# Cross-Layer Rate Adaptation for Time-Varying Channels

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# Basic Principles:

Communication in Gaussian noise:

$$\epsilon \sim e^{-\gamma/2^r} \quad \text{for} \quad \begin{cases} \epsilon : \text{error rate} \\ \gamma : \text{SNR} \\ r : \text{transmission rate [bits/channel-use]} \end{cases}$$

Typical goals:

1. Low error rate $\epsilon$,
2. High transmission rate $r$.

(We assume no control over SNR $\gamma$.)

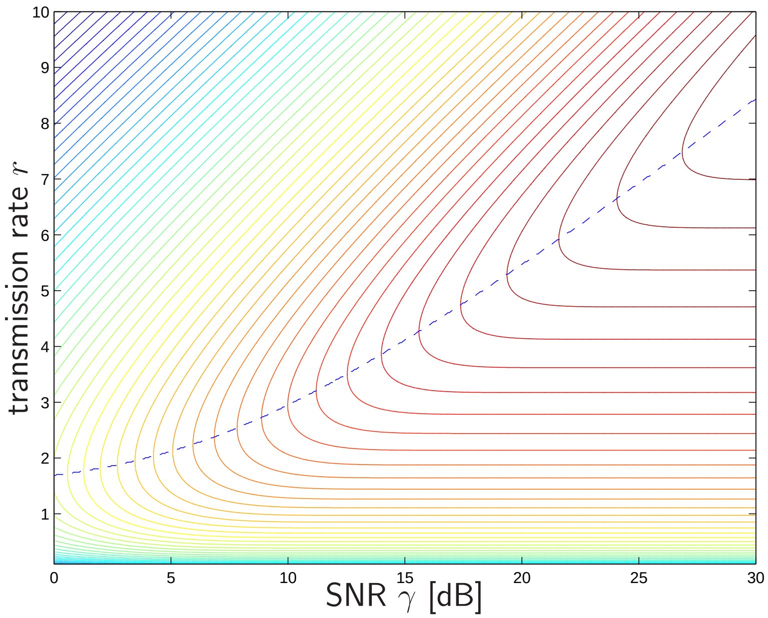
But these goals conflict! For example, we could decrease $\epsilon$ a little bit by decreasing $r$ a little bit. . . Should we do it?

# Goodput:

$G = (1 - \epsilon)r$ : the rate of *successful* communication.

- Useful because it unifies the conflicting goals of low error rate and high transmission rate.
- Plugging in the error-rate relationship $\epsilon \sim e^{-\gamma/2^r}$, we find

$$G \sim (1 - e^{-\gamma/2^r})r.$$

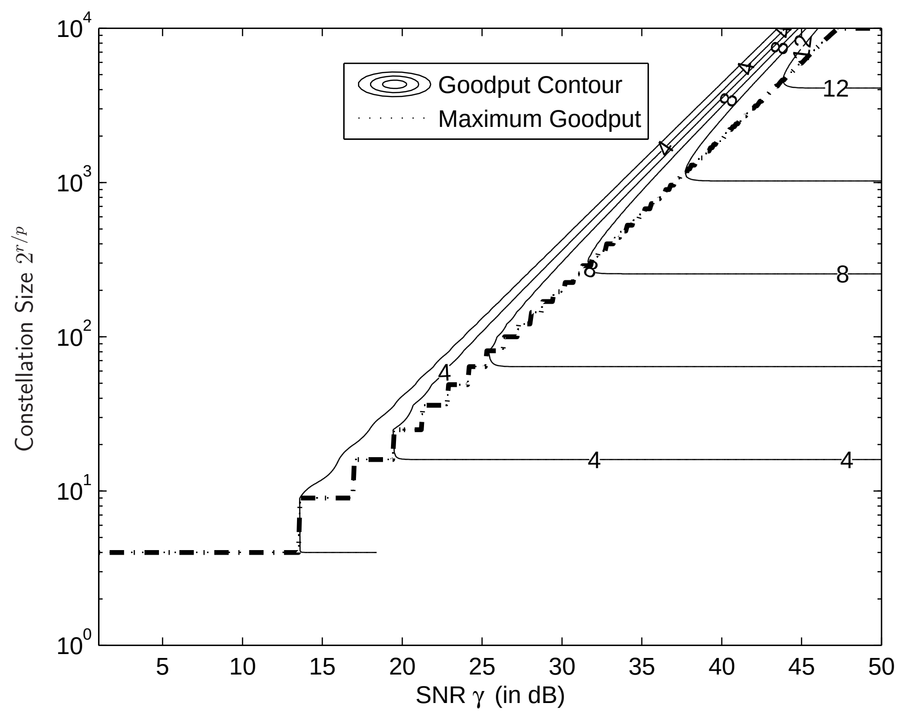



Notice that there is an optimal transmission rate $r$ for every SNR $\gamma$.

# Goodput (cont.):

As a concrete example, consider the goodput per $p$-length packet of uncoded square-QAM symbols, where packet error rate equals

$$\epsilon(r,\gamma) \;=\; 1-\left(1-2\left(1-\frac{1}{\sqrt{2^{r/p}}}\right)Q\left(\sqrt{\frac{3\gamma}{2^{r/p}-1}}\right)\right)^{2p} \quad :$$



## Rate Adaptation:

- If we knew the SNR $\gamma$, we could easily select the goodput-maximizing transmission rate.
- But in practice the SNR varies as a result of
  - Multipath fading,
  - Interference.
- While tracking the SNR may be straightforward at the receiver, it is often non-trivial at the transmitter.

