Transmission Latency and Communication over Time-Varying Channels

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My Brief Background…

(Sep 2003 -) Postdoctoral Teaching Fellow, University of British Columbia, Department of Electrical and Computer Engineering

(May 2000- Jun 2003) PhD Studies, University of Victoria, Department of Electrical Engineering

(1996 - 1999), Faculty of Electrical Engineering in Belgrade, M.Sc. studies, **M.Sc. Thesis Title**: "Application of Non-linear One-dimensional Maps in Generation of Error-Correction Block Codes"

Presentation Outline

- Problem Formulation and Introduction
- Cross-layer optimization for transmission delay minimization
- Analyzed Transmission Models
  - (1) Real-Time Traffic (e.g. videophone over wireless)
  - (2) Constant-Rate playback over time-varying channels
- Channel Model: Finite State Markov Model
- Mathematical Framework: Stochastic Control and MDP's (needed for (1))
  - Solution Techniques
- Selected Extensions
  - Power and rate resource allocation for OFDM schemes
  - Resource allocation for imperfectly known channel models
  - Resource allocation for imperfect or delayed channel state information
  - Multiuser Systems

(2) Constant-Rate playback over time-varying channels

Problem Formulation and Introduction

- Modern and future wireless networks will support different services with a wide range of quality of service requirements such as delay, rate, BER

- Consideration of Transmission Latency is of crucial interest for some applications (real-time high quality audio, video transmission)

- However, time-varying nature of a wireless channel poses a challenging task to delivering a wide variety of services

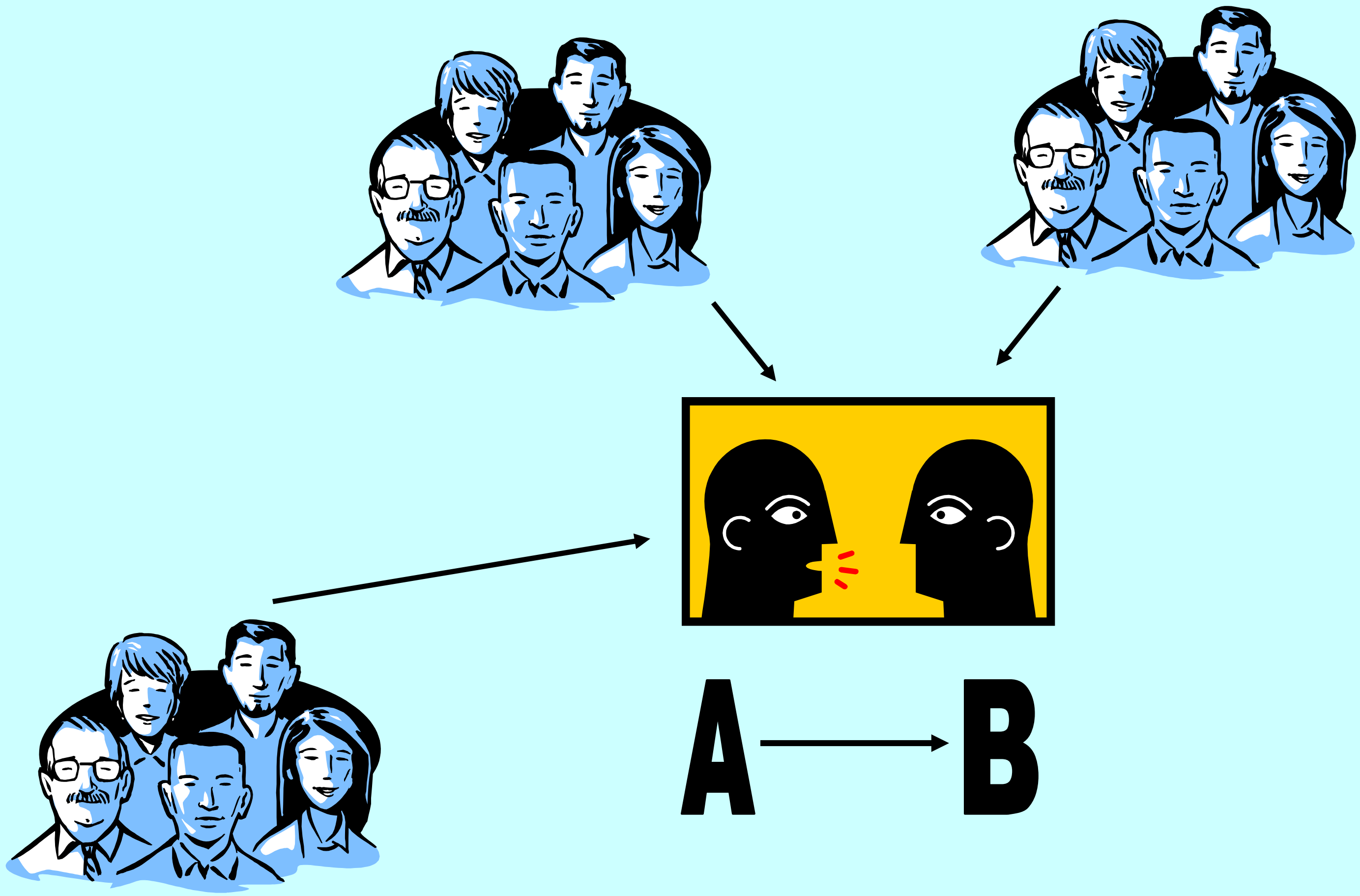
  - the effect is similar to congestion in wireline networks
  - the need for transmission buffer
  - transmitted signals are delayed

- Does these methods only apply to wireless channels?

- The solution is through adaptation of transmission parameters based on the *current state* and the *statistical model* of the channel and supported traffic

