Physics-based Control of Energy Systems Ranging from Smart Buildings and Power Grid to Smart Hybrid Electric Vehicles

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Director of Energy Mechatronics Laboratory
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WISE Seminar at
University of Waterloo

Aug. 02, 2017

Outline

- About Michigan Tech and Me!
- Control of Building Energy Systems
- Control of Automotive Energy Systems

Part I:
About Michigan Tech and me!

Michigan Tech

Student Enrollment 7000
83% in STEM


AVERAGE SNOWFALL IS 5.3 METER!

Michigan Tech's Winter Carnival 2017

My Background

Controls
(Sliding Mode, Model Predictive, Adaptive Control, Modern Control, …)

Energy-Themo Fluids
(Thermodynamics, Combustion, HVAC, Renewables,…)

Experimentation
(Thermal-Mechanical-Electrical Systems, Control Software, Electronics,…)

Energy Mechatronics

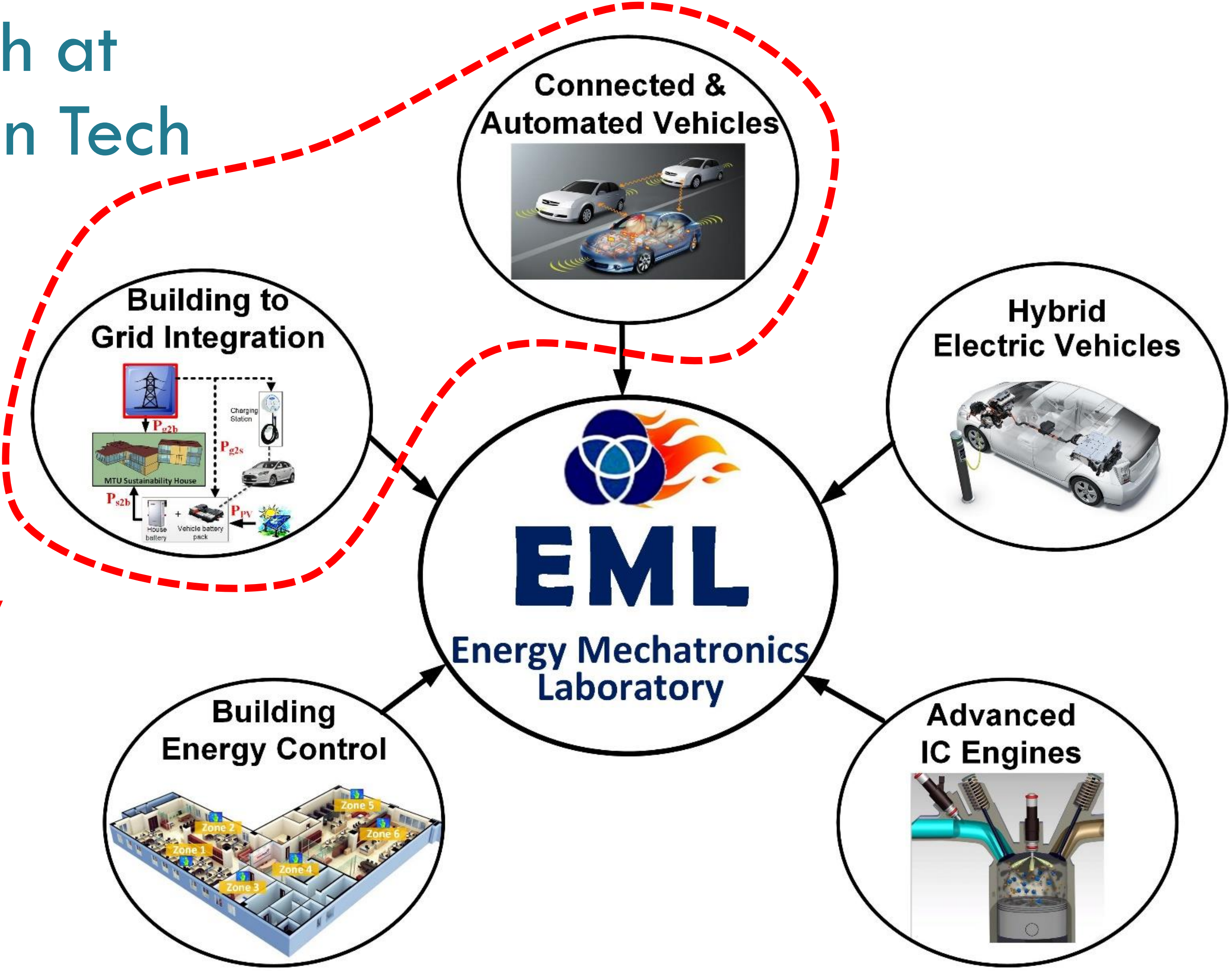
Research at Michigan Tech

EML

Energy Mechatronics Laboratory

Focus: Increasing efficiency of energy systems through utilization of advanced control techniques

Research at Michigan Tech



Smart City/ Community

EML Students

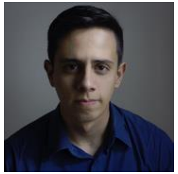
Current: 6 PhD, 4 MS, 2 BS


Joe Tripp (PhD)


Behrouz Khoshbakht (PhD)


Lexy Krisztian (BS)


Drew Hanover (BS)


Vinicius Bonfochi (PhD)


Amir Khamenian (PhD)


Akshat A. Raut (MS)


Mayank Darji (MS)


Chethan R. Reddy (PhD)


Mohamed Toub (Visiting PhD)


Rajeshwar Yadav (MS)


Prithvi Reddy (MS)

Graduated: 5 PhD, 12 MS


Dr. Ali Solouk


Dr. Meysam Razmara


Dr. Boopathi Mahadevan


Dr. Reza Amini


Dr. Mehran Bidarvatan


Madhura Paranjape (MS)


Deepak Kothari (MS)


Hrishikesh Saigaonkar (MS)


Vishal Thakkar (MS)


Nithin Teja Kondipati (MS)


Jeremy Dobbs (MS)


Kaveh Khodadadi (MS)


Mohammad Nazemi (MS)


Kaushik Kannan (MS)

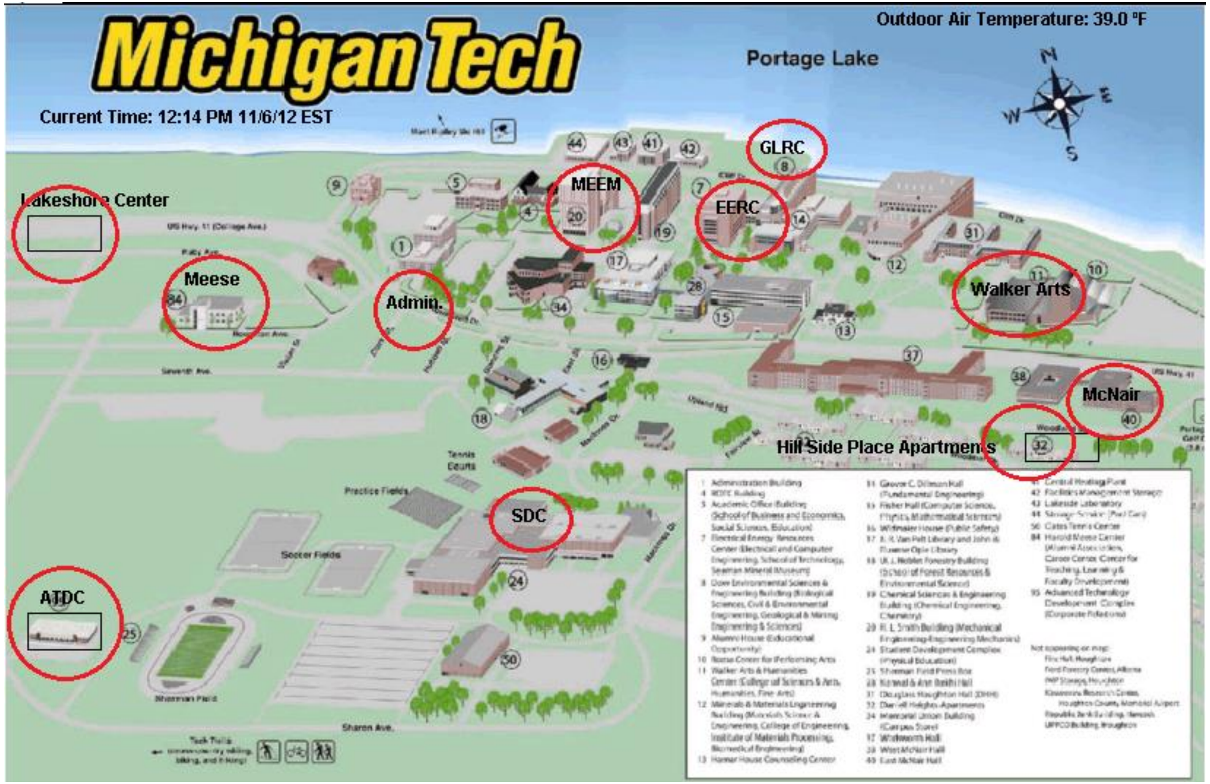

Jayant Arora (MS)

Part II:
Control of building energy systems

Part II: Control of building energy systems

- Modeling of building energy systems
- Predictive control of building HVAC systems
- Building-to-grid optimization

Building Research Test Bed



HVAC System at Lakeshore Center

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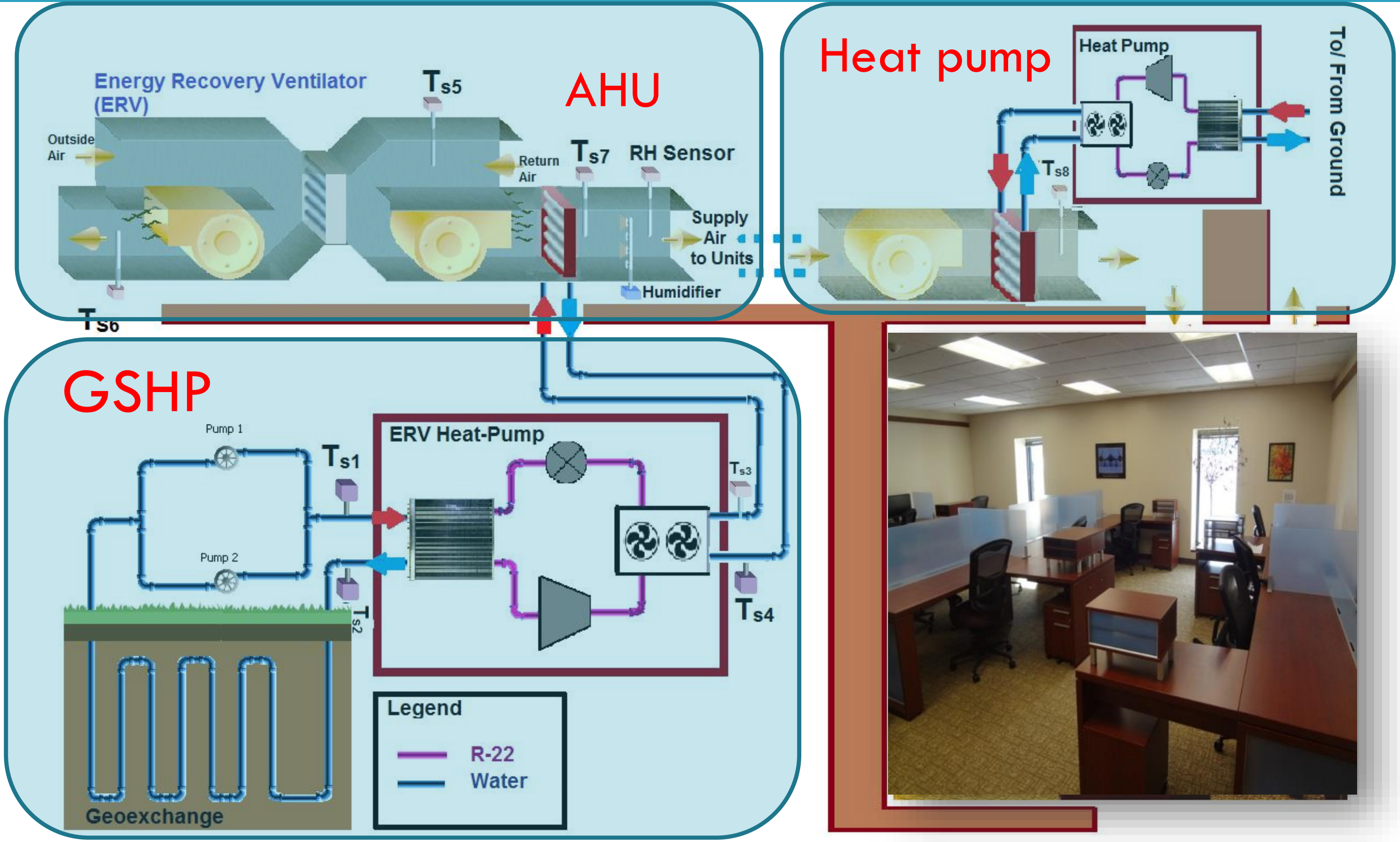
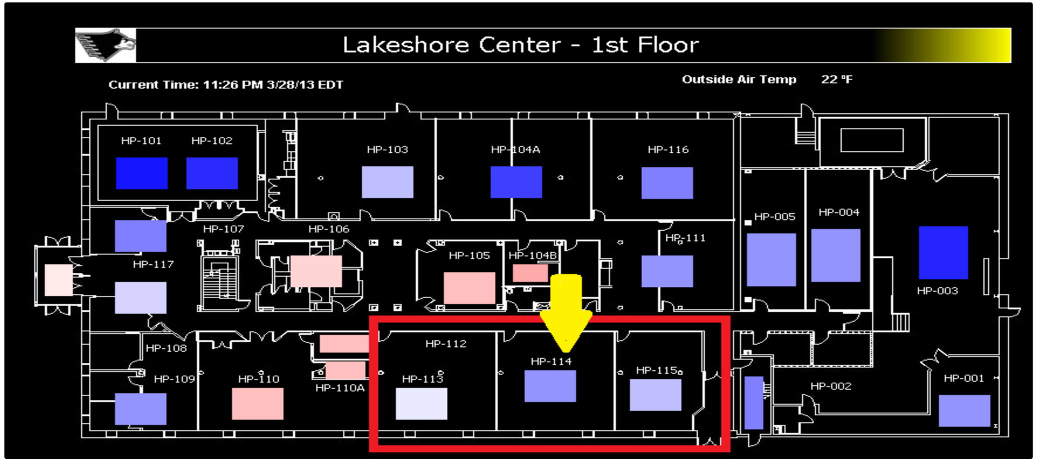
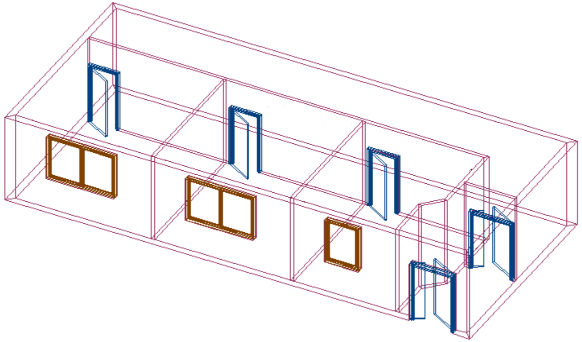
HVAC System at Lakeshore Center