  For example, the feedback of receiver-estimated SNR requires a low-latency backward-channel that requires additional
  - bandwidth,
  - power, and
  - complexity.

## A Cross-Layer Approach:

Automatic Repeat reQuest (ARQ):

- A link-layer technique used in many systems.
- For each packet, the receiver sends an ACK if it was received correctly or a NAK otherwise.
- Used to ensure strict end-to-end error rates (e.g., $10^{-10}$) while keeping the physical layer practical (e.g., $\epsilon \sim 10^{-3}$).

The Main Idea:

- Use link-layer ARQ feedback for physical-layer rate adaptation.

$\rightsquigarrow$ *"Cross-layer rate adaptation"*

# Problem Formulation:

*Naive Goal*: Choose rates to maximize total goodput over $T$ packets:

$$[r_1^*, \ldots, r_T^*] = \underset{[r_1,\ldots,r_T]\in\mathcal{R}^T}{\arg\max} \sum_{t=1}^{T} G(\gamma_t, r_t).$$

where $\mathcal{R}$ is the set of allowed rates.

- If $\{\gamma_t\}_{t=1}^T$ was known perfectly, calculating $\{r_t^*\}_{t=1}^T$ would be easy.
- But, of course, SNR $\gamma_t$ is not perfectly known!

## Problem Formulation (cont.):

*Revised Goal*: Maximize total *expected* goodput over $T$ packets:

$$[r_1^*, \ldots, r_T^*] = \underset{[r_1,\ldots,r_T]\in\mathcal{R}^T}{\arg\max}\ \mathrm{E}\left\{\sum_{t=1}^{T} G(\gamma_t, r_t)\right\}.$$

- If the statistics of $\gamma_t$ were known and decoupled from the rates $\{r_k\}_{k\neq t}$, then it would still be relatively easy to calculate $\{r_t^*\}_{t=1}^T$:

$$r_t^* = \underset{r_t\in\mathcal{R}}{\arg\max}\,\mathrm{E}\{G(\gamma_t, r_t)\} = \underset{r_t\in\mathcal{R}}{\arg\max}\int G(\gamma_t, r_t)p(\gamma_t)dt.$$

- But the knowledge of $\gamma_t$ will depend on the previously received ACK/NAKs, which depend on the previously chosen rates!

  *The current rate choice affects not only the immediate goodput but also the future SNR-knowledge (and hence future rate selection)!*

$\Rightarrow$ *A classical tradeoff between* **exploitation** *and* **exploration**.

## Observations:

- If rates are chosen purely based on "exploitation" (i.e., to maximize short-term goodput), it is not clear whether the feedback will be adequately informative about changes in SNR.
- One could imagine a scheme that periodically inserts pilot packets, i.e., packets dedicated purely to "exploration." But is the sacrifice in short-term goodput justified?

*What is the optimal rate assignment?*

## Rate Adaptation via Degraded Error-Rate Feedback:

Two very different approaches to causal rate adaptation:

- via degraded SNR feedback (straightforward):

$$r_t^* = \arg\max_{r_t \in \mathcal{R}} \mathrm{E}\left\{ G(\gamma_t, r_t) \mid \hat{\boldsymbol{\gamma}}_{t-d} \right\}$$

- via degraded error-rate feedback (more interesting):

$$r_t^* = \arg\max_{r_t \in \mathcal{R}} \mathrm{E}\left\{ G(r_t, \gamma_t) + \sum_{k=t+1}^{T} G(r_k^*, \gamma_k) \,\middle|\, \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d} \right\}.$$

Notation:

$d$ : feedback delay ($d \geq 1$),

$\hat{\boldsymbol{\gamma}}_{t-d} = [\hat{\gamma}_1, \ldots, \hat{\gamma}_{t-d}]$ : previous SNR estimates,

$\hat{\boldsymbol{\epsilon}}_{t-d} = [\hat{\epsilon}_1, \ldots, \hat{\epsilon}_{t-d}]$ : previous error-rate estimates

$\boldsymbol{r}_{t-d} = [r_1, \ldots, r_{t-d}]$ : previous transmission rates.

Notice: From now on, we consider *generic* degraded error-rate feedback $\hat{\boldsymbol{\epsilon}}_{t-d}$.

# Optimal Rate Adaptation:

Optimal rate selection, i.e.,

$$r_t^* = \arg\max_{r_t \in \mathcal{R}} \mathrm{E}\left\{ G(r_t, \gamma_t) + \sum_{k=t+1}^{T} G(r_k^*, \gamma_k) \;\middle|\; \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d} \right\}$$

can be recognized as a *dynamic program*. Denoting the optimal expected goodput for current and future packets by

$$\bar{G}_{t:T}^*(\hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d}) \triangleq \mathrm{E}\left\{ \sum_{k=t}^{T} G(r_k^*, \gamma_k) \;\middle|\; \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d} \right\},$$

we can write the Bellman equation as

$$\begin{aligned} \bar{G}_{t:T}^*(\hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}) = \max_{r_t \in \mathcal{R}} \Big\{ & \mathrm{E}\{G(r_t, \gamma_t) \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}\} \\ & + \mathrm{E}\{\bar{G}_{t+1:T}^*([\hat{\boldsymbol{\epsilon}}_{t-1}, \hat{\epsilon}_t], [\boldsymbol{r}_{t-1}, r_t]) \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}\} \Big\} \end{aligned}$$

for the case $d = 1$. (For $d > 1$, the expression is more complicated.)

