

# On User Strategies in Networks Implementing Congestion Pricing

Tobias Harks

[harks@zib.de](mailto:harks@zib.de)



Zuse Institute  
Berlin (ZIB)

Tobias Poschwatta

[posch@tkn.tu-berlin.de](mailto:posch@tkn.tu-berlin.de)



TU Berlin

TKN

Telecommunication  
Networks Group

# Overview

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- Congestion Pricing Model
- Realistic User Strategies
- Download Problem
- Simulation Results
- Wireless Networks

# Pricing Model – Elastic Traffic

Sources  $s \in S$   
have information about:

$x_s \sim$  sending rate

$U_s(x_s) \sim$  concave utility  
function

$q_s = \sum_{l \in L(s)} p_l \sim$  **path price**

Links  $l \in L$   
have information about:

$c_l \sim$  link capacity

$p_l \sim$  congestion measure (**price**)

$y_l = \sum_{s \in S(l)} x_s \sim$  aggregate  
transmission rate

If a user bids  $w_s$  he receives bandwidth  $x_s = \frac{w_s}{q_s}$

Prices  $p_l$  are generated by a gradient projection algorithm:

$$\frac{d}{dt}p_l(t) = \gamma[y_l(t) - c_l]^+$$

# Optimization Interpretation

User's want to maximize their surplus:  $\max_{w_s \geq 0} U_s(\frac{w_s}{q_s}) - w_s \quad (1)$

If  $w_s$  is continuously varied according to the maximum of (1), the system converges to the unique solution of:

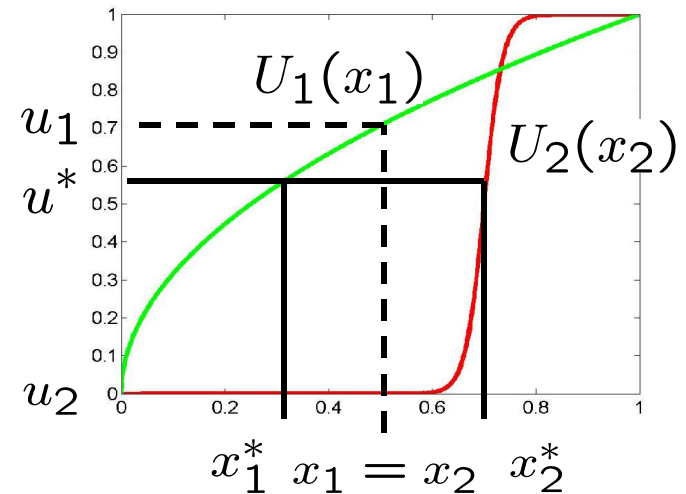
$$\begin{aligned} (P) \quad & \max_{x_s \geq 0} \quad \sum_{s \in S} U_s(x_s) \\ & s.t. \quad \sum_{s \in S(l)} x_s \leq c_l \end{aligned}$$

Kelly '99  
TCP-Fast (Low)  
Max-Min Kelly Control  
(Lougiov, 2004 Sigcomm)  
Jetmax(L., Infocom 2006)

# Real-Time Traffic - Utility Fairness

## Problem :

- we lose concavity!
- is bandwidth fairness what the user expects?



$$(P^*) \quad \max_{x_s \geq 0} \quad \sum_{s \in S} F_s(x_s) \\ \text{s.t.} \quad \sum_{s \in S(l)} x_s \leq c_l$$

# Realistic User Strategies

- Are user's preferences captured by static utility functions?
- File download with limited budget and deadline



Static utility optimization does not the job!

- Assume user has a budget  $B_s$  and wants to download a file of length  $L_s$  within time  $T_s$
- we associate with every bid  $w_s$  an increasing convex cost function  $C_s(w_s)$

