Stochastic Optimal Control for Advanced Propulsion Systems

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Motivation

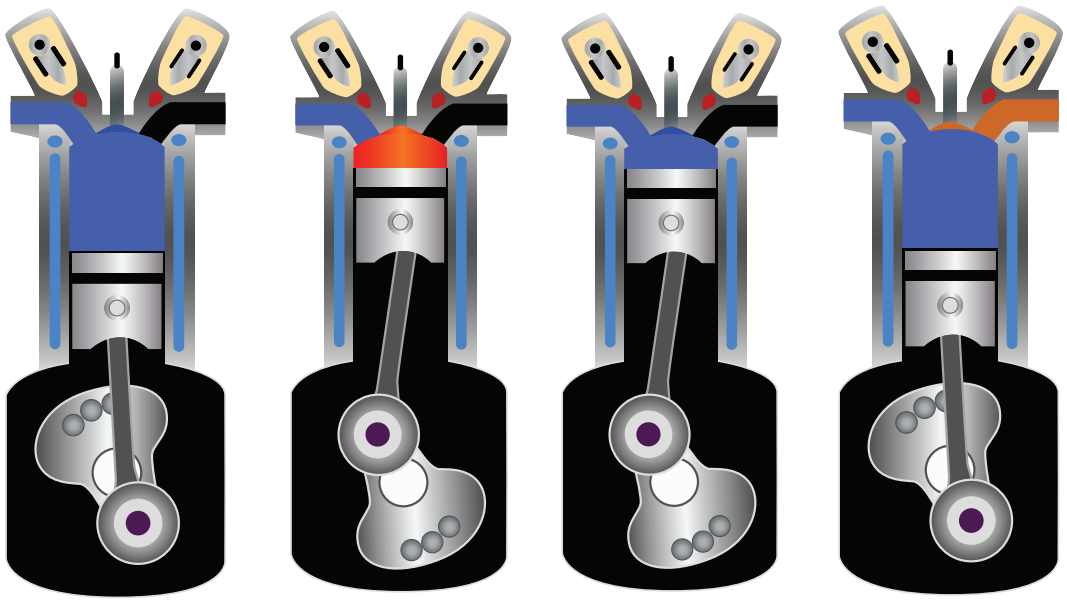
- New technologies in mechatronics and actuators have enhanced the complexity of modern automotive systems.
- Computational learning methods towards making autonomous intelligent systems have become necessary.
- The evolution of such systems is modeled as a controlled Markov chain.
- The problem is formulated as a sequential decision-making under uncertainty.

Research objective

- To establish a rigorous mathematical framework for modeling the control problem of advanced propulsion systems.
- To formulate numerical algorithms that can solve these problems.
- To develop self-learning and adaptive control alorithms to address deviations of the system operation from expected behavior.
- The emphasis is on applications related to HEVs/PHEVs, engines and emissions systems.

Self-learning control of advanced propulsion systems

- Develop the fundamental theory and control algorithms for analyzing, and controlling advanced propulsion systems that can learn to improve their performance over time while interacting with their environment.