## Optimal Rate Adaptation (cont.):

The solution to this dynamic program is a *partially observable Markov decision process* (POMDP), which is

- generally *intractable* when the SNR process $\{\gamma_t\}$ is *continuous* Markov,
- can be solved numerically when the SNR process $\{\gamma_t\}$ is *discrete* Markov, but at *great cost*: both complexity and memory increase exponentially with the horizon length $T$ and the number of states used for $\gamma_t$.

$\Rightarrow$ *Not practical to implement!*

## Greedy Adaptation:

- What if we maximize only the *short-term* reward?
- This corresponds to the *greedy* scheme

$$\hat{r}_t \triangleq \arg\max_{r_t \in \mathcal{R}} \mathrm{E}\left\{G(r_t, \gamma_t) \;\middle|\; \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d}\right\},$$

which should be much easier to implement.

*So, how bad is this greedy scheme (relative to optimal)?*

## Upper Bounding the Optimal Performance:

- For the optimal POMDP-based scheme, implementation and (exact) analysis do not appear to be feasible.
- But can we *upper bound* the performance of the optimal scheme?

*If we find an upper bound, and the greedy scheme performs close to this upper bound, then the greedy scheme must be close to optimal.*

## The Causal Genie:

Consider optimal rate selection under *non-degraded* error-rate feedback:

$$r_t^{\text{cg}} \triangleq \arg\max_{r_t \in \mathcal{R}} \mathrm{E}\left\{ G(r_t, \gamma_t) + \sum_{k=t+1}^{T} G(r_k^{\text{cg}}, \gamma_k) \;\middle|\; \boldsymbol{\epsilon}_{t-d}, \boldsymbol{r}_{t-d} \right\}.$$

Because $\boldsymbol{\gamma}_{t-d}$ can be uniquely determined from $(\boldsymbol{\epsilon}_{t-d}, \boldsymbol{r}_{t-d})$, we have

$$r_t^{\text{cg}} \triangleq \arg\max_{r_t \in \mathcal{R}} \mathrm{E}\left\{ G(r_t, \gamma_t) + \sum_{k=t+1}^{T} G(r_k^{\text{cg}}, \gamma_k) \;\middle|\; \boldsymbol{\gamma}_{t-d} \right\}.$$

Since future causal-genie rates $\{r_k^{\text{cg}}\}_{k>t}$ will be chosen based on perfect knowledge of ($d$-delayed) SNRs, they will not depend on $r_t$. Thus,

$$r_t^{\text{cg}} \triangleq \arg\max_{r_t \in \mathcal{R}} \mathrm{E}\left\{ G(r_t, \gamma_t) \;\middle|\; \boldsymbol{\gamma}_{t-d} \right\}.$$

*Optimal adaptation under non-degraded error-rate feedback is greedy!*

## The Causal Genie is an Upper Bound:

Since $\mathrm{E}\{G(r_t^*, \gamma_t) \mid \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d}\}$

$$\leqslant \max_{r_t \in \mathcal{R}} \mathrm{E}\{G(r_t, \gamma_t) \mid \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d}\}$$

...since $r_t^*$ is not necessarily short-term optimal

$$= \max_{r_t \in \mathcal{R}} \mathrm{E}\Big\{ \mathrm{E}\{G(r_t, \gamma_t) \mid \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d}, \boldsymbol{\epsilon}_{t-d}\} \Bigm| \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d}\Big\}$$

$$\leqslant \mathrm{E}\Big\{ \max_{r_t \in \mathcal{R}} \mathrm{E}\{G(r_t, \gamma_t) \mid \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d}, \boldsymbol{\epsilon}_{t-d}\} \Bigm| \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d}\Big\}$$

...since $\max_{r_t} \mathrm{E}\{f(r_t)\} \leqslant \mathrm{E}\{\max_{r_t} f(r_t)\}$ for any $f(\cdot)$

$$= \mathrm{E}\Big\{ \max_{r_t \in \mathcal{R}} \mathrm{E}\{G(r_t, \gamma_t) \mid \boldsymbol{\gamma}_{t-d}\} \Bigm| \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d}\Big\}$$

$$= \mathrm{E}\{G(r_t^{\mathsf{cg}}, \gamma_t) \mid \hat{\boldsymbol{\epsilon}}_{t-d}, \boldsymbol{r}_{t-d}\},$$

summing and averaging both sides gives

$$\mathrm{E}\left\{ \sum_{t=1}^{T} G(r_t^*, \gamma_t) \right\} \leqslant \mathrm{E}\left\{ \sum_{t=1}^{T} G(r_t^{\mathsf{cg}}, \gamma_t) \right\}.$$

## What Now?:

So far we've shown that

1. Optimal rate adaptation is very difficult to implement/analyze.
2. There exists a suboptimal greedy scheme which may be relatively easy to implement.
3. If the feedback was non-degraded, the optimal scheme (i.e., the "causal genie") would itself be greedy.
4. The causal genie yields an upper bound on the optimal scheme under degraded feedback.

