A perspective on deploying Machine Learning to augment classic control design

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Outline

- Control algorithms design challenges
- Machine learning for control design
  - Case study 1: Adaptive MPC with ML-based LPV for an engine application
  - Case study 2: Truck CACC with Reinforcement Learning
  - Case study 3: Truck CACC with PID-based Reinforcement Learning

Control software

Control design & algorithms – feedback controls, supervisory, governors

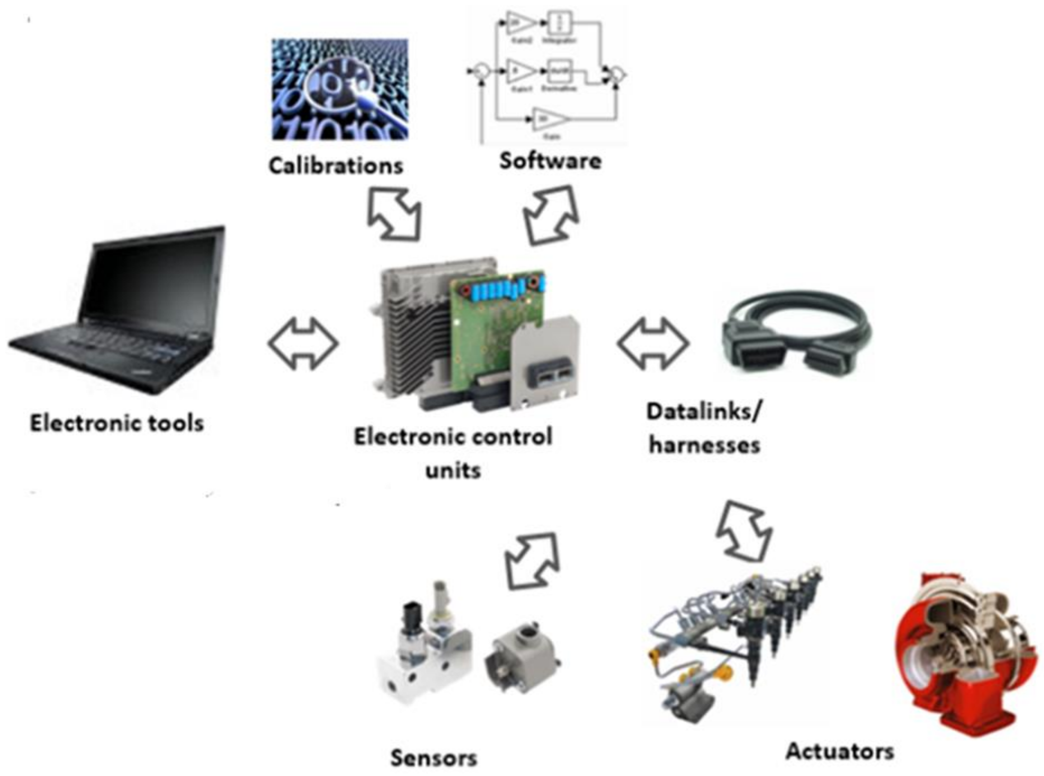
Sensing & monitoring – sensor fusion, virtual sensors & estimators

Diagnostics & prognostics – faults/failures detection, isolation, prediction, service, OBD

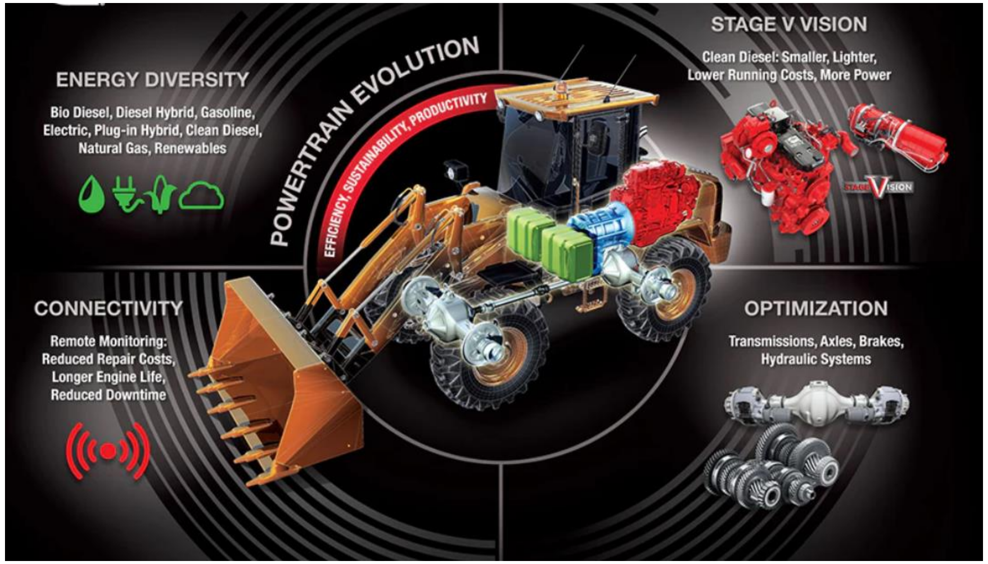
Software V&V and certification – AUTOSAR, ASPICE, ISO-26262

