Syntheses of Controls and Physics for Future Clean, Efficient, and Safe Transportation

Junmin Wang
Associate Professor
Director, Vehicle Systems and Control Laboratory (VSCL)
vscl.osu.edu

July 2014

Department of Mechanical and Aerospace Engineering
The Ohio State University
Overview of VSCL at OSU

- Vehicle Systems and Control Laboratory established in 2008
VSCL Research Thrusts

- VSCL’s research activities cover a wide and comprehensive range of modeling, estimation, control, and optimization of vehicle systems for improving energy efficiency, reducing emissions, and enhancing safety of the ground transportation.

**Energy**
- Engine/Powertrain Control & Estimation

**Emissions**
- Aftertreatment Systems Control & Estimation

**Safety**
- Vehicle Control & Estimation
VSCL’s Research Directions

- Engine modeling, estimation, and control
- Aftertreatment system modeling, estimation, control, and diagnosis
- Natural gas utilization in transportation
- Advanced combustion mode transient control
- Fuel (bio & fossil)-property-adaptive engine control
- Hybrid powertrain control and optimization
- Vehicle dynamics and control
- Driver-vehicle interactions
- Autonomous vehicle control using low-cost sensors
- Lightweight vehicle active estimation and control
- Intelligent vehicles and transportation systems
- Mechatronic systems
- Control theories on nonlinear systems and over-actuated systems
Research Funding and Sponsors

- Wang’s Total Research Funding (from Sept. 2008): $4.5M
- Research Supported by
  - National Science Foundation (NSF) and NSF-CAREER Award
  - Office of Naval Research (ONR Young Investigator Program Award)
  - U.S. Department of Energy (DOE)
  - ORAU Ralph E. Powe Junior Faculty Enhancement Award
  - General Motors Global R&D
  - Ford Motor Company
  - Tenneco Inc.
  - Honda R&D Americas
  - Eaton Corporation Innovation Center
  - OSU-CAR Industrial Consortium
  - Honda-OSU Partnership Program
  - OSU-Transportation Research Endowment Program
  - OSU-Department of Mechanical and Aerospace Engineering
VSCL Members and Publications

■ Current members: 20 researchers
  ➢ 1 post-doc researcher
  ➢ 9 Ph.D. students
  ➢ 5 Ph.D. visiting scholars
  ➢ 1 M.S. students
  ➢ 4 undergraduate research students

■ Graduated 5 Ph.D., 5 M.S., and 2 B.S. students
  ➢ Joined academia as faculty members and industry as researchers / engineers after graduation

■ Research achievements
  ➢ More than 180 peer-reviewed papers published
    • Over 80 journal articles
  ➢ 11 issued U.S. patents and 1 pending patents
  ➢ 20 manuscripts under review in journals and conferences
Transportation Fuel Consumption

U.S. transportation fuel consumption by DOE*

*U.S. Energy Information Administration | Annual Energy Outlook 2013
Transportation Emissions

- U.S. PM$_{2.5}$ and precursor emissions by EPA*

U.S. Environmental Protection Agency: The Particle Pollution Report, 2004
Transportation Safety

■ 2010 U.S. motor vehicle crashes by NHTSA*

Increasingly-Complex Vehicle Systems

- Continuously evolving automotive technologies for addressing the energy, environmental, and safety challenges in the transportation sector
  - Substantially elevating the complexity of vehicle systems
  - Comprehensive and multi-disciplinary research efforts
Introduction and Outline

■ Ever-growing demands on energy efficiency, emissions, and safety drive the technology evolution and elevate the complexities of vehicle systems
  ➢ Designs of estimation, fault diagnosis, and control systems are more challenging and more critical as well

■ Synergistic combinations of physical insight into vehicle system characteristics with theories of estimation and control may offer effective means for tackling such challenges
  ➢ Energy-efficient control of in-wheel motor electric vehicles
  ➢ Actuator-redundancy-based fault diagnosis for four wheel independently actuated electric vehicles
  ➢ Control of Diesel engine selective catalytic reduction systems

■ Concluding remarks
Electric Ground Vehicle with In-Wheel Motors

- Li-ion battery powered electric ground vehicle
  - Full-size utility terrain vehicle
  - Four independently-actuated in-wheel motors and controllers
  - Steer-, drive-, and brake-by-wire systems
  - Redundant hydraulic braking system
  - Four wheel speed sensors
  - Four independent suspensions
  - 75v-200Ah Li-ion battery pack
  - Oxford RT-3003 Navigation system
EGV Field Test Videos
In-wheel Motor EGV as an Over-Actuated System

- Electric ground vehicle (EGV) with four in-wheel motors
- Over-actuation in terms of degrees of freedom
  - Number of actuators > degrees of freedom
  - Non-unique actuation combinations for vehicle longitudinal and lateral motion control
Over-Actuated Systems

- **A general model**
  \[
  \dot{x} = f(x) + g(x)u \\
  v = Bu \\
  y = h(x) \\
  \text{s.t. } u_{\text{min}} \leq u \leq u_{\text{max}}
  \]
  State: \( x \in \mathbb{R}^n \)  
  Virtual control: \( v \in \mathbb{R}^m \)  
  Output: \( y \in \mathbb{R}^m \)  
  Control input: \( u \in \mathbb{R}^p \)  
  Control effectiveness matrix: \( B \in \mathbb{R}^{m \times p} \)

