

# NICCI: Network-Informed Control – Control-Informed Network

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# Networked control systems

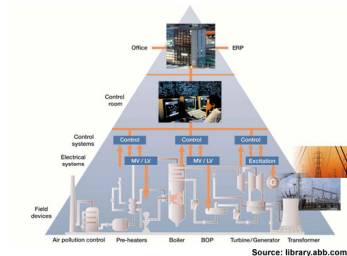
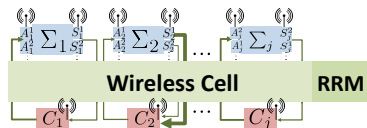


Figure: Figure illustrating modularity

- Broad Goal: Holistic control of large-scale, modular, distributed systems.
- Components share resources such as communication channels, computational resources.
- Controllers use both local (immediate) and global (delayed) information.
- Controllers act asynchronously (run on their own clocks).



# Resource aware control – control aware resource

- Due to the large scale of systems being considered, resources such as communication channels and processors may be constrained.
- RRM is responsible for “sequential decision making” with regards to communication.
- ‘Quality of control’ and ‘RRM decisions’ are mutually influential.
- There may be other resource managers, eg. computational resources.

Goal: Develop and analyze algorithms for distributed control of large-scale systems (process and radio) under resource constraints.



# Chapter I: Radio Resource Management (RRM)

# RRM for short-term dependability

- Let's start with the RRM-side.
- Issue: Dependable communication
  - ▶ Over fading channels.
  - ▶ With short deadlines.
  - ▶ And limited diversity (related to number of stochastically independent channels).
  - ▶ But with some limited prediction (deadline longer than coherence time).
- Bad combination – but what is achievable?



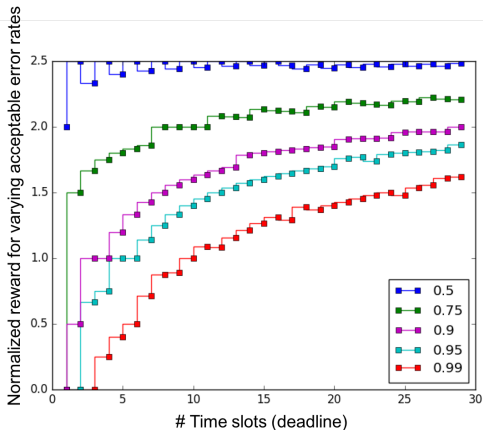
# First approach: Markov model for fading channel

- Markov chain extracted from Clark's model
  - ▶ States correspond to Signal-to-noise ratio (SNR) regions
  - ▶ Which in turn correspond to Modulation/Coding Scheme (MCS) performance at negligible transmission error rate.
- Under these assumptions:
  - ▶ What is the *time-limited capacity*, for an acceptable model prediction error?
    - ★ In a sense: Real-time version of outage capacity.
  - ▶ Can it be communicated to a control system as options?
- Formulate as Markov reward (no. of bits that can be transmitted) model.



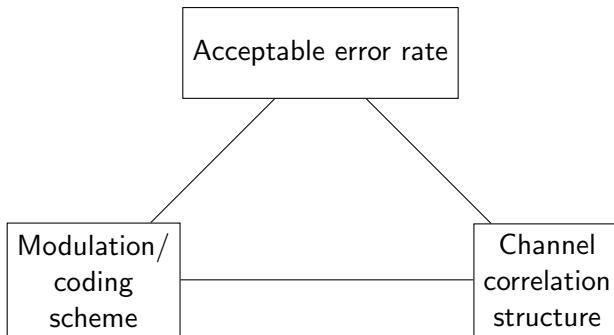
# Time-limited capacity: First hints at results

- What is the (normalized, per time slot) **available capacity** for **different acceptable error rates** over **increasing number of time slots**?
- **Observation:** Clear dependence on acceptable error rate.





