

On the Optimal Trade-off between SRPT and Opportunistic Scheduling

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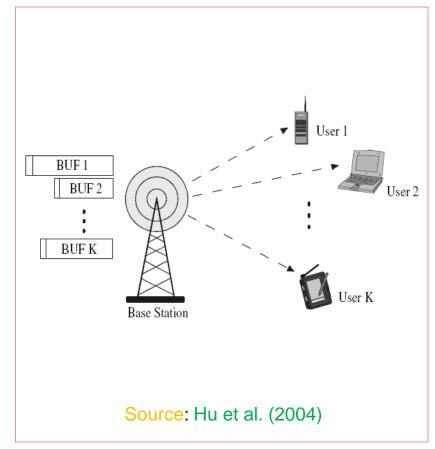
Outline

- Introduction
- Optimal scheduling problem
- Solution
- Examples
- Lower and upper bounds
- Summary



Research problem

- Downlink data transmission in a cellular system
- Traffic = elastic flows
 - file transfers using TCP
- Scheduling decisions in each time slot
 - time scale of milliseconds
- Traffic dynamics in a longer time scale
 - time scale of seconds+
- Optimal scheduler for flow-level performance?



Flow-level performance

- Performance is expressed as throughput or flow delay
 - Mean flow delay would describe how long file transfers on the average last
- Importance of the time scale
 - Users do not care about delays of individual packets, but only about the total time to transmit a file of a given size
- Flow-level models try to characterize the system at the time-scale where users experience the performance

Schedulers

Channel-aware schedulers

- Scheduling based on channel information
- Scheduler may prefer users with a good channel
- Opportunistic scheduling
- Examples: MR, PF
- Size-based schedulers
 - Scheduling based on flow size information
 - Scheduler may prefer users with a short flow
 - Example: SRPT

Fundamental trade-off

- Opportunistic scheduling
 - Select the user that has instantaneously good channel
 - Aggregate mean service rate increases with the number of users (opportunistic gain, multiuser diversity gain)
 - However, a user with a long remaining service time blocks the others

• SRPT

- Select the user that has the least remaining service time
- The number of flows is reduced most efficiently
- However, opportunistic gain is lost due to suboptimal channel (later on also due to a smaller number of flows)

Combining opportunistic and size-based scheduling

- Tsybakov (2003)
 - Dynamic programming approach (time-slot scale)
- Hu et al. (2004)
 - Heuristic approach: TAOS (time-slot scale)
- Lassila and Aalto (2008)
 - Another heuristic approach: SRPT-P (time-slot scale)
- Sadiq and de Veciana (2010)
 - Time-scale separation (flow scale)
 - Transient system
 - Optimality result for nested polymatroids
 - Cf. optimality of SRPT-FM, Raj et al. (2004)

Our contribution

- Time-scale separation (flow scale)
 - In fact, abstract capacity regions
- Transient system
- Optimality result for compact and symmetric capacity regions
 - includes nested polymatroids
 - requires an implicit condition related to capacity regions
 - optimal policy applies the SRPT-FM principle
- Conservative upper bound for the mean delay

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- Service system where the service capacity is adjustable depending on the current number of jobs
- When there are k jobs with sizes

$$s_1 \ge \ldots \ge s_k$$

 C_2

0.4

choose a rate vector

$$\mathbf{c}_k = (c_{k1}, \dots, c_{kk}) \in C_k$$

and serve job i with rate c_{ki}

• Assume: Capacity regions C_k compact and symmetric

Transient system

- Assume that there are n jobs in the system at time 0
- What is the optimal way to make the system empty?
- Our objective: Minimize the mean delay (or flow time)
- Define: Flow time (or total completion time) for policy π

$$T^{\pi} = \sum_{i=1}^{n} t_i^{\pi}$$

where t_i is the completion time of job i

• Define: Operating policies

$$\Pi_n = \{ \pi = (\mathbf{c}_1, \dots, \mathbf{c}_n) : \mathbf{c}_k \in C_k \text{ for all } k \}$$



