Network aware control and control aware network

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Overview

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Networked control systems
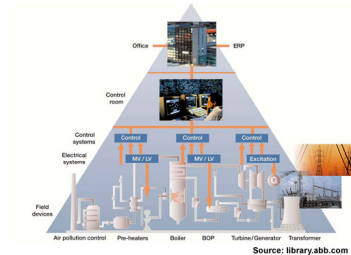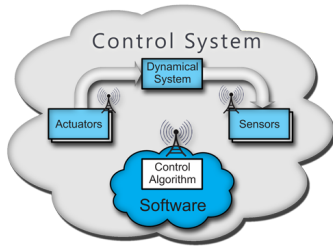
Figure: Source: www.heemels.tue.nl

Source: library.abb.com

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.

Chapter I: Radio Resource Management (RRM)

Prof. Holger Karl

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).

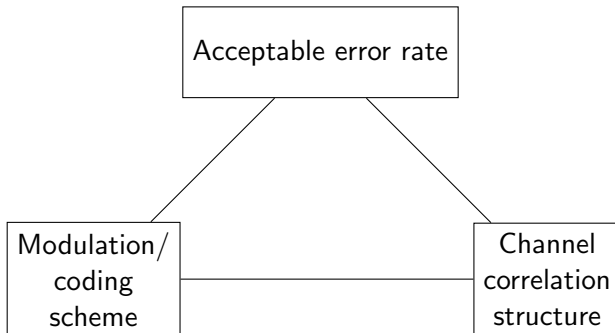- Bad combination – but what is achievable?

First approach: Markov model for fading channel

- Markov chain extracted from Clark's model
  - States correspond to 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

Acceptable error rate

Modulation/ coding scheme

Channel correlation structure

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
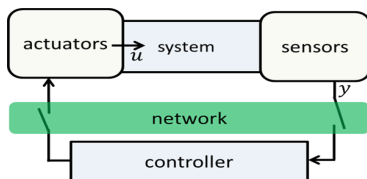- **Observation**: Rate of increase depends on acceptable error rate
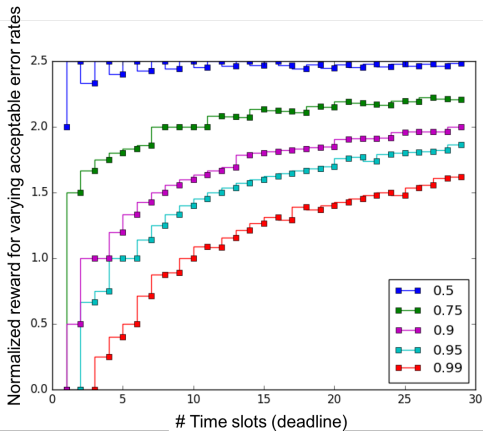
Chapter II: Constrained MPCs given a communication schedule

Markus Kögel and Prof. Rolf Findeisen

MPC under reliable communication schedule

- Dynamics: (i) Unknown but bounded uncertainties (ii) Discrete time linear systems (iii) noisy measurements.
- Communications networks: (i) Reliable (ii) Single link available: either **to actuator** *or* **from sensor**.
- Challenge: When/what/where to send/receive to maximize control performance.

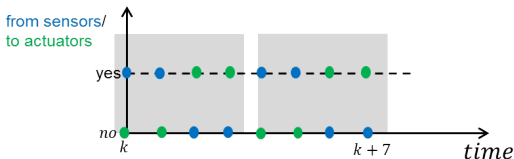# Different possible communication choices provided by the RRM

Figure: Fixed reliable communication schedule

- What to communicate (how much data):
  - ▶ **Naive solution:** Sensors send y_k while controllers send u_k. If no data is received at time k, then the actuators use $u_k = 0$ or $u_k = u_{k-1}$.

  - ▶ **General Case:** Multiple measurements/ commands in each packet
    (a) Piggy back old measurements, e.g., send y_k and y_{k-1} at k.
    (b) Send input sequences, e.g., send u_k and u_{k+1} at k.

- Requirement: Simple performance evaluation and avoid influence of tuning.

Exploit robust output feedback MPC

- We start with the basics of robust output feedback MPC.
- **Framework:** (i) LTI system with bounded process noise,
  $x_{k+1} = Ax_k + Bu_k + w_k$, where $x_k \in \mathbb{X}$, $u_k \in \mathbb{U}$ and $w_k \in \mathbb{W}$.
  (ii) There exist constraints on x_k and u_k.
  (iii) Sensor measurements, bounded noise: $y_k = Cx_k + v_k$, $v_k \in \mathbb{V}$.

- **Robust output feedback MPC:**
  - ▶ **Tube approach:** Decompose dynamics into (a) **nominal system** (no noise) + MPC and (b) **error systems + fixed linear controller**.
  - ▶ **Control objective: Worst case optimal set-point tracking:**
    - ★ Minimize back-off from constraints (set $\mathbb{Z}$) - tune "tube controller".

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Our contribution
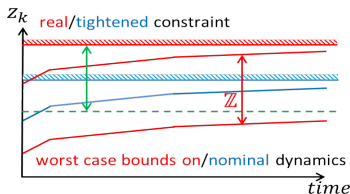

Figure: "Economic performance" $Z_k = Fx_k + Gu_k$

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

Chapter III: Reinforcement Learning

Arun Ramaswamy and Prof. Daniel E. Quevedo
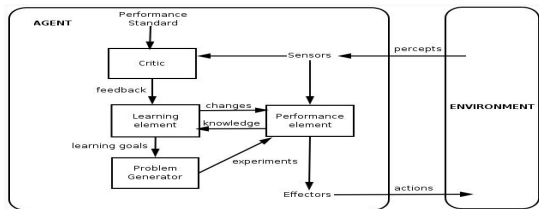
Multi-agent systems perspective

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

- 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 it's 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

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

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

- $\nu(i, n)$ 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 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

- Basic idea of PGD is the existence of a parameterization $\pi(\theta)$ (policy objective function), Sutton et. al. [5]. 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 AAVI is offline, AAPGD is online.

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 [4].

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.
- RRM-side: 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!!

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