Asymptotically Optimal Load Balancing in Large-scale Heterogeneous Systems with Multiple Dispatchers

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THE OHIO STATE UNIVERSITY

IFIP Performance'20

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Joint work with...

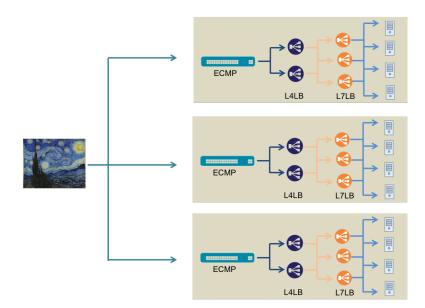


Ness Shroff, OSU

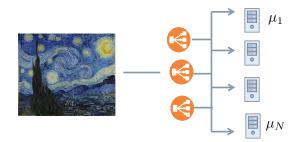


Adam Wierman, Caltech

Load Balancing...



The Building Block...



Key features:

- Multiple dispatchers
- Heterogeneous servers

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- Stability? or even delay?

Our Proposed Design Framework: LED

The Local-Estimation-Driven (LED) framework...

- 1. **Memory:** Each dispatcher has a local memory storing its own estimates of each server's queue length (often outdated)
- 2. **Dispatching:** the dispatching decision at each dispatcher is made purely based on local memory
- 3. **Updating:** the local memory is updated with the true queue length via messages between dispatchers and servers

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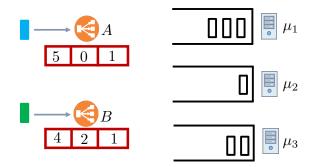
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Key contributions...

- 1. Sufficient conditions on dispatching and updating strategies: throughput optimality and delay optimality in heavy traffic
- 2. Shed light on recently proposed open problem on LB with delayed information [David Lipshutz'19]

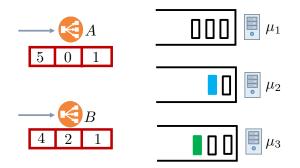
One Concrete Example...



Memory: Each dispatcher keeps its own local estimates (often outdated)...

- Dispatcher A 'believes' that: server 1 with queue length 5, server 2 with 0, and server 3 with 1
- Dispatcher B 'believes' that: server 1 with queue length 4, server 2 with 2, and server 3 with 1

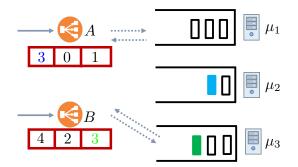
One Concrete Example...



Dispatching strategy: Local-Join-Shortest-Queue (L-JSQ)

- each dispatcher independently routes new arrivals to the server with the shortest local estimates
- e.g., Dispatcher A routes to server 2, Dispatcher B routes to server 3

One Concrete Example...



Updating strategy: Push-based update via sampling

- each dispatcher independently randomly samples d servers with probability p
- update its corresponding local estimates with the true queue lengths

Related Works...

- 1. LB in multiple dispatchers:
 - JIQ in [Lu et al' 11]: consider homogeneous servers; JIQ is unstable in general for fixed number of heterogeneous servers [Zhou et al' 17]
 - Pull-based algorithm in [Stolyar' 17]: heterogeneous server pools in the large-system regime; assume homogeneous loads across dispatchers

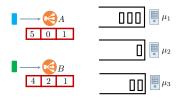
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 - All of them consider a single dispatcher
- 3. Most related to ours is the recent work [Vargaftik et al' 20]
 - They only consider one particular dispatching strategy, i.e., Local-JSQ.
 - They only investigate stability

Model...



- ► *M* dispatchers and *N* servers in discrete-time.
- Arrival: total number of arriving tasks A_Σ(t) with rate λ_Σ, general distribution ¹
 - $A_{\Sigma}(t)$ integer-valued *i.i,d* across time-slots
 - $A_{\Sigma}(t) = \sum_{m=1}^{M} A^{m}(t)$, $A^{m}(t)$ arrivals at dispatcher m
 - ▶ assume $\mathbb{P}(A^m(t) > 0) \ge p_0 > 0, \quad \forall (m, t) \in \mathcal{M} \times \mathbb{N},$
- Service: average number of tasks can be served at server k is μ_k, general distribution.
 - ► S_n(t) is integer-valued, *i.i.d* across time and independent of arrival and queue lengths
- Memory: $\widetilde{\mathbf{Q}}^m(t)) = (Q_1^m(t), \dots, Q_N^m(t))$
- System states: $Z(t) = (\mathbf{Q}(t), \{\widetilde{\mathbf{Q}}^1(t))), \dots, \widetilde{\mathbf{Q}}^M(t)\})$

¹with all moments bounded by absolute constants

Metrics...

