Machine Learning-Based Diesel Engine-Out Emissions Model and Control Using the Learning-Based Control Technique

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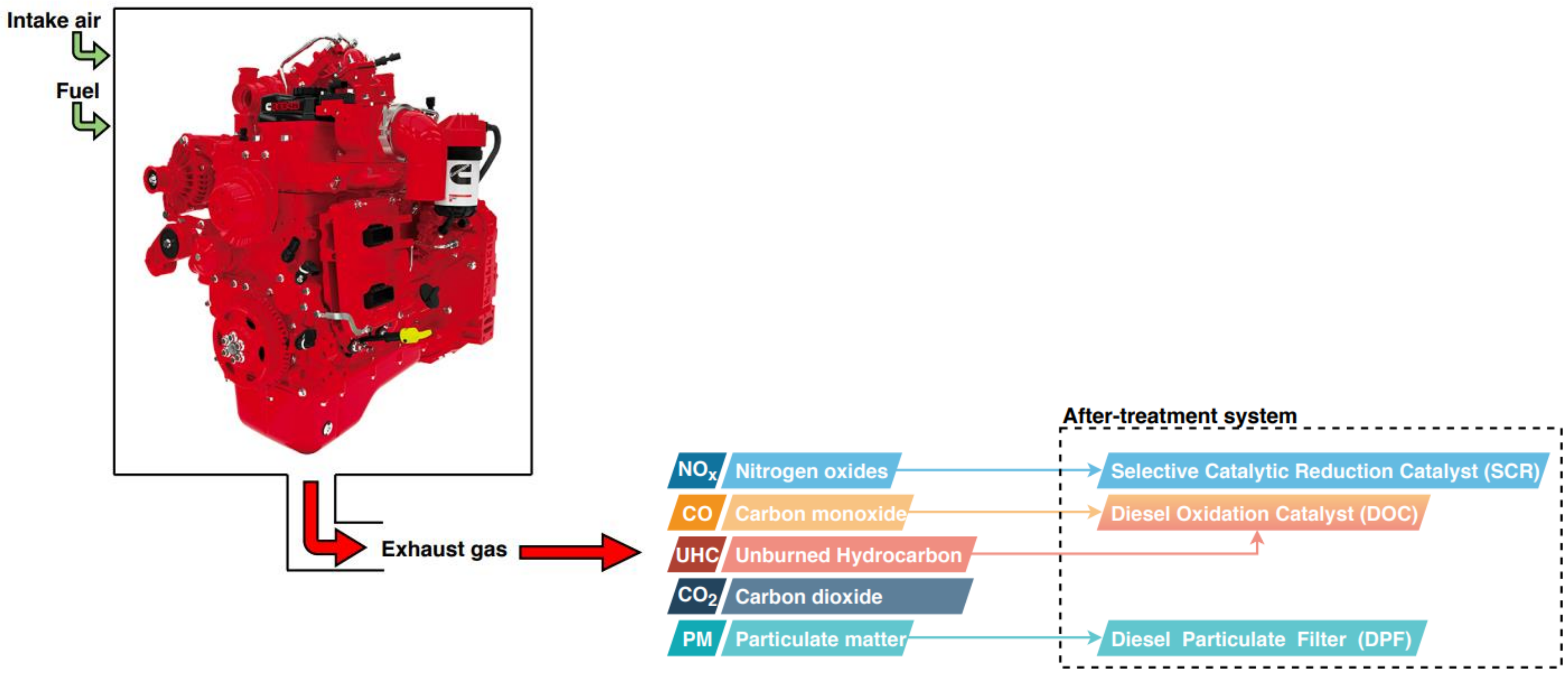
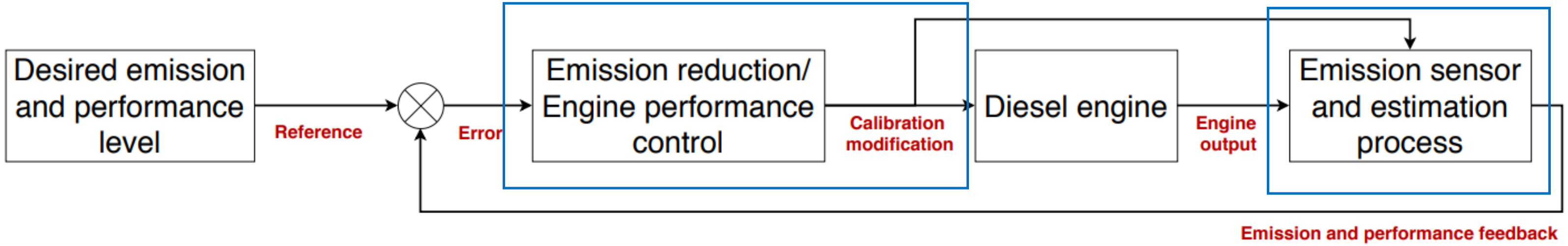
Motivation - Diesel engine-out emission



Motivation - Emission control using feedback control

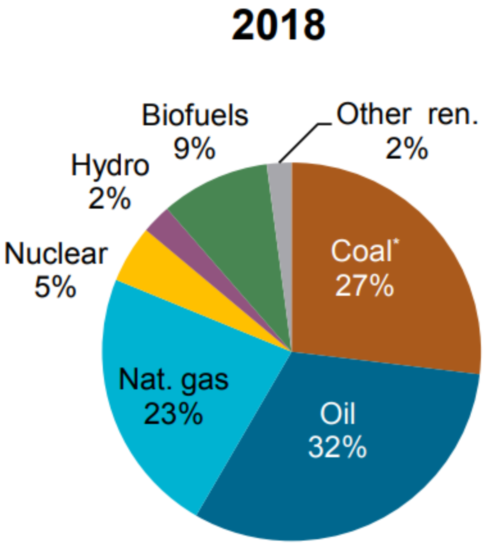
Benefits of using engine-out emission feedback: [1]

- Modify calibration in the real driving cycle to meet real driving cycle emission standard
- Decrease the effort of engine calibration
- Emission reduction besides using the after-treatment systems

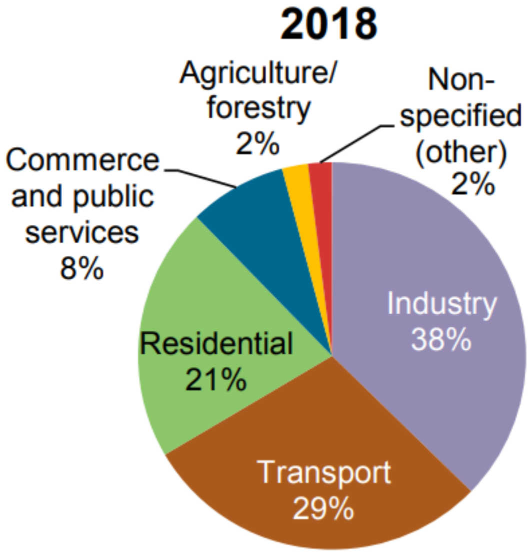


[1] Frédéri Tschanz et al, "Feedback control of particulate matter and nitrogen oxide emissions indiesel engines" *Control engineering practice*, 2013.