- **Characteristics**
  - A fat matrix \( B: \ p > m \)  
    \( \iff \) solutions are not unique
  - Advantages by utilizing actuation redundancy
    - Fault tolerance
    - Task prioritization
    - Actuation reconfiguration
    - Performance extension

- **Require real-time implementable control allocation algorithms**
CA for Over-Actuated Systems

- Block diagram for general control systems

- Control allocation

- Separate CA module from control design for distribution
- Generalizable high-level control designs
- Low-level CA realizes additional functions
## Existing CA for Over-Actuated Systems

<table>
<thead>
<tr>
<th>Existing CA methods</th>
<th>Formulations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct CA</td>
<td>( v = Bu )</td>
</tr>
<tr>
<td></td>
<td>( u_{\text{min}} \leq u \leq u_{\text{max}} )</td>
</tr>
<tr>
<td>Error minimization</td>
<td>( \min J = | v - Bu | ) s.t. ( u_{\text{min}} \leq u \leq u_{\text{max}} )</td>
</tr>
<tr>
<td>Control minimization</td>
<td>( \min J = | u - u^p | ) s.t. ( v = Bu ) ( u_{\text{min}} \leq u \leq u_{\text{max}} )</td>
</tr>
<tr>
<td>Mixed minimization</td>
<td>( \min J = | Bu - v | + \varepsilon | u - u^p | )</td>
</tr>
</tbody>
</table>

- Do not explicitly consider system power minimization
- All assume control efforts / magnitudes are directly proportional to the power consumptions
Motivation of EECA

- High energy-consuming over-actuated systems
  - Airplanes, ships, and ground vehicles
- Control efforts / magnitudes could not directly relate to system power consumptions
  - Motor efficiency

- Control allocation with explicit consideration on actuator efficiencies can be beneficial – Energy-Efficient Control Allocation (EECA)
EECA Design and Applications to Vehicles

- Challenges of EECA and applications to electric vehicles
  - Explicitly incorporate actuator efficiency functions
  - Different operating modes of actuators
    - Driving and braking of electric motors
    - Different contributions to the system virtual control and power consumptions
  - EECA algorithm optimality, convergence, and real-time capability
  - Combination with electric vehicle motion control

EECA Formulation: Single-Mode Actuators

- Explicitly consider the actuator efficiencies (rather than the Euclidean-norm of the actuator magnitudes) in the CA scheme for true energy efficiency optimization

\[
\begin{align*}
\min J &= \| W_v (Bu - v_d) \| + \lambda P_c \\
\text{s.t.} & \quad u_{\text{min}} \leq u \leq u_{\text{max}} \\
\end{align*}
\]

\[
P_c = \sum_{i=1}^{p} P_{ci}(u_i) = \sum_{i=1}^{p} \frac{P_{oi}(u_i)}{\eta_{oi}(u_i)}
\]

- Nonlinear (and nonconvex) optimization problem

- How to seamlessly incorporate the actuator operating modes into the EECA optimization formulation?

  - Actuators’ operating modes affect both virtual control and power consumption
  - EECA needs to optimally dictate both actuators’ magnitudes and modes
EECA Formulation: Dual-Mode Actuators

- Introduce a *virtual actuator* concept to augment the systems to address the challenge.

\[
\dot{x} = f(x) + g(x)v \\
v = B_a [u \quad u']^T \quad u' \in R^q, \ 1 \leq q \leq p \quad \text{: virtual actuator vector} \\
y = h(x) \\
B_a \in R^{m \times (p+q)} \quad \text{: augmented control effectiveness matrix}
\]

\[
\min J = \|W_v (B_a [u \quad u']^T - v_d)\| + \lambda P_c
\]

\[
\text{s.t.} \quad \begin{cases}
    u_{\min} \leq u \leq u_{\max} \\
    u_{\min}' \leq u' \leq u_{\max}' \\
    u_i u_i' = 0, \ i = 1, \ldots, q
\end{cases}
\]

\[
P_c = \sum_{i=1}^{p} \frac{P_{oi} (u_i)}{\eta_{oi} (u_i)} - \sum_{i=1}^{q} P_{ii} (u_i') \eta_{ii} (u_i')
\]

- Nonlinear (and nonconvex) optimization problem with compatibility conditions.

\[P_{oi}, \eta_{oi}: \text{Actuator output power and efficiency in energy consuming mode}\]

\[P_{ii}, \eta_{ii}: \text{Actuator input power and efficiency in energy gaining mode}\]
Novel Algorithms Needed to Solve EECA

■ Characteristics of the proposed EECA scheme
  ➢ Constrained nonlinear (and nonconvex) optimization problem