In this paper, we consider both throughput optimality and delay optimality in heavy traffic...

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Definition (Throughput Optimality)

A LB policy is throughput optimal if the system is positive recurrent under any $\epsilon>0$ and all the moments of $\|\overline{\mathbf{Q}}^{(\epsilon)}\|$ are finite

Note: this definition is stronger than simple stability

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Definition (Heavy-traffic Delay Optimality)

A LB policy is said to be heavy-traffic delay optimal in steady-state if the steady-state queue length vector $\overline{\mathbf{Q}}^{(\epsilon)}$ satisfies

$$\lim_{\epsilon \downarrow 0} \epsilon \mathbb{E} \left[\sum_{n=1}^{N} \overline{Q}_{n}^{(\epsilon)} \right] = \lim_{\epsilon \downarrow 0} \epsilon \mathbb{E} \left[\overline{q}^{\epsilon} \right],$$

where $\mathbb{E}\left[\bar{q}^{\epsilon}\right]$ is the mean queue length in resource-pooling system. Resource-pooling system: pool all the service into one super single server

Dispatching Preference...

► Fix a dispatcher m, let σ_t(·) be a permutation of (1, 2, ..., N) that satisfies

$$\widetilde{\mathcal{Q}}^m_{\sigma_t(1)}(t) \leq \widetilde{\mathcal{Q}}^m_{\sigma_t(2)}(t) \leq \ldots \leq \widetilde{\mathcal{Q}}^m_{\sigma_t(N)}(t).$$

- P_n^m(t): probability of routing to server n at dispatcher m in time-slot t (again, based on local estimates)
- ► Δ^m_n(t) : preference of the *n*-th shortest local estimate at dispatcher *m*, given by

$$\Delta^m_n(t) := \mathcal{P}^m_{\sigma_t(n)}(t) - rac{\mu_{\sigma_t(n)}}{\sum \mu_n}$$

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- ∆ⁿ_n(t) > 0 means that policy has stronger preference of *n*-th shortest local estimates compared to (weighted) random routing
- Note that $\sum_{n=1}^{N} \Delta_n^m(t) = 0$
- Key: how to allocate the zero-sum?

$\delta\text{-tilted}$ Sum Condition

$$\Delta^m_n(t) := P^m_{\sigma_t(n)}(t) - rac{\mu_{\sigma_t(n)}}{\sum \mu_n}$$

Definition

Fix a dispatcher *m*, for all $1 \le j \le N - 1$, $\sum_{n=1}^{j} \Delta_n^m(t) \ge \delta$ for some constant $\delta \ge 0$ at each time-slot *t*.

Intuitions: for any first k (k < N) shortest local estimates, it has at least δ total preference

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Examples: suppose all μ_n are equal and $\widetilde{\mathbf{Q}}^m(t)$ = (5,0,1)

▶ δ -tilted Sum Condition satisfied with all $\mathbf{P}^m(t)$ s.t. for some $\delta \ge 0$

• $P_2^m(t) \ge \delta + 1/3$, $P_2^m(t) + P_3^m(t) \ge \delta + 2/3$, and $\sum P_n^m(t) = 1$

Implications:

- this condition also generalizes previous definition in [Zhou et al' 17,18]
- as a result, it allows us to establish new results (e.g., L-Pod), discussed later

Main Results

We have the following sufficient condition (informal) for throughput optimality...

Define: $\mathcal{I}_n^m(t)$ indicates server *n*'s true queue length is updated at dispatcher *m*

Theorem

Consider an LED policy if

- dispatching strategy satisfies δ -tilted sum condition for some $\delta \geq 0$
- updating strategy satisfies that $\mathbb{E} \left[\mathcal{I}_n^m(t) \mid Z(t) \right] > p$ for any Z(t), m, n and some p > 0

Then, it is throughput optimal

Remark:

This directly generalizes LSQ policy in [Vargaftik et al' 20] in terms of stability

Main Results

We have the following sufficient condition (informal) for heavy-traffic delay optimality...