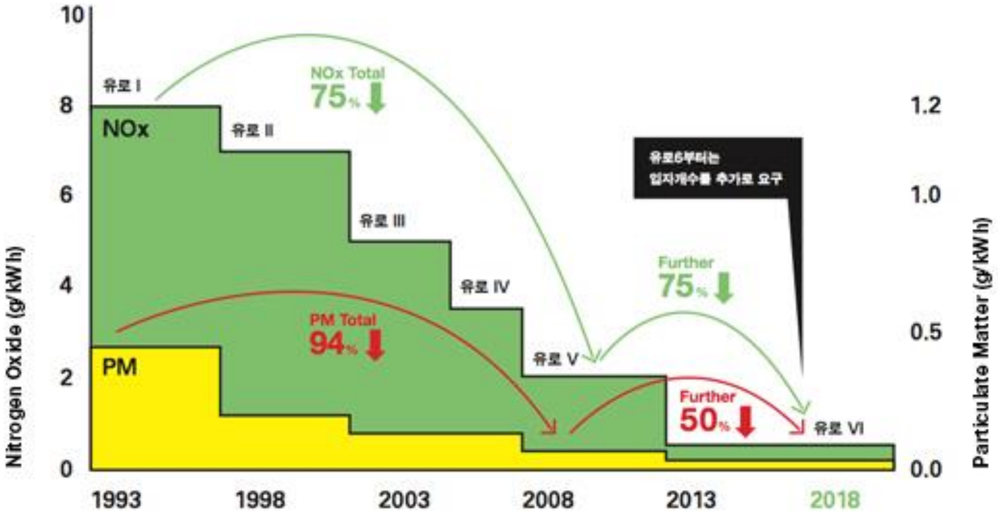
ECU/ECM base software – service & abstraction layers, IO interface