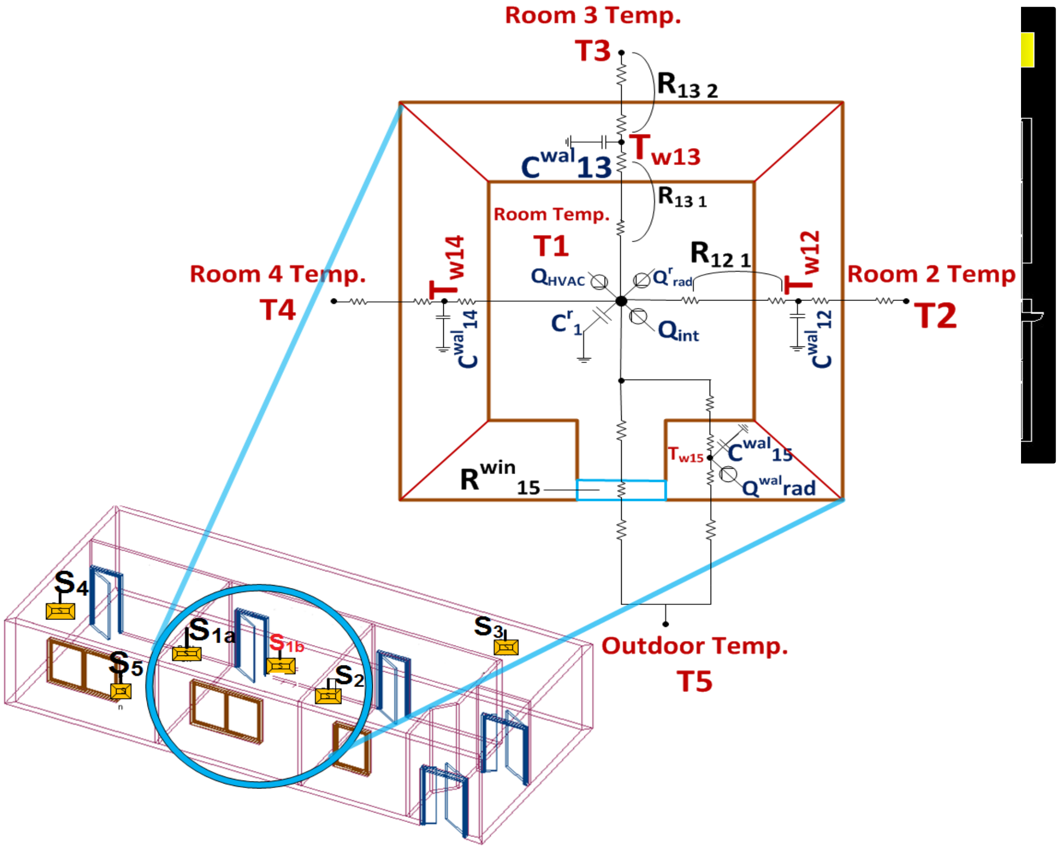


Building Thermal Modeling-RC Model





Building Thermal Modeling-RC Model



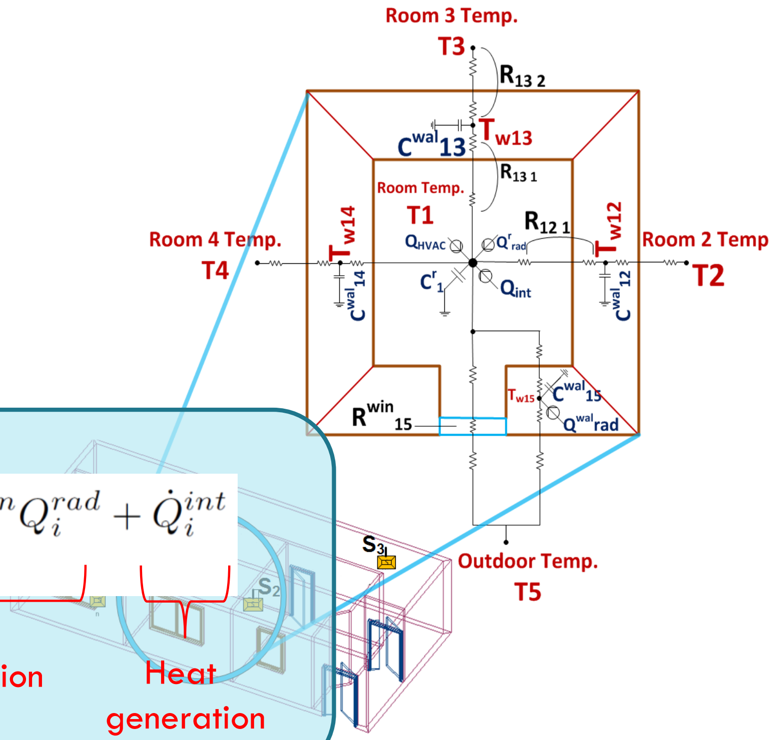
Building Thermal Model

Energy balance for a **wall** node:

$$C^w_{i,j}\frac{dT^w_{i,j}}{dt} = \underbrace{\sum_{k\in\mathcal{N}^w_{i,j}} \frac{T^r_k - T^w_{i,j}}{R^k_{i,j}}}_{\text{Conduction \& convection}} + \underbrace{r_{i,j}\alpha_{i,j}A^w_{i,j}Q^{rad}_{i,j}}_{\text{Radiation}}$$

Energy balance for a **room** node:

$$C^r_i\frac{dT^r_i}{dt} = \underbrace{\sum_{k\in\mathcal{N}^r_i} \frac{T^k - T^r_i}{R^k_{i,j}}}_{\text{Conduction \& convection}} + \underbrace{\dot{m}^r_i\bar{c}_p(T^s_i - T^r_i)}_{\text{HVAC heat flow}} + \underbrace{\pi_i\tau^w_i A^{win}_i Q^{rad}_i}_{\text{Radiation}} + \underbrace{\dot{Q}^{int}_i}_{\text{Heat generation}}$$

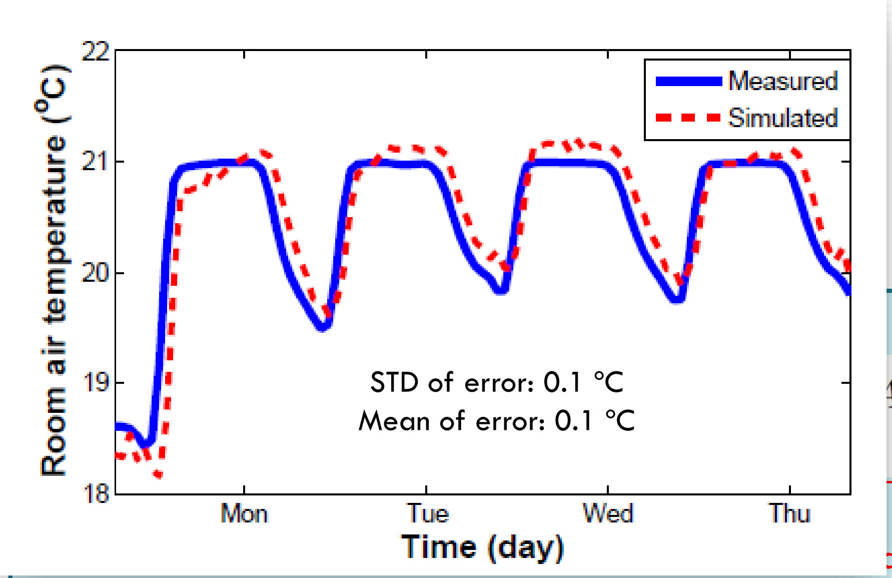


Maasoumi, Shahbakhti, et. al, *2013 ASME DSC Conf.*

Building Thermal Model

Energy balance for a **wall** node:

$$C^w_{i,j}\frac{dT^w_{i,j}}{} = \sum \frac{T^r_k - T^w_{i,j}}{} + r_{i,j}\alpha_{i,j}A^w_{i,j}Q^{rad}_{i,j}$$



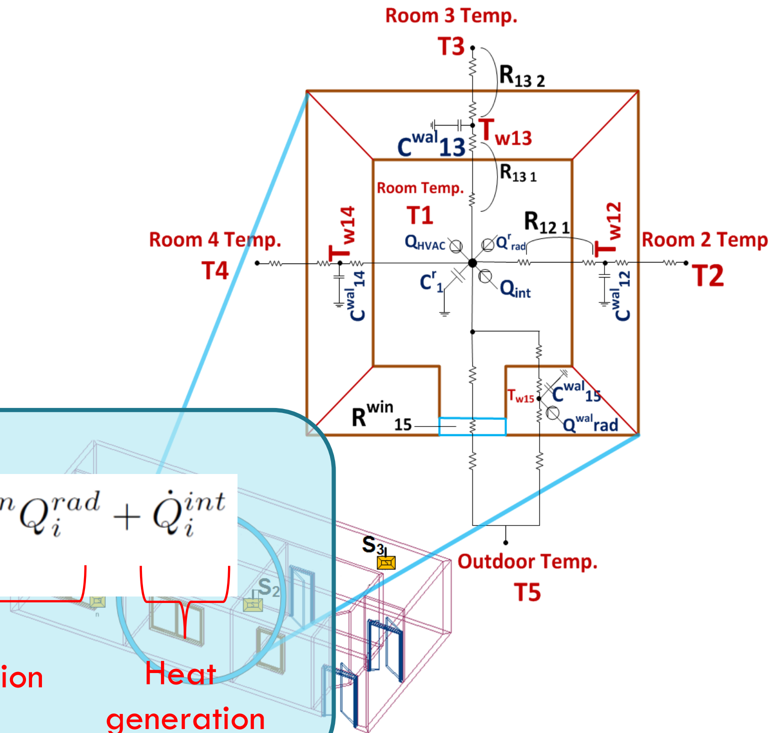
$$A^{win}_i Q^{rad}_i + \dot{Q}^{int}_i$$

convection

flow

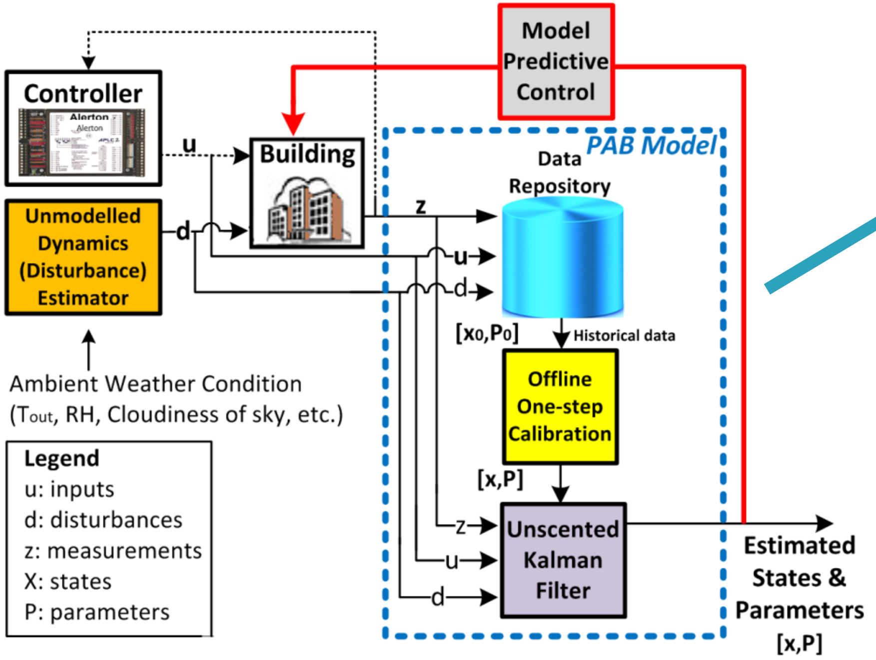
diation

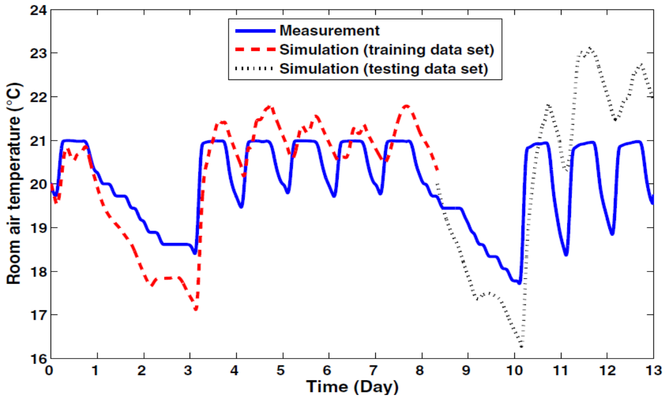
Heat generation

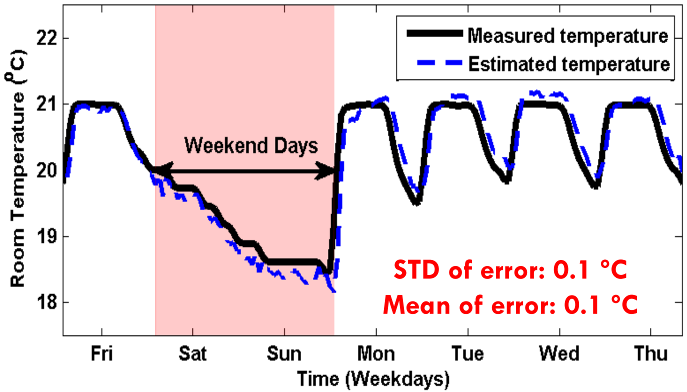


Maasoumi, Shahbakhti, et. al, *2013 ASME DSC Conf.*

Parameter Adaptive Building (PAB) Model







M. Maasoumy, M. Shahbakhti, et. al, " Handling Model Uncertainties in Model Predictive Control for Energy Efficient Buildings ", *J. of Energy and Buildings*, 2014.

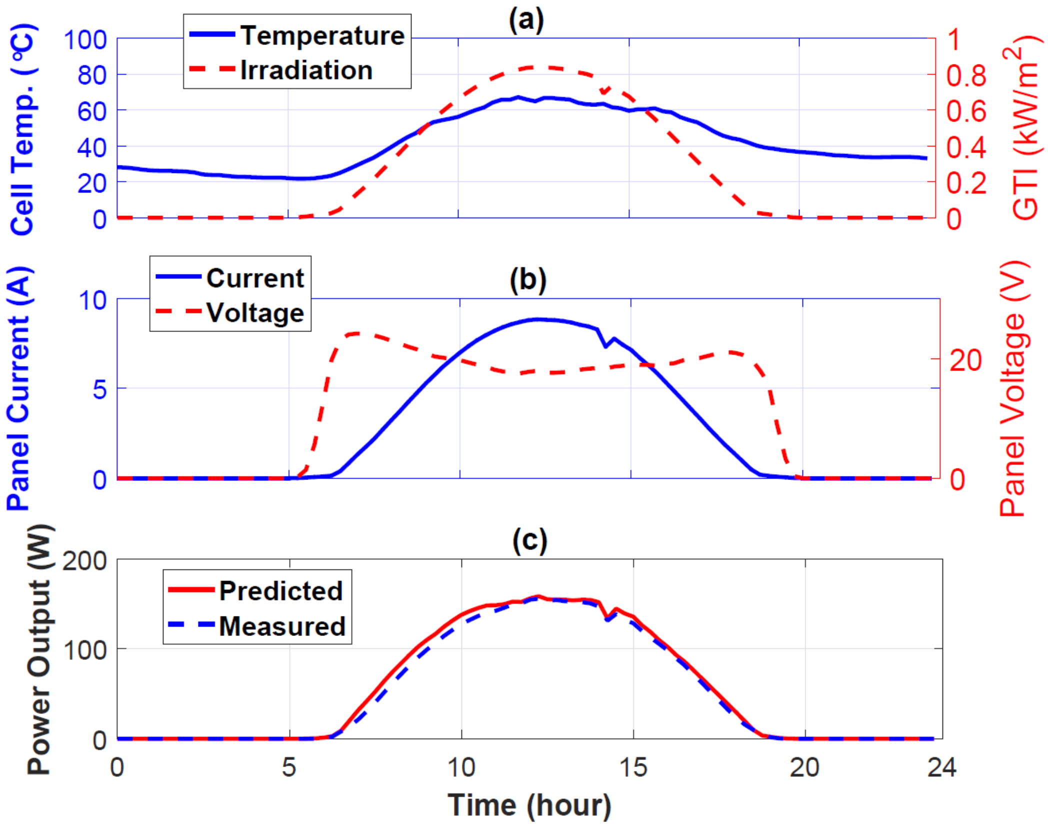
Modeling:

Photovoltaic Single Diode Modeling

Photo credit: Michigan Tech's Keweenaw Research Center

Modeling:

Photovoltaic Single Diode Modeling



Exergy vs. Energy

- The **1st Law** of Thermodynamics is related to energy conservation
- The **2nd Law** of Thermodynamics concerns entropy generation and irreversibility which cause deficiency
- **Exergy** is based on the 1st and 2nd Laws of Thermodynamics and is relevant to quality of energy
- **Exergy** is defined as the maximum useful work during a process in a specific environment
- **Exergy** is a more precise metric compared to energy to evaluate energy systems. (e.g. HVAC systems, IC engines, power-plants, etc.)

