DEEP REINFORCEMENT LEARNING OF CLOSED LOOP POWERTRAIN CONTROLLERS

- MATHWORKS REINFORCEMENT LEARNING TOOLBOX

Vivek Venkobarao and Gautham T. Sidharthan

External

TODAYS TRANSFORMATION IN POWERTRAIN CONTROLS

Emission laws getting stringent with faster development time

Need to develop and customize the new generation of control functions. (Like AI based)

Place of AI/ML in new generation control functions

MATLAB Reinforcement learning toolbox really helped in fast prototyping

AI BASED MODEL BASED CONTROL FUNCTION

WHY AI IN POWERTRAIN CONTROL SYSTEMS

> **Challenges in powertrain control**

> Designing accurate and scalable mathematical models for vehicle powertrain components which have highly complex and non-linear behavior in real-time operation.

> The real-time environment of a vehicle is very stochastic in nature making control and parameterization of these components very cumbersome using conventional control algorithms (e.g. PID, PI, etc.)

> Environmental concerns of climate change and the resulting ultra low emission requirements set by legislation demand accurate control algorithms with shorter product development lifecycles.

> **Need of the hour**

> Parametrization space is increasing and the effort to cover all operation conditions with a traditional approach leads to an exponential increasing effort.

> The usage of data driven approaches opens up plenty of possibilities and requires well evaluated decisions about architecture and potential side effects or disadvantages

> The control problem and the requirements must be translated into mathematical optimum criteria for a numerical optimization.

CHALLENGES OF THE CONVENTIONAL RL

PAIN OF AN AI DEVELOPER

- **Why Reinforcement Learning**
- Stochastic and non perfect nature of environment
- Reinforcement learning algorithms maintain a balance between exploration and exploitation
- Reinforcement Learning algorithms like DDPG, a combination of value-based algorithms and deep learning exist for a wide variety of problem classes.
- This approach is driven by the objective to reduce significantly human parametrization effort.

- **Challenges in implementation**
  - The policy that maps the selected actions based on the observations from the environment. DNN is used.
  - The learning algorithm continuously updates the policy parameters based on the actions, observations, and rewards.
  - Realizing DDPG Agent

REINFORCEMENT LEARNING

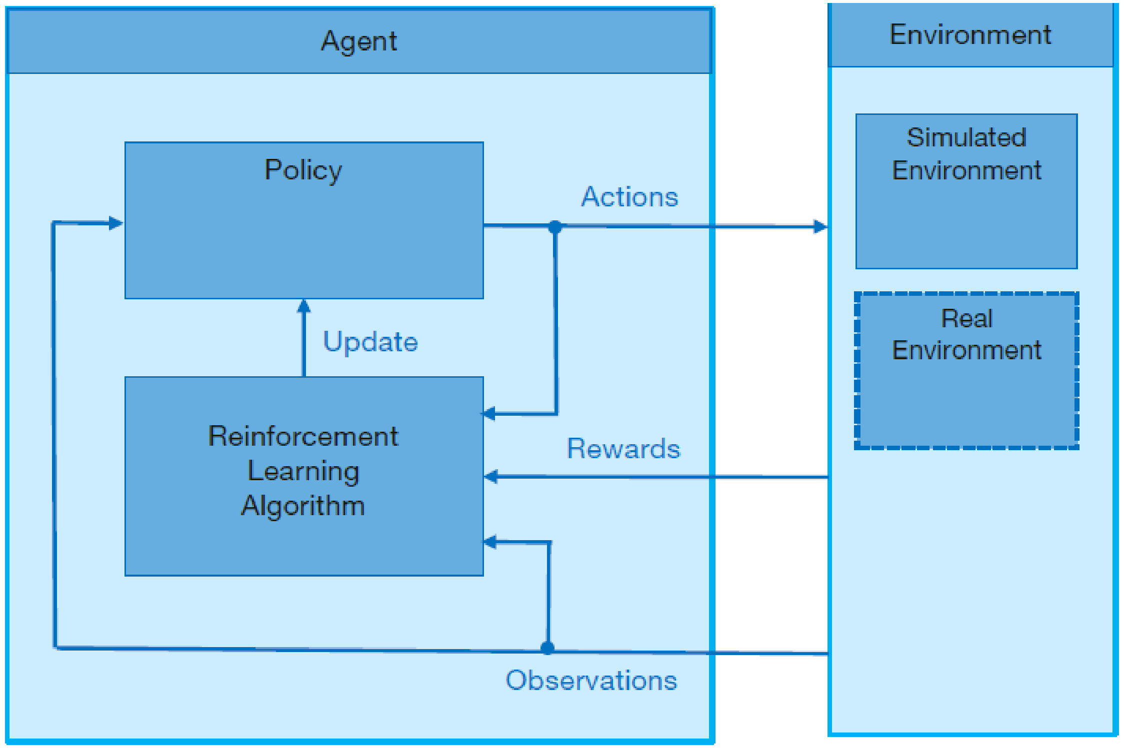
REINFORCEMENT LEARNING FRAMEWORK FOR CONTINUOUS CONTROL ENVIRONMENTS