<table>
<thead>
<tr>
<th>Single-mode EECA</th>
<th>Dual-mode EECA</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \min J = |W_v(Bu - v_d)| + \lambda P_c )</td>
<td>( \min J = |W_v(B_{a[u u']}^T - v_d)| + \lambda P_c )</td>
</tr>
</tbody>
</table>
| s.t. \( u_{\min} \leq u \leq u_{\max} \) | s.t. \( \begin{cases} u_{\min} \leq u \leq u_{\max} \\
                              u_{\min} \leq u' \leq u'_{\max}
\end{cases} \\
                              u_i u'_i = 0, \ i = 1, ..., q \) |
| \( P_c = \sum_{i=1}^p p_{ci}(u_i) = \sum_{i=1}^p \frac{p_{oi}(u_i)}{\eta_{oi}(u_i)} \) | \( P_c = \sum_{i=1}^p \frac{p_{oi}(u_i)}{\eta_{oi}(u_i)} - \sum_{i=1}^q p_{ii}(u_i')\eta_{ii}(u'_i) \) |

■ Existing algorithms and issues
  ➢ Nonlinear programming algorithms: active-set, interior-point, etc.
  ➢ Sensitive to initial values: influence on optimality of solutions
  ➢ Not real-time implementable: search steps and direction at each step

■ Challenges on EECA algorithms development
  ➢ Real-time implementable
  ➢ Free to initial condition selection
  ➢ Globally optimal in certain cases
KKT Conditions

■ Karush-Kuhn-Tucker (KKT) conditions
  ➢ Define a Lagrangian function to combine cost function and constraints
  ➢ Set first derivatives to zero to obtain algebraic equations
  ➢ Plus complementarity conditions

■ Advantages
  ➢ Algebraic equations, free to initial condition selection
  ➢ No step or search direction selections, offline calculation, fast enough

■ Disadvantages
  ➢ Necessary conditions, not sufficient
  ➢ Local minima, not global

■ Modifications
  ➢ For the EECA scheme, further direct examination (comparison) can exclude maximum and local minima to obtain the global minimum
KKT-Based EECA: Single-mode Actuators

- **Single-mode**
  \[ \min J = \| W_v (Bu - v_d) \| + \lambda P_c \]
  \[ \text{s.t. } u_{\min} \leq u \leq u_{\max} \]
  \[ \min J = \| W_v (Bu - v_d) \|^2 + \lambda P_o^T \frac{1}{\eta_o(u)} \]
  \[ \text{s.t. } \left\{ \begin{array}{l} u - u_{\min} \geq 0 \\ u_{\max} - u \geq 0 \end{array} \right. \]

- **Lagrangian function**
  \[ L(u, \lambda, \bar{\lambda}) = J(u) - \lambda^T (u - u_{\min}) - \bar{\lambda}^T (u_{\max} - u) \]

- **KKT conditions**
  \[ \frac{\partial L(u, \lambda, \bar{\lambda})}{\partial u} \bigg|_{u=u^*, \lambda=\bar{\lambda}^*, \lambda=\bar{\lambda}^*} = 2B^T W_v W_v (Bu^* - v_d) + \lambda \left( \begin{array}{c} \partial P_{oi}(u^*) \\ \eta_{oi}(u^*) - P_{oi}(u^*) \end{array} \right) = 0 \]
  \[ \lambda_i^* (u^* - u_{\min})_i = 0 \quad \bar{\lambda}_i^* (u_{\max} - u^*)_i = 0 \]
  \[ u^* - u_{\min} \geq 0 \quad u_{\max} - u^* \geq 0 \quad \lambda^* \geq 0 \quad \bar{\lambda}^* \geq 0 \]
KKT-based EECA: Dual-mode Actuators

- **Dual-mode actuator EECA**

\[
\min J = \left\| W_v \left( B_a \left[ u^T \quad u'^T \right] - v_d \right) \right\|^2 + \lambda \left( P_o^T (u) \frac{1}{\eta_o (u)} - P_i^T (u') \eta_i (u') \right) \\
\text{s.t.} \begin{cases}
    u - u_{\min} \geq 0 \\
    u_{\max} - u \geq 0 \\
    u' - u'_{\min} \geq 0 \\
    u'_{\max} - u' \geq 0 \\
    u_i u'_i = 0
\end{cases}
\]

- **Lagrangian function**

\[
L(u, u', \lambda, \overline{\lambda}, \lambda', \overline{\lambda'}) = J(u, u') - \lambda^T (u - u_{\min}) - \overline{\lambda}^T (u_{\max} - u) - \lambda'^T (u' - u'_{\min}) - \overline{\lambda'}^T (u'_{\max} - u')
\]

- **KKT conditions**

\[
\frac{\partial L(u, u', \lambda, \overline{\lambda}, \lambda', \overline{\lambda'})}{\partial u} = 2 B_v^T W_v \left( B_a \left[ u^T \quad u'^T \right]^T - v_d \right) + \lambda \frac{\text{diag} \left( \frac{\partial P_o (u_i^*)}{\partial u} \eta_o (u_i^*) - P_o (u_i^*) \frac{\partial \eta_o (u_i^*)}{\partial u} \right)}{\eta_o^2 (u^*)} - \lambda^* + \overline{\lambda}^* = 0,
\]

\[
\frac{\partial L(u, u', \lambda, \overline{\lambda}, \lambda', \overline{\lambda'})}{\partial u'} = 2 B_q^T W_v \left( B_a \left[ u'^T \quad u'^T \right]^T - v_d \right) - \lambda \left[ \nabla_u P_i (u''^*) \eta_i (u'') + \nabla_u \eta_i (u'') P_i (u'') \right] - \lambda'^* + \overline{\lambda'}^* = 0,
\]

