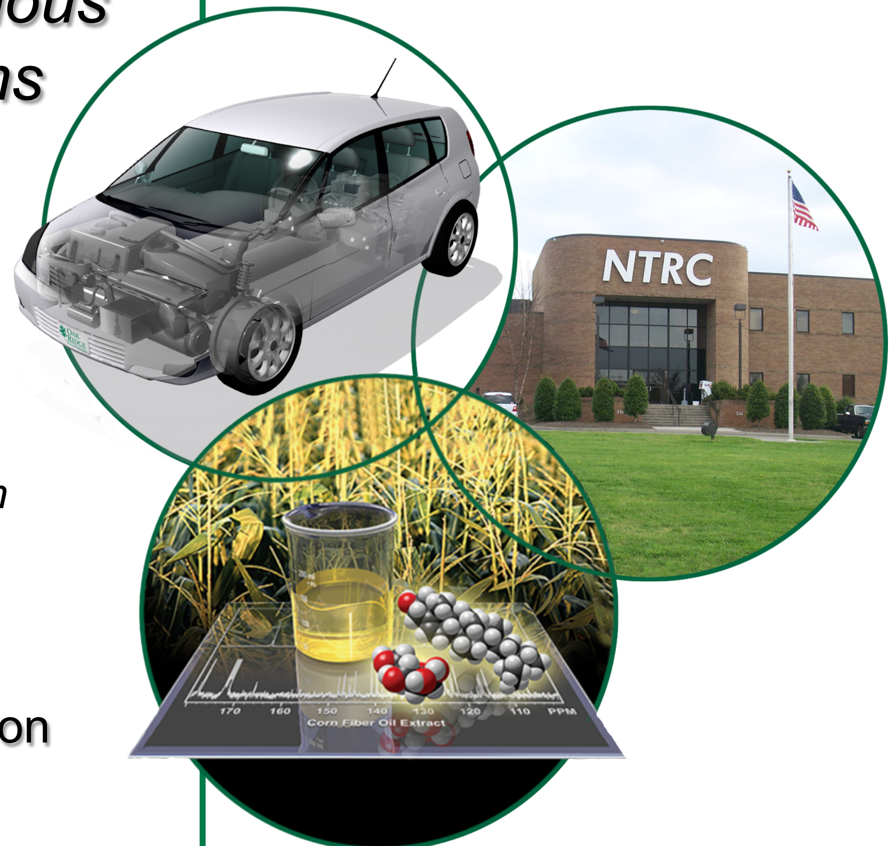
Self-Learning Identification and Stochastic Control for Autonomous Intelligent Propulsion Systems



Andreas A. Malikopoulos
Alvin M. Weinberg Fellow
Oak Ridge National Laboratory
Energy & Transportation Science Division

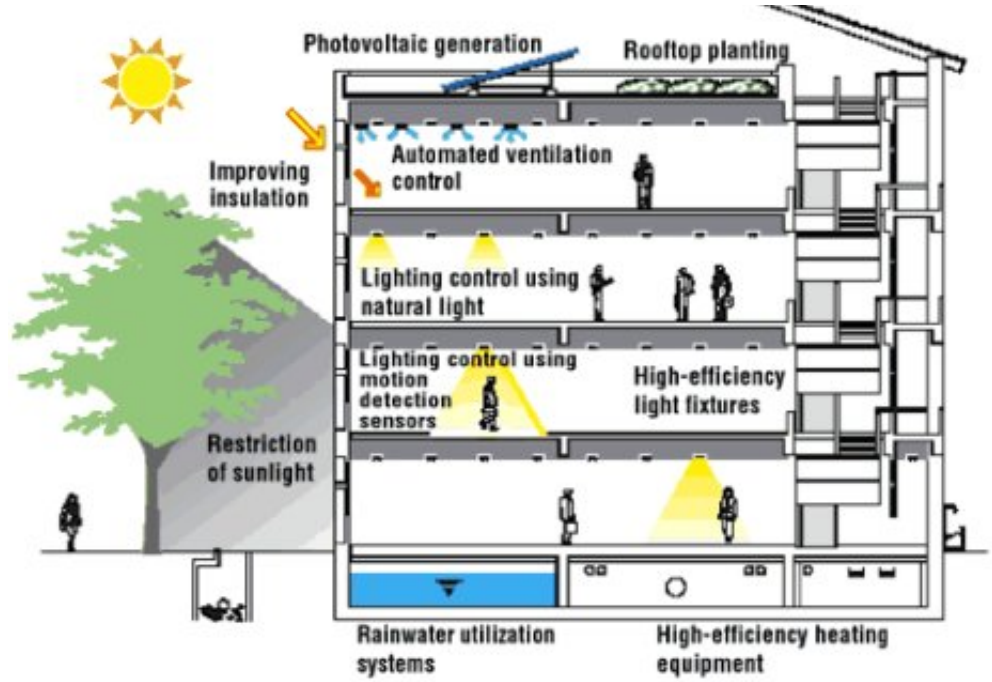
2011 DOE Crosscut Workshop
on Lean Emissions Reduction Simulation

April 19, 2011
Dearborn, MI

U.S. DEPARTMENT OF ENERGY

OAK RIDGE NATIONAL LABORATORY
MANAGED BY UT-BATTELLE FOR THE DEPARTMENT OF ENERGY

“Autonomy” and “Intelligence” in Artifacts



Images from Google

…why do we need Autonomous Intelligent Propulsion Systems…?

Outline

- Optimization and control of vehicle propulsion systems
  - Transient operation
- Making autonomous intelligent propulsion systems
  - Theoretical framework
- Case study
- Concluding remarks