Motivation - world energy usage



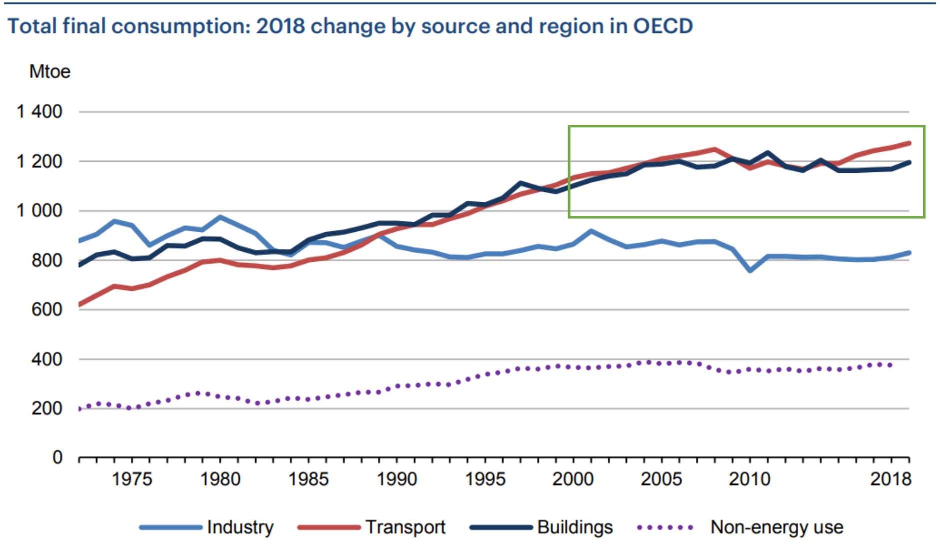
Total energy supply by fuel[2]



World total final consumption by sector[2]

[2] IEA (2020), *World Energy Balances: Overview*, IEA, Paris

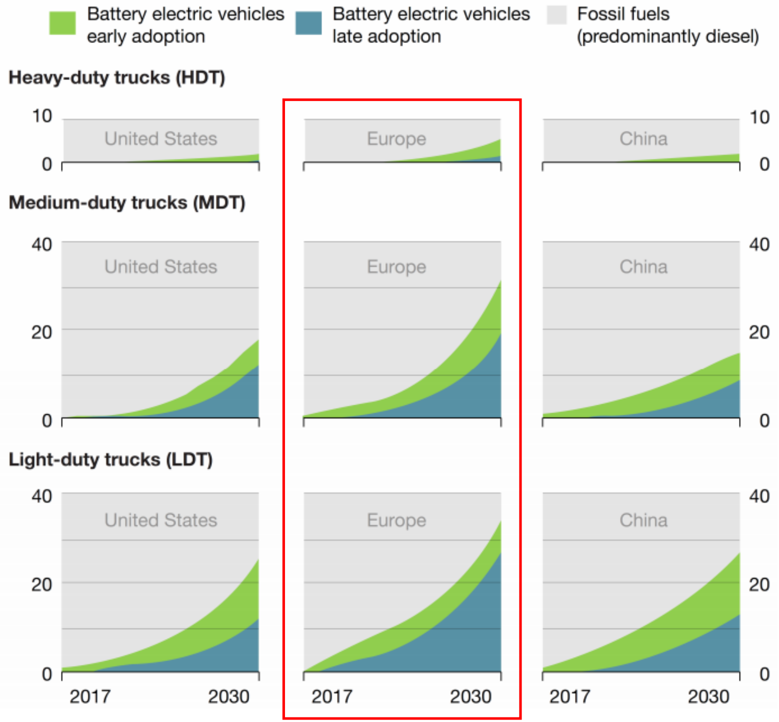
Motivation - world energy usage



Total final consumption: 2018 change by source and region in OECD (Organization for Economic Co-operation and Development)[2]

[2] IEA (2020), World Energy Balances: Overview, IEA, Paris

Motivation - Hybridization and electrification



Key points: [3]

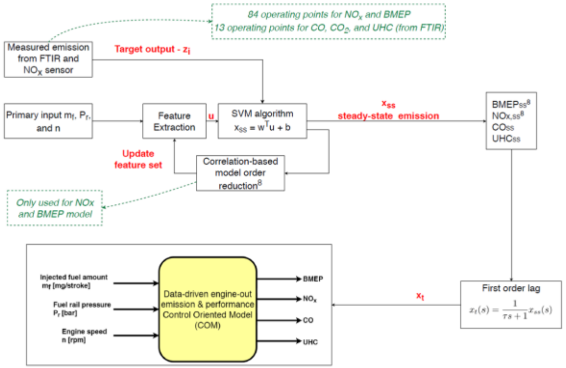
- In the best scenario, battery-electric commercial vehicles could reach (Europe):
  - 5% for heavy-duty truck
  - 31% for medium-duty truck (Europe)
  - 34% for light-duty truck
- Low uptake for heavy-duty trucks especially for US and China

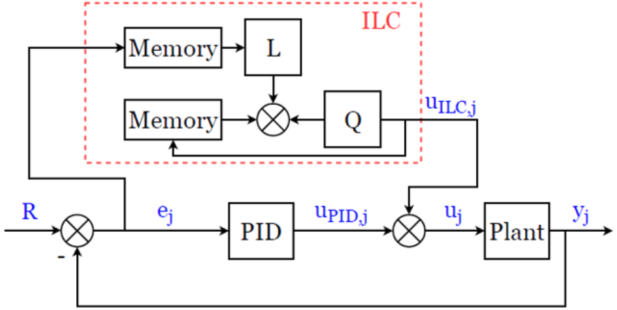
[3] Heid, Bernd, et al. "What's Sparking Electric-Vehicle Adoption in the Truck Industry?." McKinsey & Company, Sept. 2017.