# Download Problem – Optimal Control

- file length at time  $t$ :  $l_s(t) = \int_0^t x_s(\tau) d\tau, \quad 0 \leq t \leq T_s$
- Spend budget at time  $t$ :  $b_s(t) = \int_0^t w_s(\tau) d\tau, \quad 0 \leq t \leq T_s$

$$\min_{w_s \in W_s} \int_0^T C_s(w_s(t)) dt$$

$$s.t. : \dot{l}_s = x_s = \frac{w_s}{q_s}$$

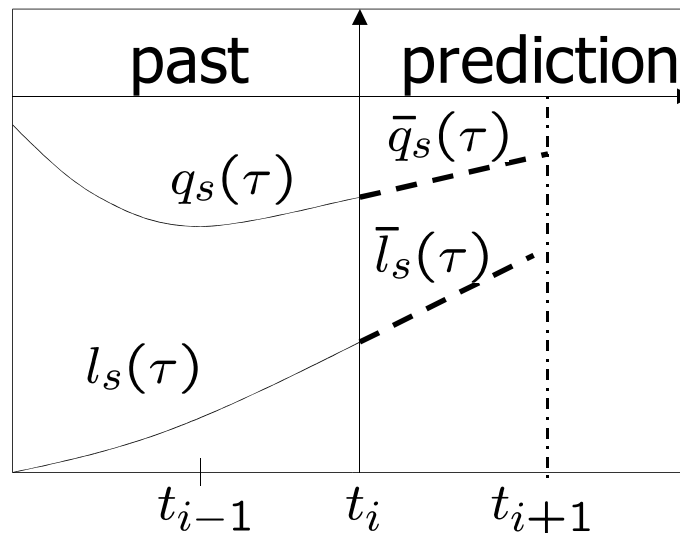
$$\dot{q}_s = f_s(\{x_i | i \text{ uses links of } L(s)\})$$

$$l_s(0) = 0, \quad l_s(T_s) = L_s, \quad q_s(0) = q_s^0$$

$$b_s(T_s) \leq B_s, \quad W_s = [w_s^{\min}, w_s^{\max}]$$

# Model Predictive Control

- congestion level  $q_s(t)$  will fluctuate with level of usage  $\longrightarrow$  system uncertainties!
- online problem!
- Approach: Divide  $[0, T]$  in  $N$  intervals of length  $T/N$
- Linear Prediction:  $\dot{q}_s(t) = \zeta_s^i, t \in [t_i, t_{i+1}], \zeta_s^i \in \mathbb{R}$





# Linear Predicting Control

- Solve for every time slot  $[t_i, t_{i+1}]$  the following problem:

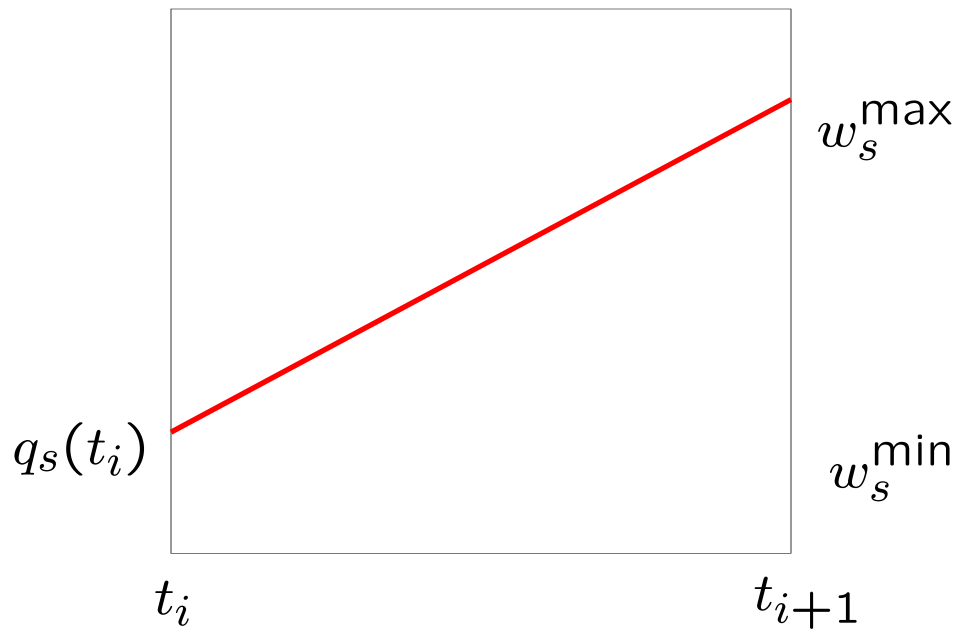
$$\begin{aligned} & \min_{\bar{w}_s \in W_s} \int_{t_i}^{t_{i+1}} C_s(\bar{w}_s(t)) dt \\ \text{s.t. : } & \dot{\bar{l}}_s = \frac{\bar{w}_s}{\bar{q}_s}, \\ & \dot{\bar{q}}_s = \zeta_s^i, \zeta_s^i \in \mathbb{R} \\ & \bar{l}_s(t_i) = 0, \quad \bar{l}_s(t_{i+1}) = h \frac{L - l_s(t_i)}{T_s - t_i} \\ & \bar{q}_s(t_i) = q_s(t_i), \quad W_s = [w_s^{\min}, w_s^{\max}] \end{aligned}$$