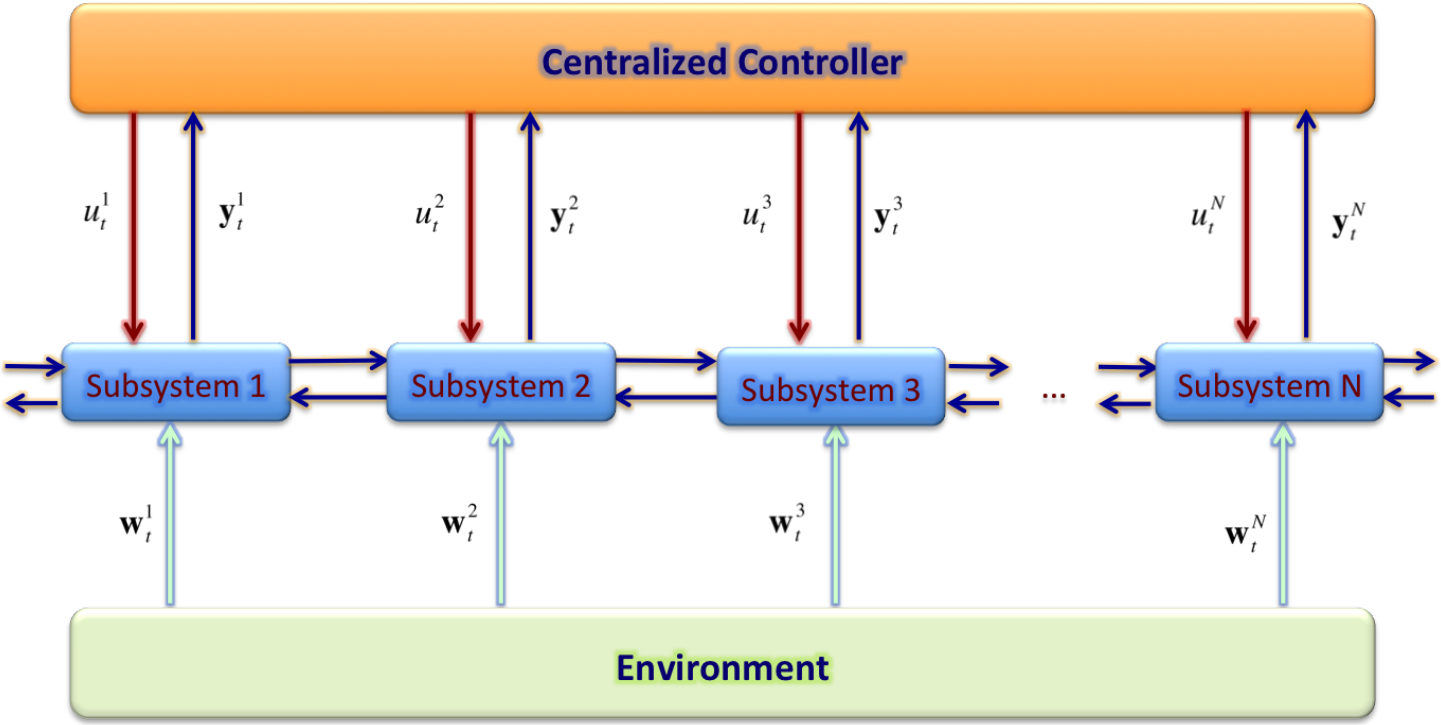
Outline

- General model
- Power management control of hybrid electric vehicles (HEVs): series mode
- Optimization of cold start emissions and fuel consumption of plug-in electric vehices (PEVs)

Notation

- Random variables are denoted by upper case letters, e.g., X.
- The realization of the random variables is denoted by the corresponding lower case letter, e.g., x.
- The space of their realizations is denoted by script letters, e.g., $\mathcal{S}$.
- Subscripts denote time and superscripts denote the subsystem, e.g., X_t^i denotes the state of subsystem i at time t.
- Bold letters denote $\mathbf{x_t}$ denote the vector of the realization x_t^i of each subsystem i at time t.

The model



- Controlled system: $\mathbf{x_{t+1}} = \mathbf{f}(\mathbf{x_t}, \mathbf{u_t}, \mathbf{w_t}), \mathbf{y_t} = \mathbf{h}(\mathbf{x_t}, \mathbf{v_t})$
- Controlled subsystem, i: $x_{t+1}^i = f^i(x_t^i, u_t^i, w_t^i), y_t^i = h^i(x_t^i, v_t^i)$
- Controller: $u_t^i = \mu(\mathbf{x_t})$
- Objective: $min_{\pi \in \Pi} \lim_{T \to \infty} \frac{1}{T+1} E\left[\sum_{t=0}^{T} k(\mathbf{x_t}, \mathbf{u_t})\right]$

Controlled Markov chain

The model consists of:

- A state space $\mathcal{S}$ of the system.
- A control space $\mathcal{U}$ of the controller.
- The state-dependent constraints; that is, for each state $i \in \mathcal{S}$, we are given a nonempty set $\mathcal{C}(i) \subset \mathcal{U}$ of admissible control actions.
- The set of admissible state/action pairs

$$\Gamma \colon = \{(i, u) | i \in \mathcal{S} \text{ and u} \in \mathcal{C}(i)\}.$$

- A function $k \colon \Gamma \to \mathbb{R}$ called the cost function (cost-per-stage).
- The transition probability matrix $P(\cdot, \cdot)$ on $\mathcal{S}$ given Γ.

Problem formulation

- A control policy π is a sequence of functions μ which map the system's state space, $\mathcal{S}$, to the controller's control action space, $\mathcal{U}$.
- The long run average cost per unit time is

$$J(\pi) = \min_{\pi \in \Pi} \lim_{T \to \infty} \frac{1}{T+1} E\left[\sum_{0}^{T} k(X_t, U_t)\right]. \tag{1}$$

- A control policy π is optimal if

$$J^* = J(\pi) = \inf\left\{J(\pi) | \pi \in \Pi\right\}. \tag{2}$$

Equilibrium control policy

- A control policy $\pi^* = \{\mu_1, \mu_2, ..., \mu_i, ..., \mu_N\}$ is an equilibrium control policy if the policy yields the saddle point of the product of the stationary probability distribution β and cost function k, that is

$$k^*(1, \mu_1) < k^*(2, \mu_2) < ... < k^*(i, \mu_i) < ... < k^*(n, \mu_n) \quad (3)$$