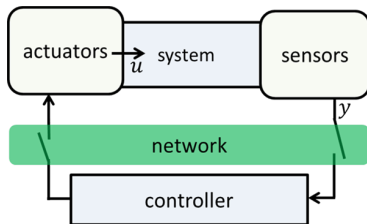
# Closing Remarks: Influencing factors in time-limited capacity



# Chapter II: Output Feedback MPC with Scheduled Communications



# Motivation and setup



- Dynamics: (i) unknown, but bounded uncertainties, (ii) discrete time, linear systems, (iii) noisy measurements.
- Communications networks: (i) reliable, (ii) limited communication.
- Challenge: When/what/where to send to maximize performance.

# Communication scheduling - basic idea

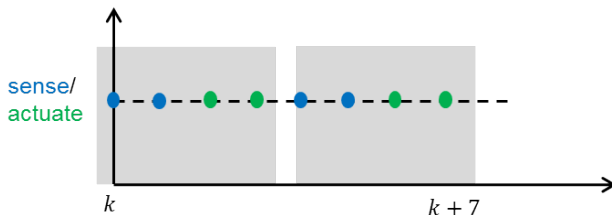
- **Toy example:**

- ▶ either sensor sends  $y_k$  or controller sends  $u_k$ .  
If no data is received, then actuator uses  $u_k = u_{k-1}$ .
- ▶ Question: when to sense and when to actuate?

- **Solution approach to optimize communication:**

- ▶ consider fixed communication schedule
- ▶ compare schedules, select the one with best performance

Requires: Efficient performance evaluation, avoid controller tuning.



Communication schedule

# Problem setup and contribution

- **Considered system class:**

- (i) LTI system with process noise,  $x_{k+1} = Ax_k + Bu_k + w_k$ ,  $w_k \in \mathbb{W}$ .
- (ii) State and input constraints:  $x_k \in \mathbb{X}$  and  $u_k \in \mathbb{U}$ .
- (iii) Noisy measurements:  $y_k = Cx_k + v_k$ ,  $v_k \in \mathbb{V}$ .

- **Robust output feedback MPC** (model predictive control):

- ▶ **Tube approach:** Decompose dynamics into (a) nominal system + MPC and (b) error systems + **“tube controller”**.
- ▶ **Performance:** For example worst case optimal set-point tracking:

⇒ “Minimize” distance from optimality - tune “tube controller”!

- **Contribution:**

- ▶ Automated, efficient optimal controller design for given schedule
- ▶ Allows for comparison between different schedules.
- ▶ Guarantees on closed loop behavior (constraint satisfaction, stability).



## Chapter III: Reinforcement Learning Approach

# Multi-agent systems perspective

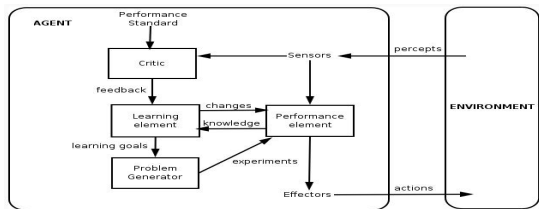


Figure: Point-of-view of one agent, one of many! (source: wikipedia)

- RRM and controllers are viewed as autonomous agents.
- These agents interact with a stochastic environment.
- Model of this environment is **unknown**.
- Requirements for offline algorithms: **availability of labeled data**.
- In case of online algorithms: **learn the model on-the-go**.

# Motivation: Dynamic programming approach

- Develop and analyze approximate, asynchronous value iteration and policy gradient algorithms.
- Value iteration is given by  $J_{n+1} = TJ_n$ , where  $TJ(i) := \min_{\pi} E_{\pi} [g(i, \pi(i), j) + J(j)]$  is the Bellman operator.
- We mutate its stochastic iterative counterpart:

$$J_{n+1} = J_n + a(n) (TJ_n - J_n + M_{n+1}).$$

- We also mutate policy gradient descent given by:

$$\theta_{n+1} = \theta_n - a(n) [\nabla_{\theta} \pi(\theta) + M_{n+1}].$$

- **Summary:** Re-engineer for large-scale distributed asynchronous systems with lossy, delay-prone communication systems.