Engine Operation

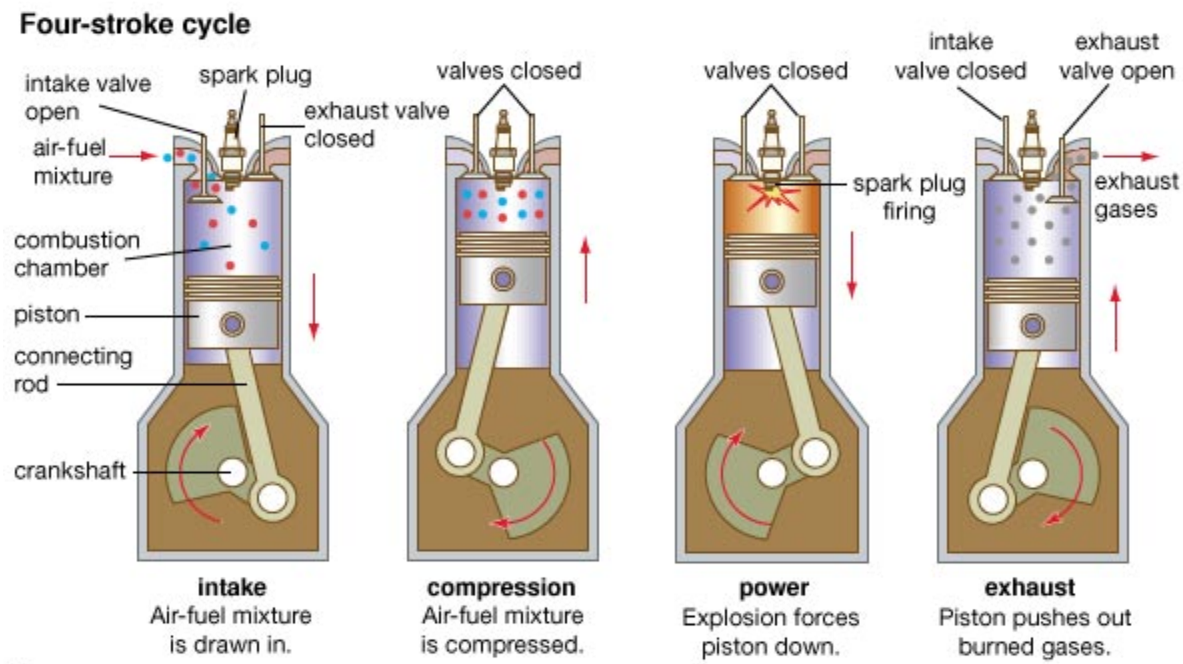


Image from Encyclopedia Britanica

Control of Engine Operation

- The Electronic Control Unit (ECU) in a vehicle is an embedded system that aims to control engine operation.
  - The ECU receives signals from several sensors and uses this information to maintain optimal engine operation with respect to fuel economy and emissions.

- Increasing demand for improving fuel economy while meeting emission regulations has enhanced the functional range of ECUs.

- Current ECUs perform a variety of control tasks providing values of engine variables that are referenced by several actuators.

Engine Calibration

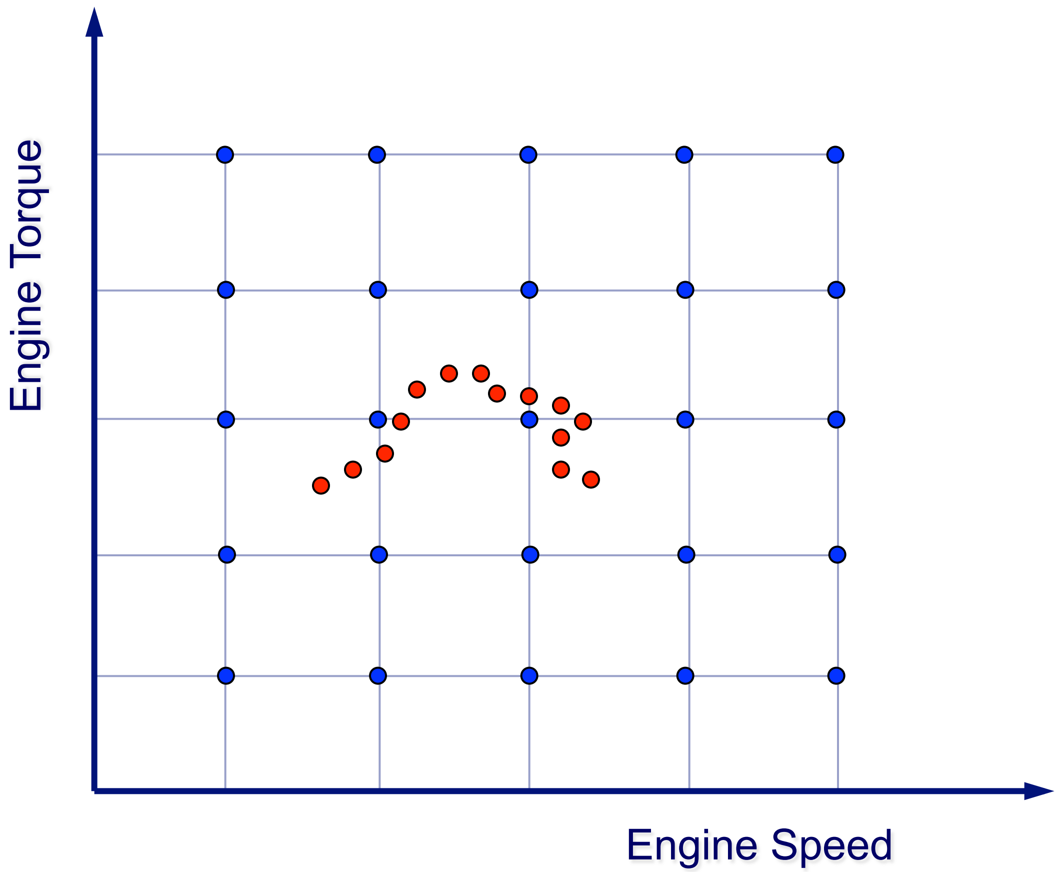
- The optimal values of these variable are essential for achieving high engine performance and fuel economy while meeting emission standards.

- Engine calibration is suited for realizing the optimal values of these variables associated with different engine operating points.

- More formally, engine calibration is defined as the procedure required to optimize one or more engine performance indices, e.g., fuel economy, emissions, engine power, etc., with respect to the engine controllable variables.

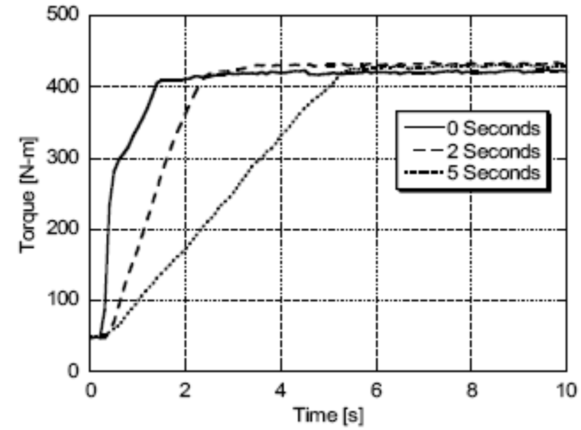
Engine Calibration (Cont.)

- State-of-the-art calibration methods of ECUs derive static maps that provide the values of several controllable variables with respect to steady-state engine operating points.