\[
\lambda_i^* (u^* - u_{\min})_i = 0 \quad \overline{\lambda}_i^* (u_{\max} - u^*)_i = 0 \quad \lambda^*_i (u''^* - u'_{\min})_i = 0 \quad \overline{\lambda}'_i^* (u'_{\max} - u'')_i = 0
\]

\[
\begin{aligned}
    u^* - u_{\min} \geq 0 \quad u_{\max} - u^* \geq 0 \quad u''^* - u'_{\min} \geq 0 \quad u'_{\max} - u''^* \geq 0 \quad \overline{\lambda}^* \geq 0 \quad \lambda^* \geq 0 \quad \overline{\lambda}'^* \geq 0 \quad \lambda'^* \geq 0
\end{aligned}
\]
From KKT-based to Adaptive EECA

- Limitations of the KKT-based EECA
  - Computational effort and algorithm complexity grow quickly with the number of actuators and constraints
  - Distribution of virtual control at each sampling time

- Adaptive EECA
  - Define a proper Lagrangian function
  - Define an optimal set and a corresponding Lyapunov function
  - Adaptive control distributions will asymptotically approach the optimal set along the decreasing direction of the Lyapunov function

- Advantages
  - Asymptotically optimal distributions, not necessary within each sampling time
  - Real-time implementable with low sensitivity to the number of actuators

- Disadvantages
  - Cannot guarantee the global optimality, usually locally optimal
Adaptive EECA

- **Formulation: dual-mode actuators**
  \[
  \min J_e = \frac{1}{2} \left( B_a [u \quad u'] - v_d \right)^T W_v \left( B_a [u \quad u'] - v_d \right) + \sigma P_c
  \]
  s.t.
  \[
  u_{\min} \leq u \leq u_{\max} \quad \quad u'_{\min} \leq u' \leq u'_{\max}
  \]
  \[
  (u_i - \varepsilon)(u_i' + \varepsilon) = 0, i = 1, \ldots, 4
  \]

- **Lagrangian function**

\[
L(v_d, u, u', \lambda) = \frac{1}{2} \left( B_a [u^T \quad u'^T]^T - v_d \right)^T W_v \left( B_a [u^T \quad u'^T]^T - v_d \right) + \sigma \left( \sum_{i=1}^{p} \frac{P_{oi}(u_i)}{\eta_{oi}(u_i)} - \sum_{i=1}^{q} P_{ii}(u_i')\eta_{ii}(u_i') \right)
\]
\[
+ \sum_{i=1}^{4} \lambda_i (u_i - \varepsilon)(u_i' + \varepsilon) - \mu \sum_{i,j=1}^{4} \log C_{ij}(u, u')
\]

- **Optimal set**

\[
E^* = \left\{ (u, u', \lambda) | \partial L/\partial u = \partial L/\partial u' = \partial L/\partial \lambda = 0_{4\times1} \right\}
\]

- **Lemma**
  - Local minima are achieved iff the optimal set is reached
Adaptive EECA

■ Theorem

\[ \{u, u', \lambda\} \rightarrow E^* \quad \text{as} \quad t \rightarrow \infty \quad \text{when the following update laws for control inputs and Lagrangian multipliers are applied:} \]

\[
\begin{align*}
\dot{u} &= -\Gamma_1 \alpha + \phi_1 \\
\dot{u}' &= -\Gamma_2 \beta + \phi_2 \\
\dot{\lambda} &= -\Gamma_3 \gamma + \phi_3
\end{align*}
\]

\[
\begin{pmatrix}
\alpha \\
\beta \\
\gamma
\end{pmatrix} = 
\begin{pmatrix}
\frac{\partial^2 L}{\partial u^2} & \left( \frac{\partial^2 L}{\partial u' \partial u} \right)^T & \left( \frac{\partial^2 L}{\partial \lambda \partial u} \right)^T \\
\frac{\partial^2 L}{\partial u \partial u'} & \frac{\partial^2 L}{\partial u'^2} & \left( \frac{\partial^2 L}{\partial \lambda \partial u'} \right)^T \\
\frac{\partial^2 L}{\partial u \partial \lambda} & \frac{\partial^2 L}{\partial u' \partial \lambda} & 0
\end{pmatrix} \begin{pmatrix}
\frac{\partial L}{\partial u} \\
\frac{\partial L}{\partial u'} \\
\frac{\partial L}{\partial \lambda} \\
\frac{\partial L}{\partial \lambda'}
\end{pmatrix}_{12} = H
\]

\[
\alpha^T \phi_1 + \beta^T \phi_2 + \gamma^T \phi_3 + \tau = 0
\]

\[
\tau = \left( \frac{\partial L}{\partial u} \frac{\partial^2 L}{\partial u \partial u'} + \frac{\partial L}{\partial u'} \frac{\partial^2 L}{\partial u \partial u''} \right) \dot{v}_d + \left( \frac{\partial L}{\partial u} \frac{\partial^2 L}{\partial u \partial \delta} + \frac{\partial L}{\partial u'} \frac{\partial^2 L}{\partial u' \partial \delta} \right) \dot{\delta}
\]