# Linear Cost Function

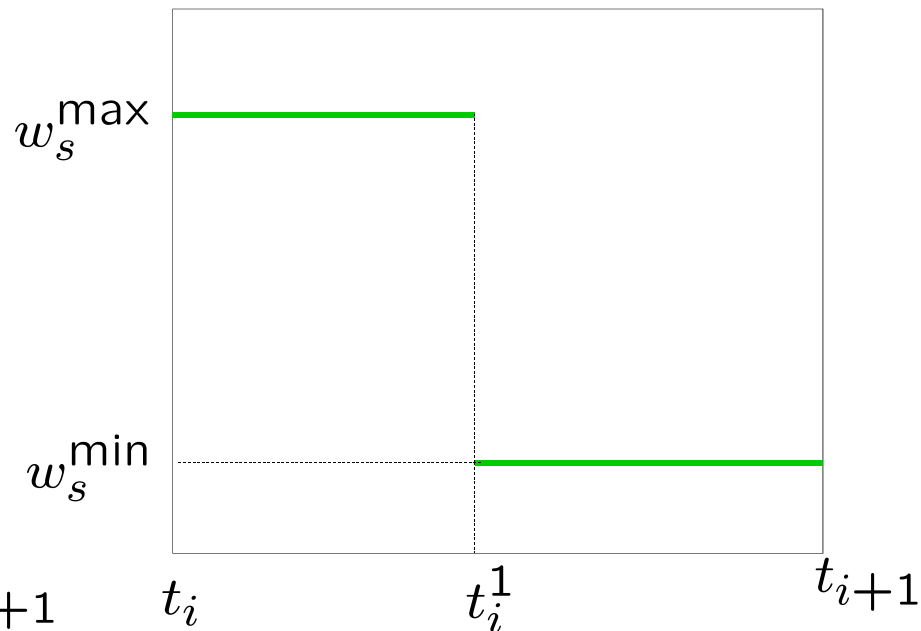
- In the original pricing scheme:  $C_s(w_s) = w_s$