Scope of the presentation

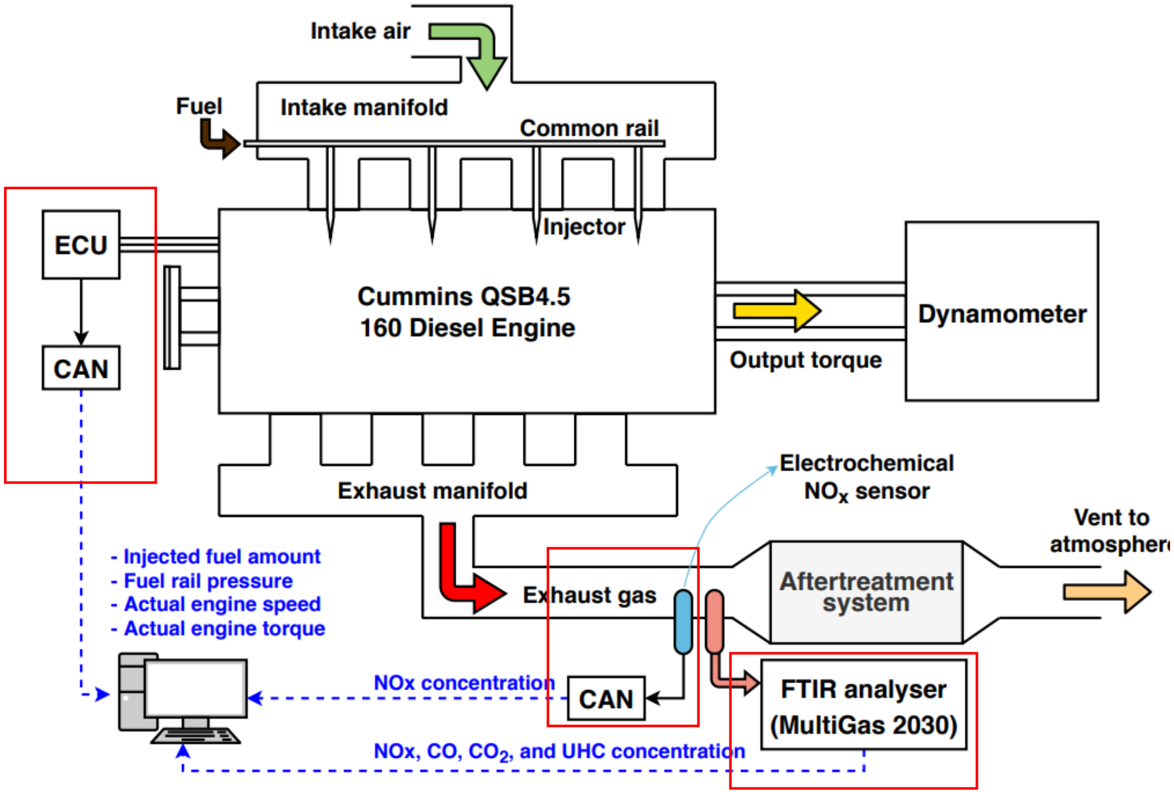
Part I: Model order reduction using Machine Learning to model emission