Telematics/wireless communication – V2X, Edge/Cloud

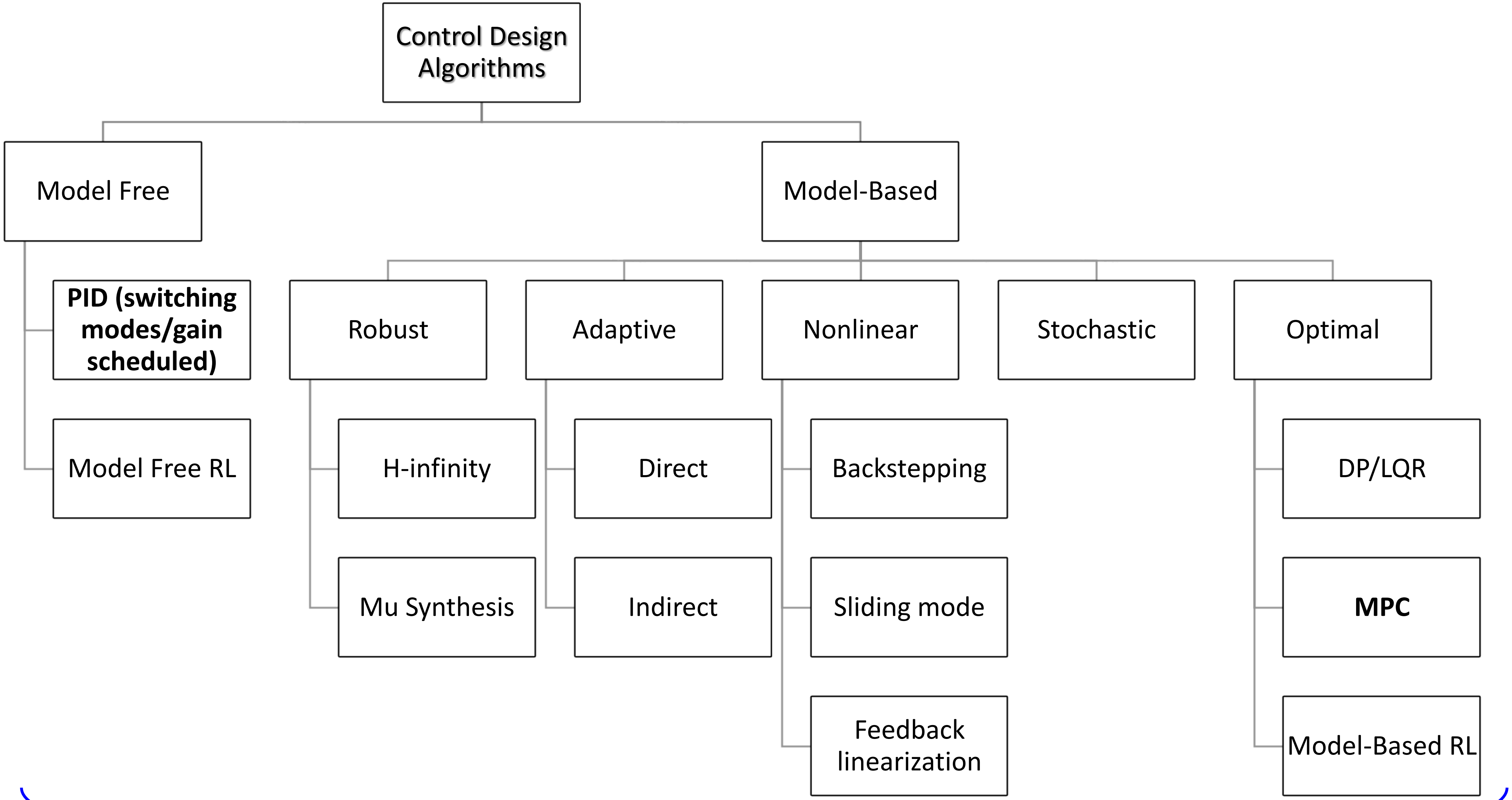


Controls challenges in commercial vehicle market





- **Complexity** with adoption of emerging technologies
  - New-energy powertrains: EV, fuel cell, hybrid, alternative fuels
  - Connectivity and Automation
- **Optimal** performance - profit margin
  - Operational efficiency e.g. individual vehicle to fleet
  - Reduce robustness margins with **adaptation/learning**
- **Constraints** are growing
  - Regulatory compliance for safety & emissions
  - Warranty & service cost reduction
- **Time to market** reduction
  - **Systematic & scalable** design
  - **Calibration** effort reduction



Next generation control design and algorithms?

** Note: It is not a comprehensive list.*

Machine learning (ML) to bridge the gap?

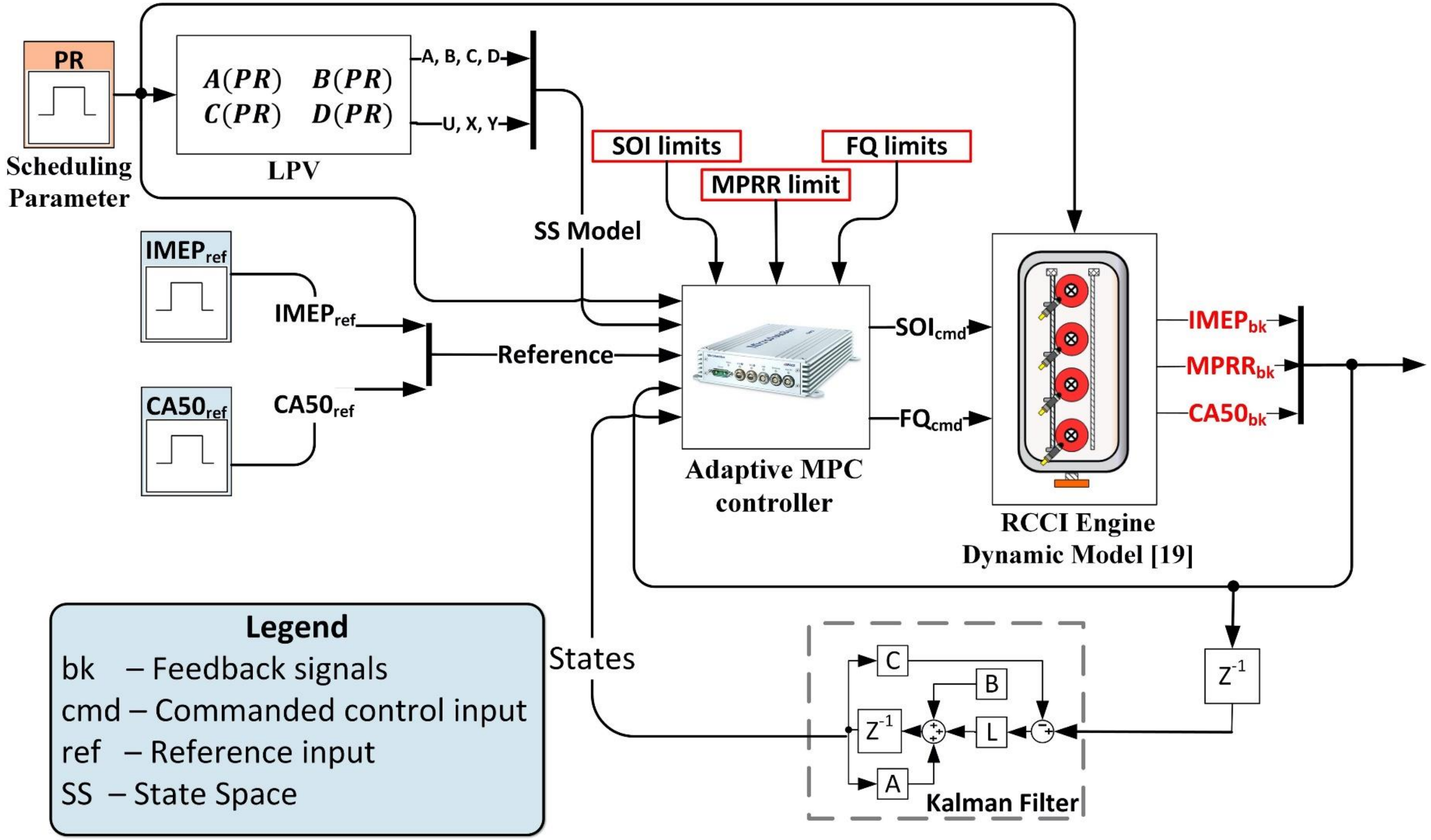
- Case study 1: Adaptive MPC with ML-based LPV developed models for an engine application
  - Utilize machine learning to develop models structured for control design
- Case study 2: Truck CACC with Reinforcement Learning
  - Pure data driven approach with deep learning and RL algorithms
- Case study 3: Truck CACC with PID-based Reinforcement Learning
  - RL with imposed control structure on agent

