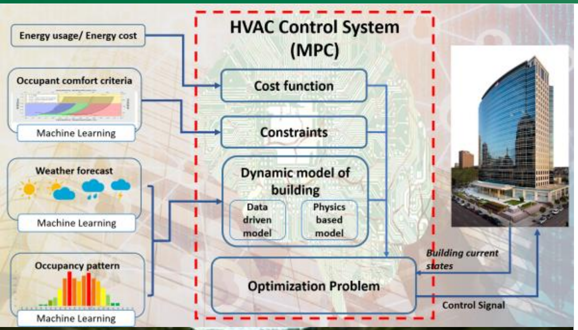
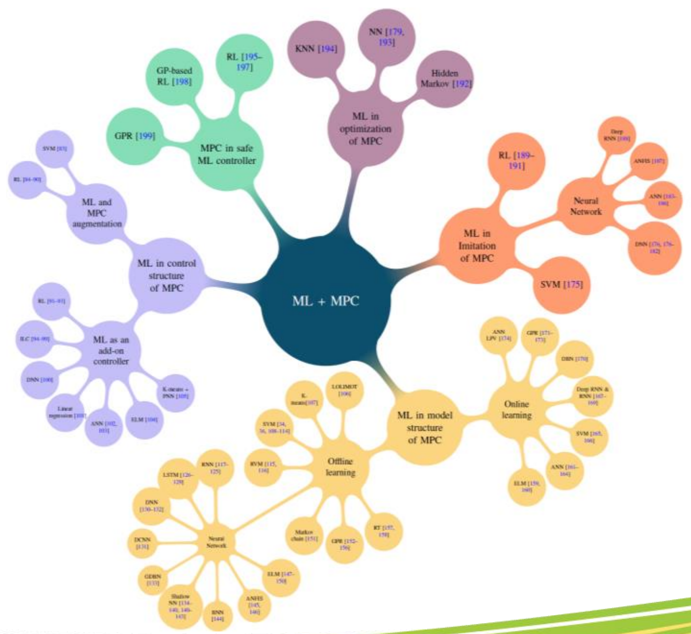
Machine Learning Control Workshop

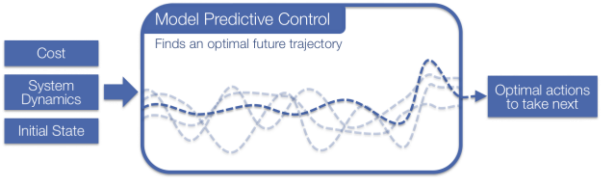
CSME CONGRESS

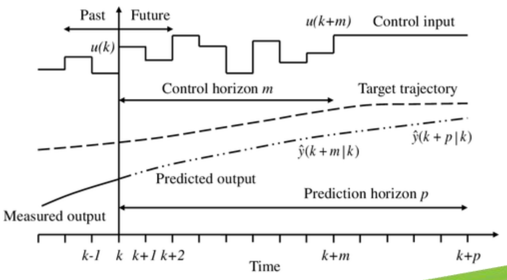
Mahdi Shahbakhti

Jun. 5, 2022









Model Predictive Control

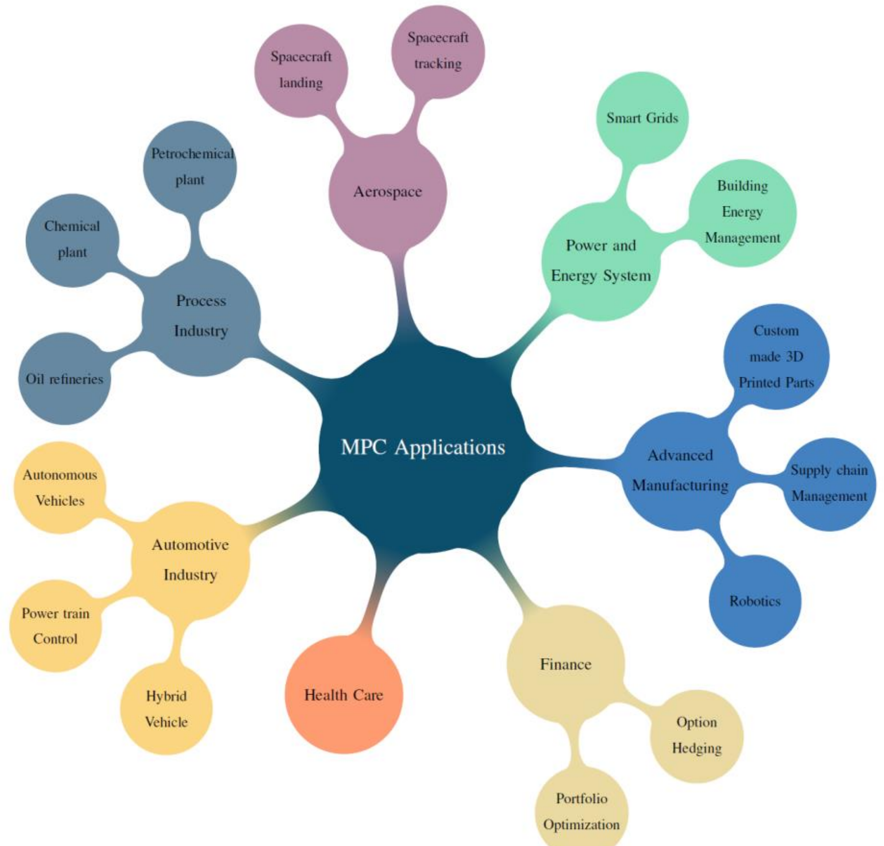
MPC Impact

Control technology survey results ranked by industry impact

Rank and Technology	High-Impact Ratings	Low- or No-Impact Ratings
PID control	100%	0%
Model predictive control	78%	9%
System identification	61%	9%
Process data analytics	61%	17%
Soft sensing	52%	22%
Fault detection and identification	50%	18%
Decentralized and/or coordinated control	48%	30%
Intelligent control	35%	30%
Discrete-event systems	23%	32%
Nonlinear control	22%	35%
Adaptive control	17%	43%
Robust control	13%	43%
Hybrid dynamical systems	13%	43%

Source: T. Samad. A survey on industry impact and challenges thereof, IEEE Control Systems Magazine, 2017.

1970 – 1990	1991 – 2000	2001 – 2005	2006 – 2010	2011 - 2021
- Developing MPC theory - Implementing MPC in the petrochemical and process industry	- Nonlinear MPC - Robust MPC	- Hybrid MPC - Distributed MPC - Stochastic MPC - Explicit MPC	- Economic MPC - Fast MPC (Online optimization)	- Real-time nonlinear/ nonconvex MPC