Part II: NOx reduction using learning-based controller

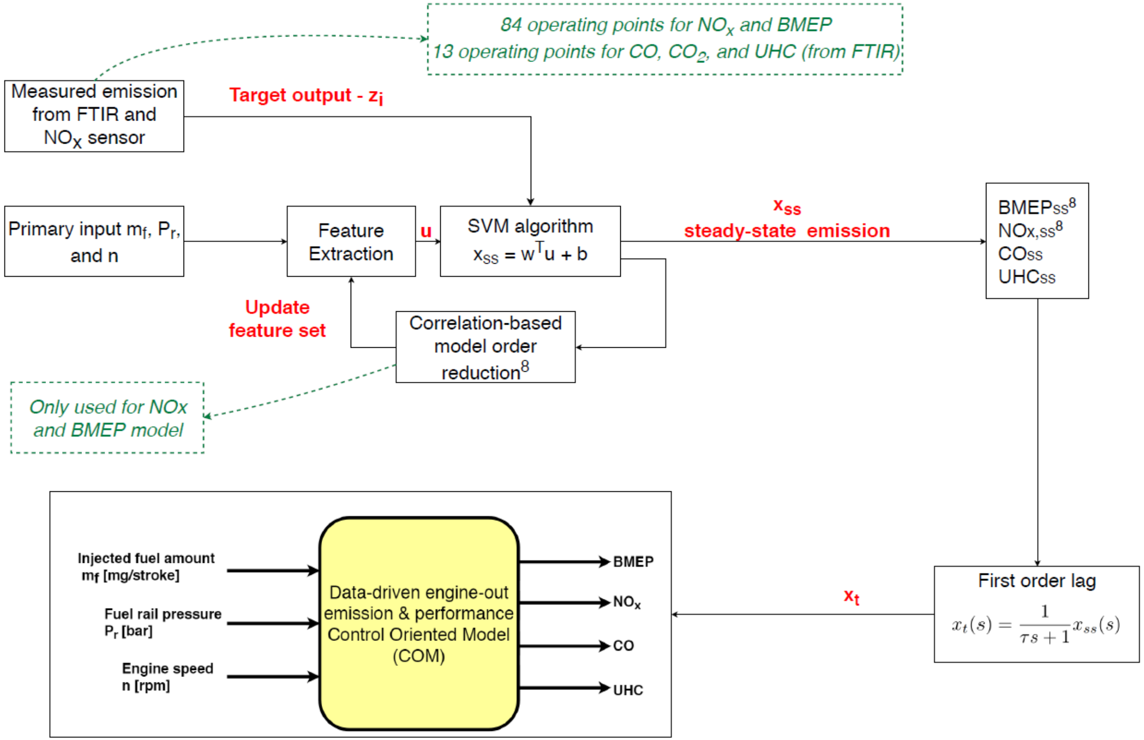




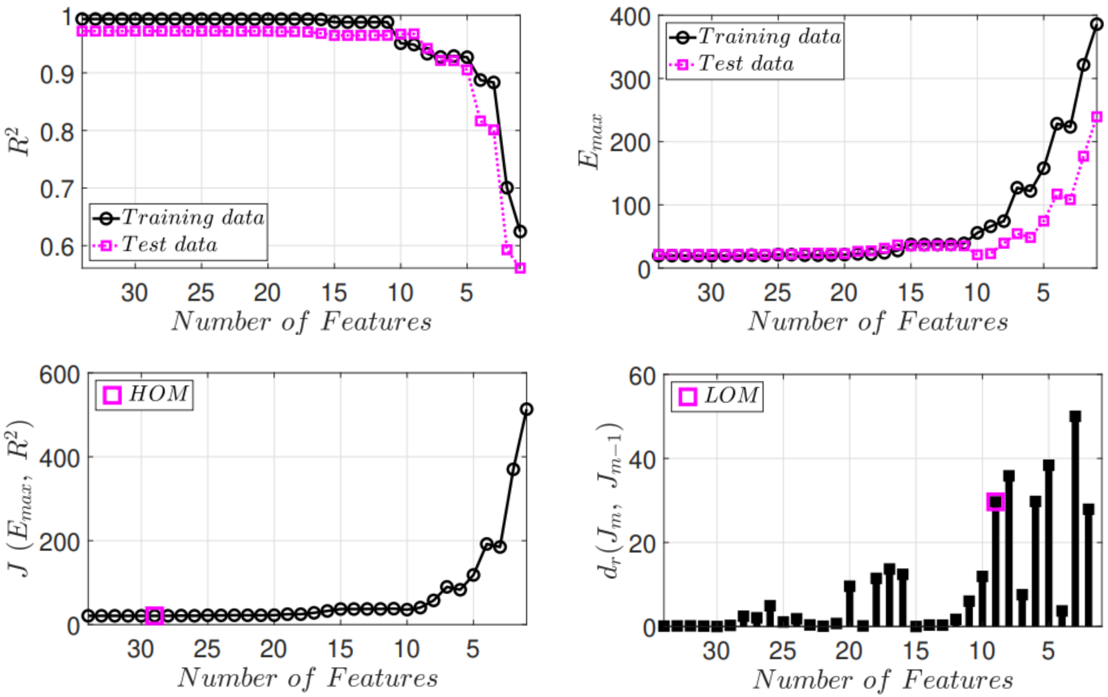
Part I: Diesel engine experimental setup



Part I: Modeling procedure based on SVM



Part I: Model order reduction: Steady-state NOx prediction



Maximum error (R^2), squared correlation coefficient (R^2), and cost function ($J(E_{max}, R^2)$) vs number of features

Part I: NOx model- FOM, HOM, and LOM- ANN vs SVM

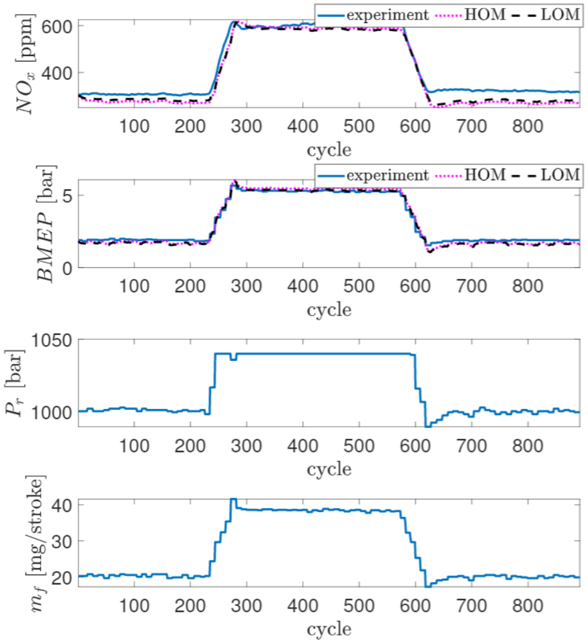
Performance of the NO_x full-order model (FOM), high-order model (HOM), and low-order model (LOM).

Model type	FOM		HOM		LOM	
Number of features	34		29		9	
Training method	SVM	ANN	SVM	ANN	SVM	ANN
$E_{max,tr}$(ppm)	19.6888	25.6473	19.5689	27.3405	66.02	57.9259
$E_{max,ts}$(ppm)	21.660	60.7375	21.6665	47.7841	22.91	60.2836
R^2_{tr}	0.9934	0.9969	0.9934	0.9837	0.9490	0.9891
R^2_{ts}	0.9725	0.9775	0.9725	0.9664	0.9677	0.9760
$J(E_{max}, R^2)$(ppm)	21.0106	39.9824	20.9490	37.0706	40.58	54.67
Training time (ms)	9.47	240.6	11.07	202.0	13.10	194.5

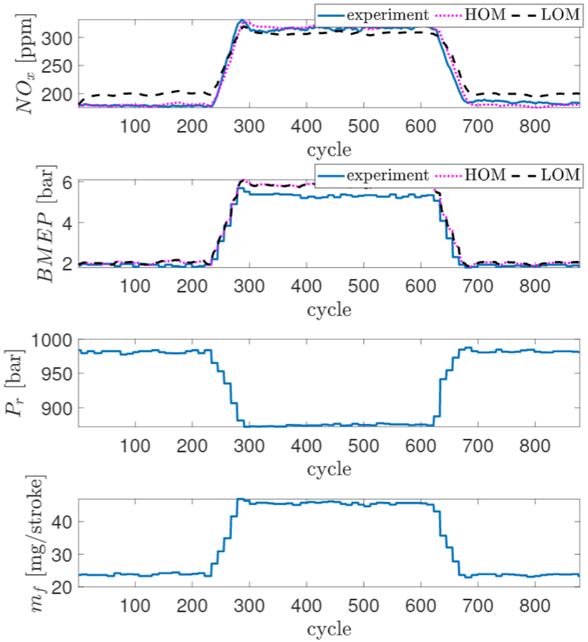
Performance of the BMEP full-order model (FOM), high-order model (HOM), and low-order model (LOM).