Exergy vs. Energy

- The 1st Law of Thermodynamics is related to energy conservation
- The 2nd Law of Thermodynamics concer… irreversibility which cause deficiency
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- Exergy is defined as the maximum usef… specific environment
- Exergy is a more precise metric compa… energy systems. (e.g. HVAC systems, IC engines…

Stirling Engine

$$E_1 = m_w u_w = 42\ kJ$$
$$X_1 = m_w[(u_w - u_0) + P_0(v_w - v_0) - T_0(s_w - s_0)] = 1\ \text{kJ}$$

After adding ice

$$E_2 = m_w u_w = 42\ kJ$$
$$X_2 = m_w[(u_w - u'_0) + P'_0(v_w - v'_0) - T'_0(s_w - s'_0)] = 18\ \text{kJ}$$

Exergy is a more pr…

Building Exergy Model

$$\dot{X}^r_{dest_i} = \overbrace{\sum_{k \in N^r_i} (1 - \frac{T_0}{T^r_i}) \dot{Q}_i^{H.T.,k}}^{\dot{X}_i^{H.T.,r}} - \dot{W}^r_i + \sum_{in} \dot{m}\psi - \sum_{out} \dot{m}^r_i \psi - \frac{dX^r_i}{dt}$$

$$\dot{X}_i^{H.T.,r} = \sum_{k \in N^r_i} (1 - \frac{T_0}{T^r_i})(\frac{T^k - T^r_i}{R^k_{i,j}})$$

$$\psi = (h - h_0) - T_0(s - s_0) + \frac{V^2}{2} + gz$$

$$\frac{dX^r_i}{dt} = m_i^{room}(\frac{dh}{dt} - T_0 \frac{ds}{dt})$$

$$\dot{X}^r_{dest_i}[k] = \sum_{k \in N^r_i} (1 - \frac{T_0[k]}{T^r_k[k]})(\frac{T^r_k[k] - T^r_i[k]}{R^k_{i,j}}) +$$
$$\dot{m}^r_i[k][\bar{c_p}(T^s_i[k] - T^r_i[k]) - T_0[k]\bar{c_p} \ln(\frac{T^s_i[k]}{T^r_i[k]})]$$
$$+ \frac{m_i^{room}}{T_{sample}}[\bar{c_p}(T^r_i[k] - T^r_i[k-1])$$
$$- T_0[k]\bar{c_p} \ln \frac{T^r_i[k]}{T^r_i[k-1]}]$$

$$\Delta h = \int \bar{c_p} dT$$

$$\Delta s = \int_1^2 \bar{c_v} \frac{dT}{T} + R \cdot ln \frac{v_2}{v_1}$$

Building Thermal and Exergy Model

$$d_t = g(Q_{rad_i}(t), \dot{Q}_{int}(t), T_{out}(t))$$

$$\dot{x}_t = f(x_t, u_t, d_t, t)$$

$$y_t = Cx_t$$

Nonlinear System Dynamics
(Bilinear due to Inputs multiplication)

Discretized System Dynamics

$$x_{k+1} = \begin{cases} A_d x_k + B_d u_k + E_d d_k & k\epsilon[5, 6, \ldots, 18] \\ A_n x_k + B_n u_k + E_n d_k & k\epsilon[19, \ldots, 24, 1, \ldots, 5] \end{cases}$$

Input: Supply air temperature

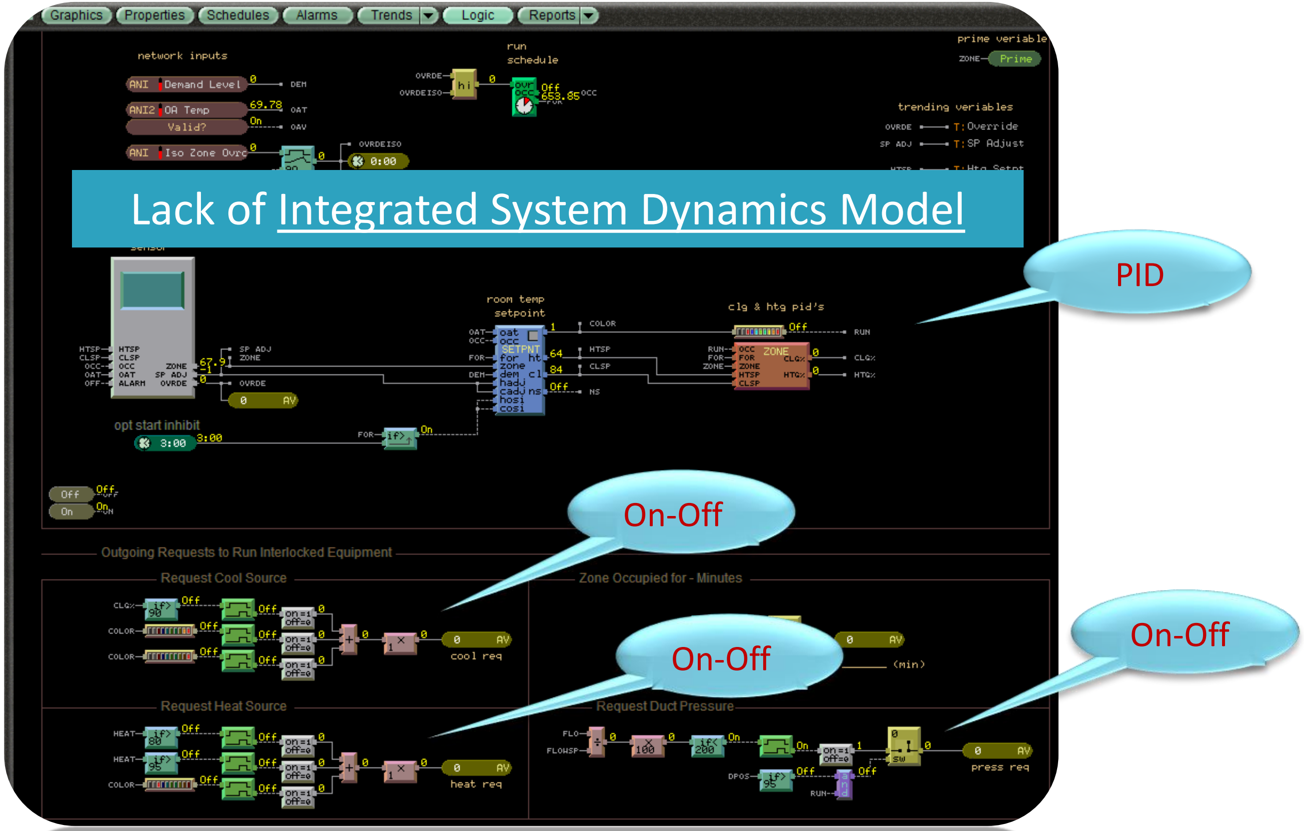
States: Room air temperature & neighboring zones temperature

Output: Room air temperature

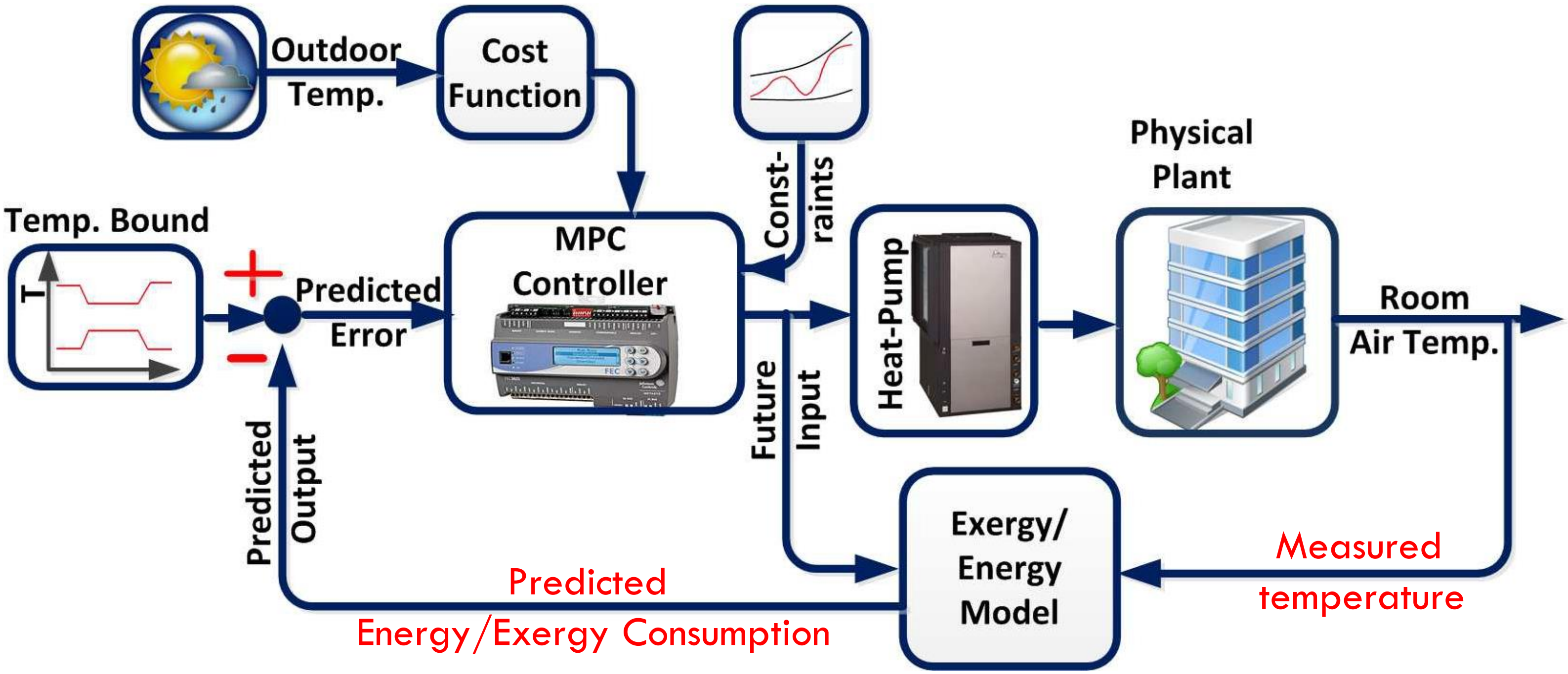
Part II: Control of building energy systems

- Modeling of building energy systems
- Predictive control of building HVAC systems
- Building-to-grid optimization

Existing HVAC Control Logics



Model Predictive Control of HVAC Systems



M. Razmara, M. Shahbakhti, et. al., " Optimal Exergy Control of HVAC Systems ", *Journal of Applied Energy*, 2016.

MPC formulation

Controllers:
- Rule-based controller (RBC)
- Energy-based MPC (EMPC)
- Exergy-based MPC (XMPC)

EMPC:

$$\min_{U_t,\bar{\epsilon},\underline{\epsilon}} \boxed{\{|I_e|_1 + \rho(|\bar{\epsilon}_t|_1 + |\underline{\epsilon}_t|_1)\}}$$

subject to:

$$x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k|t} + Ed_{t+k|t}$$
$$y_{t+k|t} = Cx_{t+k|t}$$

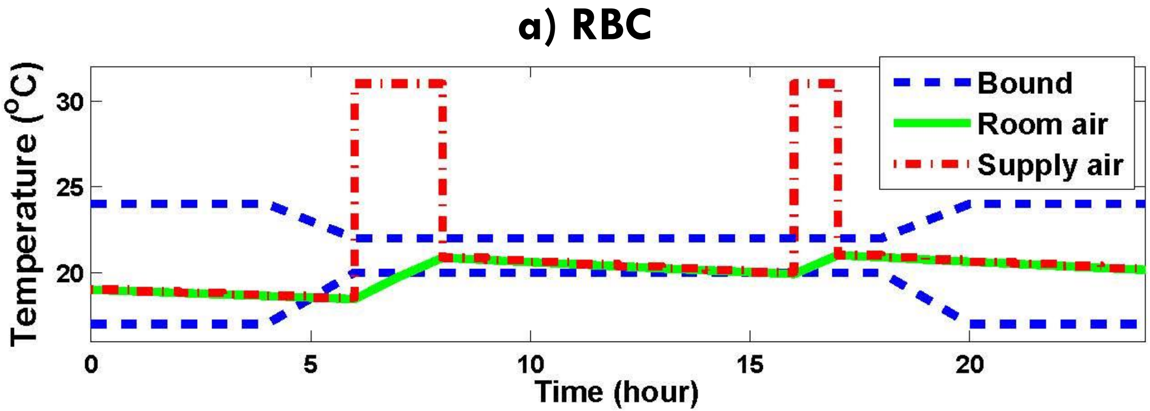
$$\underline{\mathcal{U}}_{t+k|t} \leq u_{t+k|t} \leq \overline{\mathcal{U}}$$
$$\underline{\delta\mathcal{U}} \leq u_{t+k+1|t} - u_{t+k|t} \leq \delta\overline{\mathcal{U}}$$
$$\underline{T}_{t+k|t} - \underline{\varepsilon}_{t+k|t} \leq y_{t+k|t} \leq \overline{T}_{t+k|t} + \overline{\varepsilon}_{t+k|t}$$
$$\underline{\varepsilon}_{t+k|t}, \overline{\varepsilon}_{t+k|t} \geq 0$$

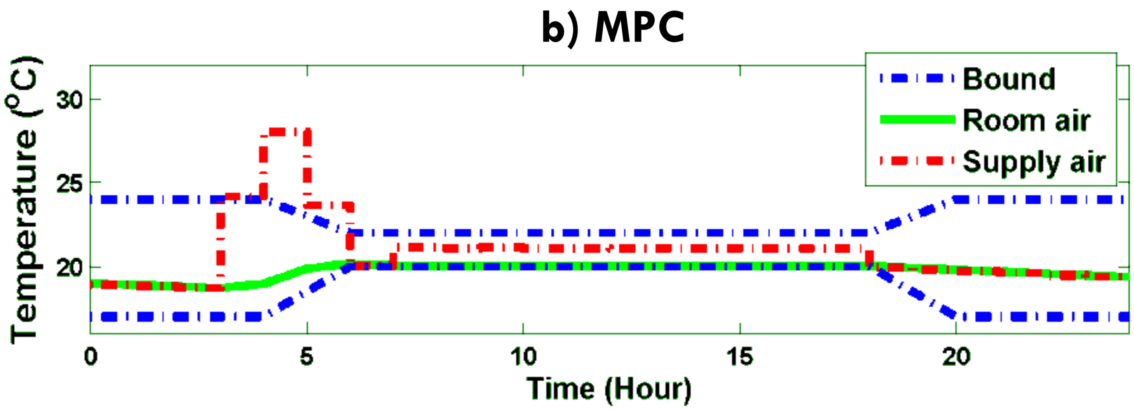
$$I_e = \int_{t=1}^{24} [P_c(t) + P_h(t) + P_f(t)]\, dt$$
$$P_c(t) = \dot{m}_i^r(t)\bar{c_p}[T_{r_i}(t) - T_c(t)]$$
$$P_h(t) = \dot{m}_i^r(t)\bar{c_p}[T_h(t) - T_{r_i}(t)]$$
$$P_f(t) = \alpha(\dot{m}_i^r)^3$$

XMPC:

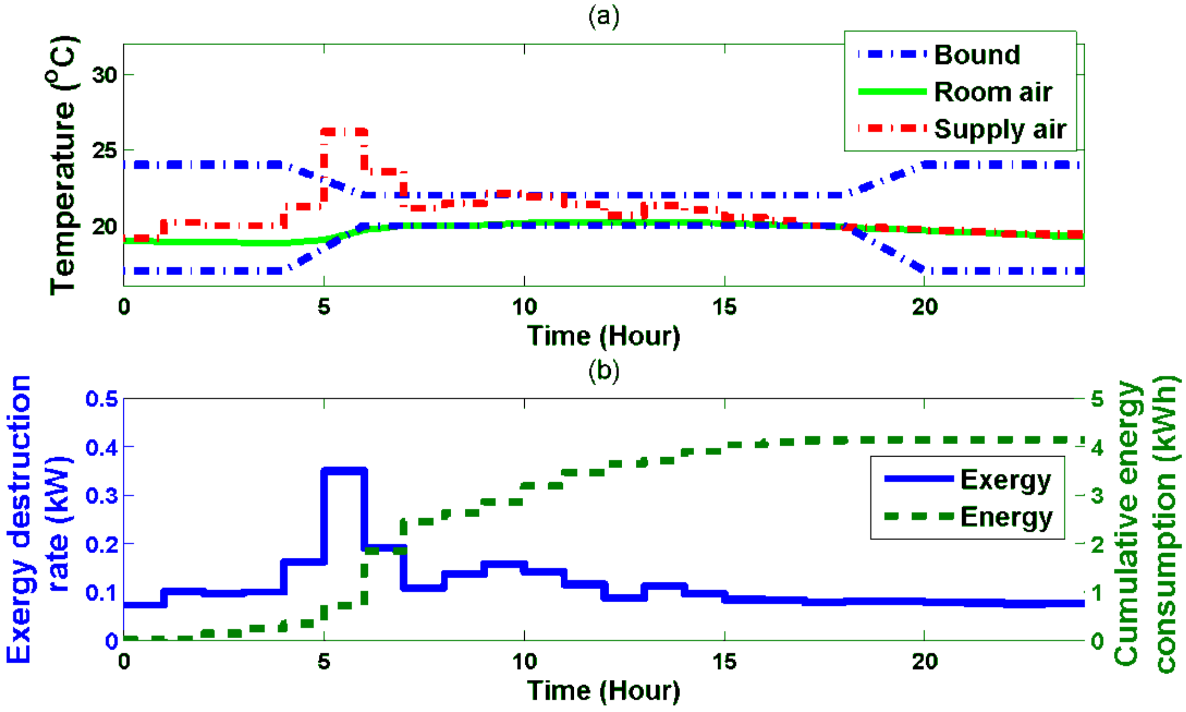
$$\min_{U_t,\bar{\epsilon},\underline{\epsilon}} \{\dot{X}_{dest_t} + \rho(|\bar{\epsilon}_t|_1 + |\underline{\epsilon}_t|_1)\}$$

Results: Rule-Based Control vs. MPC





Results: Exergy-Based MPC (XMPC)



M. Razmara, M. Shahbakhti, *et.al.*, " Optimal Exergy Control of HVAC Systems ", *Applied Energy*, 2015.

Results: Comparison Table

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Controller type	Exergy destruction $[kWh]$	Energy consumption $[kWh]$	Reduction in exergy destruction* w/r to RBC [%]	Reduction in energy consumption* w/r to RBC [%]
XMPC	2.7	4.2	22	36
EMPC	2.8	4.6	18	24
RBC	3.3	5.7	-	-

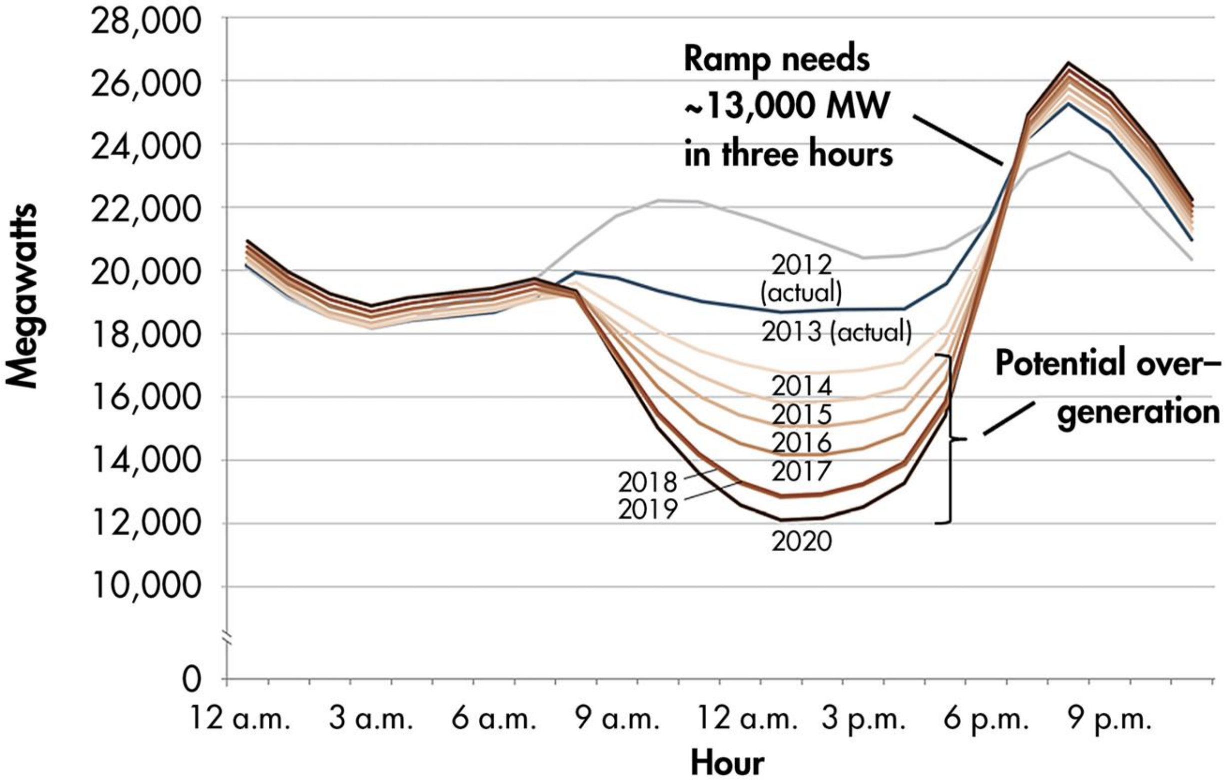
*Saving percentage is calculated by $\frac{(x_0 - x)}{x}$, where x_0 is result of RBC controller.