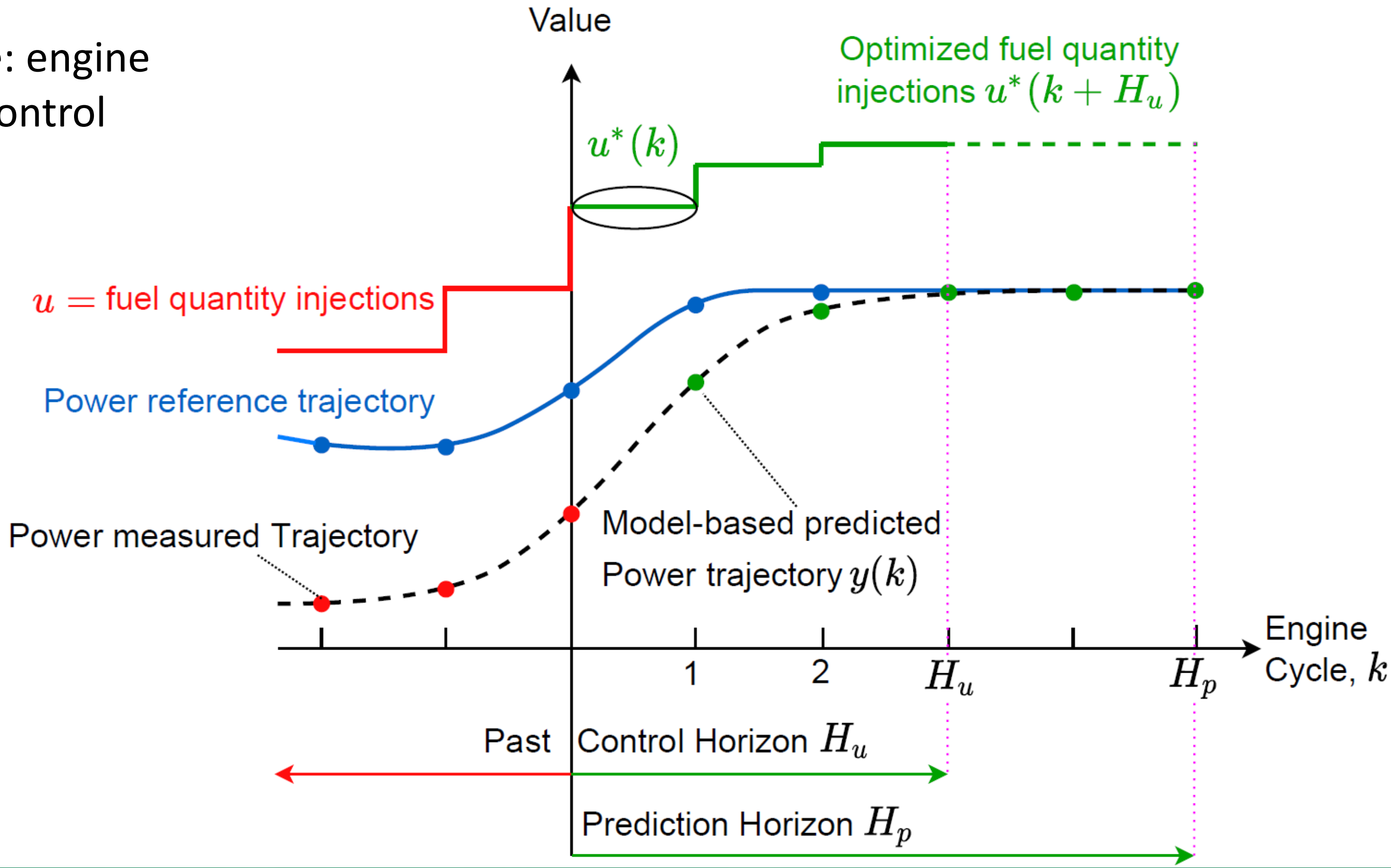
MPC Benefits

- Implicitly considers constraints on state, input and output variables;
- Provides closed loop control performance and stability for the optimal problem with constraints;
- Exploits the use of a future horizon while optimizing the current control law;
- Possibility of both offline and real-time implementation;
- Flexible to handling of delays, and non-linearity in the model.

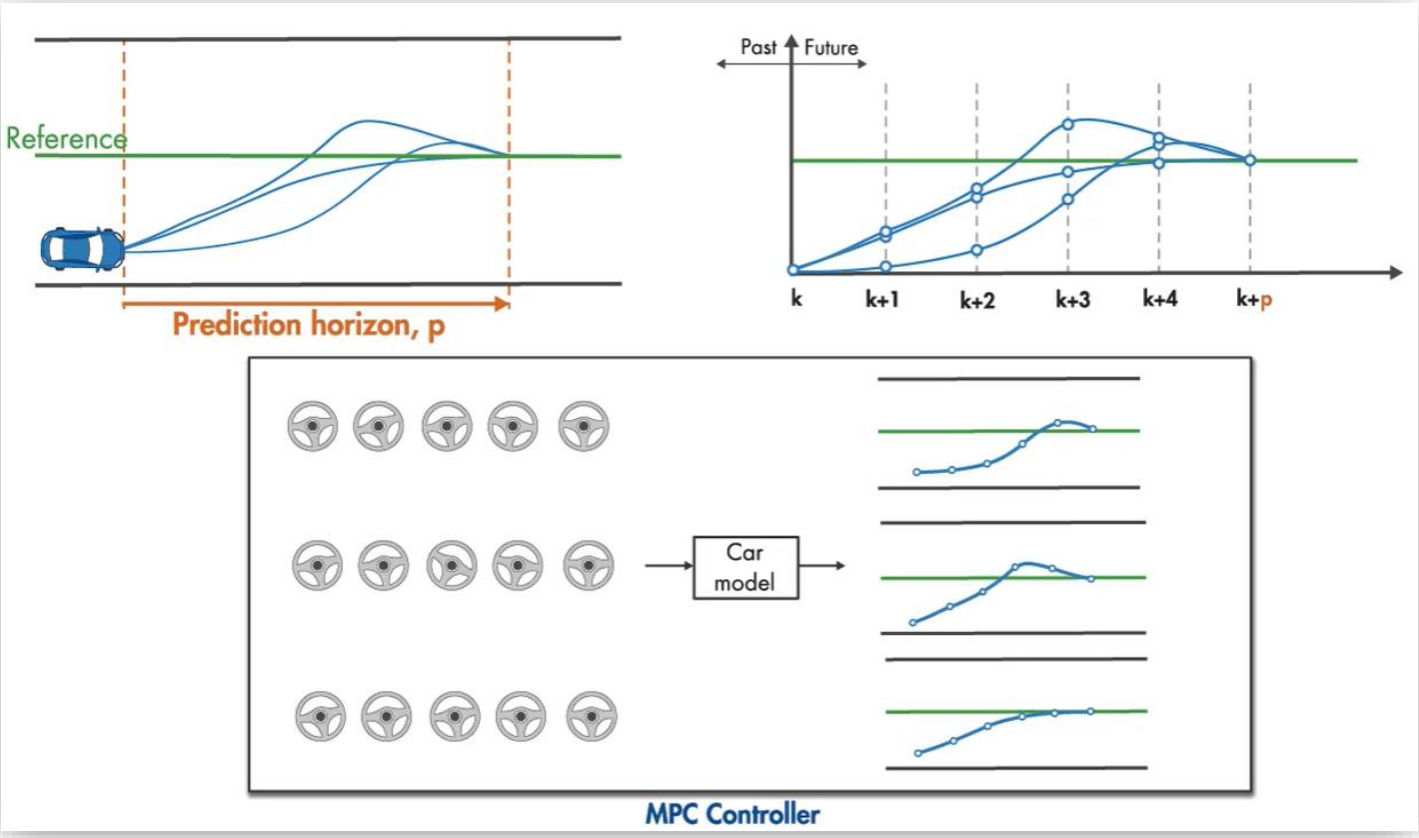
MPC Concept

Control horizon and prediction receding horizon

Example: engine power control



Concept Illustration



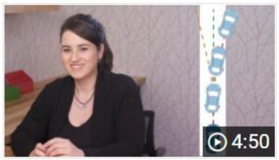
https://www.mathworks.com/videos/understanding-model-predictive-control-part-2-what-is-mpc--1528106359076.html

Interesting Videos

MATLAB® Tech Talks

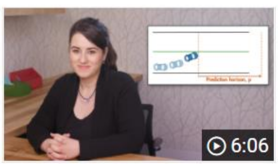
Taking you from learning to mastering

https://www.mathworks.com/videos/series/understanding-model-predictive-control.html



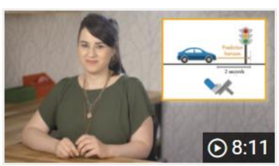
Part 1: Why Use MPC?

