Scheduling Impatient Customers in a Multiclass Many-Server Queue Performance 2020 38th International Symposium on Computer Performance, Modeling, Measurements and Evaluation

Amy R. Ward *joint work with Amber Puha



Paper link: https://faculty.chicagobooth.edu/Amy.Ward/papers/Puha-Ward-Weak-Convergence-2019.pdf



Why Do We Care About Scheduling?



An Early (Deterministic) Scheduling Problem

Processing time V_1 Processing time V_2 Processing rate $\mu_1 = 1/V_1$ Processing rate $\mu_2 = 1/V_2$ Waiting cost c_1 Waiting cost c_2

Objective: Determine the schedule that minimizes the waiting cost.

Schedule	Cost
(1,2)	c_2V_1
(2,1)	c_1V_2

We prefer the schedule (1,2) iff $c_2V_1 < c_1V_2$, or, equivalently, $c_2\mu_2 < c_1\mu_1$. The very appealing $c\mu$ rule: Order classes and give priority in that order.

The $c\mu$ Rule

<u>Optimal</u>

- In the Stochastic Setting; Pinedo (1983)
- When there are due dates; Smith (1956) and Pinedo (1983)
- Multiclass (mc) M/G/1 with feedback; Klimov (1974)

Asymptotically Optimal

- Convex delay costs in mc G/G/1; van Mieghem (1995)
- Heterogeneous servers in mc G/G/N; Mandelbaum and Stoylar (2004)
- Server pools in mc G/M/N; Gurvich and Whitt (2009)

Q: What happens when jobs will not wait forever?

We will study this question in a many-server queue with abandonment.

The $c\mu$ Rule when Jobs may Abandon



Atar, Giat, Shimkin (2010) The $\tilde{c}_{j}\mu_{j}/\theta_{j}$ rule asymptotically minimizes long-run average cost in a M/M/N+M queue the overloaded regime $(\tilde{c}_{j} = c_{j} + \theta_{j}a_{j})$.

The $c\mu$ and $\tilde{c}\mu/\theta$ rules is a **static priority (SP) scheduling policy** in the sense that the decision of who to next serve does not depend on system state.



Assume overloaded regime.

Admissible scheduling policy is HL, non-anticipating, does not have wild oscillations.

Connection to learning: Should be easier if an ao policy has a simple form.
Any questions?



Talk Outline

1. Provide a fluid model relevant for a large class of non-preemptive HL scheduling policies.

- > Show limit points of scaled state processes are fluid model solutions (PW, Theorem 1).
- Establish tightness (PW, Theorem 2).

- 2. Formulate and solve a fluid control problem for an overloaded system.
 - > Characterize fluid invariant states (PW, Proposition 1).
 - > Provide weak convergence theorem for appropriate scheduling policy (PW, Theorem 3).

Some Works Related to Step 1

(Provide fluid model relevant for a large class of HL scheduling policies.)

- Single Class Fluid Model for G/GI/N and G/GI/N+GI.
 - Whitt (2006) proposed a Fluid Model.
 - Liu and Whitt (2012) calculate fluid performance measures.
 - Reed (2009) and Kaspi and Ramanan (2011) proved convergence, without abandonment.
 - Kang and Ramanan (2010 and 2012) proved convergence, with abandonment.
 - Provided the framework for approaching the multiclass case.
- Multiclass Scheduling.
 - Atar, Kaspi and Shimkin (2014) analyzed SP for multiclass G/GI/N+GI, and show asymptotic optimality of SP for G/GI/N+M.
 - We generalize to a large class of admissible policies that include SP.

The State Space

Primitive inputs:

- Arrival counting processes for each class;
- Sequence of i.i.d. service times for each class;
- Sequence of i.i.d. deadlines for each class.

The ν Measure (for given Class j)

Note: Depends on Scheduling Control.

since a customer began service, and shifts to the right at rate 1.

The η Measure (for given Class j)

Note: Independent of Scheduling Control.

Each dot is a unit atom whose position represents the time elapsed since a customer arrival, and shifts to the right at rate 1 until its potential abandonment time.

entered service

Customers in queue

The Fluid Model State Space and Auxiliary Functions

(Proportion of class j fluid in service);

(Instantaneous departure rate); (Cumulative departure process); (Queue-length process); (Class j head-of-line wait time process);

(Cumulative abandonment process);

(Cumulative entry-into-service process).

