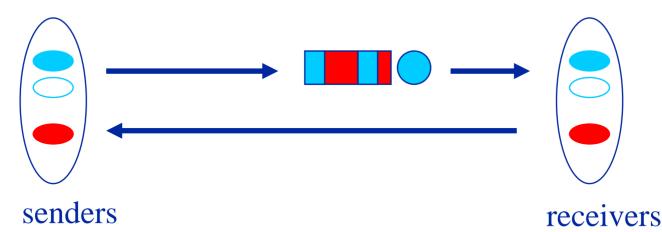
Congestion control algorithms

Frank Kelly, Cambridge (joint work with Ruth Williams, UCSD) Workshop on Algorithmic Game Theory DIMAP, Warwick, March 2007

Fluid model for a network operating under a fair bandwidthsharing policy K & W Ann Appl Prob 2004
On fluid and Brownian approximations for an Internet congestion control model. W. Kang, K, N.H. Lee & W CDC 2004
State space collapse and diffusion approximation...
W. Kang, K, N.H. Lee & W forthcoming

End-to-end congestion control



Senders learn (through feedback from receivers) of congestion at queue, and slow down or speed up accordingly. With current TCP, throughput of a flow is proportional to

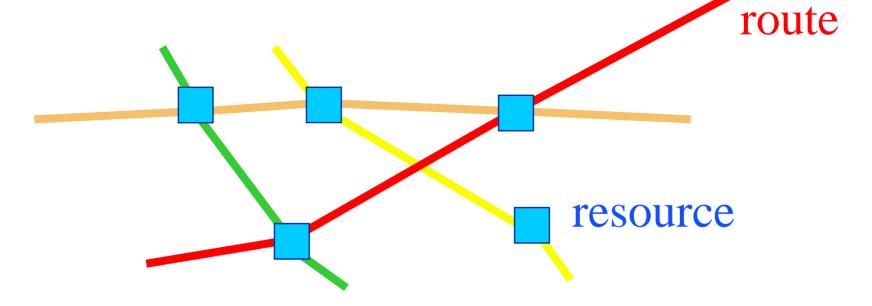
T = round-trip time, p = packet drop probability. (Jacobson 1988, Mathis, Semke, Mahdavi, Ott 1997, Padhye, Firoiu, Towsley, Kurose 1998, Floyd and Fall 1999)

Model definition

- We want to describe a network model, with fluctuating numbers of flows
- We first need
 - notation for network structure
 - abstraction of rate allocation
- Then we need to define the random nature of flow arrivals and departures

Network structure (J, R, A)

- set of resources J
- *R* set of routes
- $A_{jr} = 1$ if resource *j* is on route *r* $A_{jr} = 0$ otherwise



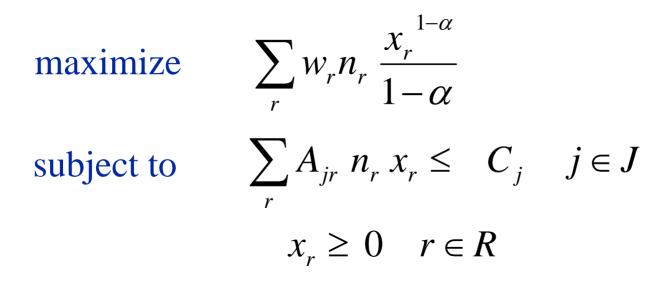
Rate allocation

- w_r weight of route r
- n_r number of flows on route r
- x_r rate of each flow on route r

Given the vector $n = (n_r, r \in R)$ how are the rates $x = (x_r, r \in R)$ chosen ?

Optimization formulation

Suppose x = x(n) is chosen to



(weighted α -fair allocations, Mo and Walrand 2000)

$$0 < \alpha < \infty$$
 (replace $\frac{x_r^{1-\alpha}}{1-\alpha}$ by $\log(x_r)$ if $\alpha = 1$)

Solution $x_{r} = \left(\frac{W_{r}}{\sum_{j} A_{jr} p_{j}(n)}\right)^{1/\alpha} \qquad r \in R$

 $p_j(n)$ - shadow price (Lagrange multiplier) for the resource *j* capacity constraint