Learn about model predictive control (MPC). MPC han
input-output interactions, deals with constraints, has p
used in industries such as auto and aero.



Part 2: What Is MPC?

Learn how model predictive control (MPC) works. MP
make predictions about future plant outputs. It solves
each time step to find the optimal control action that
output to the desired reference as close as possible.



Part 3: MPC Design Parameters

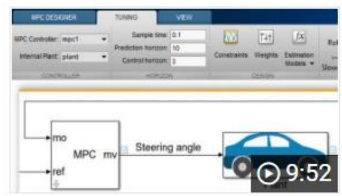
To successfully control a system using MPC, you need
parameters. Learn how to select the controller sample
horizons, and constraints and weights.

Part 4: Adaptive, Gain-Scheduled, and Nonlinear MPC

Learn about the type of MPC controller you can use ba
constraints, and cost function. Options include the line
gain-scheduled, and nonlinear MPC.

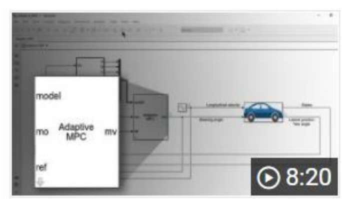
Part 5: How To Run MPC Faster

Learn which techniques you can u
methods, such as explicit MPC an
your applications with small samp



Part 6: How to Design an MPC Co
Control Toolbox

Learn how to design an MPC cont
using Model Predictive Control To



Part 7: Adaptive MPC Design with

Learn how to deal with changing p
uses an autonomous steering veh
controller's design.

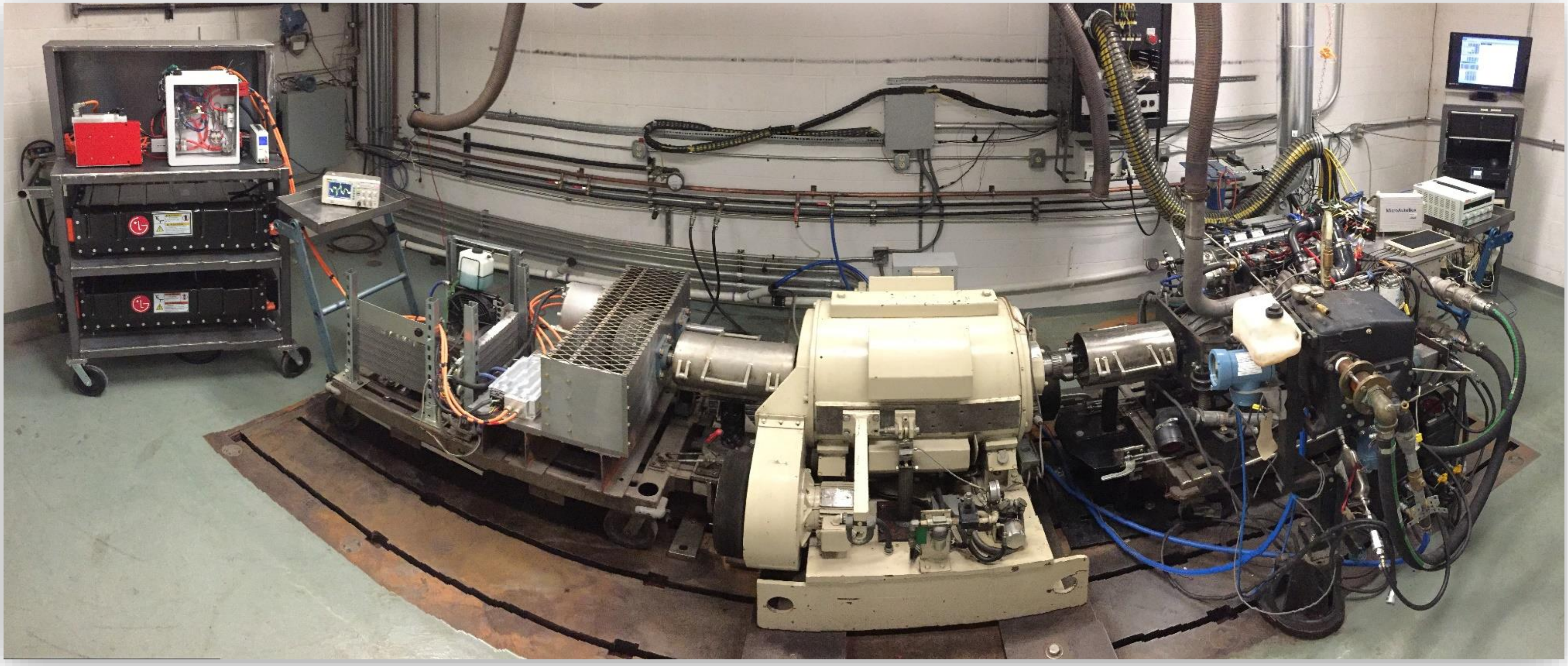
MPC Formulation

$$
\begin{aligned}
\min_{u_0,\ldots,u_{N-1}} \quad & \overbrace{J_f(x_N)}^{\text{Terminal cost}} + \overbrace{\sum_{k=0}^{N-1} J(x_k,\, y_k,\, r_k,\, u_k,\, s_k)}^{\text{Stage cost}} \\
\text{s.t.} \quad & x_{k+1} = f(x_k,\, u_k,\, d_k), \quad y_k = g(x_k,\, u_k,\, d_k) \quad k \in \mathbb{N}_0^{N-1} \\
& x_k \in \mathcal{X}, \quad u_k \in \mathcal{U} \quad k \in \mathbb{N}_0^{N-1} \\
& X_N \in \mathcal{X}_f \quad x_0 = x(t)
\end{aligned}
$$

- *x, y, u, r, s, d* are states, outputs, inputs, references, slack variables, disturbances;
- N is the prediction horizon;
- *J, f , g*, are the cost function, state function, output function;
- *X, U*, and X_f are state constraint set, input constraint set, and terminal state constraint set.

MPC Example: HEV

<u>Plant</u>: Multi-Mode Powertrain for a Hybrid Electric Vehicle (HEV)



MPC Example: HEV

MPC Structure

Cost Function:

$$J(u(t)) = \int_0^T (\dot{m}_f(P_{bat}, t) + \Gamma.F_{p1} + \Lambda.m_{ij} + \Psi.F_{p2})dt$$

Engine ON/OFF Penalty

Mode-Switching Penalty

Gear-Shifting Penalty

Hard Constraints:

$$|SOC_f - SOC_0| \leqslant 0.01$$

$$0.3 \leqslant SOC(t) \leqslant 0.7$$

$$P_{bat,min} \leqslant P_{bat}(t) \leqslant P_{bat,max}$$

$$P_{eng,min}(\omega_{eng}) \leqslant P_{eng}(t, \omega_{eng}) \leqslant P_{eng,max}(\omega_{eng})$$

$$\omega_{eng,min} \leqslant \omega_{eng}(t) \leqslant \omega_{eng,max}$$

$$0 \leqslant P_{motor}(t) \leqslant 100\ kW$$

$$0 \leqslant \omega_{motor}(t) \leqslant 8000\ RPM$$

$$Temp_{\ exh}\ (\omega_{eng,min}, T_{eng,min}) \geqslant 300\ ^{\circ}C$$

$$\omega_{eng} \leqslant \quad 1500 \quad rpm \qquad , if \ \ V_{veh} \leqslant 40 km/h$$