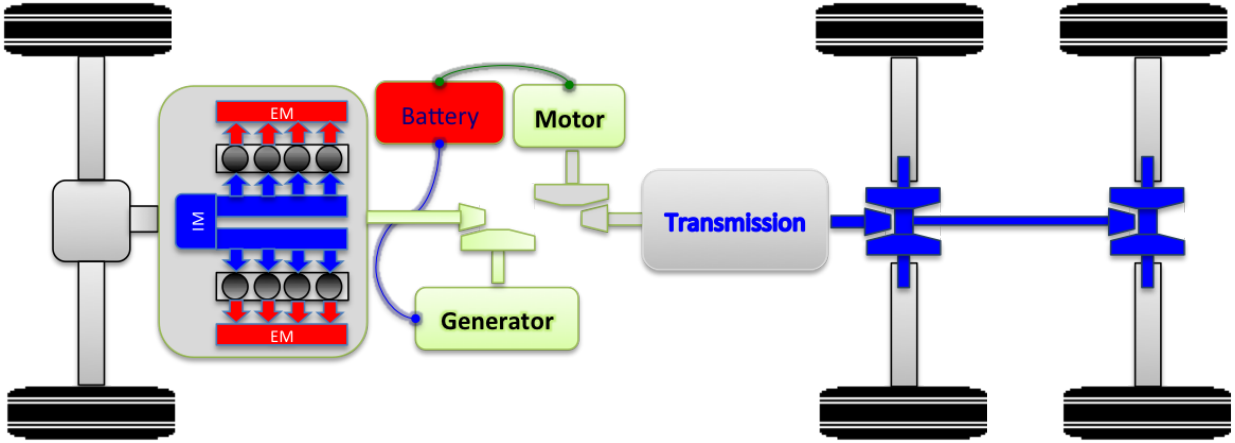
$$\beta_1^* > \beta_2^* > ... > \beta_i^* > ... > \beta_n^*, \forall i \in \mathcal{S}. \quad (4)$$

- The equilibrium control policy is an optimal policy[1].

[1] A. A. Malikopoulos, "Equilibrium Control Policies for Markov Chains," in *50th IEEE Conference on Decision and Control and European Control Conference, Orlando, Florida, December 12-14, 2011.*

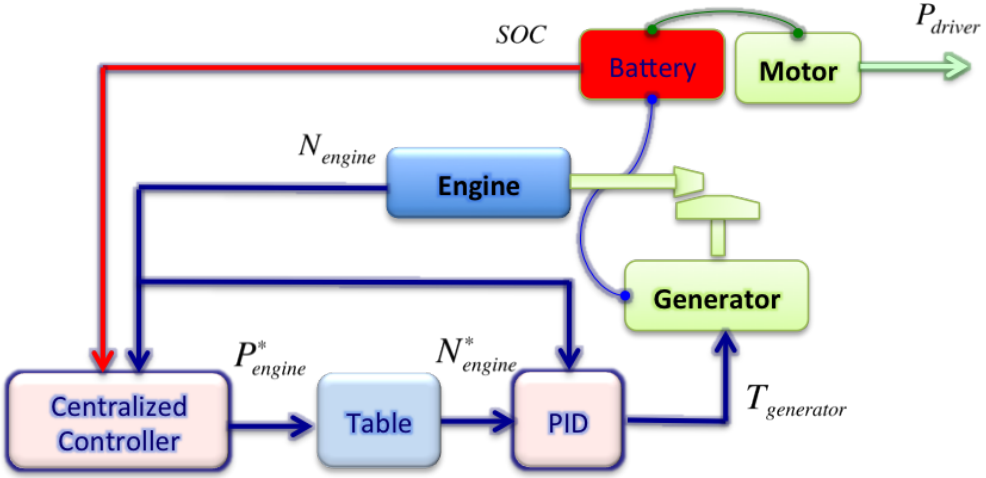
Power management control in a hybrid electric vehicle: series mode

- Power management control based on the equilibrium control policy

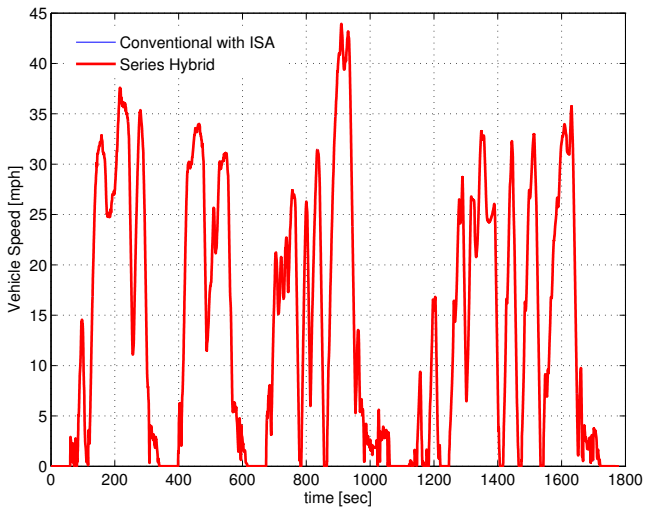


Control scheme

- State of the system: $X_t = N_{engine}$
- Control action: $U_t = P_{engine}$
- Disturbance: $W_t = SOC$