Model type	FOM		HOM		LOM	
Number of features	34		20		6	
Training method	SVM	ANN	SVM	ANN	SVM	ANN
$E_{max,tr}$(ppm)	0.3560	0.4006	0.3526	0.3859	0.810	0.5435
$E_{max,ts}$(ppm)	0.3513	0.4484	0.3477	0.4151	0.2998	0.4732
R^2_{tr}	0.9978	0.9987	0.9978	0.9953	0.9947	0.9961
R^2_{ts}	0.9957	0.9959	0.9957	0.9961	0.9962	0.996
$J(E_{max}, R^2)$(ppm)	0.3548	0.4250	0.3513	0.4020	0.4952	0.5091
Training time (ms)	35.9	199.8	9.2	218.0	9.5	214.7

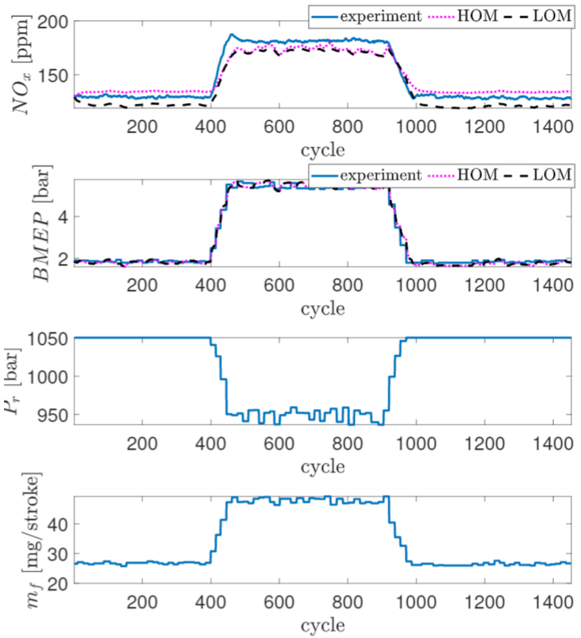
Part I: NOx and BMEP Control Oriented Model



Transient response at engine speed= 1250rpm

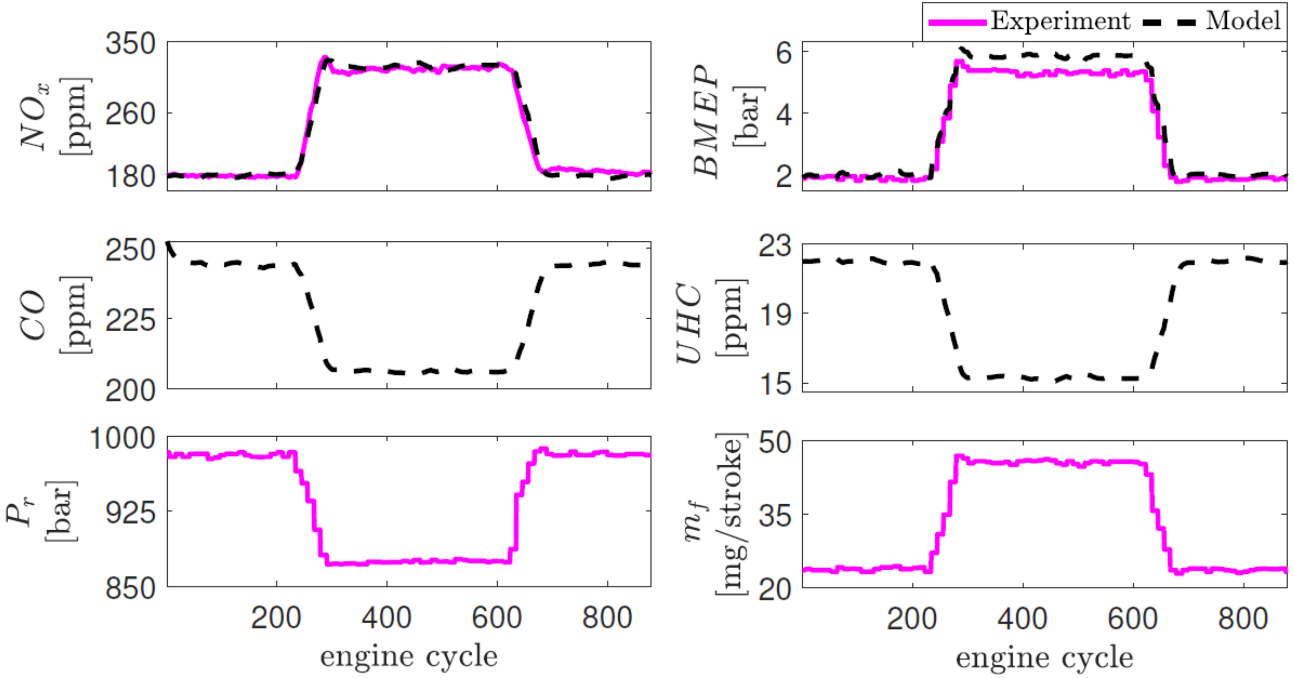


Transient response at engine speed= 1500rpm



Transient response at engine speed= 2000 rpm

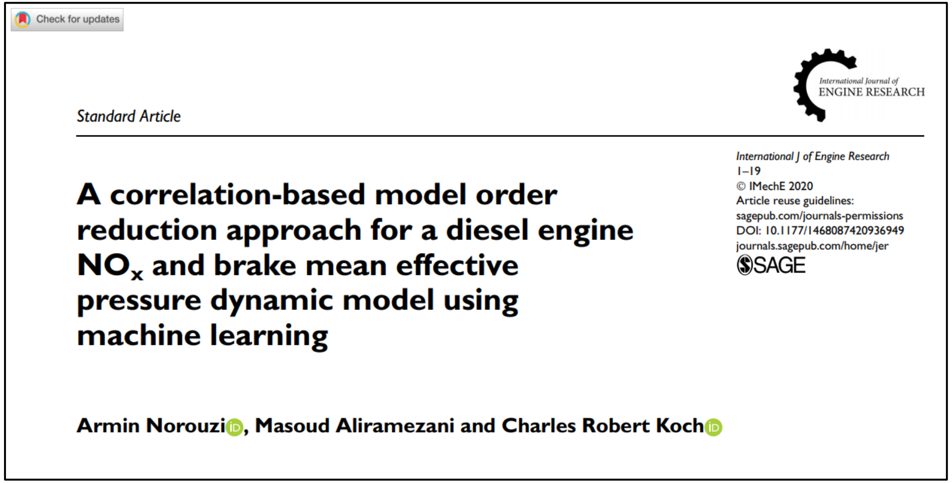
Part I: Emission and performance Control Oriented Model (COM)