> The goal of reinforcement learning is to train an agent to complete a task within an uncertain environment.

> The agent receives observations and a reward from the environment and sends actions to the environment.

> The reward is a measure of how successful an action is with respect to completing the task goal.

> A DDPG agent is an actor-critic reinforcement learning agent that computes an optimal policy that maximizes the long-term reward.

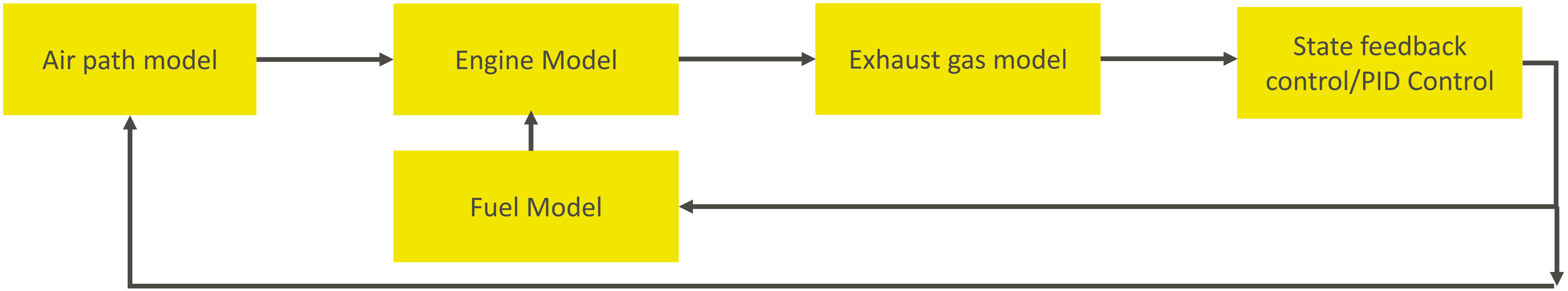


Reference Architecture for Reinforcement Learning

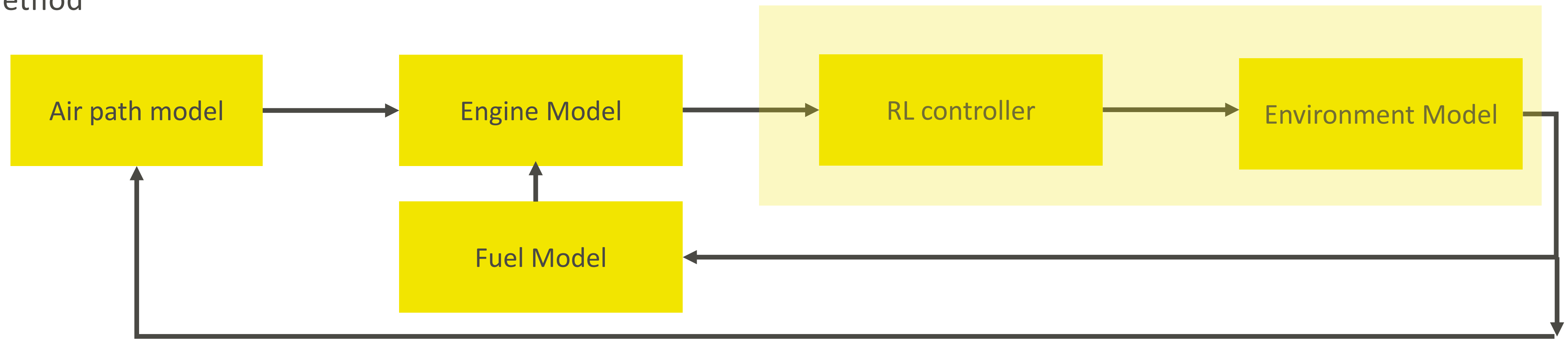
CASE STUDY – POWERTRAIN CONTROLLER

ACCELERATED PROTOTYPING

> Conventional Method



> Proposed Method



CHOICE IN IMPLEMENTATION

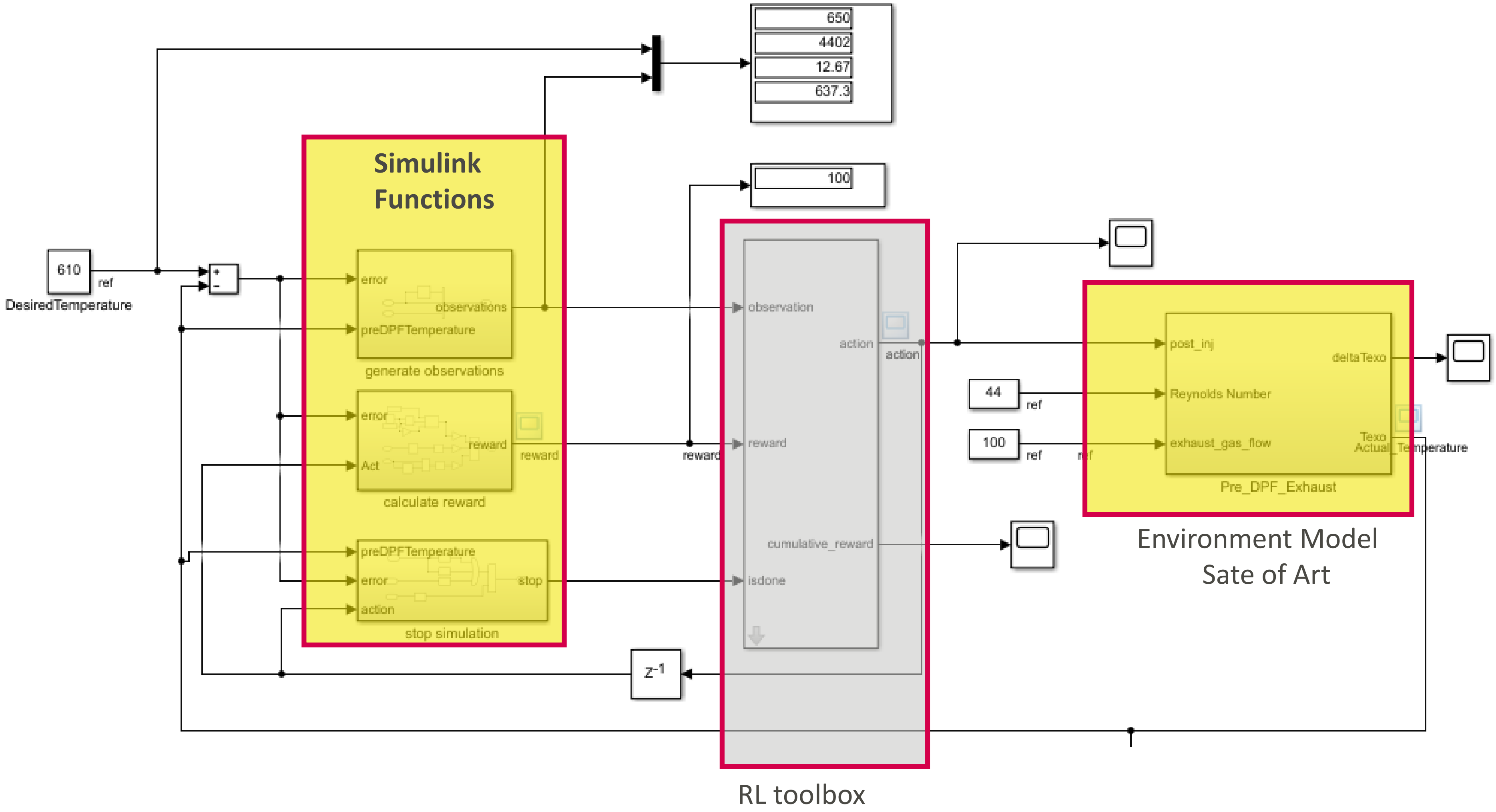
REINFORCEMENT LEARNING REALIZATION OPTIONS