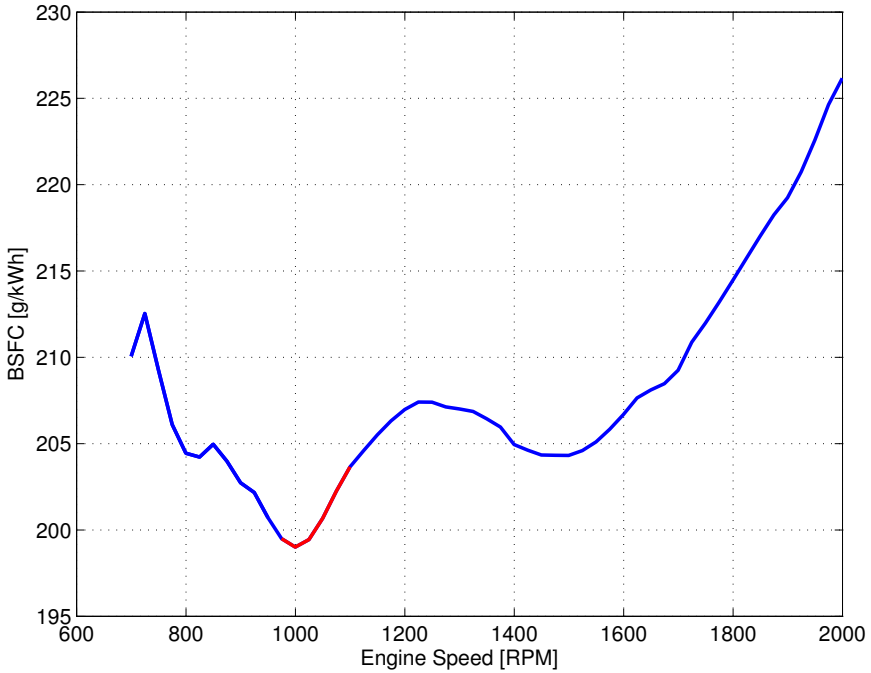


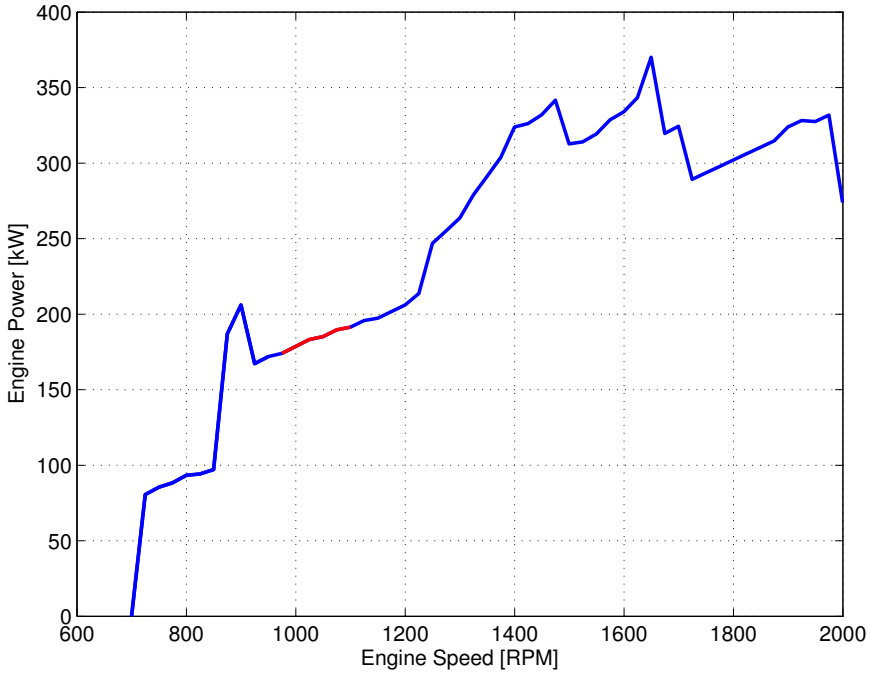
- Driving cycle



Centralized controller yielding the equilibrium control policy

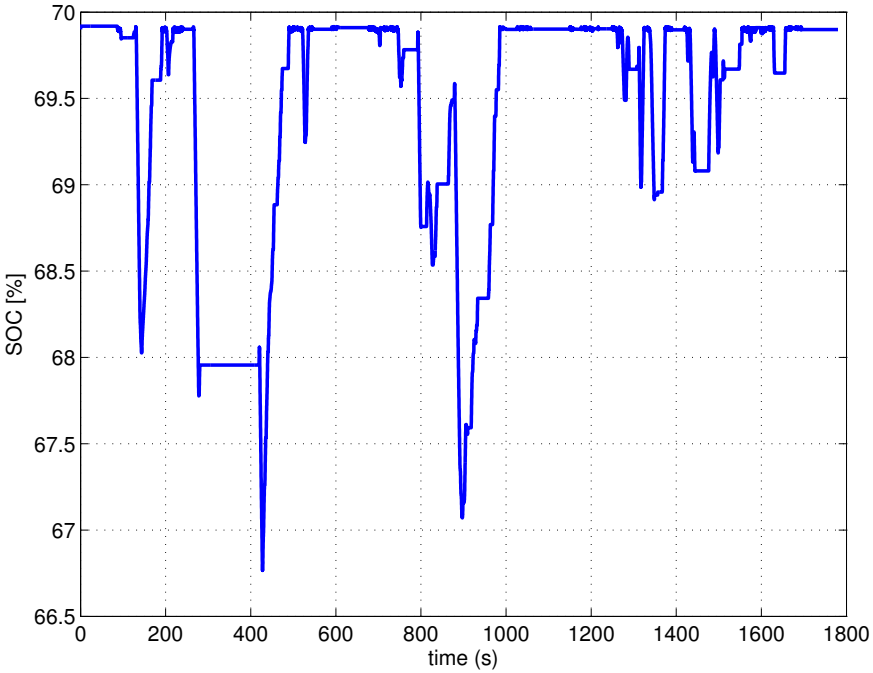
- Optimal BSFC with respect to engine speed
- Optimal engine power with respect to engine speed



