Resource Allocation for Latency sensitive Wireless Systems

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Ph.D. Thesis Defense

Outline

Introduction

Part One

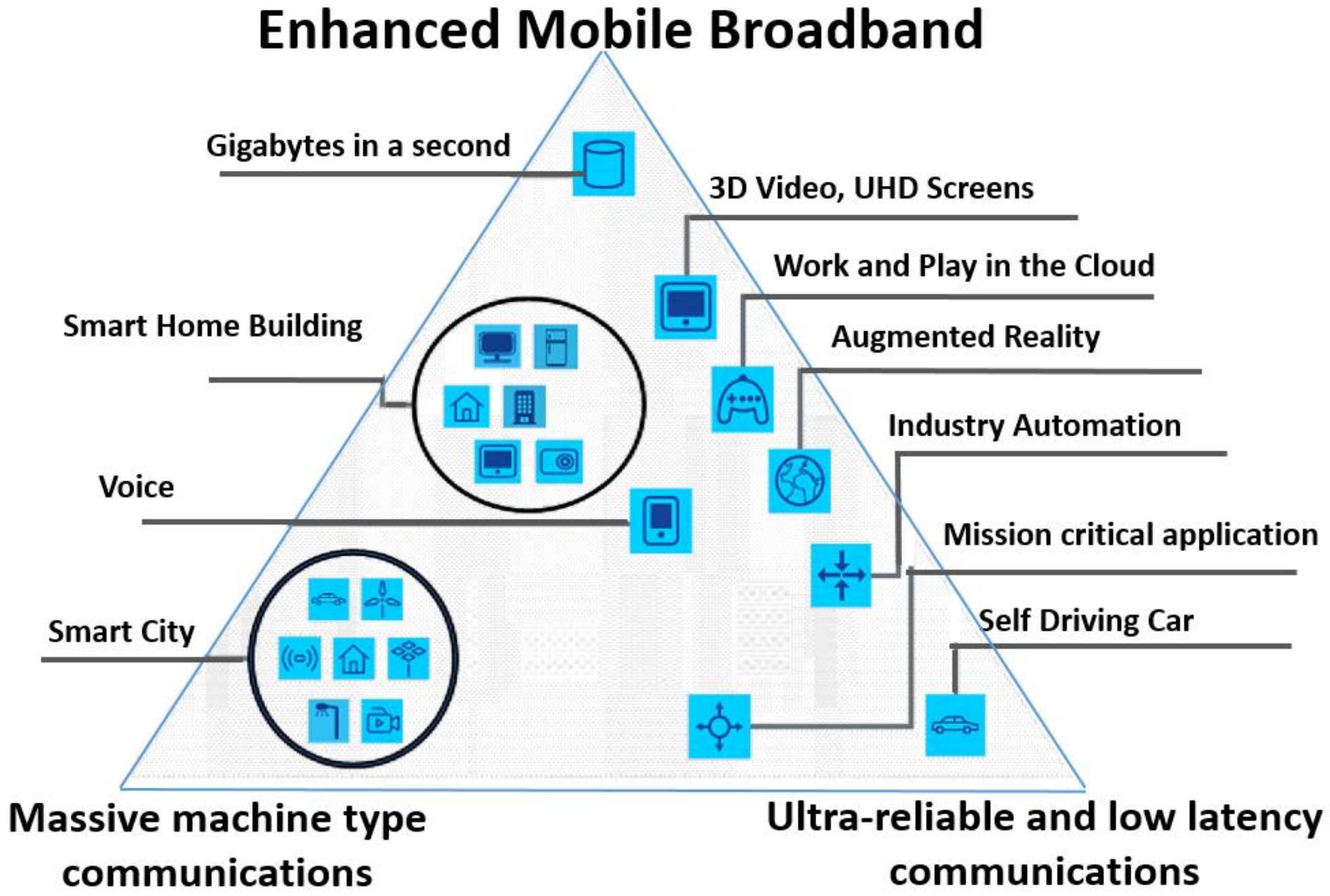
- Retransmission under strict Latency & Reliability constraints?
- Energy – Latency tradeoff characterization.
- How to optimally tune resources (power,blocklength,…)?
- The effect of CSI

Part Two

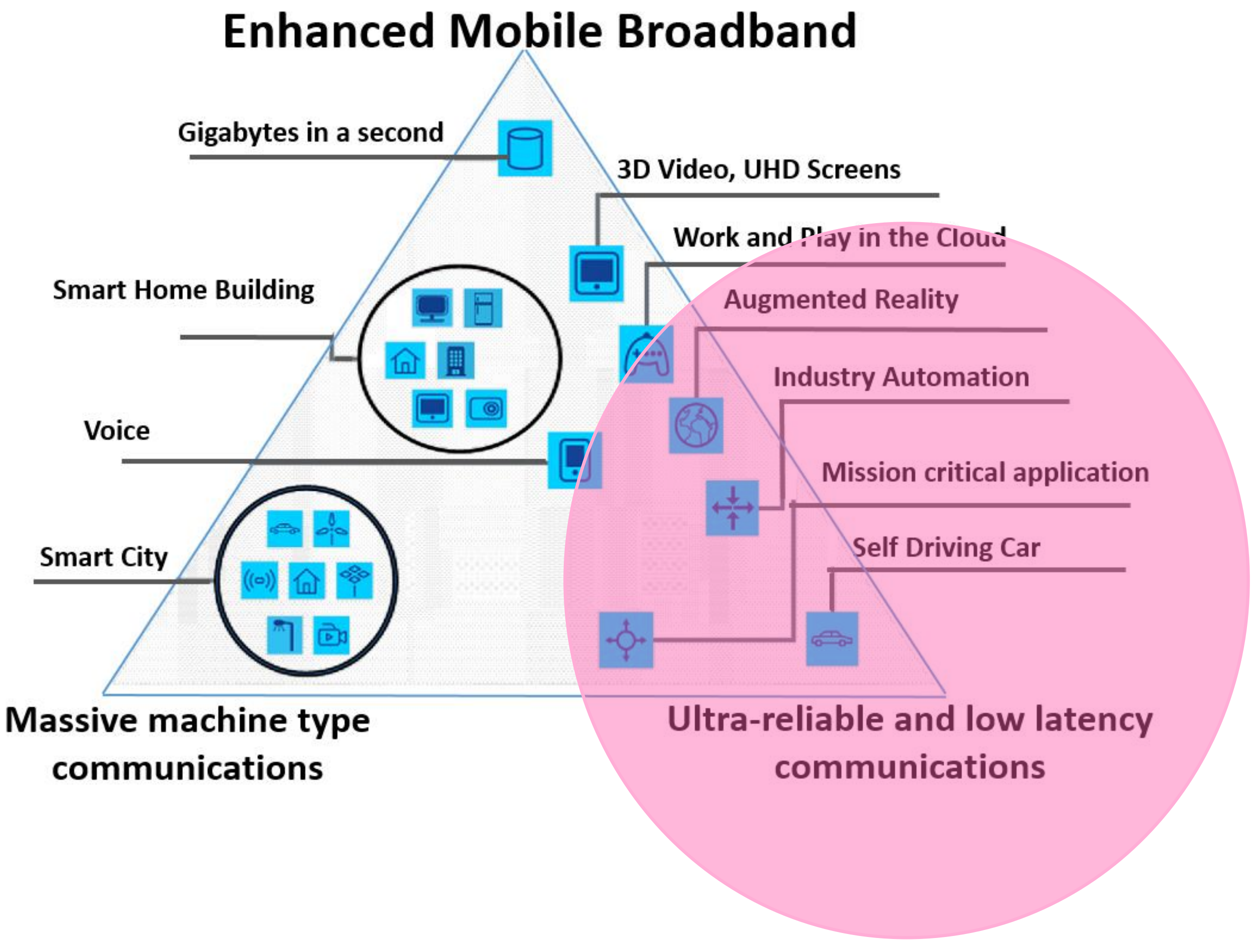
- How to allocate bandwidth in multi class user traffic?
- Deep Reinforcement Learning
- Full and Statistical CSI

Conclusions

5G Vision


Enhanced Mobile Broadband
Gigabytes in a second
3D Video, UHD Screens
Work and Play in the Cloud
Smart Home Building
Augmented Reality
Industry Automation
Voice
Mission critical application
Smart City
Self Driving Car
Massive machine type communications
Ultra-reliable and low latency communications

Our focus



Use case	Latency (ms)	Reliability (PEP)	Data size (bytes)
Industrial automation	$0.25 - 10$	$10^{-6} - 10^{-9}$	$10 - 300$
Smart grids	$5 - 50$	10^{-6}	$80 - 1000$
Intelligent transport systems	$5 - 100$	$10^{-3} - 10^{-5}$	$500 - 1k$
Telemedicine	$1 - 10$ (haptics) $20 - 100$ (video, audio)	10^{-5}	$200 - 4k$

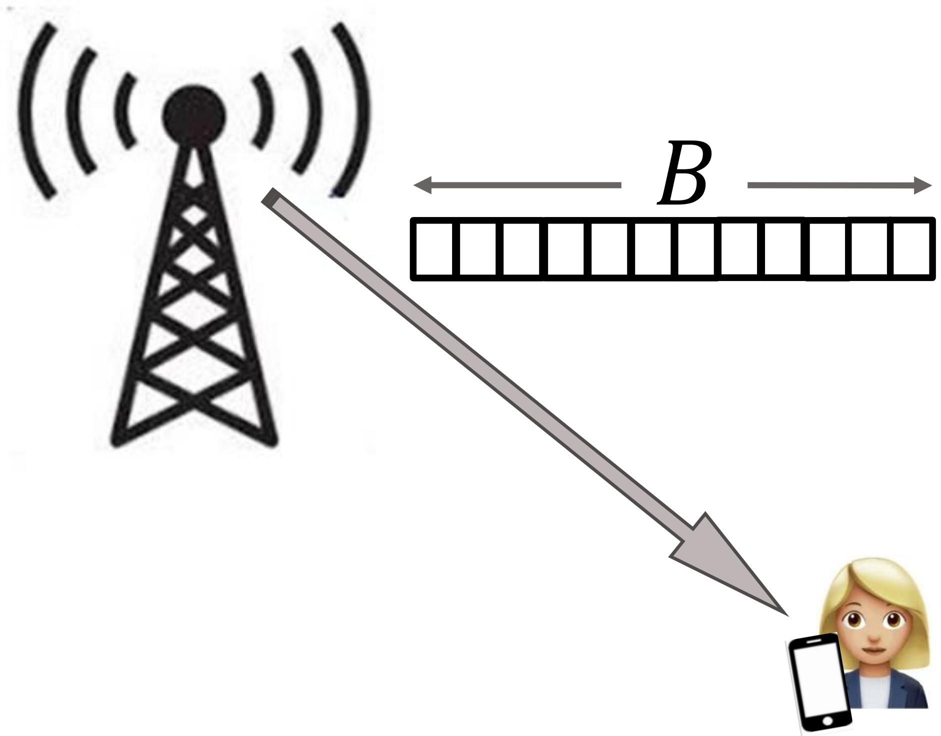
URLLC : 1 ms , 10^{-5} , 32 bytes

Part One

System Model

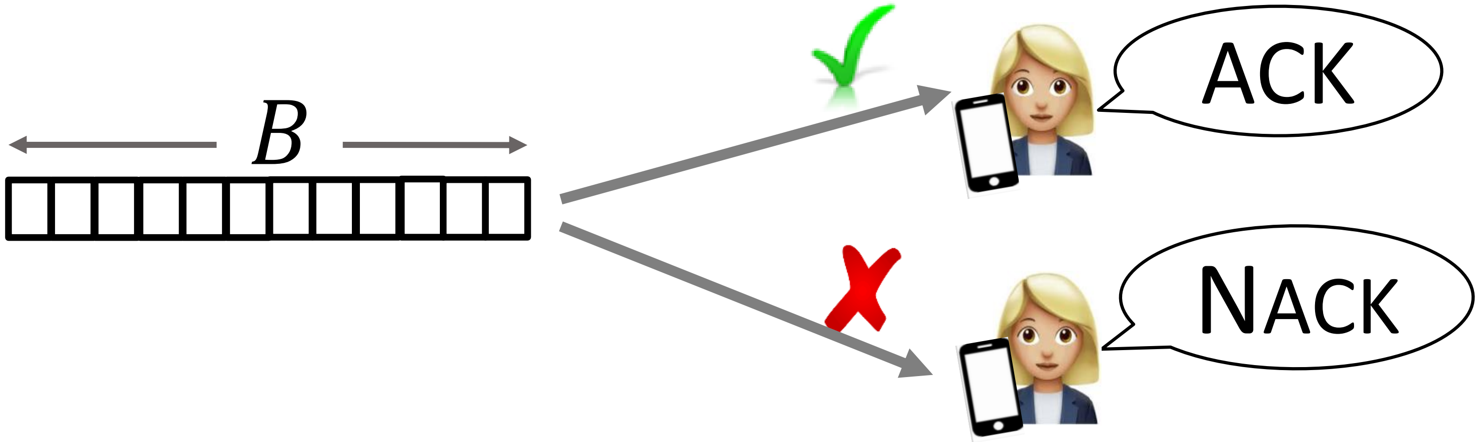
URLLC is tough!

