Applying Reinforcement Learning to Process Control

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ESI Seminar

Carnegie Mellon University

West Virginia University

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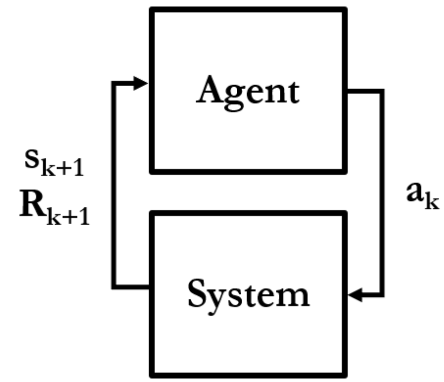
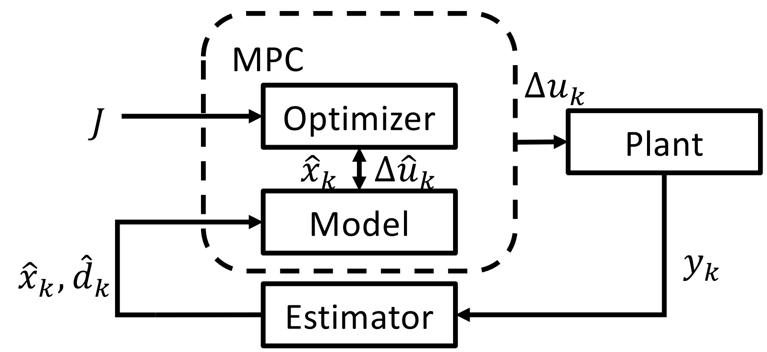
Motivation and Background

- Reinforcement learning (RL) is a machine learning method that learns from active sampling of system performance
- Integration of RL with a process controller such as PID or MPC can exploit strengths of both and addresses some of the weaknesses
- RL can also be used by itself at the supervisory or higher layer controller





RL Basics

- Learning based on a value function and/or a control policy
  - Algorithms with a fixed policy – focused on learning a value function given the fixed policy (e.g., Q-Learning, SARSA)
  - Some algorithms where the policy is learned with a value function – actor-critic methods; parameterized policy and value function used for control an updates
  - General goal is to maximize expected sum of rewards:

$$Q^{\pi}(s,a) = E\left\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} | s_t = s, a_t = a\right\}$$

RL Basics: State-action-reward-state-action (SARSA)

$$Q^{\pi}(s,a) = E\left\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} | s_t = s, a_t = a\right\}$$

- Episodic learning for tasks with fixed starting and terminal states
- Continuing learning where these cannot be defined

$$\widehat{\boldsymbol{q}}(s,a) \;=\; w^T q = \sum_{i=1}^{d} w_i q_i$$

$$q_i(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{\|c_i - x\|^2}{2\sigma^2}}$$

$$\delta = R + \gamma Q(s_{k+1}, a_{k+1}) - Q(s_k, a_k)$$

$$\mathbf{w} \leftarrow \mathbf{w} + \alpha\delta\nabla\widehat{\boldsymbol{q}}(s_k, a_k)$$

$$a_k = \underset{a}{\operatorname{argmax}}\, \widehat{\boldsymbol{q}}(s,\cdot)$$

Sutton, R.S., Barto, A.G., 2018. Reinforcement Learning: An Introduction, 2nd ed. Bradford, Cambridge, MA, USA.

Tuning Learning and Learning Metrics

- RL has multiple hyperparameters:

$$\alpha \in (0,1], \gamma \in [0,1], \varepsilon \in [0,1]$$

  - α is the learning rate, γ is the discount factor
  - ε controls the rate of exploration vs. exploitation under an ε-Greedy policy
- Goal is to achieve stable learning to an optimal policy
  - Learn Q(s,a) such that action (a) can be selected greedily for all states (s)
- Results show in terms of episode return (G):

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

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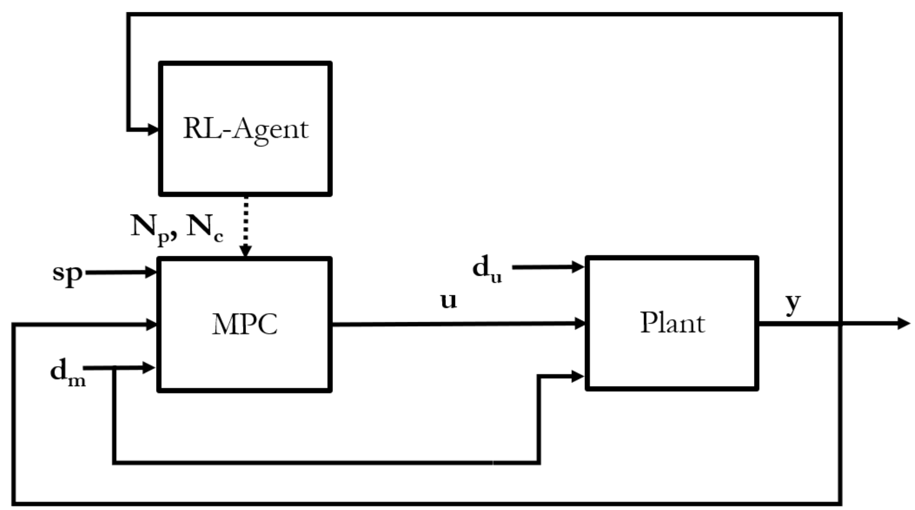
RL MPC

- RL agent is applied to select controller tuning parameters online
  - Underlying MPC controls the plant
- Output feedback to the agent is the RL state and is the subject of the RL reward function:

$$R_k \equiv -\left\| y_{sp} - y_{k+1} \right\|^2$$



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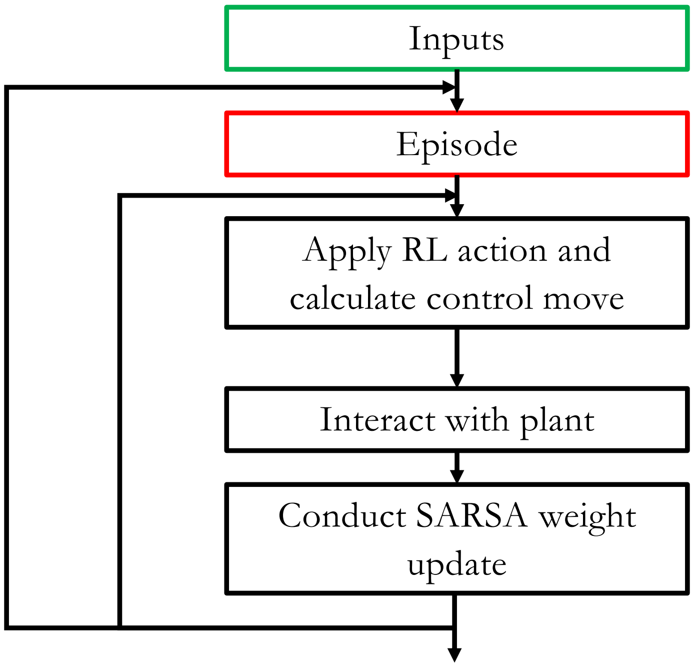
RL-MPC Algorithm