Theorem

Consider an LED policy if

- dispatching strategy satisfies δ-tilted sum condition for some strictly positive constant δ
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- both δ and p are independent of ϵ

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Then, it is heavy-traffic delay optimal

Remark:

- This directly implies a large class of LED policies are heavy-traffic delay optimal, including the specific one LSQ in [Vargaftik et al' 20]
- This also sheds light on heavy-traffic delay optimality in delayed queue length information, raised in [David Lipshutz'19]
- Moreover, the single dispatcher with accurate information is just a special case of ours

Examples of 'nice' dispatching strategies

- 1. L-JSQ: Local-Join-Shortest-Queue (i.e., the LSQ in [Vargaftik et al' 20])
 - choose $i^* \in \arg\min_n \{\widetilde{Q}_n^m\}$
 - $\Delta_1^m(t) = 1 \mu_{\sigma_t(1)}/\mu_{\Sigma} > 0$ and all others are less than 0
 - It can be easily seen that δ -tilted sum condition is satisfied

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- 2. L-JBA: Local-Join-Below-Average
 - Let $\overline{Q}^m(t) = \frac{1}{N} \sum_n \widetilde{Q}_n^m(t)$ and $\mathcal{A} := \{n : \widetilde{Q}_n^m(t) \le \overline{Q}^m(t)\}$
 - ▶ Then, for each $i \in A$, $P_i^m(t) = \mu_i / \sum_{n \in A} \mu_n$, and for $i \notin A$, $P_i^m(t) = 0$.
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- 3. L-Pod: Local-Power-of-d
 - randomly samples d servers, join the one with the shortest local estimates
 - \blacktriangleright it turns out that even with heterogeneous servers, L-Pod can still satisfy $\delta\text{-tilted}$ sum as long as the services rates meet a certain condition

More on L-Pod

Proposition

Suppose the service rate vector $\boldsymbol{\mu} \in \mathbb{R}^{N}_{+}$ satisfies

$$\frac{\sum_{n=1}^{j} \mu_{[n]}}{\mu_{\Sigma}} + \delta \le 1 - \frac{\binom{N-j}{d}}{\binom{N}{d}} \qquad \forall 1 \le j \le N-1,$$
(1)

for some constant $\delta \ge 0$, in which $\mu_{[n]}$ is the n-th largest service rate. Then, L-Pod satisfies the δ -tilted sum condition.

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Remark:

- For the single dispatcher with accurate queue length information (which is a special case of ours), [Hurtado-Lange and Maguluri' 20]) derived similar conditions
- If d = 1, the only possible μ and δ are $\mu_n = \mu$ for all n and $\delta = 0$
- If d = N, then all $\boldsymbol{\mu} \in \mathbb{R}^N_+$ satisfies (1) with $\delta = \mu_{min}/\mu_{\Sigma} > 0$

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- 1. Push-based: each dispatcher takes the initiative to sample servers
 - ► e.g., at the end of each time-slot, w.p. p̃ > 0 to randomly sample d queues and update the local estimates with the true lengths
 - ▶ thus, $\mathbb{E}\left[\mathcal{I}_n^m(t) \mid Z(t)\right] \ge p > 0$ is satisfied with $p = \tilde{p}d/N$

Examples of 'nice' updating strategies

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 - ▶ thus, $\mathbb{E}\left[\mathcal{I}_n^m(t) \mid Z(t)\right] \ge p > 0$ is satisfied with $p = \tilde{p}d/N$
- 2. Pull-based: each server takes the initiative to sample dispatchers
 - e.g., at the end of each time-slot, if server *n* finishes one or more tasks, it randomly samples one dispatcher
 - if $Q_n = 0$, it reports w.p. 1
 - if $Q_n > 0$, it reports w.p. $\tilde{p} > 0$
 - ▶ it has been verified in [Vargaftik et al' 20]), this satisfies $\mathbb{E} \left[\mathcal{I}_n^m(t) \mid Z(t) \right] \ge p > 0$ for arbitrarily small $\tilde{p} > 0$

Of course, there are many more...

