

Networks: Design, Analysis and Optimization

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Research Domain

- Scheduling Theory
- Queueing Theory
- Stochastic optimal control
- Game Theory
- and their application to the performance evaluation, conception and dimensioning of communication networks and distributed systems.

Outline of the talk

• Introduction to Stochastic Processes

• Three examples of on-going research

Stochastic Process

- A stochastic process $(N(t))_{t\geq 0}$ is a sequence of random variables indexed by t .
- Randomly evolving dynamical system
- Characterization by first order statistics
	- distribution $\mathbb{P}(N(t) \leq y)$ as a function of t
	- mean $\mathbb{E}[N(t)]$ and variance $\mathbb{E}[N(t)]$
	- Simulation, Analysis, Comparison, Optimization, Control...?

Transient vs. Steady-State

Let $N = \lim_{t \to \infty} N(t)$ denote number of customers in steady-state. Simplest random-walk: $N \rightarrow N+1$ at rate λ and $N \to N-1$ at rate μ . Then $\mathbb{P}(N=n) = (\lambda/\mu)^n (1-\lambda/\mu)$.

Analysis of Steady-State

- Let $\pi_j = \lim_{t \to \infty} \mathbb{P}(N(t) = j)$ denote the steady-state probability
- The number of times the **process departs** from state j is equal to the number of times the process arrives to this state.

- In equilibrium it holds $\pi_j = \sum_i \pi_i p_{ij}$
- Questions: Existence, uniqueness, closed-form, numerical <u>resolution</u>

Little's law: Relation between mean number of jobs and Mean response time

$$
\int_0^t N(s)ds = T_1 + T_2
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In general we have

$$
\frac{1}{t} \int_0^t N(s)ds \approx \frac{1}{t} \sum_{i=1}^{A(t)} T_i
$$

and thus Little's Law states: $\mathbb{E}[N] = \lambda \mathbb{E}[T]$

Jackson, BCMP and Kelly networks

Jackson, BCMP and Kelly networks

 $\mathbb{P}(N_1=n_1, N_2=n_2, \ldots, N_K=n_K)=\Pi^K_{i=1}$ $i=1$ $\mathbb{P}(N_i = n_i)$ where $\mathbb{P}(N_i = n_i) = (\lambda/\mu)^{n_i} (1 - \lambda/\mu)$.

In steady-state the queues behave as if they were isolated and independent from each other.

• Heavy-Traffic, when the system is in saturation [VAN09]

$$
\lim_{\lambda \to \mu} (\mu - \lambda) \mathbb{P}(N_1 = n_1, N_2 = n_2, \dots, N_K = n_K) \stackrel{d}{=} X \cdot (\rho_1, \rho_2, \dots, \rho_K)
$$

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• Fluid limit. For large Δ , $N(\Delta t) \approx N(\Delta(t-\epsilon)) + \lambda \Delta \epsilon - \mu \Delta \epsilon$. In certain cases it holds $\lim_{\Delta\to\infty}$ $N(\Delta t)$ $\frac{d\Delta t}{\Delta}$ = n(t) where n(t) is the solution of an ordinary differential equation. For the previous example $\frac{dn(t)}{dt}$ $\frac{d u(t)}{dt} = \lambda - \mu$. Performance Evaluation and Optimal Control [APZ08]

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- Sample-path Comparison [VAB09]

If $\vec{W}^{\pi}(0) = \vec{W}^{\tilde{\pi}}(0)$, then

i) N_0^{π} $\tilde{\gamma}_0^{\pi}(t) \geq N_0^{\tilde{\pi}}$ $\int_0^{\tilde{\pi}}(t)$ and W_0^{π} $W^{\pi}_{0}(t)\geq W^{\tilde{\pi}}_{0}$ $\tilde{0}^{\pi}(t),$

ii) W_0^{π} $W^{\pi}_{0}(t) + W^{\pi}_{i}(t) \geq W^{\tilde{\pi}}_{0}$ $\tilde{\frac{\pi}{0}}(t)+W_i^{\tilde{\pi}}(t)$

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- ii) W_0^{π} $W^{\pi}_{0}(t) + W^{\pi}_{i}(t) \geq W^{\tilde{\pi}}_{0}$ $\tilde{\frac{\pi}{0}}(t)+W_i^{\tilde{\pi}}(t)$
	- Mean Field Limit, Large deviations and Differential Traffic T h e o r y

Heavy-Traffic: State space collapse

Three examples

- Size-based Scheduling
- Conservation Law in queues
- Server Farms

Fair Policy: Processor Sharing Policy

- Processor-Sharing (PS): All present jobs in the system get a fair share of service. If there are N jobs, each job gets served at $\mathrm{rate_1}/N.$
- An acceptable model for (i) data networks at high load (ii) web servers and (iii) CPU
- Well-studied [Kleinrock, Yashkov, Cohen, Kelly, Boxma, Robert]

Example 1: Size-based scheduling

- Experimental evidence: Mice and Elephants traffic pattern, 80% of the connections are short, 5% of largest flows make up for 95% of the load
- Preferential treatment to short connections?
- Evaluate the performance consequences:
	- To what extent is the performance of large connections degraded?
	- What happens to the average number of connections? What are the consequence?

$2\mathrm{PS}(\mathrm{a})$

Jobs are classified into two groups depending on the amount of service they have received.

- High Priority: Jobs that have obtained less units of service than a .
- Low Priority: Jobs that have obtained more units of service than a . Within one priority level, jobs are served according to PS.