- ❖ Diversity: Frequency, Space, Time
- ❖ *What about retransmissions?*

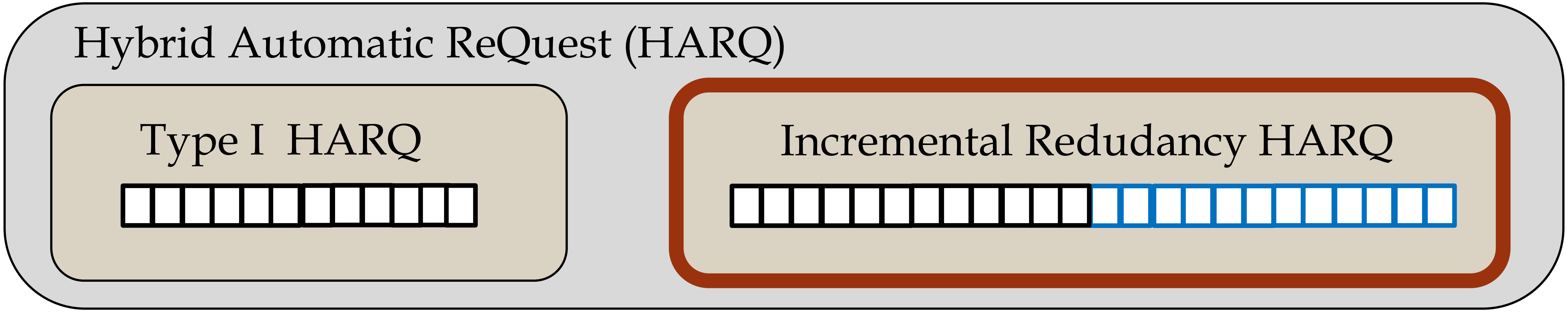


- Point to Point
- B Information Bits

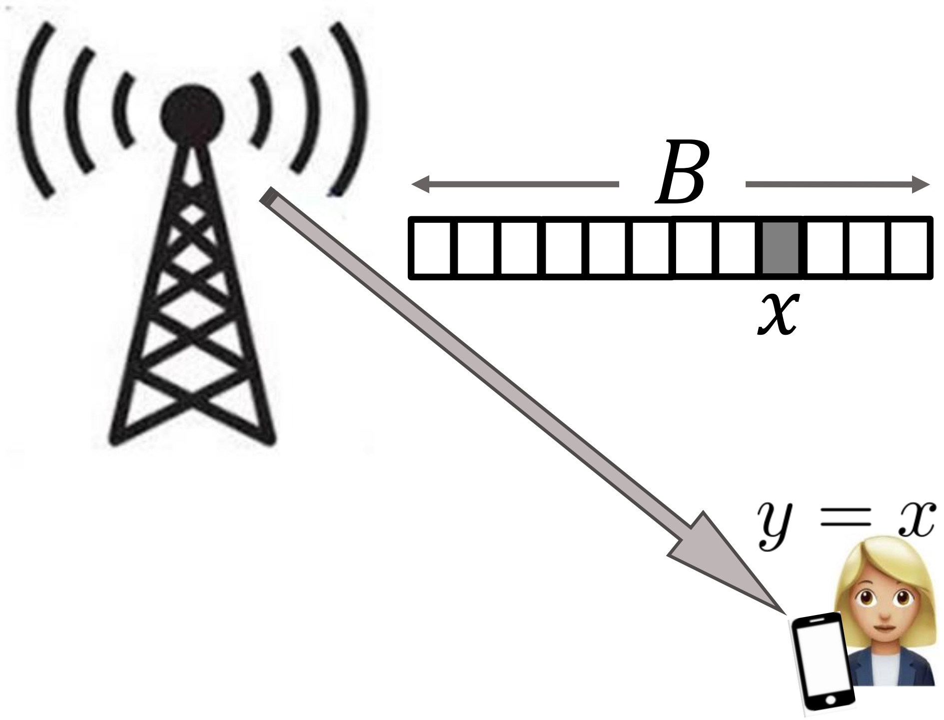
System Model



In case of NACK it will be transmitted:



System Model



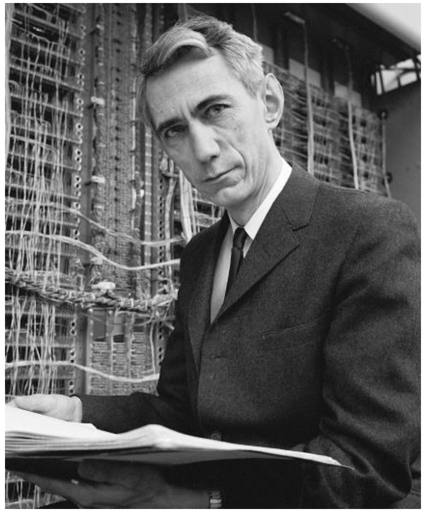
$y = x + z$

- AWGN: $z \sim \mathcal{CN}(0,1)$
- *Received power*:

$$P = \frac{EnergyPacket}{n},\ n = \#\text{symbols}$$

- *Data Rate*:

$$\frac{B}{n} = \log_2(1+P)$$



Shannon (1916-2001)

Assumption: $n \to \infty$

Finite Blocklength ($n < \infty$)

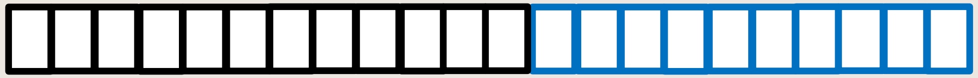
$$\frac{B}{n} \approx \log_2(1+P) - \frac{Q^{-1}(\varepsilon)}{\sqrt{n}} \underbrace{\sqrt{1 - \frac{1}{(1+P)^2}}}_{\text{dispersion } V} \log_2 e + \cdots$$

$$\Rightarrow \varepsilon \approx Q\left(\frac{n \ln(1+P) - B \ln 2}{\sqrt{n \frac{P(P+2)}{(P+1)^2}}} \right)$$

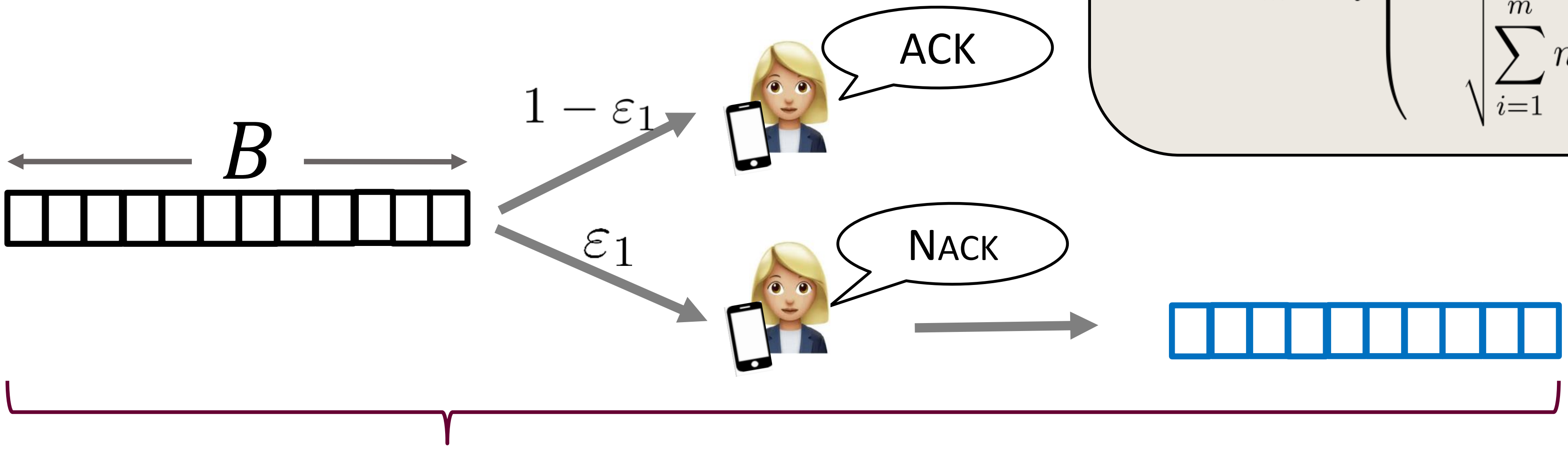
* Y. Polyanskiy, H.V. Poor, S. Verdú, "*Channel coding rate in the finite blocklength regime* ", IEEE Trans. on Inf. Theory, vol. 56, no. 5, Apr. 2010
* M. Hayashi, "*Information spectrum approach to second-order coding rate in channel coding*", IEEE Trans. on Inf. Theory, vol. 55, no. 11, Nov. 2009

Sharpening System Model

Incremental Redundancy-HARQ

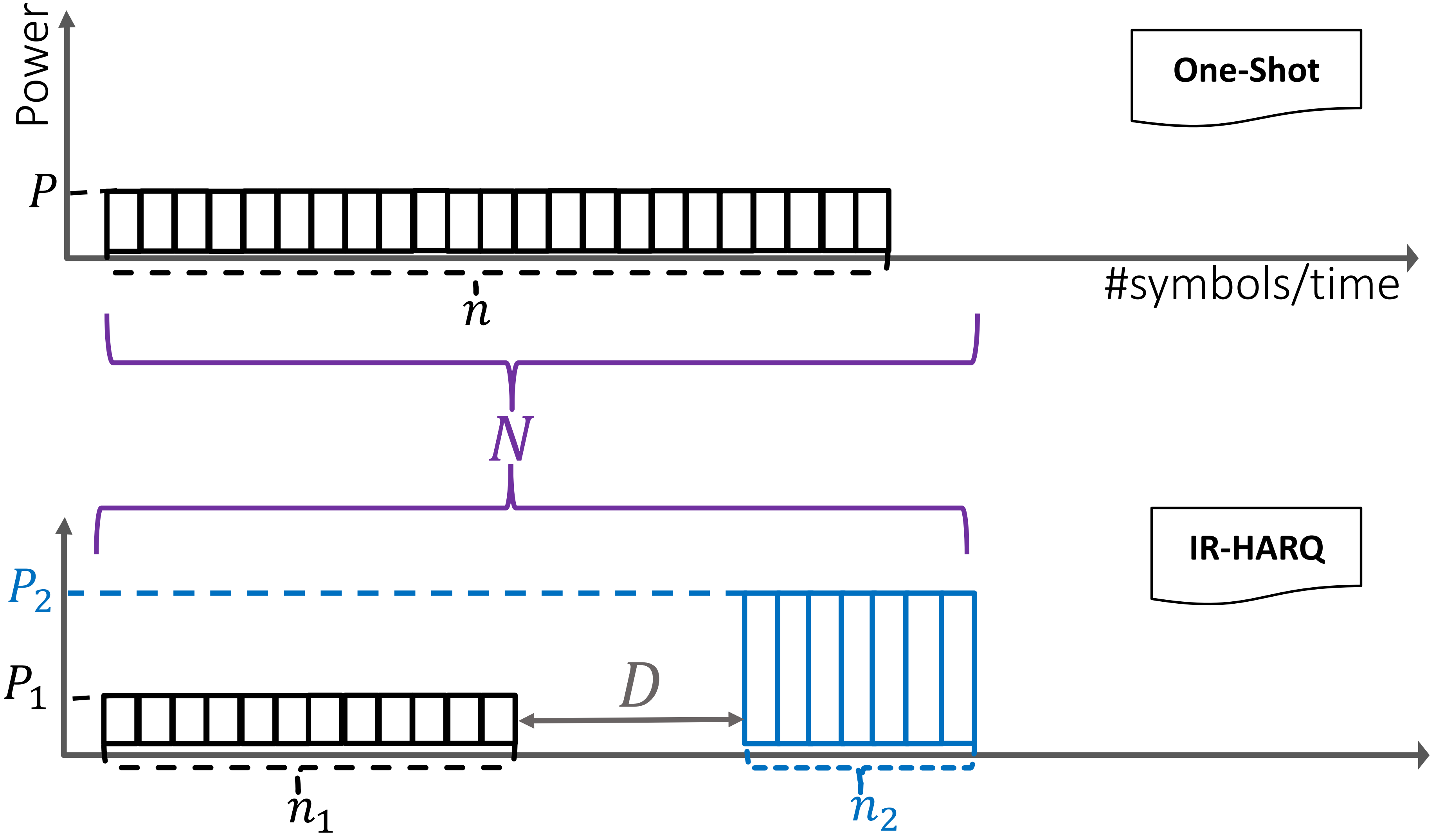


$$\varepsilon_m \approx Q\left(\frac{\sum_{i=1}^{m} n_i \ln(1+P_i) - B\ln 2}{\sqrt{\sum_{i=1}^{m} n_i \frac{P_i(P_i+2)}{(P_i+1)^2}}}\right)$$



$$\mathbb{P}(✗) \approx \varepsilon_2$$

One-shot or HARQ-IR?



Minimization $\mathbb{E}[\text{ Energy}]$

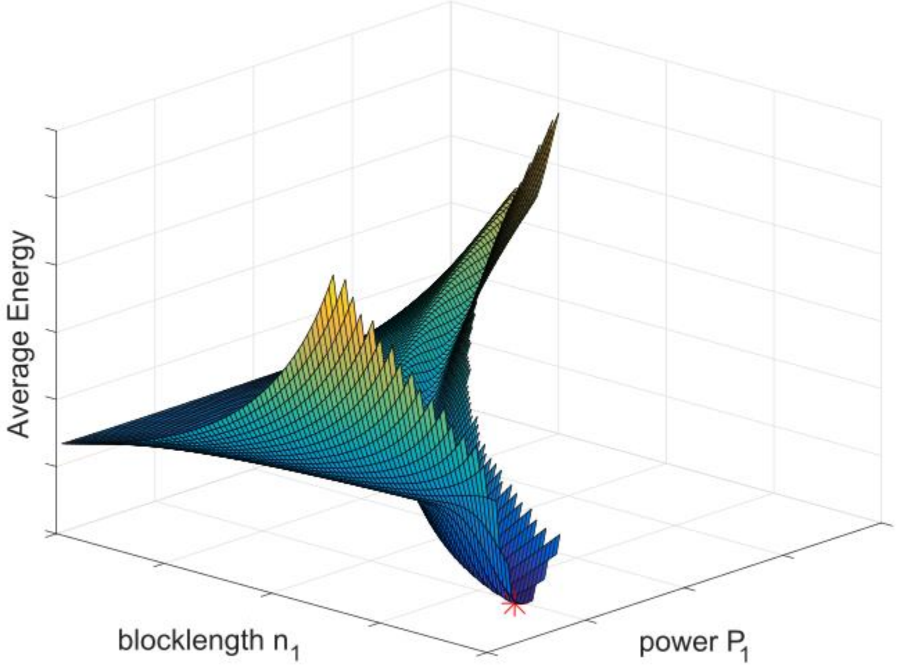
$$\min_{n_1,P_1,n_2,P_2} \quad n_1 P_1 + n_2 P_2 \varepsilon_1 \quad (\mathbb{E}[\text{ Energy}])$$