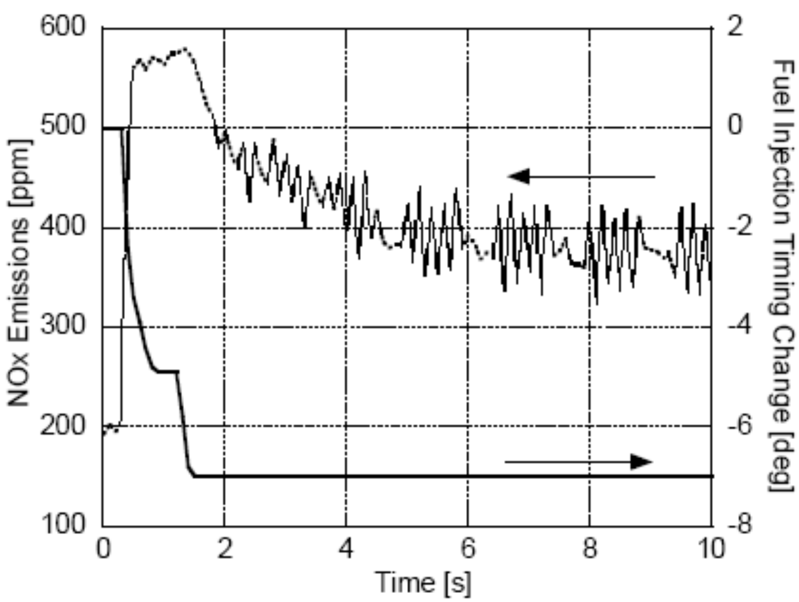


Transient Engine Operation

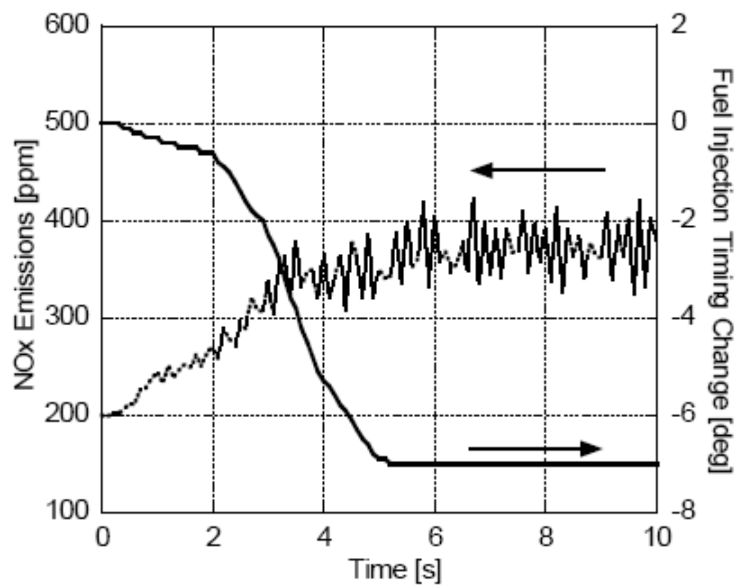
- Impact of 1-9 bar transient load (BMEP) step at 2000 rpm
  (Hagena, J.R., *et al.* 2006).



Instantaneous load increase

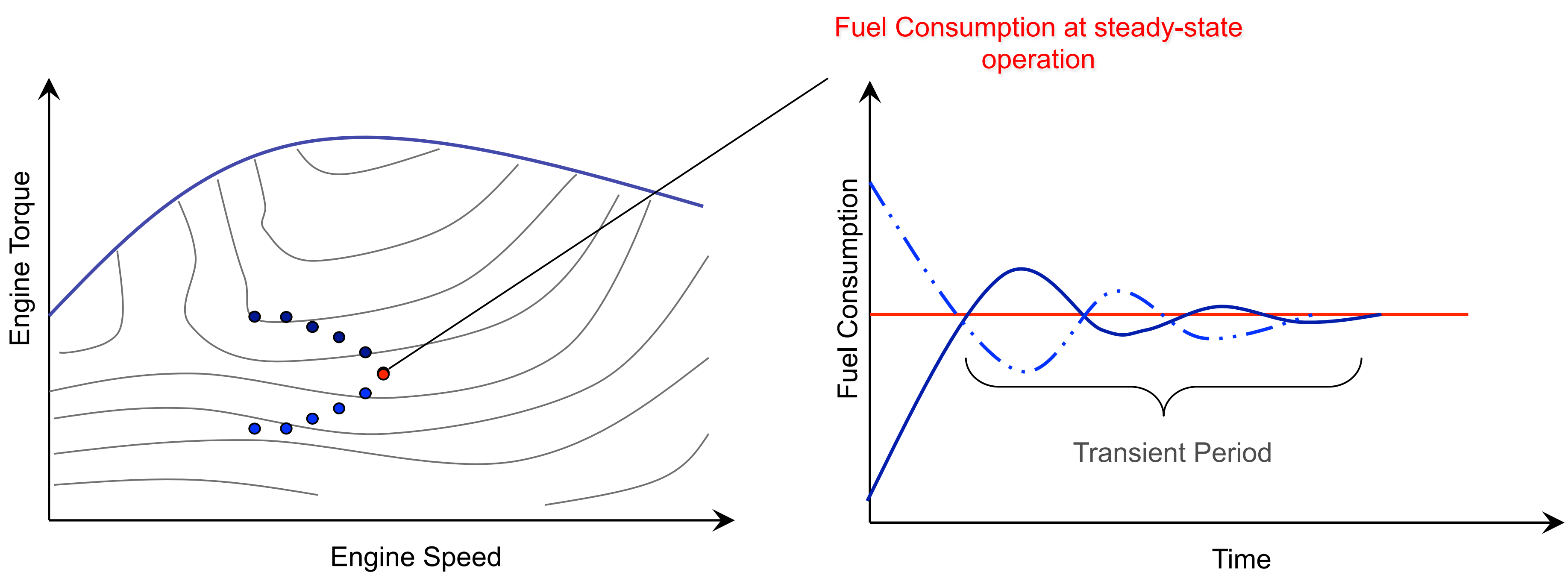


5-second load increase



Transient Engine Operation (Cont.)

- Transients immediately before the steady-state operating points that constitute the baseline for engine calibration are associated with different fuel consumption and emission values.

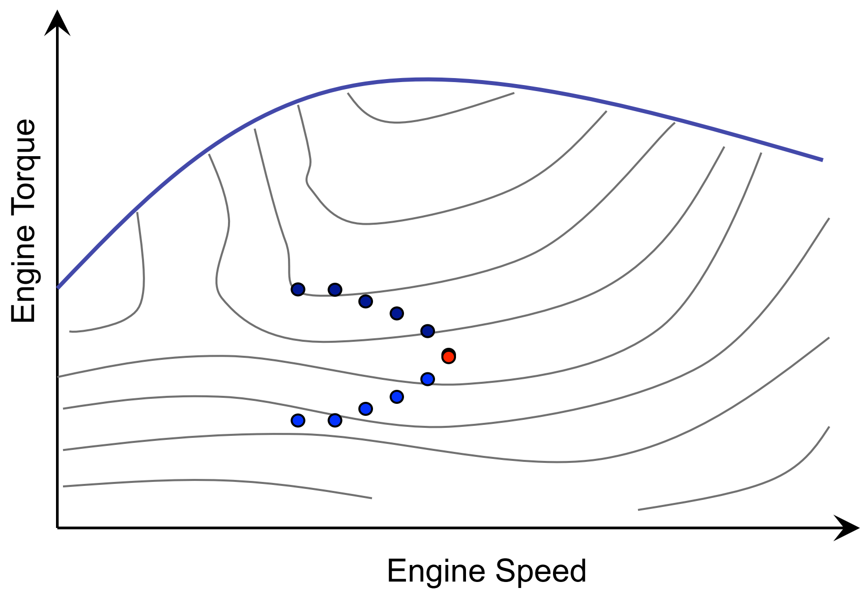


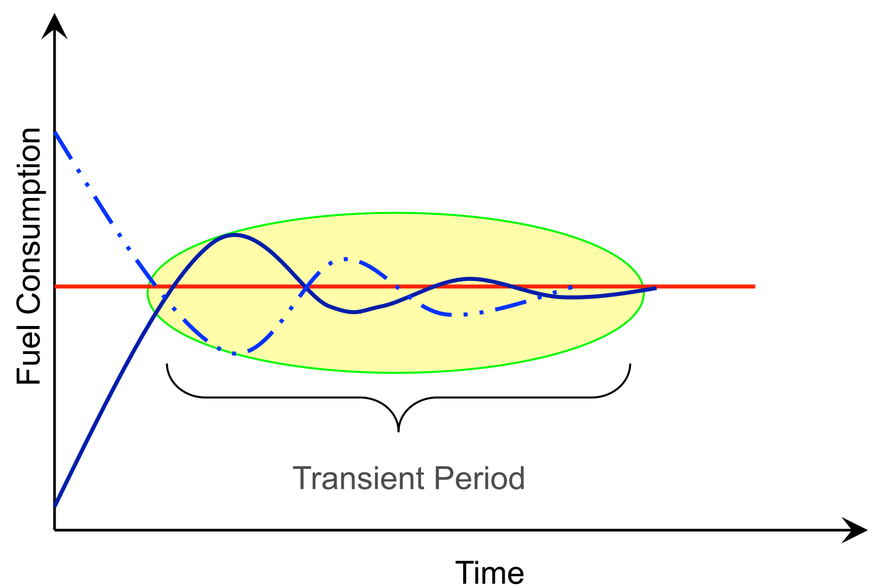
Transient Engine Operation (Cont.)