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Trivial case: One job

• Define:

$$G_1^* = \frac{1}{c_1^*}, \quad c_1^* = \max_{c_1 \in C_1} c_1$$

• Now

$$T^* = \min_{\pi \in \Pi_1} T^{\pi} = s_1 G_1^*, \ \pi^* = (\mathbf{c}_1^*)$$



Simple case: Two jobs

If job 2 (i.e., the shorter one) completes first, then

$$T^{\pi} = 2\frac{s_2}{c_{22}} + (s_1 - \frac{s_2}{c_{22}}c_{21})\frac{1}{c_1^*} = \frac{s_2}{c_{22}}(2 - \frac{c_{21}}{c_1^*}) + \frac{s_1}{c_1^*}$$

0.6

0.4

0.2

 C_2

0.4

0.6

0.8

• Otherwise

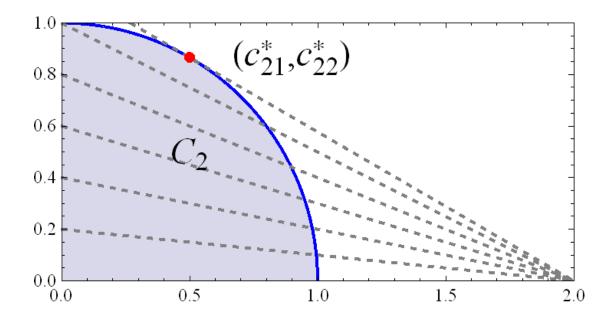
$$T^{\pi} = 2\frac{s_1}{c_{21}} + (s_2 - \frac{s_1}{c_{21}}c_{22})\frac{1}{c_1^*} = \frac{s_1}{c_{21}}(2 - \frac{c_{22}}{c_1^*}) + \frac{s_2}{c_1^*}$$

• Let us minimize (a function not depending on sizes!)

$$g(\mathbf{c}_2) = \frac{1}{c_{22}} (2 - \frac{c_{21}}{c_1^*}), \ \mathbf{c}_2 \in C_2$$



Geometric interpretation





 $\begin{array}{c} 1.0 \\ 0.8 \\ 0.6 \\ 0.4 \\ 0.2 \\ 0.0 \\$

• Define:

$$G_2^* = g(\mathbf{c}_2^*) = \min_{\mathbf{c}_2 \in C_2} g(\mathbf{c}_2)$$

• Result: Now if

$$G_1^* < G_2^*$$

then (due to the symmetry property!)

$$T^* = \min_{\pi \in \Pi_2} T^{\pi} = s_2 G_2^* + s_1 G_1^*, \ \pi^* = (\mathbf{c}_1^*, \mathbf{c}_2^*), \ \mathbf{c}_{21}^* \le \mathbf{c}_{22}^*$$



• Justification:

$$T^{\pi} \ge \min\{s_{2}g(c_{21}, c_{22}) + s_{1}G_{1}^{*}, s_{1}g(c_{22}, c_{21}) + s_{2}G_{1}^{*}\}$$

$$\ge \min\{s_{2}G_{2}^{*} + s_{1}G_{1}^{*}, s_{1}G_{2}^{*} + s_{2}G_{1}^{*}\}$$

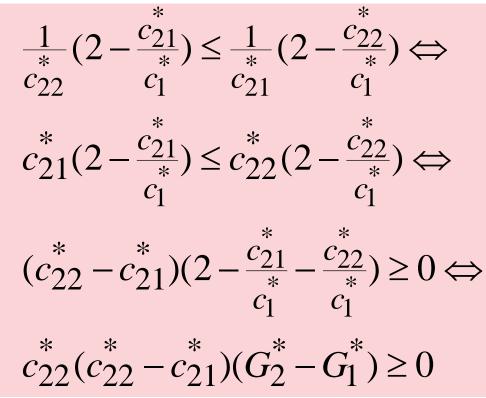
$$= s_{2}G_{2}^{*} + s_{1}G_{1}^{*} \qquad [\text{since } G_{2}^{*} > G_{1}^{*}]$$

$$T^{\pi^{*}} = s_{2}g(c_{21}^{*}, c_{22}^{*}) + s_{1}G_{1}^{*} \qquad [\text{since } c_{22}^{*} \ge c_{21}^{*}]$$

$$= s_{2}G_{2}^{*} + s_{1}G_{1}^{*}$$

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Required additional result:



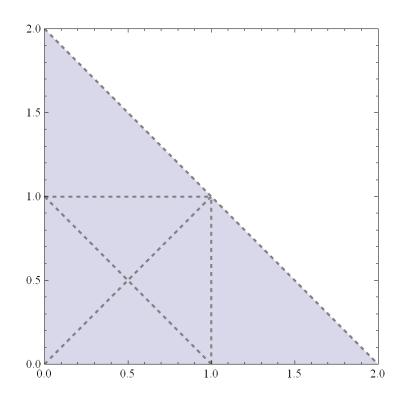


• Equivalent condition:

$$G_2^* > G_1^* \iff$$

 $c_{21} + c_{22} < 2 \cdot c_1^*$

- Suffient condition: nested capacity regions
- Note: However, capacity regions are not required to be nested



General case: n jobs

• **Define** (recursively):

$$G_k^* = \min_{\mathbf{c}_k \in C_k} g_k(\mathbf{c}_k), \quad g_k(\mathbf{c}_k) = \frac{1}{c_{kk}} \left(k - \sum_{i=1}^{k-1} c_{ki} G_i^* \right)$$

• Theorem 1: If

$$G_1^* < \ldots < G_n^*$$

then

$$T^* = \min_{\pi \in \Pi_2} T^{\pi} = \sum_{k=1}^n s_k G_k^*, \ \pi^* = (\mathbf{c}_1^*, \dots, \mathbf{c}_n^*)$$



General case: n jobs (cont.)

• In addition,

$$c_{k1}^* \le \dots \le c_{kk}^*$$
 for all k

- Thus, the optimal policy applies the **SRPT-FM principle**:
 - the shortest job is served with the highest rate,
 - the second shortest job is served with the second highest rate,
 - etc.
- Note also that the optimal rate vector does not depend on the absolute sizes (only on their order)

General case: n jobs (cont.)

• Necessary condition:

$$G_1^* < \ldots < G_k^* \implies c_{k1} + \ldots + c_{kk} < k \cdot c_1^*$$

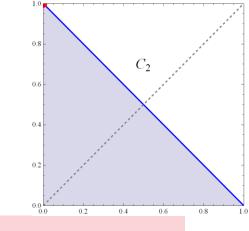


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Single-server queue

Consider capacity regions



$$C_k = \{ \mathbf{c}_k \ge 0 : \sum_{j=1}^k c_{kj} \le 1 \}$$

• Now

$$G_{k}^{*} = k \qquad (i)$$

$$c_{kj}^{*} = \begin{cases} 0, & j < k \\ 1, & j = k \end{cases} \qquad (i)$$

(increasing in k)

(increasing in j)



Infinite-server queue

 C_2

Consider capacity regions

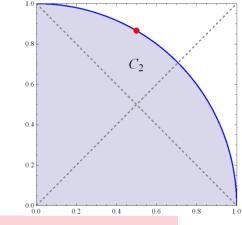
$$C_k = \{ \mathbf{c}_k \ge 0 : \sum_{j=1}^k c_{kj} \le k, c_{kj} \le 1 \,\forall j \}$$

• Now

$$G_k^* = 1$$
 (constant)
 $c_{kj}^* = 1$ (constant)



Alpha-balls



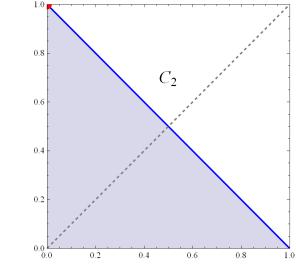
• Let $\alpha > 1$ and consider capacity regions