Observe alignment with square-root formula when

$$\alpha = 2$$
, $w_r = 1/T_r^2$, $p_r \approx \sum_j A_{jr} p_j$

Examples of α -fair allocations

maximize
$$\sum_{r} w_{r} n_{r} \frac{x_{r}^{1-\alpha}}{1-\alpha}$$

subject to
$$\sum_{r} A_{jr} n_{r} x_{r} \leq C_{j} \quad j \in J$$
$$x_{r} \geq 0 \quad r \in R$$

$$x_r = \left(\frac{W_r}{\sum_j A_{jr} p_j(n)}\right)^{1/\alpha} r \in R$$

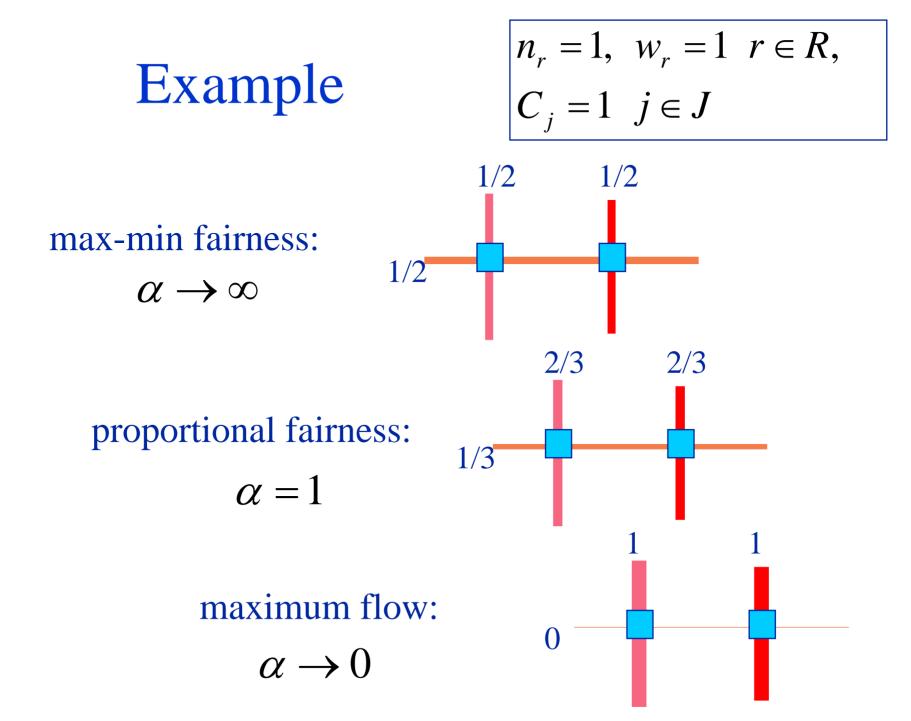
$$\alpha \to 0 \quad (w = 1)$$

$$\alpha \to 1 \quad (w = 1)$$

$$\alpha = 2 \quad (w_r = 1/T_r^2)$$

$$\alpha \to \infty \quad (w = 1)$$

- maximum flow
- proportionally fair
- TCP fair
- max-min fair



Flow level model

Define a Markov process $n(t) = (n_r(t), r \in R)$ with transition rates

- $n_r \rightarrow n_r + 1$ at rate v_r $r \in R$ $n_r \rightarrow n_r - 1$ at rate $n_r x_r(n) \mu_r$ $r \in R$
- Poisson arrivals, exponentially distributed file sizes

- let $\rho_r = \frac{v_r}{\mu_r}$ $r \in R$,

the *load* on route *r*

Stability? (i.e. positive recurrence?)

Suppose vertical streams have priority: then condition for stability is

$$\rho_0 < (1 - \rho_1) (1 - \rho_2)$$

and not

$$\rho_0 < \min\{1 - \rho_1, 1 - \rho_2\}$$

(Bonald and Massoulie 2001)

Fairness leads to stability

Suppose
$$\sum_{r} A_{jr} \rho_{r} < C_{j} \quad j \in J$$

and resource allocation is weighted α -fair. Then the Markov process $n(t) = (n_r(t), r \in R)$ is positive recurrent (De Veciana, Lee and Konstantopoulos 1999; Bonald and Massoulie 2001).