Asymptotic throughput of $2PS(a)$

Theorem [AAB06]: The throughput obtained by large jobs is the same under both systems

$$
\lim_{x \to \infty} \frac{x}{\mathbb{E}[T^{2PS}|X=x]} = \frac{x}{\mathbb{E}[T^{PS}|X=x]}
$$

Comparison between $2PS(a)$ and PS

Theorem [AA05]: If the hazard rate of the distribution function is decreasing:

 $\mathbb{E}[N^{2PS}]\leq \mathbb{E}[N^{PS}]$

Example 2: Conservation Law for single server queues

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Let $W(t)$ denote the total work in the system at time t. The evolution of $W(t)$ is **independent** of the scheduling policy.

Conservation Law for single server queues

Theorem [A07]: In a single server queue with M classes with arbitrary $\text{scheduling discipline} \pi$:

$$
\sum_{j=1}^{M} \lambda_j \int_0^{\infty} \mathbb{E}[T_j^{\pi}|X_j = x] \mathbb{P}(X_j > x) dx = \mathbb{E}[W]
$$

- Application to comparison of policies $\mathbb{E}[T^{\pi_1}] \leq \mathbb{E}[T^{\pi_2}]$ [A07]
- Characterization of large sojourn times $\lim_{x\to\infty} \mathbb{E}[T_j^{\pi}|X_j=x]$ [AAB08]

Example 3: Server farms

• Diverse applications : e-service industry, database systems, grid computing clusters

Design problem: What is the optimal routing policy?

- Centralized setting: dispatcher takes decisions
- Decentralized setting: requests take decisions

Decentralized setting: Wardrop equilibrium

Total flow from S to N is 6

Wardrop equilibrium: 3 units travel via W , and 3 via E

Total Delay: $(10 \times 3) + (3 + 50) = 83$

Comparing the Global and Individual: Braess' Paradox

A new link is added:

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There are 3 possible routes with the same delay:

 $(10 \times 4) + (2 + 50) = 92$

 $(10\times4) + (2+10) + (10\times4) = 92$

Adding a new link increases everyone's delay!

Example application

Internet based source code repositories - SourceForge, Google Code: Source files are hosted on several mirror sites

- Decision is taken either by the central unit or by the downloader
- Downloads progress in parallel \Rightarrow Processor Sharing (PS) at each server

Centralized setting

 $\bullet\,$ Solve the following mathematical program :

Decentralized setting

Equilibrium: A strategy **p** is an equilibrium if for each class $i = 1, ..., K$ and each queue k used by class i,

> $\mathbb{E}[c_k T_k(\mathbf{p})|i] = \min_{i=1}$ $j=1,...,K$ $\mathbb{E}[c_jT_j(\mathbf{p})|i]$

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$$

Potential Games. The distributed non-cooperative game can be transformed into the standard convex optimization problem

$$
\min_{\mathbf{p}} \quad \sum_{k=1}^{C} c_k \log \left(\frac{1}{1 - \rho_k(\mathbf{p})} \right)
$$
\n
$$
\text{subject to} \quad 0 < \rho_j < 1, \quad \sum_j r_j \rho_j = \overline{\eta}.
$$

 \Rightarrow The game belongs to a particular type of games known as "Potential Game" [Shapley et al. 1996]

Comparing the Global and Individual

Price of Anarchy: [Papadimitriou 98] Defined as the ratio between the performance (mean delay) obtained by the Wardrop equilibrium and the global optimal solution.

 \Rightarrow A measure for the inefficiency of the decentralized scheme.

$$
PoA = \sup_{\vec{\lambda}, \vec{c}, \vec{r}} \left(\frac{\text{Performance Decimalized Setting}}{\text{Global optimum}} \right); \quad PoA \in [1, \infty)
$$

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Theorem [AAP08]. For every θ , there exist c_j and r_j , $j \in S$, such that $PoA > \theta$.

 \Rightarrow The PoA is unbounded.

If $c_k = 1$, then $PoA \le C$ [Haviv and Roughgarden, 2007].

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Theorem [ABP09]. If there are K selfish users, then $PoA =$ √ K

Missing result...

$$
\text{Max}_{\vec{\lambda}:\sum_{k}\lambda_{k}=\Lambda} \quad \sum_{i=1}^{K} D_{i}(\mathbf{p}_{1}^{*}(\vec{\lambda}), \dots, \mathbf{p}_{\mathbf{K}}^{*}(\vec{\lambda}))
$$
\nwhere\n
$$
\mathbf{p}_{1}^{*}, \dots, \mathbf{p}_{\mathbf{K}}^{*} \text{ is s.t.}
$$
\n
$$
D_{i}(\mathbf{p}_{1}^{*}, \dots, \mathbf{p}_{\mathbf{K}}^{*}) = \min_{\mathbf{p}_{i}:\sum_{j=1}^{L} p_{ij} = \lambda_{i}} D_{i}(\mathbf{p}_{1}^{*}, \dots, \mathbf{p}_{i-1}^{*}, \mathbf{p}_{i}, \mathbf{p}_{i+1}^{*}, \dots, \mathbf{p}_{\mathbf{K}}^{*})
$$

Conjecture: The solution is $\vec{\lambda} = (\Lambda/K, \ldots, \Lambda, K)$?

Conclusions and Future work

- Interaction between Game Theory and Queueing
- Wireless Systems. Capacity Changes over time.
	- Need for new mathematical model and paradigms
- Wired Networks. Internet will be everywhere. Elastic (web, email, ...) and Streaming (VoIP, video-on-demand) applications with very different QoS requirements
	- Need for new mathematical models for the design and performance evaluation of such networks.
- Power might be the key performance criteria!
- Peer-to-Peer Networks, AdHoc Networks