➡ Optimal control is bang-bang

*Linear Prediction*



*Optimal Control*

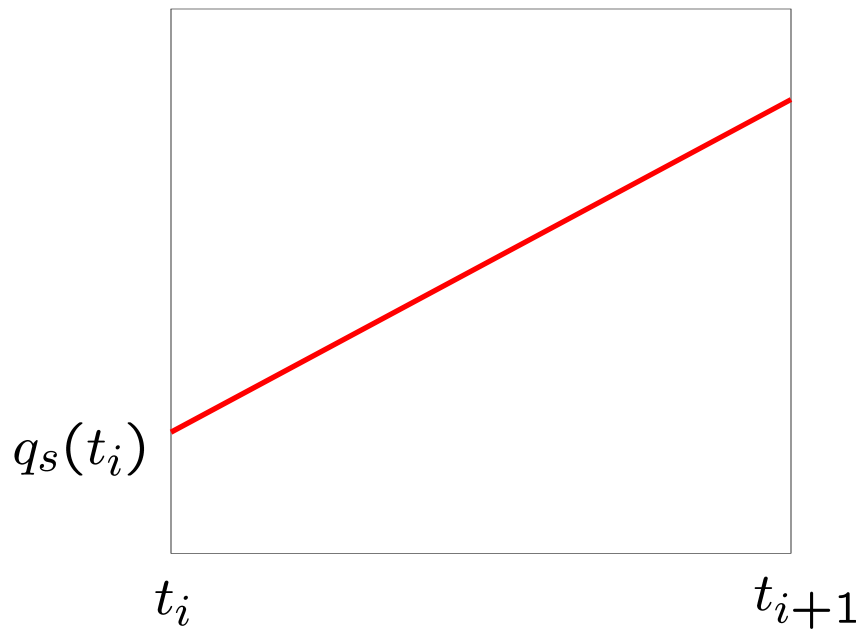


# Convex Cost Function

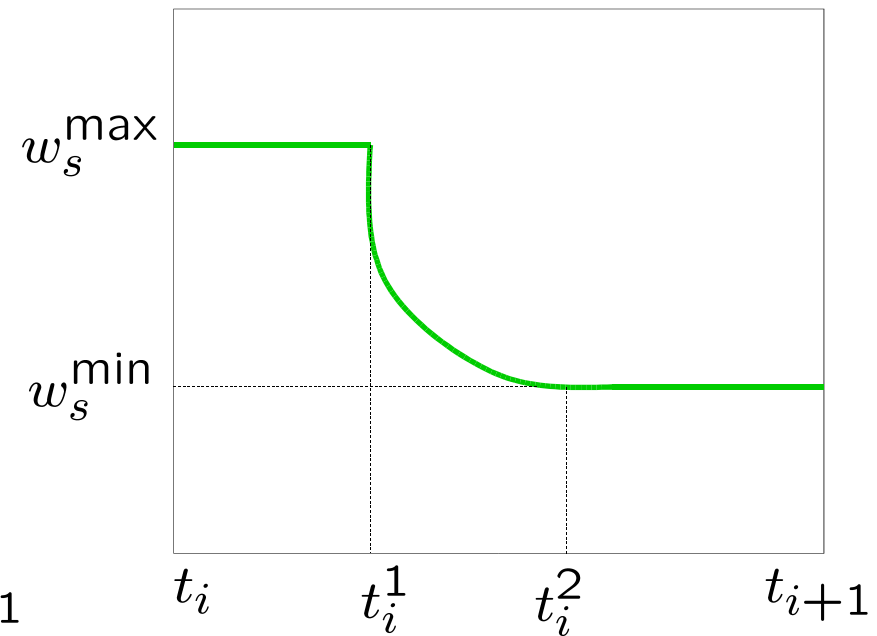
- If the cost function is slightly changed (strictly convex)

$$C_s(w_s) = \frac{w_s^{1+\epsilon}}{1+\epsilon}, \epsilon > 0 \quad \longrightarrow \quad \text{Continuous optimal control}$$