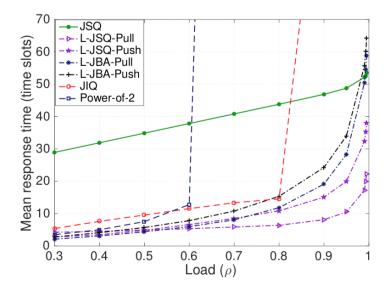
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 - Thus, how can we avoid this?

Answer: LED could be one solution due to its intrinsic randomness



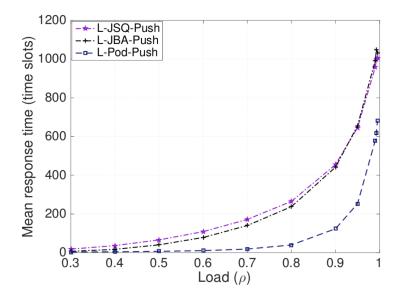
Inaccurate information helps...

100 heterogeneous servers, 10 dispatchers



Randomness further helps...

- 100 homogeneous servers, 10 dispatchers
- update probability is small $\tilde{p} = 0.01$



2. Question: Can each dispatcher work independently with simple implementations?



- 2. Question: Can each dispatcher work independently with simple implementations?
 - Without communication across dispatchers
 - Answer: For LED, we have
 - each dispatcher totally works independently
 - immediate dispatching, i.e., no waiting for update
 - simple and fast implementations, e.g., min-heap



3. Question: How much communication between dispatchers and servers?



- 3. Question: How much communication between dispatchers and servers?
 - Minimize the messages between dispatchers and servers
 - Answer: For LED, we have
 - the sampling and reporting probabilities can be arbitrarily small
 - of course, for practical performance, these parameters can be tuned to trade-off between messages and performance



4. Question: Can we say something about performance guarantee?



- 4. Question: Can we say something about performance guarantee?
 - Stability? or even delay?

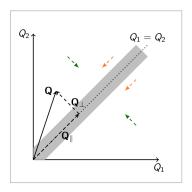
Answer: For LED, we have

- throughput optimality
- delay optimality in heavy traffic



Main ideas behind proofs

- The main techniques are based on drift-based [Eryilmaz and Srikant'12])
- In particular, we utilize the sufficient conditions for throughput and heavy-traffic optimality in [Zhou et al'17], illustrated as follows



 Throughput optimality needs positive drift
, obtained via

$$\sum_{t=1}^{\mathcal{T}} \mathbb{E}\left[\langle \mathbf{Q}, \mathbf{A} - \mathbf{S}
angle \mid \mathbf{Q}
ight] pprox - \epsilon \left\| \mathbf{Q}
ight\|$$

 Heavy-traffic optimality needs positive drift A, obtained via

$$\sum_{t=1}^{T} \mathbb{E}\left[\left\langle \mathbf{Q}_{\perp}, \mathbf{A} - \mathbf{S} \right\rangle \mid \mathbf{Q} \right] \approx -\delta \left\| \mathbf{Q}_{\perp} \right\|$$

Main ideas behind proofs

Three additional challenges arise in our settings...

- 1. A more general dispatching condition (i.e., δ -tilted sum condition)
 - it exists even when the queue lengths are accurate
 - ▶ we draw inspirations from [Hurtado-Lange and Maguluri' 20]) to have a nice bound on the inner product between Q and A
- 2. Outdated queue lengths information
 - our strategy is to do a decomposition
 - first, establish necessary drifts via dispatching strategy, assuming the queue lengths are accurate
 - second, bounding the error via update condition
- 3. System state includes local estimates
 - hence, for throughput optimality, they should also be bounded

Conclusion...

The LED combined with sufficient conditions give affirmative answers to all key questions...

- 1. Question: With multiple dispatchers, does Join-Shortest-Queue still beats others in performance? Answer: I ED could be one solution due to its intrinsic randomness
- Question: Can each dispatcher work independently with simple implementations?
 Answer: LED achieve independence, easy implementations
- 3. Question: How much communication between dispatchers and servers? Answer: LED, has the flexibility to tune the probability \tilde{p}
- 4. Question: Can we say something about performance guarantee? Answer: LED, can be throughput optimal and delay optimal in heavy traffic

Future Works

There are several interesting directions for LED...