- The sequences of engine operating points are designated by the accelerator pedal position rates (driver's driving style).
- The huge number of different sequences encountered from different "driving styles" prohibits *a-priori* optimization.
- Those sequences associated with the driver's driving style can be estimated, and thus, the values of the controllable variables can be derived in real-time.

Research Hypothesis

- Transient engine operation can be addressed by
  - Estimating the sequences of engine operating point transitions designated by the driver, and
  - Deriving the values of the controllable variables for these sequences.





Research Objective

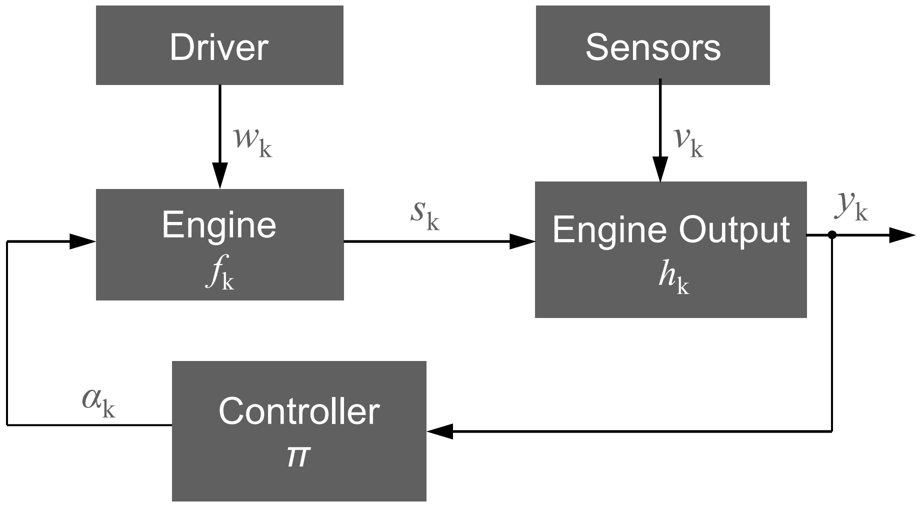
- The research objective is to make the engine of a vehicle an autonomous intelligent system capable of realizing its optimal calibration while the driver drives the vehicle.

- Through this approach the engine should be able to:
  - progressively perceive the driver's driving style, and
  - learn to optimize one or more engine performance indices, e.g., fuel consumption, emissions, etc, for this particular driving style; namely, personalize engine calibration for each driver.

Research Objective (Cont.)

- Two major problems are involved:
  - Engine identification problem
    - The estimation of engine operating point transitions requires the realization of engine operation.
  - Stochastic control problem
    - Selecting the values of controllable variables that optimize specified engine performance indices, e.g., fuel consumption, emissions, engine power, etc, for the derived realization.

Stochastic System Model



$$s_{k+1} = f_k(s_k, \alpha_k, w_k), \quad k = 1, 2, \ldots$$

$$y_k = h_k(s_k, v_k),$$

where

- k indexes discrete time (decision epochs),
- s_k is the state (engine operating point),
- α_k is the control action (value of the controllable variable),
- w_k is the accelerator pedal position (unknown disturbance),
- f_k is a function that describes how the state is updated,
- h_k is a function that describes how the engine output is updated,
- v_k is the unknown measurement error or noise, and
- $\pi = \{\mu_0, \mu_1, \ldots,\}$ is the control policy, where μ_k is a sequence of functions, $a_k = \mu_k(s_k)$.

Modeling Engine Operation as a Controlled Markov Chain

- Engine operation is modeled as a controlled Markov chain.

- The evolution of a Markov chain can be seen as the motion of a notional particle which jumps between the states of the state space at each decision epoch.

- The problem of engine calibration is thus reformulated as a sequential decision-making problem under uncertainty.

