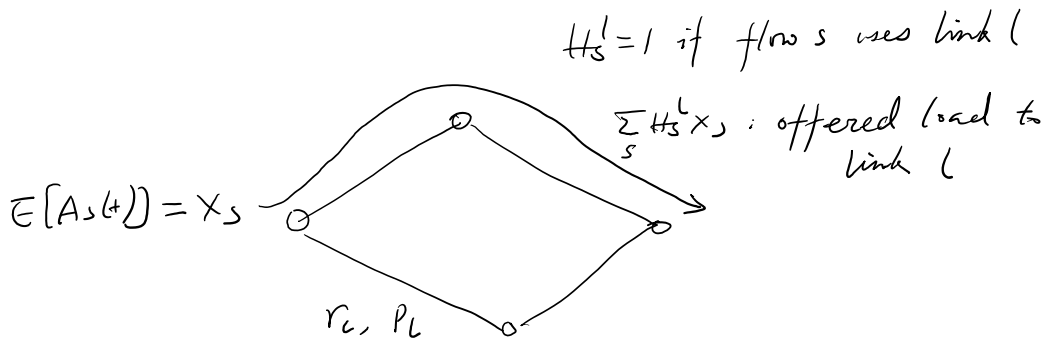


# Lec15-mwf

Saturday, February 3, 2018 10:53 AM



$$\vec{r}(t) = g(\vec{p}(t), K(t))$$

$\nearrow$  rate-power function       $\uparrow$  global action vector       $\nwarrow$  global channel state

$$\vec{p}(t) \in \mathcal{H}$$

$$P[K(t) = k] = \lambda_k$$

## Capacity Region

$$\left[ \sum_s H_S^l X_S \right] \in \sum_k \lambda_k \text{Conv-hull} \{ g(\vec{p}, k) \mid \vec{p} \in \mathcal{H} \}$$

$\nwarrow \mathcal{R}$  : capacity region

## Throughput-Optimal Scheduling

$$q^l(t+1) = \left[ q^l(t) + \sum_s H_S^l A_s(t) - r^l(t) \right]^+$$

$\nwarrow$  random arrivals       $\uparrow$  projection to  $[0, +\infty)$

$E[A_S(t)] = X_S$

$$\vec{p}(t) = \arg \max_{\vec{p} \in \mathcal{H}} \sum_l q^l r^l$$

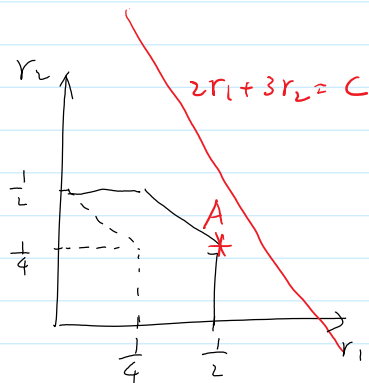
$\uparrow$

$$\begin{aligned}
 - \quad \vec{p}(+) &= \underset{\vec{p} \in \mathcal{A}}{\operatorname{argmax}} \sum r^l r^l \\
 \vec{r} &= f(\vec{p}, K(+)) \quad \uparrow \text{ gives larger weight to } r^l \text{ if } p^l \text{ is large.}
 \end{aligned}$$

## Maximizing a weighted-sum

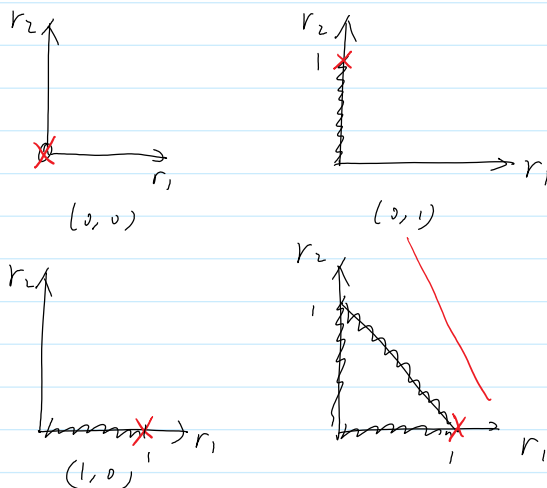
- Over this capacity region, suppose we want to maximize a weighted-sum

$$2r_1 + 3r_2$$



## Three important facts

- ① The point A can be seen as the average of the maximizing rate vector at each channel state



$$(0,0) \times \frac{1}{4} + (0,1) \times \frac{1}{4} + (1,0) \times \frac{1}{4} + (1,0) \times \frac{1}{4} = \left(\frac{1}{2}, \frac{1}{4}\right)$$

