

# Scheduling for Multiclass Many-server Queues with Abandonment: the $c\mu/\theta$ Rule and its Generalizations

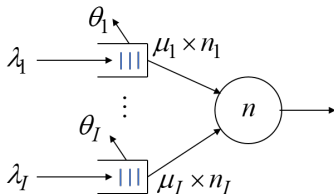
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- The first part is joint work with Chanit Giat and Rami Atar (Technion).
- The second part is joint work with Zhenghua Long, Hailun Zhang and Jiheng Zhang (HKUST)

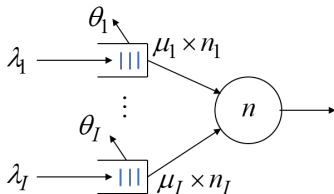
# THE BASIC MODEL



Consider a queueing systems with:

- $n$  identical servers
- Finite set  $\mathcal{I} = \{1 \dots I\}$  of customer classes
- Poisson arrivals, with rates  $\lambda_i, i \in \mathcal{I}$
- Exponential service times, with means  $\mu_i$
- *Impatient customers*: exponential patience time, with mean  $\theta_i$

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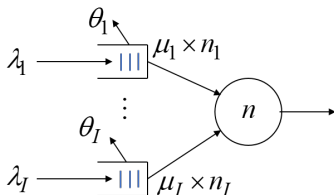
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We focus here on the case of an **overloaded system**:

$$\sum_i \frac{\lambda_i}{\mu_i} > 1$$

# COST PARAMETERS



- Waiting cost parameter  $c_i$

Our cost function:

$$J(T) = \frac{1}{T} \mathbb{E} \int_0^T \sum_{i=1}^I c_i Q_i(t) dt$$

(for large  $T$ ).

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Since patience is exponentially-distributed,

$$\mathbb{E}(dN_t^{aban}(t)) = \theta_i Q_i(t),$$

and this cost reduces to the previous one with  $c_i \leftarrow c_i + \gamma_i \theta_i$ .



# PRIORITY RULES

- For the single-server queue with no abandonment, the optimal scheduling policy is the celebrated  $c\mu$  index rule [Cox & Smith 1951, etc.]
- For the same queue with convex delay costs, the generalized  $c\mu$  rule is asymptotically optimal under the heavy-traffic diffusion regime [Van Mieghem 1995].

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- We wish to find a simple scheduling policy, which is close to optimal under suitable conditions.

# FLUID SCALING

- We consider the case of **many servers**, namely  $n \rightarrow \infty$ .
- Accordingly, we let  $\lambda_i^n = n\lambda_i$ .  
 $\mu_i, \theta_i$  and the cost parameters are not scaled.

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The scaled cost function:

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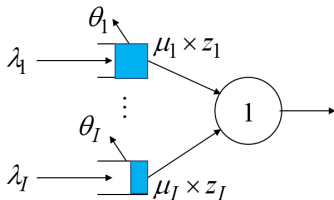
- Many-server fluid approximations of queueing systems with abandonments were studied, among others, by [Mandelbaym, Massey & Reiman 1998], [Whitt 2004] ( $M/M/n + M$ ).  
[Whitt 2006] suggested a heuristic model for the  $G/GI/n + G$  queue.
- *Control* problems in the queueing regime were considered for example in [Bassamboo, Harrison & Zeevi 2007], who considered suboptimal routing and admission control policies that track the solution of the fluid model.

# OUR PLAN

- Use a simplified fluid model to get some ideas for effective policies.
- Translate these policies to the original (stochastic) system.

# THE FLUID MODEL

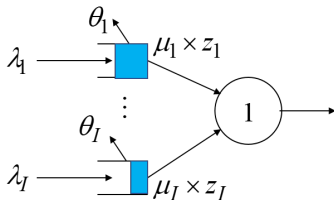
- Let us scale the arrival, departure and abandonment processes by  $\frac{1}{n}$ , assume that they are stationary, and focus on their rates. We arrive heuristically at the following static fluid model:



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- Flow balance equations (with fixed queue lengths):

$$\lambda_i = z_i \mu_i + \theta_i q_i$$

if  $\lambda_i \geq z_i \mu_i$ , otherwise  $q_i = 0$ .



# THE FLUID LP PROBLEM

- Our optimization problem:

$$\min_{\{z_i\}} \sum_i c_i q_i$$

$$\text{s.t. } \lambda_i = \mu_i z_i + \theta_i q_i; \quad z_i \geq 0, \sum_i z_i \leq 1; \quad q_i \geq 0 \implies z_i \leq \frac{\lambda_i}{\mu_i}$$

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- Substituting for  $q_i$ :

$$\sum_i c_i q_i = \sum_i c_i \frac{\lambda_i - \mu_i z_i}{\theta_i} = (\dots) - \sum_i z_i \frac{c_i \mu_i}{\theta_i}$$

- The solution now is obvious...