*Linear Prediction*

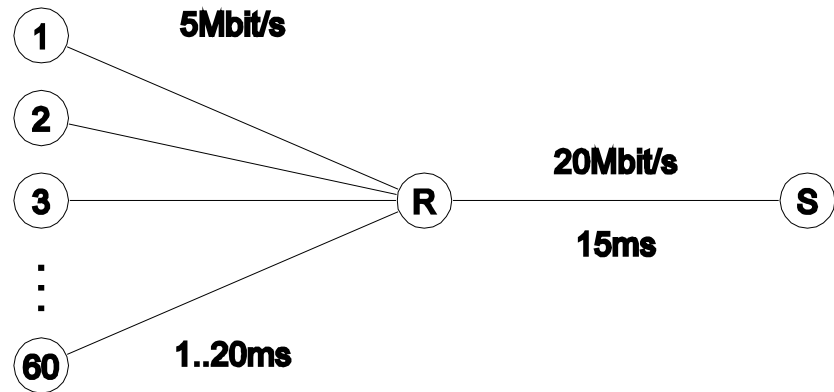


*Optimal Control*

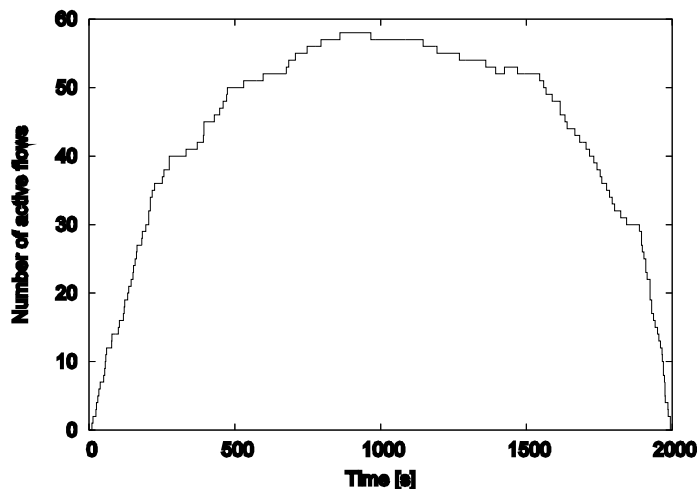


# Simulation Setup

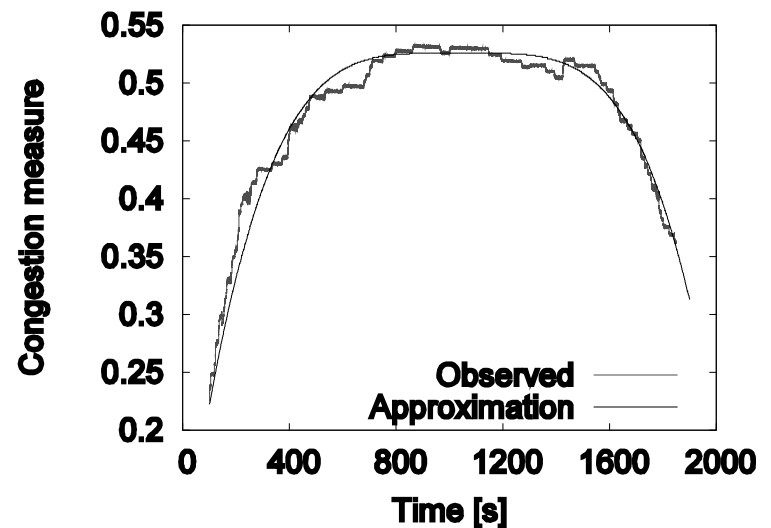
- network topology



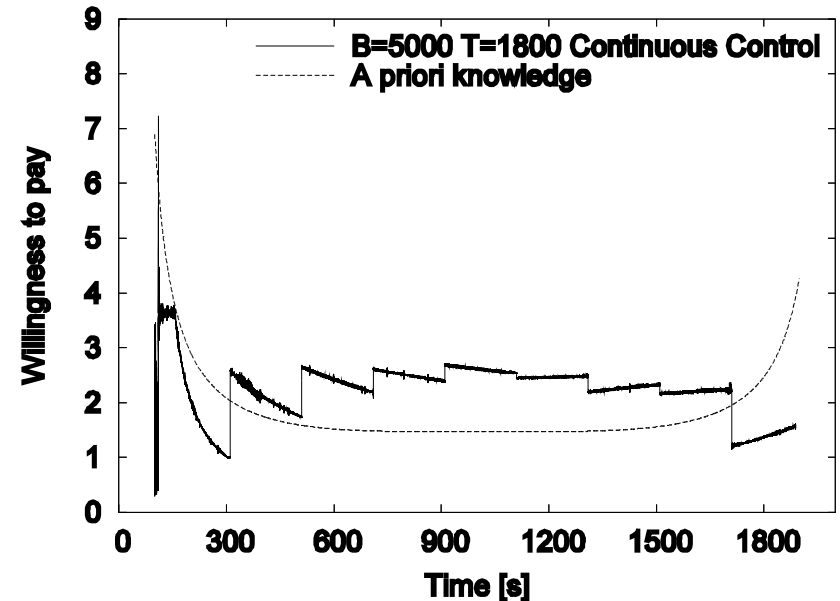
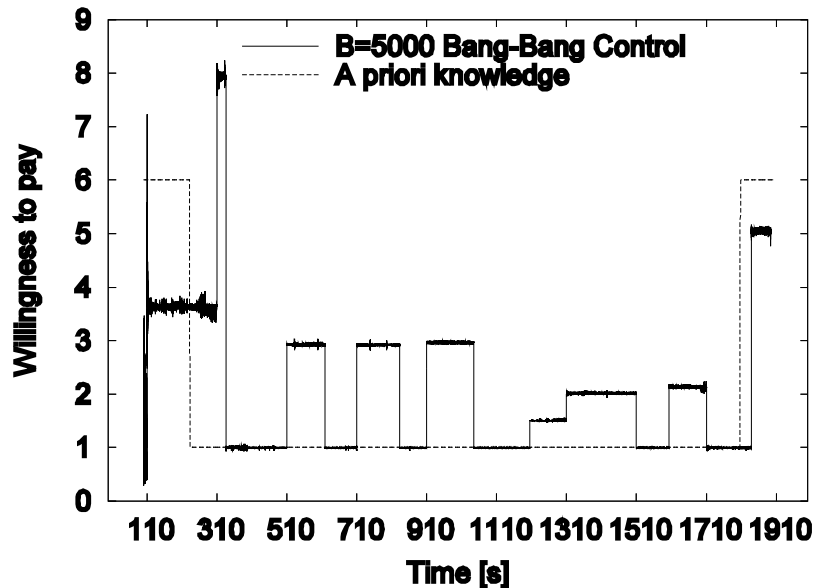
- number of active flows (up to 60)