M. Razmara, M. Shahbakhti, *et.al.*, " Optimal Exergy Control of HVAC Systems ", *Applied Energy*, 2015.

Part II: Control of building energy systems

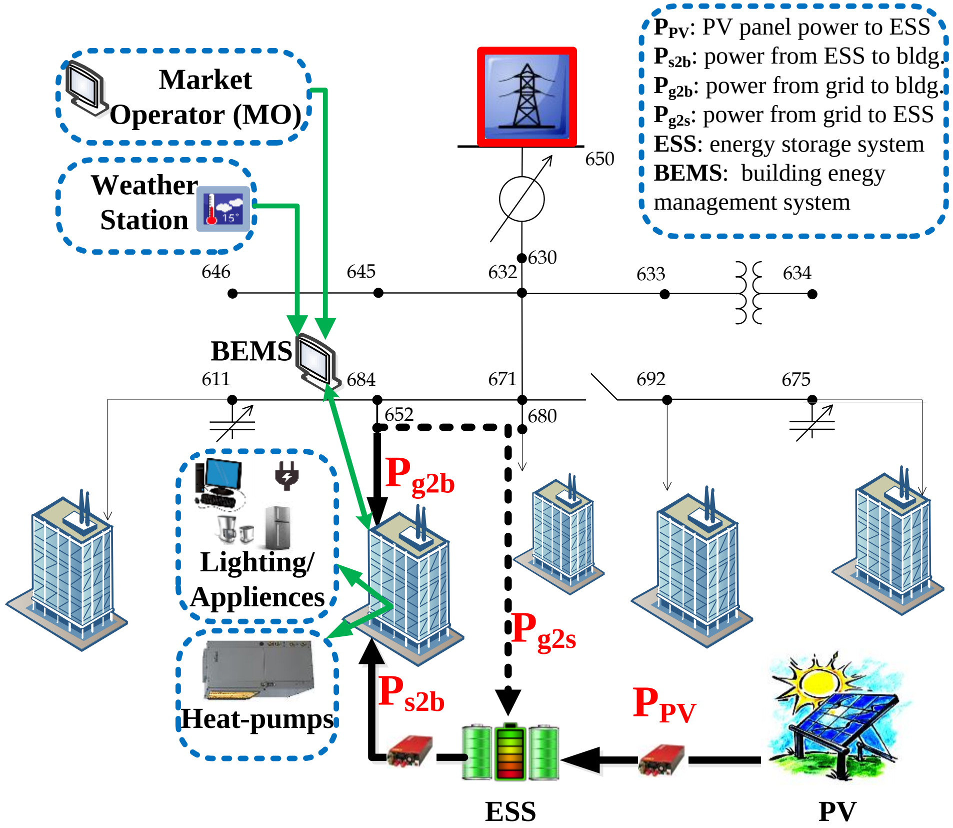
- Modeling of building energy systems
- Predictive control of building HVAC systems
- Building-to-grid optimization

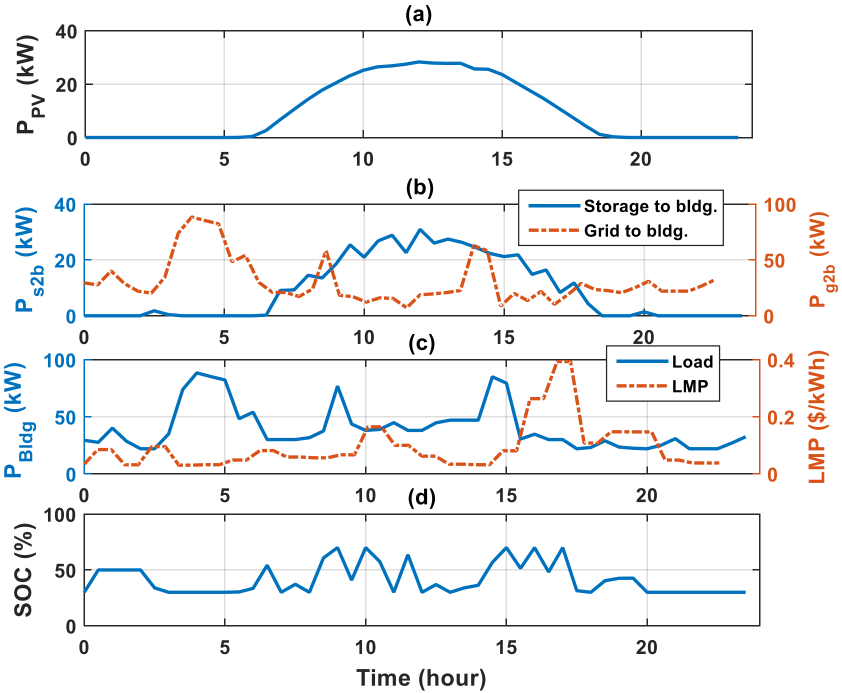
Motivation: Rapid renewable penetration and ramp rate during peak hours



Source: California ISO, Net Load on CASIO system. http://www.caiso.com/informed/Pages/CleanGrid/TodaysRenewables.aspx. Accessed Feb 28th 2017.

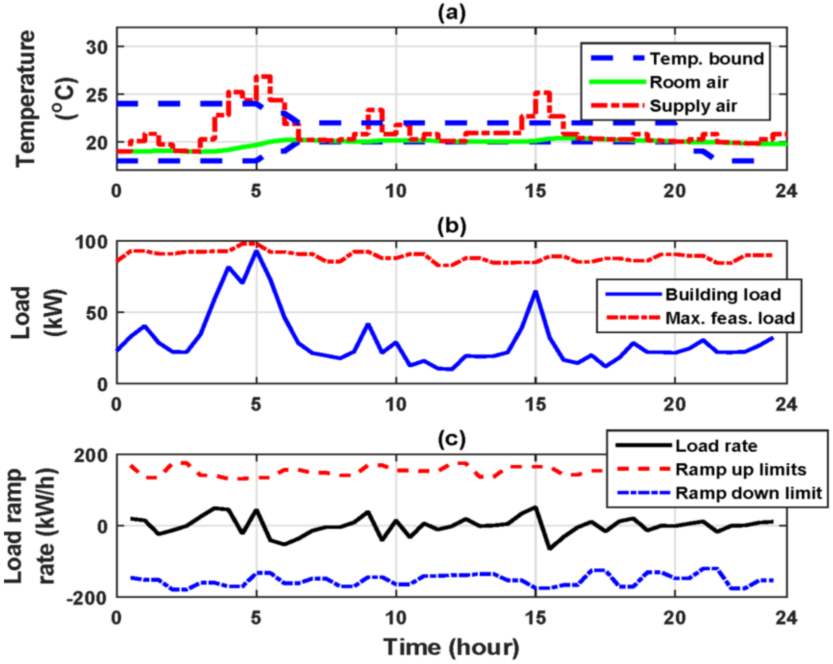
Demand Response via B2G system with PV panels and energy storage system (ESS)



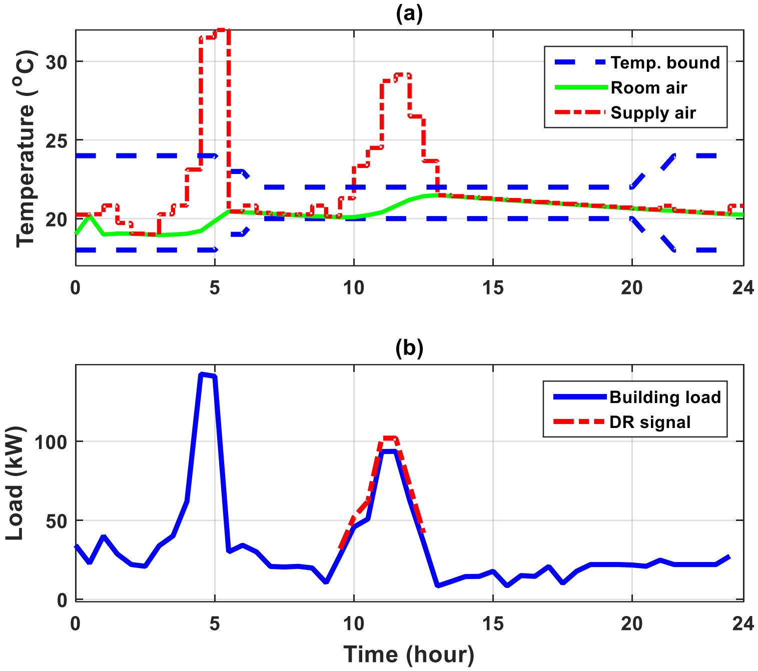


Building load and ramp rate controls

- Ramp rate control



- Load following



M. Razmara, M. Shahbakhti, *et.al.*, " Building-to-grid Predictive Power Flow Control for Demand Response and Demand Flexibility Programs ", *Applied Energy*, 2017.

Probability of providing benefits from proposed bidirectional B2G controls based on Monte-Carlo simulations

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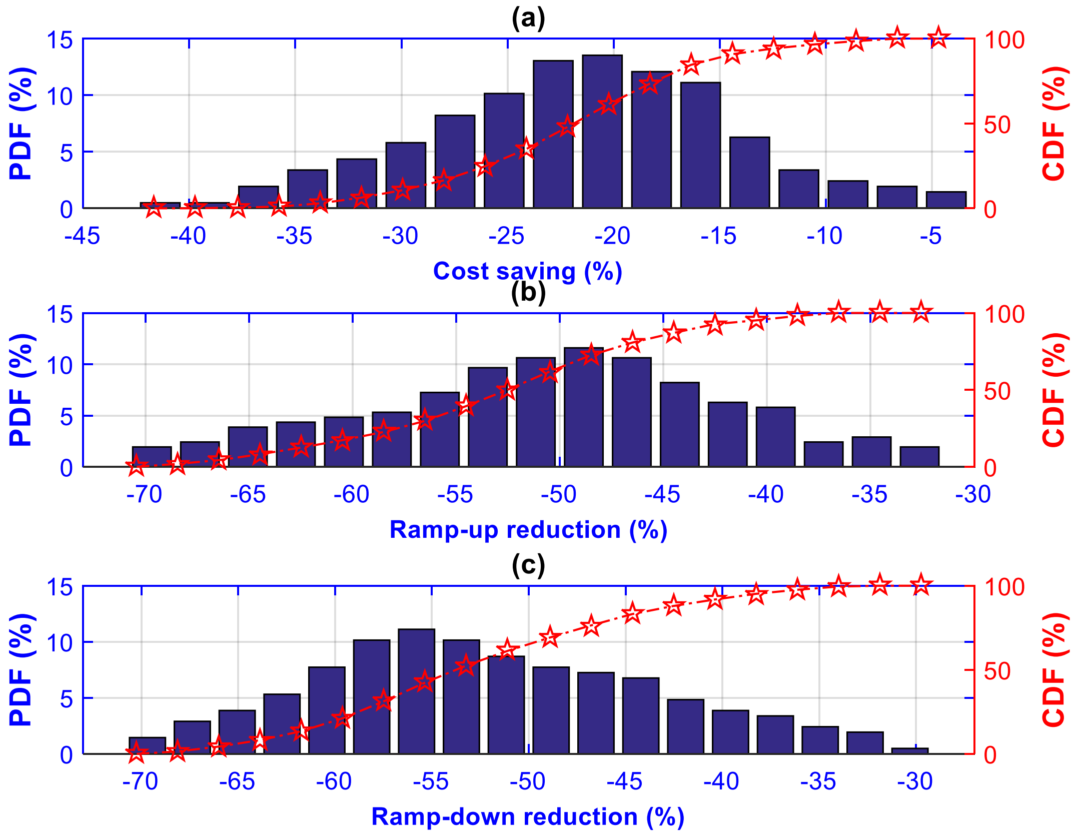


M. Razmara, M. Shahbakhti, *et.al.*, " Building-to-grid Predictive Power Flow Control for Demand Response and Demand Flexibility Programs ", *Applied Energy*, 2017.

Summary (I)

- Model-based predictive control for buildings
  - requires an accurate dynamic model of buildings and renewable sources → *Parameter Adaptive Building Model;*
  - can optimize HVAC system performance by integrating system dynamics;
  - can achieve 36% reduction in energy consumption in building HVAC systems, using exergy-wise MPC.

Summary (II)

- Bi-directional building-to-grid (B2G) optimization
  - can help the power grid to employ the flexibility of buildings HVAC system to prevent problems such as duck-curve, over generation, and intermittent production;
  - can reduce monthly electricity costs 5-42%, compared to the unoptimized rule-based control;
  - can help to reduce load ramp-rate by 30-70% in buildings

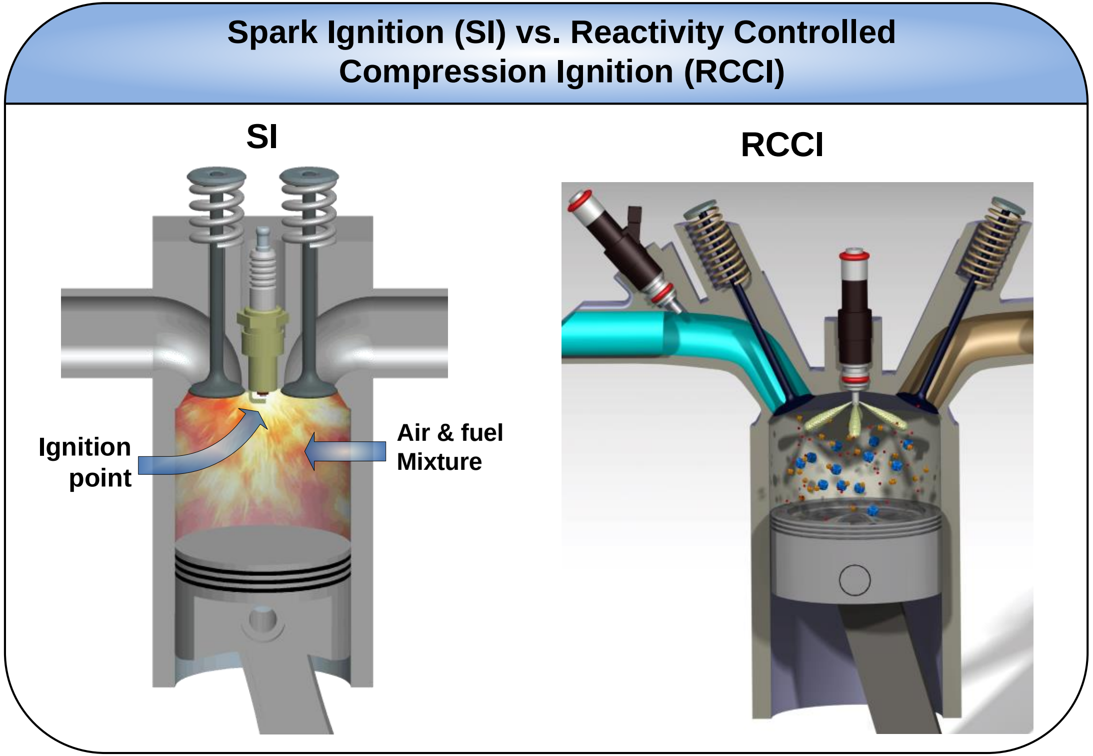
Part III:
Control of Powertrain and Hybrid Electric Vehicles