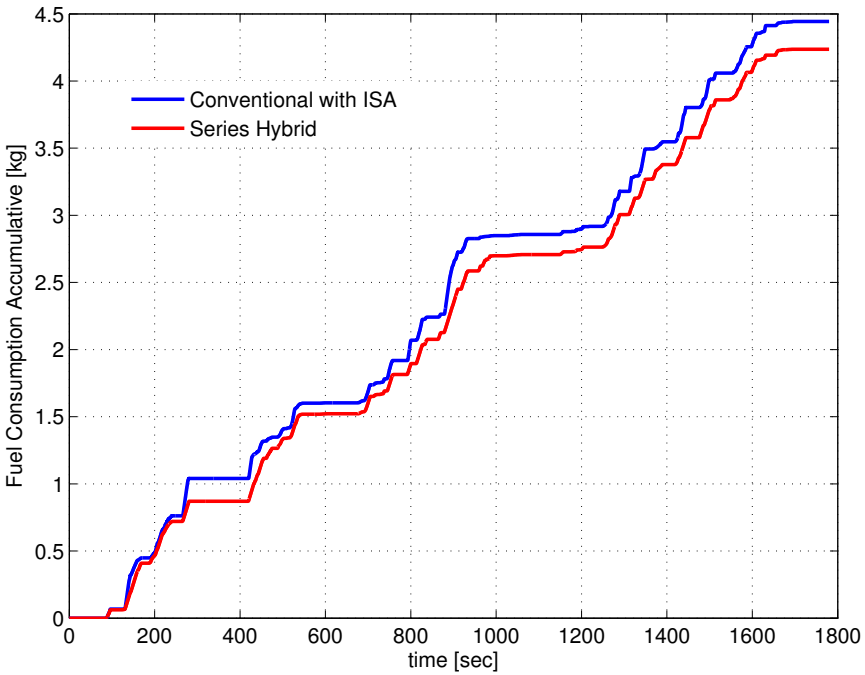


Simulation results

- SOC variation

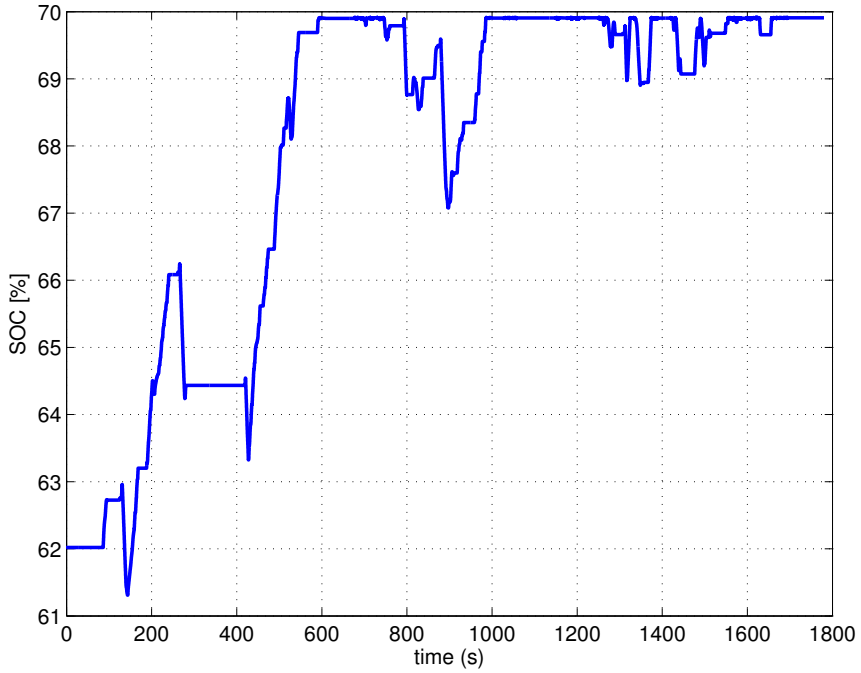


- Fuel consumption

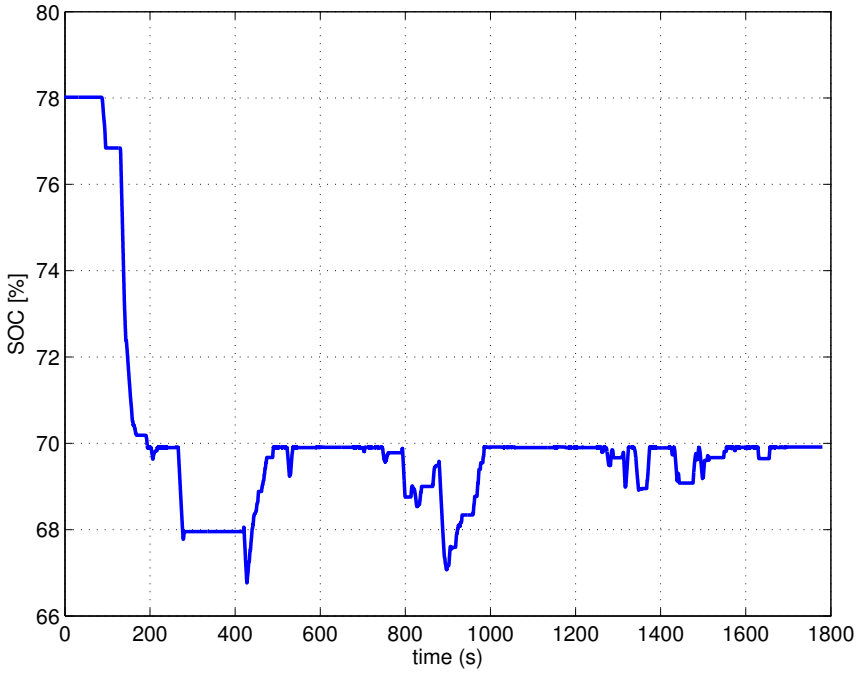


Simulation results (Cont.)

- SOC variation with 62% initial SOC



- SOC variation with 78% initial SOC



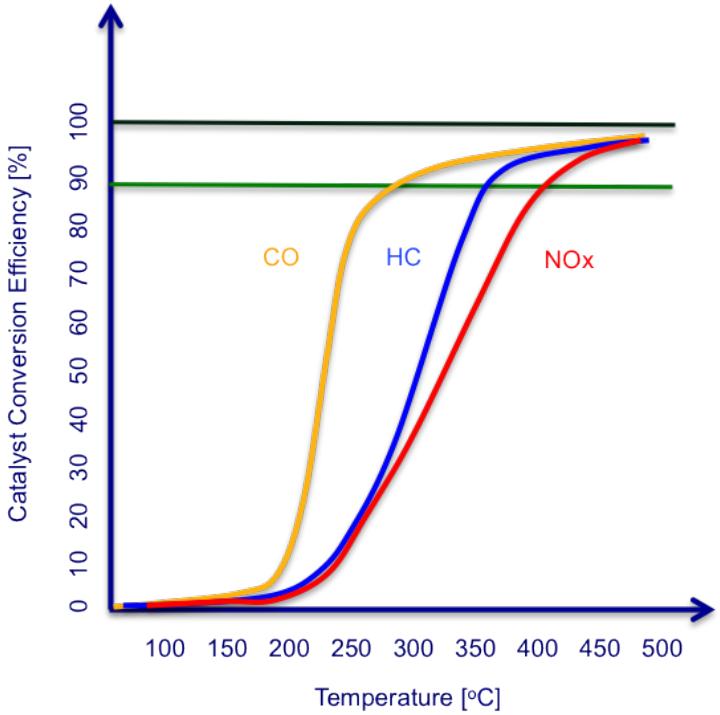
Optimization of cold start emissions and fuel consumption of PEVs

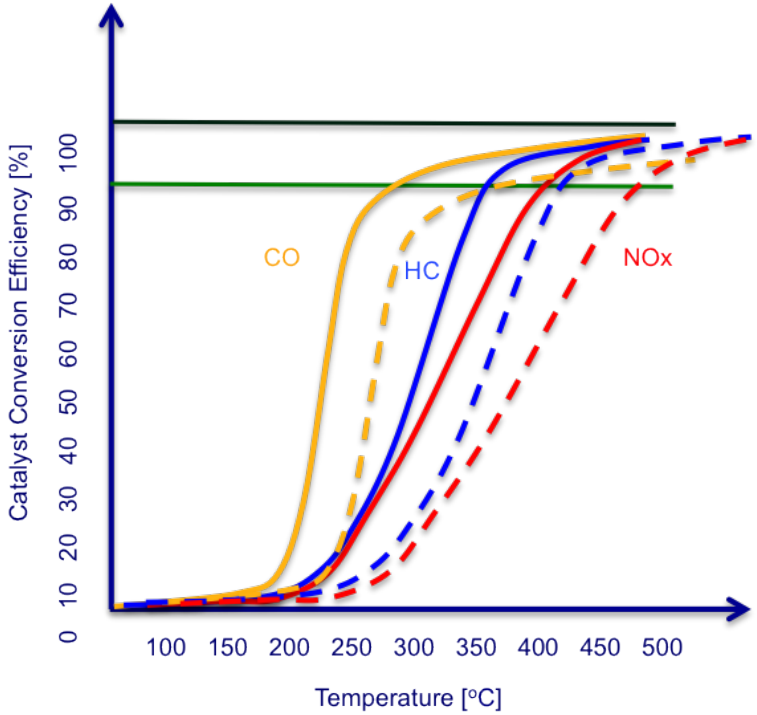
Joint work with Zhiming Gao and C. Stuart Daw

- Optimize catalyst warming up process for the purpose of mitigating tailpipe emissions in PEVs exposed to multiple engine cold start events.
- Integrate optimal engine and catalyst cold start strategies with the supervisory PEV power management controller with the aim to improve fuel economy.
- Develop a self-learning control scheme able to address catalyst aging effects that lower overall catalyst conversion efficiency.