■ Proof: Lyapunov-like function and its derivative

\[
V(u, u', \lambda, v_d) = \frac{1}{2} \left( \frac{\partial L}{\partial u} \frac{\partial L}{\partial u'} + \frac{\partial L}{\partial u} \frac{\partial L}{\partial u''} + \frac{\partial L}{\partial \lambda} \frac{\partial L}{\partial \lambda} \right)
\]

\[
\dot{V}(u, u', \lambda, v_d) = -\alpha^T \Gamma_1 \alpha - \beta^T \Gamma_2 \beta - \gamma^T \Gamma_3 \gamma
\]
Actuator Efficiency Calibrations

- In-wheel motor efficiency maps and functions
  - Driving efficiency
  - Braking efficiency

- Experimental data
  - 4th-order polynomial
  - 3rd-order polynomial
In-wheel Motor Efficiency Modification

■ Reasons for modifying motor efficiencies
  ➢ Efficiencies vary with manufacture defects / inconsistence, fatigue / failure of electric circuits / elements, different working conditions / health statuses

■ Principle and hardware realizations

![Diagram showing modified combining efficiency and integrated efficiency](image)

- Battery
- Inserted power resistor pack
- Motor controller
- BLDC in-wheel motor

■ Efficiency scaling

![Graphs showing efficiency scaling](image)

- Driving efficiency
- Regenerative braking efficiency

Experimental data:
- 4th-order polynomial \( \eta_d \)
- 3rd-order polynomial \( \eta_b \)
- Power resistor modification
- \( \alpha_r \eta_d \)
- \( \alpha_r \eta_b \)
EGV Longitudinal Motion Control

■ Vehicle longitudinal motion model

\[
\dot{x} = -\frac{C_a}{m_v} x^2 - \frac{2J}{m_v R_{\text{eff}}} (\dot{\omega}_f + \dot{\omega}_r) + \frac{1}{m_v R_{\text{eff}}} v_d
\]

\[
v_d = Bu = \begin{bmatrix} T_1 \\ T_2 \end{bmatrix}
\]

■ High-level control

\[
v_d = m_v R_{\text{eff}} \left[ \frac{C_a}{m_v} x^2 + \frac{2J}{m_v R_{\text{eff}}} (\dot{\omega}_f + \dot{\omega}_r) + \dot{x}_r - k (x - x_r) \right]
\]

■ Rule-based EECA

\[
v_d = \frac{1}{1 + \alpha_r} v_d + \frac{\alpha_r}{1 + \alpha_r} v_d = T_1 + T_2 \quad \Rightarrow \quad \begin{cases} 
T_1 = \frac{1}{1 + \alpha_r} v_d \\
T_2 = \frac{\alpha_r}{1 + \alpha_r} v_d \\
, \quad \text{if} \quad \eta_f (T_1) = \alpha_r \eta_r (T_2)
\end{cases}
\]
# EGV Longitudinal Motion Control: Experiments

## Test scenario 1

![Graph showing longitudinal speed (km/h), virtual control (V), torque (Nm), and power consumption (W) for Test scenario 1.](image1)

<table>
<thead>
<tr>
<th>Average Power Consumption (kW)</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule-based EECA</td>
<td>2.6165</td>
<td>6.5335</td>
</tr>
<tr>
<td>A-EECA</td>
<td>2.3158 (↓11.5%)</td>
<td>6.1102 (↓6.5%)</td>
</tr>
<tr>
<td>KKT-based EECA</td>
<td>2.1093 (↓19.4%)</td>
<td>5.9970 (↓8.2%)</td>
</tr>
</tbody>
</table>
**EGV Planar Motion Control**

- **Control-oriented model**

\[
\dot{x}_1 = x_2 x_3 - \frac{C_a}{m_v} x_1^2 + \frac{1}{m_v} \left( \frac{-J}{R_{eff}} \Delta_{1x} \dot{\omega} + \Delta_{1y} F_Y \right) + v_1
\]

\[
\dot{x}_2 = -x_1 x_3 + \frac{1}{m_v} \left( \frac{-J}{R_{eff}} \Delta_{2x} \dot{\omega} + \Delta_{2y} F_Y \right) + v_2
\]

\[
\dot{x}_3 = \frac{1}{I_z} \left( \frac{-J}{R_{eff}} \Delta_{3x} \dot{\omega} + \Delta_{3y} F_Y \right) + v_3
\]

\[
v_d = \begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix}^T = Bu
\]

\[
B_{3x4} = \begin{bmatrix} \Delta_{1x}^T / m_{eff} & \Delta_{2x}^T / m_{eff} & \Delta_{3x}^T / I_z R_{eff} \end{bmatrix}^T
\]

\[
u = \left[ T_{\beta} \quad T_{fr} \quad T_{rl} \quad T_{rr} \right]^T
\]

- **High-level SMC: robust**

\[
v_1 = -x_2 x_3 + \frac{C_a}{m_v} x_1^2 - \frac{1}{m_v} \left( \frac{-J}{R_{eff}} \Delta_{1x} \dot{\omega} + \Delta_{1y} \hat{F}_Y \right) + \dot{x}_r - k_1 \text{sign}(s_1)
\]

\[
v_2 = x_1 x_3 - \frac{1}{m_v} \left( \frac{-J}{R_{eff}} \Delta_{2x} \dot{\omega} + \Delta_{2y} \hat{F}_Y \right) + \dot{x}_r - k_2 \text{sign}(s_2)
\]

\[
v_3 = - \frac{1}{I_z} \left( \frac{-J}{R_{eff}} \Delta_{3x} \dot{\omega} + \Delta_{3y} \hat{F}_Y \right) + \dot{x}_r - k_3 \text{sign}(s_3)
\]