Heavy traffic

We're interested in what happens when we approach the edge of the achievable region, when

 $\sum A_{jr} \rho_r \approx C_j \quad j \in J$

Balanced fluid model

Suppose
$$\sum_{r} A_{jr} \rho_{r} = C_{j} \quad j \in J$$

and consider differential equations

$$\frac{\mathrm{d}n_r(t)}{\mathrm{d}t} = v_r - n_r x_r(n)\mu_r \qquad (n_r > 0) \qquad r \in R$$

First let's substitute for the values of $x_r(n)$, $r \in R$, to give:

$$\frac{\mathrm{d}n_r(t)}{\mathrm{d}t} = v_r - n_r \mu_r \left(\frac{w_r}{\sum_j A_{jr} p_j(n)}\right)^{1/\alpha} \quad r \in \mathbb{R}$$

(care needed when
$$n_r = 0$$
).

Thus, at an invariant state,

$$n_r = \frac{v_r}{\mu_r} \left(\frac{\sum_j A_{jr} p_j(n)}{w_r} \right)^{1/\alpha} \quad r \in \mathbb{R}$$

State space collapse

The following are equivalent:

- *n* is an invariant state
- there exists a non-negative vector pwith $\sqrt{\sum_{i=1}^{1/\alpha}}$

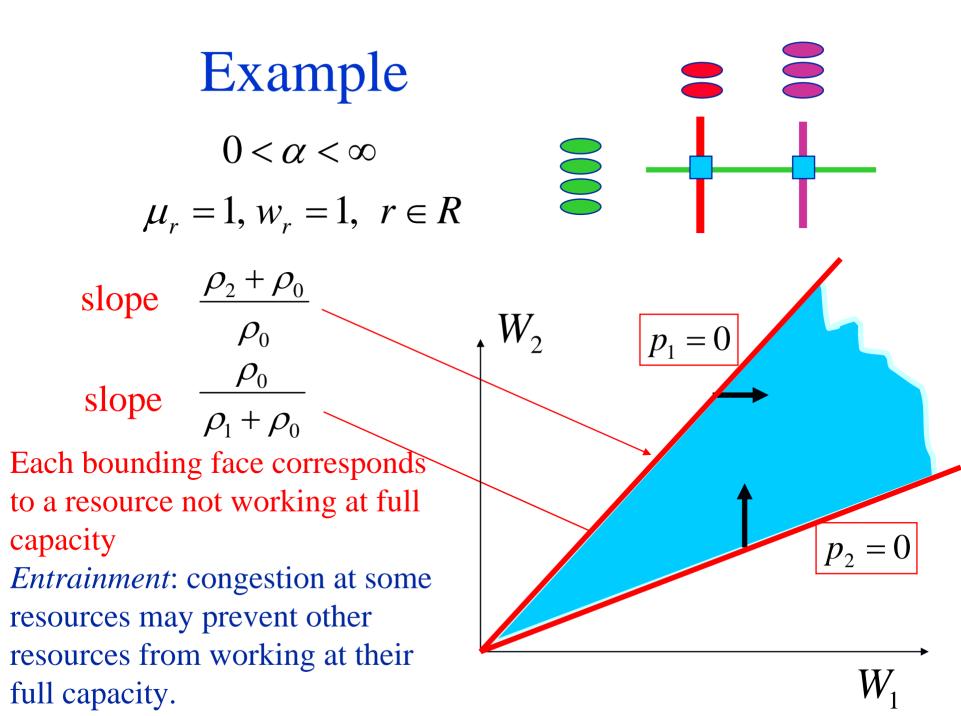
$$n_r = \frac{v_r}{\mu_r} \left(\frac{\sum_j A_{jr} p_j}{w_r} \right)^{1/\alpha} \quad r \in \mathbb{R}$$

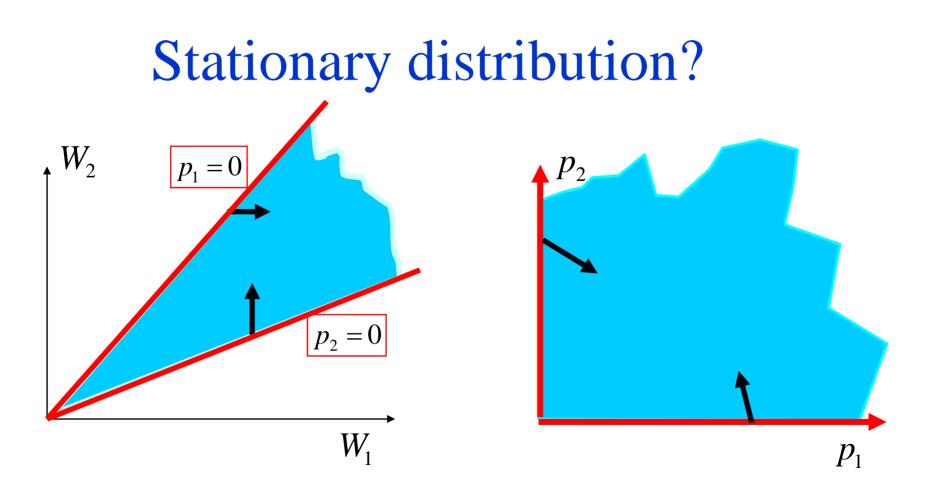
Thus the set of invariant states forms a J dimensional manifold, parameterized by p.