Thus, we'd like to know how the *greedy scheme* compares to the *best fixed-rate scheme* and to the *causal genie*.

*But first: How do we actually implement the greedy scheme?*

# Implementing the Greedy Scheme:

(Let's assume delay $d = 1$ for simplicity.)

The greedy rate choice can be written as

$$\hat{r}_t = \arg\max_{r_t \in \mathcal{R}} \int G(r_t, \gamma_t)\, p(\gamma_t \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}) d\gamma_t$$

using the inferred SNR distribution

$$\begin{aligned} p(\gamma_t \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}) &= \int p(\gamma_t \mid \gamma_{t-1}, \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1})\; p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1})\; d\gamma_{t-1} \\ &= \int \underbrace{p(\gamma_t \mid \gamma_{t-1})}_{\text{SNR prediction}} \underbrace{p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1})}_{\text{estimation of previous SNR}} d\gamma_{t-1}. \end{aligned}$$

For the last step, we assumed *Markov SNR variation*.

Next, we tackle estimation of the previous SNR...

# Implementing the Greedy Scheme (cont.):

Estimation of the previous SNR:

$$\begin{aligned} & p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}) \\ &= p(\gamma_{t-1} \mid \hat{\epsilon}_{t-1}, \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-1}) \\ &= \frac{p(\hat{\epsilon}_{t-1} \mid \gamma_{t-1}, \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-1})\ p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-1})}{\int p(\hat{\epsilon}_{t-1} \mid \gamma'_{t-1}, \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-1})\ p(\gamma'_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-1})\ d\gamma'_{t-1}} \\ &= \frac{p(\hat{\epsilon}_{t-1} \mid \epsilon(r_{t-1}, \gamma_{t-1}), \hat{\boldsymbol{\epsilon}}_{t-2})\ p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-2})}{\int p(\hat{\epsilon}_{t-1} \mid \epsilon(r_{t-1}, \gamma'_{t-1}), \hat{\boldsymbol{\epsilon}}_{t-2})\ p(\gamma'_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-2})\ d\gamma'_{t-1}}. \end{aligned}$$

Assuming *memoryless error degradation*: $p(\hat{\epsilon}_t \mid \epsilon_t, \hat{\boldsymbol{\epsilon}}_{t-1}) = p(\hat{\epsilon}_t \mid \epsilon_t)$,

$$\begin{aligned} & p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}) \\ &= \frac{p(\hat{\epsilon}_{t-1} \mid \epsilon(r_{t-1}, \gamma_{t-1}))\ p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-2})}{\int p(\hat{\epsilon}_{t-1} \mid \epsilon(r_{t-1}, \gamma'_{t-1}))\ p(\gamma'_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-2})\ d\gamma'_{t-1}}, \end{aligned}$$

where $p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-2})$ would have been previously calculated.

## Summary of Greedy Implementation:

For $t = 1, \ldots, T$,

1. Measure $\hat{\epsilon}_{t-1}$ and compute the pdf (as a function of $\gamma_{t-1}$)

$$p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}) = \frac{p(\hat{\epsilon}_{t-1} \mid \epsilon(r_{t-1}, \gamma_{t-1}))\, p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-2})}{\int p(\hat{\epsilon}_{t-1} \mid \epsilon(r_{t-1}, \gamma'_{t-1}))\, p(\gamma'_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-2}, \boldsymbol{r}_{t-2})\, d\gamma'_{t-1}}$$

2. Compute the pdf

$$p(\gamma_t \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}) = \int p(\gamma_t \mid \gamma_{t-1})\, p(\gamma_{t-1} \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}) d\gamma_{t-1}$$

3. Choose the greedy rate

$$\hat{r}_t = \arg\max_{r_t \in \mathcal{R}} \int G(r_t, \gamma_t)\, p(\gamma_t \mid \hat{\boldsymbol{\epsilon}}_{t-1}, \boldsymbol{r}_{t-1}) d\gamma_t$$

end;

When $t = 1$, skip steps 1 & 2 and use $p(\gamma_1 \mid \hat{\boldsymbol{\epsilon}}_0, \boldsymbol{r}_0) = p(\gamma_1)$ in step 3.

## Modifications for Block Update:

- So far, we have assumed that the transmission rate is adapted once per packet.
- To reduce complexity, we could instead adapt the rate once per block of $n$ packets. For this, we...
  - Treat the SNR as if it were *fixed* across each block.
  - Treat the packet error rate as if it were *fixed* across each block.
- This block updating modification can be applied to both the greedy scheme and the causal genie scheme.
- We expect performance to decrease with block length $n$ due to
  - The block-fading channel approximation.
  - The delay imposed by the block update.

# Numerical Results:

Next, we present some numerical results that demonstrate (perhaps surprisingly) that, using packet-level ARQ, *greedy rate adaptation performs relatively close to the upper bound on the optimal rate allocation and much better than fixed-rate adaptation.*

In particular, we examine the following:

- With a fully backlogged transmitter,
  - steady-state goodput vs feedback delay $d$,
  - steady-state goodput vs block size $n$,
  - steady-state goodput vs channel fading rate.
- With a finite input-buffer & a bursty arrival process,
  - average buffer occupancy,
  - packet drop rate.