- **Pseudo-inverse (P-CA)**

\[u = B^\dagger v_d\]
EGV Planar Motion Control: Experiments

- **Test scenario 1**
  - Control performance
    - Total Energy (kJ) Scenario 1
      |       | Scenario 1 |
      |-------|------------|
      | P-CA  | 70.090     |
      | A-EECA| 66.086     |
    - 5.7% energy saving by EECA
  - Torque distributions
EGV Planar Motion Control: Experiments

- Scenario 2
  - Control performance

<table>
<thead>
<tr>
<th>Total Energy (kJ)</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-CA</td>
<td>45.878</td>
</tr>
<tr>
<td>A-EECA</td>
<td>42.477</td>
</tr>
</tbody>
</table>

7.4% energy saving by EECA

- Torque distributions
Actuator-redundancy-based Fault Diagnosis for FWIA Electric Vehicles

- Four wheel independently actuated (FWIA) electric vehicles

- In-wheel motor faults
  - Performance and stability heavily rely on the proper operations of the in-wheel motors
  - Increased number of motors and motor drivers elevates the chance of a fault
  - When a fault occurs, the faulty wheel may fail to provide the expected torque

Fault Diagnosis for In-Wheel Motors

- In-wheel motor fault types
  - Motor torque stuck at a fixed value
  - Motor torque loss of effectiveness fault

- Fault diagnosis objective
  - Identify which motor is in fault
  - Identify the fault type, one of the two types

- Challenges
  - Two wheels on the same side of a FWIA vehicle have vary close control effects on the vehicle longitudinal speed and yaw rate dynamics
    - The control effects of the two wheels on the same side will be identical if the vehicle runs on a straight line

- Utilize the actuation redundancy for fault diagnosis design
Actuator Redundancy based Fault Diagnosis

■ Structure of the fault diagnosis method

Task 1

\[ u_1, \omega_1 \]

\[ \text{TRFC Estimation} \]

\[ \hat{\mu}_1 \]

\[ u_2, \omega_2 \]

\[ \text{TRFC Estimation} \]

\[ \hat{\mu}_2 \]

\[ u_3, \omega_3 \]

\[ \text{TRFC Estimation} \]

\[ \hat{\mu}_3 \]

\[ u_4, \omega_4 \]

\[ \text{TRFC Estimation} \]

\[ \hat{\mu}_4 \]

Task 2

\[ \mu \text{ Calculation and Selection} \]

\[ \bar{\mu}_1 \]

\[ u_1 \]

\[ r_1 \]

\[ \bar{\mu}_2 \]

\[ u_2 \]

\[ r_2 \]

\[ \bar{\mu}_3 \]

\[ u_3 \]

\[ r_3 \]

\[ \bar{\mu}_4 \]

\[ u_4 \]

\[ r_4 \]

Task 3

\[ \text{Residual Calculation} \]

\[ \bar{\mu} \]

\[ u_1 \]

\[ r_1 \]

\[ \bar{\mu} \]

\[ u_2 \]

\[ r_2 \]

\[ \bar{\mu} \]

\[ u_3 \]

\[ r_3 \]

\[ \bar{\mu} \]

\[ u_4 \]

\[ r_4 \]
Proposed Fault Diagnosis Method

■ Task 1: Tire-road friction coefficient (TRFC) estimation
   Step 1: Estimate the wheel longitudinal force
    \[ I \ddot{\omega}_i = -R_{eff} F_{xi} + T_i, \quad (i = fl; fr; rl; rr) \]
    • Estimator dynamics
      \[ \dot{\hat{F}}_{xi} = -\frac{I}{R_{eff}} \chi_i - \frac{I}{R_{eff}} \rho_i \omega_i, \quad \dot{\chi}_i = -\rho_i \chi_i - \rho_i \left( \frac{u_i k_{0i}}{I} + \rho_i \omega_i \right) \]
   Step 2: Estimate the TRFC with tire model
    • Estimator dynamics
      \[ \hat{\mu}_i = L_i \cdot \text{sign} \left( \hat{F}_{xi} - \bar{F}_{xi}(\hat{\mu}_i, s_i) \right) \]
      \[ L_i > \frac{\left| \dot{\hat{F}}_{xi} - \frac{\partial \bar{F}_{xi}}{\partial s_i} \frac{ds_i}{dt} \right|_{\max}}{\left| \frac{\partial \bar{F}_{xi}}{\partial \hat{\mu}_i} \right|_{\min}} \]

■ Task 2: TRFC calculation and selection

  \[ \bar{\mu} = \frac{1}{3} \sum_{j=1, j\neq i}^{4} \hat{\mu}_j, \quad \text{with} \quad i = \arg \max \left\{ \hat{\mu}_k - \frac{1}{4} \sum_{j=1}^{4} \hat{\mu}_j \right\} \]