- Essentially a Cross-layer optimization approach

A Simple Illustration



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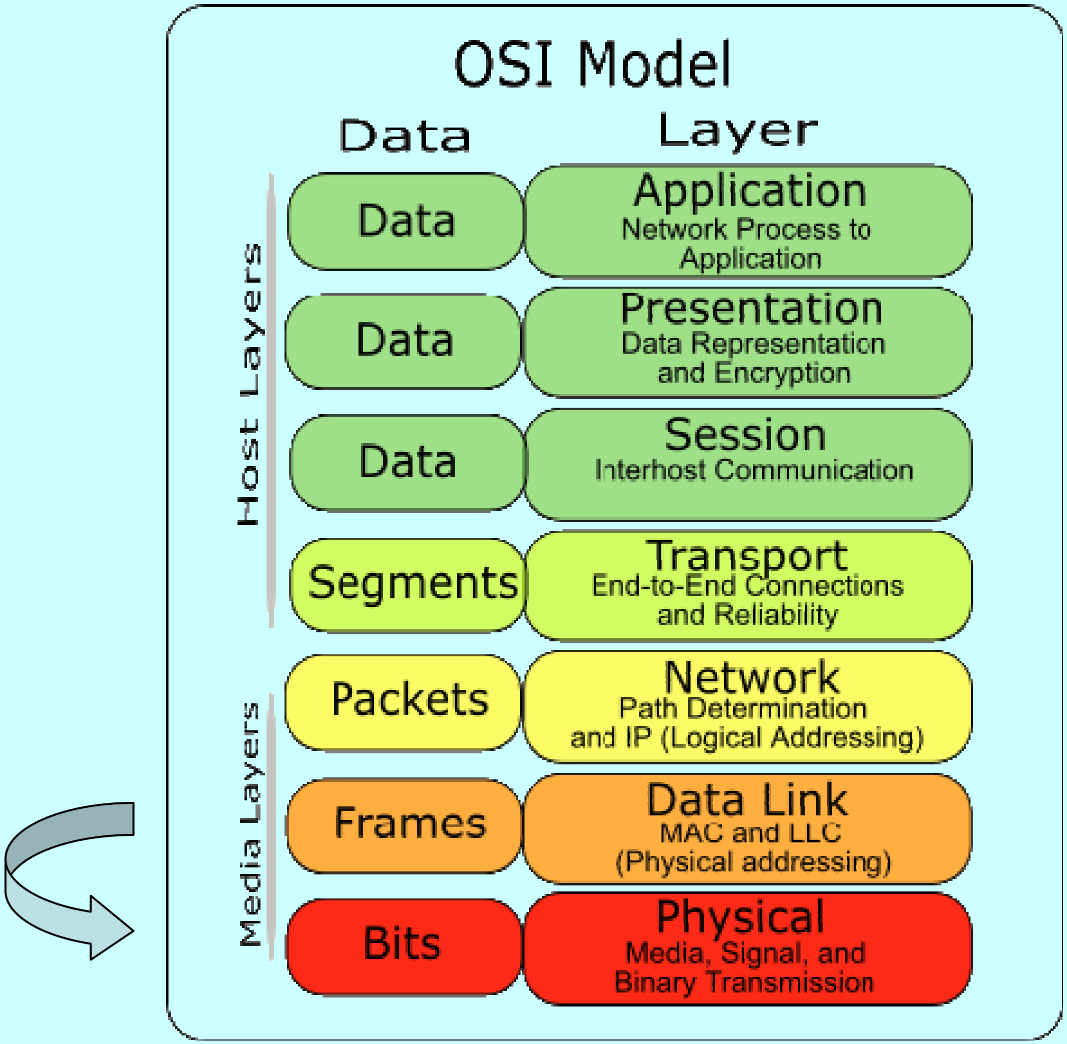
OSI Model



Data Link (Layer 2) At this layer, data packets are encoded and decoded into bits. It furnishes transmission protocol knowledge and management and handles errors in the physical layer, flow control and frame synchronization. The data link layer is divided into two **sublayers**: The **Media Access Control** (MAC) layer and the **Logical Link Control** (LLC) layer. The MAC sublayer controls how a computer on the network gains access to the data and permission to transmit it. The LLC layer controls frame synchronization, flow control and error checking.

Physical (Layer 1) This layer conveys the bit stream - electrical impulse, light or radio signal -- through the network at the electrical and mechanical level. It provides the hardware and software means of sending and receiving data on a carrier.

Cross-layer Optimization

- The conventional approach: Each layer considered separately

- Why do we need cross-layer optimization (CLO)?
  - Advantages of CLO
  - Disadvantages CLO

Cross-layer Optimization (Example)

- **No Cross-layer optimization**
  - **Example: Physical Layer Power allocation (Power Control)**

$$
\left.
\begin{aligned}
& P_{av} = \min_{R(h)} E\left[P(R(h),h)\right] \\
& s.t. \quad E\left[R(h)\right] \geq \overline{R}
\end{aligned}
\right\}
$$

Power Minimization under Average Rate Constraint

Delay-limited case

$$
\left.
\begin{aligned}
& P_{av} = \min_{R(h)} E\left[P(R(h),h)\right] \\
& s.t. \quad R(h) \geq \overline{R}
\end{aligned}
\right\}
$$

Power Minimization under Hard Rate Constraint

Delay-unlimited case (Waterfilling)

- ***h*** **is the flat fading channel state**
- **Example: Data Layer**
  - **MAC protocols such FIFO**
  - **ARQ protocols**
  - **Rate control algorithms independent channel condition**

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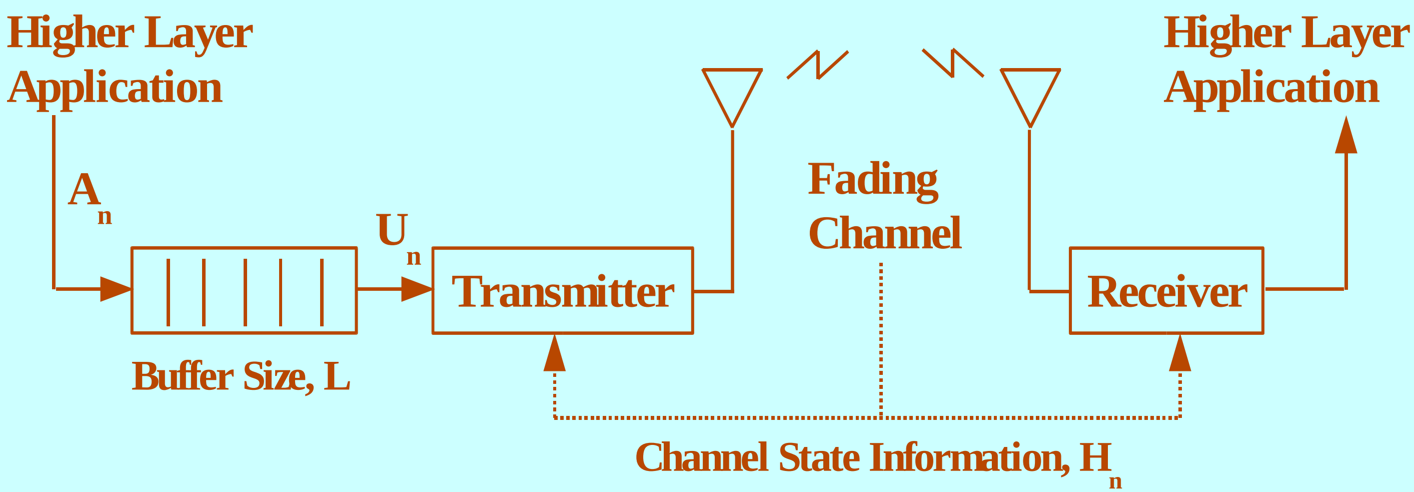
(1) Real-Time Traffic