Part I: summary

- Correlation-based model order reduction:
  - Two model for NOx and BMEP:
    - High accuracy of the high-order mode
    - Acceptable accuracy of low-order mode
    - NOx and BMEP models are valid for large range of operating points
- CO and HC model:
  - limited operation points
- Control oriented model:
  - BMEP, NOx, UHC and CO

Published article: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A correlation-based model order reduction approach for a diesel engine NO_x and brake mean effective pressure dynamic model using machine learning

Armin Norouzi, Masoud Aliramezani and Charles Robert Koch

Part II: learning-based controller

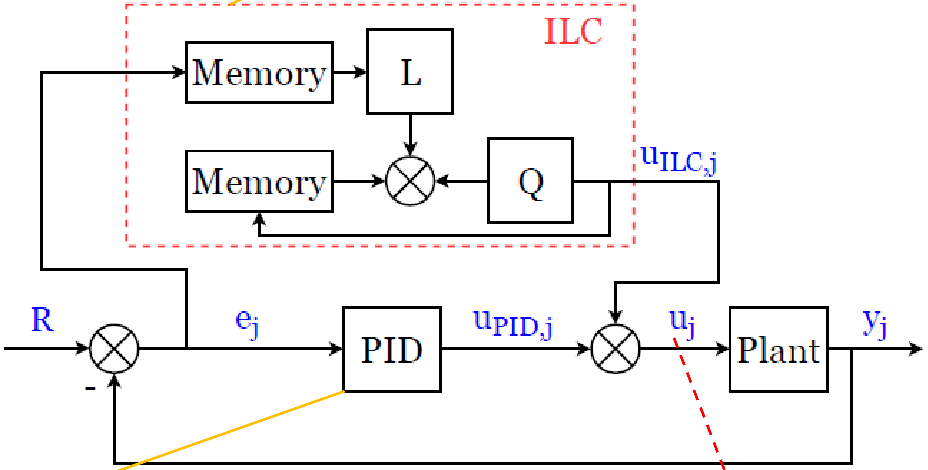
- Iterative Learning Control[4]:
  - ILC is used to improve the tracking performance of systems with repeated dynamics
  - ILC uses previous control inputs and errors to generate new control input:

- Key benefits[5]:
  - Model-free design
  - Simple structure
  - Add-on controller

[4] Owens, David H. "Iterative learning control: an optimization paradigm," *Springer* , 2015.
[5] Xu, Jian-Xin, et. al. "Real-time iterative learning control: design and applications." *Springer Science & Business Media*, 2008.

Part II: Plug-in Iterative Learning Controller with parallel structure

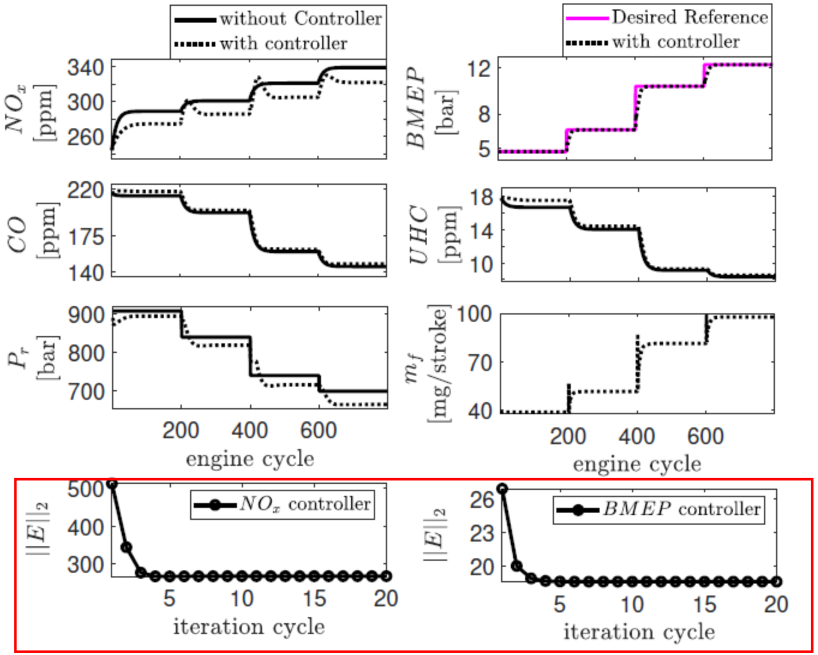
$$U_{j+1}(z) = U_j(z) + PE_j(z) + D\frac{1}{1-z^{-1}}E_j(z)$$



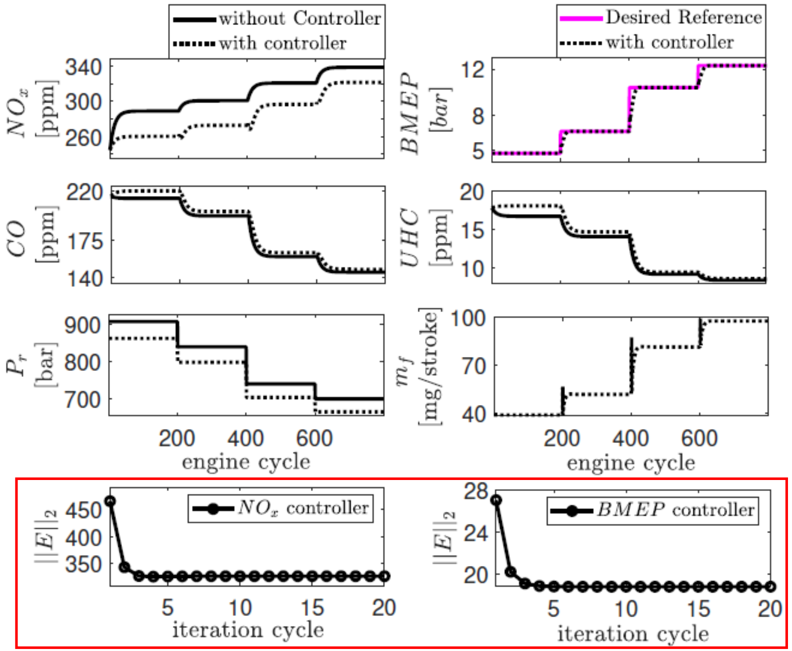
$$U_{c,j}(z) = (K_p + \frac{K_i}{1-z^{-1}} + K_d(1-z^{-1}))E_j(z)$$

$$U_j(z) = U_{ILC,j}(z) + U_{c,j}(z)$$

Part II: Plug-in ILC for NOx reduction and BMEP tracking (ILC+PID)