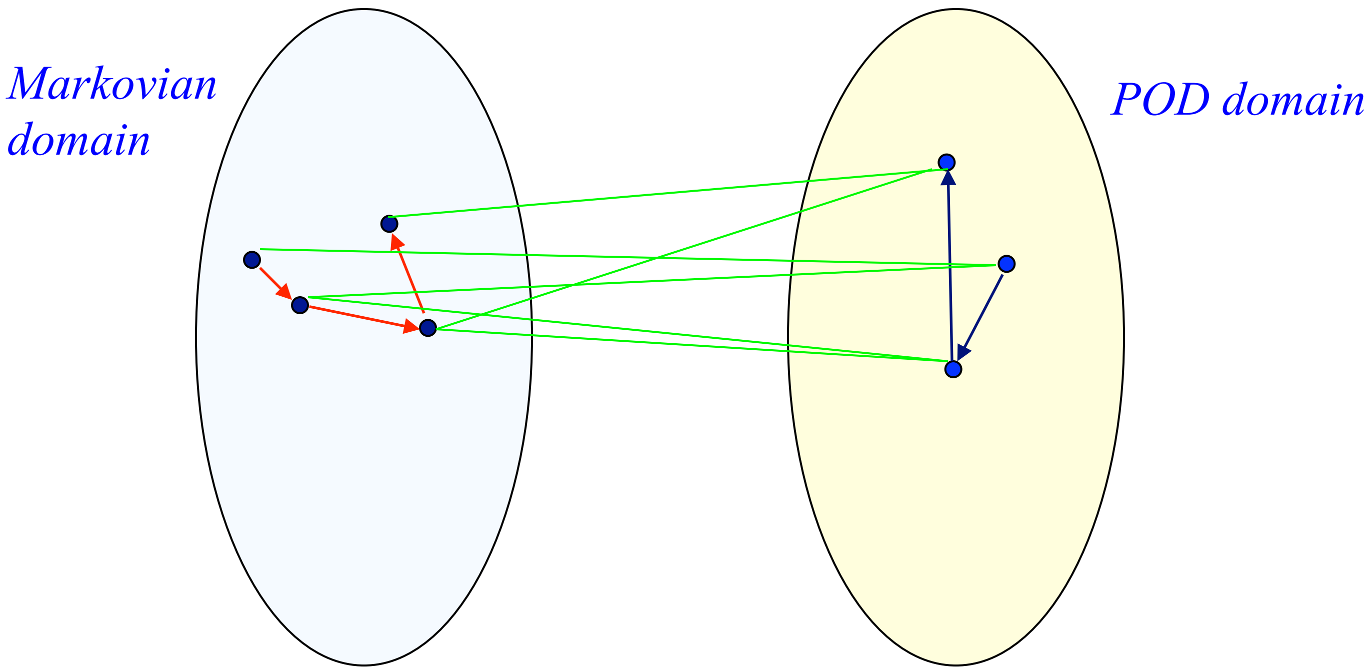
New Problem Formulation

- A controlled Markov chain is considered with:
  - Discrete time steps referred to as decision epochs
    $k = 0,1,2,\dots,M,\ M \in \aleph,$
  - a finite state space $\mathrm{S} = \{1,2,\dots,N\},\ N \in \aleph,$
    - Engine operating domain
  - a finite action space $\mathcal{A} = \bigcup_{i \in \mathcal{S}} A(i), \forall i \in \mathcal{S},$
    - Feasible set of the values of controllable variables
  - the transition probability matrix $\mathbf{P}_{ij}(a), \forall i, j \in \mathcal{S}, \forall a \in \mathcal{A},$
    where $\mathbf{P} : \mathcal{S} \times \mathcal{S} \times \mathcal{A} \to [0,1],\ \mathrm{P}_{ij}(s_{k+1} = j \mid s_k = i, a_k),$
    - Realization of engine operating point transitions
  - The transition cost (or reward) matrix $\mathbf{R}_{ij}(a), \forall i, j \in \mathcal{S}, \forall a \in \mathcal{A},$
    where $\mathbf{R} : \mathrm{S} \times \mathrm{S} \times \mathrm{A} \to \Re,\ R_{ij}(s_{k+1} = j \mid s_k = i, a_k).$
    - Engine performance indices, e.g., fuel consumption, emissions, etc

The Predictive Optimal Decision-making Learning Model

- The Predictive Optimal Decision-making (POD) [1,2,3] computational learning model consists of a state-space representation

$$\tilde{S} := \{\tilde{s}_{k+1}^{ij} \mid \tilde{s}_{k+1}^{ij} \equiv s_k = i \underset{\mu(s_k)\in A(s_k)}{\longrightarrow} s_{k+1} = j\}$$



1. Malikopoulos, A.A., Papalambros, P.Y., and Assanis, D.N., "A Real-Time Computational Learning Model for Sequential Decision-Making Problems Under Uncertainty," *ASME J. Dyn. Sys., Meas., Control, Vol.131, No. 4, 2009, 041010(8).*
2. Malikopoulos, A.A.., "Convergence Properties of a Computational Learning Model for Unknown Markov Chains," *ASME J. Dyn. Sys., Meas., Control, Vol.131, No. 4, 2009, 041011(7).*
3. Malikopoulos, A.A., "A Lookahead Control Algorithm for Discrete-Time Stochastic Systems," *Proceedings of the 2010 ASME Dynamic Systems and Control Conference (DSCC), Boston, MA, Sep. 13-15. (to appear)*

Basic Assumptions

- The Markov chain is homogeneous

$$P_{ij}(s_{k+1} = j \mid s_k = i) = P_{ij}(s_1 = j \mid s_0 = i), \forall k \geq 0, \forall i, j \in \mathcal{S}.$$

- The states of the Markov chain are ergodic, namely, they are positive recurrent and aperiodic.

- The Markov chain is irreducible, that is, for every pair of states $i \neq j, \forall i, j \in \mathcal{S}$, the states intercommunicate $i \leftrightarrow j, \forall i, j \in \mathcal{S}$.

Convergence of the POD Model to Stationary Distribution

Theorem 1 [1] : The POD state representation generates the stationary distribution ρ_i of the Markov chain.

Sketch of Proof:

- Since the chain is ergodic with irreducible states, it is quarantined that the chain has a unique stationary distribution

$$\rho_i = \mu_i^{-1}, \forall i \in \mathcal{S}.$$

- The partition of the POD model is irreducible, that is

$$\tilde{S}_i \leftrightarrow \tilde{S}_j, \forall i, j \in S.$$

- The mean recurrence of each partition $\tilde{S}_i$ is equal to the mean recurrence time of its corresponding state, that is

$$\mu_i = \mu_{\tilde{S}_i}, \forall i \in S.$$

- The stationary distribution of the Markov chain is given by the mean recurrence time of each partition, namely

$$\rho_i = \mu_{\tilde{S}_i}^{-1}, \forall i \in S.$$

1. Malikopoulos, A.A.., "Convergence Properties of a Computational Learning Model for Unknown Markov Chains," *ASME J. Dyn. Sys., Meas., Control, Vol.131, No. 4, 2009, 041011(7).*

Case Studies

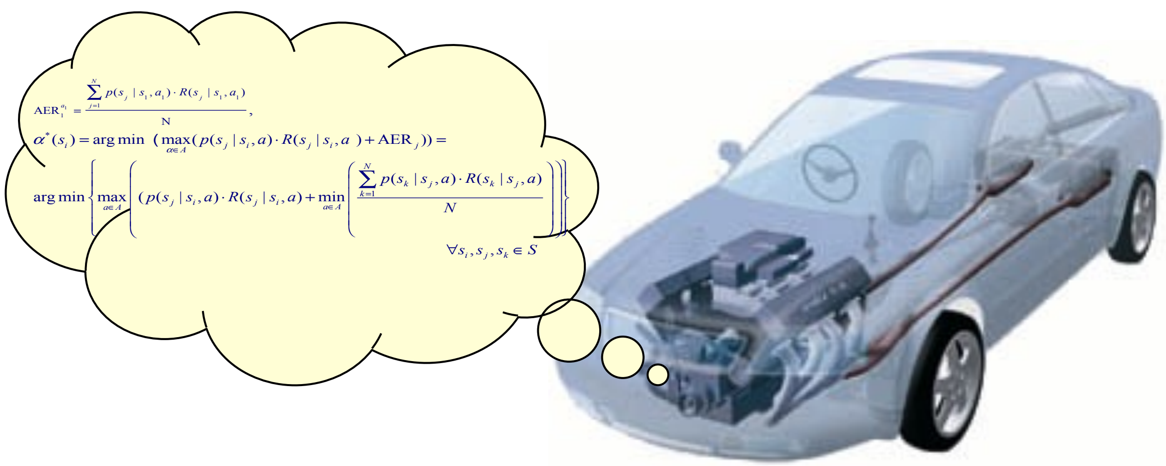
- To validate the efficiency of the POD computational learning model various case studies have been conducted including:
  - Cart-pole balancing problem [1]
  - Vehicle cruise-control application [1]
  - Autonomous intelligent propulsion systems [2,3,4]
    - Gasoline engine with respect to spark ignition angle over aggressive acceleration profiles.
    - Diesel engine with respect to injection timing over an acceleration and deceleration profile.
    - Diesel engine with respect to injection timing and VGT over a segment of the FTP-75 driving cycle.

1. Malikopoulos, A.A., Papalambros, P.Y., and Assanis, D.N., "A Real-Time Computational Learning Model for Sequential Decision-Making Problems Under Uncertainty," *ASME J. Dyn. Sys., Meas., Control, Vol.131, No. 4, 2009, 041010(8).*
2. Malikopoulos, A.A., Papalambros, P.Y., and Assanis, D.N., "Online Self-Learning Identification and Stochastic Control for Autonomous Internal Combustion Engines," *ASME J. Dyn. Sys., Meas., Control, Vol.132, No. 2, 2010, 024504(6).*
3. Malikopoulos, A.A., Assanis, D.N., and Papalambros, P.Y., "Real-Time, Self-Learning Optimization of Diesel Engine Calibration," *ASME J. Eng. Gas Turbines Power, Vol. 131, No. 2, 2009,022803(7).*
4. Malikopoulos, A.A., Assanis, D.N., and Papalambros, P.Y., "Optimal Engine Calibration for Individual Driving Styles," *Proceedings of the Society of Automotive Engineers World Congress,* Detroit, MI, April 14-17, 2008.