Workloads

Let
$$W_j(n) = \sum_r A_{jr} \frac{n_r}{\mu_r}$$

the *workload* for resource *j*, and let $\alpha = 1$ Define diagonal matrices $\rho = diag(v_r / \mu_r, r \in R), w = diag(w_r, r \in R)$ Then W lies in the polyhedral cone $\{W: W = A\mu^{-1}\rho w^{-1}A^T p, p \ge 0\}$

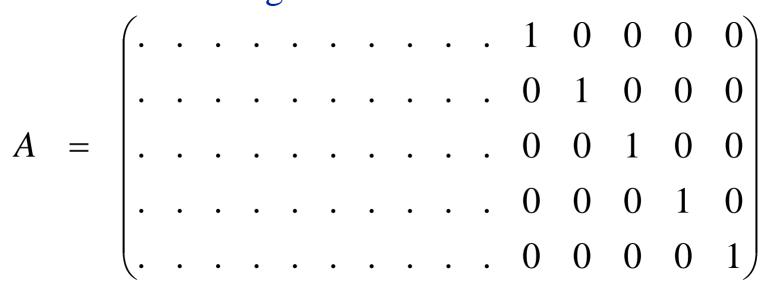




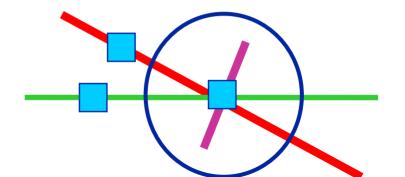
Look for a stationary distribution for W, or equivalently, p. Williams (1987) determined sufficient conditions, in terms of the reflection angles and covariance matrix, for a SRBM in a polyhedral domain to have a product form invariant distribution – a skew symmetry condition

Local traffic condition

Assume the matrix A contains the columns of the unit matrix amongst its columns:



i.e. each resource has some local traffic -



Product form under proportional fairness $\alpha = 1, w_r = 1, r \in R$

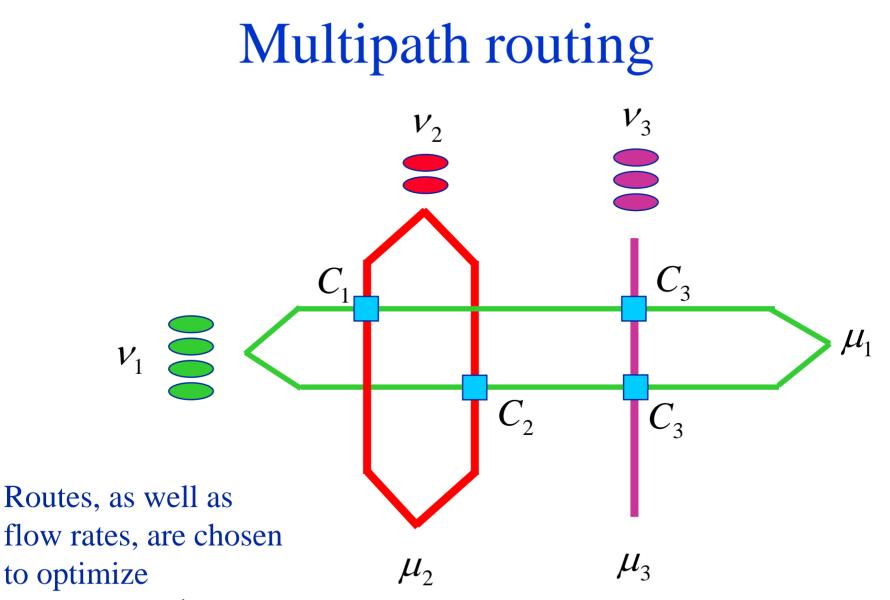
Under the stationary distribution for the reflected Brownian motion, the (scaled) components of pare independent and exponentially distributed. The corresponding approximation for n is