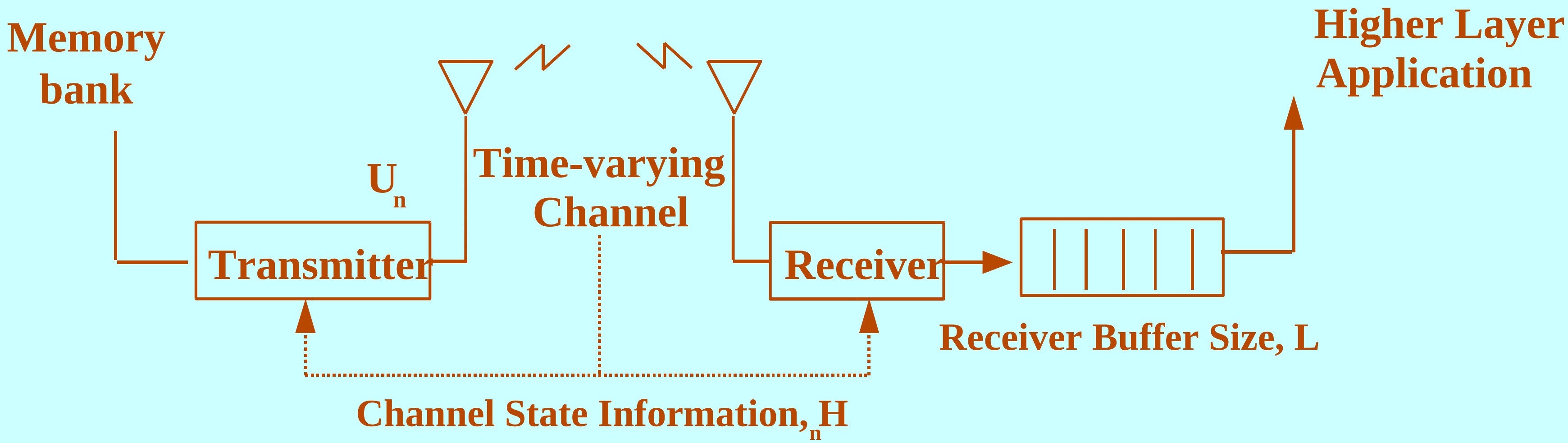
- Consider a single user with a finite transmission buffer that is communicating over a fading channel:



- Let A_n denote the number of packets arriving at the buffer between time slots n-1 and n. It is assumed that $\{A_n\}$ forms an ergodic Markov chain.
- Transmission adaptation parameters can include power, error-correction or source coding rate
- At the beginning of the n-th time slot, the scheduler takes U_n packets from the buffer and maps these into a rate cU_n codeword

(2) Constant-Rate playback

- Consider a transmission from an "unlimited" memory bank to a single user equipped with receiver buffer over a time-varying channel



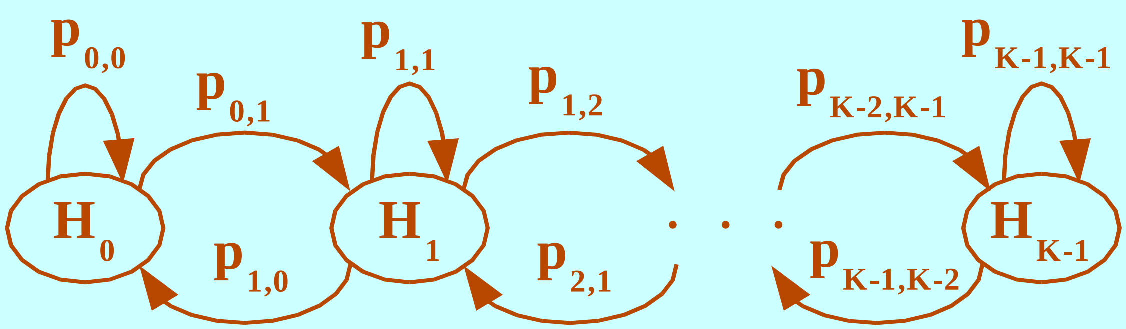
- At the beginning of the *n*-th time slot, the scheduler takes U_n packets from the buffer and maps these into a rate cU_n codeword

- In this case the data is first buffered for a fixed amount of time in the Receiver Buffer and than it is read out at a constant rate

- The goal is to have as few as possible receiver buffer outages

Channel Model: FSMC

- For example, a slowly varying flat Fading Rayleigh channel can be represented as a Finite State Markov Chain (FSMC) as shown in figure:



- Channel can also be modeled as an Auto Regressive (AR) model

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Markov Decision Processes (MDP)

- **A MDP is a model for sequential decision making when outcomes are uncertain.**

- **A MDP is described by the following ingredients:**

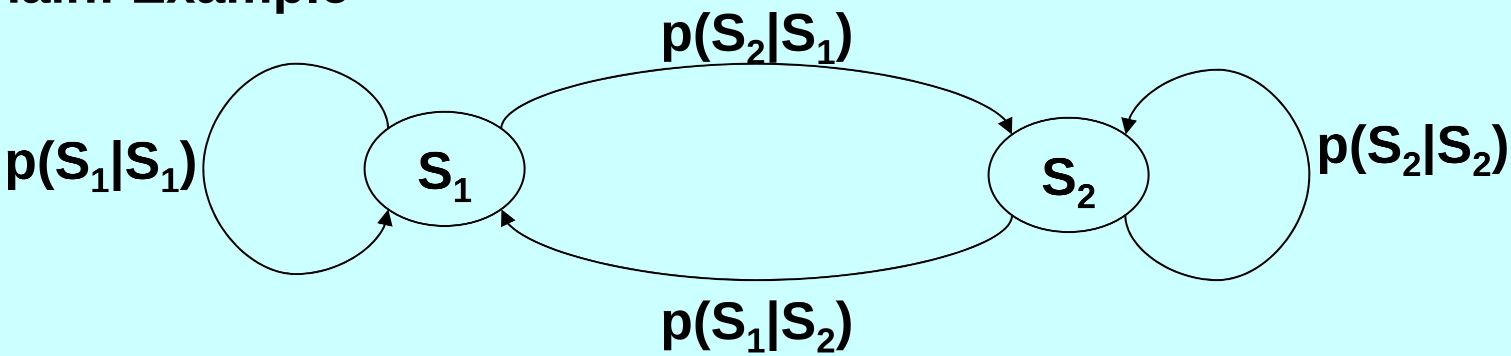
  - **A set of decision epochs or time slots, T = {1,2,…,*m*}**
  - **A set of states, $\Sigma=\{s_1,s_2,\ldots,s_Q\}$**
  - **A set of actions, $U=\{u_1,u_2,\ldots,u_U\}$**
  - **A set of state and action dependent transition probabilities, $p(s_j|s_i,u_i)$**
  - **A set of state and action dependent immediate costs, $g(s_i,u_i)$**

- **A decision rule μn prescribes a procedure for action selection in each state at a specified time slot:**