$$\text{s.t.} \quad n_1 + n_2 \leqq N - D \qquad \text{(Latency)}$$

$$\varepsilon_2 \leqq 1 - T_{\text{rel}} \qquad \text{(Reliability)}$$

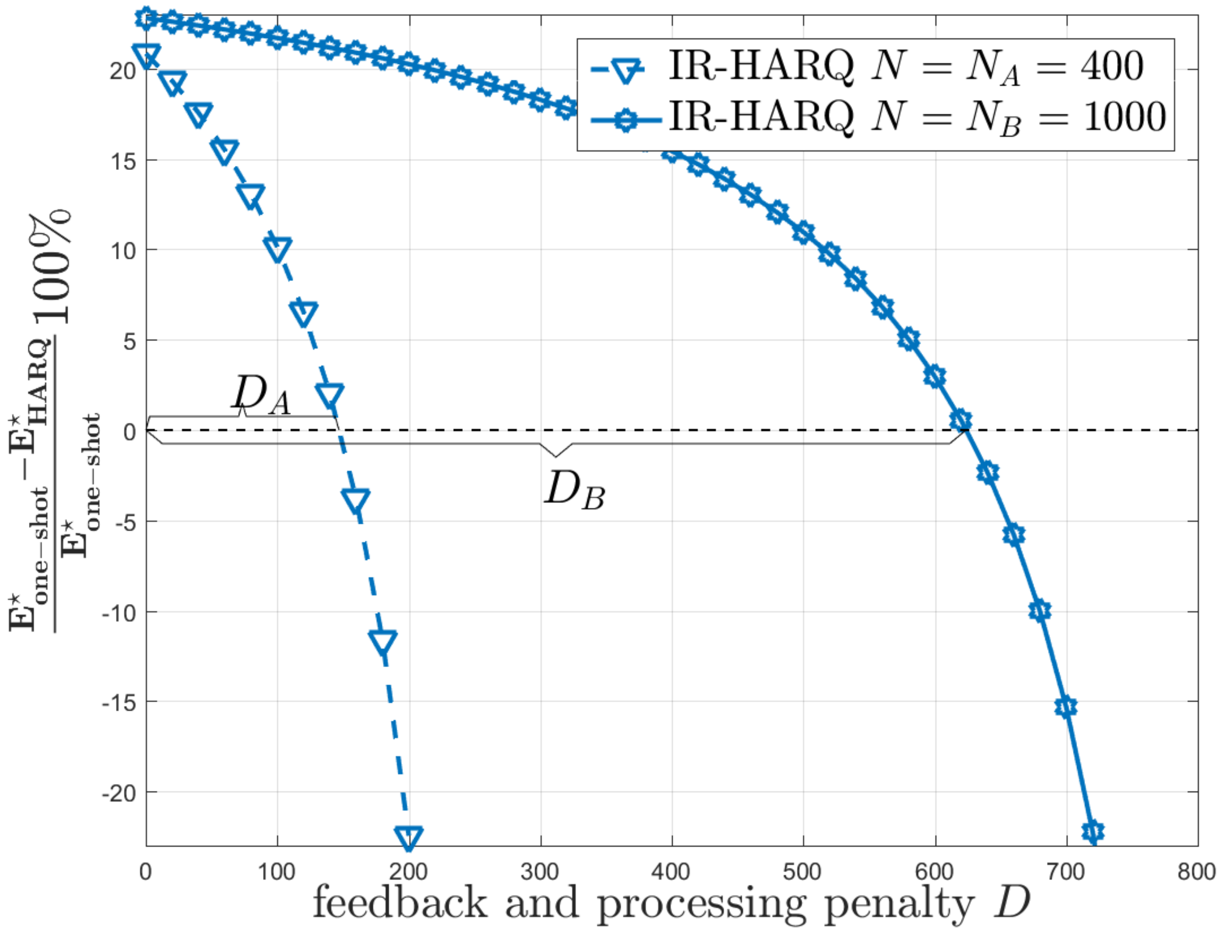
Even though **Non-Convex**:

→ 2-D grid search

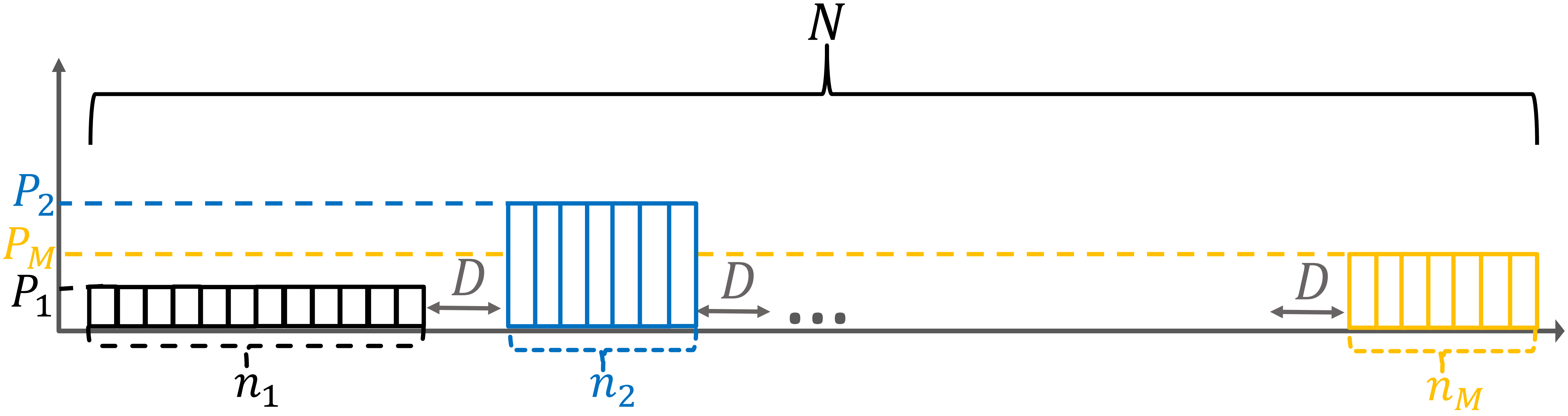


Initial Results

- D = 0:
  - Up to 25% Energy Economy
  - Benefits due to “early termination”
- D > 0:
  - Same logic but diminishing benefits.
  - If increased much, one-shot better since powers are increasing exponentially to meet URLLC constraints.



General Case ($M > 2$)



- ❑ Best M? Best Configuration?
- ❑ ~~Convexity~~

"Simple" case feedback delay $D = 0$

$$\min_{M, n_1, \cdots, n_M, P_1, \cdots, P_M} \quad \sum_{m=1}^{M} n_m P_m \varepsilon_{m-1} \quad (\mathbb{E}[\text{ Energy}])$$

$$\text{s.t.} \quad \sum_{m=1}^{M} n_m = N \qquad \text{(Latency)}$$

$$\varepsilon_M = Q\left(\frac{\sum_{i=1}^{m} n_i \ln(1+P_i) - B \ln 2}{\sqrt{\sum_{i=1}^{m} n_i \frac{P_i(P_i+2)}{(P_i+1)^2}}} \right) = 1 - T_{\text{rel}} \quad \text{(Reliability)}$$

“Simple” case feedback delay $D = 0$

$$\min_{M, n_1, \cdots, n_M, P_1, \cdots, P_M} \quad \boxed{\sum_{m=1}^{M}} n_m P_m \varepsilon_{m-1}$$

$$\text{s.t.} \quad \boxed{\sum_{m=1}^{M}} n_m = N$$

$$\varepsilon_M = Q\left(\frac{\boxed{\sum_{i=1}^{m}} n_i \ln(1 + P_i) - B \ln 2}{\sqrt{\boxed{\sum_{i=1}^{m}} n_i \frac{P_i(P_i + 2)}{(P_i + 1)^2}}} \right) = 1 - T_{\text{rel}}$$

So what if ***Dynamic Programming*** since: $\sum_{i=1}^{m} x_i = x_m + \sum_{i=1}^{m-1} x_i$

Goal: Construct state such that:

$$\text{Energy}^{\star}(S_{m+1}) = \min_{\forall \text{ possible } S_m} \{\text{Energy}^{\star}(S_m) + \Delta\text{Energy}(S_{m+1}, S_m)\}$$