- In general,

$$\begin{aligned} & \max \quad \sum_i w_i r_i \\ & \text{sub to} \quad [r_i] \in \sum_k \lambda_k \text{Conv-hull}\{g(\vec{p}, k) \mid \vec{p} \in \Phi\} \end{aligned}$$

$$= \sum_k \lambda_k \cdot \left\{ \begin{array}{l} \max \sum_i w_i r_i \\ \text{sub to } [r_i] \in \text{Conv-hull}\{g(\vec{p}, k) \mid \vec{p} \in \Phi\} \end{array} \right.$$

② The maximizer of a weighted-sum over a convex hull always occurs at the extreme points

$$\begin{aligned} & \max \sum_i w_i r_i \\ & \text{sub to} \quad [r_i] \in \text{Conv-hull}\{g(\vec{p}, k) \mid \vec{p} \in \Phi\} \\ & = \max \sum_i w_i r_i \\ & \text{sub to} \quad [r_i] \in \{g(\vec{p}, k) \mid \vec{p} \in \Phi\} \end{aligned}$$

③ For any  $[r_i^*] \in \Omega$

$$\sum_i w_i r_i^* \leq \max \sum_i w_i r_i \\ \text{sub to } [r_i] \in \Omega$$

## Throughput-optimal scheduling - 10min

Sunday, January 27, 2008 11:29 AM

Consider the following dynamics.

Let  $q^l$  denote the queue length of link  $l$ .

Consider a slotted system.

- w.l.o.g. assume the length of a slot is 1.
- the channel state is fixed within a time slot,  $K(t)$
- our scheme also uses a fixed action within a time slot,  $\vec{p}(t)$
- the capacity of each link is also fixed within a time slot

$$\vec{r}(t) = f(\vec{p}(t), K(t))$$

The queue-length then evolves as

$$q^l(t+1) = [q^l(t) + \sum_s H_s^l A_s(t) - r^l(t)]^+ \quad \mathbb{E}[A_s(t)] = X_s$$

random arrivals  $\nearrow$ projection to  $\uparrow$   
 $[0, +\infty)$

---

Key intuition:

We need to make sure queues do not explode to infinity.

- To drain queues faster, we would like to choose  $\vec{p}(t)$  such that  $\vec{r}(t)$  is large  
 $\uparrow$   
a vector

If the current rate of link  $l$  cannot support the offered load,

$\Rightarrow \rho^l$  will increase

$\Rightarrow$  should increase  $r^l$ , possibly at the cost of other links

---

Consider the following policy:

Pick  $\vec{p}(t)$  at each time such that

$$\vec{p}(t) = \underset{\vec{p} \in \mathcal{A}}{\operatorname{argmax}} \sum \rho^l r^l$$

$\vec{r} = f(\vec{p}, K(t))$

$\uparrow$  gives larger weight to  $r^l$  if  $\rho^l$  is large.

We will show that this scheduling policy will be able to stabilize all queues for any offered load  $\vec{\lambda} \in \Lambda$ .

Note: The policy does not require knowledge of  $\vec{\lambda}$  or  $\Pi$

It only needs the current channel state  $K(t)$

- queue-length based
  - adaptive
  - online solution.
-

Why some other policies will not work?

- (1) choose the schedule that maximizes

$$\sum_t r_t$$

or  $\sum_t w_t r_t$ , where  $w_t$  is fixed.