- path price



# Bang-Bang and Continuous Control



Significant Improvement for overdimensioned budgets!  
Comparison to approach [Gibbens/Kelly ,99]



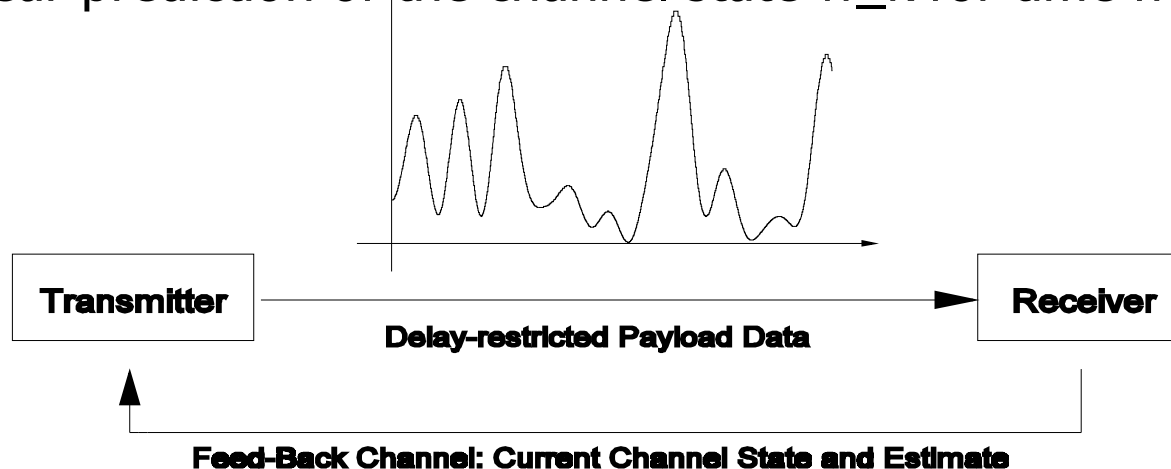
20% Cost savings (B=5000)

# Energy Efficient Data Transfer in Wireless Networks (Joint Work with James Gross and Ana Aguiar (TKN))

- Capacity is given by the Shannon capacity formula:

$$C(t) = \log_2(1 + v(t)) = \log_2 \left( 1 + \frac{p(t)(h(t))^2}{n(t)} \right)$$

- We define the channel state as :  $q_k = \frac{h(t_k)^2}{n(t_k)}$
- Problem: Transfer data of length  $d$  within time  $T$  energy efficiently!
- Dividing the horizon in  $N$  time frames
- Linear prediction of the channel state  $w_k$  for time frame  $k$



# Dynamic Programming Results

Approximation of the cost function for sending data  $D$  in frame  $k$  by second order polynomial :

$$c_k(w_k, D_k) \approx \frac{aD_k^2 + bD_k + c}{w_k}$$

- This leads to the optimal scheduling problem:

$$\begin{aligned} \min \quad & E \{ \sum_{k \in N} c_k(w_k, D_k) \} \\ \text{s.t.} \quad & \sum_{k \in N} D_k = d_1 \end{aligned}$$

- Optimal policy (data scheduling) is given by:

# Optimal Power Control

$$\mu_k(d_k, w_k) = \frac{\prod_{i=k+1}^N E_i w_k d_k}{1 + \prod_{i=k+1}^N E_i w_k}, \quad \mu_N(d_N, w_N) = d_N$$

$$J_k(d_k, w_k) = \frac{d_k^2 \prod_{i=k+1}^N E_i}{1 + w_k \prod_{i=k+1}^N E_i}, \quad J_N(d_N, w_N) = \frac{d_N^2}{w_N}$$

- Determine an energyefficient power control strategy in order to transfer  $D_i$  within frame  $i$ :

$$\begin{aligned} & \min_{p \in [0, P_{Max}]} \int_{t_i}^{t_{i+1}} p(t) dt \\ & s.t. : \dot{d} = \log_2(1 + pq) \\ & \quad \dot{q} = \xi_i, \quad q(t_i) = q_0^i \\ & \quad d(t_i) = 0, \quad d(t_{i+1}) = D_i, \end{aligned}$$



# Cross Layer Optimization Projekt

- How can we benefit on the **transport layer** from channel knowledge (attenuation) of the link layer?