Part III: Control of automotive energy systems

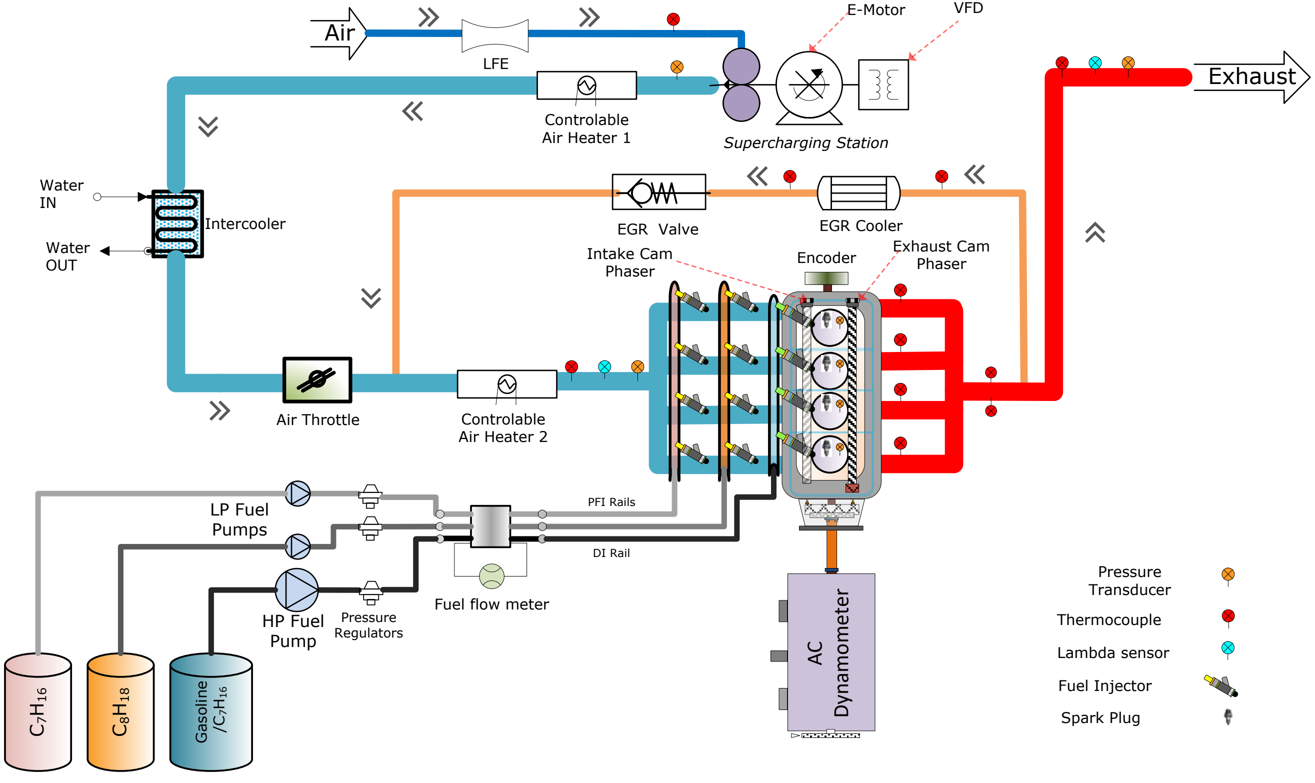
- Model-based control of advanced IC engines
- Predictive control of hybrid electric vehicles
- Control of connected and automated vehicles

Introduction

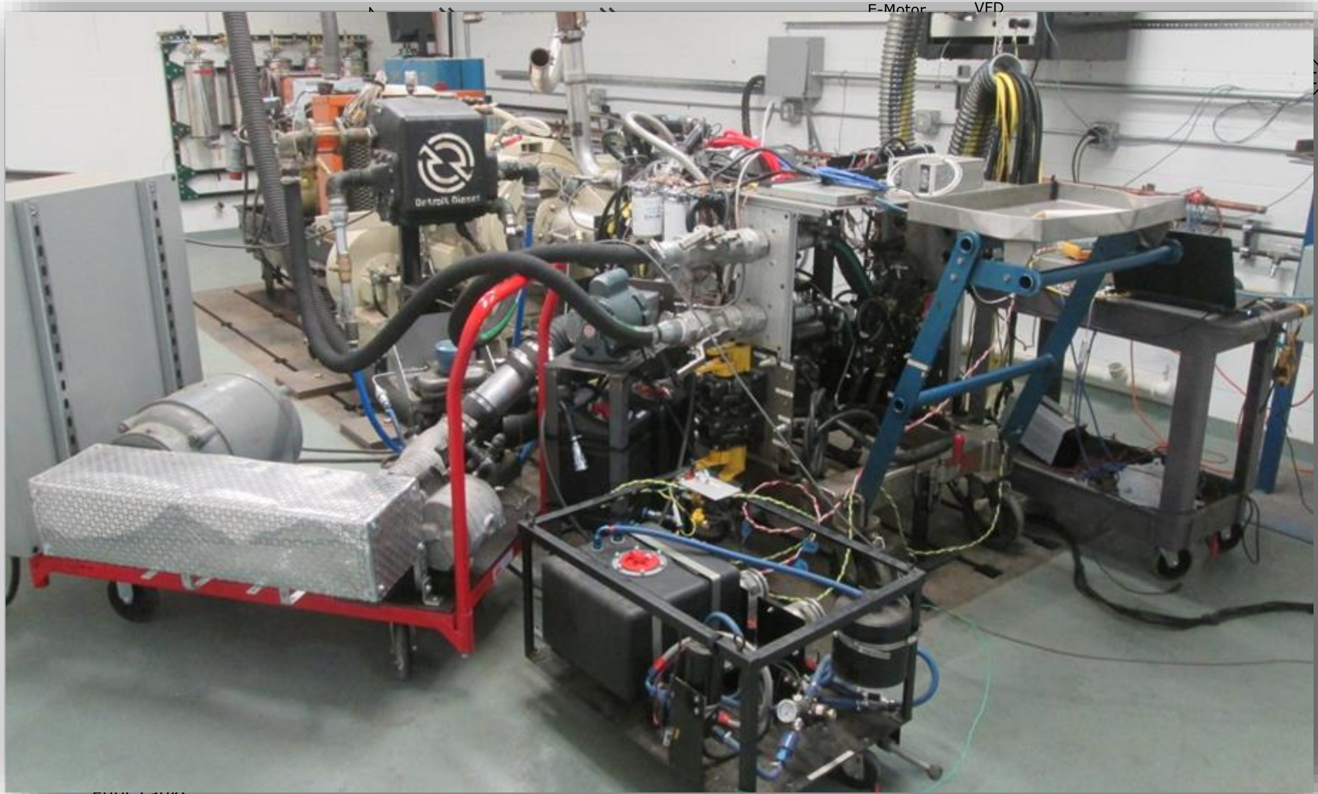
RCCI offers peak indicated thermal efficiency of 53%, with ultra low NOx and PM emissions!



Engine Experimental Setup



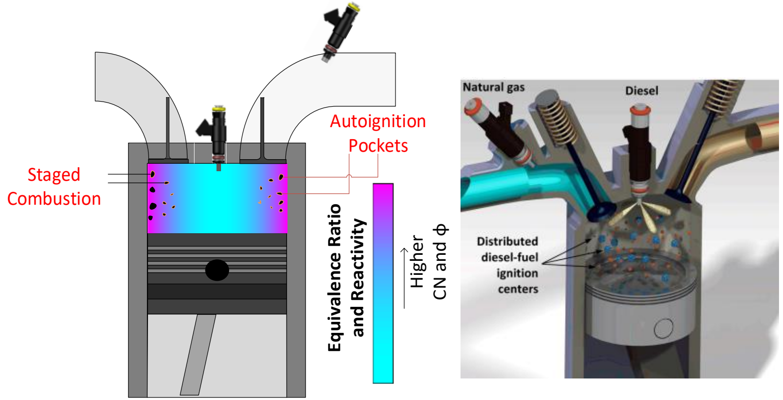
Engine Experimental Setup



Dynamic Model of RCCI Engines

Predicts cycle-by-cycle combustion phasing and load

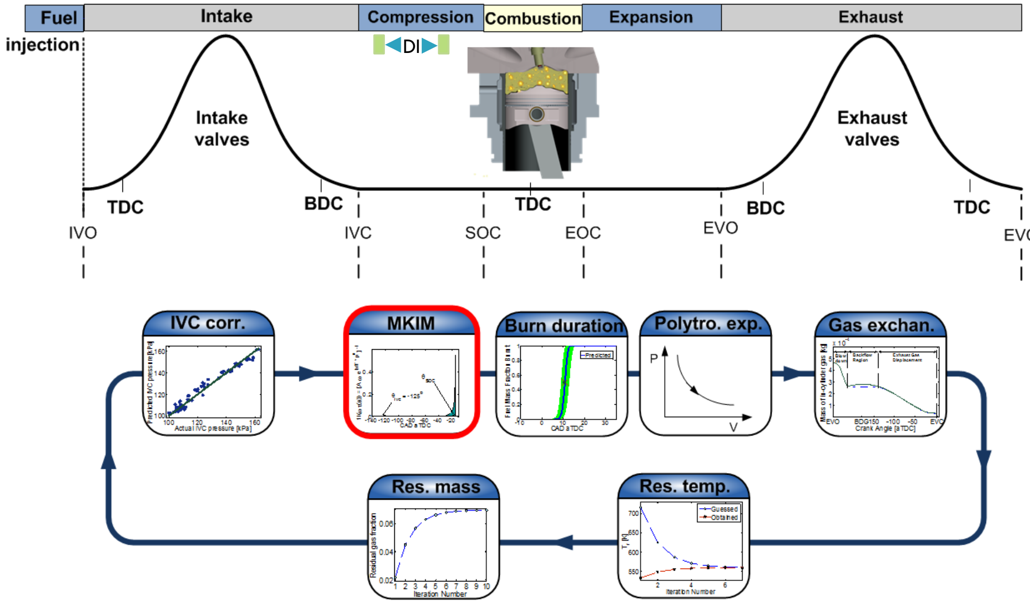
- **Phenomenological Model**



$$\int_{SOI}^{SOC} \frac{d\theta}{\underbrace{N A_2 \left(\varphi_{DI}{}^{B_{2DI}} + \varphi_{PFI}{}^{B_{2PFI}}\right) \exp\left(\frac{a}{(CN_{mix}+b)} \frac{\left(P_{IVC}\, v_c^{k_c}\right)^{D_2}}{T_{IVC} v_c^{k_c-1}}\right)}_{\tau}} + \int_{IVC}^{SOI} \frac{d\theta}{A_1 N \varphi_{PFI}^{B_1} exp\left(\frac{C_1 \left(P_{IVC}\, v_c^{k_c}\right)^{D_1}}{T_{IVC} v_c^{k_c-1}}\right)} = 1$$

* K. Sadabadi, M. Shahbakhti, A. Bharath, and R. Reitz. *"Modelling of Combustion Phasing of an RCCI Engine for Control Applications." Int. J. of Engine Research*, 2016.

- **Dynamic Model**



* K. Sadabadi, M. Shahbakhti, " Dynamic Modeling and Controller Design of Combustion Phasing of an RCCI Engine", ASME Dynamic Systems Control Conference, 2016.

Natural gas-diesel RCCI Engine Controller

State-Space Representation

$$X_{k+1} = f(X_k, u_k, d_k)$$

$$y_{k+1} = g(X_k, u_k, d_k)$$

- States

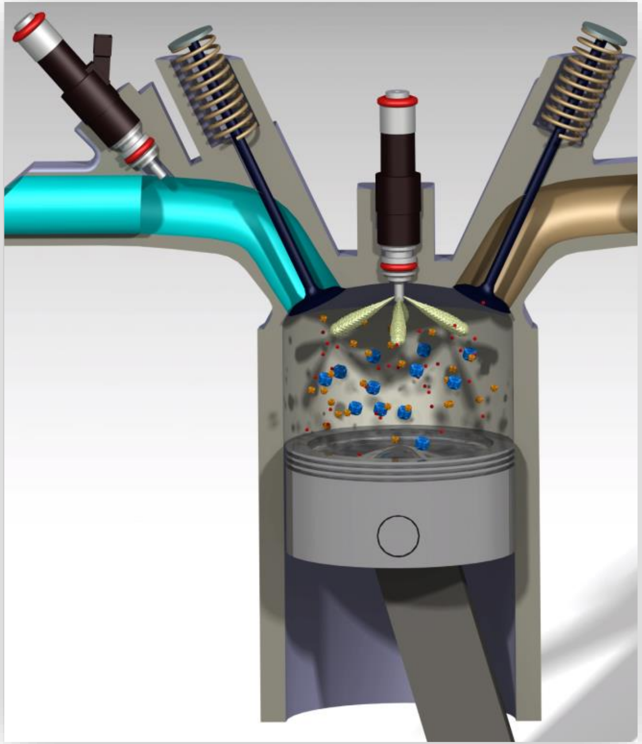
$$X = [CA50 \quad T_{soc} \quad P_{soc} \quad T_{rg} \quad m_{evc}]$$