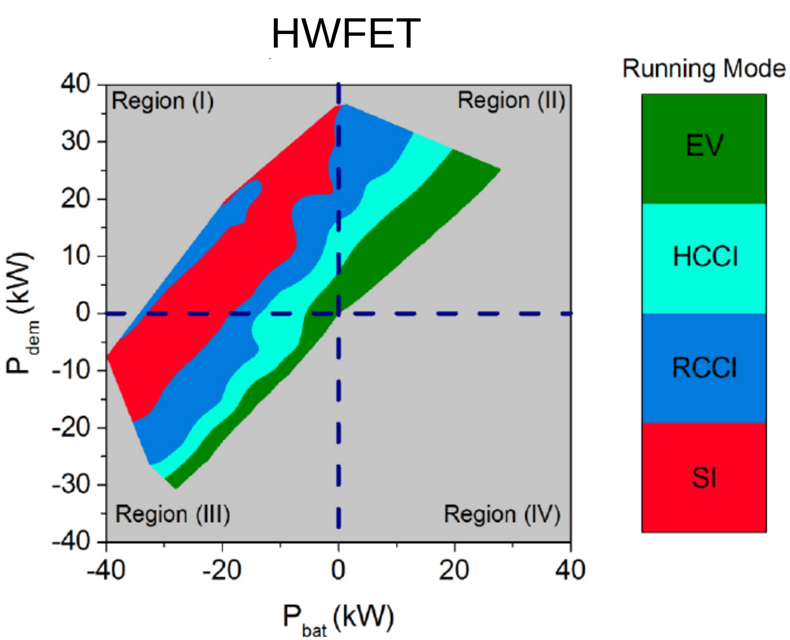
Catalyst light-off constraint

NVH constraint

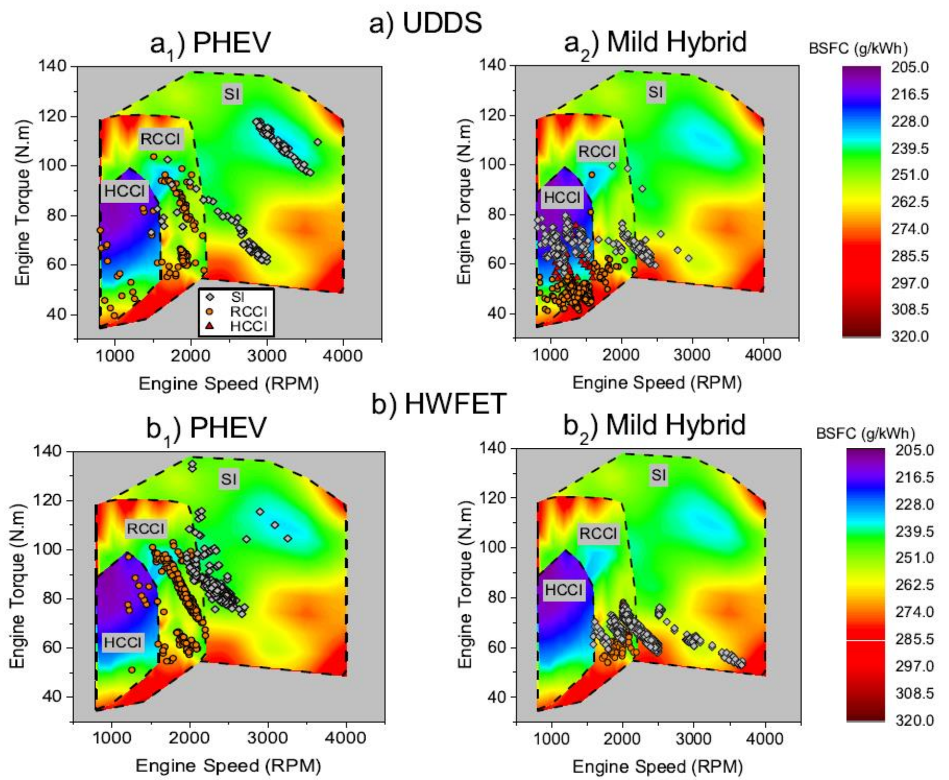
Source: A. Solouk, M. Shahbakhti, et. al., *Energy Conversion and Management, 2018.*

MPC Example: HEV

Results: Optimal Operating Mode during Vehicle Drive Cycles



Source: A. Solouk, M. Shahbakhti, et. al., *SAE Int. J. of Alternative Powertrains, 2017.*



Source: A. Solouk, M. Shahbakhti, et. al., *Energy Conversion and Management, 2018.*