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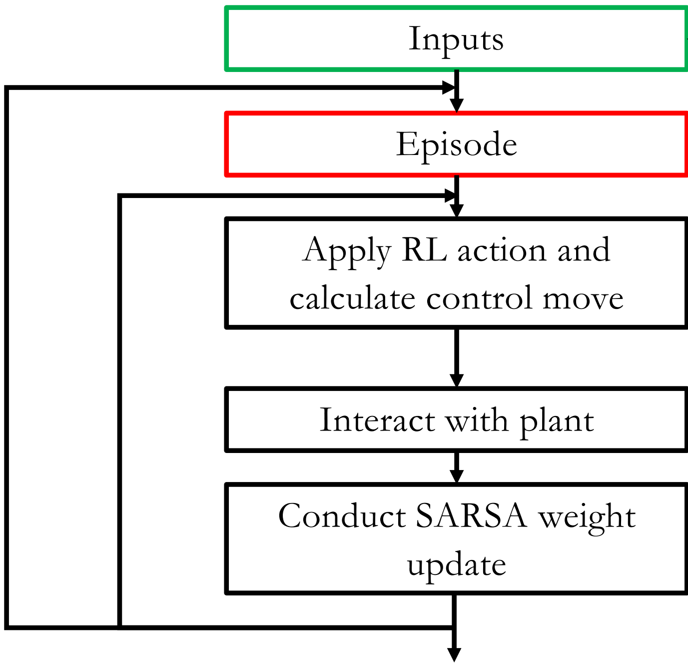

- $\hat{q}(s, a)$ a value function approximator with weights w
- (α, ε) $\in$ (0,1], $\gamma \in$ [0,1)
- Arbitrarily initialize w, the weights of the function approximation
- An MPC to control the plant

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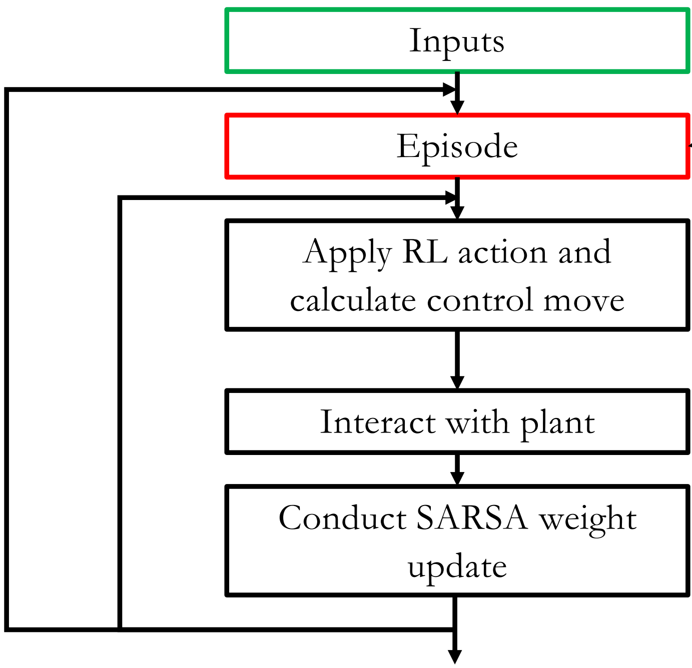

- **Initialize the plant and controller to steady-state (i.e. y = 0, u = 0 in deviation variables)**
- **Selection an initial action (a_0) under the current policy (i.e. ε-Greedy)**

ε-Greedy Search Algorithm

Inputs:

ε ϵ (0,1]

For each evaluation:

Draw P from a uniform distribution

If P > ε

$$a_k = \underset{a}{\operatorname{argmax}}\,\hat{\boldsymbol{q}}(s,\cdot)$$

If P < ε

$$select\ a_k = a \in A\ randomly$$

Break ties randomly

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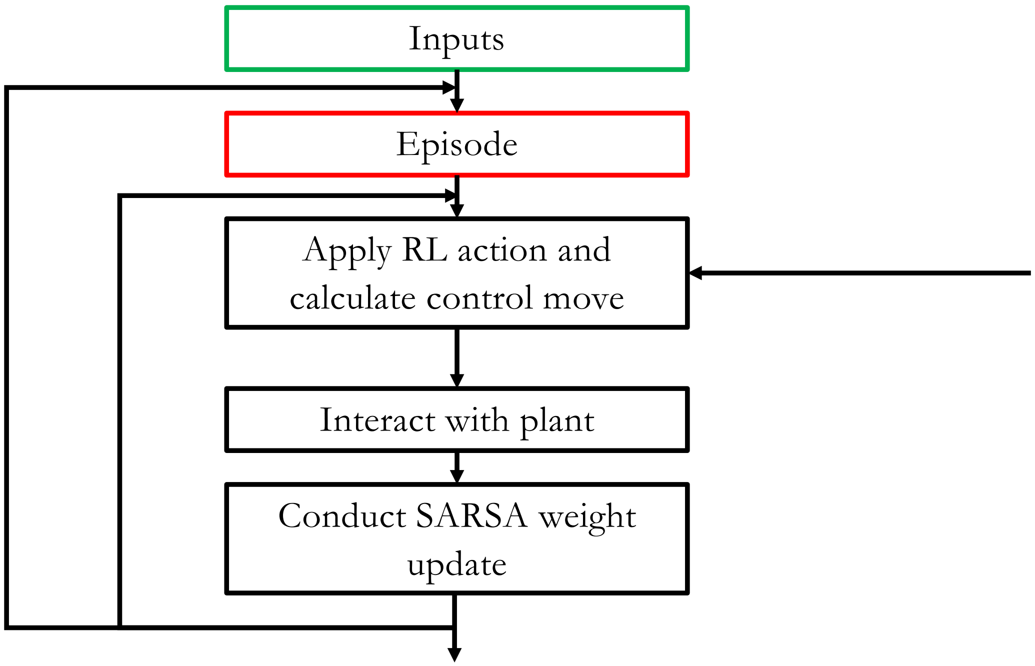