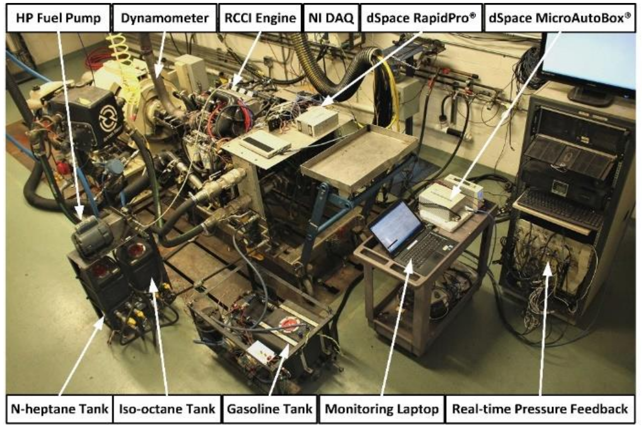
****MPC:** Model Predictive Control **LPV:** Linear Parameter Varying **RL:** Reinforcement learning **CACC**: Cooperative Adaptive Cruise Control*

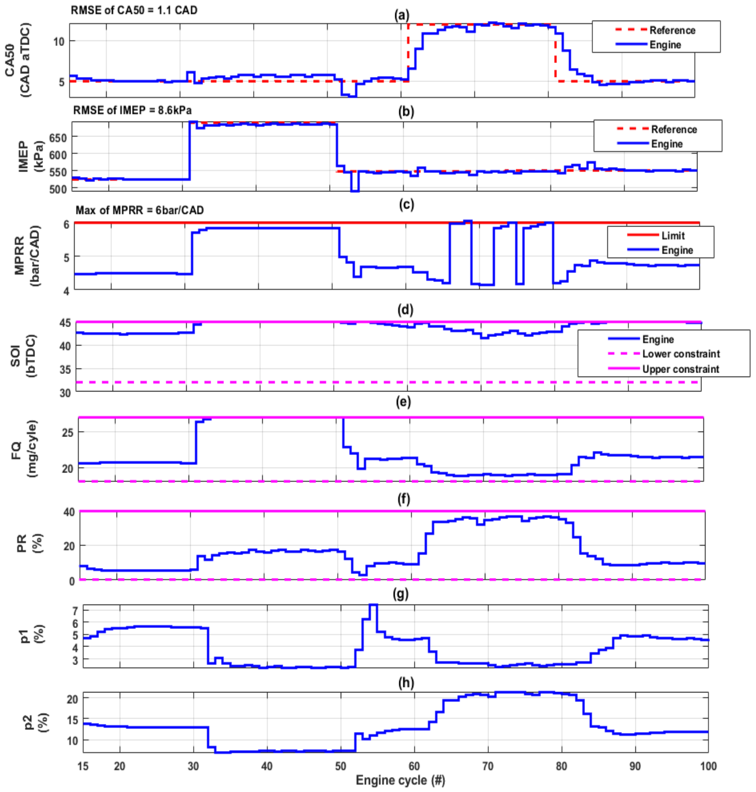
Case study 1: Control-oriented Modeling and Predictive Control of Advanced Dual Fuel Natural Gas Engines

NSF GOALI/Collaborative Research: MTU, UGA and Cummins

$$
\begin{aligned}
X_{k+1} &= W_1\Phi_1(p_k)X_k + W_2\Phi_2(p_k)U_k + W_3\Phi_3(p_k)Y_k \\
Y_k &= W_4\Phi_4(p_k)X_k + E_k
\end{aligned}
$$







"Data-driven Modeling and Predictive Control of Maximum Pressure Rise Rate in RCCI Engines," 2020 IEEE CCTA, 2020, pp. 94-99

ML-based system identification for control design

- **Pros**
  - Enables to deploy model-based control design from control theory with proven stability, robustness and optimality
  - Utilizes advancement in ML to improve system identification methods
- **Cons**
  - Needs controls engineering and design expertise
  - Quality of input/output measured data (excite system dynamics, signal-to-noise ratio, sampling/frequency resolution)