# Approximate asynchronous Value Iteration

## Re-engineered value iteration algorithm

$$J_{n+1}(i) = J_n(i) + \mathbf{a}(\nu(i, n)) I\{i \in Y_n\} \times (\mathcal{A}T(J_{n-\tau_{1i}(n)}(1), \dots, J_{n-\tau_{di}(n)}(d))(i) - J_n(i) + M_{n+1}(i)).$$

- $\nu(i, n)$  is the number of times that agent  $i$  was active till time  $n$ .
- $Y_n \subseteq \{1, \dots, d\}$  denotes the active agents at time  $n$ .
- $0 \leq \tau_{ij}(n) \leq n$ . Delay faced by agent  $j$ , at time  $n$ , in receiving information from agent  $i$ .
- $\mathcal{A}$  is the approximation operator (obtained as a consequence of a supervised learning algorithm).
- $M_{n+1}$  is the Martingale difference noise.



# Approximate asynchronous Policy Gradient Descent (AAPGD)

- Basic idea of PGD is the existence of a parameterization  $\pi(\theta)$  (**policy objective function**), Sutton et. al. <sup>1</sup>. The goal is to find a local minimizer  $\hat{\theta}$ .

## Re-engineered policy gradient descent

$$\theta_{n+1}(i) = \theta_n(i) - a(\nu(i, n))I\{i \in Y_n\} (\textcolor{red}{A} \nabla_{\theta} \pi_i(\theta_{n-\tau_{1i}(n)}(1), \dots, \theta_{n-\tau_{di}(n)}(d)) + M_{n+1}).$$

- It allows for “finite-difference” implementations of GD using SPSA or SPSA-C (simultaneous perturbations stochastic approximations).
- In the above equation, we may replace the **gradient terms** with **sub-gradients**, our analysis still carries through, verbatim.
- While approximate asynchronous value iteration is offline, AAPGD is online.**



R.S. Sutton et al. "Policy gradient methods for reinforcement learning with function approximation." Advances in neural information processing systems. 2000.



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# Our contribution

- Developed sufficient conditions for convergence and stability (boundedness of the iterates).
- We completely characterize the limiting sets of the algorithms. For example,  $\{J \mid \|TJ - J\|_{\omega,p} \leq \epsilon\}$  is the limiting set of the re-engineered value iteration scheme.
- Stability ( $\sup_{n \geq 0} \|x_n\| < \infty$  a.s.) is always a concern in approximate dynamic programming, reinforcement learning approaches.
- Our stability conditions are Lyapunov function based, extending Ramaswamy and Bhatnagar<sup>2</sup>

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<sup>2</sup>A. Ramaswamy and S. Bhatnagar (2017). Conditions for Stability and Convergence of Set-Valued Stochastic Approximations: Applications to Approximate Value and Fixed point Iterations with Noise. Submitted in September, 2017.

# Summary

- We studied the Markov reward model for communication networks, currently being used in ML approaches.
- Output feedback MPCs that allow for comparison between given communication schedules.
- Value iteration and policy gradient algorithms, re-engineered for our setting.

# Current and Future Work

- RRM-side:
  - ▶ Use Markovian rewards (previously studied) to develop multi-arm bandit based algorithms.
  - ▶ For more general rewards we are currently looking at deep reinforcement learning algorithms.
- Controller-side: Value iteration networks and deep Q networks in the setting of distributed systems with lossy delayed communications.
- Experimental aspects of the project: Run an intelligent RRM and model-free controller in tandem.
- Final goal: The RRM learns the optimal scheduling taking into account the control issues. The controller is distributed and accounts for dynamic resource availabilities. **ONLINE!!**



# The End



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A. Ramaswamy and S. Bhatnagar (2017). Conditions for Stability and Convergence of Set-Valued Stochastic Approximations: Applications to Approximate Value and Fixed point Iterations with Noise. Submitted in September, 2017.



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