Autonomous Intelligent Diesel Engine

- Four-cylinder, 1.9L turbocharged diesel engine
  - Real-time, self-learning optimization of engine calibration with respect to injection timing and Variable Geometry Turbocharged (VGT) vane position.

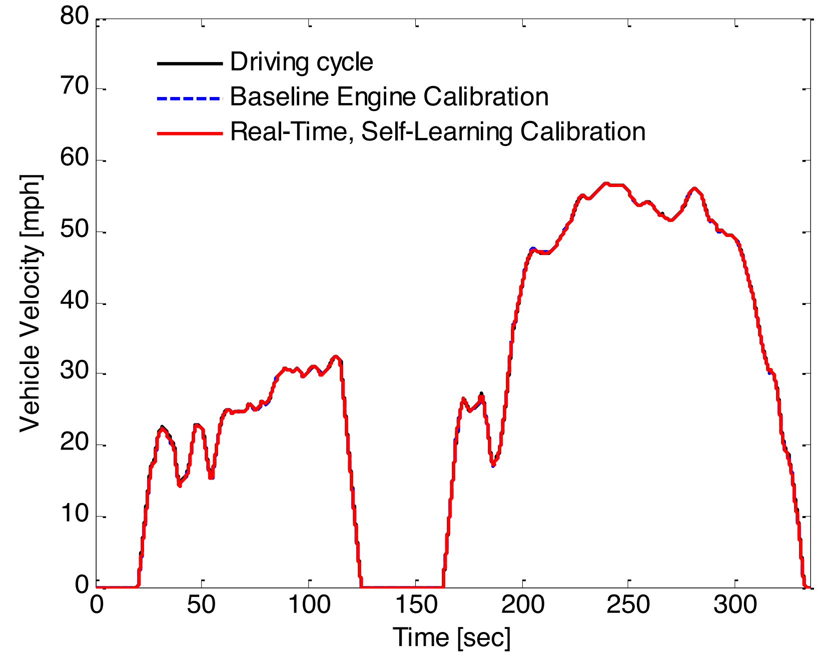
- The objective is to maximize engine torque, while the driver drives the vehicle, with respect to injection timing and VGT.



Autonomous Intelligent Diesel Engine: Optimal Injection Timing and VGT

- The vehicle model was run repeatedly over the same speed profile (segment of FTP-75 driving cycle), to represent a situation in which the driver desires a particular vehicle's speed profile deemed characteristic of his/her driving style.

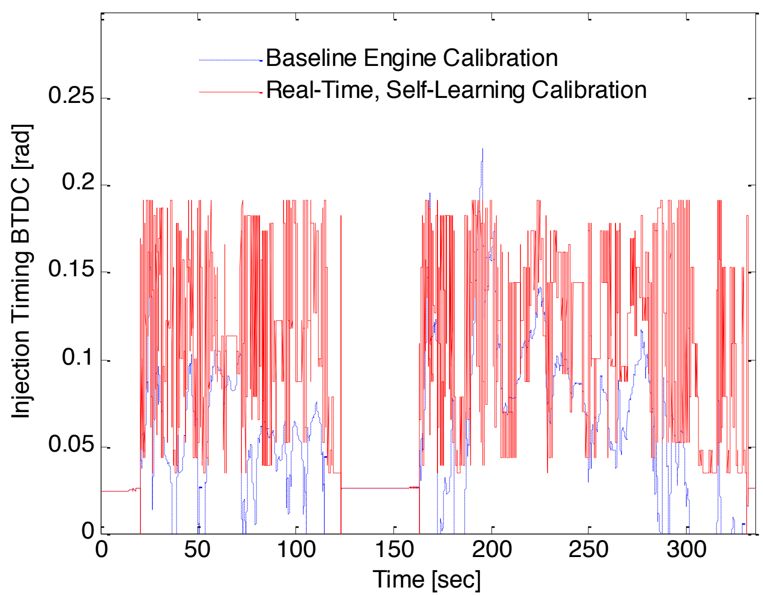
- The belief implicit here is that if the controller can successfully capture this profile, then it will also be able to capture engine realization designated by a driver in long term.



Autonomous Intelligent Diesel Engine: Results

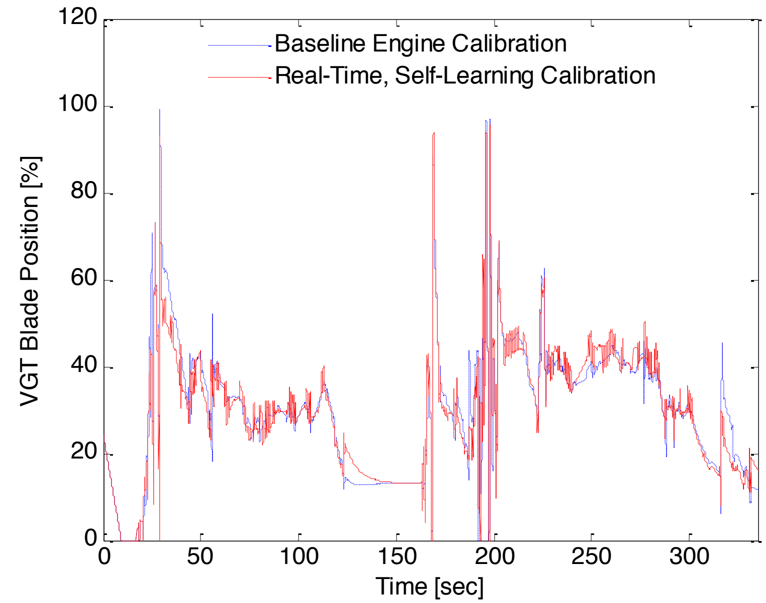
- Optimal injection timing and VGT through learning.

Injection Timing BTDC [rad]



Time [sec]

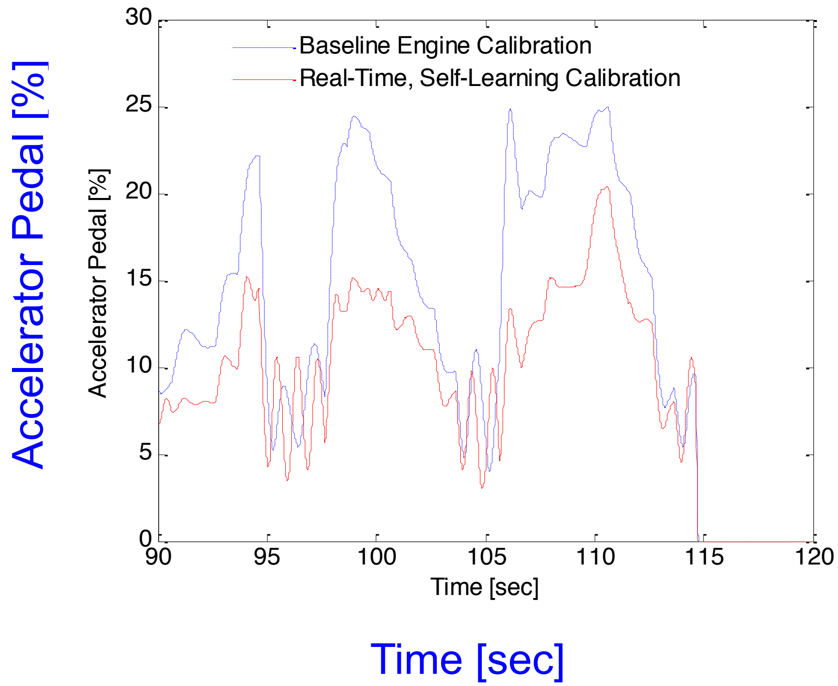
VGT blade Position [%]