Aftertreatment challenges

- Current stoichiometric TWC catalysts lightoff at higher temperatures.
- Poisoning and aging shift lightoff to even higher temperatures[2].

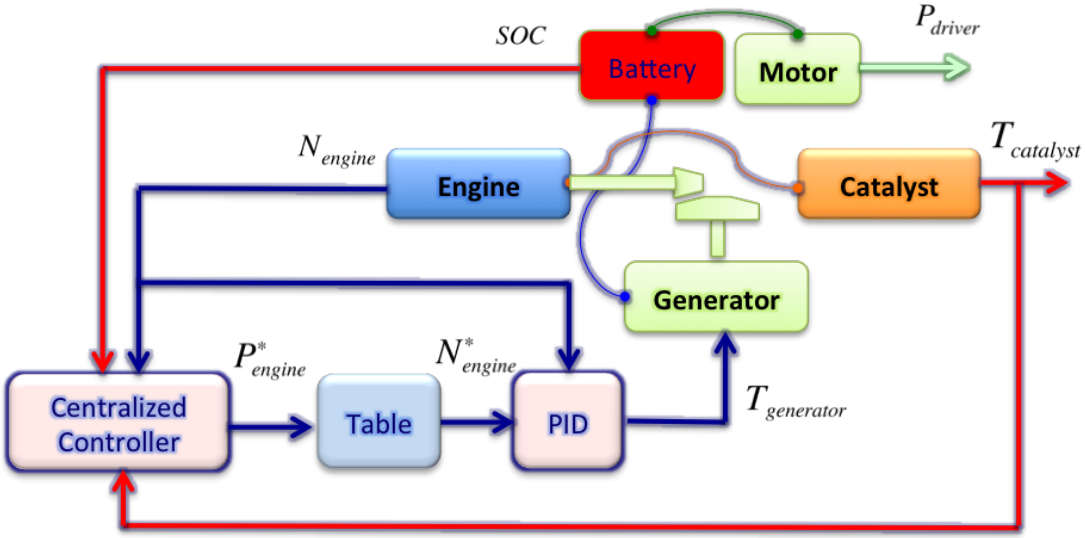




[2] ACEC Future Aftertreatment Strategy Report to the Advanced Powertrain Leadership Council, *U.S. DRIVE, November 8, 2011.*

Control scheme

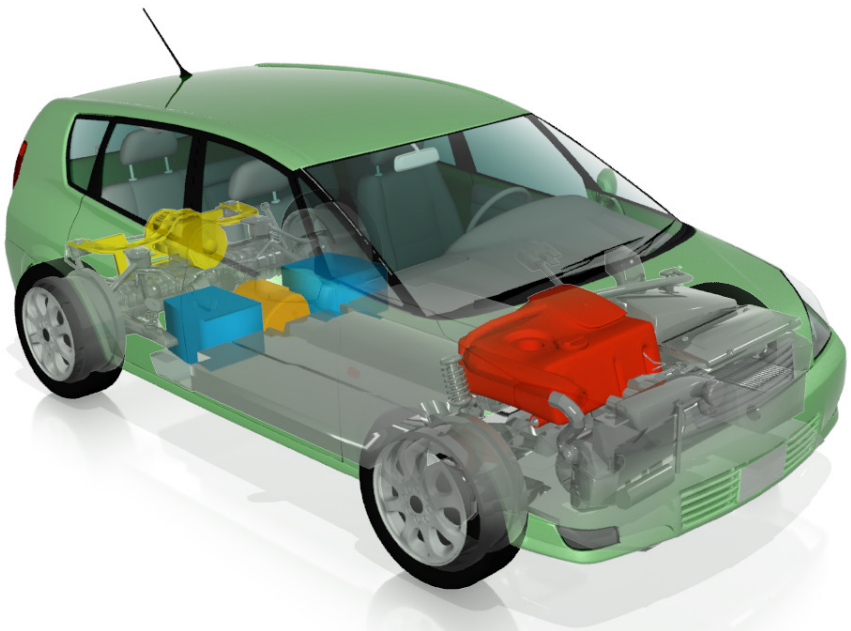
- State of the system: $X_t = T_{catalyst}$
- Control action: $U_t = P_{engine}$
- Disturbance: $W_t = SOC$
- Cost function: $k = (X_t, U_t)$=fuel consumption and catalyst conversion efficiency