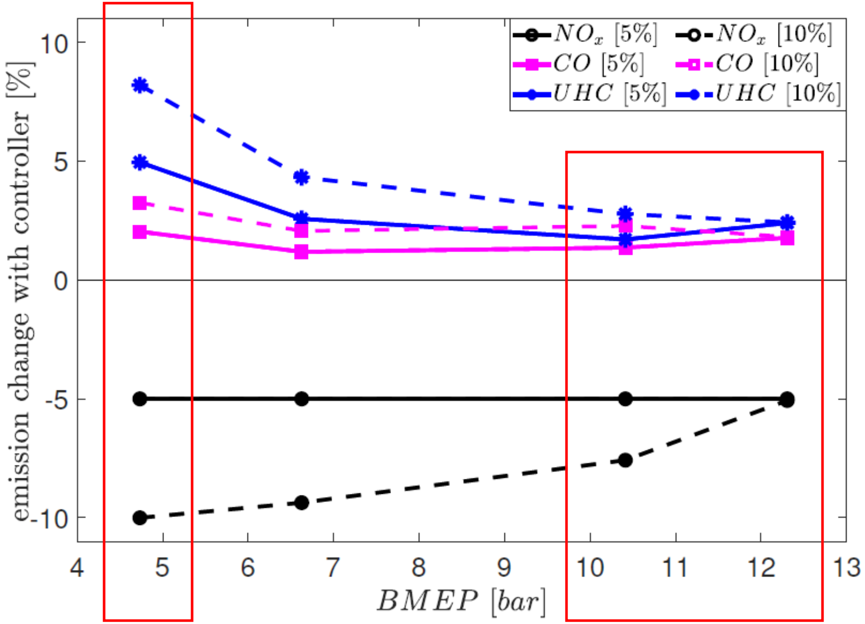


Target = 5 percent NO_x reduction



Target = 10 percent NO_x reduction

Part II: Plug-in ILC for NOx reduction and BMEP tracking- Results and Discussions



NO_x Reduction vs CO and UHC change in steady state for both 5 percent and 10 percent NO_x reduction goal

Part II: Summary

- Learning-based controller design,
- NOx reduction levels while maintaining the desired engine load,
- Advantage of considering UHC and CO in NOx reduction strategy.

Published article:

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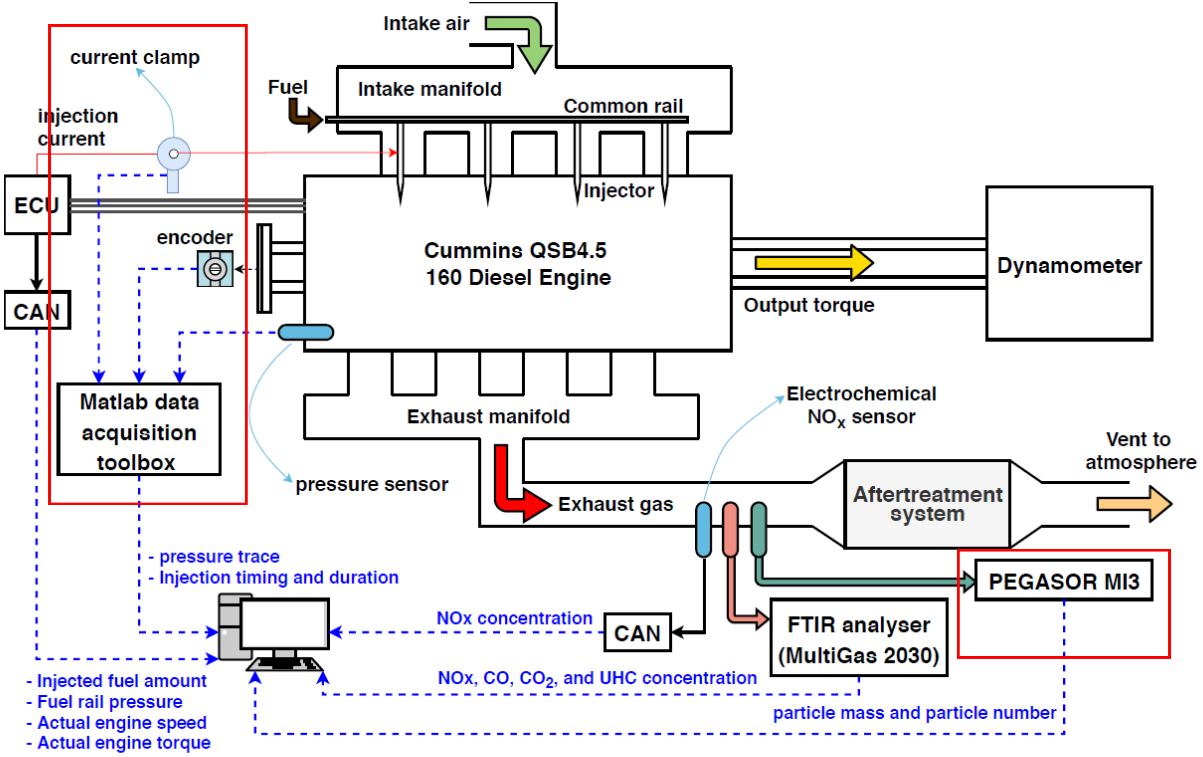
August 24-26, 2020. Montréal, Canada