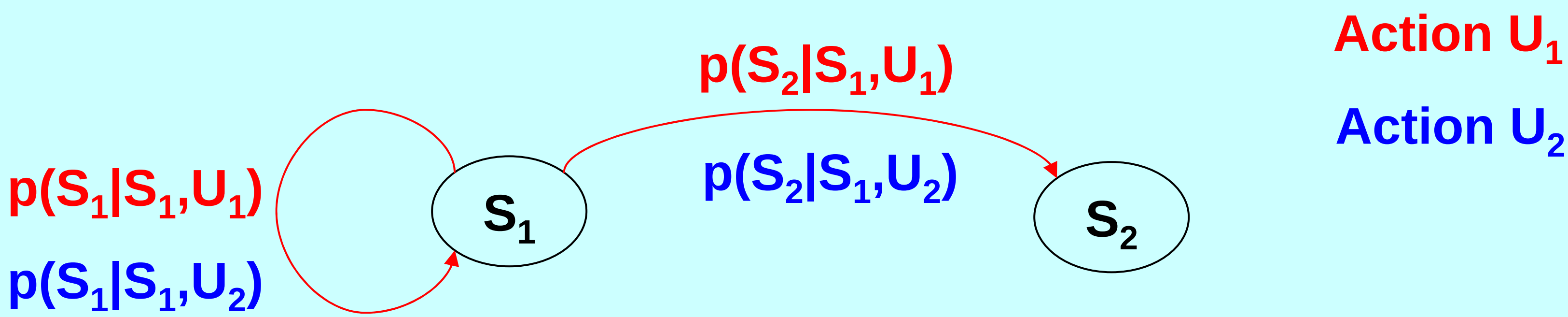
$$\mu_n : S \mapsto U_S$$

- **The decision rule to be used at all time slot is called policy $\pi=\{\mu_1,\mu_2,\ldots,\mu_m\}$.**

Markov Chain: Example



Markov Decision Processes: Example for state S_1



The Optimization Criterion

- **The average cost optimization criteria for Markov Decision Processes**

$$C^* = \inf_{\pi} \mathrm{E}\left[\lim_{N\to\infty} \frac{1}{N} \sum_{i=1}^{N} g(s_n, u_n) \right]$$

- **This is just an optimization problem over a set of feasible policies π**

- **A relatively simple solution is possible using dynamic programming**

Constrained MDPs

- What happens if in addition to the immediate costs, *g(s,u),* there is an another cost *d(s,u)* that corresponds to a constraint? I.e. optimization problem is:

$$C^* = \inf_{\pi} \mathrm{E}\left[\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} g(s_n,u_n)\right]$$

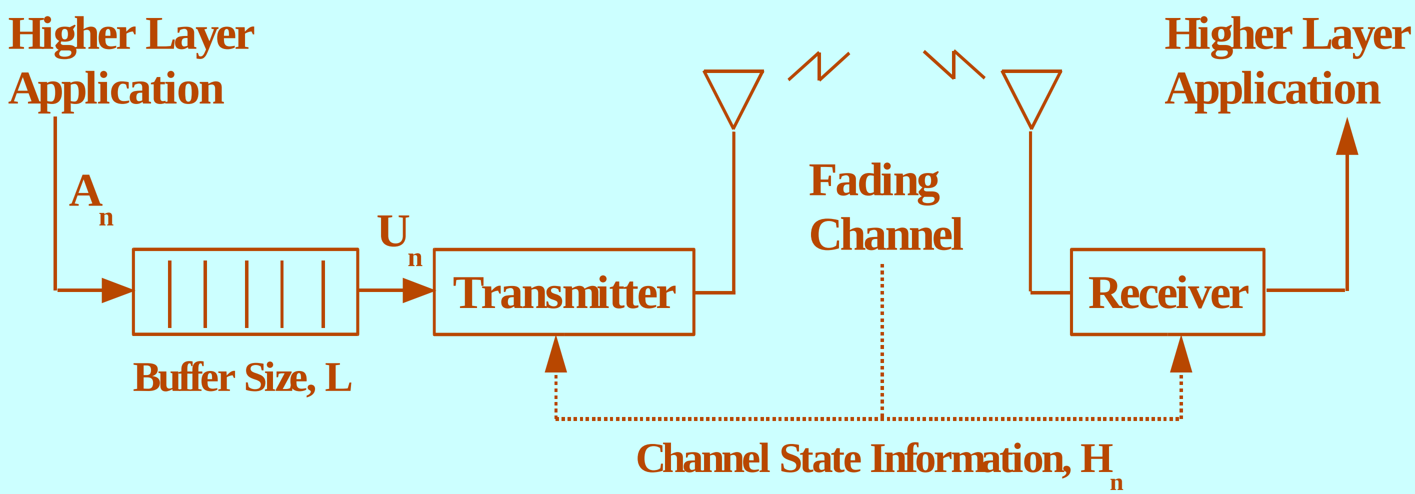
$$s.t. \lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} d(s_n,u_n) \le \overline{D}$$

- The answer can be found in the theory of Constrained Markov Decision Processes (CMDP). CMDP can be expressed as equivalent unconstrained MDP using Lagrangian Approach:

$$C^*(\overline{D}) = \min_{\pi} \sup_{\lambda>0} E\left[\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \left(g(s_n,u_n) + \lambda d(s_n,u_n)\right)\right] - \lambda \overline{D}$$

- Note that policies do not have to be deterministic in CMDPs. In general optimal policies for CMDPs are randomized.

(1) Real-Time Traffic



- How to formulate state space and costs in the real-time traffic model (1)
  - State space include: Buffer + Incoming Traffic + Fading Channel
  - Immediate cost g(s,a) can be e.g. transmission power
  - Constraint cost d(s,a) can be related to buffer delay