   Final TRFC is calculated with the three estimates that are most close to each other
   Faulty motor is the one with the most different estimated TRFC
Proposed Fault Diagnosis Method Cont’d

■ Task 3: Fault type estimation

- Define a new variable as \( \kappa_i = k_i u_i / I \), \((i = fl, fr, rl, rr)\)
- The estimation of the variable is
  \[
  \begin{align*}
  \hat{\kappa}_i &= \eta_i + \gamma_i \omega_i \\
  \hat{\eta}_i &= -\gamma_i \eta_i - \gamma_i \left( -\frac{R_{\text{eff}} \bar{F}_{\text{xi}}(s_i, \bar{\mu})}{I} + \gamma_i \omega_i \right)
  \end{align*}
  \]
- Define the residual as
  \( r_i = \kappa_{0i} - \hat{\kappa}_i \), \( \kappa_{0i} = k_{0i} u_i / I \)
- The threshold is chosen as
  \[
  \begin{cases}
  |r_i| < \xi_t, \text{ no fault occurs} \\
  |r_i| > \xi_t, \text{ with a fault}
  \end{cases}
  \]
  \[
  \xi_t = \sqrt{2 \left| \frac{\dot{\kappa}_i}{\kappa_{0i}} \right|_{\text{max}}^2 / \gamma_i^2 + 2 R_{\text{eff}}^2 \left| \varepsilon_i \right|_{\text{max}}^2 / I^2}
  \]
- Fault type identification
  \[
  \begin{cases}
  \kappa_{0i} - r_i \approx C_{1i}, \quad \text{Motor torque is stuck at a fixed level} \\
  \frac{r_i}{\kappa_{0i}} \approx C_{2i}, \quad \text{Loss of effectiveness fault}
  \end{cases}
  \]
Experimental Results - I

- In-wheel motor torque is stuck at a fixed level

Vehicle and wheel speeds

Motor control inputs

Friction coefficient estimations

$C_{1rr}$ is (almost) a constant—torque stuck fault
Experimental Results - II

- In-wheel motor loss-of-effectiveness fault

**Vehicle longitudinal speed**

**Motor control inputs**

**Friction coefficient estimations**

\[C_{2rr}\] is (almost) a constant—loss-of-effectiveness fault
Diesel Powertrain System

- Fully-instrumented medium-duty Diesel engine and aftertreatment systems
  - Two-stage turbocharging, dual-loop EGR, high-pressure throttle valve, EGR cooler with by-pass, inter-cooler by-pass
  - 8 AVL GH/U13P cylinder pressure transducers for all the cylinders
  - dSPACE MicroAutoBox + ECU hookup control system
  - ETAS-INCA system
  - A dual-channel Horiba MEXA emission measurement system
  - An AVL precision fuel balance with fuel thermal conditioning
  - DOC-DPF-SCR aftertreatment systems
  - Advanced emission sensors, e.g. NO$_x$ and ammonia sensors
  - Flexible fuel supply systems
  - High- and low-speed data acquisition system
Selective Catalytic Reduction (SCR) Systems Principles

1. NO\textsubscript{x} emission from engine
2. Inject AdBlue (urea water solution)
3. Exhaust gas and urea go through mixer achieve uniform distribution
4. Urea be converted to NH\textsubscript{3} at upstream of SCR catalyst
5. Part of NH\textsubscript{3} be adsorbed on the SCR catalyst substrate
6. NO\textsubscript{x} react with the adsorbed NH\textsubscript{3} to become N\textsubscript{2} and H\textsubscript{2}O
7. Some NO\textsubscript{x} and NH\textsubscript{3} can exist to tailpipe (undesired)
SCR System Control Objectives

- Control the urea injection rate to
  - Reduce tailpipe NO\textsubscript{x} emission
  - Reduce tailpipe NH\textsubscript{3} slip

- Due to natural of SCR, low tailpipe NO\textsubscript{x} emission (high SCR NO\textsubscript{x} conversion) requires rich NH\textsubscript{3} in the catalyst, which is like to cause high NH\textsubscript{3} slip
  - Conflicting objectives

AdBlue Injector
(urea water solution)

SCR Control

Engine

Mixer

SCR Catalyst

Tailpipe

- NO\textsubscript{x}
- NH\textsubscript{3}
- N\textsubscript{2}
- Urea
- H\textsubscript{2}O

THE OHIO STATE UNIVERSITY

45
Ammonia Storage Distribution Control (ASDC)

- SCR system
  - Assume all states inside the catalyst and out of the catalyst are homogeneous to generate ODE models
  - However, the actual ammonia distribution in SCR is not homogeneous and the distribution profile significantly affects the SCR NO\textsubscript{x} conversion efficiency and NH\textsubscript{3} slip
    - Use two cells to allow better control authority on the ammonia distribution profile along the SCR
SCR System ASDC Strategy

- **ASDC Strategy**
  - Selected controlled variable: Ammonia coverage ratio:
    - Directly affect NO_x reduction rate and NH_3 adsorption and desorption rates
  - Two-catalyst based control architecture:

![Diagram of SCR System](image)