- Control inputs

$$u = [PR, SOI, FQ]$$

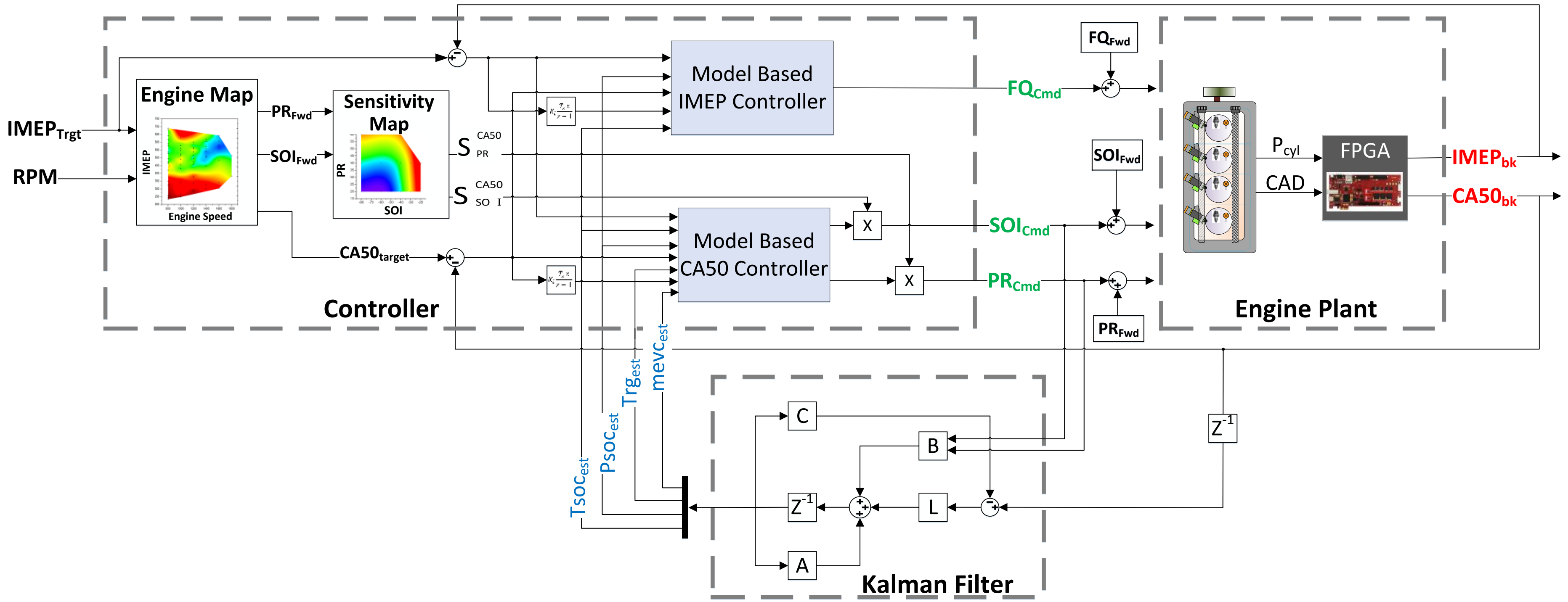
- Disturbance

$$d = [T_{man}]$$

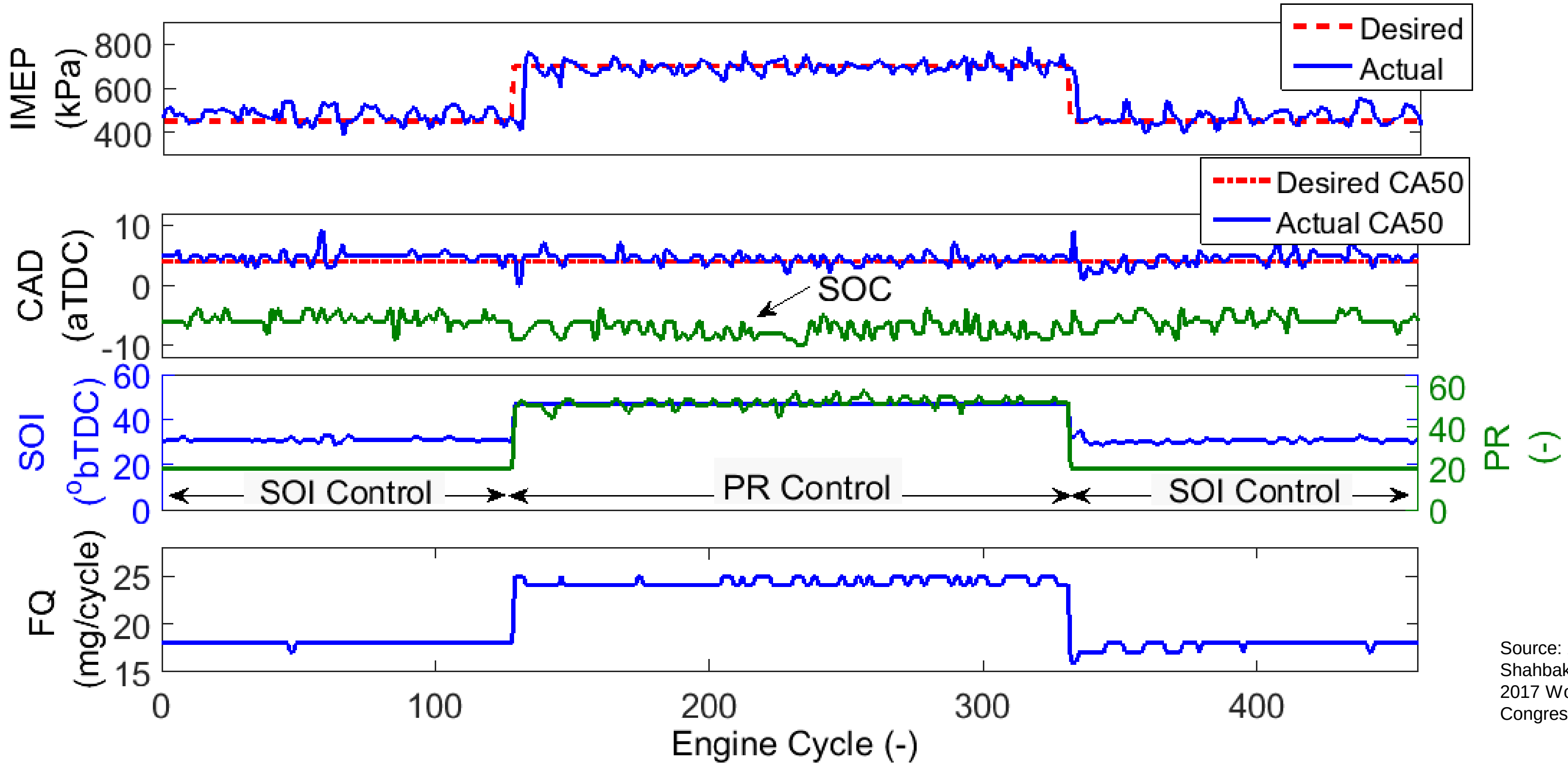


RCCI Engine Controller

Block Diagram



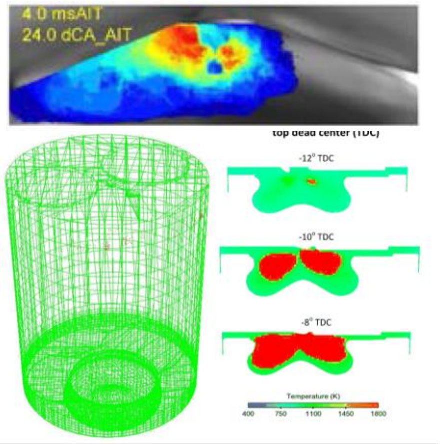
Experimental Control Results



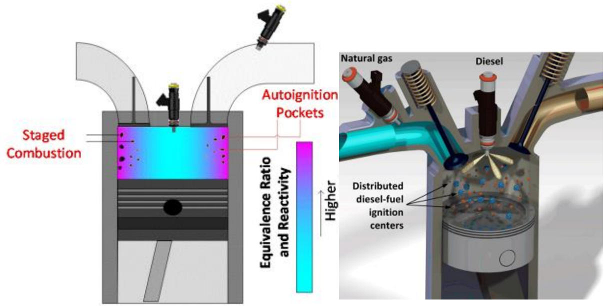
Source: Arora & Shahbakhti, SAE 2017 World Congress.

Summary

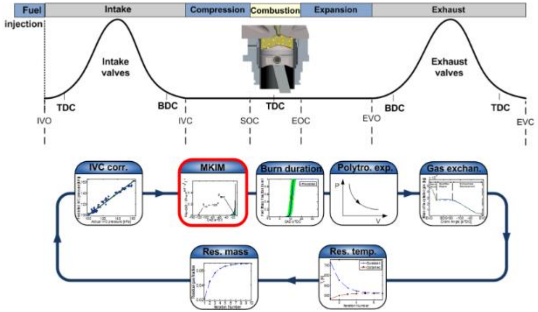
I. Optical Engine Data/ Detailed Combustion Model



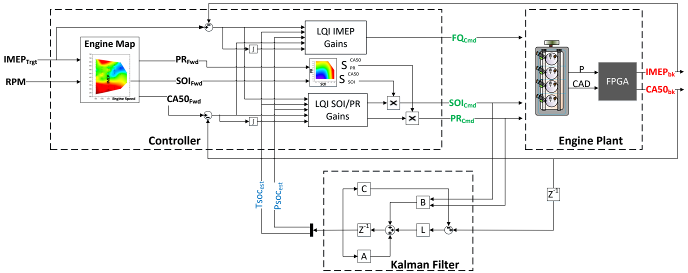
II. Phenomenological Combustion Model



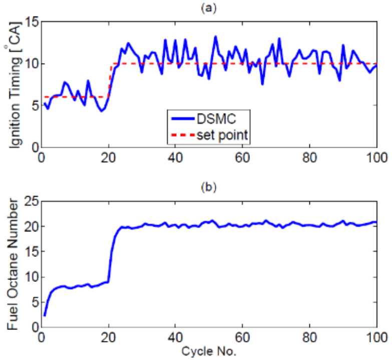
III. Control Dynamic Model



IV. Model-based Controller Design



V. Combustion Control



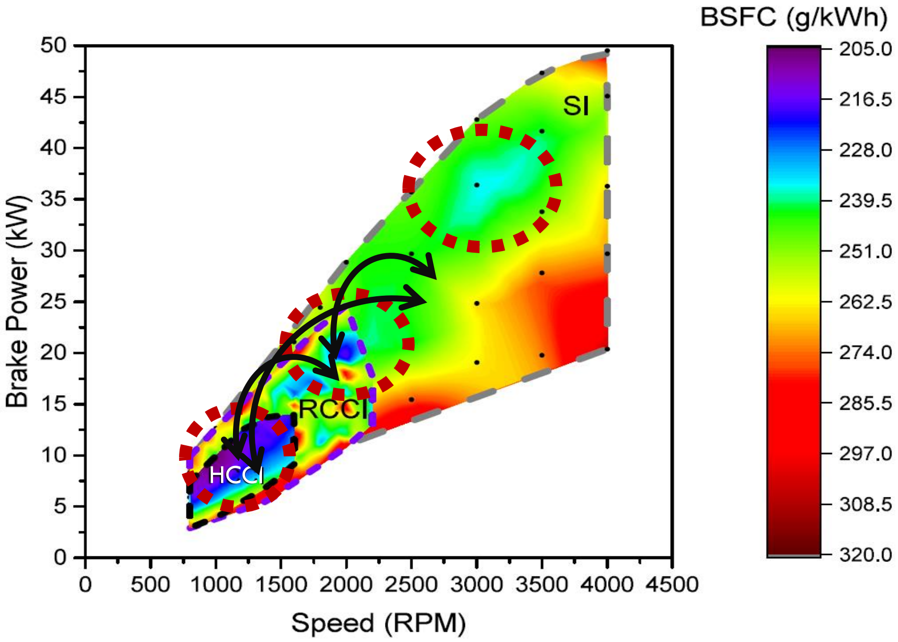
Part III: Control of automotive energy systems

- Model-based control of IC engines
- Predictive control of hybrid electric vehicles
- Control of connected and automated vehicles

Motivation

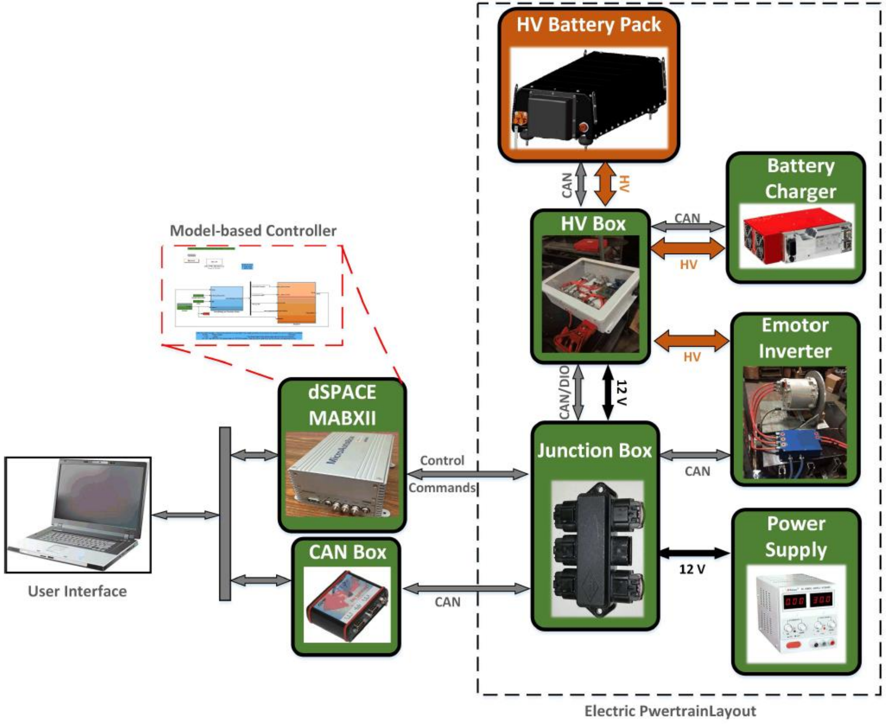
Electrified multi-mode powertrain for best fuel conversion efficiency

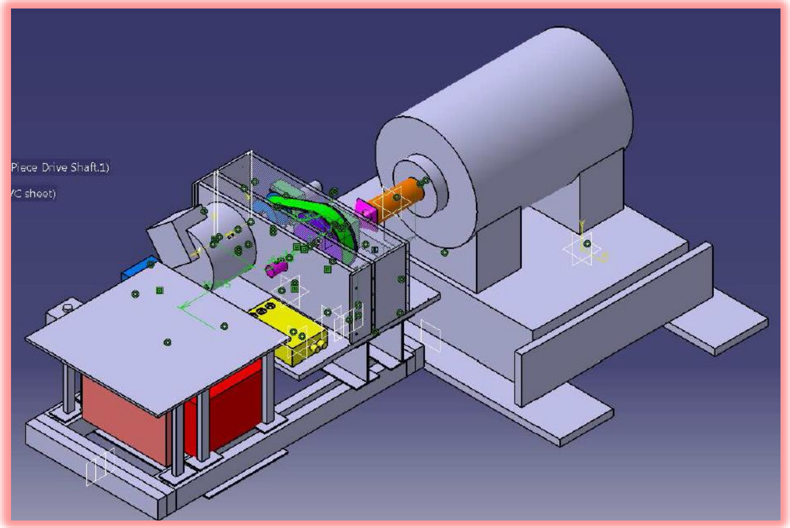
- SI mode is more efficient in the high power region.
- RCCI mode is more efficient in the medium power region.
- HCCI mode is more efficient in the low power region.



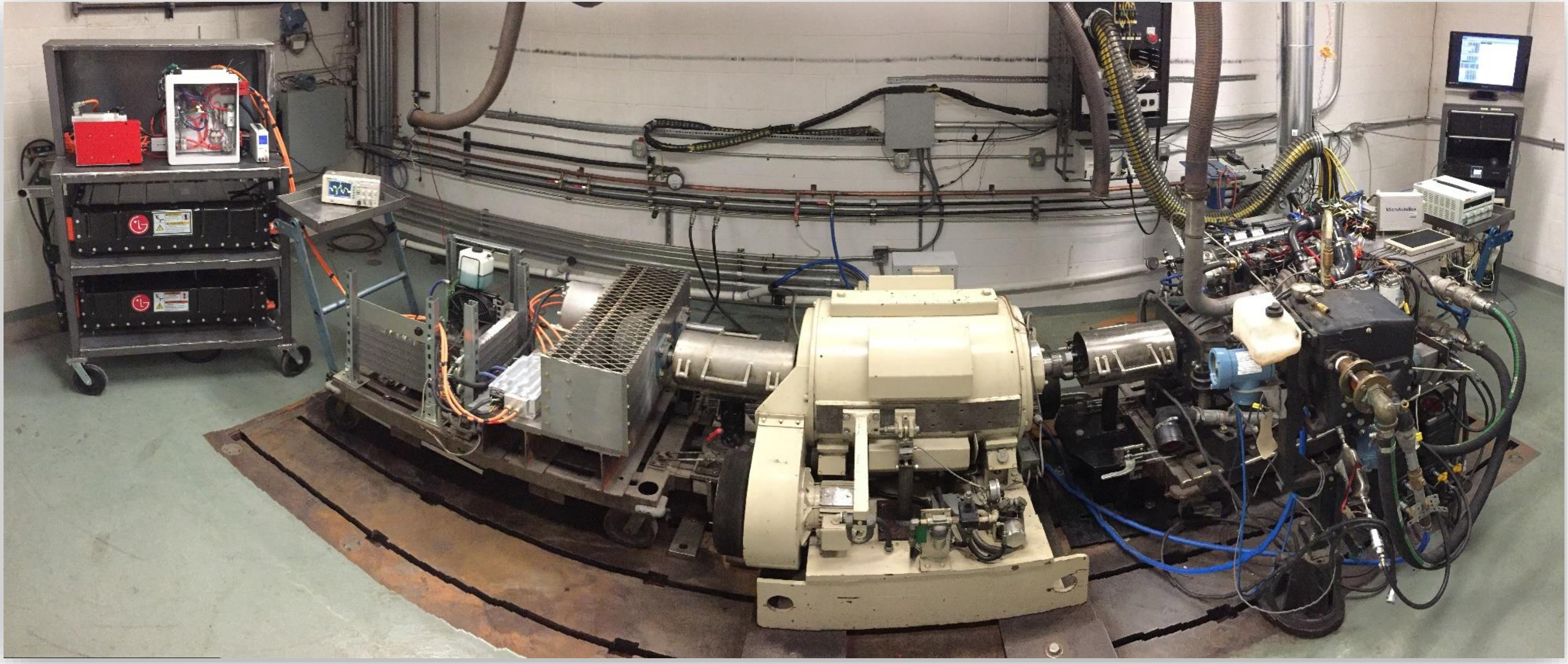
Electrification helps to utilize the best engine points and minimize engine transients!