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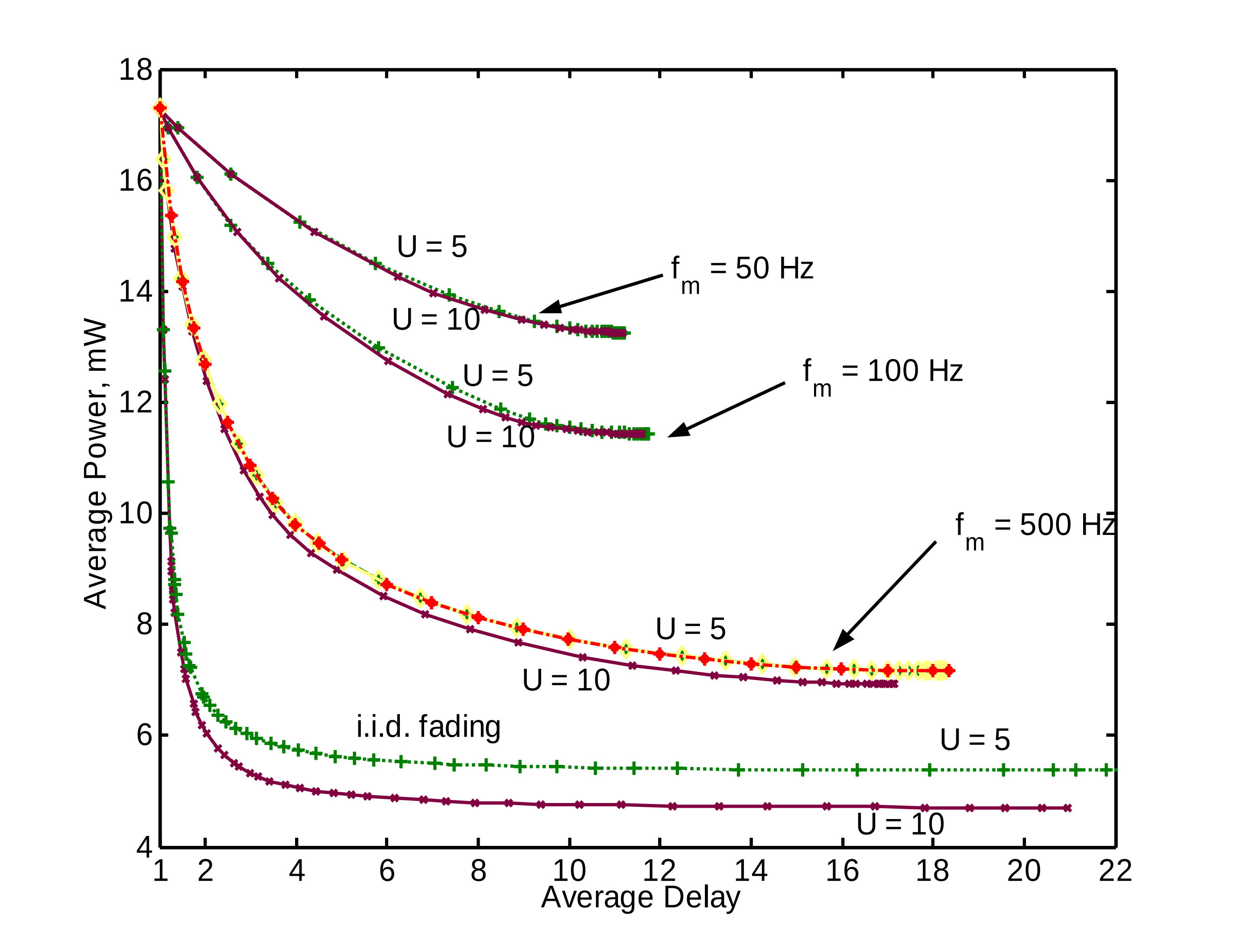
Solution Techniques

- Optimal policy for a MDP model can be found using
  - Relative Value Iteration
  - Policy Iteration
- The details of these algorithms can be found in

  "Dynamic Programming and Optimal Control" vol. 1 and 2. by D. Bertsekas

- Another advantage of Value Iteration algorithms is that several general structural results on the shape of optimal policies can be derived by just considering the general analytical form of immediate and constrained costs.

Sample Results (1)



- As fading rate ↑, the rate of decrease of average power ↑.
- As the number of actions ↑, average power ↓

Comparison with Single-layer Optimization

- **Example: Physical Layer Power allocation (Power Control)**

$$\left.\begin{aligned} P_{av} &= \min_{R(h)} E\left[P(R(h),h)\right] \\ s.t. &\quad E\left[R(h)\right] \geq \overline{R} \end{aligned}\right\}$$

Power Minimization under Average Rate Constraint

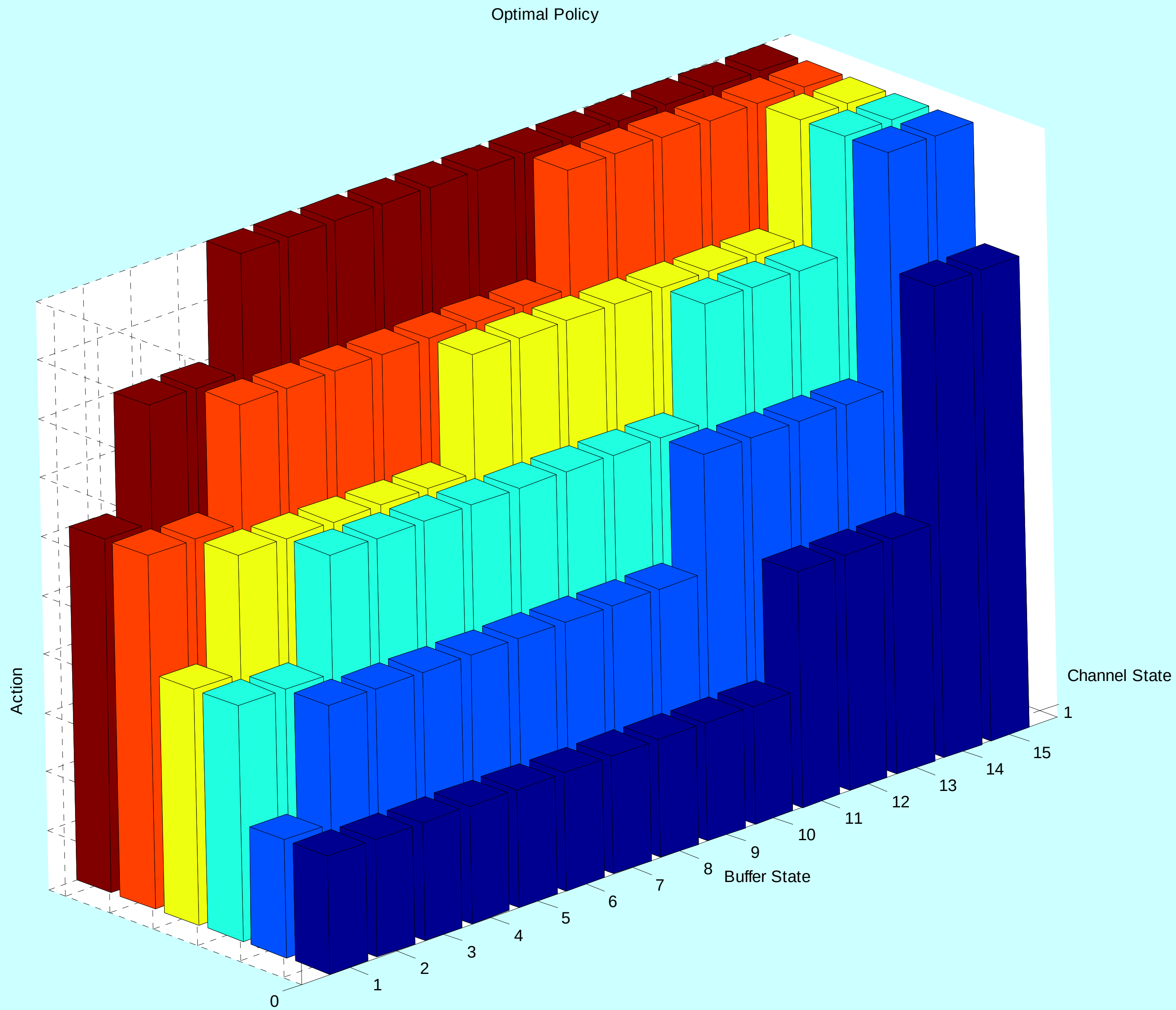
Delay-limited case

$$\left.\begin{aligned} P_{av} &= \min_{R(h)} E\left[P(R(h),h)\right] \\ s.t. &\quad R(h) \geq \overline{R} \end{aligned}\right\}$$