# THE FLUID SOLUTION

- Renumber the classes in *decreasing* order of the index  $\frac{c_i \mu_i}{\theta_i}$

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- Set

$$(z_1, \dots, z_I) = \left( \frac{\lambda_1}{\mu_1}, \dots, \frac{\lambda_{k-1}}{\mu_{k-1}}, z_k, 0, \dots, 0 \right)$$

where

$$k = \min\{j : \sum_1^j \frac{\lambda_i}{\mu_i} > 1\}, \quad z_k = 1 - \sum_1^{k-1} z_i$$

This yields

$$(q_1, \dots, q_I) = (0, \dots, 0, q_k > 0, \frac{\lambda_{k+1}}{\theta_{k+1}}, \dots, \frac{\lambda_I}{\theta_I})$$

# THE FULL INDEX

- Substituting  $c_i \leftarrow c_i + \gamma_i \theta_i$  gives

$$\frac{c\mu}{\theta} \rightarrow \frac{(c + \gamma\theta)\mu}{\theta} = \left(\frac{c}{\theta} + \gamma\right)\mu$$

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- We note that in [Ayesta, Jacko & Novak 2017], the same index (with some additional cost terms) is derived using the Whittle index for restless bandits.

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- Fix priority rule: Assign servers to waiting customers with the highest  $\frac{c\mu}{\theta}$  index. (Preemptive or nonpreemptive.)

Advantages:

✓ No server idleness

✓ Policy does not depend on  $(\lambda_i)$

# ASYMPTOTIC OPTIMALITY

- Denote by  $v^*$  the optimal value of the fluid LP problem.
- Recall that  $J^{n,T}(\pi) = \frac{1}{nT} \mathbb{E}^\pi \int_0^T \sum_{i=1}^I c_i Q_i^n(t) dt$
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- We show first that

$$\liminf_{T \rightarrow \infty} \liminf_{n \rightarrow \infty} J^{n,T}(\pi_n) \geq v^*$$

for any sequence  $\{\pi_n\}$  of policies (not necessary stationary).

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[Atar, Giat & Sh. 2010]

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[Atar, Giat & Sh. 2010]
- We repeat the above for the ergodic cost: Limits taken in the opposite order.

[Atar, Giat & Sh. 2011]

# The Controlled Process and General Policies

- The processes involved (for given  $n$  - omitting the  $n$  superscript)
  - ▶  $A_i, D_i, R_i$ : cumulative number of arrivals / service completions / reneging on  $[0, t]$ .
  - ▶  $X_i, Q_i, Z_i$ : Number of jobs in the system / queue (unserved) / service at  $t$ ;  $X_i = Q_i + Z_i$ .

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- Stochastic Primitives:  $(\tilde{A}_i, \tilde{D}_i, \tilde{R}_i) \sim$  Independent Poisson processes, with rates  $n\lambda_i, \mu_i, \theta_i$ ; and IC's  $X_i(0)$ .
- Define

$$D_i(t) = \tilde{D}_i\left(\int_0^t Z_i(s)ds\right), \quad R_i(t) = \tilde{R}_i\left(\int_0^t Q_i(s)ds\right)$$

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item Additional relations:

$$X_i(t) = X_i(0) + (A_i - D_i - R_i)(t)$$

$$Q_i \geq 0, \quad 0 \leq Z_i \leq n$$



# Policies

- A **policy** is now defined implicitly as any tuple
$$\pi^n = (D_i^n, R_i^n, X_i^n, Q_i^n, Z_i^n)$$
that satisfies the above-mentioned relations.
- The implied policies include history-dependent, non-stationary policies – and in fact also non-causal policies.

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## Fluid scaling:

- The time-dependent **fluid model** is obtained as the limit in  $n \rightarrow \infty$  of the scaled processes  $(\frac{1}{n}D_i^n, \frac{1}{n}R_i^n, \dots)$  (whenever the limits exist).
- When these processes converge to a constant, we obtain the static model discussed above.

# Non-exponential Patience Distributions

# General Patience Distributions

- Fluid models for (many-server) queues with abandonment and generally-distributed patience become more complicated, as they require measure-valued processes to describe the (remaining) patience of customers in the queue.
- The fluid limit of a multiclass queueing system with  $G/GI/n + GI$  queues under fixed priority policies was analyzed in Atar, Kaspi & Sh. (2014), extending the approach of Kaspi & Ramanan (2011), Kang & Ramanan (2012) to the multiclass case.