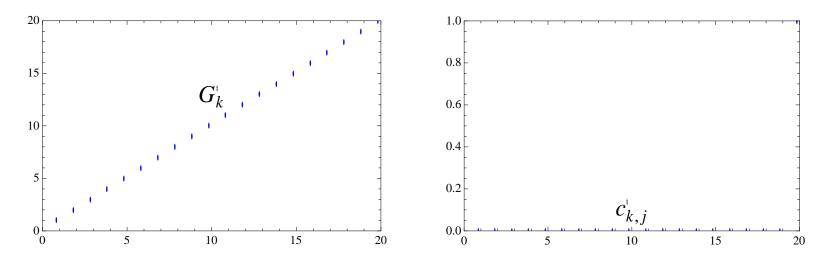
$$C_k = \{ \mathbf{c}_k \ge 0 : \sum_{j=1}^k c_{kj}^{\alpha} \le 1 \}$$

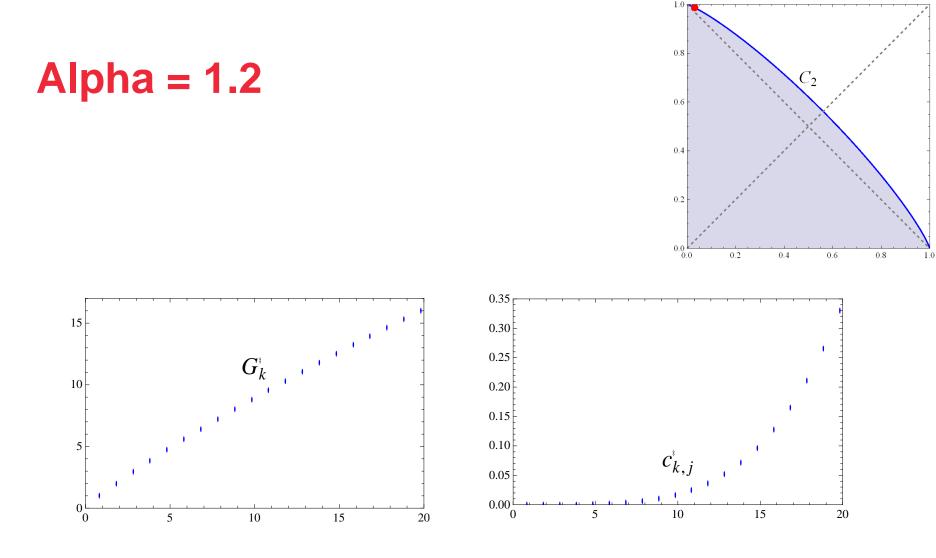
• Now

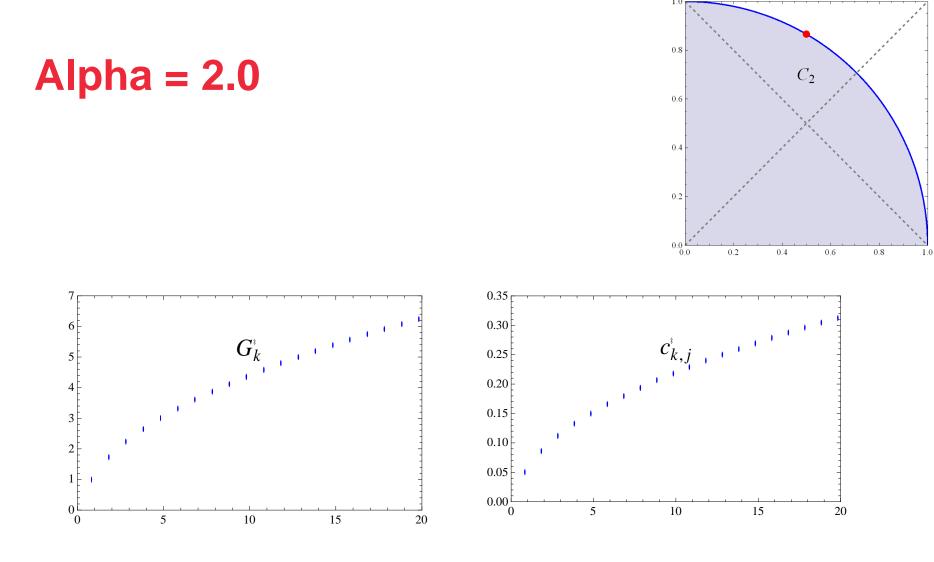
$$G_{k}^{*} = \left(k^{\frac{\alpha}{\alpha-1}} - (k-1)^{\frac{\alpha}{\alpha-1}}\right)^{\frac{\alpha-1}{\alpha}} \text{ (increasing in } k)$$
$$c_{kj}^{*} = \left(\frac{G_{j}^{*}}{k}\right)^{\frac{1}{\alpha-1}} \text{ (increasing in } j)$$

