NICCI: Network-Informed Control – Control-Informed Network

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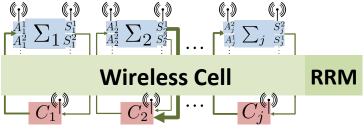
October 18, 2017

Overview

Networked control systems



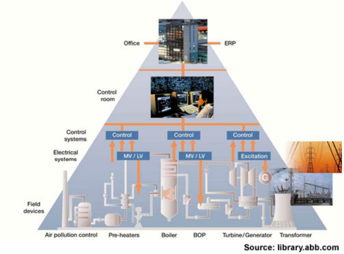


Figure: Figure illustrating modularity

- 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.
- We assume the existence of a radio resource manager (RRM) who is responsible for co-ordinating communication.
- RRM is responsible for sequential decisions in 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.

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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.

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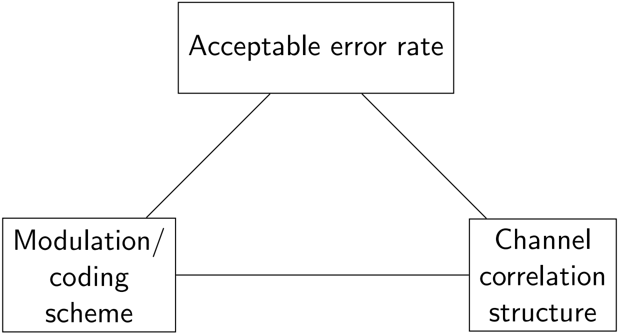
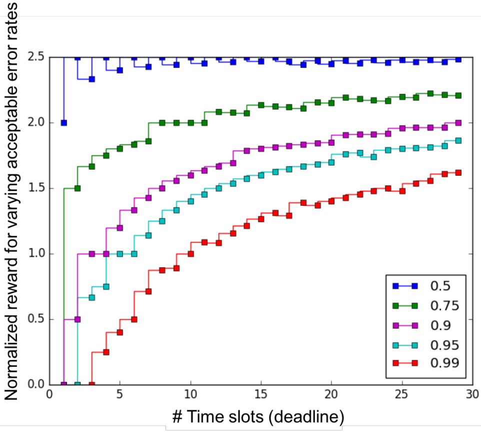
Time-limited capacity: Influencing factors



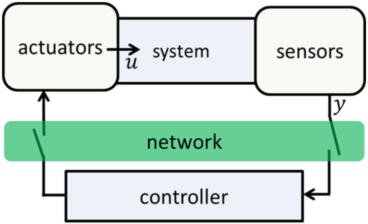
Time-limited capacity: First hints at results

- Over increasing number of time slots
- What is the (normalized, per time slot) available capacity
- For different acceptable error rates
- **Observation**: Rate of increase depends on acceptable error rate



Chapter II: Output Feedback MPC with Scheduled Communications

Motivation and setup

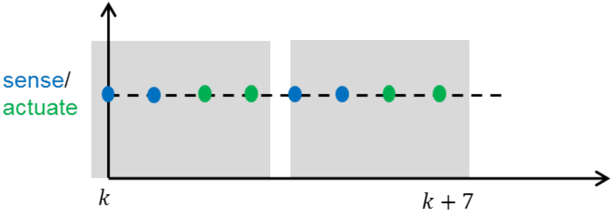


- Dynamics: (i) unknown, but bounded uncertainties, (ii) discrete time, linear systems, (iii) noisy measurements.
- Communications networks: (i) reliable, (ii) limited communication.
- Challenge: When/what/where to send to maximize performance.

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:

$\Rightarrow$ "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

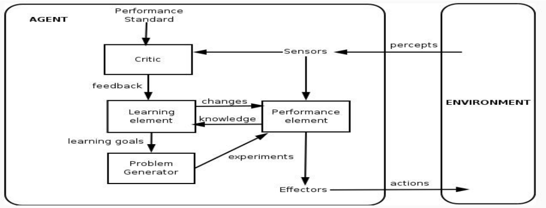


Figure: Point-of-view of one agent, one of many! (source: wikipedia)

- 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.

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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 $TJ(i) := \min_{\pi} E_\pi \left[g(i, \pi(i), j) + J(j) \right]$ is the Bellman operator.
- We mutate its stochastic iterative counterpart:

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

- We also mutate policy gradient descent given by:

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

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

Approximate asynchronous Value Iteration

Re-engineered value iteration algorithm

$J_{n+1}(i) =$

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

- $\nu(i,n)$ is the number of times that agent i was active till time n.
- $Y_n \subseteq \{1, \ldots, d\}$ 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.

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Approximate asynchronous Policy Gradient Descent (AAPGD)

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

Re-engineered policy gradient descent

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

- 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.

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

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 $(\sup_{n\geq 0}\|x_n\| < \infty \text{ a.s.})$ is always a concern in approximate dynamic programming, reinforcement learning approaches.
- Our stability conditions are Lyapunov function based, extending Ramaswamy and Bhatnagar [2]

[2] 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.
- Constrained MPCs that allow for comparison between given communication schedules.
- Value iteration and policy gradient algorithms, re-engineered for our setting.
- Proofs of convergence and boundedness of the algorithm.

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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