# Numerical Results – Setup:

- Modulation: Uncoded square-QAM, $p = 100$, packet error rate

$$\epsilon(r_t, \gamma_t) \;=\; 1 - \left(1 - 2\left(1 - \frac{1}{\sqrt{2^{r_t/p}}}\right) Q\left(\sqrt{\frac{3\gamma_t}{2^{r_t/p} - 1}}\right)\right)^{2p}.$$

- Degraded error-rate feedback: one ACK/NAK per packet.

- Estimation of block error rate:
  - Note: # NAKs per block of $n$ packets $\sim$ Binomial$(n, \epsilon_t)$.
  - Minimum-variance unbiased estimate of average error-rate over the $\lfloor \frac{t}{n} \rfloor$th block: $\hat{\epsilon}_t = \frac{\text{\# NAKs}}{n}$.
  - Degraded error-rate:

$$p(\hat{\epsilon}_t = \tfrac{k}{n} \mid \epsilon_t) \;=\; \begin{cases} \binom{n}{k} \epsilon_t^k (1 - \epsilon_t)^{n-k} & \text{for } k = 0, \ldots, n \\ 0 & \text{else.} \end{cases}$$

# Numerical Results – Setup (cont.):

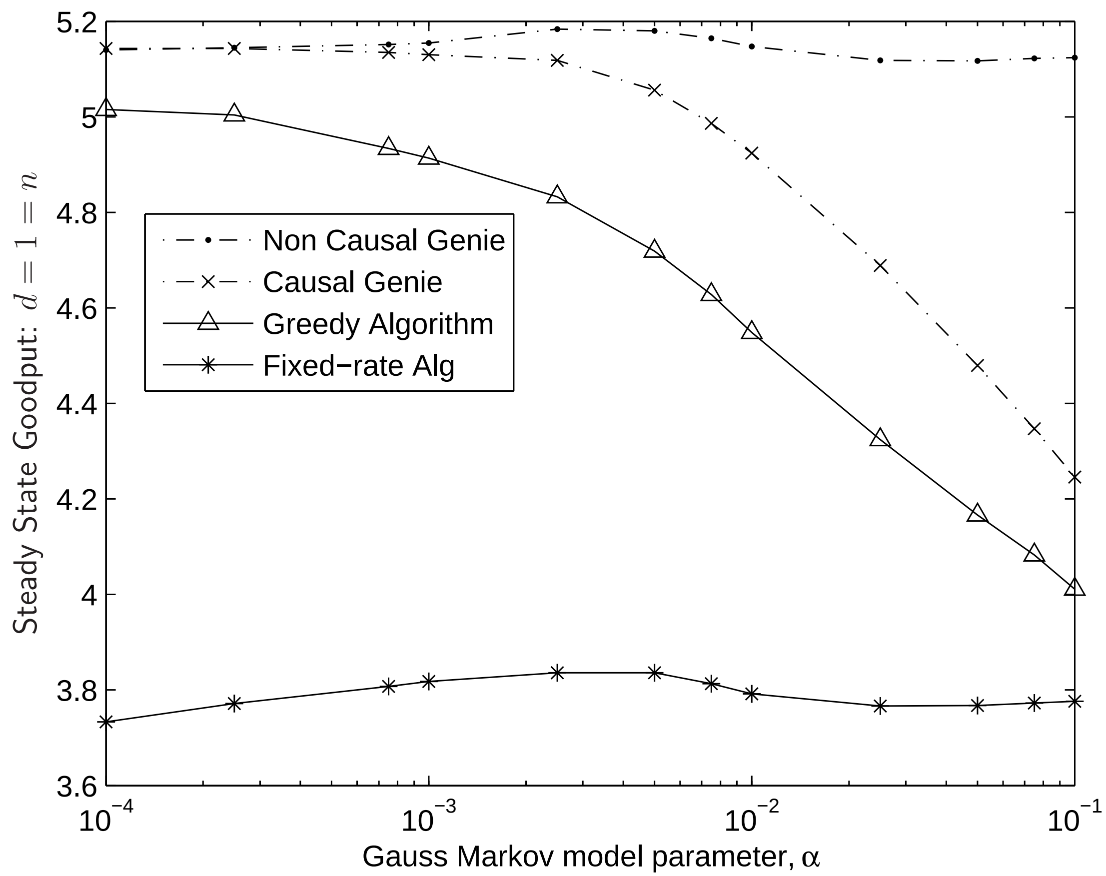
- SNR variation:
  - Rayleigh-fading channel gain via Gauss-Markov process:

$$g_t = (1-\alpha)g_{t-1} + \alpha w_t, \quad w_t \sim \mathcal{CN}(0,1) \text{ i.i.d.}$$

  - SNR: $\gamma_t = K|g_t|^2$.
  - Parameters $(\alpha, K)$ control the SNR's mean and coherence time. Usually we fix $\alpha$ and set $K$ such that $\mathrm{E}\{\gamma_t\} = 25$ dB.
- Schemes under comparison:

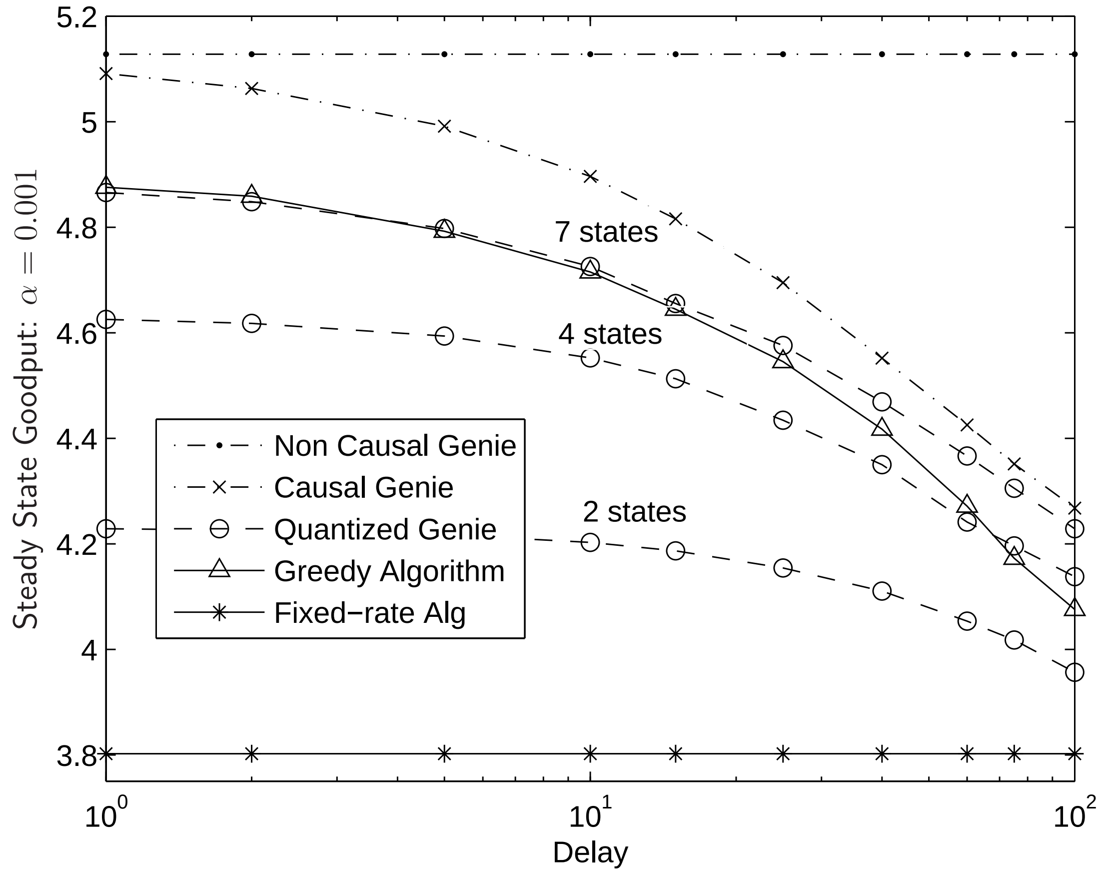
$$\begin{aligned}
\text{Fixed-rate} &: \quad r_t^{\mathsf{fr}} = \arg\max_{r_t} \textstyle\int G(r_t,\gamma_t)p(\gamma_t)d\gamma_t \\
\text{Greedy} &: \quad \hat{r}_t = \arg\max_{r_t} \textstyle\int G(r_t,\gamma_t)p(\gamma_t|\hat{\boldsymbol{\epsilon}}_{t-d},\boldsymbol{r}_{t-d})d\gamma_t \\
\text{Causal Genie} &: \quad r_t^{\mathsf{cg}} = \arg\max_{r_t} \textstyle\int G(r_t,\gamma_t)p(\gamma_t|\underbrace{\boldsymbol{\epsilon}_{t-d},\boldsymbol{r}_{t-d}}_{\boldsymbol{\gamma}_{t-d}})d\gamma_t \\
\text{Non-causal Genie} &: \quad r_t^{\mathsf{ng}} = \arg\max_{r_t} G(r_t,\gamma_t)
\end{aligned}$$

