we have

$$
\begin{aligned}
\inf _{f \in \mathcal{X}: y=\Gamma(f)(t)} \inf _{\phi \in \overline{\mathcal{C}}_{f}^{0}[0, t]}-\int_{0}^{t}( & \left.\log \left(\dot{\phi}^{(a)}(r)\right)+\Lambda^{*}\left(\dot{\phi}^{(a)}(r)-\dot{f}^{(a)}(r)\right)\right) d r \\
& +(1-t) \log \left(\frac{1-t}{1-\phi(t)}\right)+\left(\phi^{(s)}(t)-f^{(s)}(t)\right) \geq-\frac{\log p}{n}
\end{aligned}
$$

where we define $\overline{\mathcal{C}}_{f}^{0}[0, t]:=\{g \in \overline{\mathcal{C}}[0, t]: \dot{g}(s)-\dot{f}(s) \geq 0, \forall s \in[0, t]\}$ for brevity. The critical time-scale will be the optimizer of this constrained variational problem.

## 5. Conclusions

The large deviation principle derived for the 'uniform scattering' case in this paper provides the first result on the rare event behavior of the $R S / G I / 1$ transitory queue, building on the fluid and diffusion approximation results established in [17, 15, 14, 2]. Our results are an important addition to the body of knowledge dealing with rare events behavior of queueing models. In particular, a standard assumption is that the traffic model has independent increments, while our model assumes exchangeable increments
in the traffic count process by design. We believe that the results in this paper are the first to report large deviations analyses of queueing models under such conditions.

Our next step in this line of research will be to extend the analysis to queues with non-uniform arrival epoch distributions, including distributions that are not absolutely continuous. In this case, the contraction principle cannot be directly applied, complicating the analysis somewhat. In [14] we have made initial progress under a 'near-balanced' condition on the offered load process, where the traffic and service effort (on average) are approximately equal. However, it is unclear how to drop the assumption of near-balancedness. In particular, when the distribution is general, it is possible for the queue to enter periods of underload, overload and critical load in the fluid limit. This must have a significant impact on how the random variables are 'twisted' to rare outcomes. We do not believe it will be possible to exploit (3.1) to establish the LDP. A further problem of interest is to consider a different acceleration regime. In the current setting we assumed that the service times $\nu_{i}$ are scaled by the population size. However, it is possible to entertain alternate scalings, such as $\nu_{i}^{n}=n^{-1} \nu_{i}\left(1+\beta n^{1 / 3}\right)$ as in [2], or scalings that are dependent on the operational time horizon of interest. We leave these problems to future papers.

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