## Fluctuation Scaling in Large Service Systems

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## Outline

1. Introduction
2. Data-Driven Modeling with Domain Knowledge
3. Fluctuation Scaling
4. Staffing Rule
5. Concluding Remarks

Introduction

## Service Systems

## Service System


call centers, hospitals, inventory, ride-sharing, etc.

Optimizing Performance $\approx$ Managing Fluctuations

- Service operations, capacities, schedules: largely controllable
- Arrivals: exogenous, represent a primary source of uncertainty


## Data-to-Decision



- Use data and statistical tools as black magic (x)
- Modeling should be driven by both data and domain knowledge ( $\boldsymbol{\checkmark}$ )


## Standard Approach to Modeling Arrivals

1. Collect arrival data
2. Compute inter-arrival times
3. Fit a probability distribution from popular families (Exp, Gamma, Weibull, etc.)
4. Perform goodness-of-fit test

- Poisson process, renewal process, and their time-varying extensions
- M/•/.
- G/•/.
- $M(t) / \cdot / \cdot$
- $G(t) / \cdot / \cdot$
- and so on...

Does it really matter (that much)?

Data-Driven Modeling with Domain Knowledge

## Spoiler

- Poisson microstructure: inter-arrival times are indeed exponential
- Microstructure does NOT matter much for typical service decisions


## Arrivals to a Ride-sharing Platform

- Uber Pickups (NYC): daily volume 10,000~40,000 in 2014



## Hypothesis Test for Exponentiality of Inter-arrival Times

## Lemma

If $N(t)$ is an inhomogeneous Poisson process with arrival rate $\lambda(t)$, then $N\left(\Lambda^{-1}(t)\right)$ is a standard Poisson process, where $\Lambda(t)=\int_{0}^{t} \lambda(s) \mathrm{d} s$.

- Null hypothesis: arrivals follow an inhomogeneous Poisson process
- Under the null, the time-changed inter-arrival times are i.i.d. exponential
- See also Brown et al. (2005) and Kim and Whitt (2014)




## Impact on Performance?

- Zheng, Zhang, and Glynn (2018)
- Run three different arrival sequences through the same service system

1. Real arrival data
2. Split the real arrivals into intervals of length $x$ minutes; redistribute them randomly within each interval
3. Split the real arrivals into intervals of length $x$ minutes; redistribute them equally spaced within each interval

- Compare performance using synchronized service times


## Distribution of Waiting Times $(x=3)$



## Distribution of Waiting Times $(x=12)$



## Look at the Bigger Picture



- Microstructure does not seem to have much impact on performance
- Should focus on the stochastic behavior over the time scale that is compatible with the service time and matters to decisions


## Known Fact: Overdispersion



- Jongbloed and Koole (2001), Avramidis et al. (2004), Oreshkin et al. (2016)


## Why Important?

- More uncertainty in demand, more requirement for supply
- Newsvendor: if $D \sim \mathcal{N}\left(m, \sigma^{2}\right)$, then $Q^{*}=m+\beta \sigma$, where $\beta$ represents the service level
- Base stock policy under periodic review has a similar formula
- Square-root staffing rule for large service systems

$$
n \approx \frac{\lambda}{\mu}+\beta \sqrt{\frac{\lambda}{\mu}}
$$

- The term $\sqrt{\lambda}$ comes from
- $\operatorname{Var}[A(t)]=\mathbb{E}[A(t)]=\lambda t$ (Poisson arrivals)
- $\operatorname{Var}[A(t)] \sim \mathcal{O}(\lambda t)$ as $\lambda \rightarrow \infty$ (renewal arrivals)

How does fluctuation scale up?