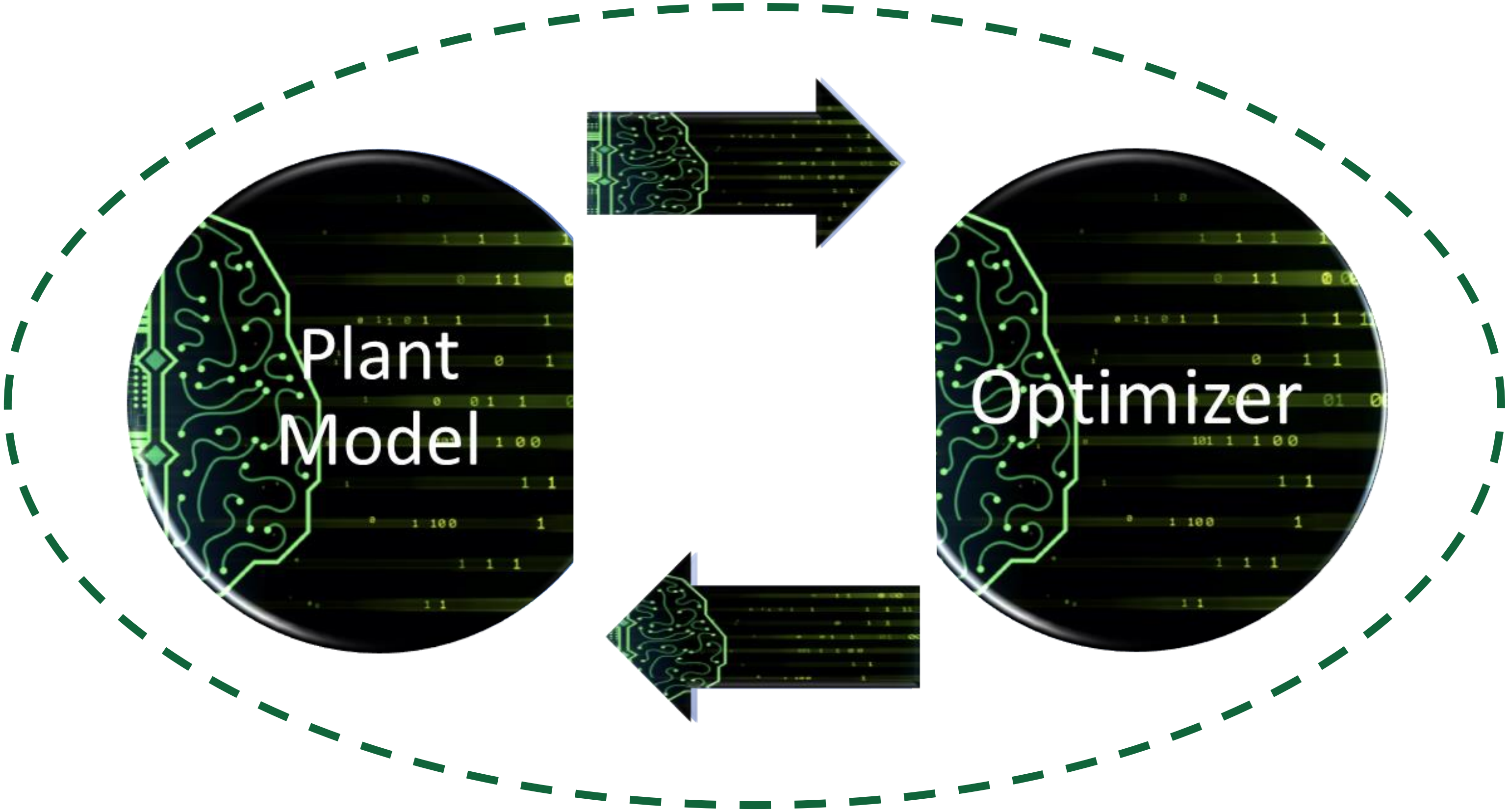
MPC Challenges

Limitations

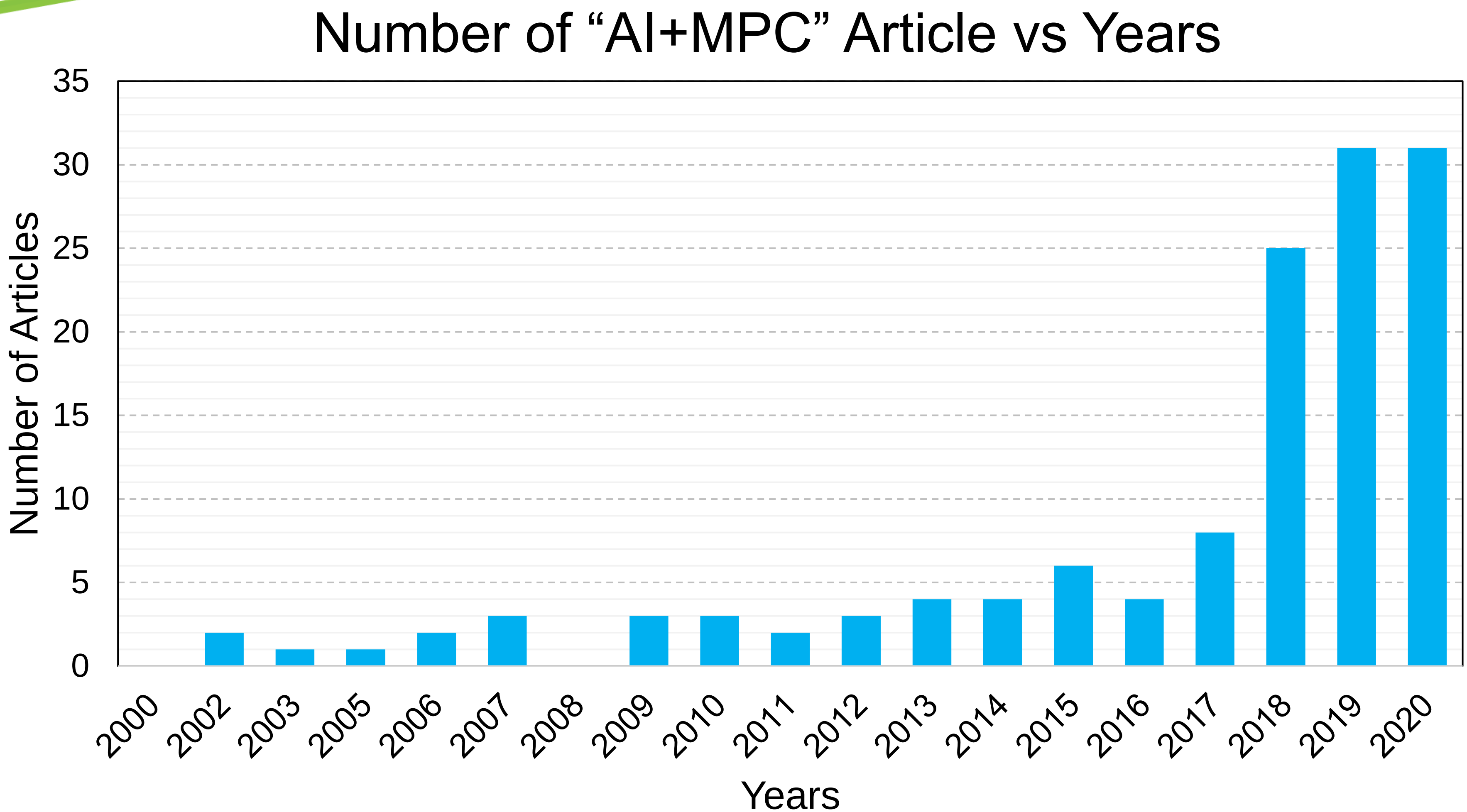
- It is difficult and time consuming to develop proper accurate enough and “scalable” control oriented plant models for MPC;
- MPC performance is sensitive to plant and disturbance model uncertainties; robust MPC leads to conservative and less optimal operation;
- High computational cost and sometimes infeasibility of real-time operation on an economic microcontroller for control of systems with fast dynamics (e.g., μs to ms);
- Process of tuning the weights (e.g. in the cost function) in MPC structure,…. can be time consuming and not fully optimal.

Machine learning can help to improve MPC performance in all these aspects!

MPC & ML Integration



Trend in Literature



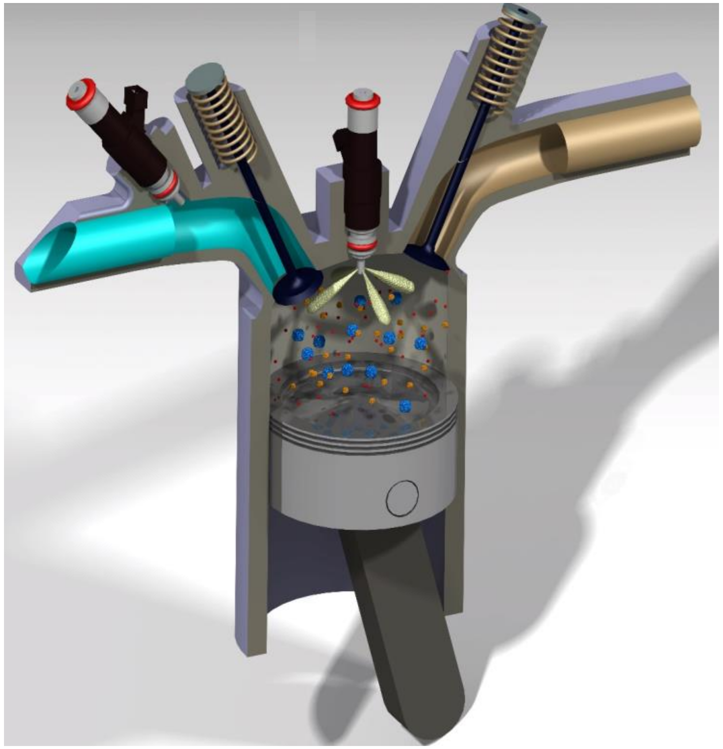
Trend in Literature

- Process control → **linear** MPC (some **nonlinear** too) — 1970-2000
- Automotive control → **explicit**, **hybrid** MPC — 2001-2010
- Aerospace systems and UAVs → **linear time-varying** MPC — >2005
- Information and Communication Technologies (ICT) (wireless nets, cloud) → **distributed/decentralized** MPC — >2005
- Energy, finance, automotive, water → **stochastic** MPC — >2010
- Industrial production → **embedded optimization** solvers for MPC — >2010
- Machine learning → **data-driven** MPC — today