- 1. Beyond the traditional heavy-traffic regime?
 - As pointed out by [Zhou et al' 18]), heavy-traffic delay optimal is a coarse metric in certain sense
 - How about waiting probability in large-system regimes?
- 2. How about continuous-time systems?
- 3. How about LED on graphs?
 - each node can serve a job or dispatches to neighbors
 - each node keeps local estimates of its neighbors
 - purely based on local memory to dispatch
 - infrequent update via communications between nodes

Thank you! Q & A

Throughput optimality...

1. We consider the Lyapunov function $W(Z(t)) = \|\mathbf{Q}(t)\|^2 + \sum_{m=1}^{M} \|\mathbf{Q}(t) - \widetilde{\mathbf{Q}}^m(t)\|_1$

2. Let $X_n^m(t) riangleq |Q_n(t) - \widetilde{Q}_n^m(t)|$, the drift is

$$D(Z(t_0)) = D_Q(t_0) + \sum_{m=1}^{M} \sum_{n=1}^{N} D_{X_n^m}(t_0)$$
(2)

where

$$D_Q(t_0) \triangleq \mathbb{E}\left[\left\| \mathbf{Q}(t_0 + T) \right\|^2 - \left\| \mathbf{Q}(t_0) \right\|^2 \mid Z(t_0) \right]$$
$$D_{X_n^m}(t_0) \triangleq \mathbb{E}\left[X_n^m(t_0 + T) - X_n^m(t_0) \mid Z(t_0) \right]$$

3. $D_{X_n^m}(t_0) \leq -pX_n^m(t) + 2T\mu_{\Sigma}$

Throughput optimality (Cont'd)

4. Turn to
$$D_Q(t_0) \triangleq \mathbb{E} \left[\|\mathbf{Q}(t_0 + T)\|^2 - \|\mathbf{Q}(t_0)\|^2 \mid Z(t_0) \right] \approx$$

 $\sum \mathbb{E} \left[\langle \mathbf{Q}, \mathbf{A} - \mathbf{S} \rangle \mid Z(t_0) \right] + K$

5. We can decompose the first term into $(\beta_n^m(t) := P_n^m(t) - \mu_n/\mu_{\Sigma})$

$$\mathsf{RHS} \approx \underbrace{\sum_{t=t_0}^{t_0+T-1} \mathbb{E}\left[\sum_{n=1}^{N} \sum_{m=1}^{M} \left(Q_n(t) - \widetilde{Q}_n^m(t)\right) \beta_n^m(t) \lambda_m \mid Z\right]}_{\mathcal{T}_1} + \underbrace{\sum_{t=t_0}^{t_0+T-1} \mathbb{E}\left[\sum_{n=1}^{N} \sum_{m=1}^{M} \widetilde{Q}_n^m(t) \beta_n^m(t) \lambda_m \mid Z\right]}_{\mathcal{T}_2} - \frac{\epsilon \mu_{min}}{\mu_{\Sigma}} \left\|\mathbf{Q}(t_0)\right\|_1.$$

6. For \mathcal{T}_1 , by update condition, we have a constant bound on it

Throughput optimality (Cont'd)

7. Turn to
$$\mathcal{T}_2 = \sum_{t=t_0}^{t_0+T-1} \mathbb{E} \left[\sum_{n=1}^N \sum_{m=1}^M \widetilde{Q}_n^m(t) \beta_n^m(t) \lambda_m \mid Z \right]$$

8. It is equal to $\sum_{t=t_0}^{t_0+T-1} \mathbb{E} \left[\sum_{n=1}^N \sum_{m=1}^M \widetilde{Q}_{\sigma_t(n)}^m(t) \Delta_n^m(t) \lambda_m \mid Z \right]$

9. The green term can be written as

$$\sum_{m=1}^{M} \left(\widetilde{Q}_{\sigma_{t}(1)}^{m}(t) \sum_{n=1}^{N} \Delta_{n}^{m}(t) \right)$$

$$+ \sum_{m=1}^{M} \left(\sum_{k=2}^{N} \left(\sum_{n=k}^{N} \Delta_{n}^{m}(t) \right) (\widetilde{Q}_{\sigma_{t}(k)}^{m}(t) - \widetilde{Q}_{\sigma_{t}(k-1)}^{m}(t)) \right)$$

$$(4)$$

10. (3) is zero as $\sum_{n=1}^{N} \Delta_n^m(t) = 0$ 11. (4) less than zero since $\sum_{n=k}^{N} \Delta_n^m(t) \le -\delta$ by δ -tilted sum condition

Heavy-traffic delay optimality...