## Fluctuation Scaling

## New Finding: Overdispersion is Amplified by Heavy Traffic



## Power Law Relationship

- Assume a linear relationship at the logarithmic scale

$$
\log (\text { Var. })=p \log (\text { Mean })+c
$$




- $p \approx 1.6$ and $R^{2}=0.99$
- Taylor's law in ecology (Taylor, 1960), also found in physics, finance, etc.
- Conjecture: change safety margin of the staffing rule

$$
\mathcal{O}\left(\lambda^{1 / 2}\right) \longmapsto \mathcal{O}\left(\lambda^{p / 2}\right)
$$

## Another Example (with Spatial Info.)

- Ride information of DiDi Chengdu in Nov. 2016: time and location
- Partition the city into $10 \times 10$ grid, partition one day into 24 hours



## Desirable Features for Arrival Model

- Overdispersion
- Fluctuation scaling with power law
- Poisson microstructure
- Analytical tractability


## Typical Treatment for Overdispersion

- Doubly stochastic Poisson process (DSPP): stochastic arrival rate
- Whitt (1999): $A(t)=N(\lambda G t)$
- $G$ is a random variable with $\mathbb{E}(G)=1$, capturing day-to-day random variation, i.e. "busyness of the day"
- This model implies Var. $\sim \mathcal{O}\left(\lambda^{2}\right)$

$$
\operatorname{Var}(N(\lambda G t))=\lambda t+\lambda^{2} t^{2} \operatorname{Var}(G)
$$

- Overestimate overdispersion: $p \in(0,1)$
- Lack of flexibility


## New Arrival Model

- $A(t):$ a DSPP with arrival rate $X(t)$

$$
\mathrm{d} X(t)=\kappa(\lambda-X(t)) \mathrm{d} t+\sigma \lambda^{\alpha} \sqrt{X(t)} \mathrm{d} B(t)
$$



- $X(t)>0$
- Equilibrium of $X(t)$ is $\lambda$
- Volatility term: $\sigma \lambda^{\alpha} \sqrt{X(t)} \sim \mathcal{O}\left(\lambda^{\alpha+1 / 2}\right)$
- So $\operatorname{Var}[A(t)] \sim \mathcal{O}\left(\lambda^{2 \alpha+1}\right): p=2 \alpha+1$


## Limit Theorem

## Theorem

Suppose $X(t)$ is initialized with its stationary distribution $\pi$ and $\alpha \in\left(0, \frac{1}{2}\right)$. Then, for any given $t>0$,

$$
\frac{A_{\lambda}(t)-\lambda t}{\lambda^{\alpha+\frac{1}{2}}} \Rightarrow \int_{0}^{t} U(s) d s
$$

as $\lambda \rightarrow \infty$, where $U(t)$ is an Ornstein-Uhlenbeck (OU) process

$$
\mathrm{d} U(t)=-\kappa U(t) \mathrm{d} t+\sigma \mathrm{d} B(t)
$$

with initial distribution being its unique stationary distribution, i.e. normal distribution with mean 0 and variance $\frac{\sigma^{2}}{2 \hbar}$.

- Critical for deriving the staffing rule


## Staffing Rule

## Service Quality v.s. Utilization

- Large queueing system: both $\lambda$ and number of servers are large
- Service quality is measured by delay probability
- Goal: find minimum number of servers to make delay probability $\leq \epsilon$
- Key: distribution of queue length


## Infinite-server Queue Approximation

- Consider an infinite-server queue with exponential service times
- Let $Q_{\lambda}(t)$ denote the number of customers in the system
- Consider the scaled number of customers

$$
\tilde{Q}_{\lambda}=\frac{Q(t)-\lambda / \mu}{\lambda^{\alpha+\frac{1}{2}}}
$$