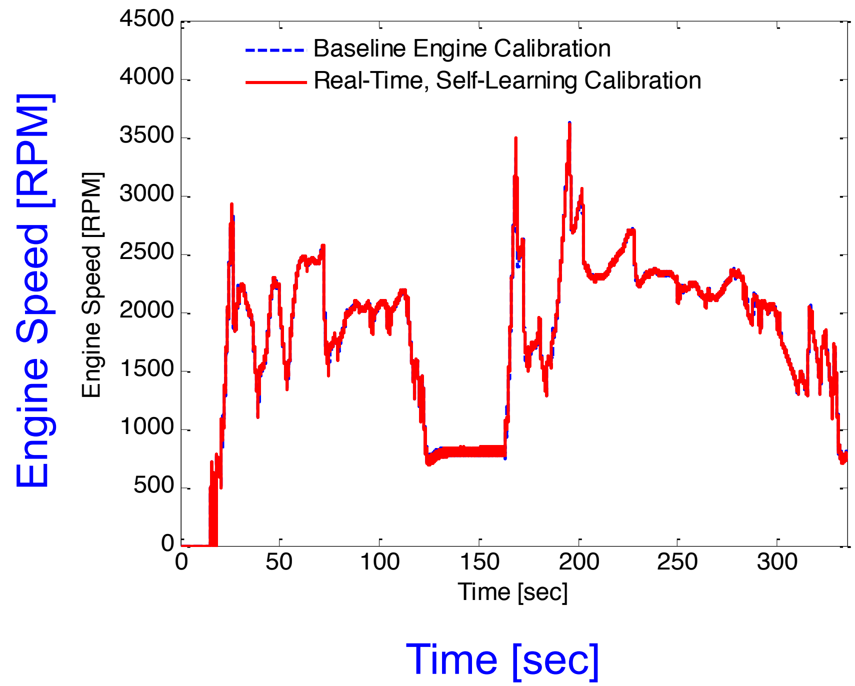


Time [sec]

Autonomous Intelligent Diesel Engine: Results (Cont.)

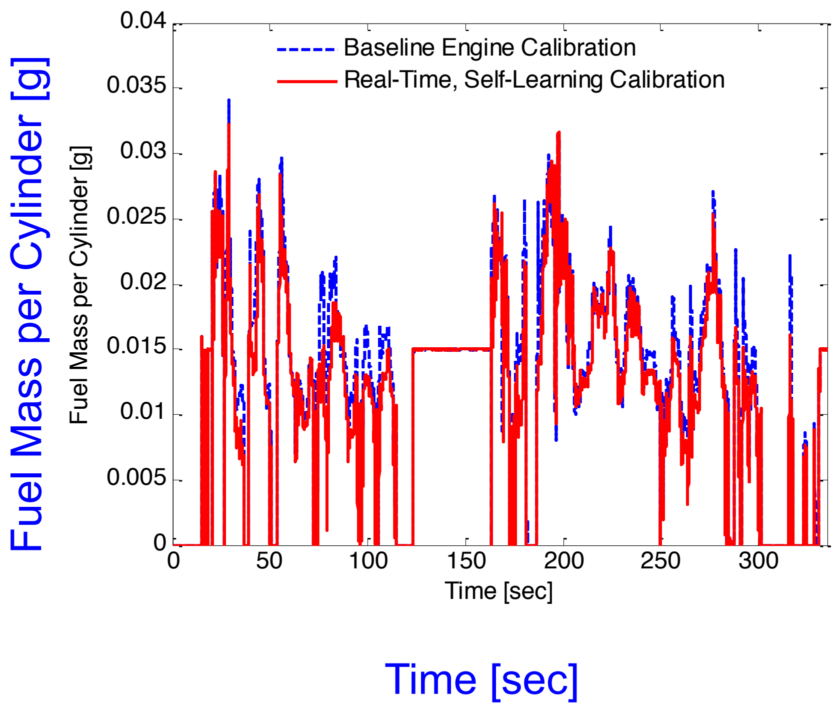
- Accelerator pedal position rate for the same engine speed.

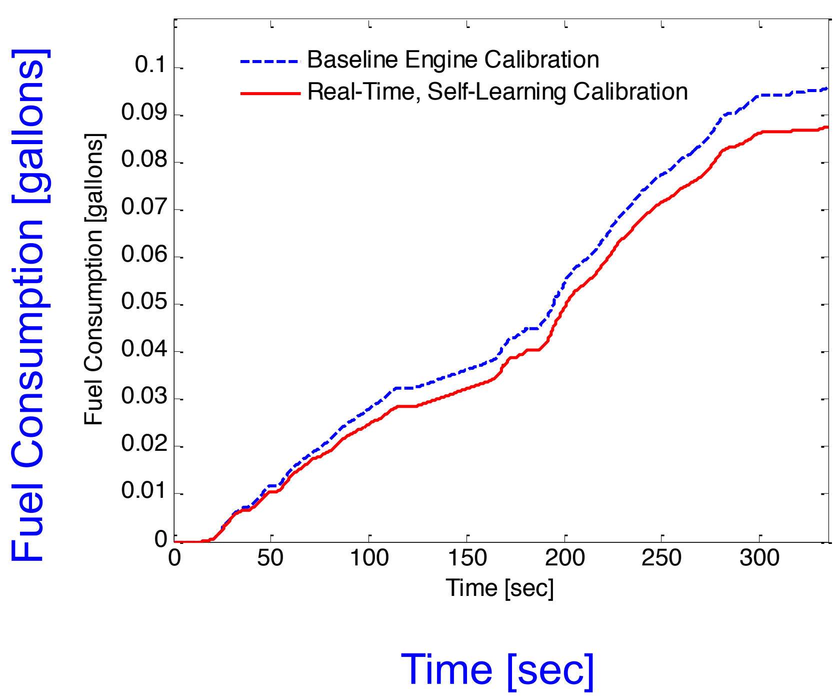




Autonomous Intelligent Diesel Engine: Results (Cont.)