Design of Hybrid Electric Powertrain Testbed

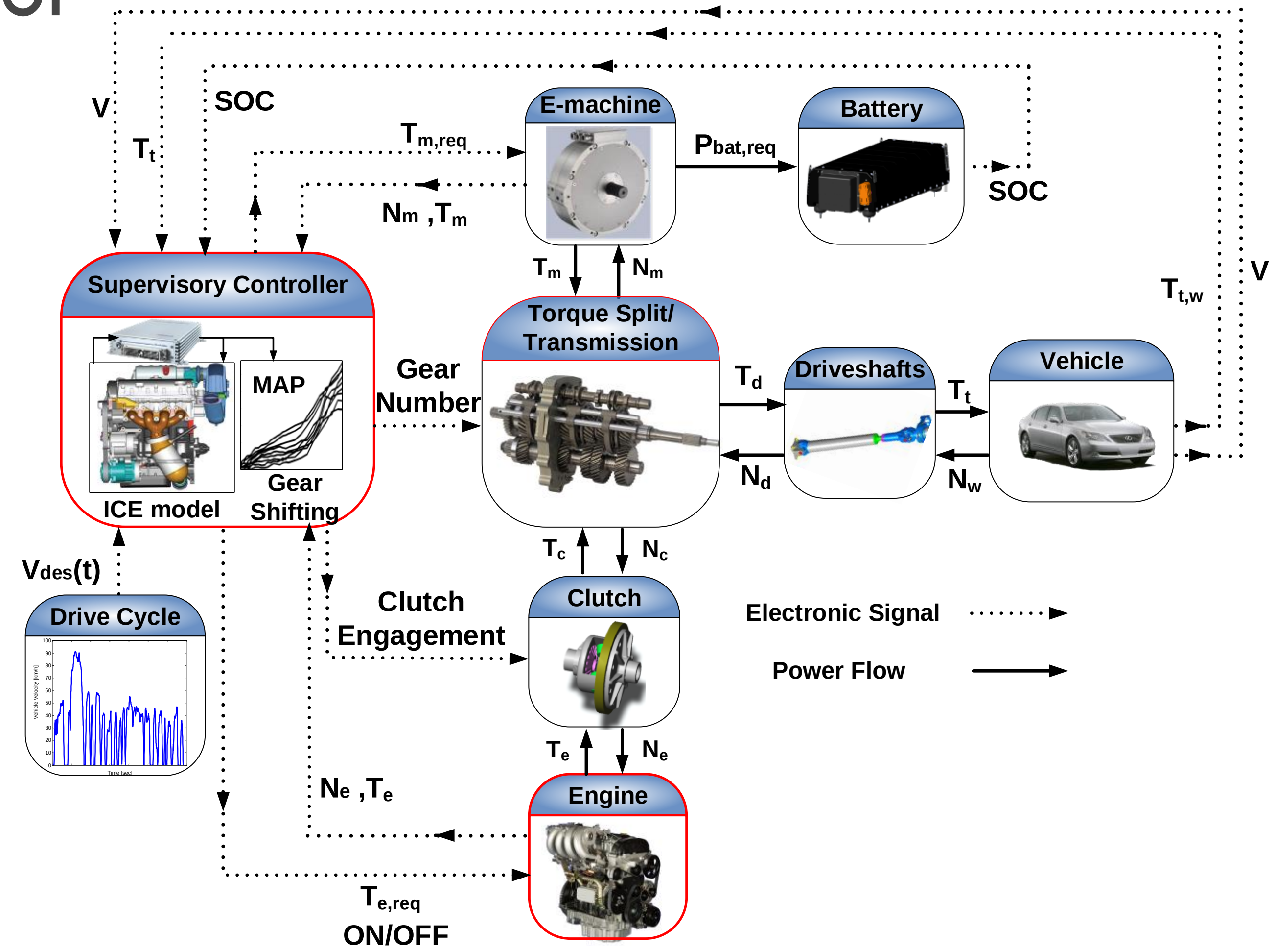




Multi-Mode Electrified Experimental Setup



HEV Models for Optimization



Design of Optimal Control for Multi-Mode Hybrid Electric Vehicle

Engine ON/OFF Penalty

Mode-Switching Penalty

Cost Function:

$$J(u(t)) = \int_0^T (\dot{m}_f(P_{bat}, t) + \Gamma.F_{p_1} + \Lambda.m_{ij} + \Psi.F_{p_2})dt$$

Gear-Shifting Penalty

Hard Constraints:

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

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

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

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

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

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

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

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

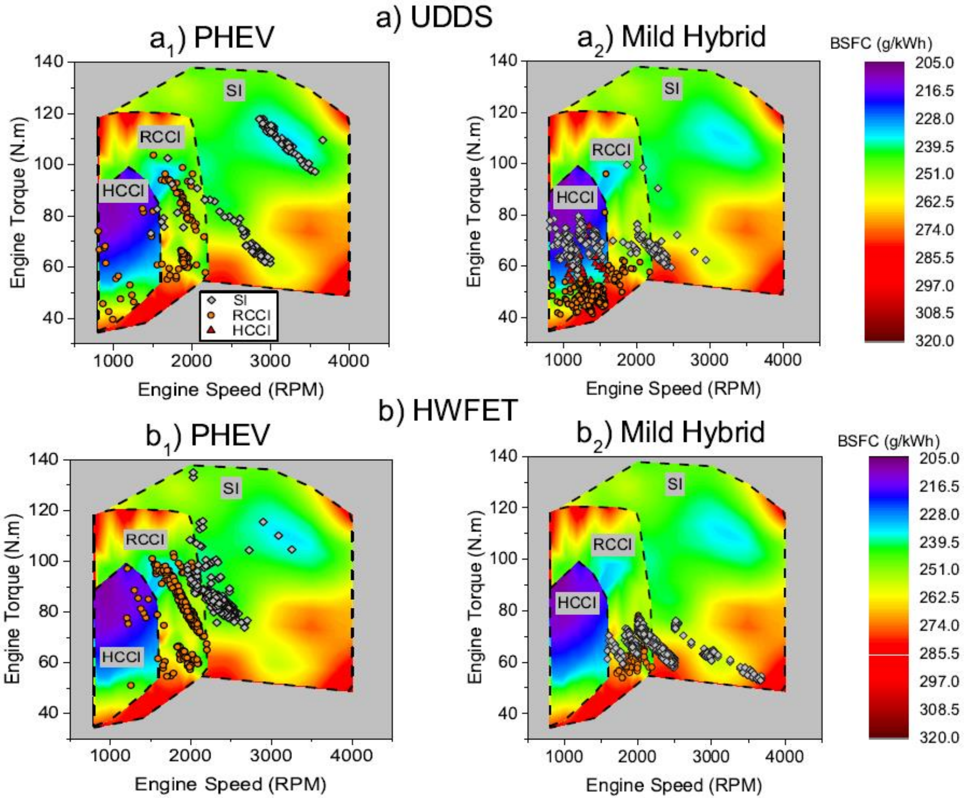
$$\omega_{eng} \leqslant \quad 1500 \quad rpm \qquad , if \quad V_{veh} \leqslant 40 km/h$$

Catalyst light-off constraint

NVH constraint

Analysis for Parallel Architecture

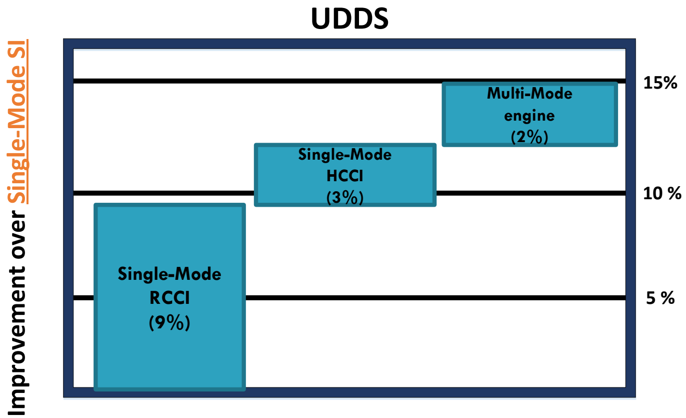
- In the PHEV, the multi-mode LTC-SI engine has less advantage compared to the mild HEV due to availability of higher electric power for locating the engine operating points in high power SI regions

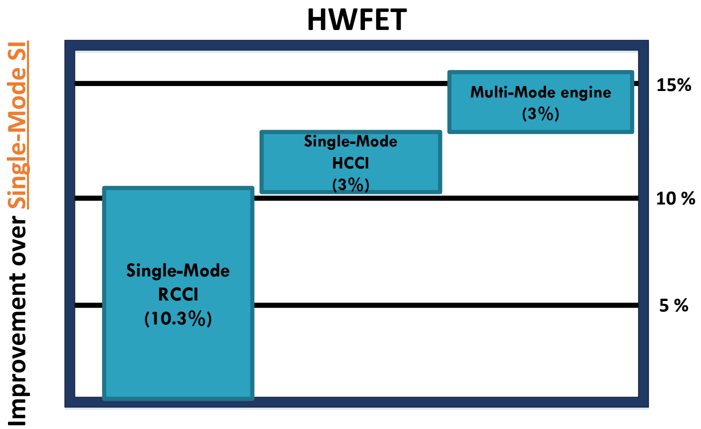


Source: A. Solouk, M. Shahbakhti, et. al., *SAE Int. J. of Alternative Powertrains, 2017.*

LTC-HEV Results

- **REx (Series) Architecture:**

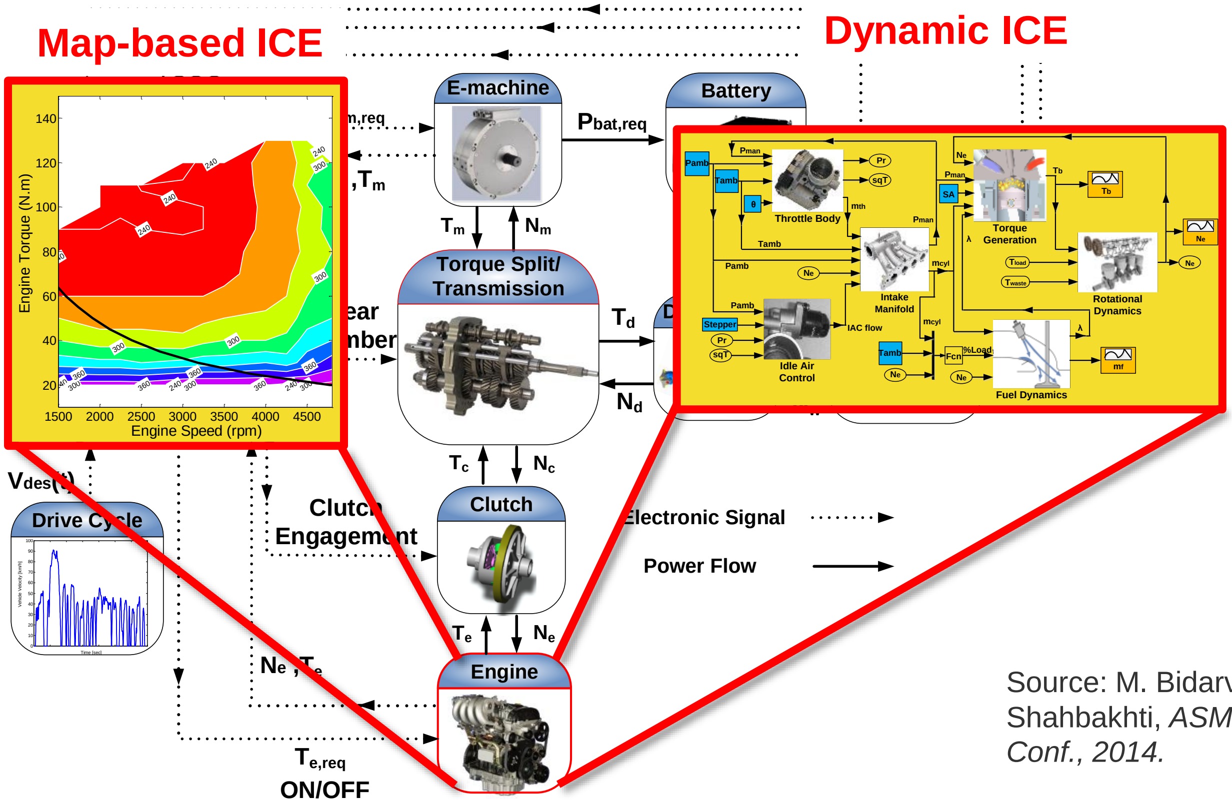




- The **REx** platform provides the higher fuel saving for the multi-mode LTC-SI, compared to the parallel hybrid electric platform.

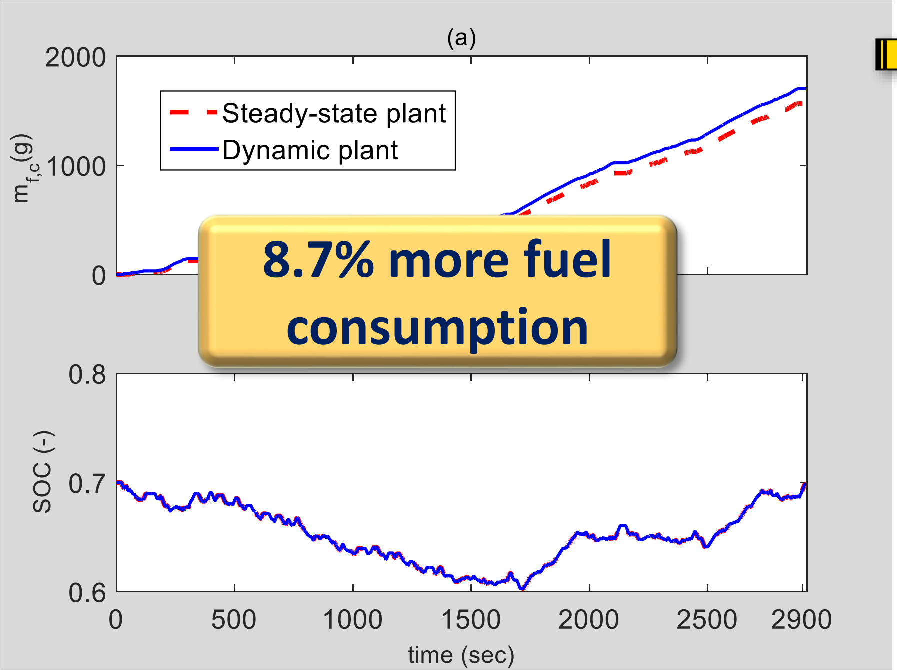
SAE Papers 2016-01-2361; 2017-01-1153

Energy Management/Control of a Hybrid electric Vehicle by Incorporating Powertrain Dynamics



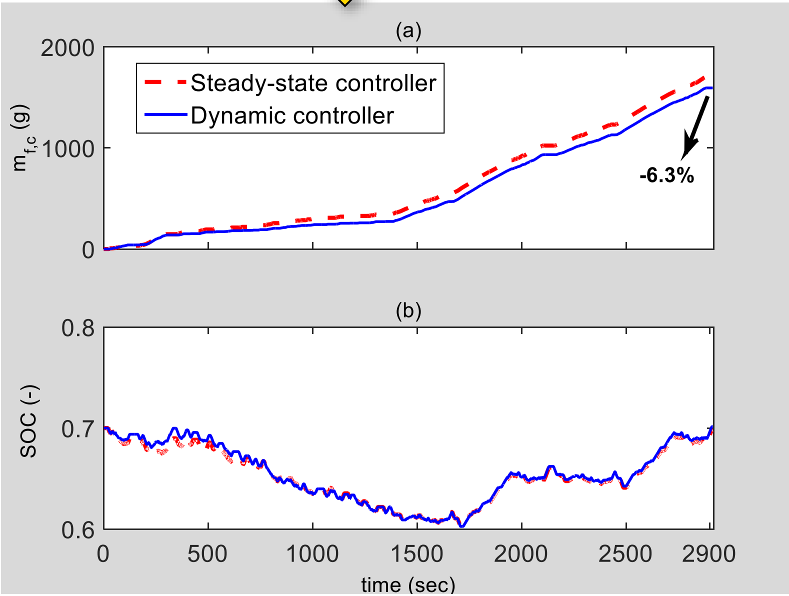
Source: M. Bidarvatan, M. Shahbakhti, *ASME Dyn Sys Ctrl Conf., 2014.*

Combined UDDS+HWFET Drive Cycle Results



8.7% more fuel consumption

$$\mathbb{J}_{dyn}(k) = \int_{t_k}^{t_k+t_p} [(\dot{m}_f(t) + \underline{\dot{m}_{f,pen}(\Delta N_e, T_e)}).Q_{hv} + \alpha.P_{bat,req}]\, dt$$



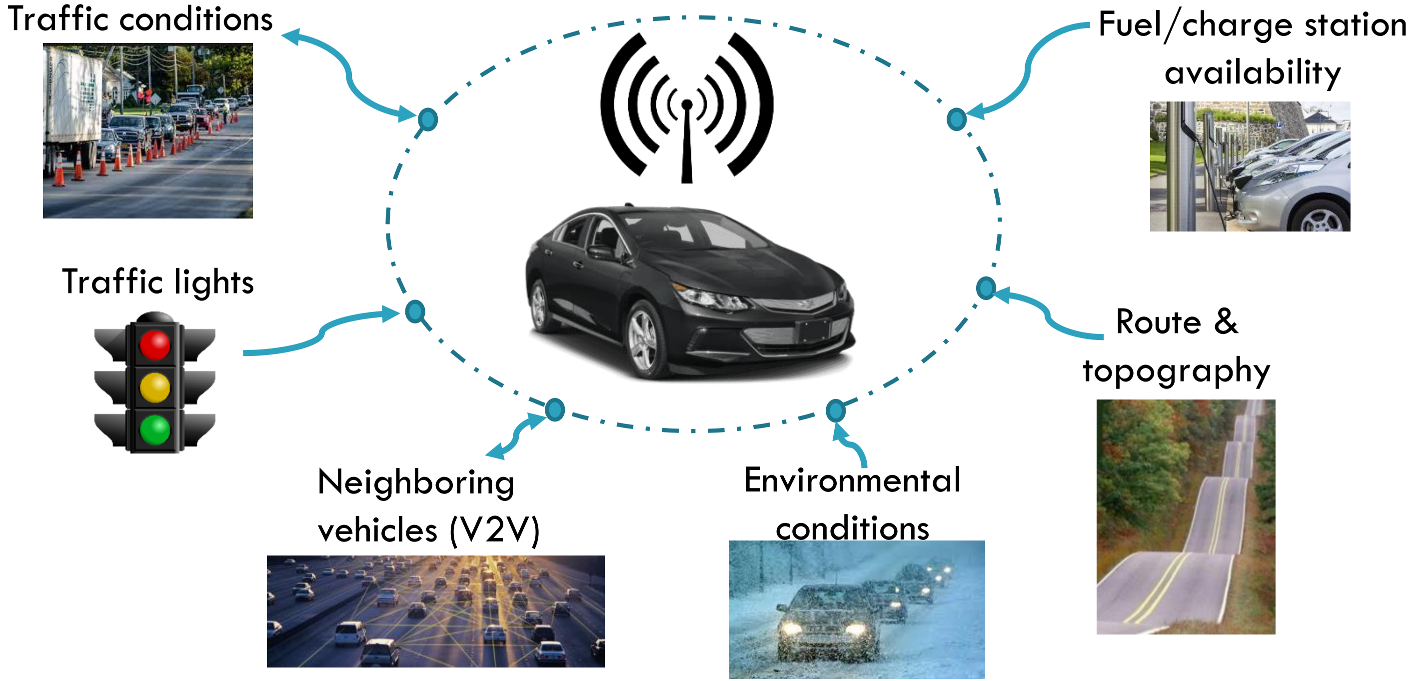
Source: M. Bidarvatan, M. Shahbakhti, *ASME Dyn Sys Ctrl Conf., 2015.*