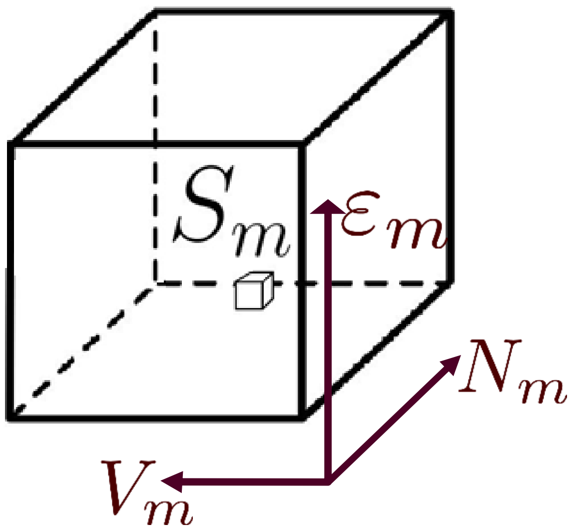
State at m^{th} round

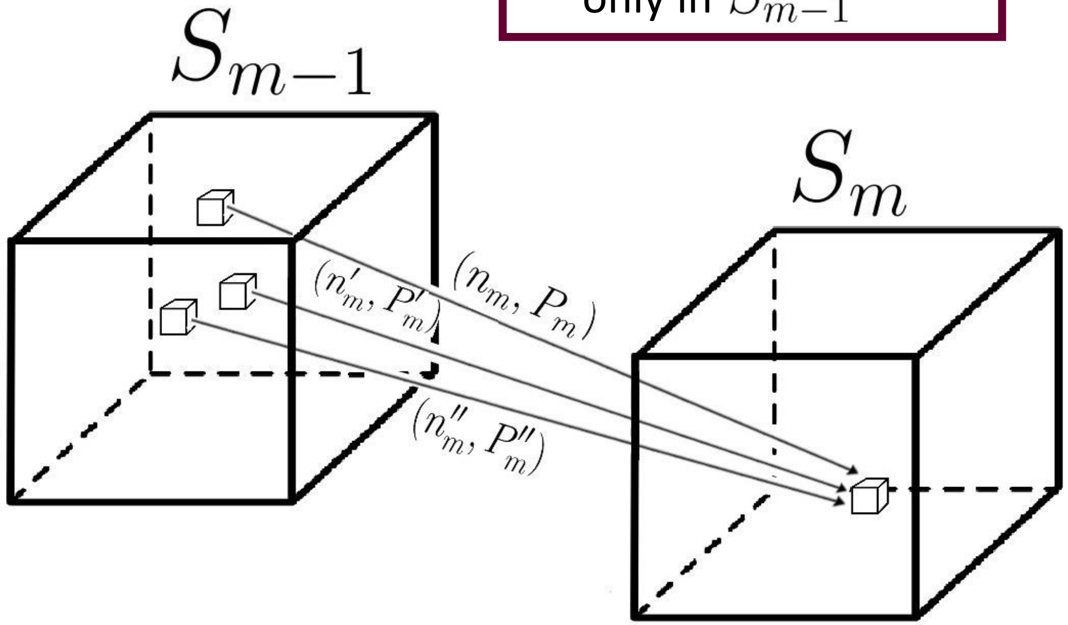
$$S_m = (N_m, V_m, \varepsilon_m)$$

Latency till m^{th}

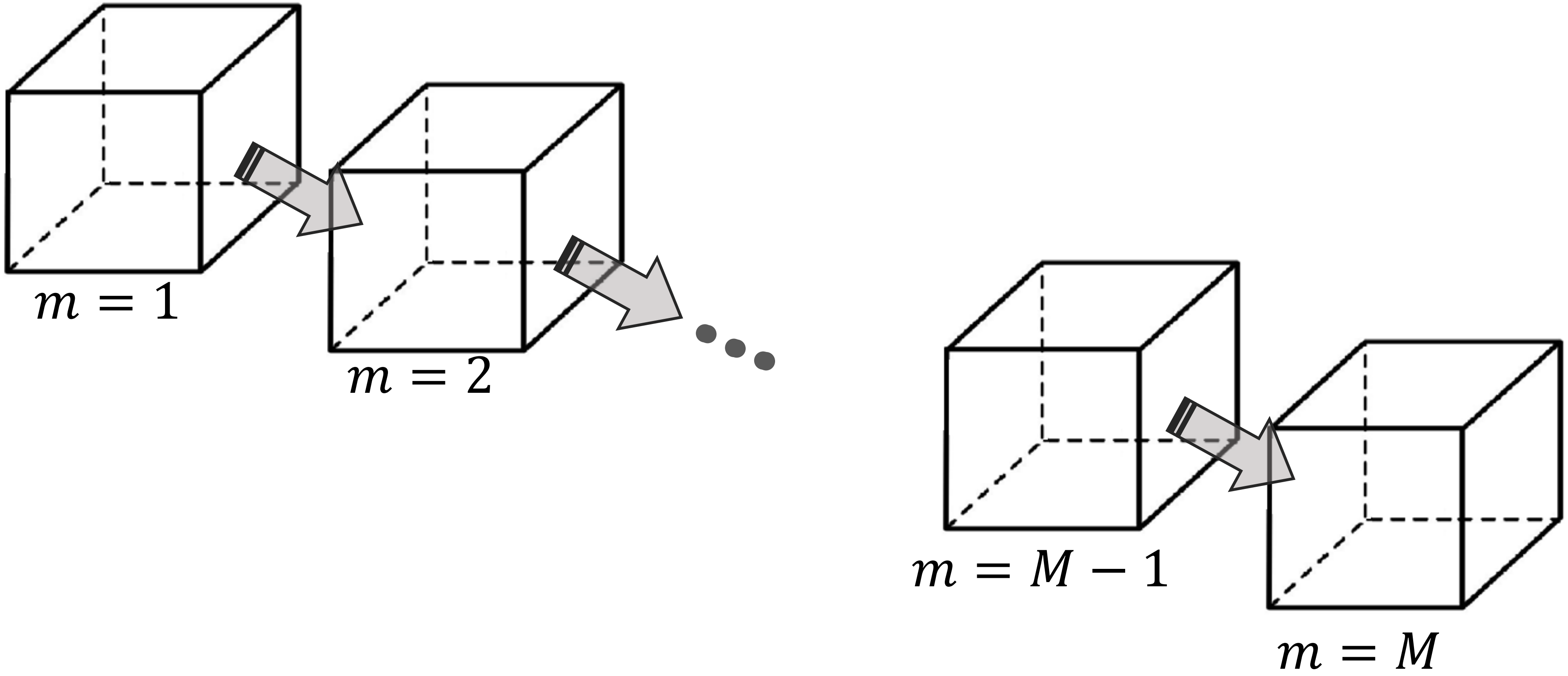
Reliability till m^{th}

- Optimality in S_m requires optimality only in S_{m-1}

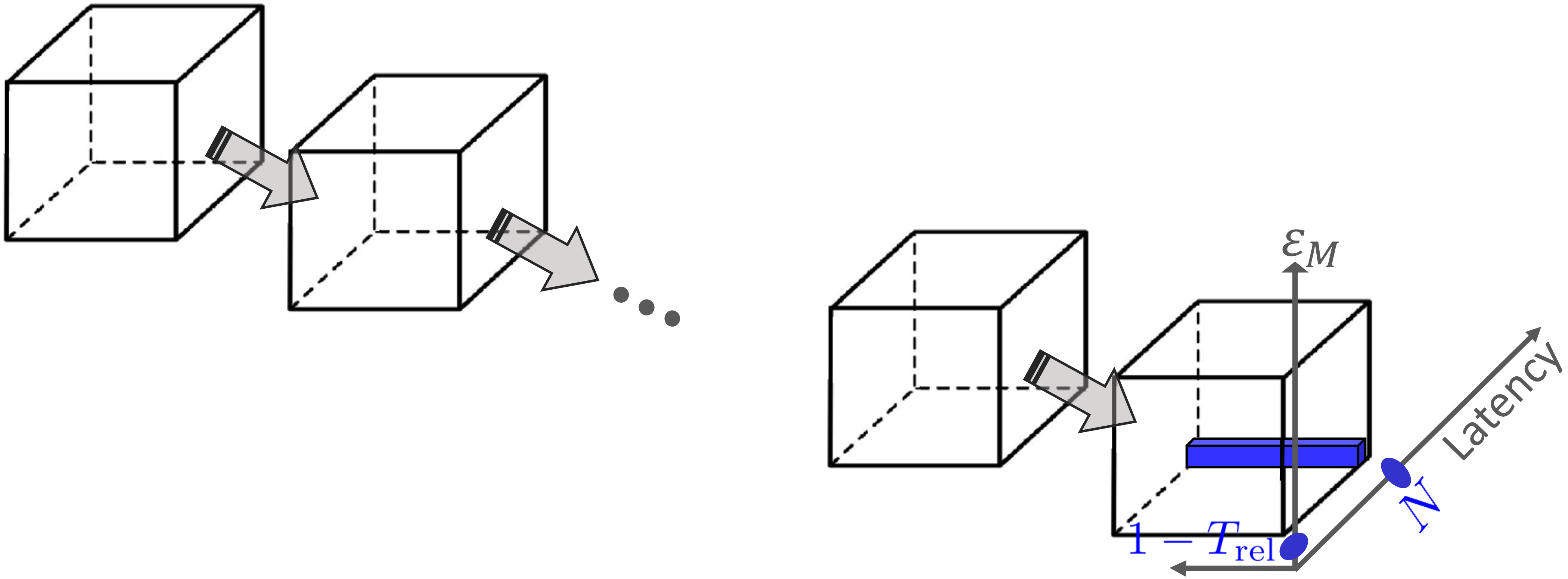




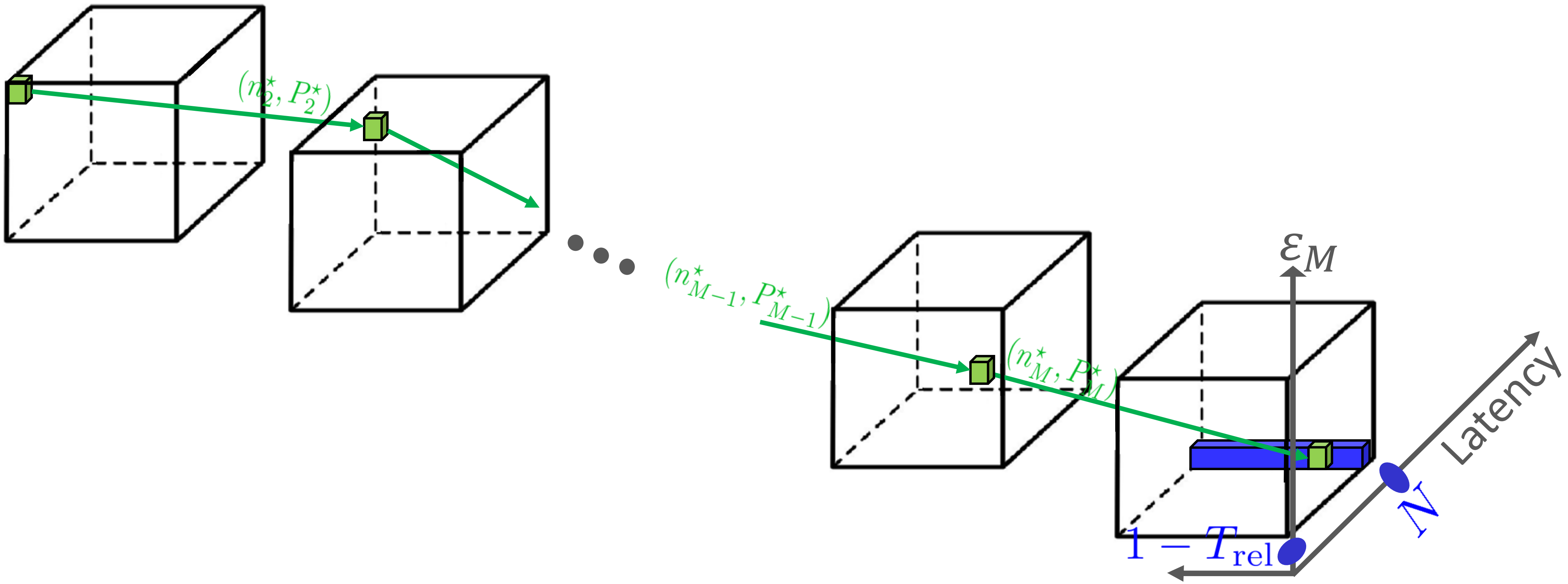
"Simple" case feedback delay $D = 0$



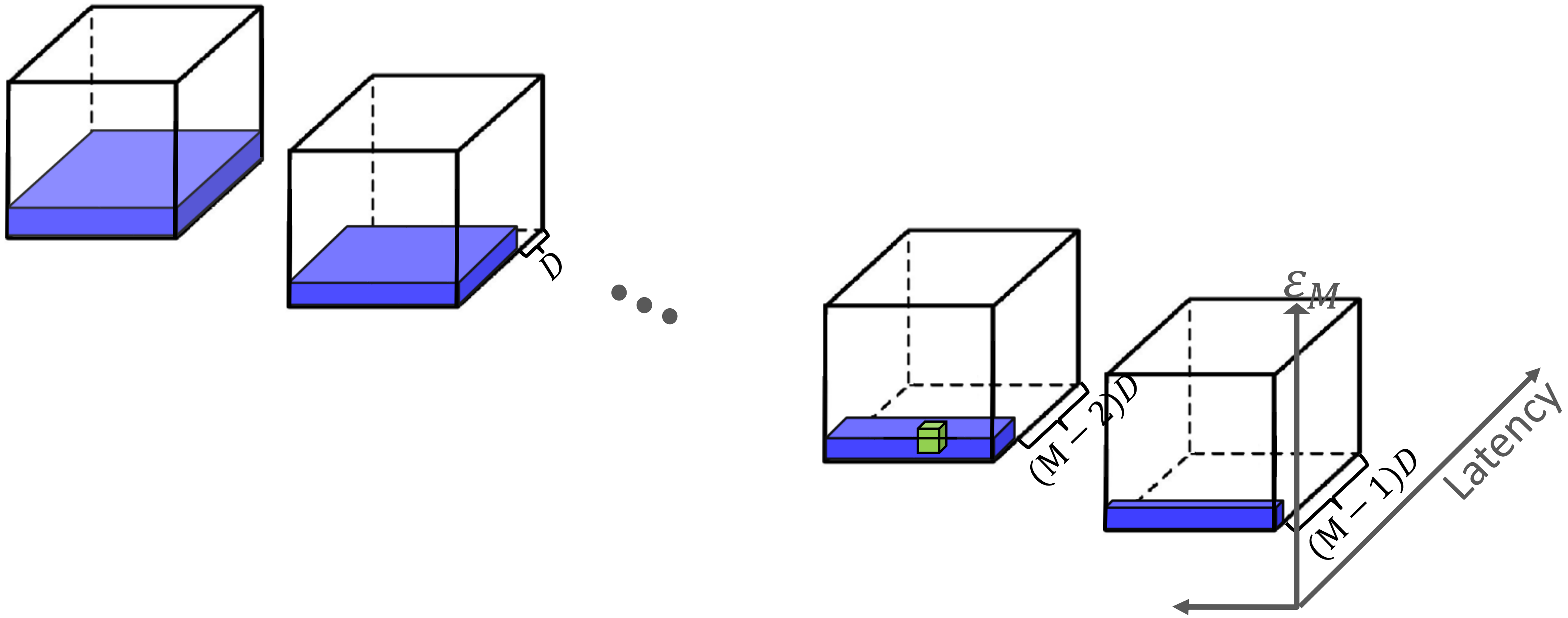
"Simple" case feedback delay $D = 0$



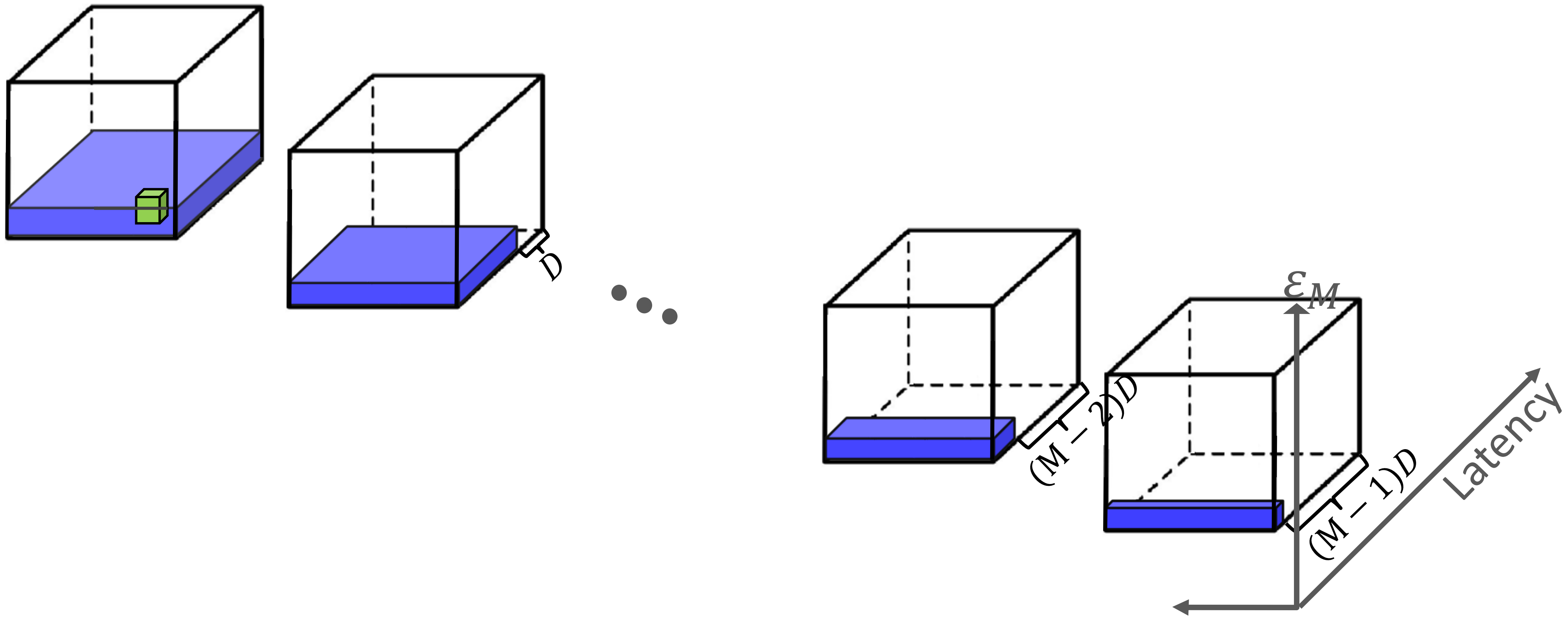
feedback delay $D = 0$, rounds $m \leq M$