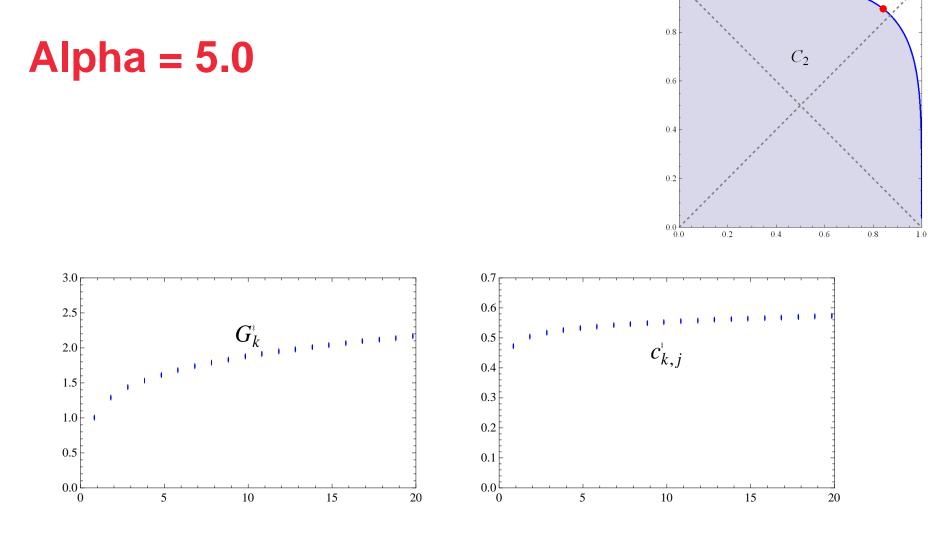
Alpha = 1.0 (single-server queue)