Complexity	Traditional Methods	MATLAB/SIMULINK
Time series Models	Need to derive time vector	Simulink to rescue
Solve the ODE	Numerical methods to be introduced	Solvers
Environment Models	Need to be recreated with time series	State of Art plant models
Action, State	Needs to be derived and implemented	Toolbox generates
Observations, Reward	Needs to be derived with time vector	Simulink to rescue
A2C(Actor and Critic)	Can use library	DL API Actor and Critic -> RL toolbox
DDPG Agent	Can use library	RL toolbox with good flexibility of playing with parameters
Component Integration	Complex – Time series and cross sectional data	Simple – MATLAB, Simulink, RL blocks in same platform

vitesco TECHNOLOGIES

ACCELERATED PROTOTYPING

PRE DPF TEMPERATURE CONTROL- OVERALL SIMULATION DIAGRAM

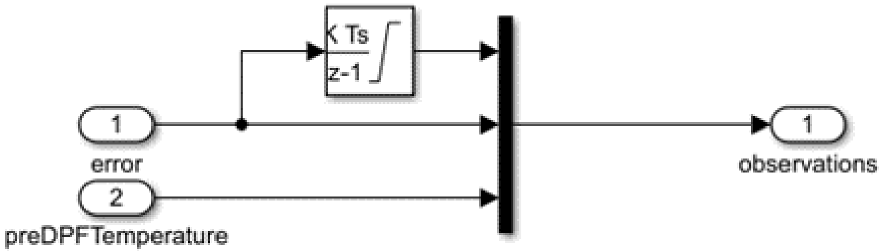


vitesco TECHNOLOGIES

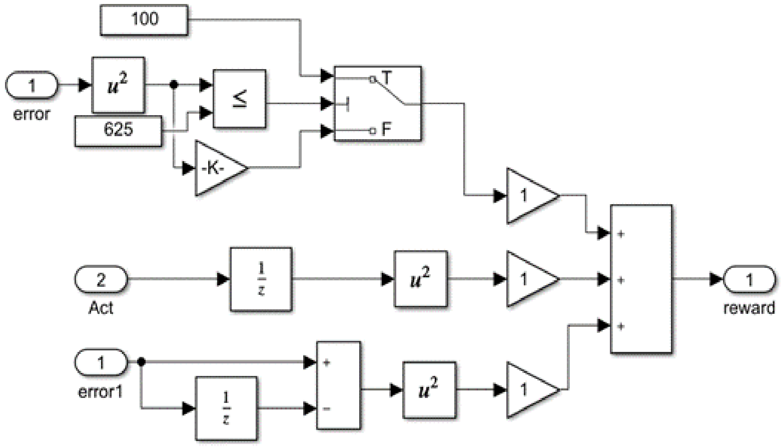
ACCELERATED PROTOTYPING

STUFF CAN BE SIMULINK

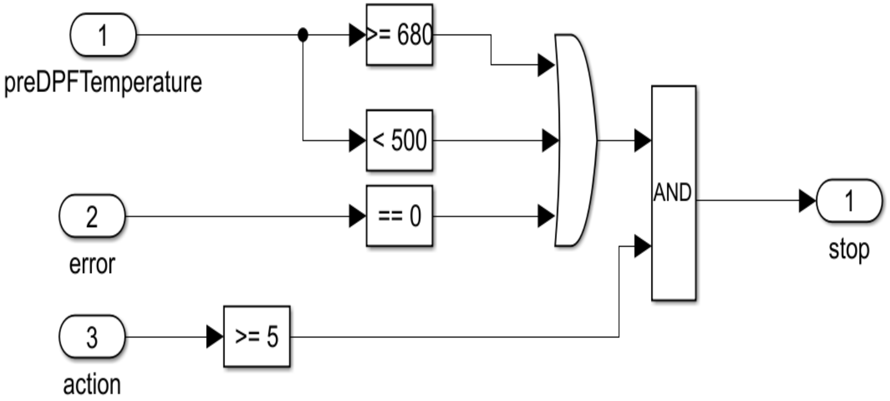
> Observations



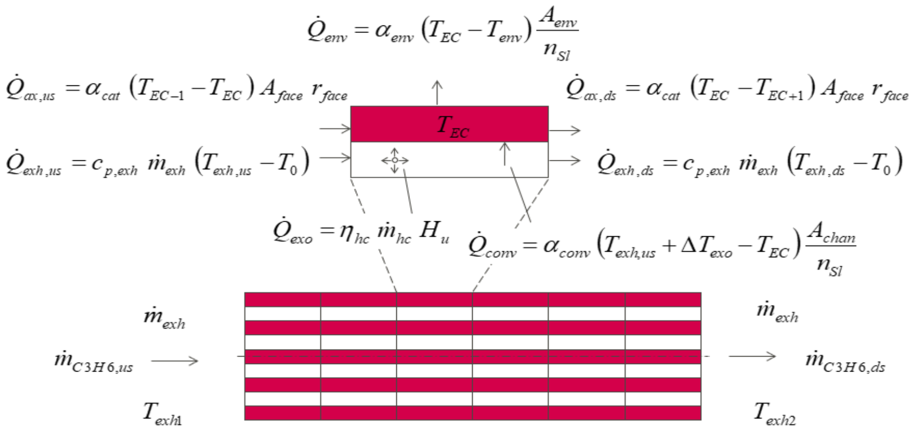
> Rewards



> Stop Criterion – when to stop



> Environment Model



ACCELERATED PROTOTYPING

STUFF WITH REINFORCEMENT LEARNING TOOLBOX

Fast Parameterization

> Critic network

```
statePath = [
    imageInputLayer([numObservations 1 1], 'Normalization', 'none', 'Name', 'State')
    fullyConnectedLayer(250, 'Name', 'CriticStateFC1')
    reluLayer('Name', 'CriticRelu1')
    fullyConnectedLayer(225, 'Name', 'CriticStateFC2')];
actionPath = [
    imageInputLayer([numActions 1 1], 'Normalization', 'none', 'Name', 'Action')
    fullyConnectedLayer(225, 'Name', 'CriticActionFC1')];
commonPath = [
    additionLayer(2,'Name', 'add')
    reluLayer('Name','CriticCommonRelu')