- **Apply** $\boldsymbol{a_k} = \begin{bmatrix} \boldsymbol{N_p} \\ \boldsymbol{N_c} \end{bmatrix}_{\boldsymbol{k}}$ **to the MPC**
- **Calculate:**

$$\boldsymbol{u_k} = \boldsymbol{u^{*} \, from \; the \; MPC}$$

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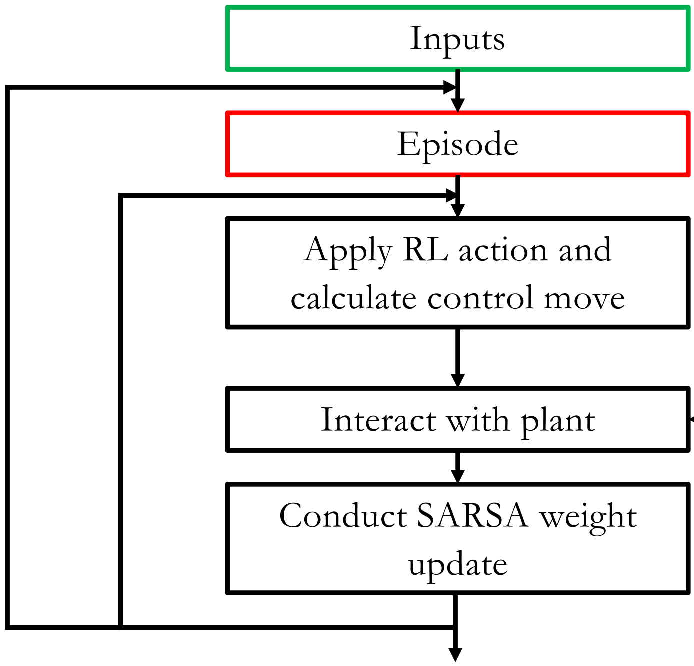

- **Apply u_k to the plant and get y_{k+1}**
- **Calculate $R_k = R(y_{k+1})$**

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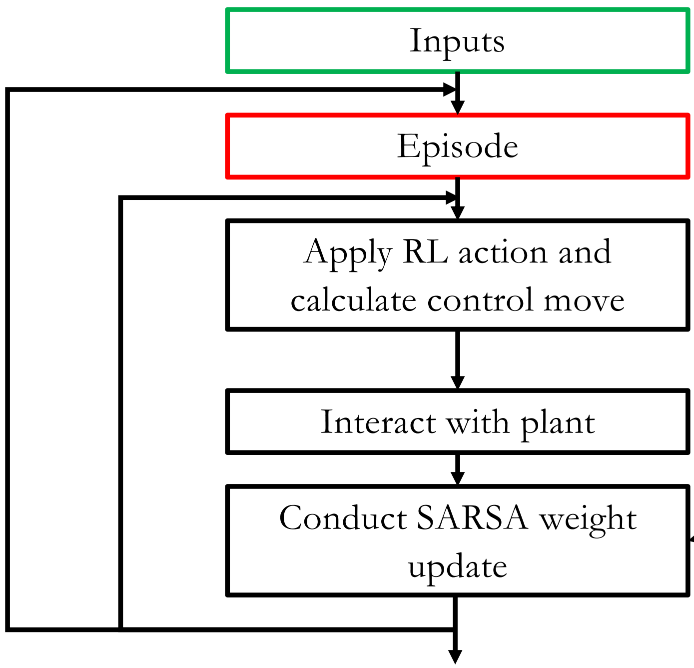

State-action-reward-state-action (SARSA)

- **Select a_{k+1} under the current policy (i.e. ε-Greedy)**
- **Calculate $\delta \leftarrow R_k + \gamma \hat{q}(y_{k+1}, a_{k+1}) - \hat{q}(y_k, a_k)$**
- **Update $w \leftarrow w + \alpha \delta \nabla \hat{q}(y_k, a_k)$**

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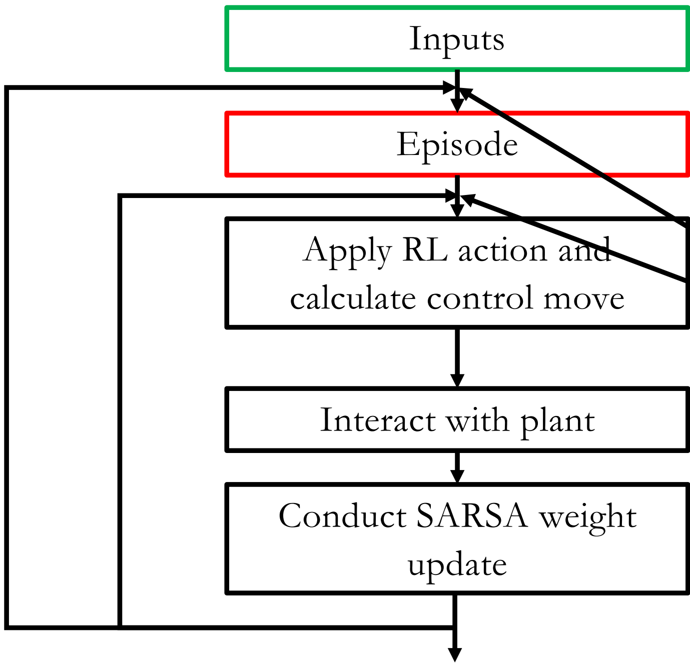

- **For each episode continue until the terminal state (or time) is reached**
- **Continue until a maximum number of episodes is reached**

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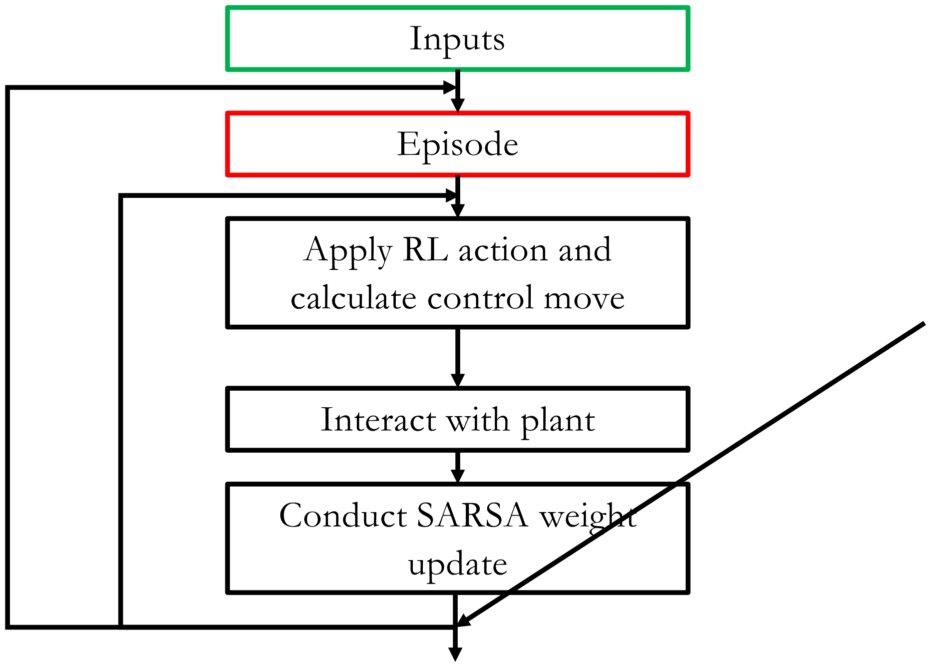