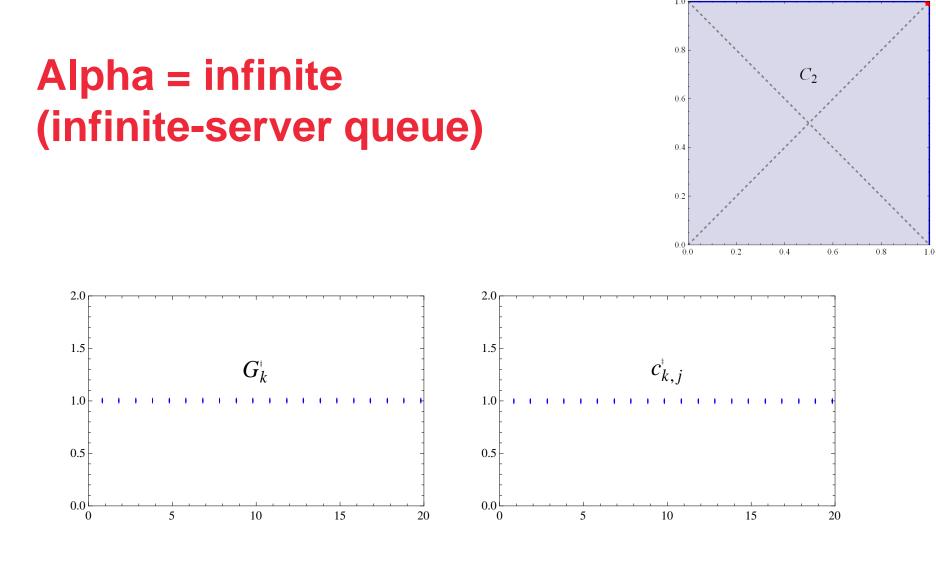








1.0



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Symmetric polymatroids

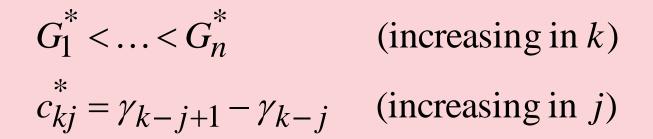


$$C_k = \{ \mathbf{c}_k \ge 0 : \sum_{i \in I} c_{ki} \le \gamma_{|I|}, I \subset \{1, ..., n\} \}$$

 C_2

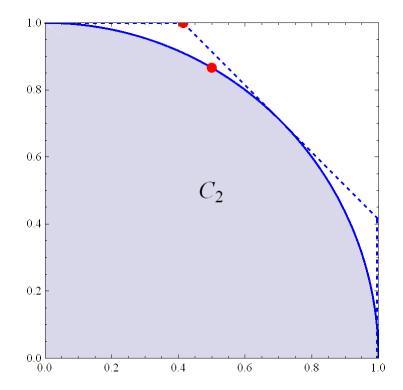
0.4

• Theorem 2: If $\gamma_1 > \gamma_2 - \gamma_1 > \ldots > \gamma_n - \gamma_{n-1}$, then



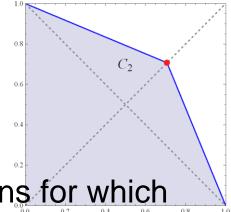
Optimality result of Sadiq and de Veciana (2010)

Optimistic (lower) bound





Symmetric OPS-limited polytopes



• Let $\gamma_1 < ... < \gamma_n$ and consider capacity regions for which C_k is the convex hull of all permutations of rate vectors

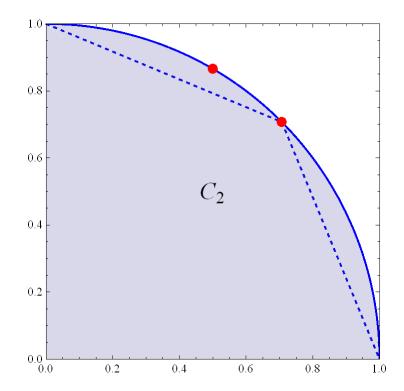
$$(0,\ldots,0,\frac{\gamma_j}{j},\ldots,\frac{\gamma_j}{j}), \quad j=0,\ldots,k$$

• Theorem 3: If $G_1^* < ... < G_n^*$, then

$$\mathbf{c}_{k}^{*} = (0, \dots, 0, \frac{\gamma_{jk}^{*}}{j_{k}^{*}}, \dots, \frac{\gamma_{jk}^{*}}{j_{k}^{*}})$$

 SRPT-OPS policy introduced in Sadiq and de Veciana (2010)

Conservative (upper) bound





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Summary

- Assumptions:
 - Abstract capacity regions (time-scale separation)
 - Transient system
- Results:
 - Optimality result for compact and symmetric capacity regions
 - Optimal rate vectors (that do not depend on absolute sizes of the flows) for each phase
 - Conservative upper bound for the mean delay
- Open questions:
 - Is it possible to make the implicit condition explicit?
 - Any idea about the truly dynamic system with random arrivals?





New results: Making the implicit condition explicit

- The implicit condition is, indeed, satisfied under the assumption that the channel conditions for different users are independent and identically distributed.
- In addition, there is a recursive algorithm for the optimal flow-level rate vectors that directly utilizes the time slot level channel model.
- It is also possible to determine explicitly how to implement the optimal rate vectors in the time slot level opportunistic scheduler.
- But this is another story ...