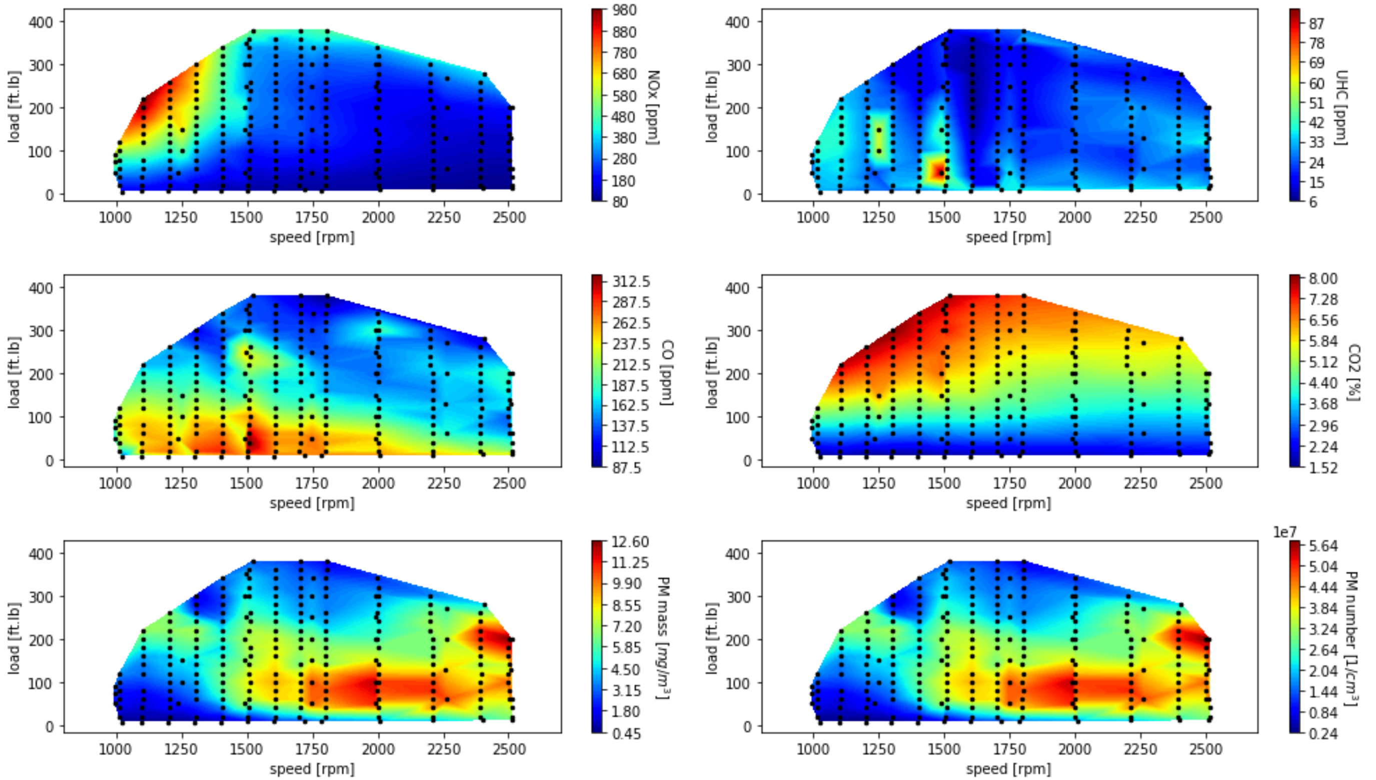
Machine Learning-based Diesel Engine-Out NOx Reduction Using a plug-in PD-type Iterative Learning Control

Armin Norouzi*, David Gordon*, Masoud Aliramezani*, Charles Robert Koch*

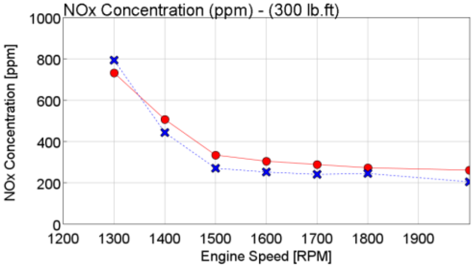
Future study- Updated experimental setup

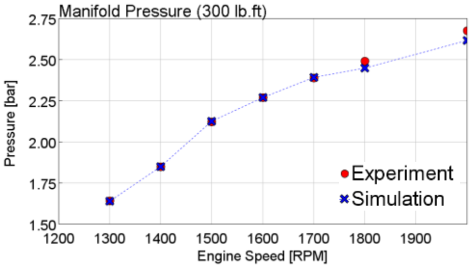


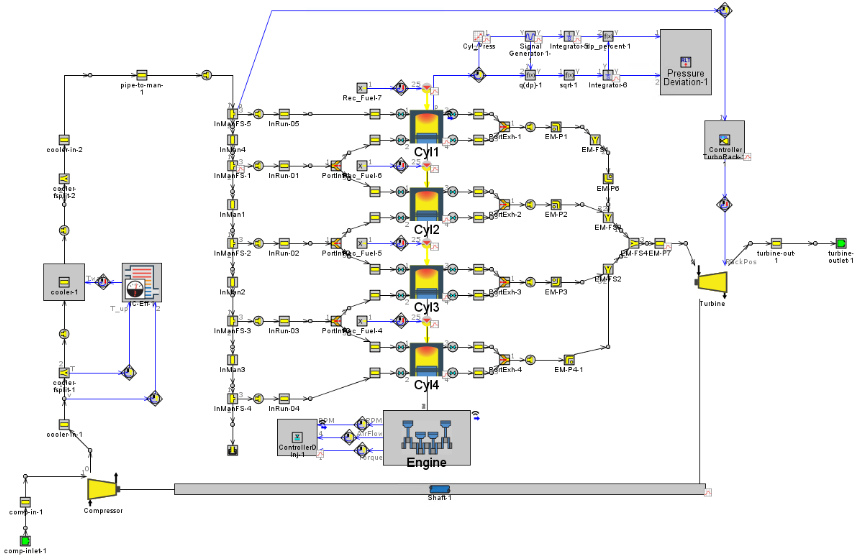
Future study: Experimental results

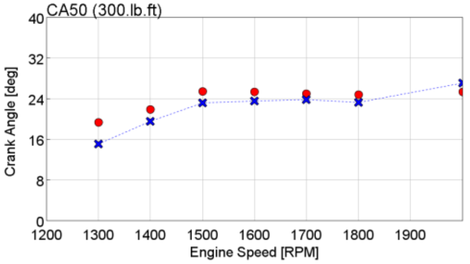


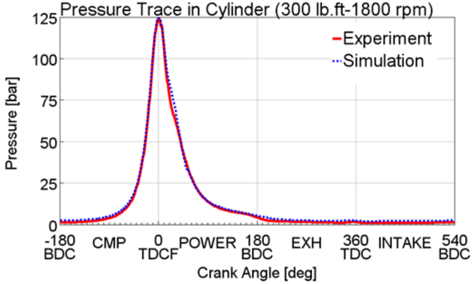
Future study: GT-power modeling for hybrid emission modeling











Questions?

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