- **Output is a weight vector which can be used for action selection, under the same policy, in an online setting**
- **Continuous learning can be carried out when implemented on true plant**

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Offline RL-MPC Algorithm

Inputs:

$\hat{q}(s, a)$ a value function approximator with weights **w**

$\alpha \epsilon (0,1]$, $\varepsilon \epsilon [0,1]$, $\gamma \epsilon [0,1]$

Arbitrarily initialize **w**, the weights of the function approximation

An MPC to control the plant

For each episode:

Initialize the plant and controller to steady-state (i.e. y = 0, u = 0 in deviation variables)

Selection an initial action (a_0) under the current policy (i.e. ε-Greedy)

For each timestep (k) of each episode:

1. Apply $a_k = \begin{bmatrix} N_p \\ N_c \end{bmatrix}_k$ to the MPC
2. Calculate:

   $u_k = u^* from\ the\ MPC$
3. Apply u_k to the plant and get y_{k+1}
4. Calculate $R_k = R(y_{k+1})$
5. Select a_{k+1} under the current policy (i.e. ε-Greedy)
6. Calculate $\delta \leftarrow R_k + \gamma \hat{q}(y_{k+1}, a_{k+1}) - \hat{q}(y_k, a_k)$
7. Update $\mathbf{w} \leftarrow \mathbf{w} + \alpha\delta\boldsymbol{\nabla}\hat{\boldsymbol{q}}(\boldsymbol{y_k}, \boldsymbol{a_k})$

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Online RL-MPC Algorithm

Inputs:

$\hat{q}$(s,a) that is differentiable, consistent with offline learning

$\alpha \in (0,1]$, $\varepsilon \in [0,1]$, $\beta \in (0,1]$

$\mathbf{w}$ from offline learning, $\overline{\mathrm{R}} = 0$

An MPC to control the plant, consistent with offline learning

For each sampling time (k), continuing while online:

1. Apply $a_k = \begin{bmatrix} N_p \\ N_c \end{bmatrix}_k$ to the MPC
2. Calculate:

   $u_k = u^*$ from the MPC
3. Apply u_k to the plant and get y_{k+1}
4. Calculate $R_k = R(y_{k+1})$
5. Select a_{k+1} under the current policy (i.e. ε-Greedy)
6. Calculate $\delta \leftarrow R - \overline{R} + \hat{q}(y_{k+1}, a_{k+1}, w) - \hat{q}(y_k, a_k, w)$
7. Update $\overline{R} \leftarrow \overline{R} + \beta\delta$
8. Update $\mathbf{w} \leftarrow \mathbf{w} + \alpha\delta\nabla\hat{\mathbf{q}}(\mathbf{y_k}, \mathbf{a_k}, \mathbf{w})$

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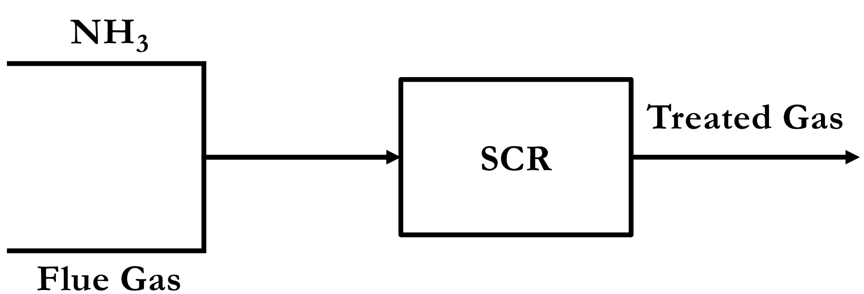
Motivating Example – SCR Control

- Control of an industrial Selective Catalytic Reduction (SCR) reactor for NOx emission reduction in a coal-fired power plant is taken as an example for this work
  - SCR model is a 1D heterogeneous plug flow reactor model with detailed kinetics

$$4\ NH_3 + 4\ NO + O_2 \rightarrow 4\ N_2 + 6\ H_2O$$

$$4\ NH_3 + 3O_2 \rightarrow 2\ N_2 + 6\ H_2O$$



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MPC of SCR

- SCR has complex dynamics with many disturbance variables
  - Adsorption/desorption kinetics lead to significant nonlinearity and time delay
  - Some of these variables are measurable, can be modeled
  - Others are not incorporated into control model

Inputs (MVs)	
Inlet Ammonia Flow	u_1
Outputs (CVs)	
Outlet NO_x Concentration	y_1
Outlet Ammonia Concentration	y_2
Modeled Disturbances	
Inlet Flue Gas Flow	d_1
Inlet NO_x Concentration	d_2
Unmodeled Disturbances	
Inlet Ammonia Temperature	d_3
Inlet Flue Gas Temperature	d_4
Inlet Dilution Air Flow	d_5

MPC of SCR for Disturbance Rejection – MPC-1

- Initial MPC formulation uses a linear model and a disturbance rejection objective
  - Servo control not regularly needed for SCR operation
- One-step ARX model identified using least-squares estimate

$$x_{k+1} = Ax_k + Bu_k$$

$$y_k = Cx_k, C = I$$

$$\Phi = (\Psi^T\Psi)^{-1}\Psi^T Y$$

$$\min_u J = y_{N_p}^T H y_{N_p} + \sum_{k=0}^{N_p-1} y_k^T Q y_k + \sum_{k=0}^{N_c} u_k^T D u_k$$

$$s.t. x_{k+1} = Ax_k + Bu_k$$

$$y_k = Cx_k$$

$$u_{i,lb} \leq u_{i,k} \leq u_{i,ub}$$

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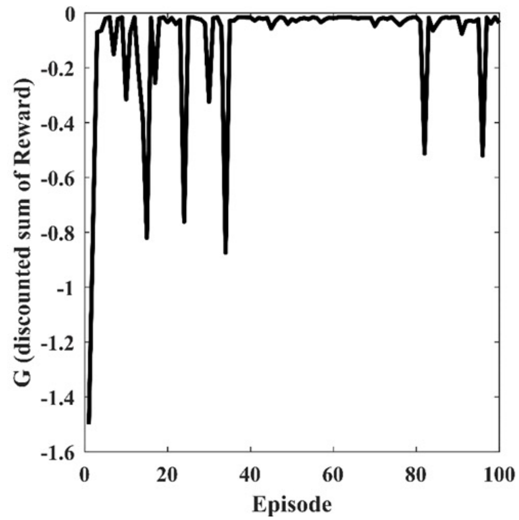
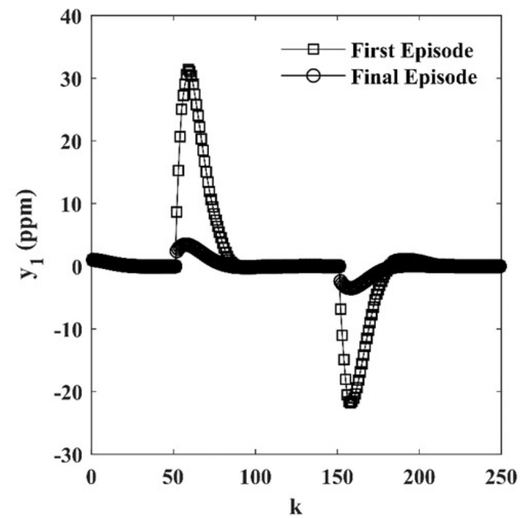
Learning Results