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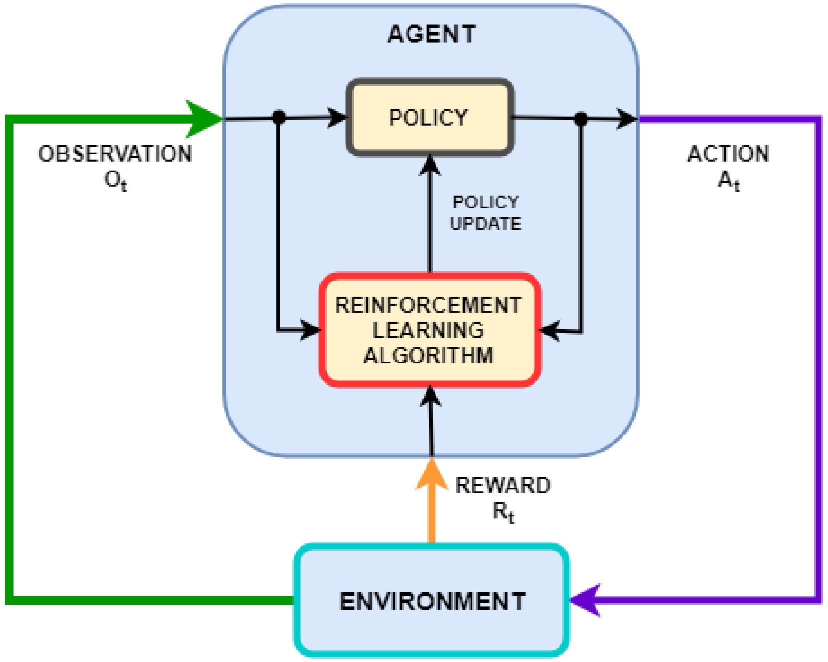
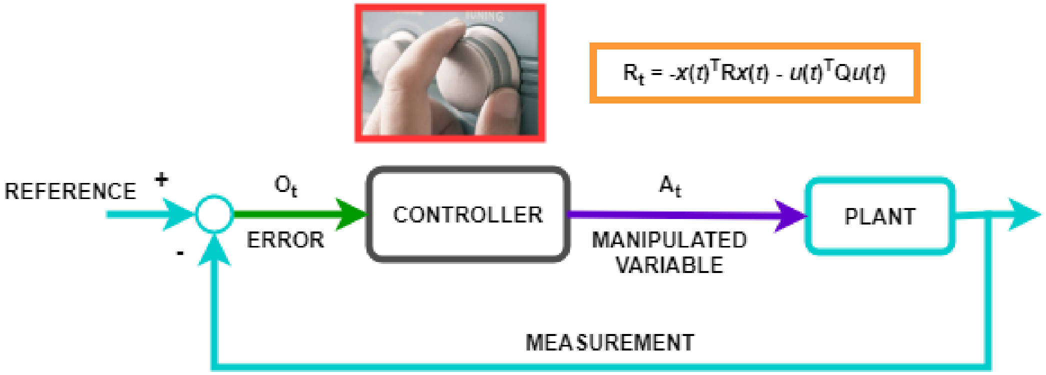
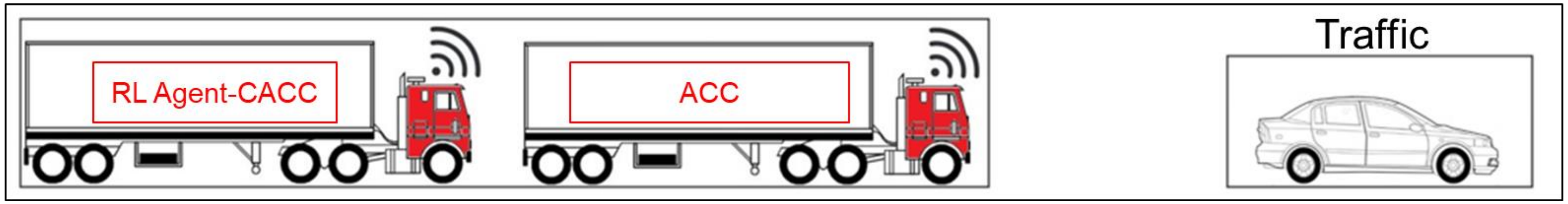
Reinforcement Learning for controls