- (2) choose the schedule that maximizes

$$\sum_t r_t \mathbb{1}_{\{p_t > 0\}}$$

(10)

## Lyapunov stability - 5min

Sunday, January 27, 2008 11:38 AM

Main theoretical approach:

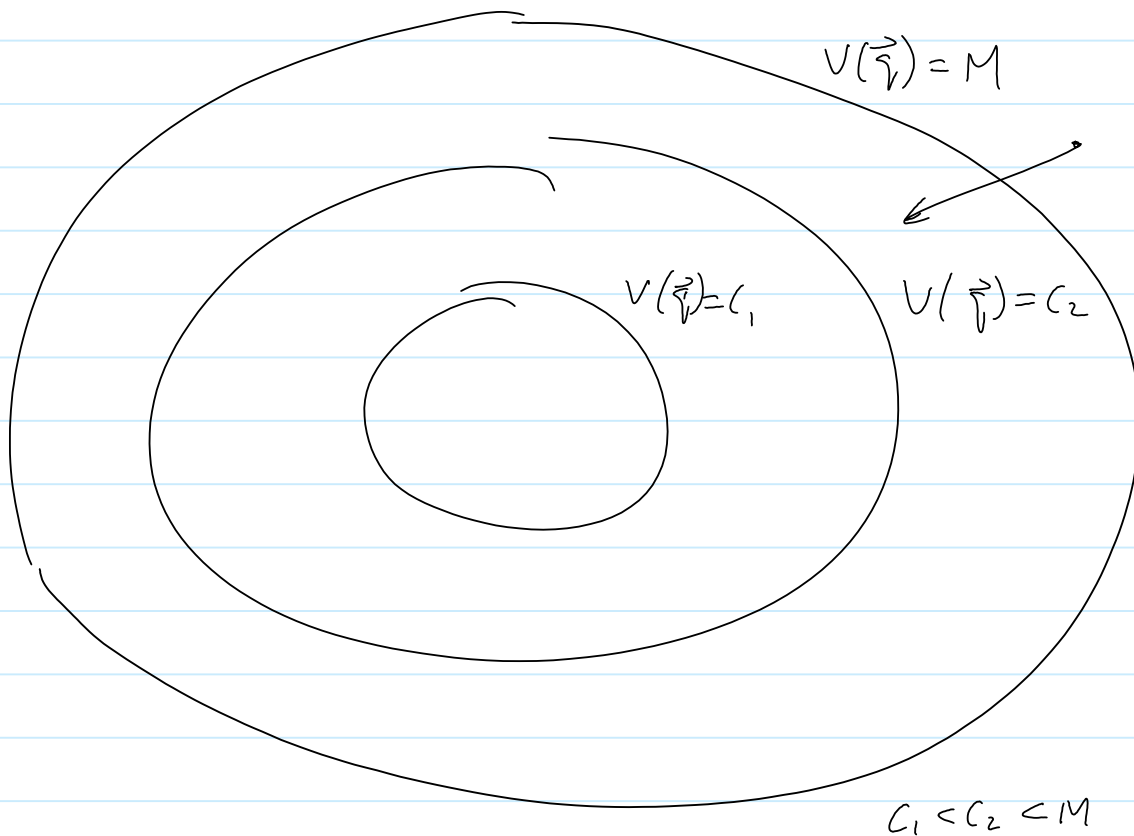
- Lyapunov stability
- Find a Lyapunov function  $V(\vec{r})$  such that

$$\textcircled{1} \quad V(\vec{r}) \geq 0 \text{ for all } \vec{r} \\ V(\vec{r}) \rightarrow +\infty \text{ as } \|\vec{r}\| \rightarrow +\infty$$

$$\textcircled{2} \quad \mathbb{E} \left[ V(\vec{r}(t+1)) - V(\vec{r}(t)) \mid \vec{r}(t) \right]$$

$$\leq -\varepsilon \|\vec{r}(t)\|$$

whenever  $\|\vec{r}(t)\| \geq M$  for  
some constants  $\varepsilon \Delta M$



A negative drift for  $V(\vec{r})$  whenever  $V(\vec{r})$  is large.

$\Rightarrow \vec{r}(t)$  cannot explode to infinity

---

Note: the negative-drift condition can be relaxed to

$$\mathbb{E} [V(\vec{r}(t+1)) - V(\vec{r}(t)) \mid \vec{r}(t)]$$

$$\leq -\varepsilon \|\vec{r}(t+1)\| + M.$$

$\uparrow$

any constant  
does not matter.