Power Minimization under Hard Rate Constraint

Delay-unlimited case (Waterfilling)

Sample Results (2)



Structural Results (1)

Theorem 2: Let the Assumptions 1, 2, 3 hold. Let the instantaneous Lagrangian cost $c([h, b, f], a; \lambda)$ (8) be submodular, jointly convex function of (b, a) and increasing in buffer state b. Let $\Psi(a)$ defined in (10) be concave increasing function of a. Then for cost constraint $\tilde{D} > 0$, the optimal randomized policy $\pi^*([h, b, f])$ is a mixed policy of two pure policies $\pi^1([h, b, f])$ and $\pi^2([h, b, f])$ that are non-decreasing functions of buffer state b (see Definition 4) such that $b < L - G(\tilde{F} - 1)^3$. Furthermore, there exists only one state $s \in \mathcal{S}$ such that $\pi^1(s) \neq \pi^2(s)$. ○

Extracted from the paper:

D.Djonin and V.Krishnamurthy, "Effect of Transmission Buffer, Fading Channel and Traffic Dynamics on the Optimal Transmission Scheduling", submitted to IEEE Trans. on Inf. Theory, 2005.

also to be presented as an invited paper at the Control Decision Conference, Seville 2005.

Structural Results (2)

Theorem 3: Let the Assumptions 1, 2, 3 hold.

(1) For any buffer length $L \in \mathcal{N}_0$, the optimal average transmission scheduling cost $C^*(\tilde{D})$ is a piece-wise linear non-increasing function of $\tilde{D} \in \mathcal{D}$ that can be expressed as

$$C^*(\tilde{D}) = \max_{\lambda \in \Lambda} \left(D(\pi^*_\lambda) - \tilde{D} \right) \lambda + C(\pi^*_\lambda) \tag{27}$$

where Λ defined as

$$\Lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_Q\} = \left\{ \arg\sup_{\lambda \geq 0} \min_{\pi \in \Phi_D} \left(J(\pi, \lambda) - \lambda \tilde{D} \right) | \tilde{D} > 0 \right\} \tag{28}$$

is a finite set.

(2) In addition to the above stated assumptions, suppose that $c([h, b, f], a; \lambda)$ is jointly convex in b, a and λ and let $\Psi(a)$ be concave increasing in a. Then $C^*(\tilde{D})$ is piece-wise linear convex non-increasing function of $\tilde{D}$. $\circ$

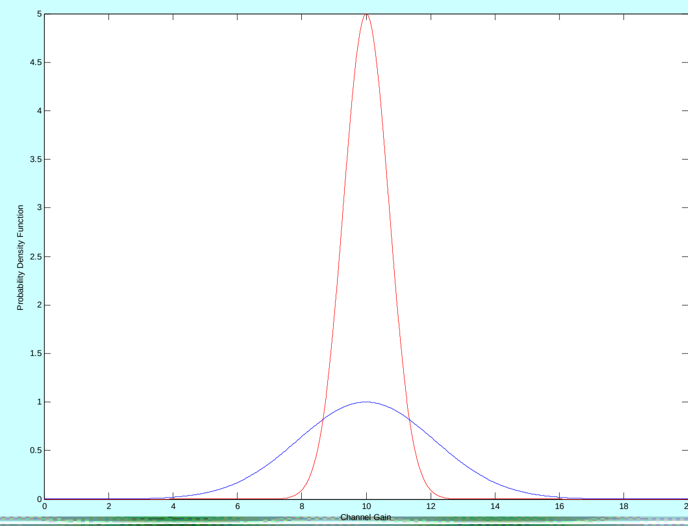
Structural Results (3)

Corollary 6: Let the Assumptions 1, 2, 3 hold. Let $\mathbf{H}_P(h)$ and $\mathbf{H}_Q(h)$ be second-order stochastically increasing in h and let $\mathbf{H}_P(h)$ be second-order stochastically dominating $\mathbf{H}_Q(h)$ for any h. If $c([h, b, f], a)$ is non-increasing and convex function of h for any $b \in \mathcal{B}$, $f \in \mathcal{F}$ and $\lambda \in \Re^+$ then

$$C_P^* \leq C_Q^* \tag{41}$$

for any feasible average buffer cost constraint $\tilde{D} \in \mathcal{D}_P \cap \mathcal{D}_Q$. ○

Example: Channels with less scattering can require less average transmission cost (e.g. power) for the same delay.



Why do we need these structural results?

- Structural Results on Optimal Policies can give us some general insights on the shape and qualitative behaviour of optimal costs and policies

- Structural Results can also lead to more efficient algorithms for finding optimal policies. Example:

	$\lambda = 0.01, \|\mathcal{S}\| = 500$	$\lambda = 100, \|\mathcal{S}\| = 500$	$\lambda = 0.01, \|\mathcal{S}\| = 100$	$\lambda = 100, \|\mathcal{S}\| = 100$
SPI Iterations	8	2	8	2
NSPI Iterations	51	3	22	3
Computational Saving	6.09	1.70	3.00	4.00