- To standardize learning results, the algorithm has been applied for 20 randomized trials
- In early episodes of learning, performance is poor both because exploration is intentionally high and because the agent has little knowledge of the system
- High final value shows learning





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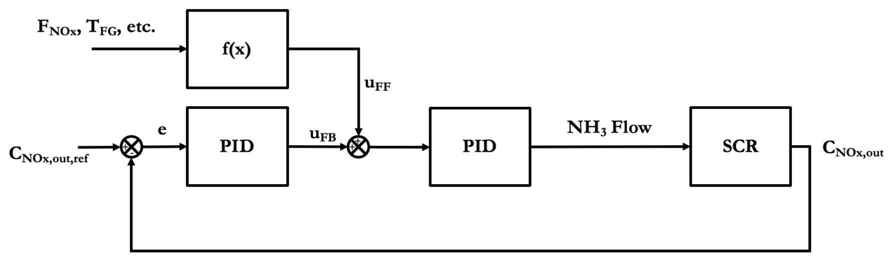
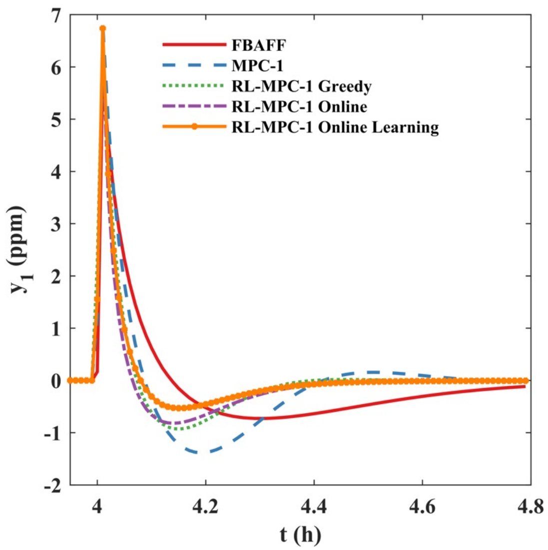
Online Control Results

- Studies for disturbance rejection
  - Unmodeled disturbances in flue gas temperature (d_4)
  - Load following: simultaneous variation of all disturbance variables following industrial profile
- Results compared with the industry-standard feedback augmented feedforward (FBAFF) controller



Online Control Results for (unmodeled) Disturbance in Flue Gas Temperature



Controller	ISE	Ratio to FBAFF	IAE	Ratio to FBAFF
FBAFF	622	--	300	--
MPC-1	685	1.10	276	0.92
RL-MPC-1 Greedy	462	0.74	255	0.85
RL-MPC-1 Online	453	0.73	250	0.83
RL-MPC-1 Online Learning	384	0.62	241	0.80

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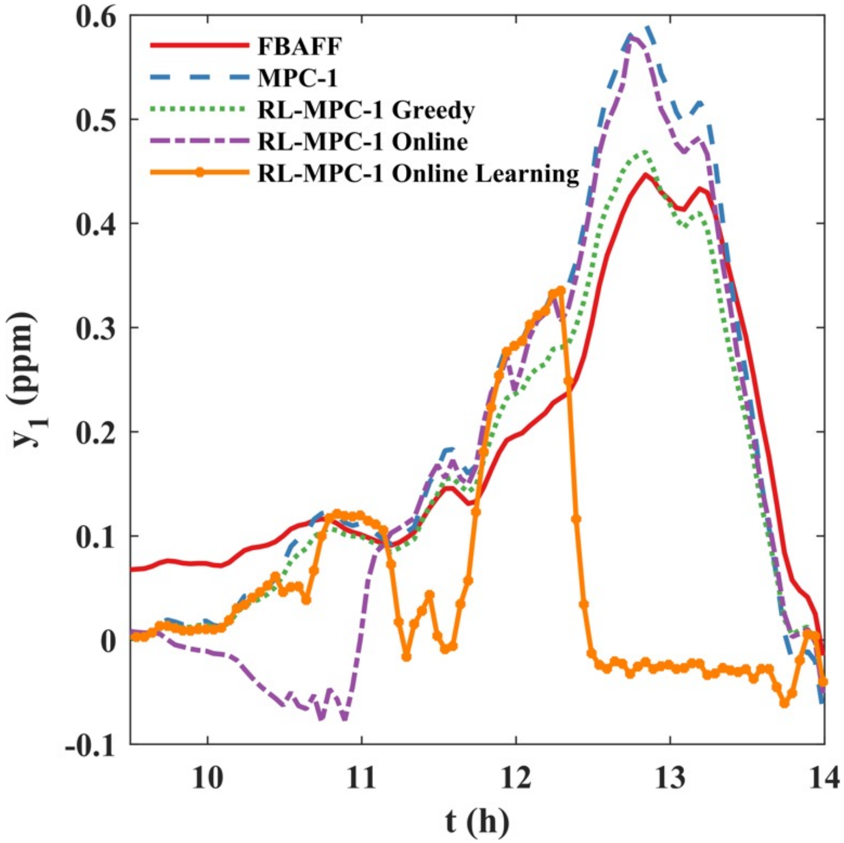
Load Following (Flue gas flowrate, temperature and inlet NO_X concentration all changing) Control Results