Approach: For the same scenario we solve for every  $k$ :

$$\begin{aligned} \min \quad & E \{ \sum_{k \in N} c_k(w_k, D_k) \} \\ \text{s.t.} : \quad & \sum_{k \in N} D_k = d_1 \end{aligned}$$

This gives the data  $D_k^*$  for every frame (RTT) , and the rate:

$$E_{rate} = \frac{D_k^*}{\text{Frame Length}}$$

Align:  $E_{rate}$  with congestion rate (window)  $x_{TCP}$

# Cross Layer Optimization Projekt

- How can we benefit on the **transport layer** from channel knowledge (attenuation) of the **link layer**?  
Approach: the same for every  $k$ :

**The End**

This gives us the **rate**:

Align: **TCP**

# Dual Problem - Decentralized Algorithms

**Wanted:**  $\left\{ \begin{array}{l} \text{Source Algorithm: } x_s(t+1) = H_s(x_s(t), q_s(t)) \\ \text{Link Algorithm: } p_l(t+1) = G_l(p_l(t), y_l(t)) \end{array} \right.$

**Using Lagrangian  
with Multiplier:**

$$L(x, p) = \sum_{s \in S} U_s(x_s) - p(y - c)$$

**Dual Problem:**

$$(D) \quad \min_{p \geq 0} \max_{x \geq 0} L(x, p)$$

**Source Algorithm:**  $x_s(t+1) = U_s'^{-1}(q_s(t))$

**Link  
Algorithm:**  $p_l(t+1) = [p_l(t) + \gamma_l(y_l(t) - c_l)]^+$

Implemented in REM (Low, 2000) using single bit (ECN)

# Results

**Definition:** A rate vector is **utility proportional fair**, if it solves Problem (P\*).

**Let the rate vector  $x = (x_s, s \in S)$  be utility proportional fair.**

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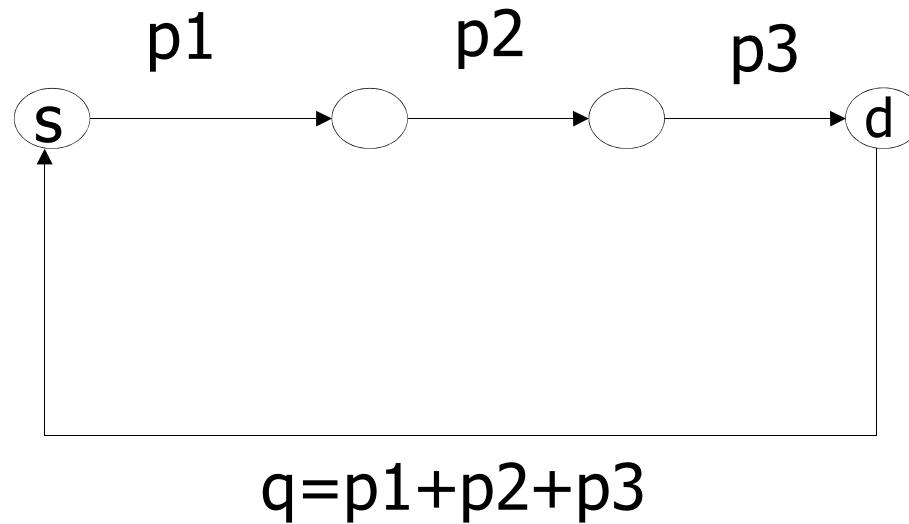
**Theorem1:** Suppose all users use the same transformation function.

- (i)  $x$  is **path utility max-min fair**.
- (ii)  $L(s_1) \subset L(s_2) \Rightarrow U_{s_1}(x_{s_1}) \geq U_{s_2}(x_{s_2})$

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**Theorem2:** Suppose all users use the same transformation function  $f_s(q_s, \kappa) = \sqrt[\kappa]{q_s}$ ,  $\kappa > 0$ . Let the sequence of rate vectors  $x(\kappa)$  be utility proportional fair. Then  $x(\kappa)$  approaches the **utility max-min fair** rate allocation as  $\kappa \rightarrow \infty$ .

# Results



- rate is a function of  $q$ 
  - $q$  is function of  $y$