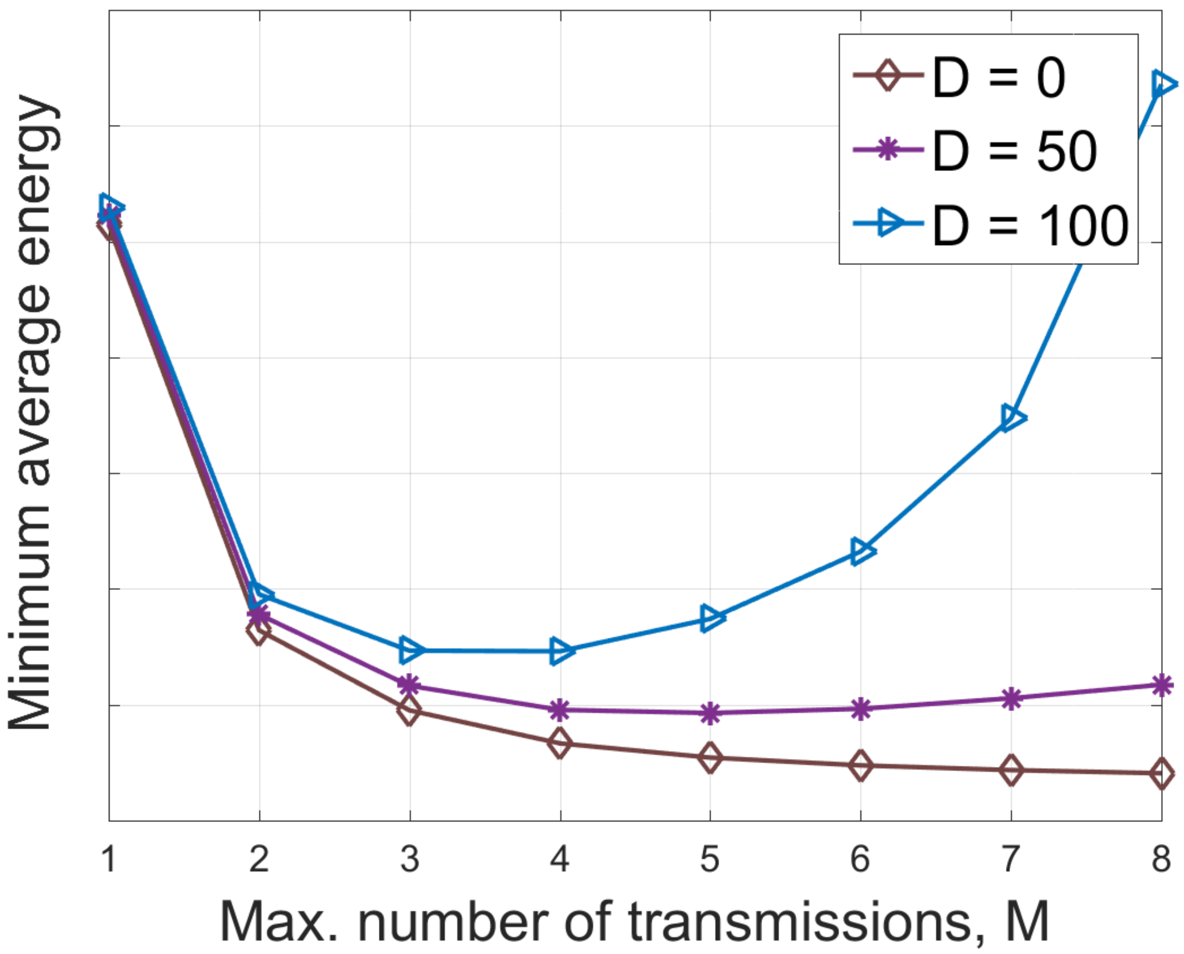
feedback delay $D > 0$



feedback delay $D > 0$



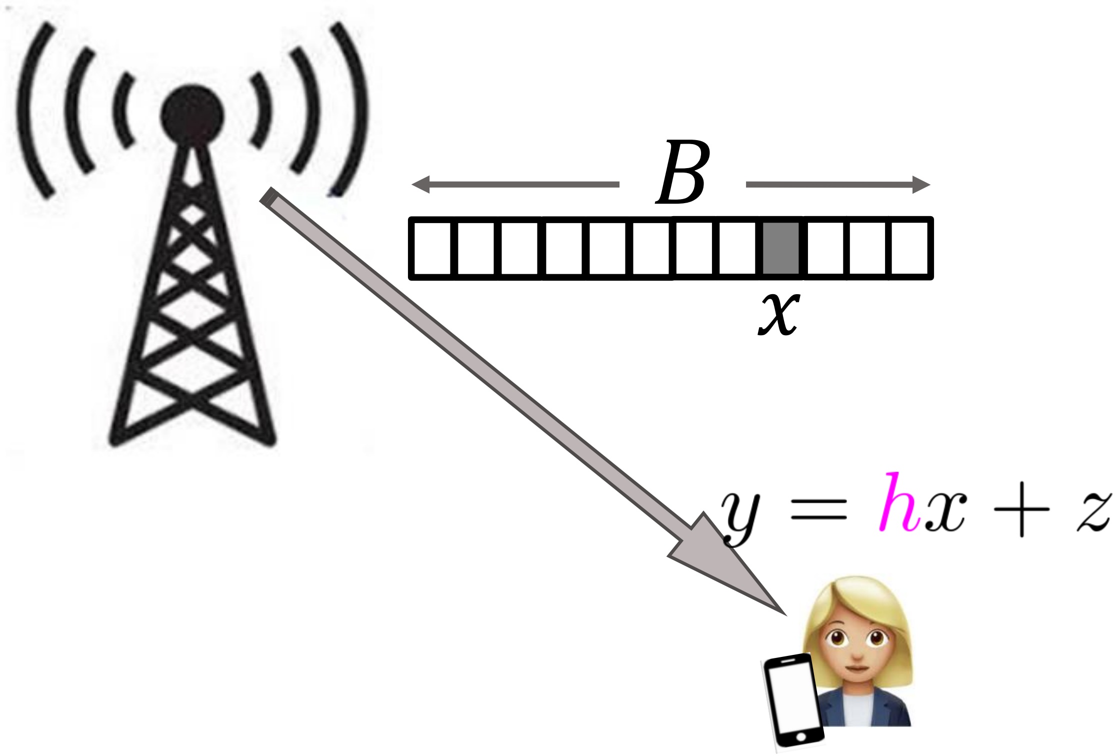
feedback delay $D > 0$



Throughput Maximization

$$\begin{aligned}
\max_{M, B, n_1, \cdots, n_M, P_1, \cdots, P_M} \quad & \color{blue}{Throughput} \\
\text{s.t.} \quad & \text{Reliability} \\
& \text{Latency} \\
& \text{Maximum Power}
\end{aligned}$$

Revisit System Model



- Received power:

$$P = |h|^2 \frac{EnergyPacket}{n}$$

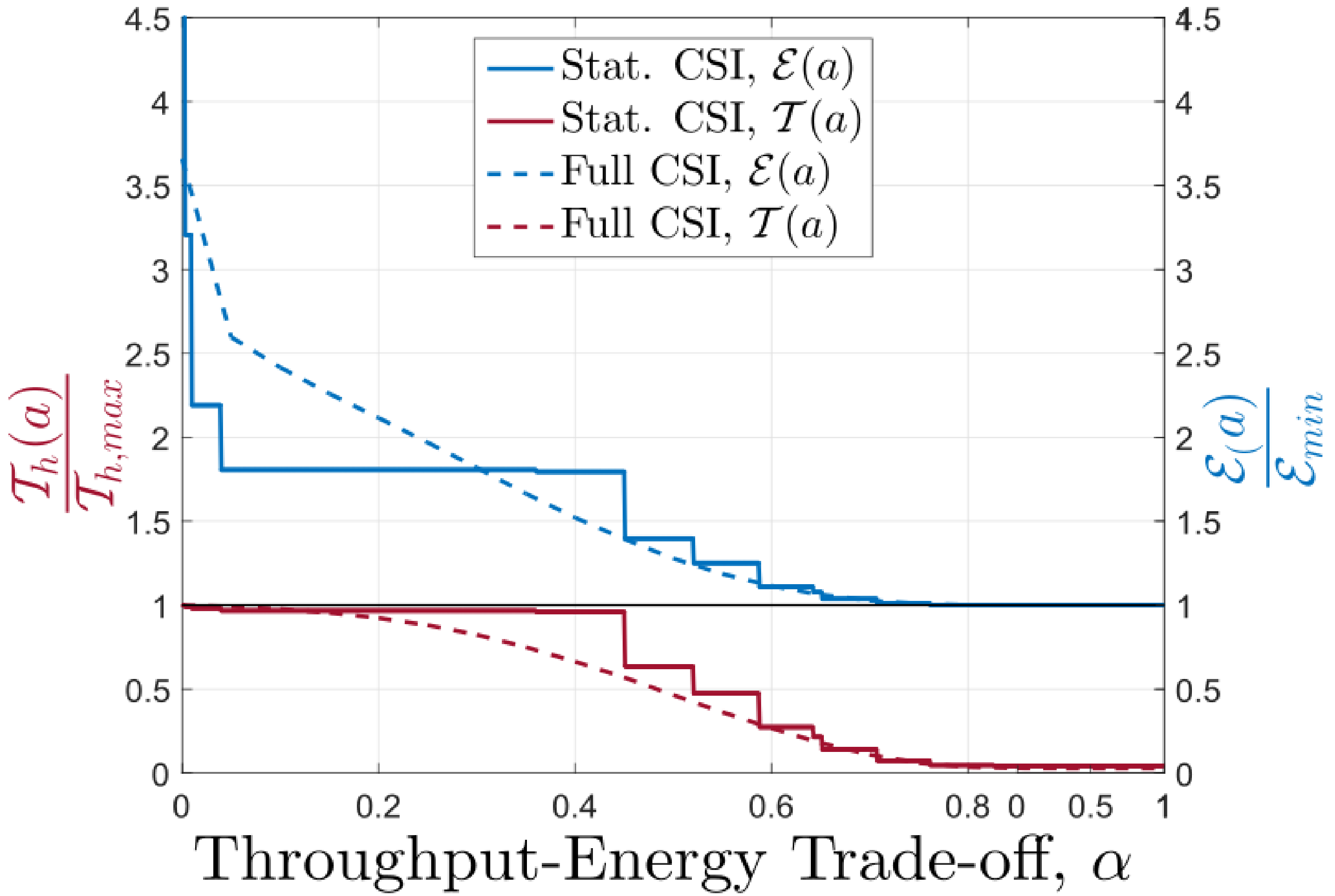
- $|h| \sim Rice(K, 1)$
  - $K = \frac{\text{Power direct path}}{\text{Power scattered path}}$
  - $K = \infty$, AWGN
  - $K = 0$, Rayleigh Fading

- Channel State Information:
  - Full CSI (h known)
  - Statistical CSI (distribution of h known)

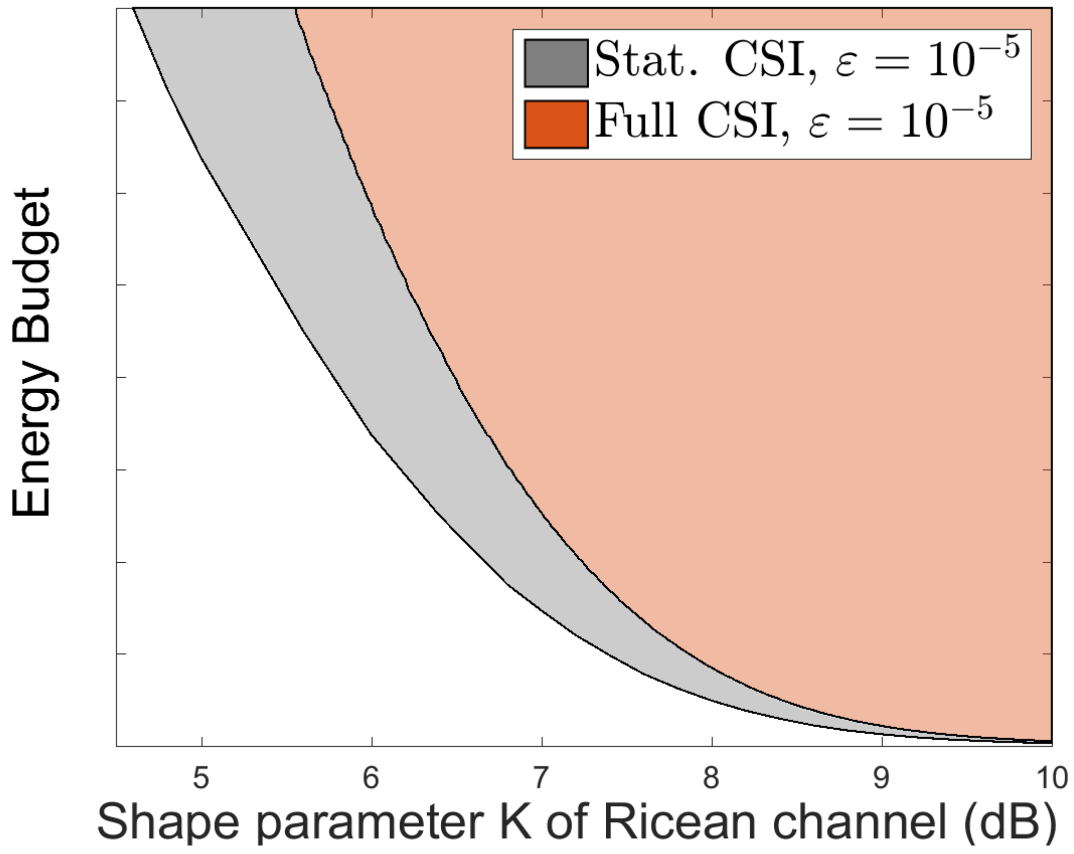
Throughput-Energy Trade-off

$$\begin{aligned} \max \quad & \mathbb{E}_h[(1-\alpha)\color{blue}{Throughput}\color{black} - \alpha\color{green}{Energy}\color{black}] \\ \text{s.t.} \quad & \mathbb{E}_h[\text{Reliability}] \\ & \text{Latency} \\ & \text{Maximum Energy/Power} \end{aligned}$$

Throughput-Energy Trade-off



Throughput-Energy Trade-off



Part Two

PHY → MAC

Similarities:

- Strict Latency Constraint L
- B information bits
- Retransmissions → Type I HARQ

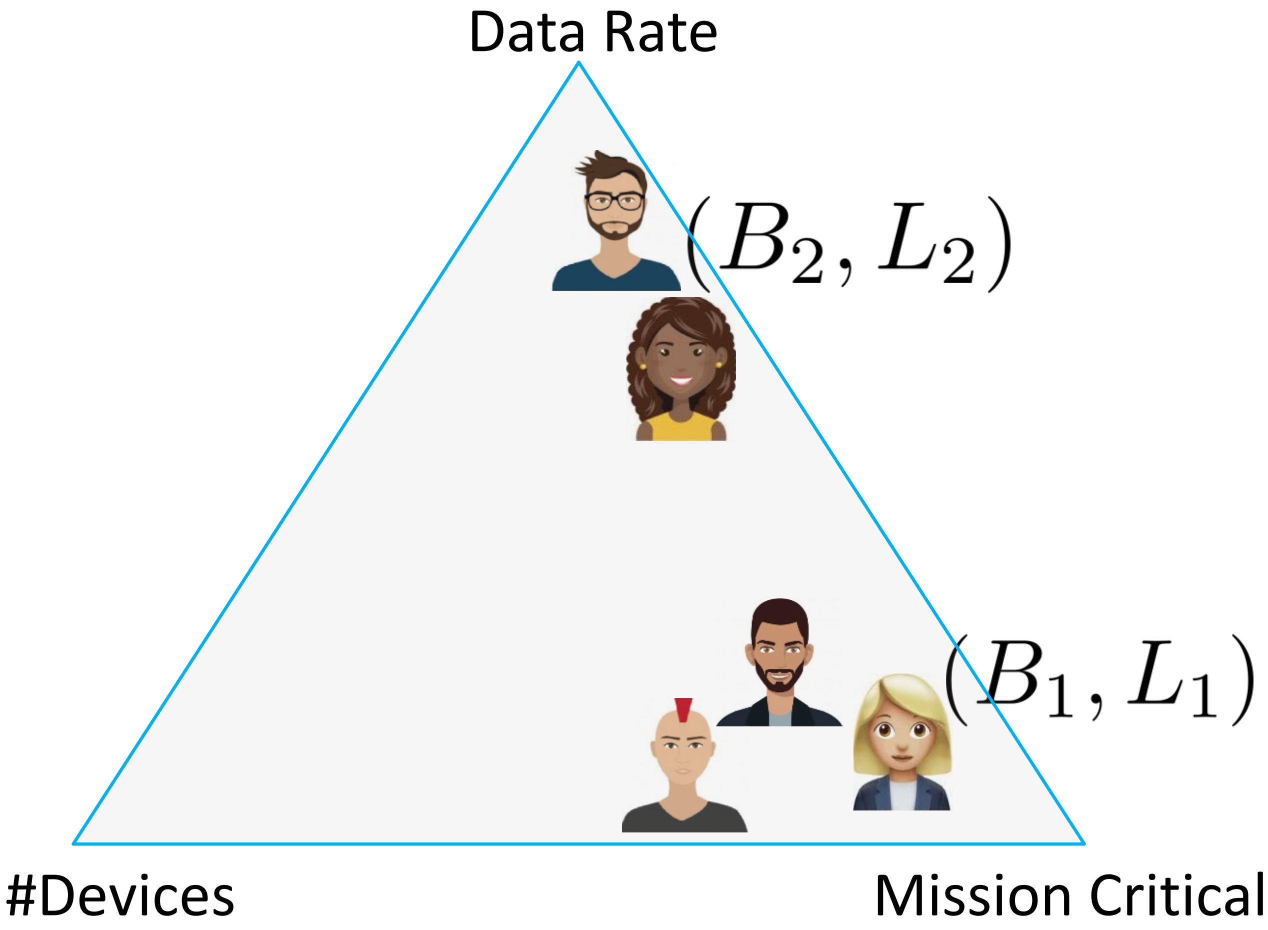
Differences:

- Back to Shannon
- h_t depends on h_{t-1}

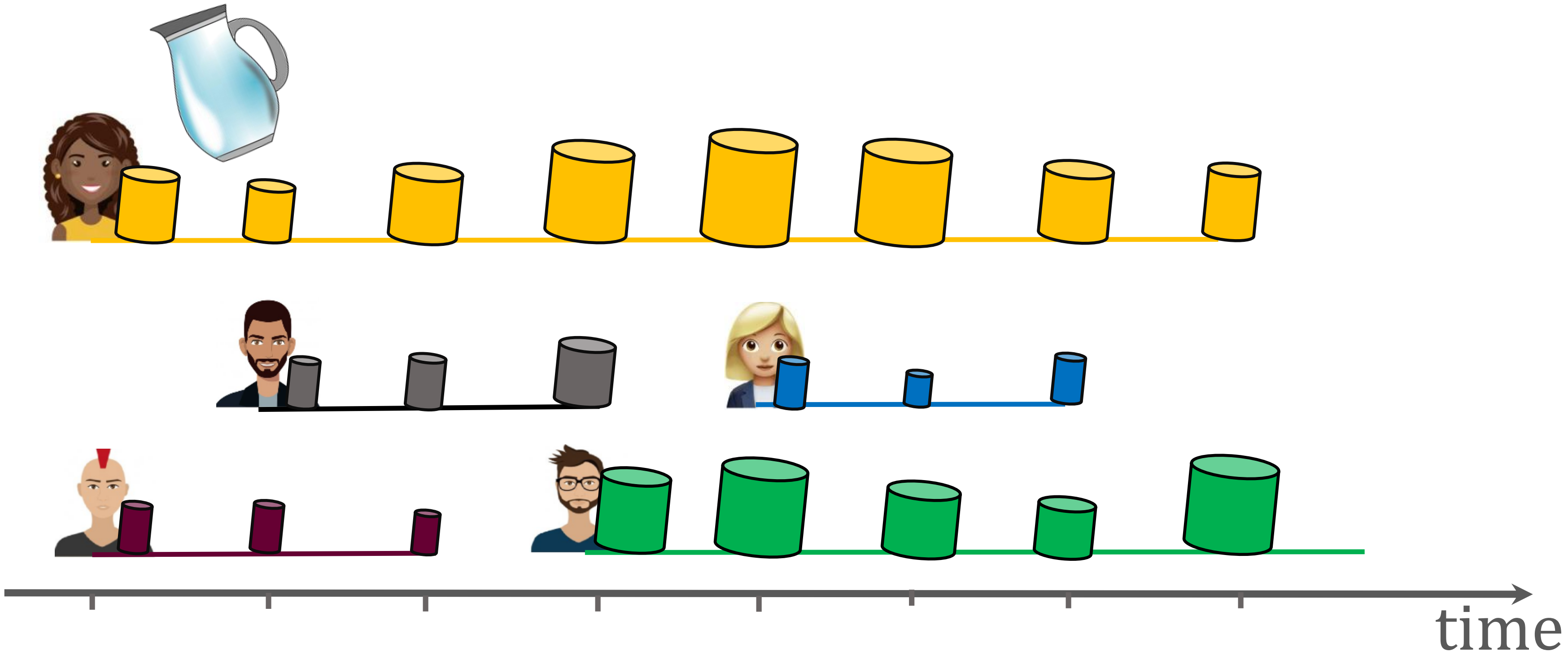
Type I HARQ

IR-HARQ

Multi Class Traffic

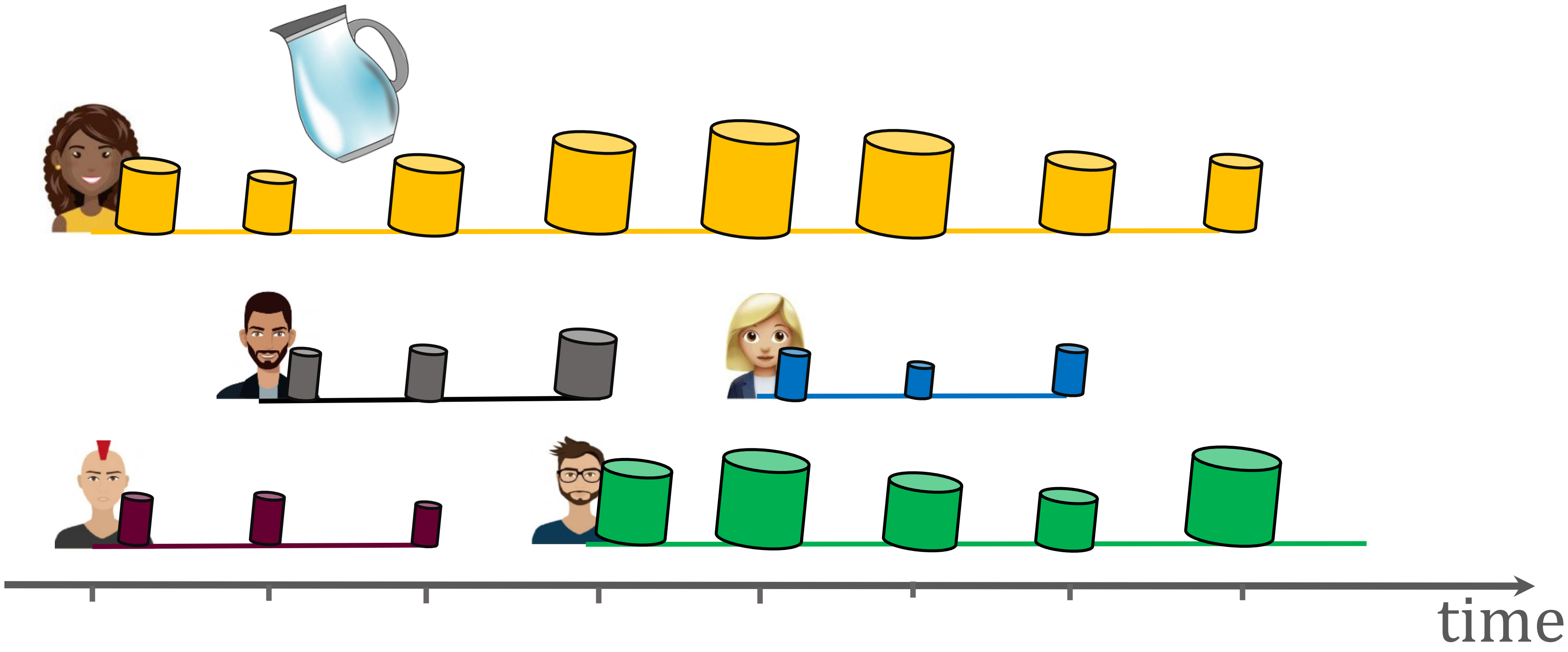


Multi Class Traffic



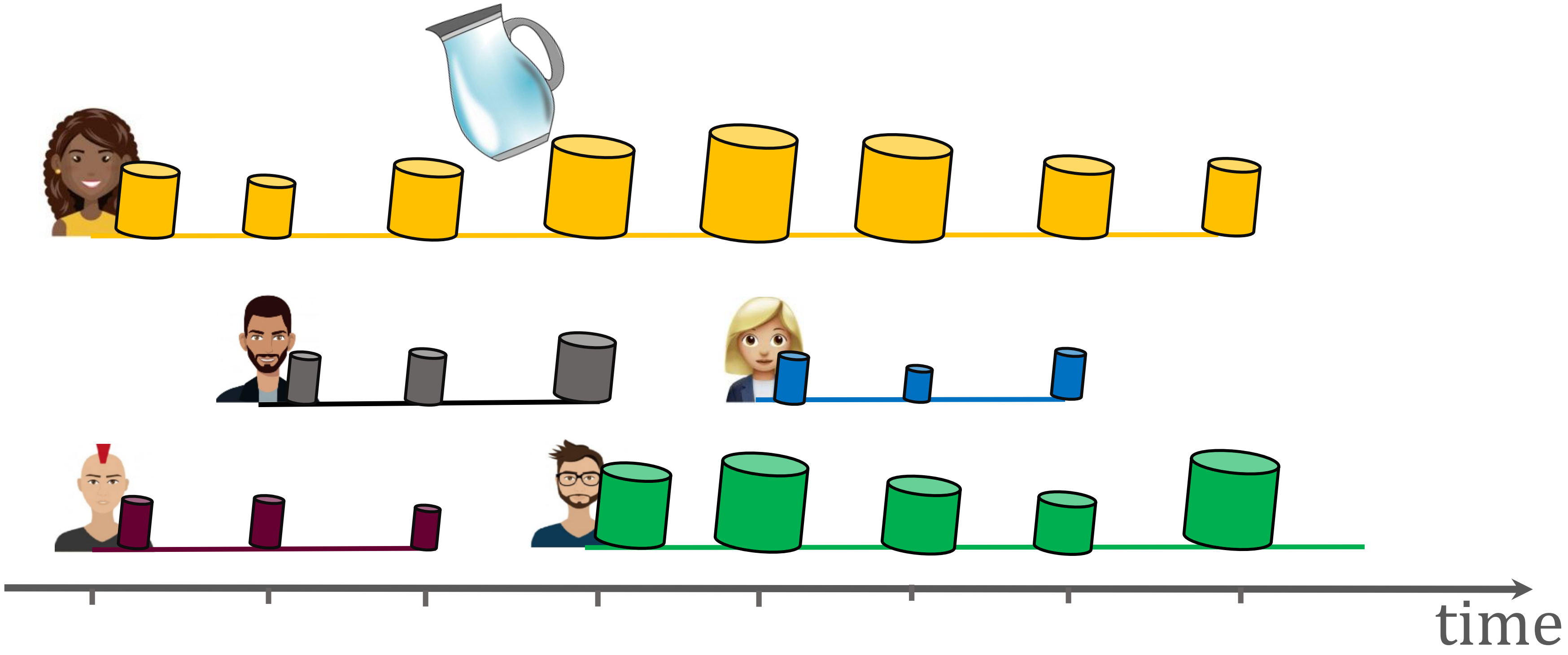
$$\text{Size Of Glass}_u = f(B_u, h_{u,t})$$

Multi Class Traffic



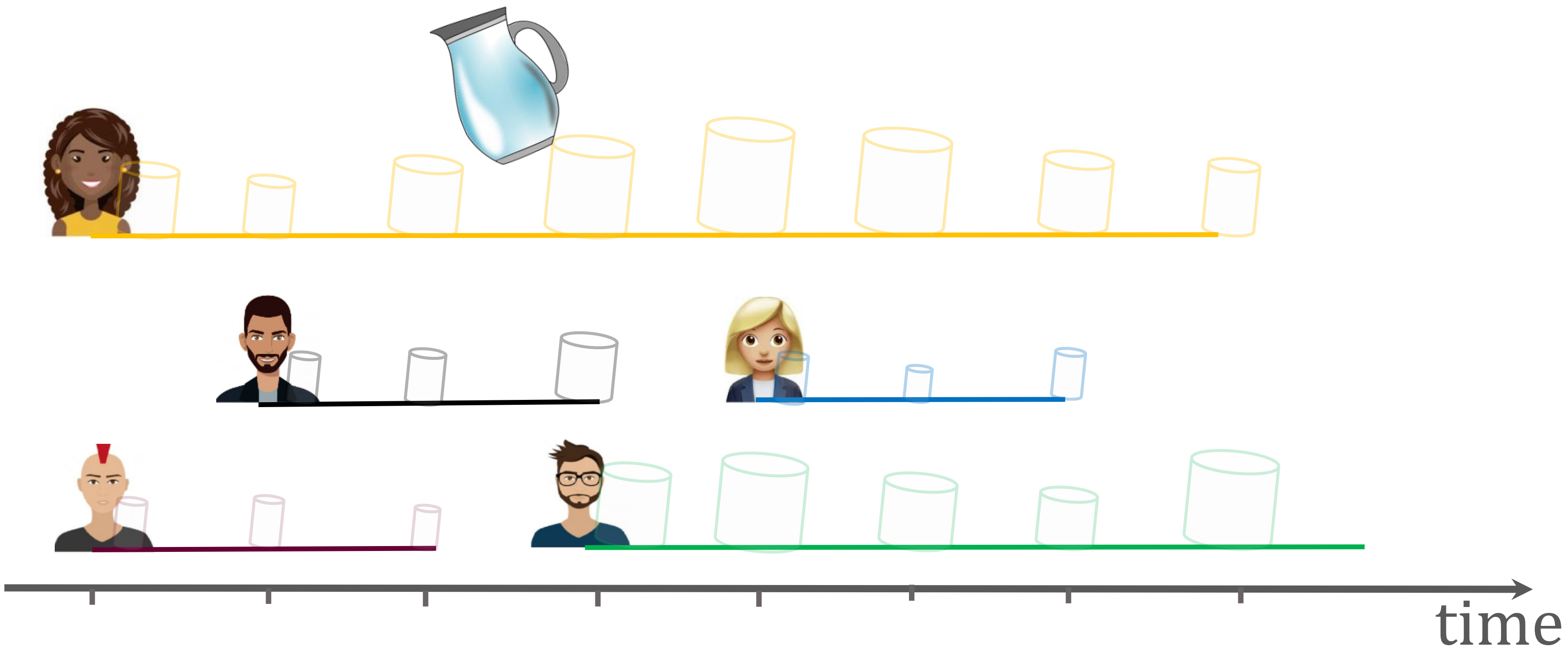
$$\text{Size Of Glass}_u = f(B_u, h_{u,t})$$