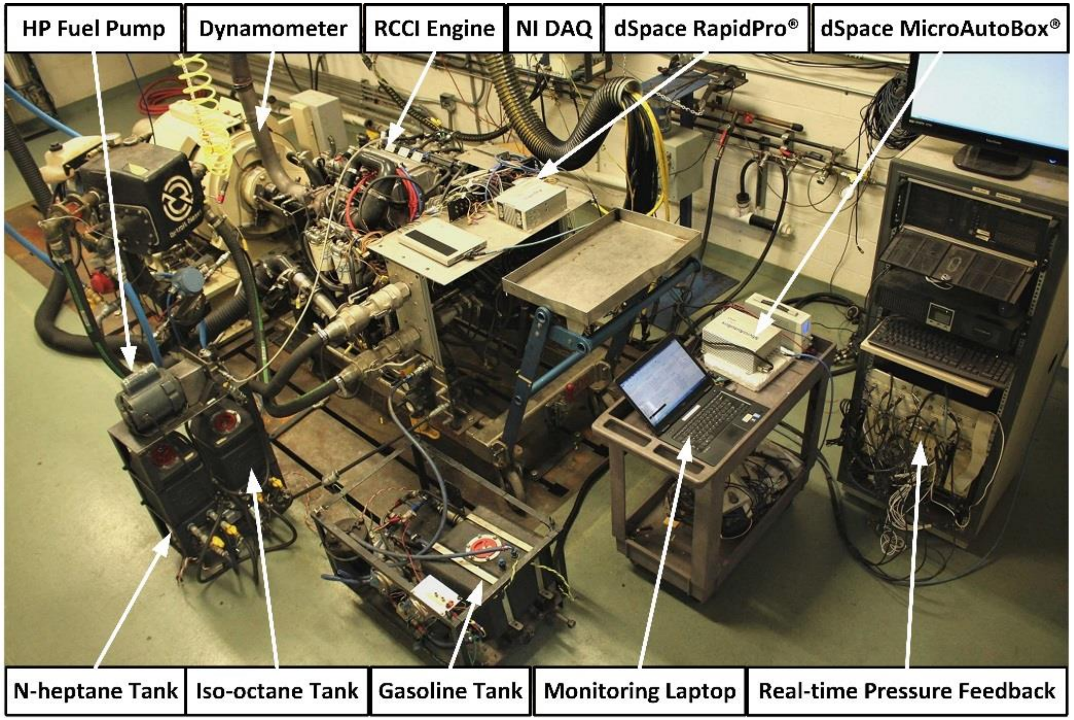
Source: http://cse.lab.imtlucca.it/~bemporad/teaching/mpc/imt/1-linear_mpc.pdf

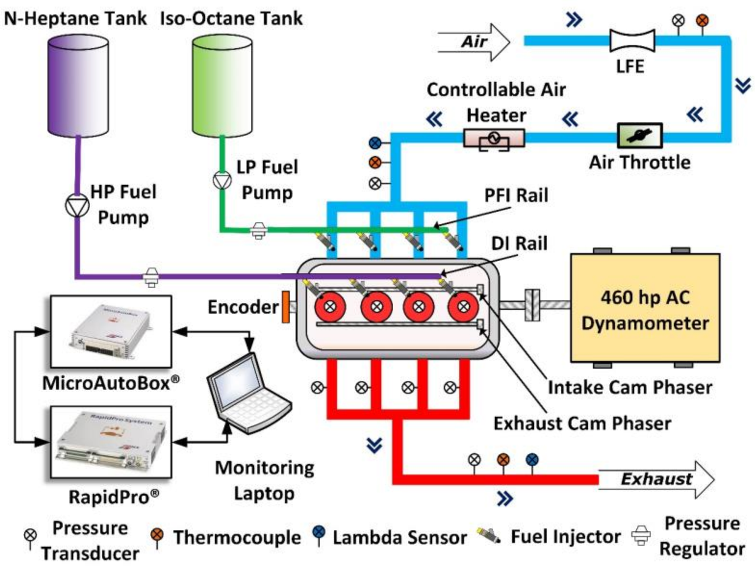
MPC example with ML-based plant model

Let's see an example: Model predictive combustion phasing control in an advanced dual fuel engine



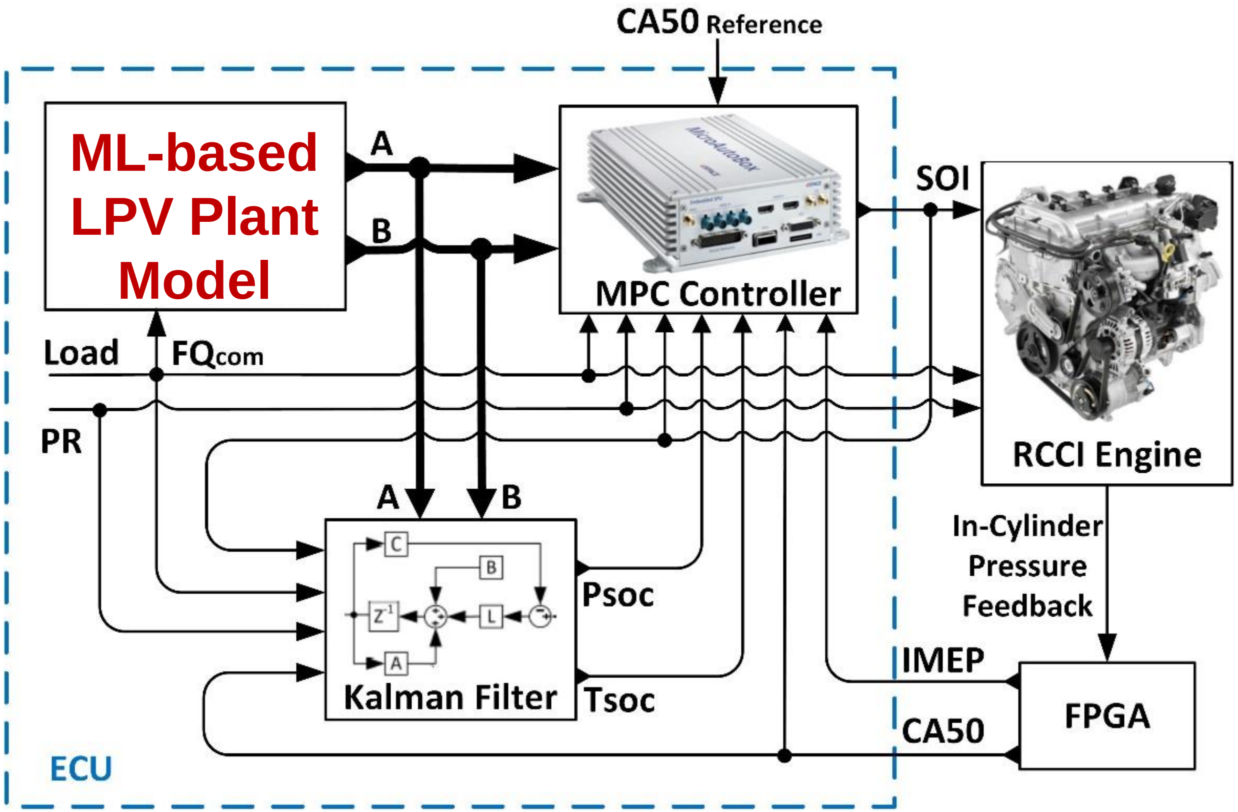
Engine Experimental Setup





MPC example with offline ML-based plant model

MPC Design using ML-based Linear Parameter Varying (LPV) Combustion Model

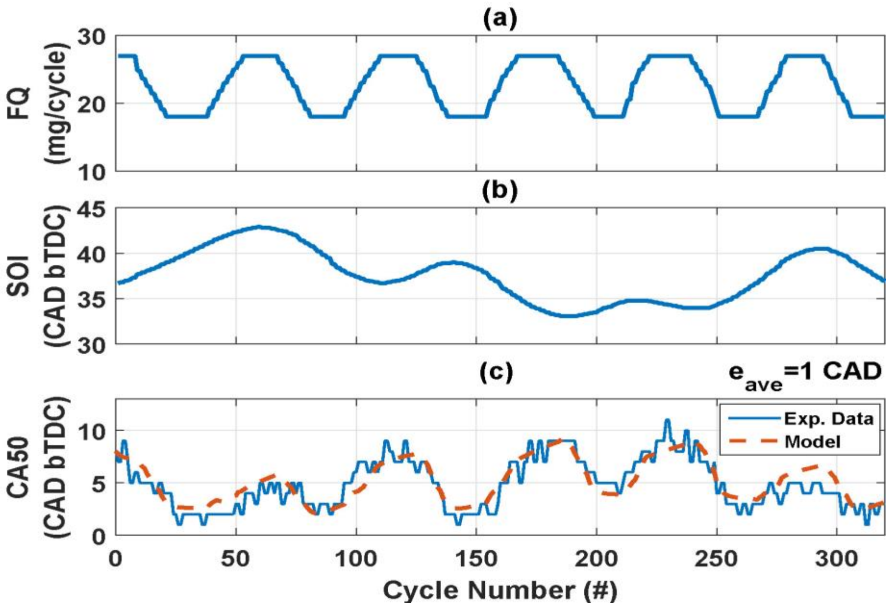


Source: B. Khoshbakht, M. Shahbakhti, et. al." Data-driven Modeling and Predictive Control of Combustion Phasing for RCCI Engines," American Control Conference, 2019.