    fullyConnectedLayer(1, 'Name', 'CriticOutput')];

criticNetwork = layerGraph();
criticNetwork = addLayers(criticNetwork,statePath);
criticNetwork = addLayers(criticNetwork,actionPath);
criticNetwork = addLayers(criticNetwork,commonPath);
criticNetwork = connectLayers(criticNetwork,'CriticStateFC2','add/in1');
criticNetwork = connectLayers(criticNetwork,'CriticActionFC1','add/in2');
```

> Actor network

```
actorNetwork = [
    imageInputLayer([numObservations 1 1], 'Normalization', 'none', 'Name', 'state')
            fullyConnectedLayer(400, 'Name', 'ActorFC1')
            reluLayer('Name', 'ActorRelu1')
            fullyConnectedLayer(300, 'Name', 'ActorFC2')
            reluLayer('Name', 'ActorRelu2')
            fullyConnectedLayer(1, 'Name', 'ActorFC3')
            tanhLayer('Name', 'ActorTanh')
            scalingLayer('Name','action','Scale',4,'Bias',-0.5)];

%actorOptions = rlRepresentationOptions('LearnRate',1e-04,'GradientThreshold',1);
%actor = rlRepresentation(actorNetwork,obsInfo,actInfo,'Observation',{'State'},'Action',{'Action'},actorOptions);

actorOpts = rlRepresentationOptions('LearnRate',1e-04,'GradientThreshold',1);
actor = rlRepresentation(actorNetwork,obsInfo,actInfo,'Observation',{'state'},'Action',{'action'},actorOpts);
```

> DDPG network

```
agentOpts = rlDDPGAgentOptions(...
    'SampleTime',Ts,...
    'TargetSmoothFactor',1e-3,...
    'DiscountFactor',1.0, ...
    'ExperienceBufferLength',1e5, ...
    'DiscountFactor',0.99,...
    'MiniBatchSize',128,...
    'ResetExperienceBufferBeforeTraining',false,...
    'SaveExperienceBufferWithAgent',true);
agentOpts.NoiseOptions.Variance = 0.3;
agentOpts.NoiseOptions.VarianceDecayRate = 1e-5;

agent = rlDDPGAgent(actor,critic,agentOpts);
```