Part III: Control of automotive energy systems

- Model-based control of IC engines
- Predictive control of hybrid electric vehicles
- Control of connected and automated vehicles

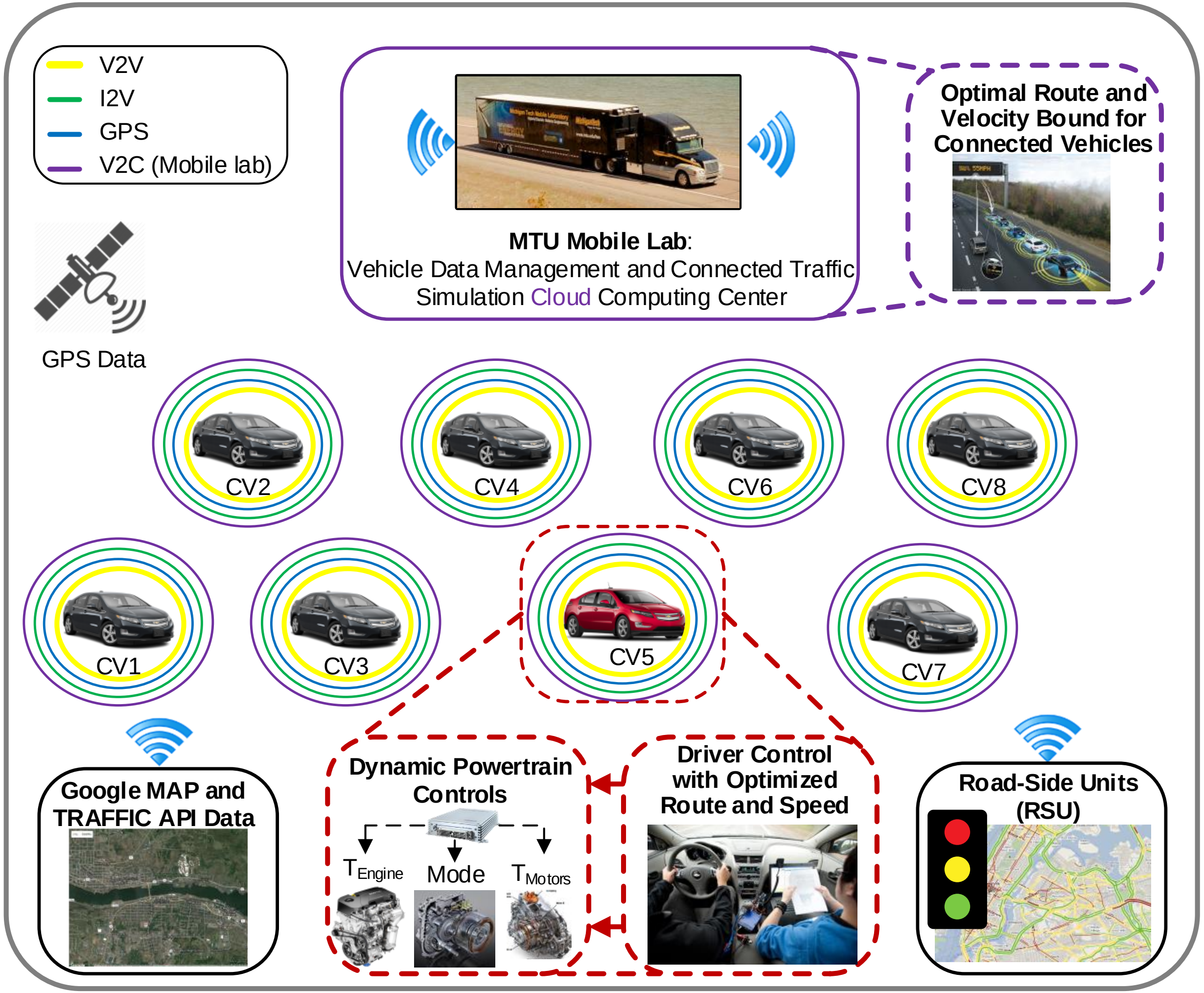
Motivation: V2X data can tell us about future power demand for vehicle controls

By 2021, all the vehicles sold in US will be connected vehicles!

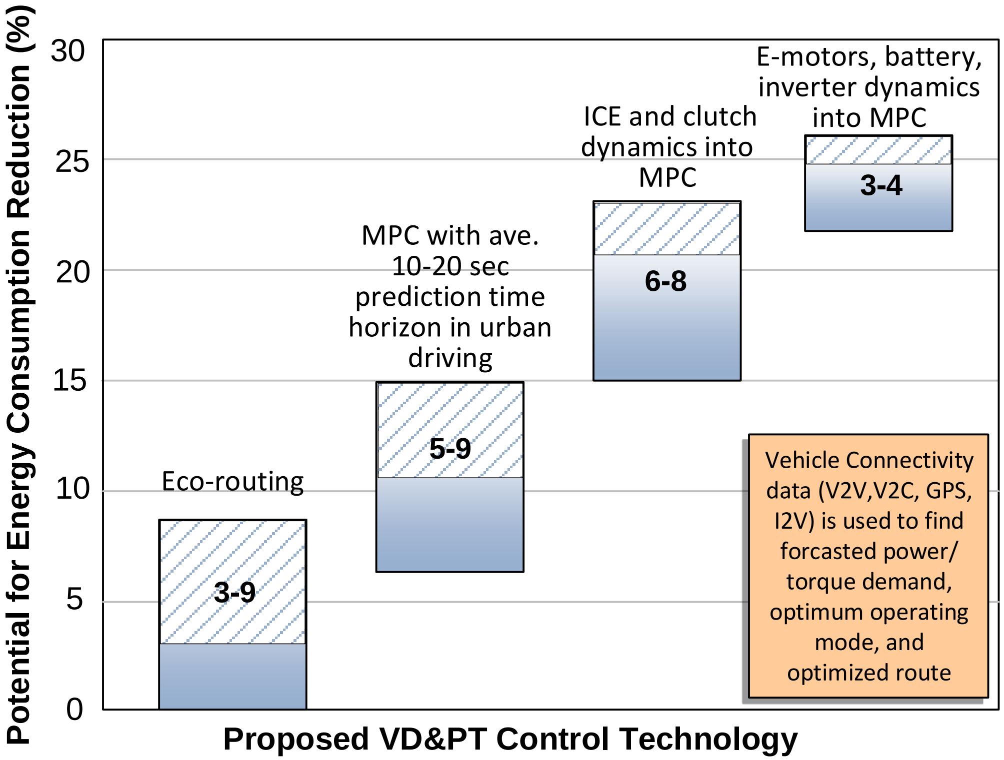


Michigan Tech-GM NextCar Project

- Vehicle dynamic and powertrain control for connected and automated vehicles
- Targets:
  - 20% reduction in energy consumption in PHEV/HEV operation
  - 6% increase in EV range



NextCar:
Projection of energy consumption reduction



NextCar: Real-time optimal (i) route selection, (ii) vehicle 5 modes selection, (iii) speed trajectory, (iv) ICE/motor torques/speeds

Optimal Routing and Velocity Bounds utilizing V2V, V2I, I2V, V2X, GPS, Traffic Data

Powertrain & Vehicle Dynamic Models including Transient Physics

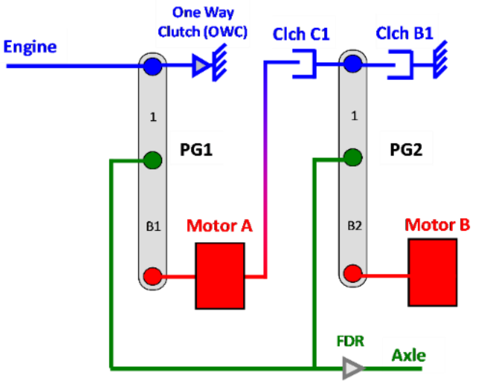
Battery SOC

Routing Planning Algorithm

Energy Optimizer Algorithm

Model Predictive Control (MPC)

MY17 Chevrolet Volt Gen2

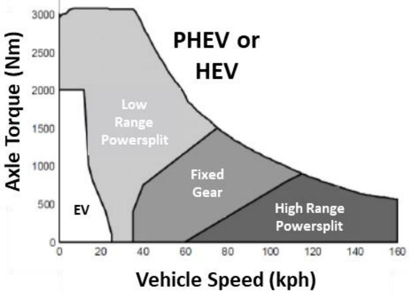


VD&PT Control Output

VD Control
- Route
- Velocity profile
- Road load profile

PT Control
- Mode selection
- Torque control
- Battery SOC profile

HMI Requested Driver Intervention
- Brake & accelerator pedals
- Regen paddle
- PT mode selection

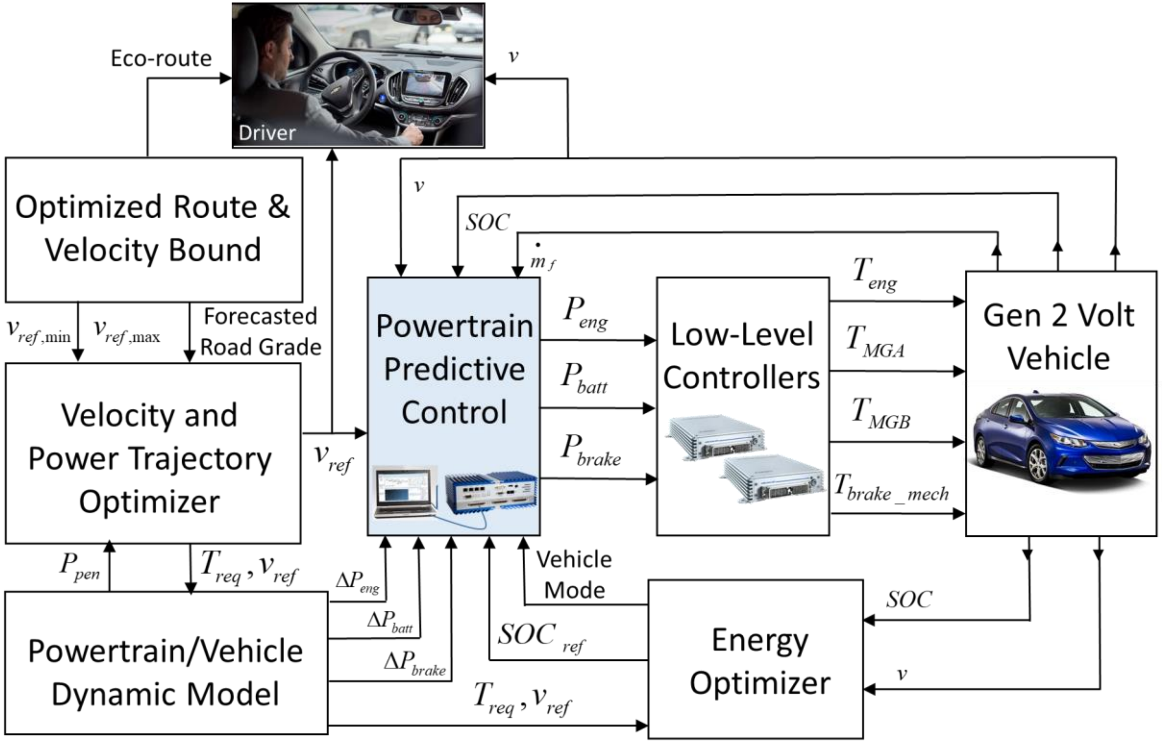


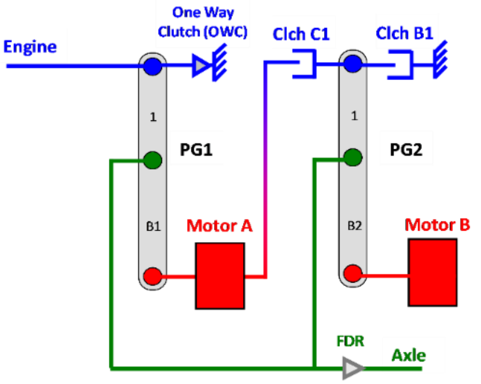
Virtual Demonstration & Validation
- Simulations
  - CAV apps & test factors

Field Demonstration & Validation
- Field testing
  - CAV apps & test factors

Image of modes: SAE 2015-01-1152

NextCar: Real-time optimal (i) route selection, (ii) vehicle 5 modes selection, (iii) speed trajectory, (iv) ICE/motor torques/speeds





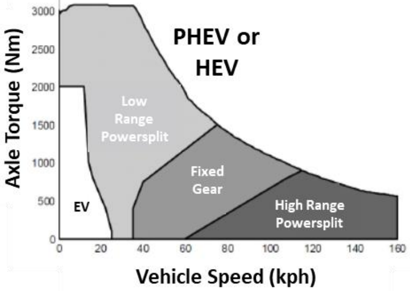


Image of modes: SAE 2015-01-1152

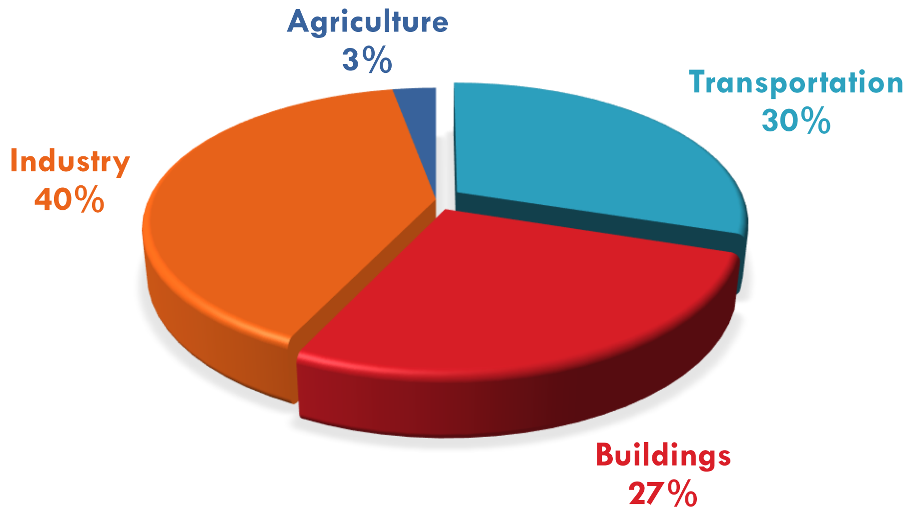
NextCar Platform

Mobile Lab traffic center

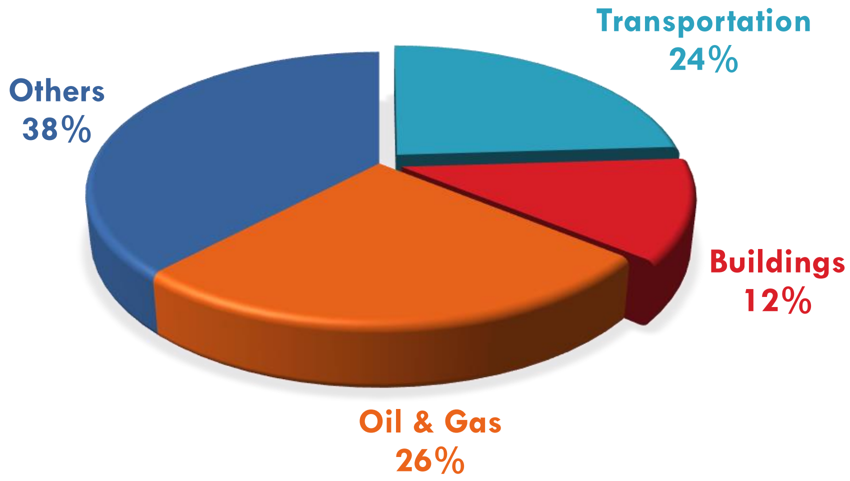
Mode selection and velocity optimization

Concluding remarks (I)

Canada Energy Consumption by End Users



Greenhouse Gas Emissions

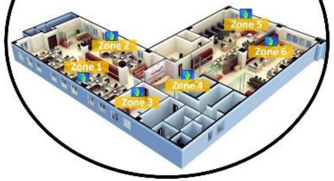


Data source: Environment Canada 2017; NRC 2016-2017

Concluding remarks (II)

Model-based Control of Building and Automotive Energy Systems

Building Energy Control



24-36% Energy Saving

Building to Grid Integration

5-42% Elec. Cost Saving

Advanced IC Engines

upto 15% Energy Saving

Hybrid Electric Vehicles

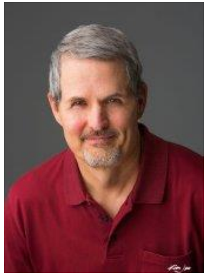
6-17% Energy Saving

Connected & Automated Vehicles

6-20% Energy Saving

Acknowledgments (I)

Current/past collaborators for materials presented



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Cummins

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U. of Georgia

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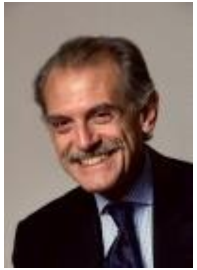
C3 IoT, California



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UC Berkeley

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Ford Motor Company

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GM

XILINX

IRESEN
Institut de Recherche en Energie Solaire et en Energies Nouvelles

THANK YOU!

Questions?

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Energy Mechatronics Laboratory