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- We outline here some initial results in the fluid model that pertains to the simpler  $G/M/n + GI$  case, along with *nonlinear* holding costs.

# Elements of the Fluid Model

- $F_i$  is the patience distribution of class  $i$ , with hazard-rate function  $h_i$ .
- $X_i(t) = Q_i(t) + B_i(t)$  is the number of class- $i$  customers in the system (# in queue + # in service).

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- $X_i(t) = Q_i(t) + B_i(t)$  is the number of class- $i$  customers in the system (# in queue + # in service).
- Cost function:

$$J_T(\pi) = \frac{1}{T} \sum_{i=1}^I \left[ \int_0^T C_i(Q_i(s)) ds + \gamma_i R_i(T) \right].$$

where  $C_i(q)$  is a no-decreasing holding cost function, and  $R_i(T)$  is the number of abandonments by time  $T$ .

# Steady State Fluid Model

- For a given non-idling scheduling policy  $\pi$ , suppose  $Q_i(t) \rightarrow q_i$ , and  $B_i(t) \rightarrow b_i$  (actually one implies the other).
- Then  $0 \leq b_i \leq \lambda_i/\mu_i$ ,  $\sum_{i=1}^I b_i = n$ , and

$$q_i = \lambda_i \int_0^{F_i^{-1}(1-b_i\mu_i/\lambda_i)} F_i^c(s) ds$$



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$$q_i = \lambda_i \int_0^{F_i^{-1}(1-b_i\mu_i/\lambda_i)} F_i^c(s) ds$$

- Therefore,

$$\lim_{T \rightarrow \infty} J_T(\pi) = \sum_{i=1}^I J_i(b_i)$$

where

$$J_i(b_i) = C_i \left( \lambda_i \int_0^{F_i^{-1}(1-b_i\mu_i/\lambda_i)} F_i^c(s) ds \right) + \gamma_i (\lambda_i - b_i \mu_i).$$

# Fluid Optimization Problem

In terms of the steady state of the fluid model, we obtain the optimization problem:

$$\begin{aligned} & \text{minimize} && \sum_{i=1}^I J_i(b_i) \\ & \text{subject to} && \sum_{i=1}^I b_i \leq n, \\ & && 0 \leq b_i \leq \frac{\lambda_i}{\mu_i}, \quad i = 1, \dots, I. \end{aligned} \tag{1}$$

The decision variables  $b_i$ 's can be intuitively understood as the amount of service resources that are assigned to class  $i$  customers in the long run.

# Fluid Optimization Problem: The concave Case

- Suppose that the holding cost functions  $C_i$  is *concave*, and the patience hazard rate functions  $h_i$  are *nondecreasing*. Then the optimization problem is **concave**.

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- Suppose that the holding cost functions  $C_i$  is *concave*, and the patience hazard rate functions  $h_i$  are *nondecreasing*. Then the optimization problem is **concave**.
- In that case the optimal solution is at the extreme point of the feasible region, which implies a fixed priority rule. In particular, there exists a fixed priority rule  $\pi^*$  such that each  $B_i(t)$  converges to the optimal solution  $b_i^*$ .
- Hence, the average cost  $J_T(\pi^*)$  converges to the optimal steady state solution as  $T \rightarrow \infty$ .

# The convex Case

- Suppose that the holding cost functions  $C_i$  are *convex*, and the patience hazard rate functions  $h_i$  are *nonincreasing*. Then the optimization problem is **convex**.
- Assuming further strict convexity and an interior solution, the KKT optimality conditions for this problem imply

$$P_i(b_i) := \frac{C'_i(\lambda_i \int_0^{F_i^{-1}(1-b_i\mu_i/\lambda_i)} F_i^c(s) ds) \mu_i}{h_i(F_i^{-1}(1-b_i\mu_i/\lambda_i))} + \gamma_i \mu_i + \alpha_i \mu_i - \beta_i \mu_i$$
$$= \text{constant}$$

along with  $\sum_i b_i = n$ .

## The convex Case - Generalized $c\mu/\theta$ rule.

- This motivates us to consider the following *dynamic* priority rule:

At time  $t$ , assign priority in decreasing order of  $P(B_i(t))$

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- This motivates us to consider the following *dynamic* priority rule:

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- Under this policy, each  $B_i(t)$  converges to the optimal solution  $b_i^*$ .
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# A General Priority Rule: The Target-Setting Policy

- Let  $(b_i^*)$  be an optimal solution of the steady-state optimization problem.
- Consider the time-varying priority rule

At time  $t$ , assign priority in decreasing order of  $P_i(t)$

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- Then similar convergence properties hold, namely  $B_i(t) \rightarrow b^*$ , and  $J_T(\pi) \rightarrow J^*$ .