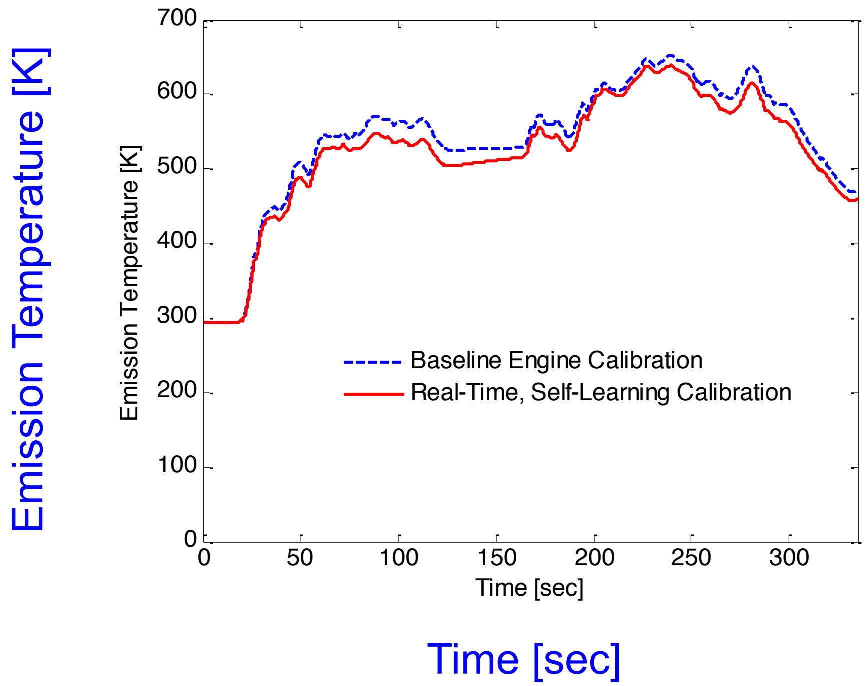
- 9.3% overall improvement of fuel economy.

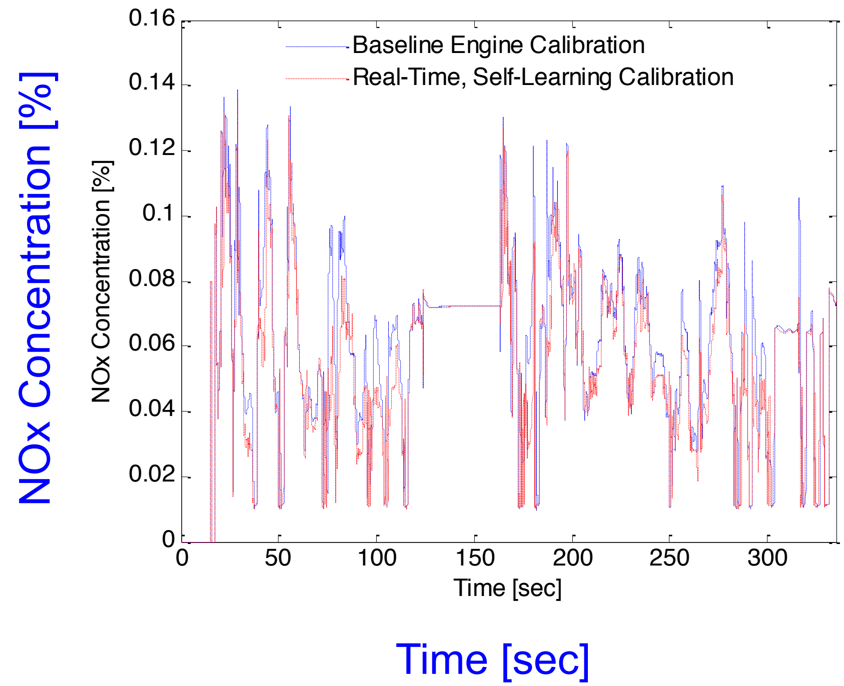




Autonomous Intelligent Diesel Engine: Results (Cont.)

- Emission temperature and NOx concentration.





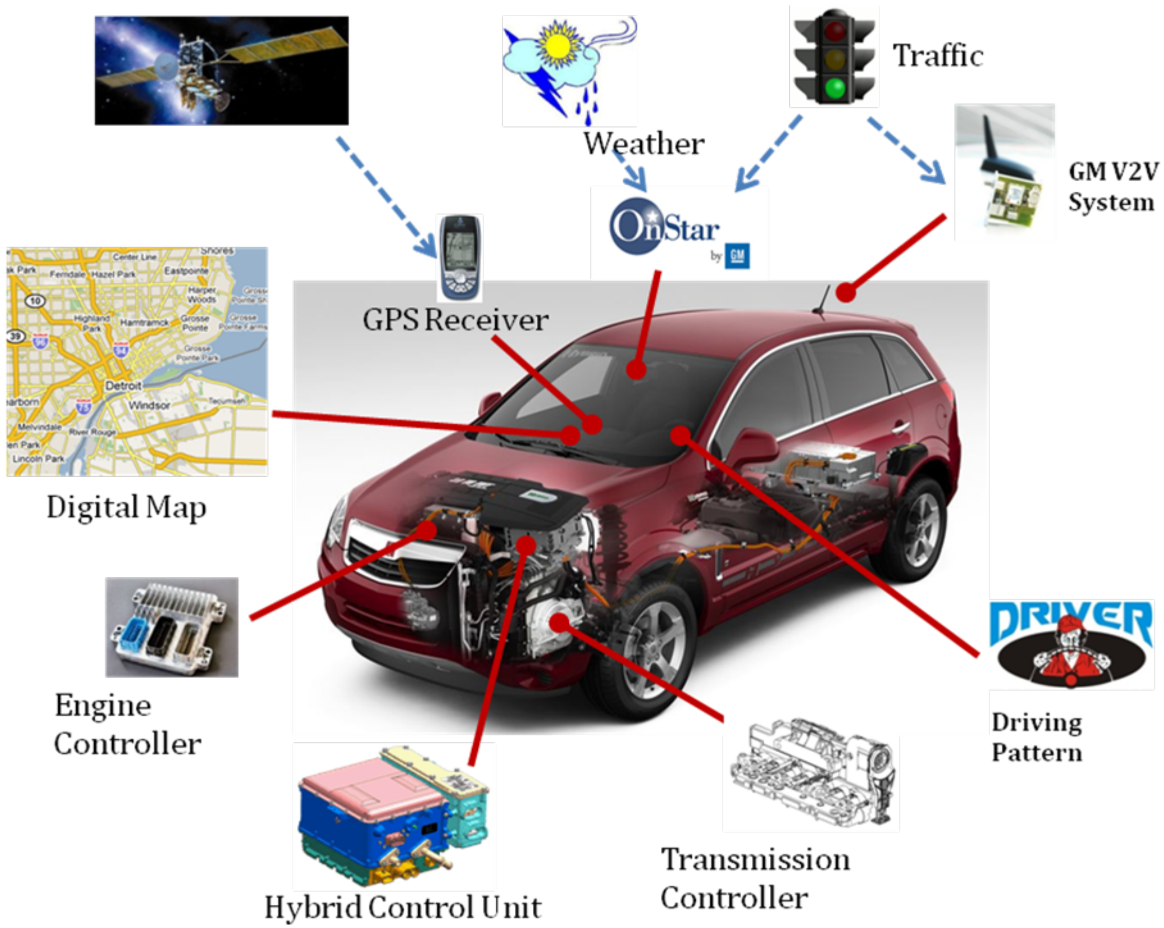
Concluding Remarks

- Current engine optimization and control methods seldom guarantee optimal engine operation for common driving habits, *e.g.,* stop-and-go driving, rapid acceleration, or rapid braking.

- The ultimate goal of this approach is to fully exploit existing propulsion technologies in terms of fuel economy and pollutant emissions.

- It aims to address the following question: "For a given propulsion system, what is the maximum efficiency that we can get with respect to our driving habits?"

Time to Revolutionize the DNA of the Automobile



Thank You for Your Attention!

Q & A