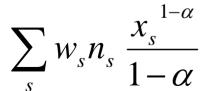
$$n_r \approx \rho_r \sum_j A_{jr} p_j \quad r \in R$$

where

$$p_j \sim \operatorname{Exp}(C_j - \sum_r A_{jr}\rho_r) \quad j \in J$$

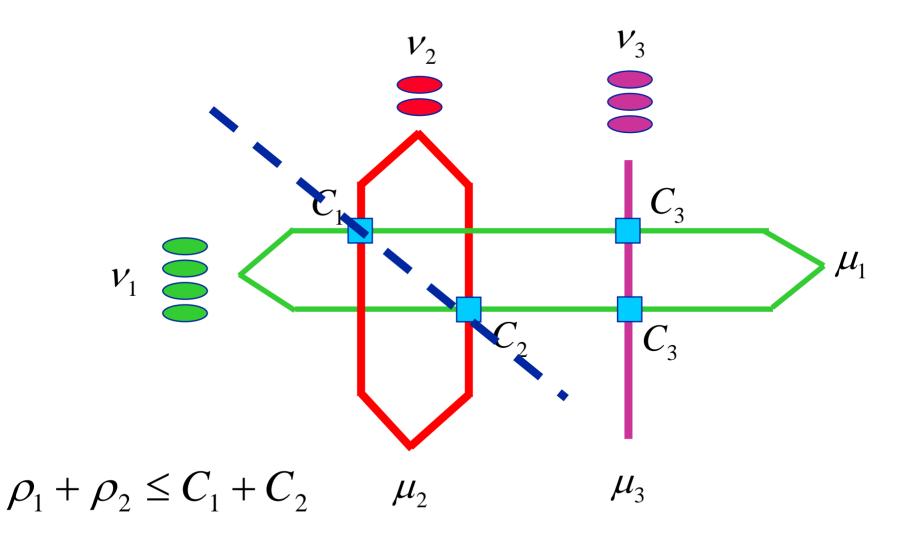
Dual random variables are independent and exponential!



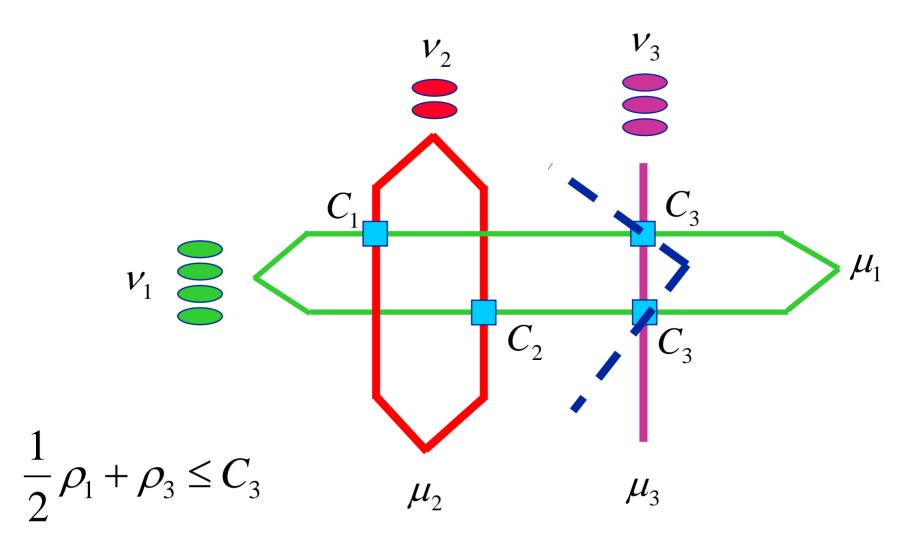


over source-sink pairs s

First cut constraint



Second cut constraint



Generalized cut constraints

In general, stability requires

$$\sum \overline{A}_{js} \rho_s < \overline{C}_j \quad j \in \overline{J}$$

- a collection of generalized cut constraints. Provided \overline{A} contains a unit matrix, we again have the approximation

where

$$n_{s} \approx \rho_{s} \sum_{j \in \overline{J}} A_{js} p_{j} \quad s \in S$$
$$_{j} \sim \operatorname{Exp}(\overline{C}_{j} - \sum_{s} \overline{A}_{js} \rho_{s}) \quad j \in \overline{J}$$

Again independent dual random variables, now one for each generalized cut constraint!