$\Rightarrow$

$$\leq -\frac{\varepsilon}{2} \|\vec{\gamma}(t)\|$$

$$\text{when } M \leq \frac{\varepsilon}{2} \|\vec{\gamma}(t)\|.$$

— When we derive the drift, we can ignore all terms that are bounded, and focus on those terms that grow with  $\vec{q}$

(15)

## Proof of throughput-optimality - 10min

Tuesday, January 29, 2008 3:14 PM

We will show that the following function can serve as the Lyapunov function

$$V(\vec{q}) = \frac{1}{2} \sum_l (q^l)^2$$

Proof: Since

$$q^l(t+1) = [q^l(t) + \sum_j H_j^l A_s(t) - r^l(t)]^+$$

$$\begin{aligned} \Rightarrow (q^l(t+1))^2 &\leq (q^l(t) + \sum_j H_j^l A_s(t) - r^l(t))^2 \\ &= (q^l(t))^2 + 2q^l(t) \left[ \sum_j H_j^l A_s(t) - r^l(t) \right] \\ &\quad + \left[ \sum_j H_j^l A_s(t) - r^l(t) \right]^2 \end{aligned}$$

If  $A_s(t)$  is finite, and  $r^l(t)$  is bounded, there exists a constant  $M_l$  such that

$$(q^l(t+1))^2 \leq (q^l(t))^2 + 2q^l(t) \left[ \sum_j H_j^l A_s(t) - r^l(t) \right] + M_l$$

$$\begin{aligned} \Rightarrow V(\vec{q}(t+1)) &\leq V(\vec{q}(t)) + \sum_l q^l(t) \left[ \sum_j H_j^l A_s(t) - r^l(t) \right] \\ &\quad + \frac{1}{2} \sum_l M_l \end{aligned}$$

$$\Rightarrow E \left( V(\vec{q}(t+1)) - V(\vec{q}(t)) \mid \vec{q}(t) \right)$$

$$\leq \sum_l g^l(t) \sum_j H_j^l X_j - \sum_l g^l(t) E[r^l(t) | g^l(t)] + \frac{1}{2} \sum_l M_l^2.$$

Intuition:

The max-weight policy is chosen to minimize the negative drift!

For any  $\vec{x}$  that lies strictly inside  $\Omega$

$$\Omega = \sum_K \lambda_K \text{Conv-hull} \{ g(\vec{p}, K) | \vec{p} \in \mathcal{H} \}$$

$$\Rightarrow (1+\varepsilon) \vec{x} \in \Omega \text{ for some } \varepsilon > 0$$

$$\Rightarrow \text{There exists } \alpha_K^m, \vec{p}_K^m \in \mathcal{H}, \sum_m \alpha_K^m = 1$$

such that

$$(1+\varepsilon) \sum_j H_j^l X_j \leq \sum_K \lambda_K \sum_m \alpha_K^m g_l(\vec{p}_K^m, K)$$

for all  $l$ .

Since  $\sum_l g^l(t) r^l(t) = \max_{\vec{r} = g(\vec{p}, K(t))} \sum_l g^l(t) r^l$

$$\Rightarrow \sum_l g^l(t) g_l(\vec{p}_K^m, K) \mathbb{1}_{\{K(t)=K\}}$$

$$\leq \sum_l g^l(t) r^l(t) \mathbb{1}_{\{K(t)=K\}}$$

for all  $k, m$

$$\Rightarrow \sum_l q^l(t) \pi_k \sum_m \alpha_k^m g(\vec{p}_k^m, k) \leq \sum_l q^l(t) E[r^l(t) \mathbb{1}_{\{k(t)=k\}} | \vec{q}(t)]$$

$$\Rightarrow \sum_l q^l(t) \sum_k \pi_k \sum_m \alpha_k^m g_l(\vec{p}_k^m, k) \leq \sum_l q^l(t) \cdot E[r^l(t) | \vec{q}(t)]$$

$$\Rightarrow (1+\varepsilon) \sum_l q^l(t) \sum_s H_s^l X_s \leq \sum_l q^l(t) E[r^l(t) | q^l(t)]$$

Hence, we have

$$E[V(\vec{q}(t+1) - \vec{q}(t)) | \vec{q}(t)]$$

$$\leq -\varepsilon \sum_l q^l(t) \sum_s H_s^l X_s + \frac{1}{2} \sum_l M_l^2$$

$$\leq -\varepsilon \cdot \left[ \min_l \sum_s H_s^l X_s \right] \left( \sum_l q^l(t) \right) + \frac{1}{2} \sum_l M_l^2$$

$$\leq -\frac{\varepsilon}{2} \left[ \min_l \sum_s H_s^l X_s \right] \left( \sum_l q^l(t) \right)$$

$$\text{if } \sum_l q^l(t) \geq \frac{\frac{1}{2} \sum_l M_l^2}{\frac{\varepsilon}{2} \left[ \min_l \sum_s H_s^l X_s \right]} \triangleq M$$