TABLE I

COMPARISON OF COMPUTATIONAL ITERATIONS OF STRUCTURED AND NON-STRUCTURED POLICY ITERATION

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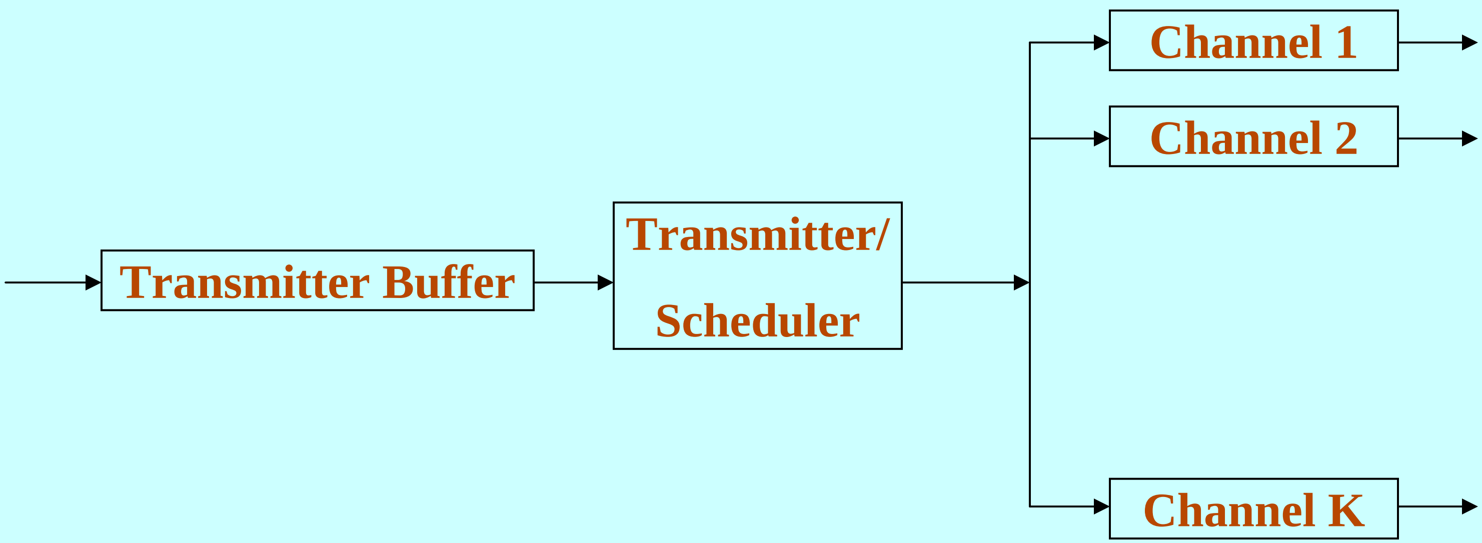
(2) Constant-Rate playback over time-varying channels

- These results apply in general for any delay-constrained multi-channel transmission problems
- Major obstacle is the dimensionality of the state and action space



Transmitter Model for OFDM systems

Power and rate resource allocation for OFDM schemes

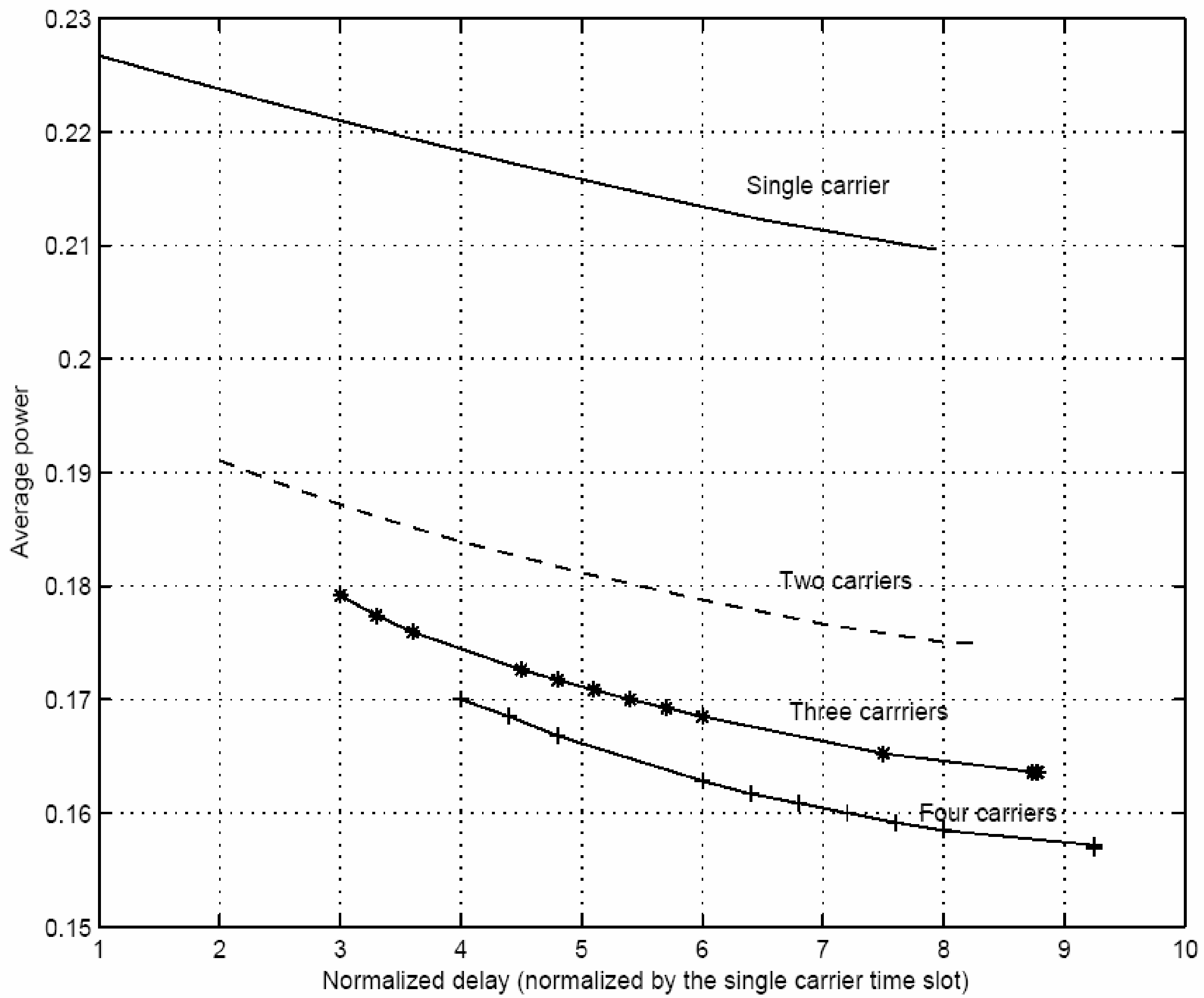


Fig. 3. Optimal delay and power tradeoffs with different number of carriers (Doppler frequency, f_d =100Hz).