# Steady-state goodput versus fading-rate parameter $\alpha$:



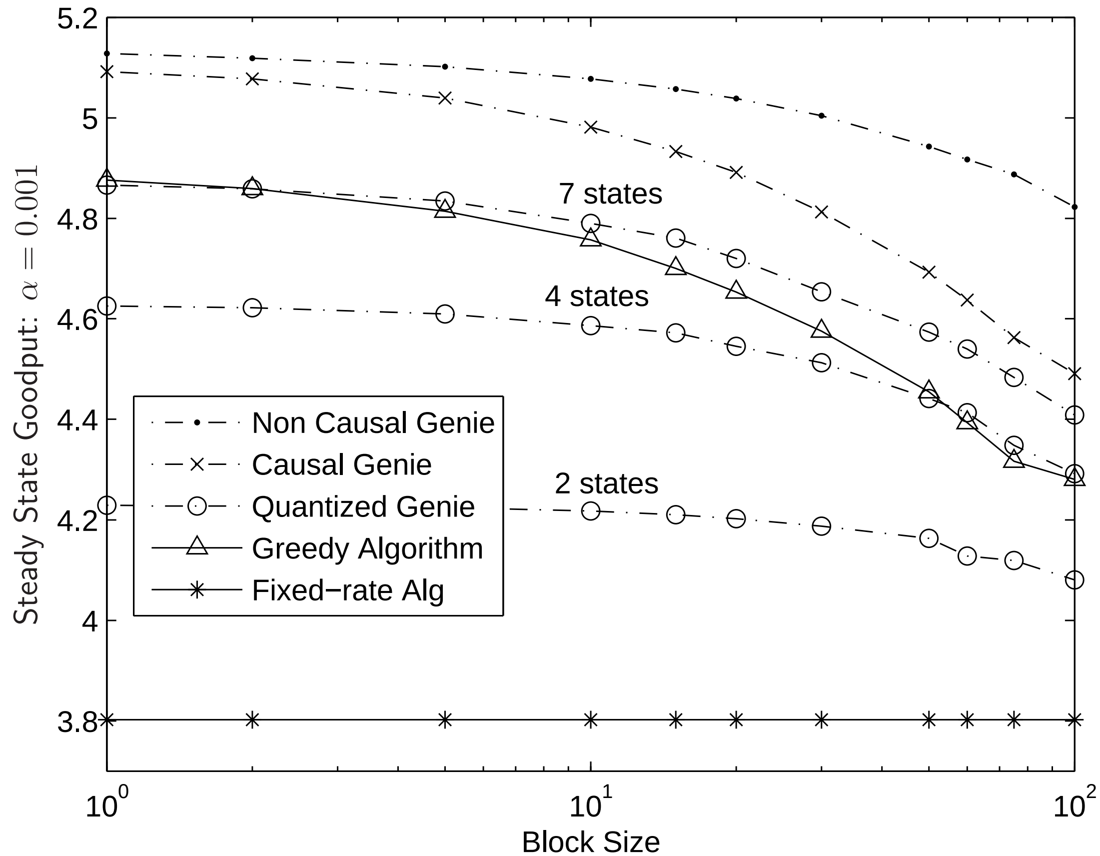

The greedy algorithm extracts most of the goodput gain achievable from the use of causal error-rate feedback, which diminishes with fading rate.

# Steady-state goodput versus feedback delay $d$:




The greedy algorithm extracts most of the goodput gain achievable from the use of causal error-rate feedback, which diminishes with delay $d$.

# Steady-state goodput versus block-size $n$:




The greedy algorithm extracts most of the goodput gain achievable from the use of causal error-rate feedback, which diminishes with block-size $n$.

# Effects of Finite Input-Buffer:

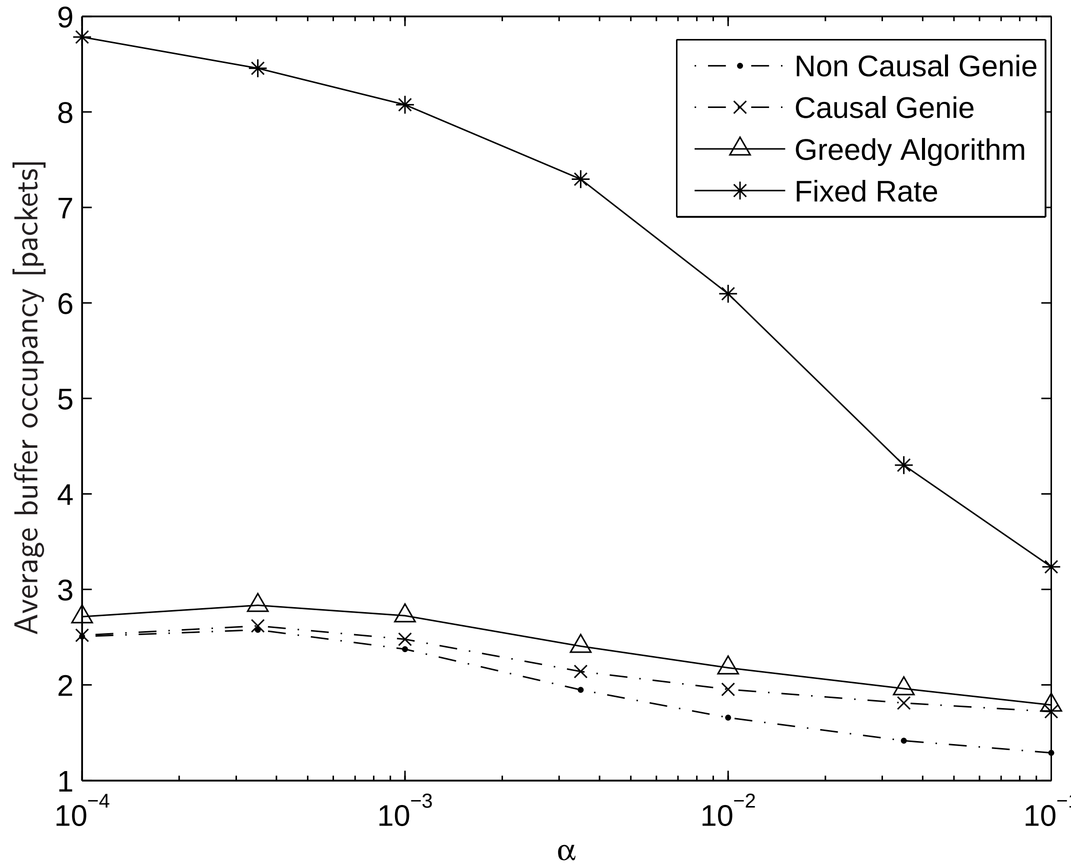
Buffer Description:

- Buffer size $= 30$ fixed-rate packets.
- Packet removed from buffer when transmitter receives an ACK.
- Overflowing packets are dropped from the buffer.