- 1. We wish to establish $\sum_{t=t_0}^{t_0+T-1} \mathbb{E} \left[\langle \mathbf{Q}_{\perp}, \mathbf{A} \mathbf{S} \rangle \mid Z \right] \approx -\delta' \| \mathbf{Q}_{\perp} \|, \, \delta'$ independent of ϵ
- 2. The key term $\sum_{t=t_0}^{t_0+T-1} \mathbb{E} \left[\langle \mathbf{Q}_{\perp}, \mathbf{A} \rangle \mid Z \right]$ can be written as

$$\sum_{t=t_{0}}^{t_{0}+T-1} \mathbb{E}\left[\sum_{n=1}^{N} Q_{\perp,n}(t) \sum_{m=1}^{M} \beta_{n}^{m}(t)\lambda_{m} \mid Z\right]$$

$$= \sum_{t=t_{0}}^{t_{0}+T-1} \mathbb{E}\left[\sum_{n=1}^{N} \sum_{m=1}^{M} \left(\widetilde{Q}_{n}^{m}(t) - \overline{Q}^{m}(t)\right) \beta_{n}^{m}(t)\lambda_{m} \mid Z\right]$$
(5)
$$+ \sum_{t=t_{0}}^{t_{0}+T-1} \mathbb{E}\left[\sum_{n=1}^{N} \sum_{m=1}^{M} \left(Q_{n}(t) - \widetilde{Q}_{n}^{m}(t)\right) \beta_{n}^{m}(t)\lambda_{m} \mid Z\right]$$
(6)
$$+ \sum_{t=t_{0}}^{t_{0}+T-1} \mathbb{E}\left[\sum_{n=1}^{N} \sum_{m=1}^{M} \left(\overline{Q}_{n}^{m}(t) - Q_{avg}(t)\right) \beta_{n}^{m}(t)\lambda_{m} \mid Z\right]$$
(7)

$$-\sum_{t=t_0} \mathbb{E}\left[\sum_{n=1}^{\infty}\sum_{m=1}^{\infty} \left(\bar{Q}^m(t) - Q_{\text{avg}}(t)\right) \beta_n^m(t) \lambda_m \mid Z\right].$$
(7)

where $\bar{Q}^m(t) := \frac{1}{N} \sum_n \widetilde{Q}_n^m(t)$ and $Q_{\text{avg}} := \frac{1}{N} \sum_n Q_n(t)$

3. By updating condition, (6) and (7) both can be upper bounded (properly chosen *T*)

Heavy-traffic delay optimality (Cont'd)

4. Turn to the green term, it can be written as

$$(5) = \sum_{t=t_0}^{t_0+T-1} \mathbb{E}\left[\sum_{m=1}^M \sum_{n=1}^N \widetilde{Q}^m_{\sigma_t(n)}(t) \Delta^m_n(t) \lambda_m \mid Z\right]$$

5. Follow the same decompositions as in (3) and (4), we have

$$(5) \leq -\delta \sum_{t=t_0}^{t_0+T-1} \mathbb{E}\left[\sum_{m=1}^M \sum_{n=1}^N \widetilde{Q}_{max}^m(t) - \widetilde{Q}_{min}^m(t)\lambda_m \mid Z\right]$$

6. By a careful sample-path analysis, we have for some constant K

$$egin{aligned} (5) &\leq -\delta f(p) \lambda_{min} \left(Q^m_{max}(t_0) - Q_{min}(t_0)
ight) + K \ &\leq -\delta' \left\| \mathbf{Q}_{ot}(t_0)
ight\| + K \end{aligned}$$