A Fluid Model Solution (Not Unique)

Non-negative, continuous, and non-decreasing J-dimensional function having domain \Re_+ ; for example, $E_j(t) = \lambda_j t$ for all j. ↓ Let E be an arrival function. Then, (X, ν, η) is a fluid model solution for E if the following hold.

(1) For each j, K_j is non-decreasing and $\sum_{j=1}^{J} B_j(t) \in [0,1]$ for all $t \ge 0$. (No service rule specified.)

(2) For all *j* and $t \ge 0$, $X_j(t) = X_j(0) + E_j(t) - R_j(t) - D_j(t)$, $0 \le Q_j(t) \le \int_0^\infty \eta_j(dy)$, and finiteness.

Non-Policy Specific Convergence

Assume

•
$$\lim_{N \to \infty} \frac{E^N}{N} = E$$
 almost surely, $\lim_{N \to \infty} \mathbb{E}\left[\frac{E_j^N(t)}{N}\right] = \mathbb{E}[E_j(t)]$, for all $t \ge 0$, and E is continuous;

- Entry-into-service process oscillations can be controlled;
- Convergence of initial conditions and "goodness" of initial fluid state;
- Hazard rates of abandonment and service time distributions are either bounded or lower semi-continuous;

PW 2020 Theorem 1

Suppose that (X, ν, η) is a distributional limit point of a sequence of fluid-scaled state processes. Then, (X, ν, η) is almost surely a fluid model solution for *E*.

PW 2020 Theorem 2

A sequence of fluid-scaled state processes is tight.

Talk Outline

- Provide a fluid model relevant for a large class of non-preemptive HL scheduling policies.
 → Show limit points of scaled state processes are fluid model solutions (PW, Theorem 1).
 → Establish tightness (PW, Theorem 2).
 - $E_j(t) = \lambda_j t$ for $t \ge 0$ and all j and $\sum_{j=1}^J \frac{\lambda_j}{\mu_j} \ge 1$.
- 2. Formulate and solve a fluid control problem for an overloaded system.
 - > Characterize fluid invariant states (PW, Proposition 1).
 - > Provide weak convergence theorem for appropriate scheduling policy (PW, Theorem 3).

Any questions?

Fluid Model Invariant States

Definition (Feasible server effort allocation).

•
$$\boldsymbol{B} = \left\{ b \in \mathfrak{R}^J_+ : b_j \leq \lambda_j / \mu_j, \sum_{j=1}^J b_j \leq 1 \right\}$$

PW 2020 Proposition 1

For each $b \in B$, there exists an invariant state such that b_i

is the proportion of server effort devoted to class *j*, and

$$Q_{j}(t) = \lambda_{j} \frac{1}{\theta_{j}} f_{j}\left(\frac{\lambda_{j} - b_{j}\mu_{j}}{\lambda_{j}}\right) \text{ for all } t \geq 0, \text{ where } f_{j}(x) = G_{e,j}^{a}\left(\left(G_{j}^{a}\right)^{-1}(x)\right).$$

$$Abandonment stationary excess cdf.$$
Abandonment cdf.

Intuition: If exponential abandonment distribution, then

$$\frac{\lambda_j}{\theta_j} f_j \left(\frac{\lambda_j - b_j \mu_j}{\lambda_j} \right) = \frac{1}{\theta_j} \left(\lambda_j - b_j \mu_j \right) = q_j.$$

Flow balance implies $\lambda_j - b_j \mu_j = \theta_j q_j.$

Fluid Model Invariant States

Definition (Feasible server effort allocation).

•
$$\boldsymbol{B} = \left\{ b \in \mathfrak{R}^J_+ : b_j \le \lambda_j / \mu_j, \sum_{j=1}^J b_j \le 1 \right\}$$

PW 2020 Proposition 1

For each $b \in B$, there exists an invariant state such that b_i

is the proportion of server effort devoted to class *j*, and

$$Q_{j}(t) = \lambda_{j} \frac{1}{\theta_{j}} f_{j} \left(\frac{\lambda_{j} - b_{j} \mu_{j}}{\lambda_{j}} \right) \text{ for all } t \geq 0, \text{ where } f_{j}(x) = G_{e,j}^{a} \left(\left(G_{j}^{a} \right)^{-1}(x) \right).$$

$$Abandonment stationary excess cdf.$$
Abandonment cdf.

How good is using the function f_i to approximate the class j mean steady-state queue-length?

Performance Measure Approximation Assume Static Priority Scheduling.

A two-class M/LN(1,4)/100 + LN(1,v) queue, with each class having arrival rate 60 per hour.