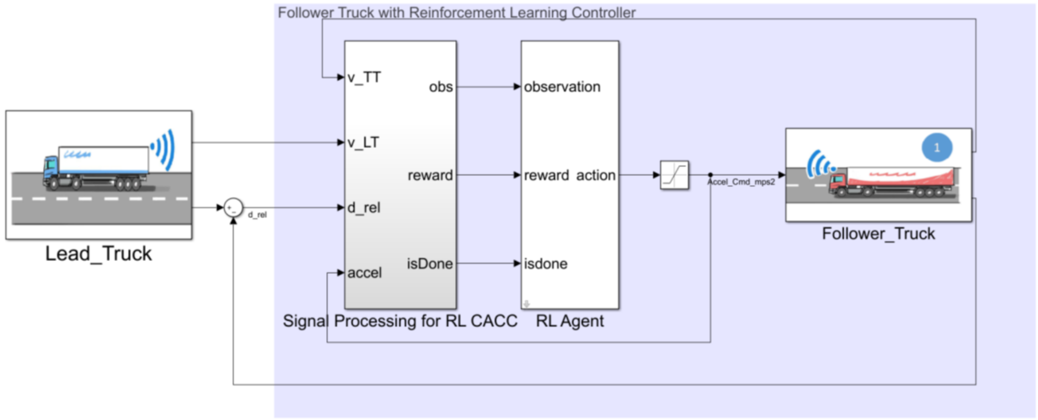


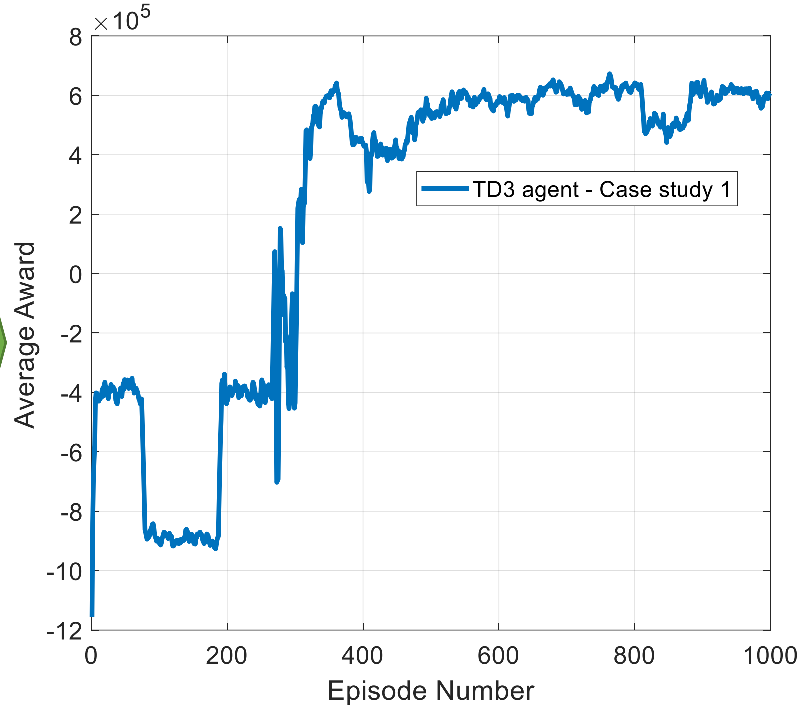


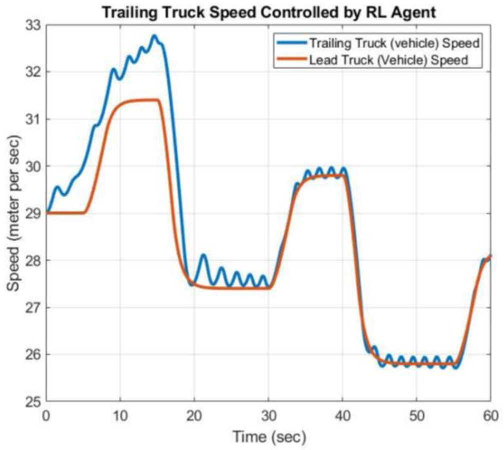
- Develop Plant/Environment Model with training scenario
- Define Observations (feedback), reward (cost function)
- Select learning algorithms e.g. DDPG, TD3
- Define the NN for agent (actor & critic)
- Train the actor (controller) with repeated episodical simulations
- Select the best agent
- Check robustness and repeat as needed

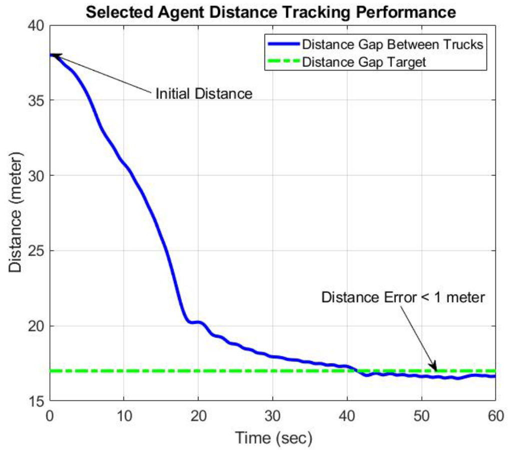
Case study 2: Truck CACC with RL











Reinforcement Learning for controls

- Pros
  - Applicable to complex systems hard to apply classic control theory
- Cons
  - Environment model to simulate different scenarios/conditions
  - Reward function engineering
    - enforce constraints
  - Hyper-parameters tuning: NN structures, learning algorithms, learning specific parameters
  - Black-box control model w/o interface for fine tuning on real system