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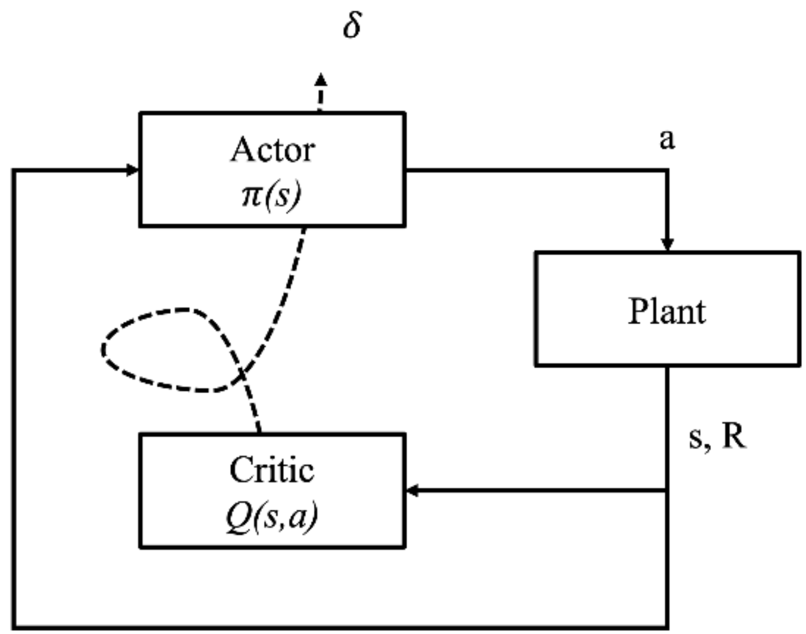
Offset-Free Actor-Critic Control Development

Actor-Critic Approaches

- Use of a parameterized value function, Q, and a parameterized policy, π, for control
- Critic weight update is the same as before
- Policy updated by the current critic
- Actor and critic, most commonly, are deep neural networks



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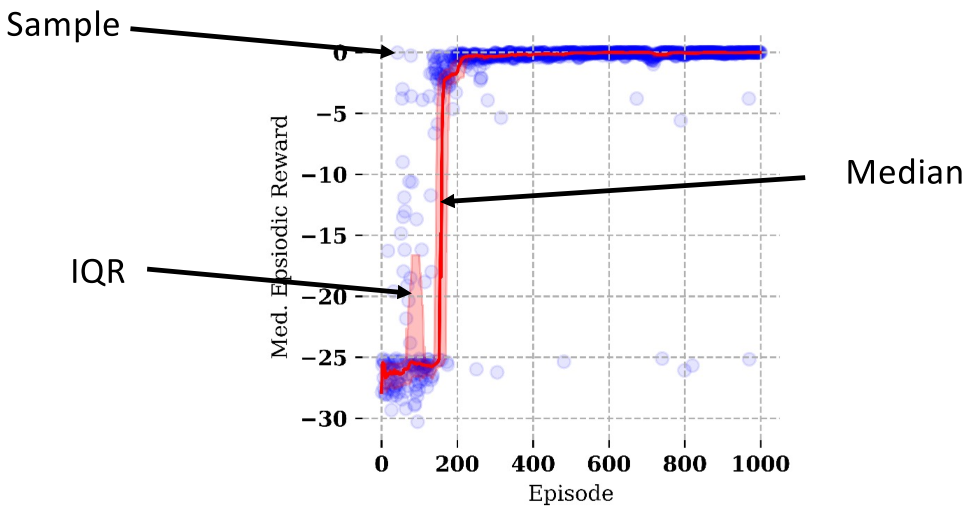
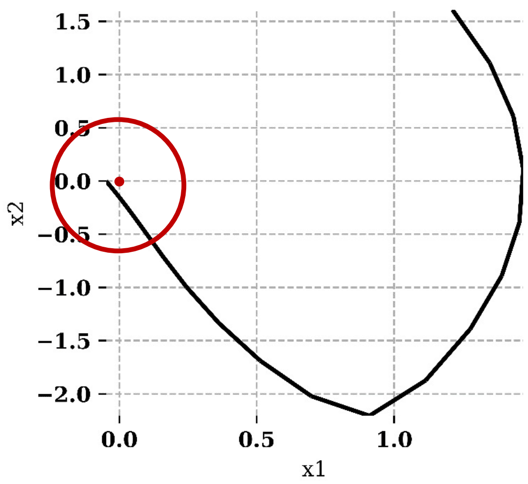
Control with Offset (Naïve Deep Deterministic Policy Gradient (DDPG))





Learning with DDPG

- Target value-function network Q and target policy network μ are parameterized by θ^Q and θ^μ, respectively:

$$\theta^{Q'} \leftarrow \tau\theta^{Q} + (1-\tau)\theta^{Q'}$$

$$\theta^{\mu'} \leftarrow \tau\theta^{\mu} + (1-\tau)\theta^{\mu'}$$

- A replay buffer *R* is used to conduct the update
- Minimize the loss, L, over the value-function network parameters

$$L(\theta^Q) = \frac{1}{N}\sum_i \left(y_i - Q(s_i, a_i|\theta^Q)\right)^2$$

$$y_i = r_i + \gamma Q'\left(s_{i+1}, \mu(s_{i+1}|\theta^{\mu'})|\theta^{Q'}\right)$$

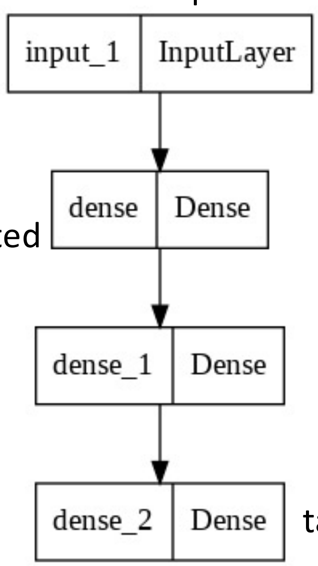
- The exploration noise for DDPG is commonly considered as an Orstein-Uhlenbeck process

$$x_{k+1} = x_k + \eta(\mu - x_k)\Delta t + \sigma\sqrt{\Delta t}\mathcal{N}(\vartheta, \sigma^2)$$