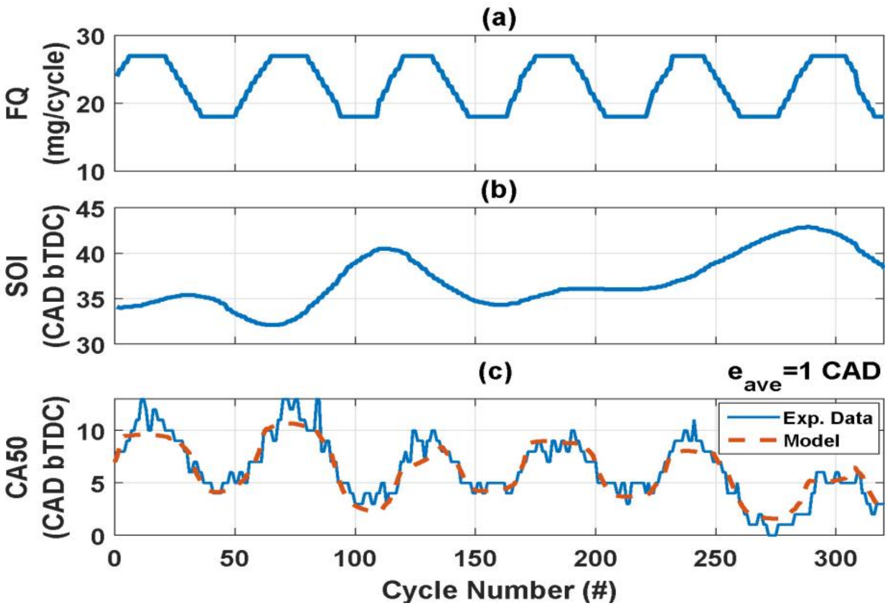
MPC example with offline ML-based plant model

LPV State Space Model Validation (sample results)

PRF20



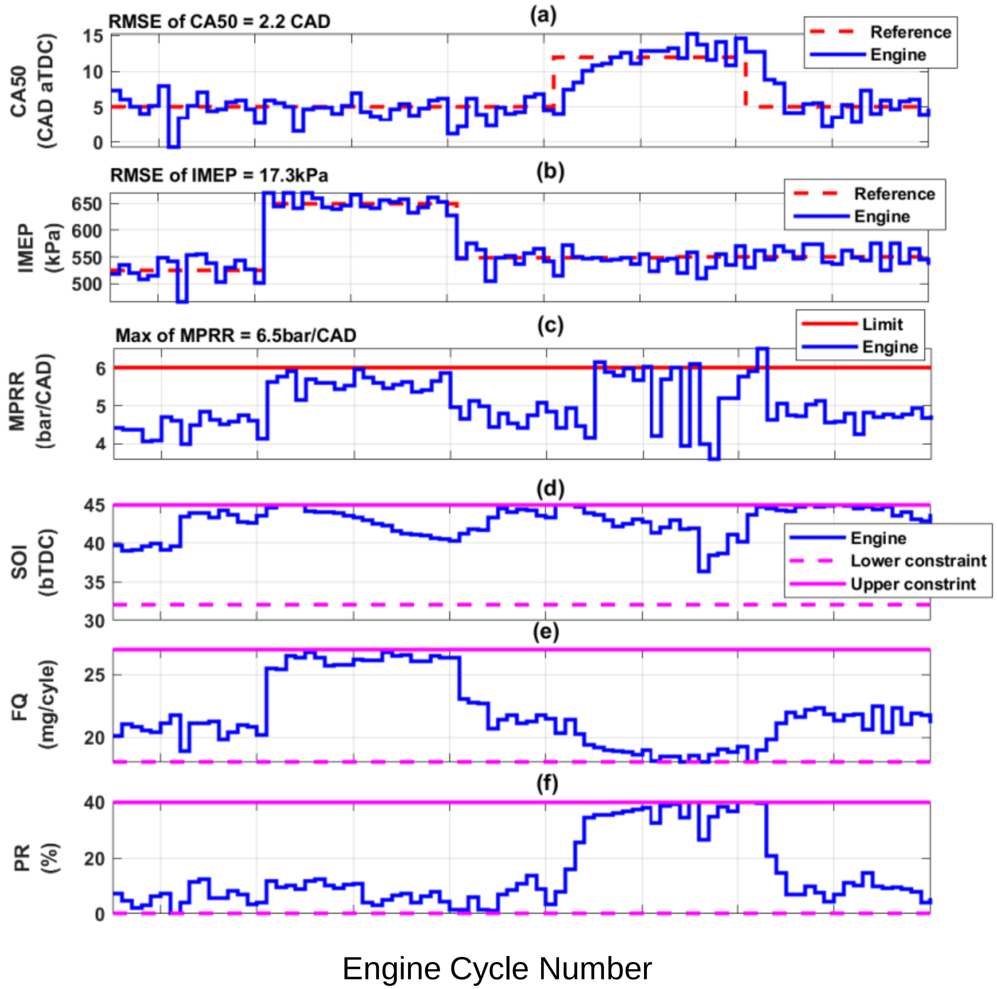
PRF40



FQ: Fuel Quantity, SOI: Start of Injection, CA50: combustion phasing, PRF: premixed ratio of two fuels

MPC example with offline ML-based plant model

Sample MIMO Control Results



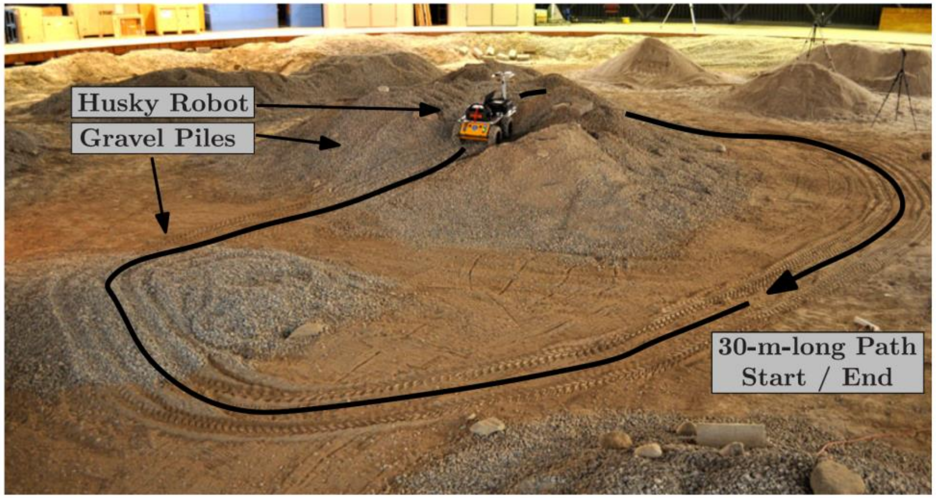
Source:
R. Sitaraman, M. Shahbakhti, et al, 2022 MECC

CA50: combustion phasing, IMEP: Indicated Mean Effective Pressure, MPRR: Maximum Pressure Rise Rate, PR: Premixed Ratio of two fuels, FQ: Fuel Quantity, SOI: Start of Injection

MPC example with <u>online</u>
ML-based plant model

Example: Learning-based Nonlinear Model Predictive Control to Improve Vision-based Mobile Robot Path Tracking

Goal: Autonomous guidance, and control of three different mobile robots under "different paths with dirt, gravel, sand, grass, inclines, and side slopes".