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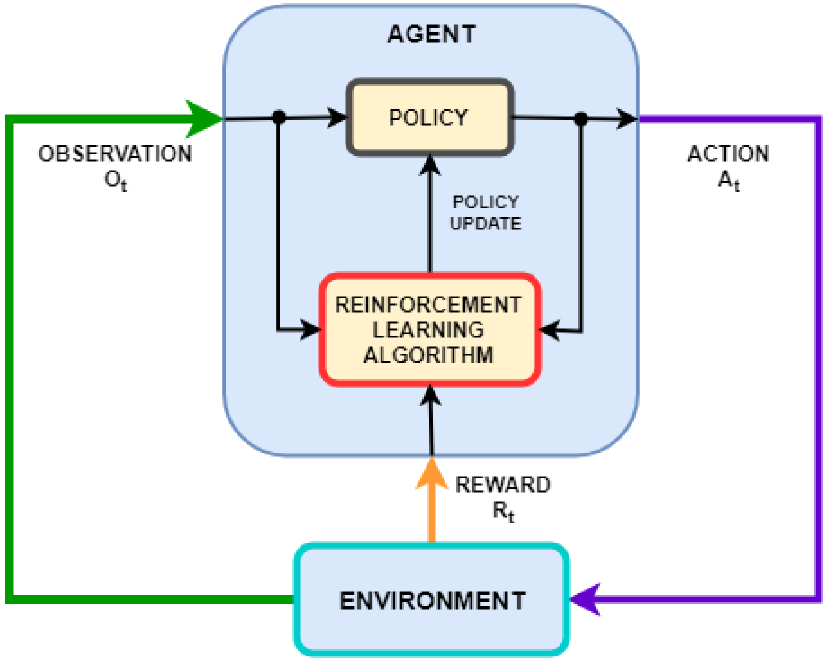
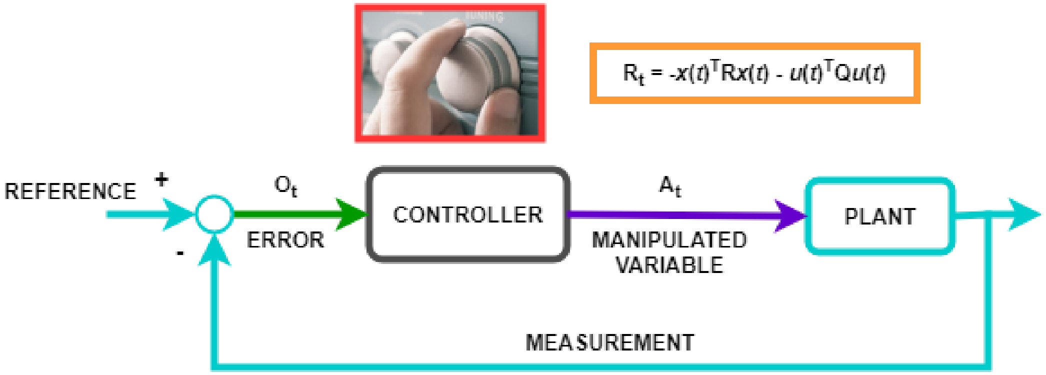
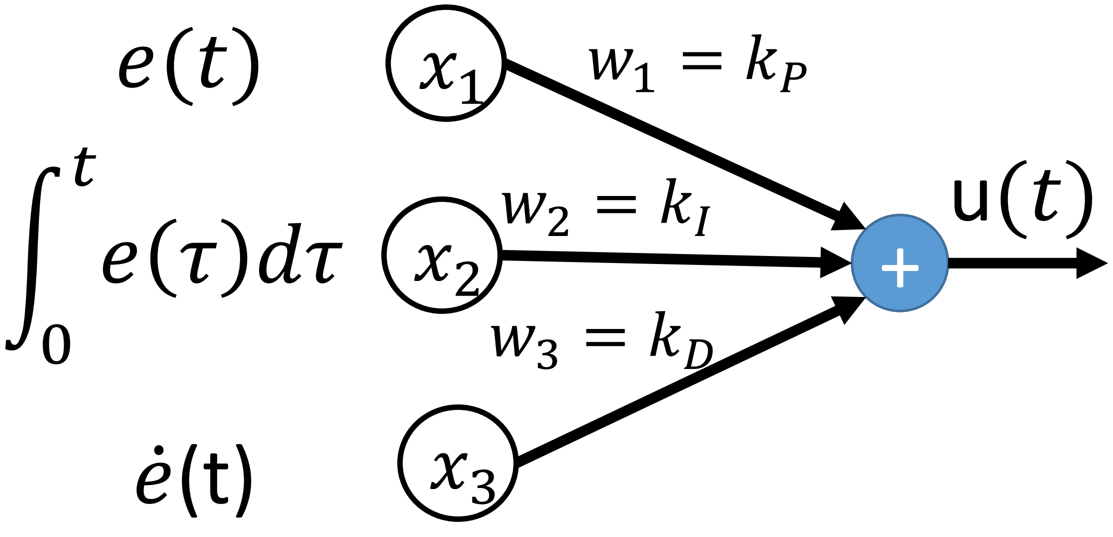
RL with imposed structure from control theory