Network Architectures

- Algorithms are implemented in Python using ML packages from TensorFlow / Keras

State Input



Fully Connected ReLU

Actor Network

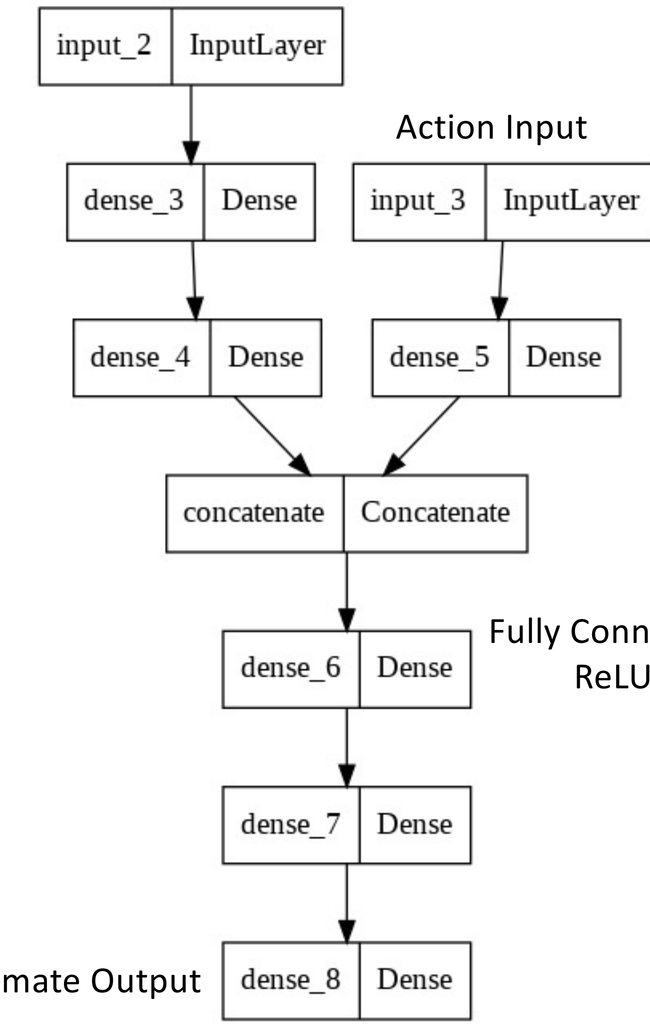
tanh or sigmoid

Action Output

Critic Network

State Input

Action Input



Fully Connected ReLU

Q Estimate Output

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Algorithm

Algorithm 7: DDPG for Offset-Free Control

Input: Initialize critic and actor networks as $Q^U\left(s, a \middle| \theta^{Q^U}\right)$, $Q^K\left(s, a \middle| \theta^{Q^K}\right)$, $\mu^U\left(s \middle| \theta^{\mu^U}\right)$, $\mu^K\left(s \middle| \theta^{\mu^K}\right)$

Initialize noise object $\mathcal{N}$

Set the target network weights $(\theta^{Q^{U\prime}}, \theta^{\mu^{U\prime}}) \leftarrow (\theta^{Q^U}, \theta^{\mu^U})$, $(\theta^{Q^{K\prime}}, \theta^{\mu^{K\prime}}) \leftarrow (\theta^{Q^K}, \theta^{\mu^K})$

Initialize the replay buffer R

Set ε

for ep = 1:Max$_{ep}$

    Set $s = s^0 \in S$

    Initialize noise objects $\mathcal{N}_1, \mathcal{N}_2$

    for k = 1:Max$_k$

        Get $a_k = \pi(s_k) = \begin{cases} \mu\left(s_k \middle| \theta^{\mu^U}\right) + \mathcal{N}_1, & if\ \|x\| > \varepsilon_k \\ \mu\left(s_k \middle| \theta^{\mu^K}\right) + \mathcal{N}_2, & else \end{cases}$

Update Actor Network

Update Target Networks

Update Critic Network

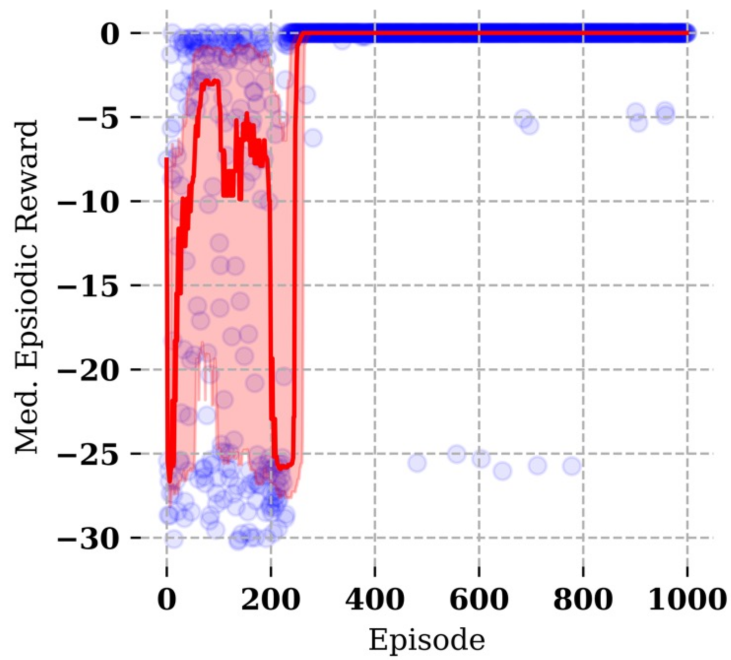
Noise for exploration

Target networks for learning stability

Apply action to plant

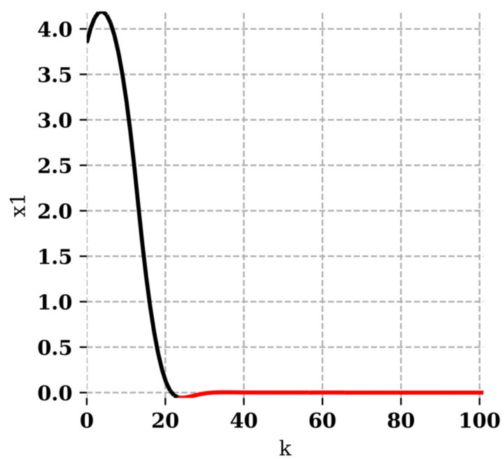
Replay buffer for learning over multiple samples