Multi Class Traffic



$$\text{Size Of Glass}_u = f(B_u, h_{u,t})$$

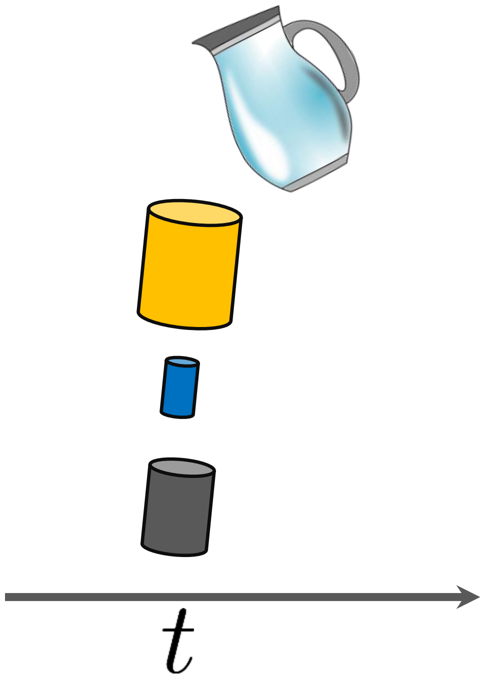
Multi Class Traffic



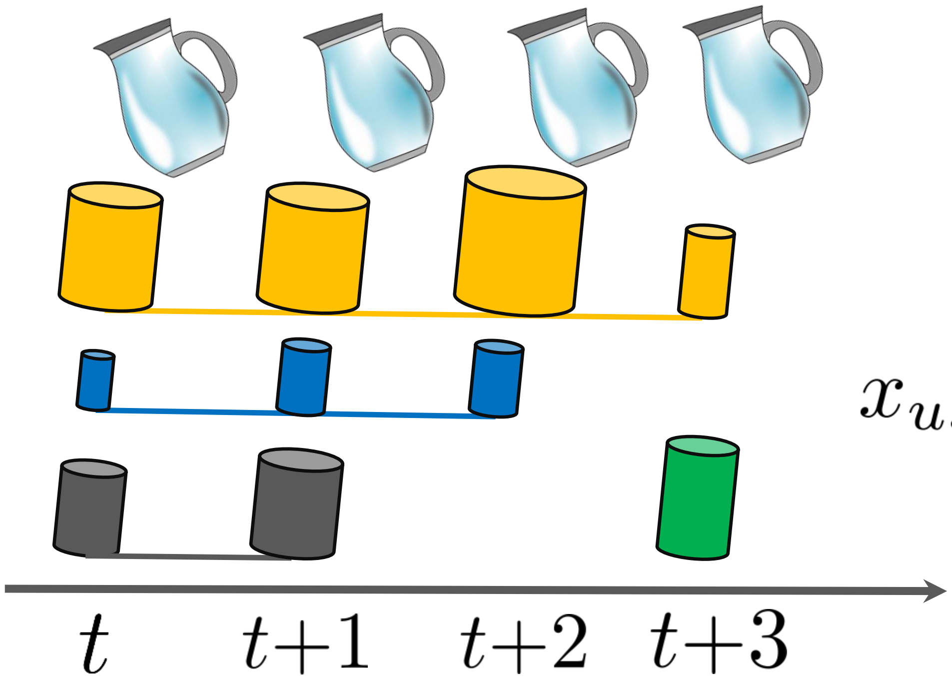
$$\text{Size Of Glass}_u = f(B_u, h_{u,t})$$

Full CSI (Benchmarks)

Greedy - Knapsack



Oracle – Integer Linear Programming(ILP)



$$x_{user,t} \in \{0,1\}$$

Reinforcement Learning (full CSI)

- *Markov Decision Process (MDP)*:

  state: $s_t = \{\forall u \in \mathrm{Users}_t \colon B_{u,t}\ ,\ \mathrm{latency}_{u,t}\ ,\ h_{u,t}\}$

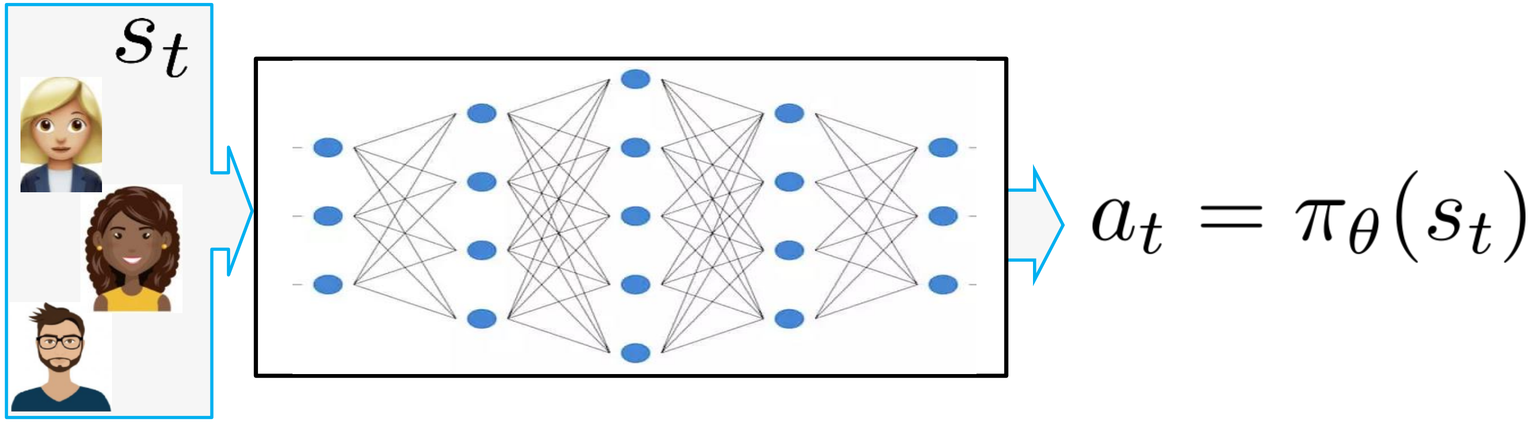
  action: $a_t = \{\forall u \in \mathrm{Users}_t \colon \mathrm{serve}_u\}$

- *Q-learning (lookup table)*:

  Let K users, C number of classes, $L_{\max}$ the maximum latency.

  $$\text{Size of Table} = K \cdot C \cdot L_{\max} \cdot \infty \cdot 2^K$$

- *Deep Deterministic Policy Gradient*:



Goal of Actor

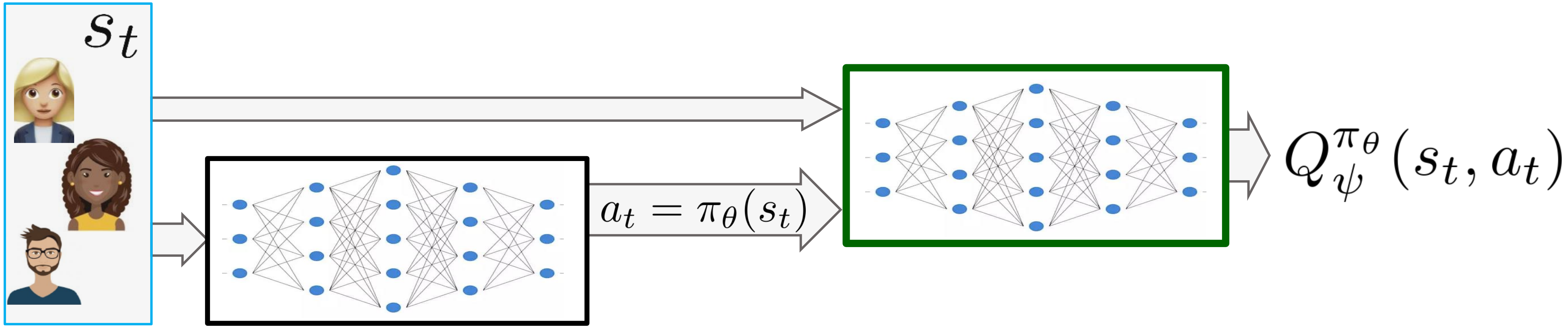
Return: $Z^{\pi_\theta}(s_t, a_t) = R(s_t, a_t) + \sum_{i=1}^{\infty} \gamma^i R(S_{t+i}, \pi_\theta(S_{t+i}))$

Value function: $Q^{\pi_\theta}(s_t, a_t) = \mathbb{E}[Z^{\pi_\theta}(s_t, a_t)]$

Goal: $J(\theta) = \mathbb{E}_{s_t}[Q^{\pi_\theta}(s_t, a_t) | a_t = \pi_\theta(s_t)]$

How to optimize θ so as to maximize the value?

Goal of Critic



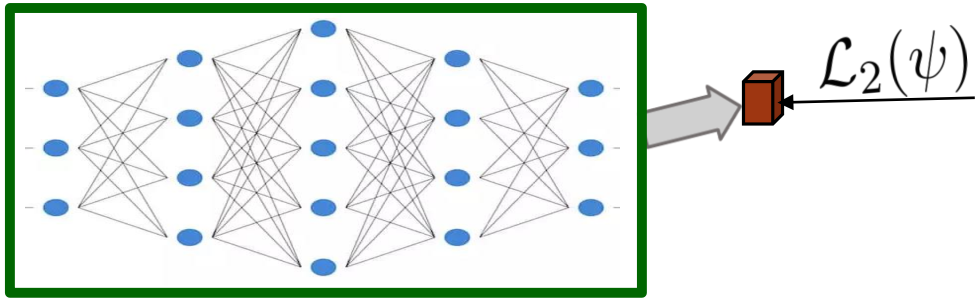
Goal: $Q_\psi^{\pi_\theta}(s_t, a_t) \approx Q^{\pi_\theta}(s_t, a_t)$

How to optimize ψ so as to improve estimation?

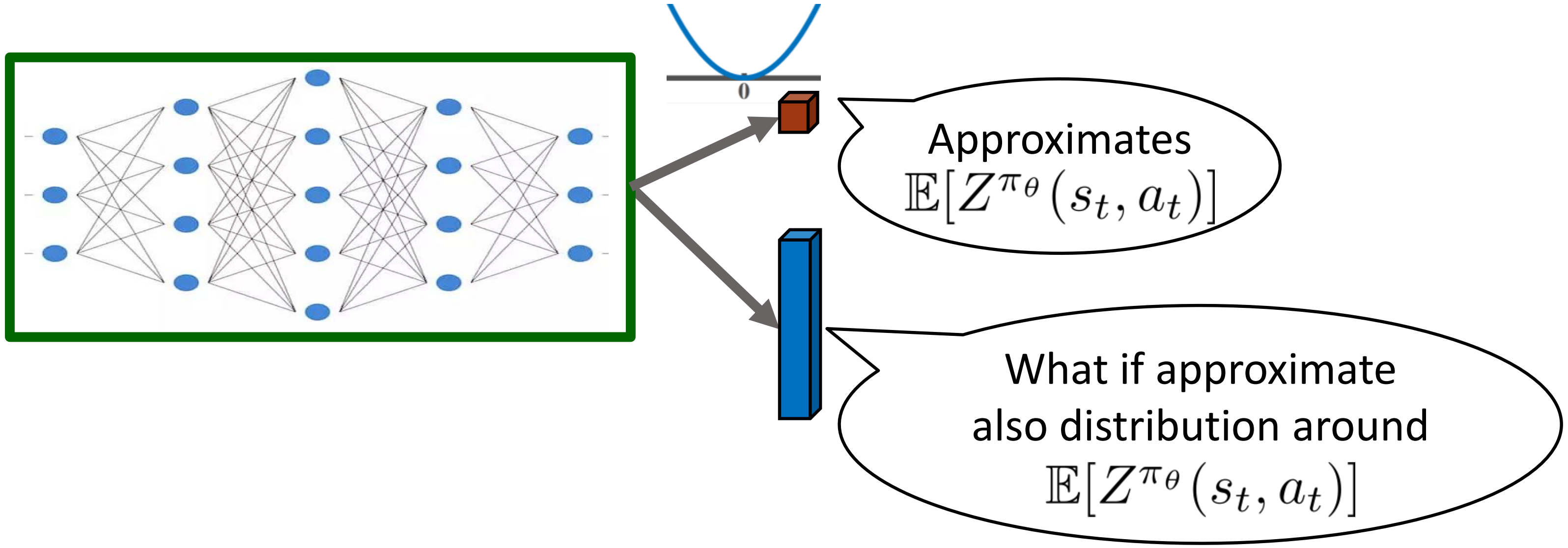
Bellman Equation

Bellman Equation: $Q^{\pi_\theta}(s_t, a_t) = R(s_t, a_t) + \gamma \mathbb{E}[Q^{\pi_\theta}(s_{t+1}, \pi_\theta(s_{t+1}))]$

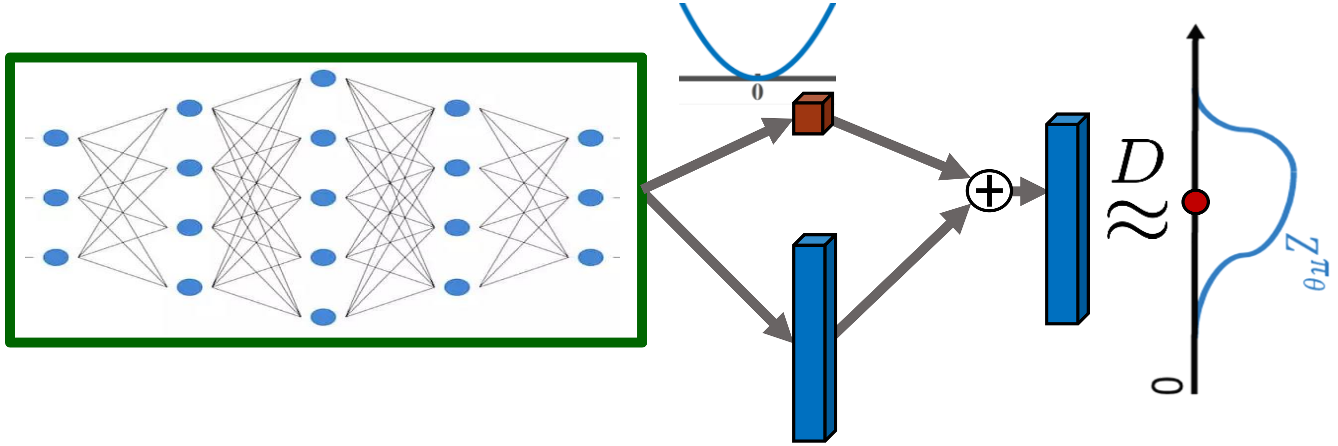
Loss Function: $\mathcal{L}_2(\psi) = \mathbb{E}[(\underbrace{Q^{\pi_\theta}_{\psi}(s_t, a_t)}_{\text{prediction}} - \underbrace{(R(s_t, a_t) + \gamma Q^{\pi_\theta}_{\psi^-}(s_{t+1}, \pi_\theta(s_{t+1})))}_{\text{target}})^2]$