Low Priority Queue Size

Predicted Approximated

(High priority queue has predicted size 0, and simulated size about 1.5 for all values of the variability *v*.)

Note that queue size decreases as variability increases.

A Fluid Control Problem

When is the solution consistent with static priority scheduling?

• If there is no holding cost; that is, $c_i = 0$.

o Digression: Return to the question from earlier in the talk regarding implications for learning.

- If the abandonment distribution has increasing hazard rate (IFR), then
 - f_i is concave, and m^* is achieved by a feasible vertex.
 - o I.E., the solution motivates a static priority policy.
- If the abandonment distribution has decreasing hazard rate (DFR), then
 - f_j is convex, and m^* could be attained by a non-vertex feasible point.
 - I.E., the solution motivates partially serving classes (not static priority).
 - o (We have numeric examples with non-vertex feasible point solution.)

Other Examples when Static Priority Scheduling is not Optimal: Non-Overloaded Regimes

- Exact MDP Analysis
 - Down, Koole and Lewis (2011)
- Single-Server System in Heavy-Traffic Asymptotic Regime
 - Ata and Tongarlak (2013)
 - Kim and Ward (2013)
- Many-Server System in Halfin-Whitt Asymptotic Regime
 - Harrison and Zeevi (2004)
 - Atar, Mandelbaum and Reiman (2004)
 - Kim, Randhawa, and Ward (2018)
- Many-Server System in Overloaded Regime
 - Long, Shimkin, Zhang, and Zhang (2020) for GI/M/N+GI

Remaining Q: How do I schedule so as to achieve b?

Weighted Random Buffer Selection (WRBS) Scheduling

A newly available server next serves class j with probability $p_j > 0$, where $\sum_{i=1}^{J} p_j = 1$.

Policy Specific Convergence

Assume

- $\lim_{N \to \infty} \frac{E^N}{N} = E$ almost surely, $\lim_{N \to \infty} \mathbb{E}\left[\frac{E_j^N(t)}{N}\right] = \mathbb{E}[E_j(t)]$, for all $t \ge 0$, and E is continuous;
- Entry-into-service process oscillations can be controlled;
- Convergence and "goodness" of initial conditions;
- Hazard rates of service distributions are either bounded or lower semi-continuous;
- Hazard rates of abandonment distributions are bounded.

PW 2020 Theorem 5

Suppose that the queue operates under WRBS policy p. Then,

Fluid-scaled state process $\left(\frac{X^{I}}{N}\right)$

$$\left(\frac{N}{N}, \frac{\nu^N}{N}, \frac{\eta^N}{N}\right) \Rightarrow (X, \nu, \eta) \text{ as } N \to \infty,$$

where (X, ν, η) is almost surely a fluid model solution for *E* that has unique law.

PW 2020 Theorem 4

For any non-idling $b \in B$, the WRBS policy with $p_j = \frac{\mu_j b_j}{\sum_{k=1}^J \mu_k b_k}$ has invariant state defined by b. and many idling.

To minimize cost asymptotically, use *b* that solves the fluid control problem.

General Roadmap for Proving Policy Specific Convergence: Application of Theorems 1 and 2

Add policy specific equations to the multiclass G/GI/N+GI queue that uniquely characterize the dynamics. (Note: The arrival process may have time-varying rates, as is true in many application settings.)

Add policy specific equations to the fluid model, and prove uniqueness of fluid model solutions^{*}.

Prove that fluid limit points of fluid-scaled state processes satisfy the fluid model policy specific equations. (Theorems 1 and 2 show that all other conditions in the definition of a fluid model solution are satisfied.)

PW 2020 Theorem 3 [The Key to Proving the Weak Convergence on the Previous Slide] Given a fluid arrival function *E*, a fluid model solution for WRBS policy *p* is unique for each initial state.

*For a given arrival function and given initial condition.

Summary and Work-in-Progress

Example with Non-Vertex Optima

(This example is developed by Amber Puha's student Jacques Coulombe.)

WRBS Policy-Specific Fluid Equations

A specified WRBS fluid model solution also satisfies

$$p_{j} \int_{s}^{t} 1\{Q_{j}(u) > 0\} dD_{\Sigma}(u) \leq K_{j}(t) - K_{j}(s) \leq p_{j} \int_{s}^{t} dD_{\Sigma}(u), 1 \leq j < J$$

and
$$I(t) = \left[I(t) - Q_{j}(t)\right]^{+}.$$