Simulation Parameters:

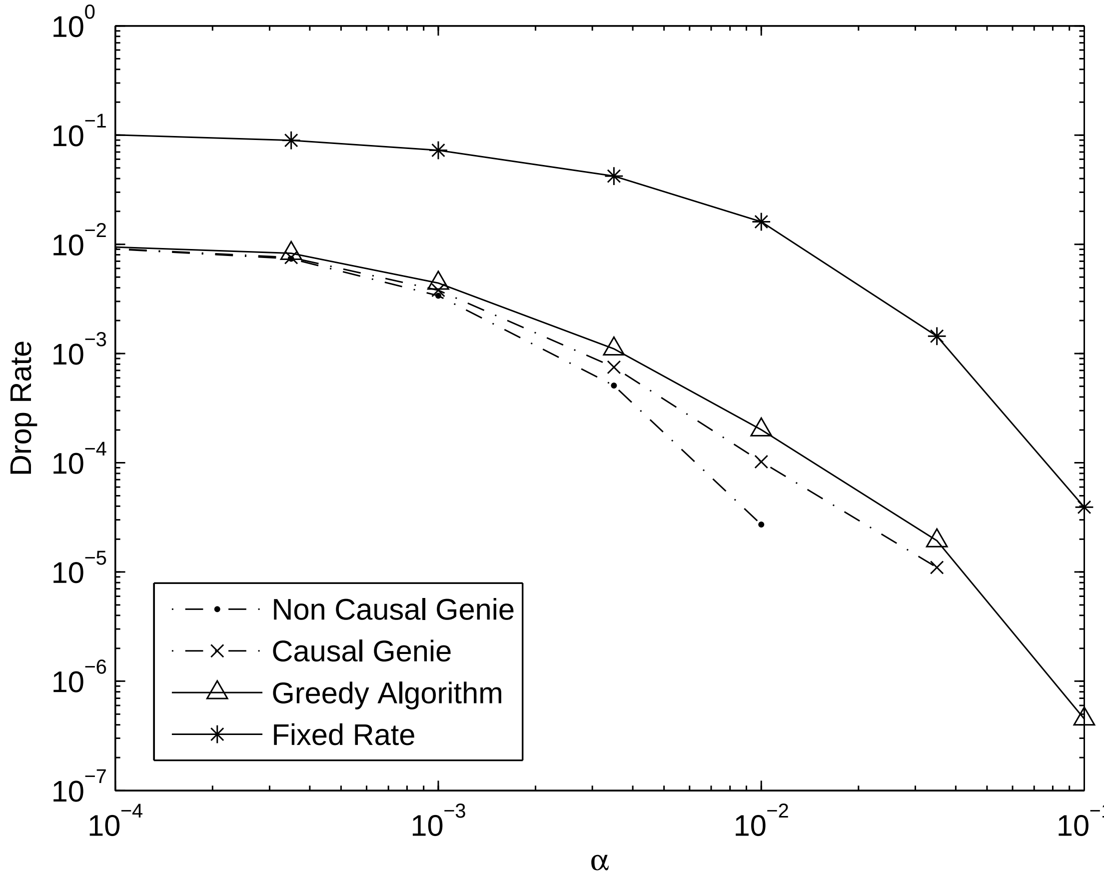
- Markov arrivals: switched between ON & OFF with transition probability $0.1$ (i.e., "bursty"). When ON, the arrival rate equalled the best fixed transmission rate under fully backlogged conditions.
- Same setup as before, including mean SNR $= 25$ dB.
- Each trial spanned $1000$ packet intervals.
- Plots show an average of $1000$ trials.

# Buffer occupancy versus fading-rate parameter $\alpha$:




The buffer occupancy of the greedy algorithm is near-optimal, whereas that of the fixed-rate algorithm is much worse, especially in slow fading.

# Drop-rate versus fading-rate parameter $\alpha$:




The drop rate attained by the greedy algorithm is near-optimal, whereas the drop rate of the fixed-rate algorithm is an order-of-magnitude worse.

## Conclusions:

- Motivation: Adapt physical-layer rate from link-layer ARQ.
- General problem: Rate adaptation via causal degraded error-rate feedback for maximization of total expected goodput.
  - Optimal rate adaptation: A POMDP... Too difficult!
  - Practical rate adaptation: Greedy algorithm.
  - Upper bound on optimal: Causal genie. (Also greedy.)
- Numerically, we examined (in fully backlogged case) steady-state goodput and (with finite-buffer & bursty arrivals) buffer occupancy & drop-rate. Greedy scheme was found to be...
  - very close to the upper bound on optimal (i.e., causal genie),
  - much better than the best fixed-rate scheme, and
  - better than the best quantized-SNR scheme with $\leq 7$ states.
- Planned future work: Use these ideas in a network setting.

*Thanks for listening!*