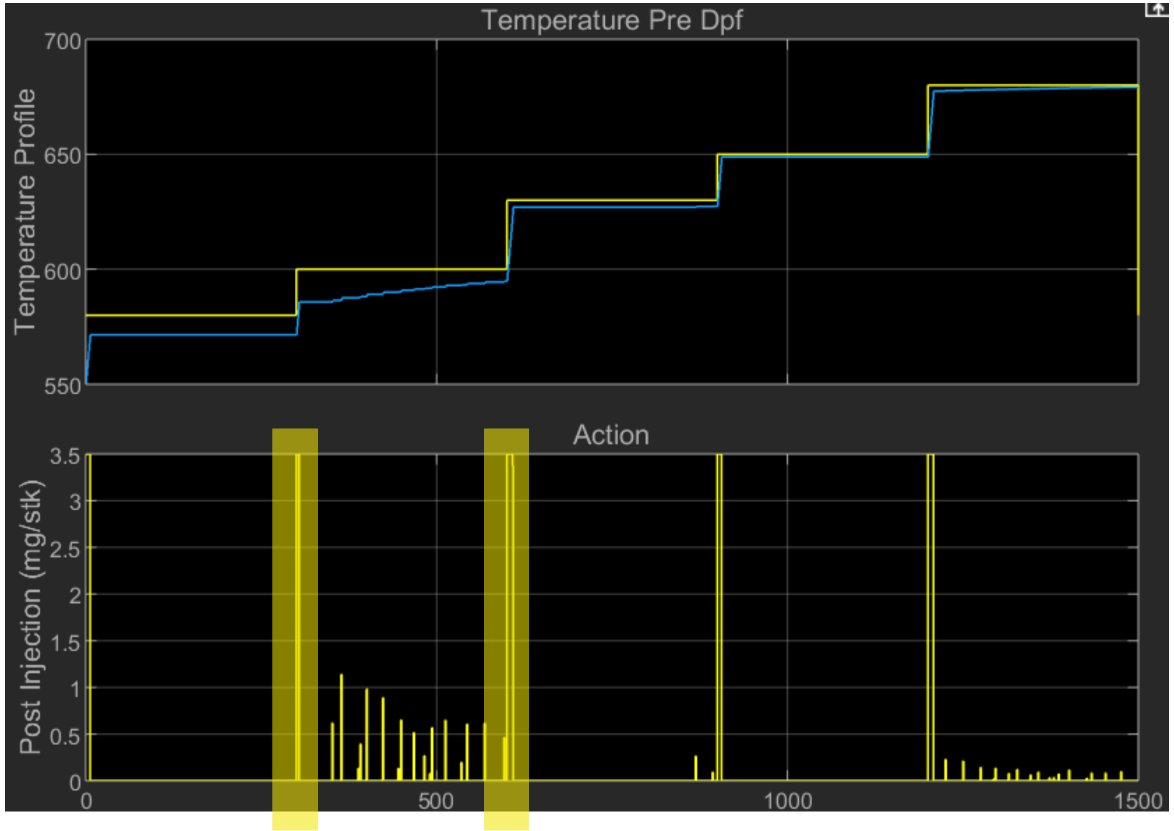
> Simulation of RL

Agents can be saved in a .mat file

```
maxepisodes = 500;
%maxsteps = ceil(Tf/Ts);
maxsteps = 200;
trainOpts = rlTrainingOptions(...
        'MaxEpisodes', maxepisodes, ...
        'MaxStepsPerEpisode', maxsteps, ...
        'Verbose', true, ...
        'Plots','training-progress',...
        'StopTrainingCriteria','EpisodeCount',...
        'SaveAgentCriteria','EpisodeCount',...
        'SaveAgentValue',103);
```