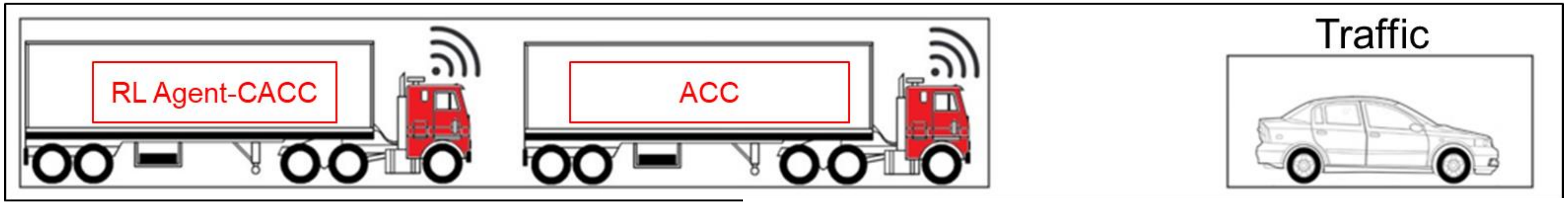


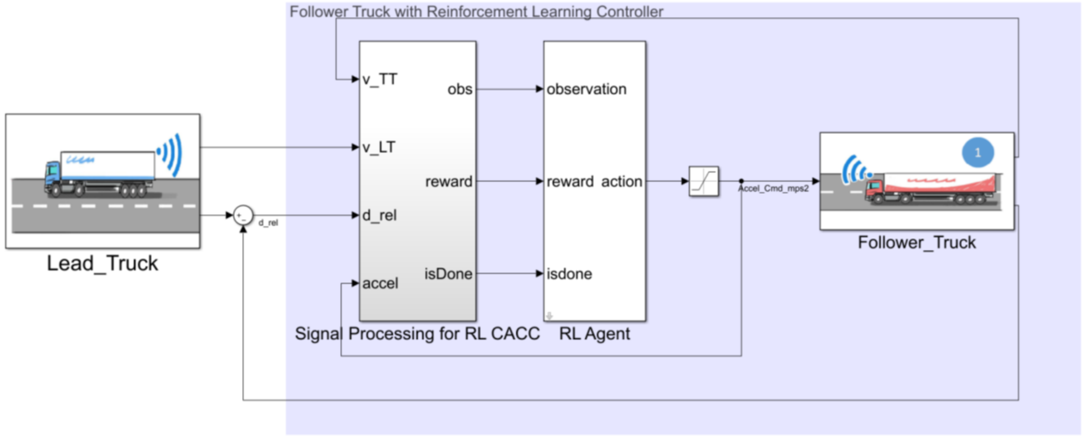


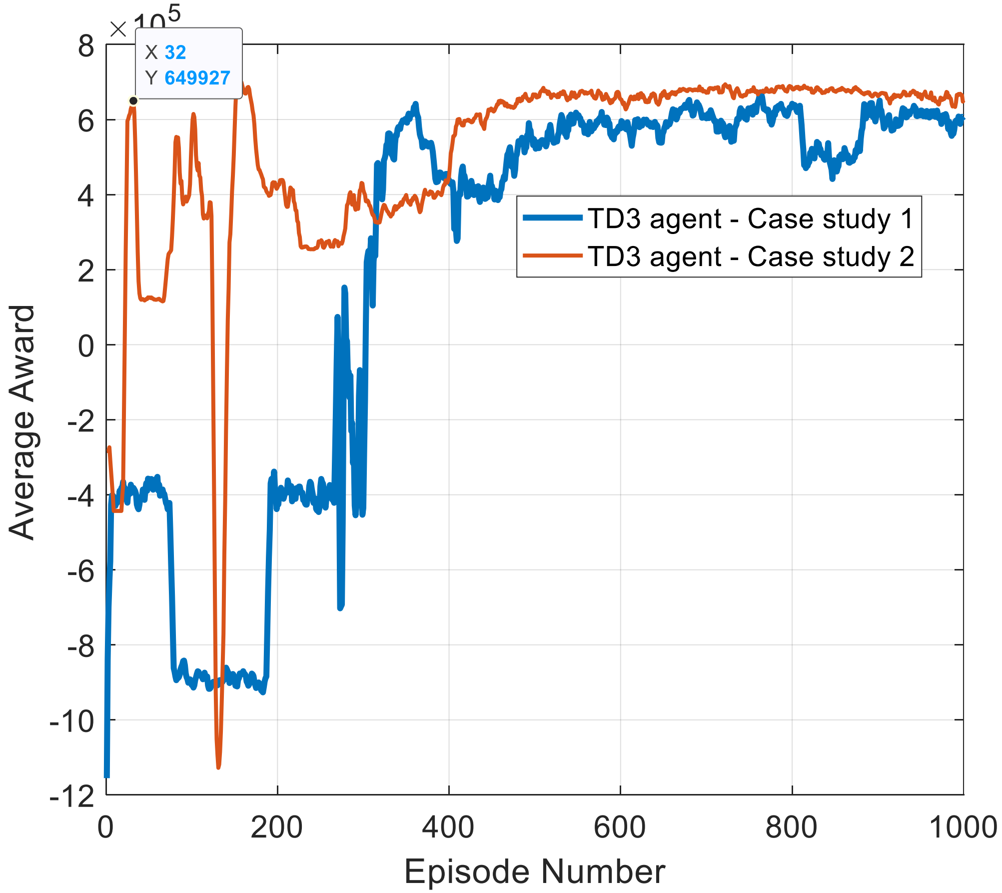
- Impose actor NN structure from control theory such as
  - PID
  - Lead/Lag
  - State feedback



Case study 2: Truck RL-based CACC design with actor NN representing PID control







RL with imposed structure from control theory

- Pros
  - Deploy methods from control theory with proven stability, robustness
  - Utilize controls development and calibration processes and tools
- Cons
  - Controls expertise
  - Environment model to simulate different scenarios/conditions

Concluding remarks

- Need for next generation control design
- Machine learning provides opportunities to enhance control design

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