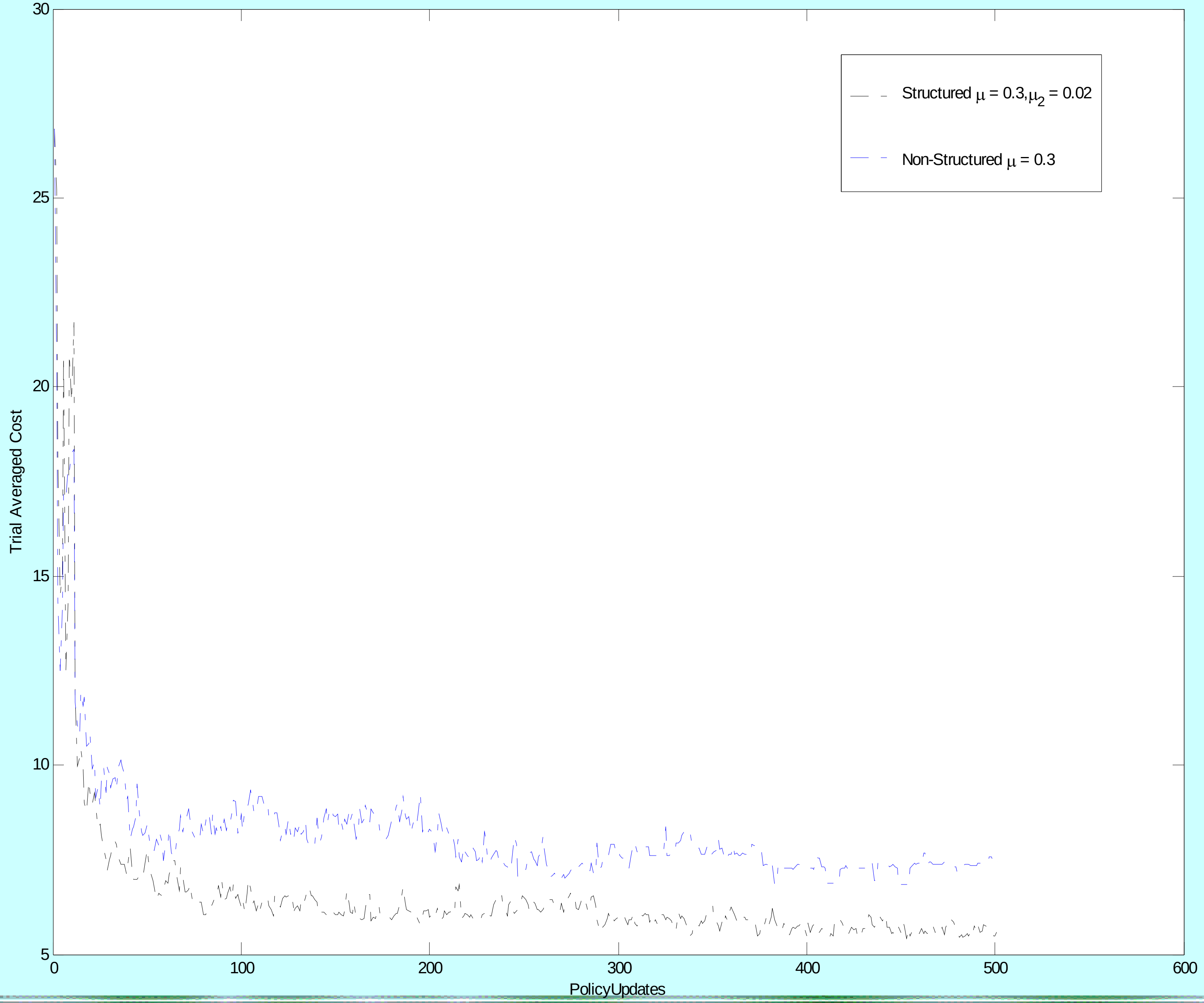
Resource allocation for imperfectly known channel models (1)

- **This a challenging problem as the policy has to be "learned" on-line as the actions are being applied and observations on the incurred cost are collected.**

- **The appropriate framework for the solution of this problem is to consider Q-learning, which is a version of stochastic approximation algorithm.**
- **For details on Q-algorithm and related topics have a look at:**

D. Bertsekas and J.Tsitsiklis, "Neuro-Dynamic Programming"

Resource allocation for imperfectly known channel models (2)

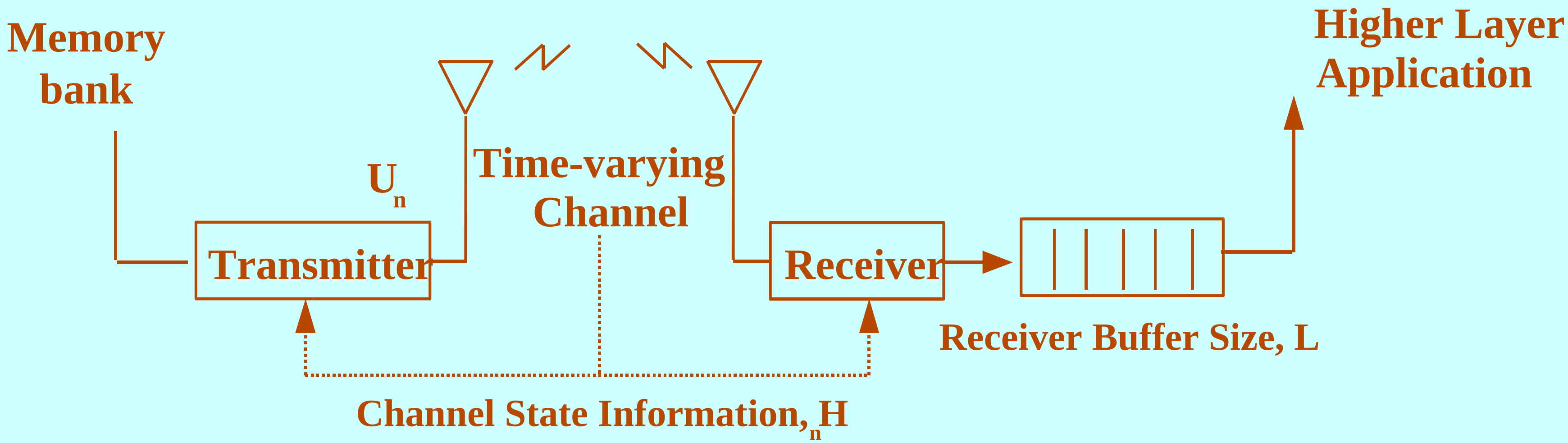


Simulation Settings:

 # Channel States = 6
 # Buffer States = 15
 # Actions = 6

(2) Constant-Rate playback

- Consider a transmission from an "unlimited" memory bank to a single user equipped with receiver buffer over a time-varying channel



- The problem can again be formulated as the CMDP with:
  - g(s,a) being power cost
  - d(s,a) being receiver buffer outage probability
  - action representing the transmission rate.

(2) Constant-Rate playback (cont'd)

- An alternative formulation that does not involve MDPs
- This approach falls somewhere in between delay-constrained and no-delay constrained resource allocation problem

$$P_{av} = \min_{R(h)} E\left[P(R(h),h)\right]$$

$$s.t. \quad E\left[R(h)\right] \geq \overline{R}$$

$$E\left[(R(h)-\overline{R})^2\right] \leq \sigma_R^2$$

- Advantages:
  - Explicit analytical expression of the rate allocation can be derived
  - By changing the parameter σ_R^2 it is possible to adjust the receiver buffer outage probability

Thank You for Your Attention !