Distributional Perspective



Distributional Perspective

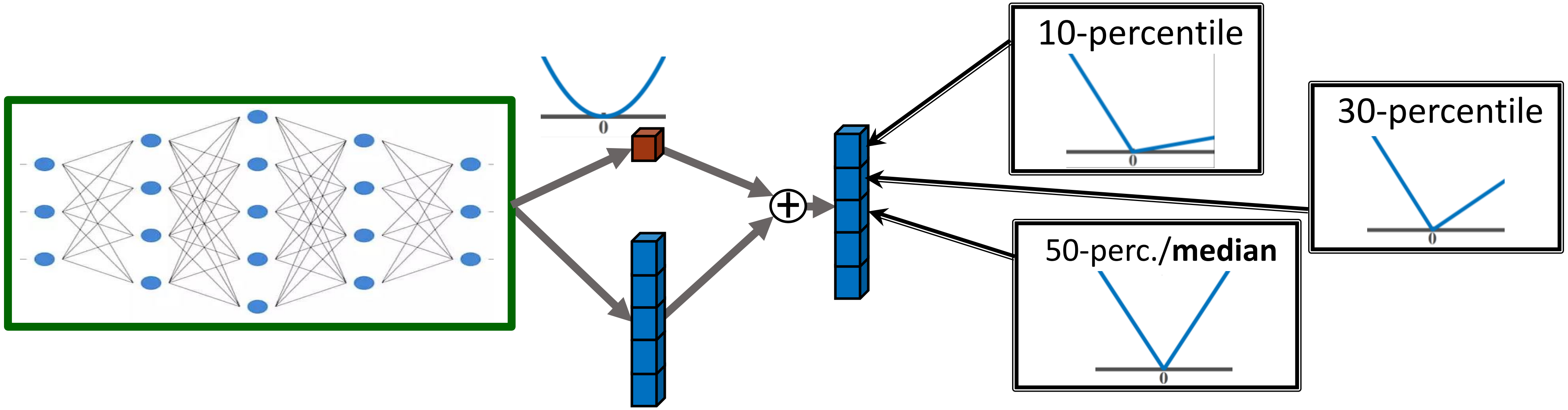


Distributional Bellman Equation:

$$Z^{\pi_\theta}(s_t, a_t) \overset{D}{=} R(s_t, a_t) + \gamma Z^{\pi_\theta}(S_{t+1}, \pi_\theta(S_{t+1}))$$

Representation of Distribution?

Distributional Perspective



Distributional Bellman Equation:

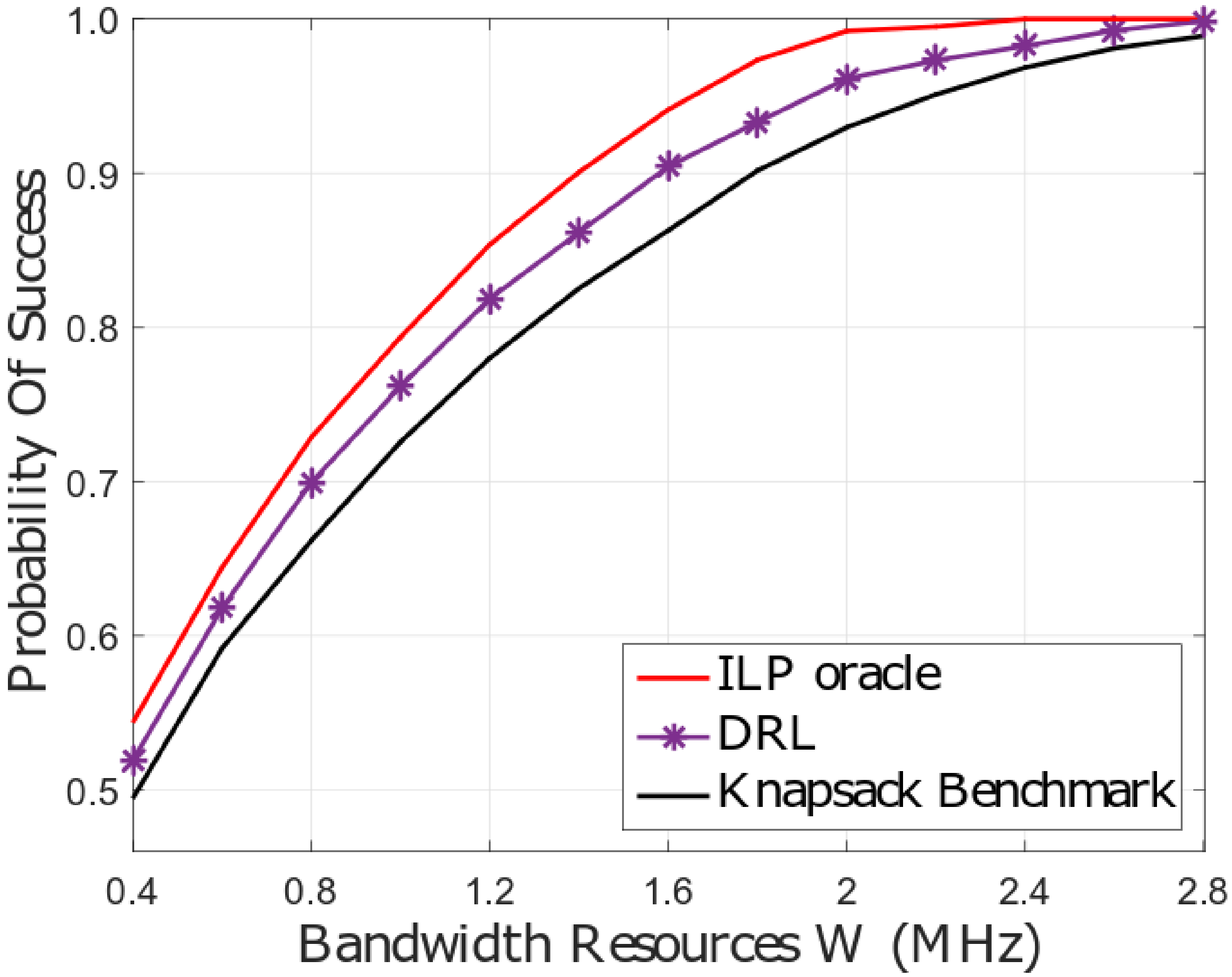
$$Z^{\pi_\theta}(s_t, a_t) \stackrel{D}{=} R(s_t, a_t) + \gamma Z^{\pi_\theta}(S_{t+1}, \pi_\theta(S_{t+1}))$$

Representation of Distribution?

Percentiles

Loss Function using Quantile Regression

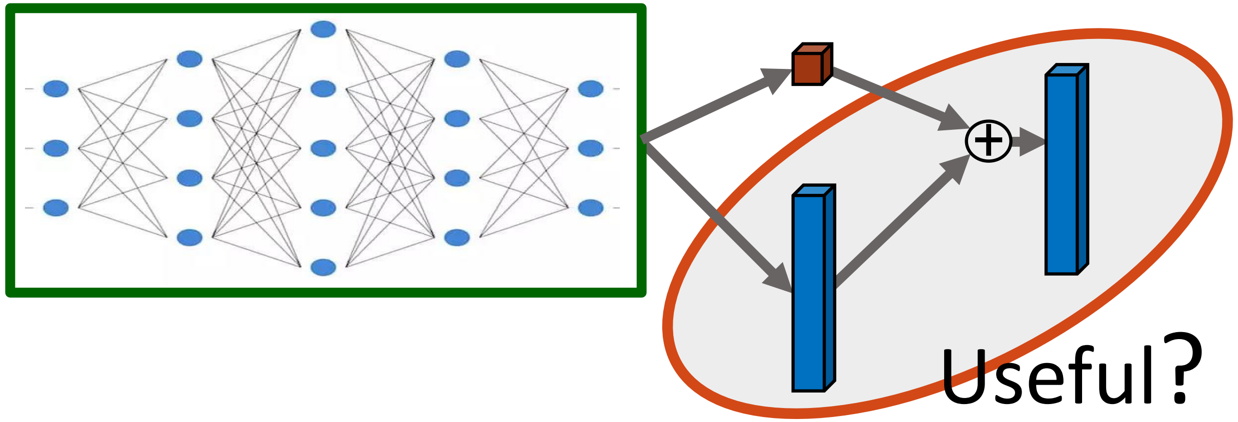
Performance

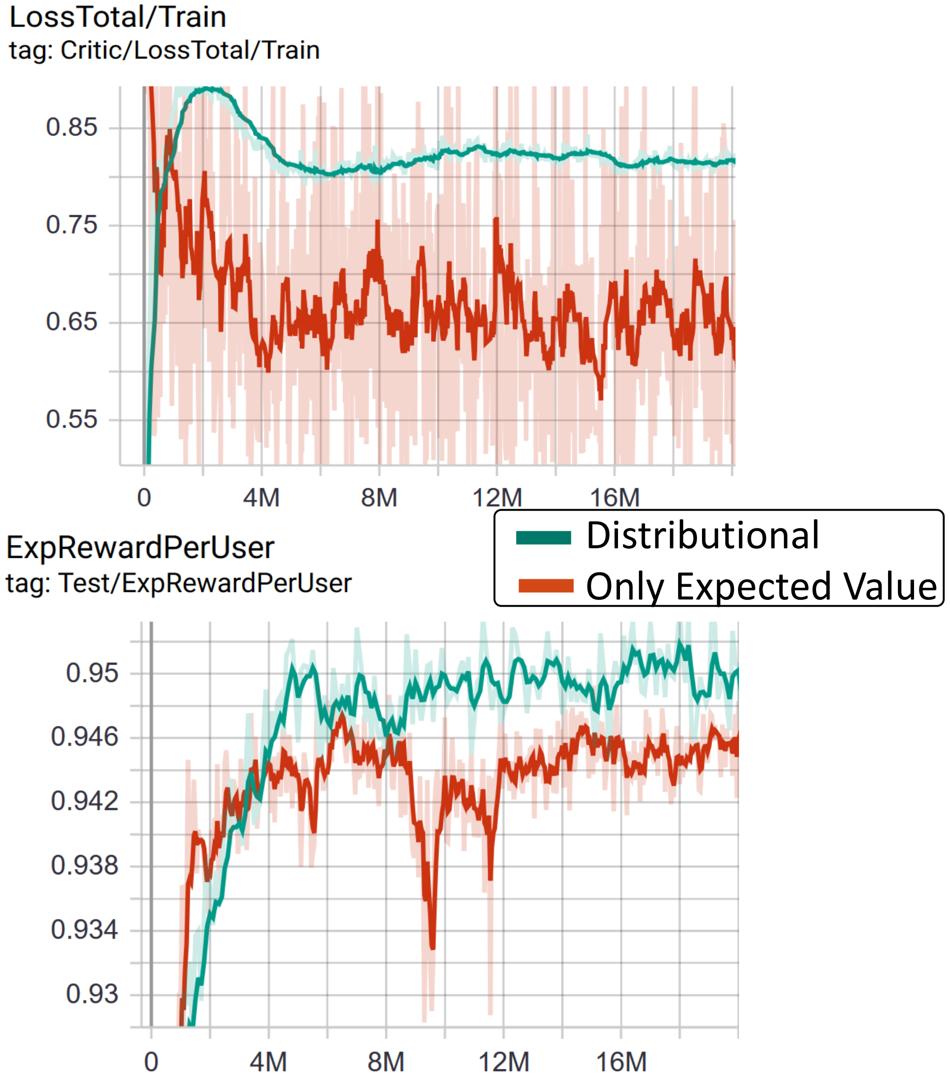


Classes Description

	B	L
class 1	256 Bytes	2
class 2	2048 Bytes	10

Why distributional?





Conclusions

Part One

- Studied energy/throughput – latency tradeoffs in URLLC
- Both AWGN and Fading channels
- IR-HARQ gains if properly tuned
- Up to 25% energy saving with reasonable delays.

Part Two

- Multi user, multi class traffic scheduling
- Combined L2 and quantile regression loss through a “dueling” architecture.
- Reinforcement Learning outperforms SoTA techniques (combinatorial, integer programming and Frank-Wolfe).

Peer-reviewed Journal

[J1] A. Avranas, M. Kountouris, and P. Ciblat, “Energy-latency tradeoff in ultra-reliable low-latency communication with retransmissions,” *IEEE Journal on Selected Areas in Communications*, vol. 36, no. 11, pp. 2475–2485, Nov. 2018.

International Conference

[C1] M. Kountouris, N. Pappas, and A. Avranas, “QoS provisioning in large wireless networks,” in *2018 16th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt)*, May 2018.

[C2] M. Kountouris and A. Avranas, “Delay Performance of Multi-Antenna Multicasting in Wireless Networks,” in *2018 IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, Jun. 2018.

[C3] A. Avranas, M. Kountouris, and P. Ciblat, “Energy-Latency Tradeoff in Ultra-Reliable Low-Latency Communication with Short Packets,” in *2018 IEEE Global Communications Conference (Globecom)*, Dec. 2018.

[C4] ——, “Throughput Maximization and IR-HARQ Optimization for URLLC Traffic in 5G Systems,” in *2019 IEEE International Conference on Communications (ICC)*, May 2019.

[C5] ——, “The Influence of CSI in Ultra-Reliable Low-Latency Communications with IR-HARQ,” in *2019 IEEE Global Communications Conference (Globecom)*, Dec. 2019.

$$\min_{n_1(g),n_2(g),P_1(g),P_2(g)} \quad \mathbb{E}_g\left[-\frac{\mathcal{T}_h(a)}{\mathcal{T}_{h,max}} + \frac{\mathcal{E}(a)}{\mathcal{E}_{min}}\right] \tag{1}$$

$$\text{s.t.} \quad n_1(g) + n_2(g) \le \mathrm{N}_\ell, \quad \forall g \tag{2}$$

$$\mathbb{E}_g[\varepsilon_2(n_1(g), n_2(g), P_1(g), P_2(g), g)] \le \varepsilon_{\text{rel}} \tag{3}$$

$$n_1(g)P_1(g) + n_2(g)P_2(g) \le \mathrm{E}_b, \quad \forall g \tag{4}$$

$$P_i(g) \le \mathrm{P}_{\max}, \quad i \in \{1,2\} \quad \forall g \tag{5}$$

$$n_i = \begin{cases} 0 & g < g_{th} \\ n_i(g) & g \ge g_{th} \end{cases}, P_i = \begin{cases} 0 & g < g_{th} \\ P_i(g) & g \ge g_{th} \end{cases}$$

$$\varepsilon_2 = \mathbb{P}(g < g_{th}) + \mathbb{P}(g \ge g_{th})\varepsilon_{on} \le \varepsilon_{\text{rel}}.$$