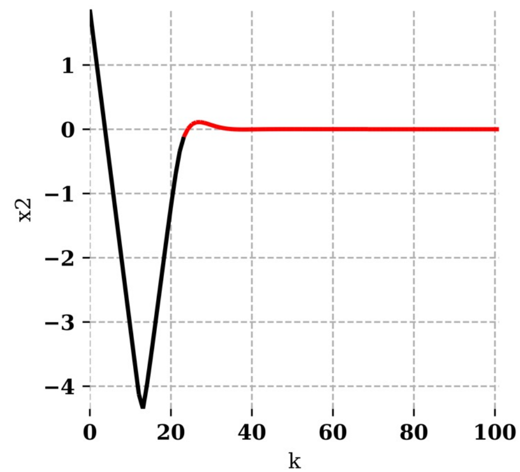
Results – Linear System

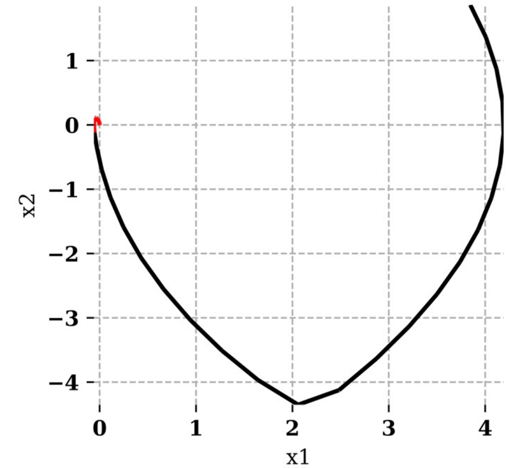


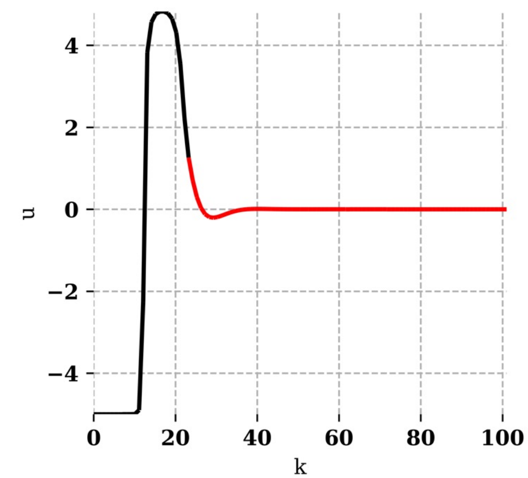
$$A = \begin{bmatrix} 1 & 0.1 \\ 0 & 1 \end{bmatrix},\ B = \begin{bmatrix} 0.005 \\ 0.1 \end{bmatrix},\ C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

Results – Linear System



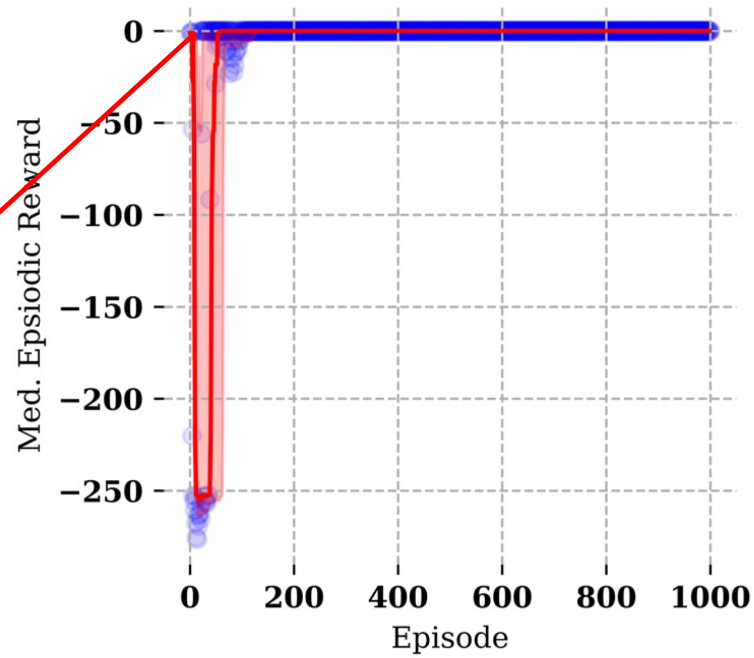




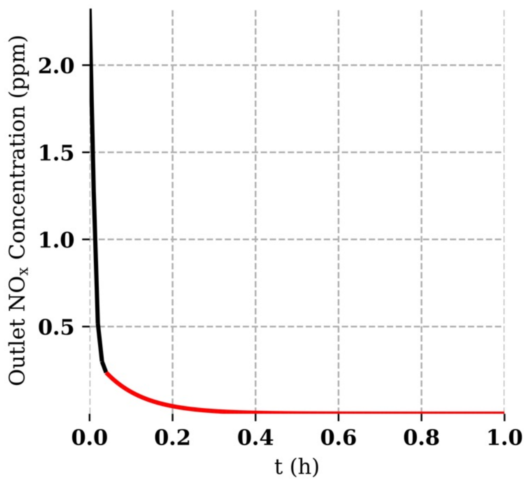


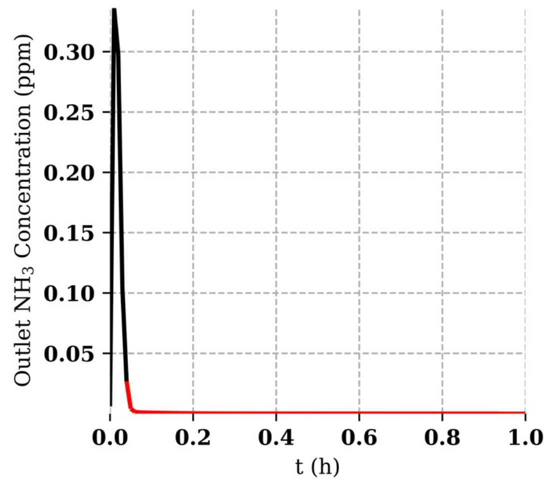
Results – SCR Control

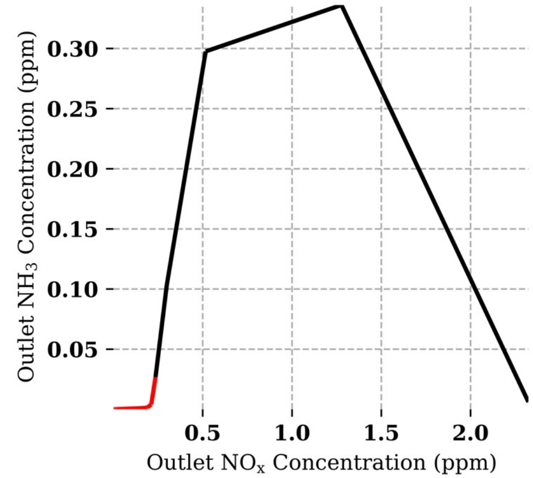
Initial reward higher than
double integrator

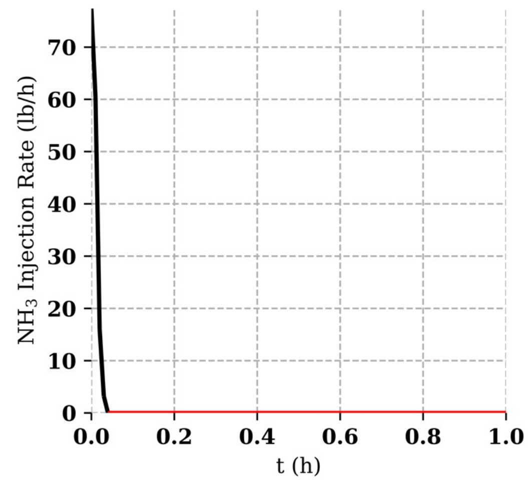


Results – SCR Control









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Conclusions

- RL-MPC algorithm developed for selecting control parameters online
- Results presented for an industrially relevant example
  - Superior performance achieved with offline learning, further improved with learning on the online system
- Developed algorithms for offset-free actor-critic control and applied to linear and nonlinear systems
- There exist considerable opportunities to exploit strengths of RL for improving the performance of control systems by using RL by itself under sufficient performance guarantee or in combination with existing controllers

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Thank you!

Questions?