Research path for "green" technologies

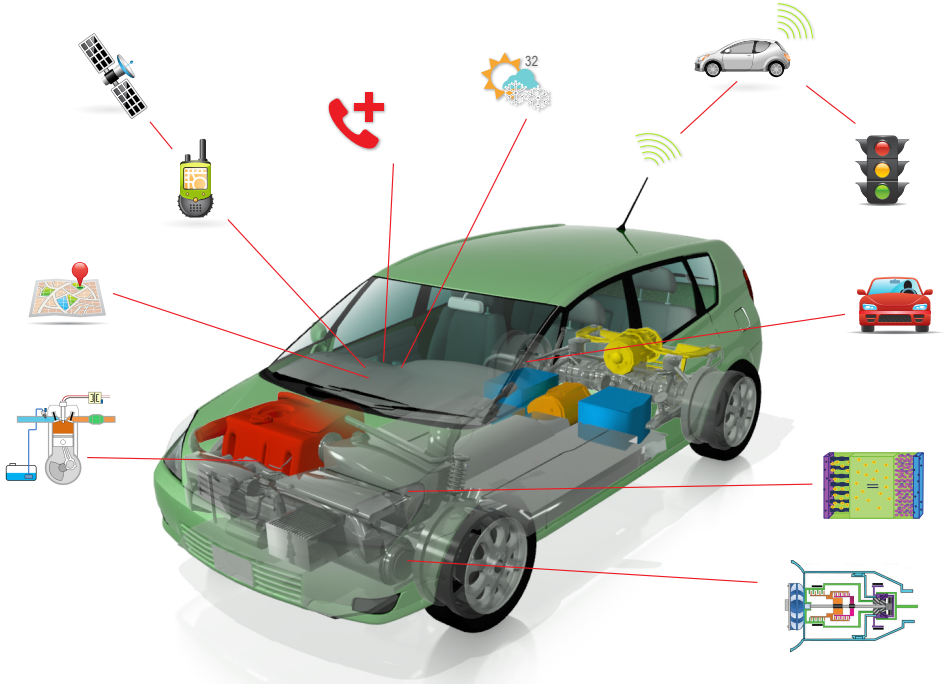
Autonomous intelligent plug-in electric vehicles (PEVs)

- Develop the theoretical framework and control algorithms for making a PEV into an *autonomous intelligent system* capable of realizing its optimal operation in real time while the driver is driving the vehicle.



*i*VEHICLE (**i**ntelligent **VE**hicle and **HI**ghway **C**ommunication **L**everaged for **E**fficiency)

- The iVEHICLE represents an exciting new approach to improving the overall efficiency of PEVs by utilizing an optimization framework and control algorithms to allow communication between PEVs and advanced traffic information systems.



Concluding remarks

- The necessity for environmentally conscious vehicle designs has led to significant investment in enhancing the propulsion portfolio with new technologies.
- Self-learning control can aim to allow continous optimal operation of advanced propulsion systems.
- Recognition of equilibrium control policies may be of value in making advanced propulsion systems capalble of realizing their optimal operation in real time while the driver is driving the vehicle.

Thank you for your Attention!

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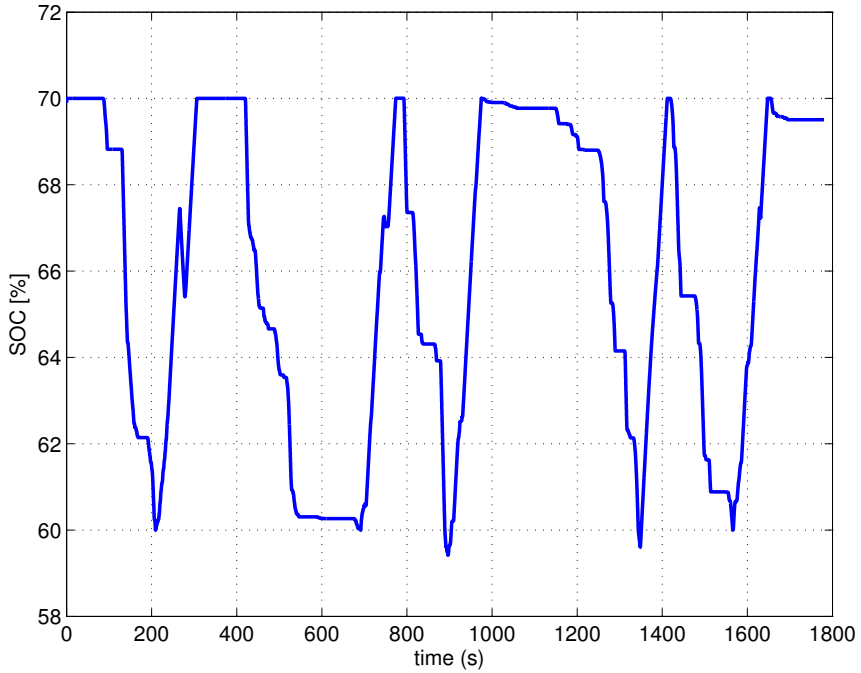
Back-up Slides

Bang-bang control

- SOC variation



- Fuel consumption