ACCELERATED PROTOTYPING

RESULTS AND DISCUSSION



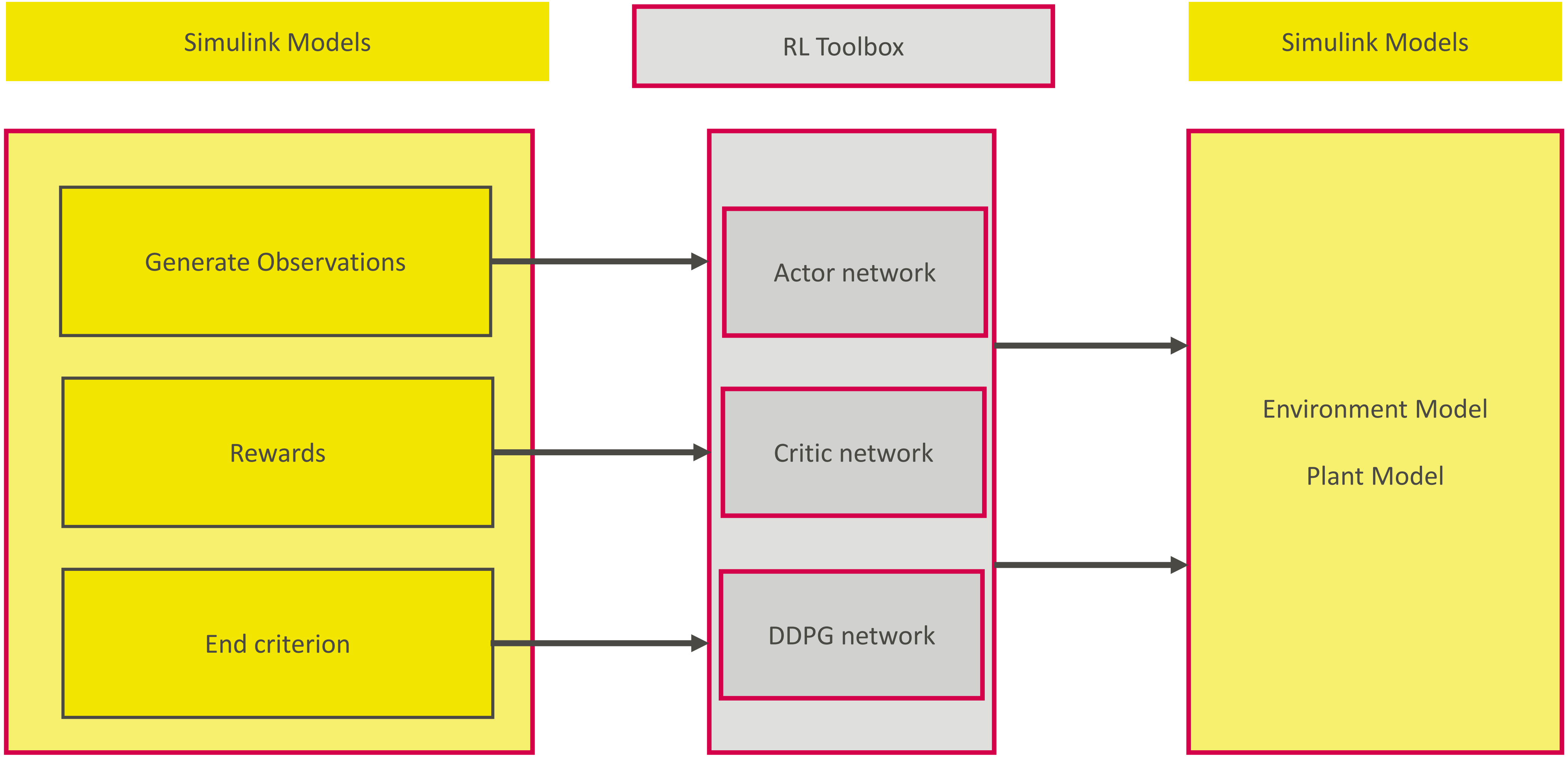
Couldn’t honor the setpoint as it was violating component protection limits
Saturation block is used to limit the action based on the current operating point

- Advantages of Reinforcement based control study
- Good transient response of the controller
- With a good environment model the RL based control provides good recommendations of the control variable
- Simulink also allows limitation for component protection
- The trained control model can be used across various operating zones
- With the usage of toolbox I could focus more on accuracy of environment model

vitesco TECHNOLOGIES

GOLDEN WORKFLOW BASED ON EXPERIENCE

RECOMMENDATION FOR FASTER DEVELOPMENT



SUMMARY

EXPERIENCE DURING CASE STUDY

- Excellent Technical support from Mathworks with dedicated calls with the Expert
- Great documentation from MATLAB with algorithms and examples on Reinforcement learning
- Manually coding the Reinforcement learning and optimization is difficult with current development timelines.
- MATLAB allows us to use Simulink to effectively so that state of art plant models can be imported.
- Usage of MATLAB Reinforcement toolbox considerably reduced the development time.
- The toolbox gave an amazing quick and fast prototyping to realize the generation of agents and optimization.
- The usage of data-driven approaches opens up plenty of new possibilities by using AI
- Deep Reinforcement Learning based algorithms are able to solve advanced control problems.

.

LETS DISCUSS