(25)

## Proof of throughput-optimality - handout

Tuesday, January 29, 2008 3:14 PM

We will show that the following function can serve as the Lyapunov function

$$V(\vec{q}) = \frac{1}{2} \sum_l (q^l)^2$$

Proof: Since

$$q^l(t+1) = [q^l(t) + \sum_j H_j^l A_j(t) - r^l(t)]^+$$

$$\Rightarrow (q^l(t+1))^2 \leq (q^l(t) + \sum_j H_j^l A_j(t) - r^l(t))^2$$

If  $A_j(t)$  is finite, and  $r^l(t)$  is bounded, there exists a constant  $M_l$  such that

$$(q^l(t+1))^2 \leq (q^l(t))^2 + 2q^l(t) \left[ \sum_j H_j^l A_j(t) - r^l(t) \right] + M_l$$

$$\Rightarrow V(\vec{q}(t+1)) \leq$$

1.2.1

$$\Rightarrow E \left( \frac{V(\vec{s}(t+1)) - V(\vec{r}(t+1))}{\vec{r}(t)} \right) \leq$$

---

Intuition:

The max-weight policy is chosen to minimize the negative drift!

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For any  $\vec{x}$  that lies strictly inside  $\Omega$

$$\Omega = \sum_K \lambda_K \text{Conv-hull} \{ g(\vec{p}, K) \mid \vec{p} \in \mathcal{H} \}$$

$$\Rightarrow (1+\varepsilon) \vec{x} \in \Omega \text{ for some } \varepsilon > 0$$

$$\Rightarrow \text{There exists } \alpha_K^m, \vec{p}_K^m \in \mathcal{H}, \sum_m \alpha_K^m = 1$$

such that

$$(1+\varepsilon) \sum_j \mathbb{H}_j^l X_j \leq \sum_K \lambda_K \sum_m \alpha_K^m g_l(\vec{p}_K^m, K)$$

for all  $l$ .

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$$\text{Since } \sum_l q^l(t) r^l(t) = \max_{\vec{r} = g(\vec{p}, K(t))} \sum_l q^l(t) r^l$$

$$\Rightarrow \sum q^l(t) g_l(\vec{p}_K^m, K) \mathbb{1}_{\{K(t)=K\}}$$

$$\leq \sum q^l(t) r^l(t) \mathbb{1}_{\{K(t)=K\}}$$

for all  $k, m$

$$\Rightarrow \sum p^l(t) \pi_k \sum_m \alpha_k^m g(\vec{p}_k^m, k) \\ \leq \sum q^l(t) E[r^l(t) \mathbb{1}_{\{k(t)=k\}} | \vec{q}(t)]$$

$$\sum_l q^l(t) \sum_k \pi_k \sum_m \alpha_k^m g_l(\vec{p}_k^m, k) \\ \leq \sum_l q^l(t) \cdot E[r^l(t) | \vec{q}(t)]$$

$$\Rightarrow (1+\varepsilon) \sum_l q^l(t) \sum_j H_j^l X_j \leq \sum_l q^l(t) E[r^l(t) | q^l(t)]$$

Hence, we have

$$E[V(\vec{q}(t+1) - \vec{q}(t)) | \vec{q}(t)] \\ \leq -\varepsilon \sum_l q^l(t) \sum_j H_j^l X_j + \frac{1}{2} \sum_l M_l^2 \\ \leq -\varepsilon \cdot \left[ \min_l \sum_j H_j^l X_j \right] \left( \sum_l q^l(t) \right) + \frac{1}{2} \sum_l M_l^2 \\ \leq -\frac{\varepsilon}{2} \left[ \min_l \sum_j H_j^l X_j \right] \left( \sum_l q^l(t) \right) \\ \text{if } \sum_l q^l(t) \geq \frac{\frac{1}{2} \sum_l M_l^2}{\frac{\varepsilon}{2} \left[ \min_l \sum_j H_j^l X_j \right]} \triangleq M$$

(25)