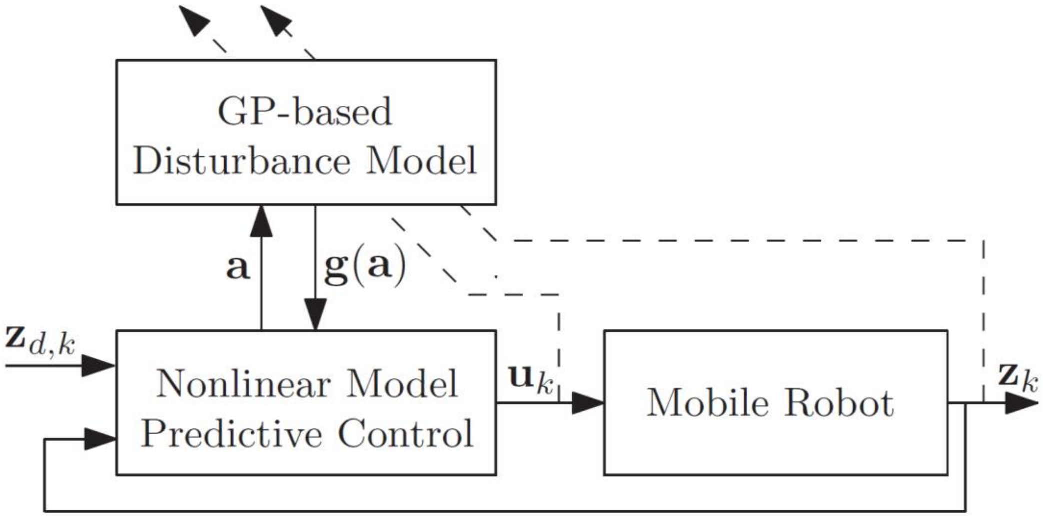
Source: C.J. Ostafew, et al, Journal of Field Robotics 33(1), 33–152 (2016)

MPC example with online ML-based plant model

The disturbance model learns kinematics and dynamics of a significantly different mass and robot design:

$$\mathbf{z}_{k+1} = \overbrace{\mathbf{f}(\mathbf{z}_k, \mathbf{u}_k)}^{a\ priori\ \text{model}} + \overbrace{\mathbf{g}(\mathbf{z}_k, \mathbf{u}_k)}^{\text{learned disturbance model}}.$$

Model disturbances as a Gaussian process based on input-output data from previous trials.



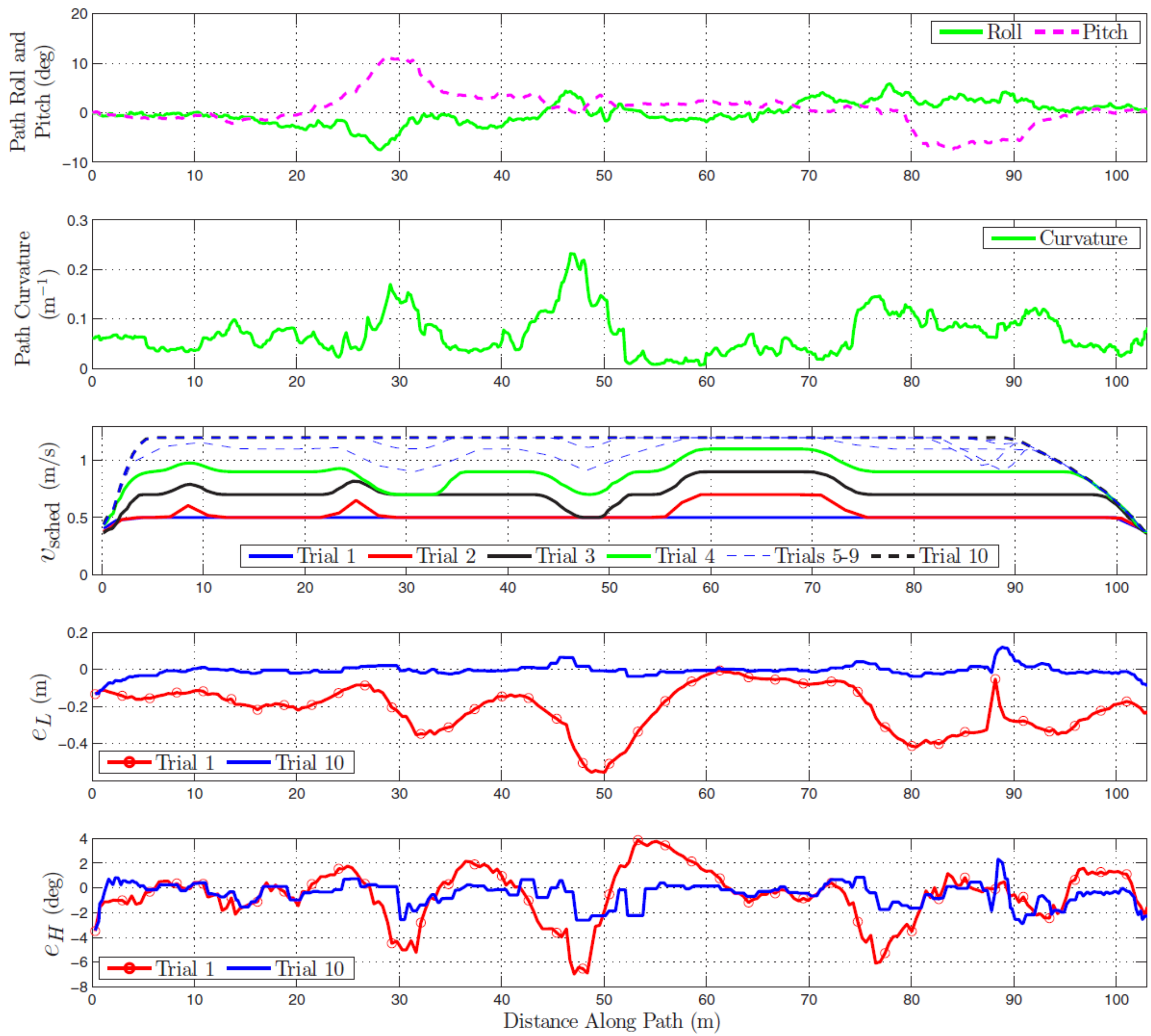
NMPC Cost function:

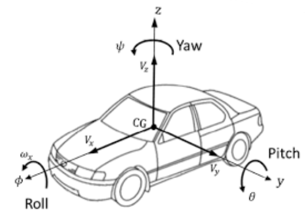
$$J(\mathbf{u}) = (\mathbf{z}_d - \mathbf{z})^T \mathbf{Q}\,(\mathbf{z}_d - \mathbf{z}) + \mathbf{u}^T \mathbf{R}\,\mathbf{u}$$

$\mathbf{u}$ is a sequence of control inputs, ***zd*** is a sequence of desired states, $\mathbf{z}$ is a sequence of predicted states

Source: C.J. Ostafew, et al, Journal of Field Robotics 33(1), 33–152 (2016)

MPC example with online ML-based plant model





M. Kissai, et al, Machines, 2019

Source: C.J. Ostafew, et al, Journal of Field Robotics 33(1), 33–152 (2016)