- Show $\tilde{Q}_{\lambda}(t)$ converges a non-degenerate limit $\tilde{Q}_{\infty}(t)$ as $\lambda \rightarrow \infty$
- Compute the stationary distribution of $\tilde{Q}_{\infty}(t)$ as $t \rightarrow \infty$, denoted by $\tilde{Q}_{\infty}$
- $n$ : number of servers in the many-server queue

$$
\epsilon \approx \mathbb{P}\left(Q_{\lambda}(t) \geq n\right)=\mathbb{P}\left(\tilde{Q}_{\lambda}(t) \geq \frac{n-\lambda / \mu}{\lambda^{\alpha+\frac{1}{2}}}\right) \approx \mathbb{P}\left(\tilde{Q}_{\infty} \geq \frac{n-\lambda / \mu}{\lambda^{\alpha+\frac{1}{2}}}\right)
$$

- Let $\beta$ solves $\mathbb{P}\left(\tilde{Q}_{\infty} \geq \beta\right)=\epsilon$, then

$$
n^{*} \approx \frac{\lambda}{\mu}+\beta \cdot \lambda^{\alpha+\frac{1}{2}}
$$

- $\beta$ can be computed explicitly


## Stationary Distribution $\tilde{Q}_{\infty}$

- By virtue of the exponential service assumption,

$$
Q_{\lambda}(t)=Q_{\lambda}(0)+A_{\lambda}(t)-N^{\prime}\left(\mu \int_{0}^{t} Q_{\lambda}(s) d s\right)
$$

where $N^{\prime}(\cdot)$ is an independent Poisson process with unit rate

$$
\begin{aligned}
Q_{\lambda}(t)-\frac{\lambda}{\mu}= & Q_{\lambda}(0)-\frac{\lambda}{\mu}+A_{\lambda}(t)-\lambda t-\mu \int_{0}^{t} Q_{\lambda}(s) \mathrm{d} s-\lambda t \\
& -N^{\prime}\left(\mu \int_{0}^{t} Q_{\lambda}(s) \mathrm{d} s\right)-\mu \int_{0}^{t} Q_{\lambda}(s) \mathrm{d} s
\end{aligned}
$$

- Scaled by $\lambda^{\alpha+\frac{1}{2}}$ and letting $\lambda \rightarrow \infty$

$$
\tilde{Q}_{\infty}(t)=\tilde{Q}_{\infty}(0)+\int_{0}^{t} U(s) \mathrm{d} s-\mu \int_{0}^{t} \tilde{Q}_{\infty}(s) \mathrm{d} s-0
$$

- Solve the equation

$$
\tilde{Q}_{\infty}(t)=\int_{0}^{t} U(s) e^{\mu(t-s)} d s
$$

- The Laplace transform of $\tilde{Q}_{\infty}(t)$ can be computed analytically
- Sending $t \rightarrow \infty$ yields the Laplace transform of $\tilde{Q}_{\infty}$
- normal distribution
- parameters can be calculated analytically
- Easy to compute $\beta$ in the staffing rule

$$
n \approx \frac{\lambda}{\mu}+\beta \cdot \lambda^{\alpha+\frac{1}{2}}
$$

by $\mathbb{P}\left(\tilde{Q}_{\infty} \geq \beta\right)=\epsilon$

## Performance in Practice

- Call center of a U.S. bank
- Use customer arrivals in weekdays in 2002
- A constant staffing level for each 30-min time period
- 48 staffing levels for a day in total
- Static staffing: no day-to-day adjusting
- Simulate the system with real customer arrivals and exponential service

| Target Quality of Service | Our Staffing Rule | Square-root Staffing Rule |
| :---: | :---: | :---: |
| 0.20 | 0.230 | 0.537 |
| 0.10 | 0.137 | 0.469 |
| 0.05 | 0.084 | 0.439 |

## Concluding Remarks

## Conclusions

- Modeling should be driven by both data and decisions
- Arrivals' microstructure is Poisson but has little impact on performance
- Stochastic behavior at longer time scale matters, e.g., overdispersion
- Overdispersion is amplified by heavy traffic
- Fluctuation scales up following a power law
- Proposed New tractable arrival model to capture the power law
- Developed the associated staffing rule with safety margin $\mathcal{O}\left(\lambda^{\alpha+1 / 2}\right)$

Questions?

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