Control-oriented Model for SCR System ASDC

Control Plant

\[
\begin{bmatrix}
\dot{C}_{NO,i} \\
\dot{C}_{NO2,i} \\
\dot{C}_{NH3,i} \\
\dot{\theta}_{NH3,i}
\end{bmatrix} = \\
\begin{bmatrix}
-r_{1,i}C_{NO,i}C_{O2,i}\theta_{NH3,i}\theta_iV_i - \frac{1}{2}r_{2,i}C_{NO,i}C_{NO2,i}\theta_{NH3,i}\theta_iV_i - r_{5,i}C_{NO,i}C_{O2,i}\theta_iV_i - \frac{F_i}{V_i} C_{NO,i} + \frac{F_i}{V_i} C_{NO,i+1} \\
-\frac{1}{2}r_{2,i}C_{NO,i}C_{NO2,i}\theta_{NH3,i}\theta_iV_i + r_{5,i}C_{NO,i}C_{O2,i}\theta_iV_i - \frac{F_i}{V_i} C_{NO2,i} + \frac{F_i}{V_i} C_{NO2,i+1} \\
-C_{NH3,i}\left[\theta_i r_{4F,i} (1 - \theta_{NH3,i}) + \frac{F_i}{V_i}\right] + \frac{1}{V_i} r_{4R,i} \theta_i \theta_{NH3,i} + \frac{F_i}{V_i} C_{NH3,i+1} \\
-\theta_{NH3,i} (r_{4F,i} C_{NH3,i} V_i + r_{3,i} C_{O2,i} + r_{4R,i} + r_{1,i} C_{NO,i} C_{O2,i} V_i^2 + r_{2,i} C_{NO,i} C_{NO2,i} V_i^2) + r_{4F,i} C_{NH3,i} V_i
\end{bmatrix},
\]

\( i = 1,2. \)
**SCR System ASDC Control Law Design**

- Backstepping based approach for controller design to handle the complicated cascade dynamics system
  
  \[
  C_{NH_3,in} = -\frac{V_2}{F_2} \left\{ G(\bar{\theta}_{NH_3,1}) \left[ \bar{\theta}_{NH_3,2} r_{4F,2} V_2 (1 - \theta_{NH_3,2}) - \dot{\bar{\theta}}_{NH_3,2} + \frac{F_2}{V_2} C_{NH_3,2} 
  \right. 
  - C_{NH_3,2} r_{4F,2} (1 - \theta_{NH_3,2}) \right. 
  \left. + \frac{1}{V_2} r_{4R,2} \theta_{NH_3,2} \dot{\theta}_2 + K_2 \dot{\theta}_{NH_3,2} |\bar{\theta}_{NH_3,2}| \right\}
  \]

  \[
  \bar{\theta}_{NH_3,1} = \theta_{NH_3,1} - \theta_{NH_3,1},
  \]

  \[
  \bar{\theta}_{NH_3,2} = \theta_{NH_3,2} - \theta_{NH_3,2},
  \]

  \[
  \dot{\bar{\theta}}_{NH_3,2} = C_{NH_3,2} - \bar{\theta}_{NH_3,2},
  \]

  \[
  \dot{\theta}_2 = \bar{\theta}_{NH_3,2} \left[ C_{NH_3,2} r_{4F,2} (1 - \theta_{NH_3,2}) - \frac{1}{V_2} r_{4F,2} \theta_{NH_3,2} \right],
  \]

  \[
  \dot{C}_{NH_3,2} = \frac{1}{r_{4F,2} V_2 (1 - \theta_{NH_3,2})} \left[ \theta_{NH_3,2} (r_{4F,2} C_{\theta_{2,2}} V_2 + r_{4R,2} \right]
  \]

- Adaptive controller design to handle the ammonia storage capacity uncertainty
  
- Several sensor and model uncertainties

  - Stability proof based on Lyapunov theory shows the controller:
    - Controls the ARC NH₃ coverage ratio to a boundary region under a prescribed limit \( \theta_1^* \)
    - Control the NCC NH₃ coverage ratio to the desired value \( \theta_2^* \)
  
  - Sensitivity analyses show the controller is robust to NOₓ sensor and some model uncertainties
SCR ASDC - Experimental Structure

- **NO\textsubscript{x} Sensor**
- **NH\textsubscript{3} Sensor**
- **Thermo.**
- **Eng. ECU**
  - Provide Exh. Flow Rate Est.

**Ammonia Storage Distribution Controller**

- **NO/NO\textsubscript{2} Observer**
- **NH\textsubscript{3} Cov. Ratio Observer**
- **EKF NO\textsubscript{x} Sensor Correction**
- **NH\textsubscript{3} Coverage Ratio Observer**
- **EKF NO\textsubscript{x} Sensor Correction**

- **AdBlue Injection**
- **Engine**
- **Exhaust Gas**
- **Upstream SCR Catalyst (NCC)**
- **Downstream SCR Catalyst (ARC)**
- **Exh. Flow Rate Est.**
- **Tailpipe**
SCR ASDC US06 Cycle Experimental Results

- **Gas concentrations along the SCRs**

  ![Graph showing gas concentrations along the SCRs](image1)

- **Zoom-in ammonia concentrations**

  ![Graph showing zoomed-in ammonia concentrations](image2)
Experimental Comparison of ASDC and LSCC

Compared with the case without distribution control (lumped single catalyst control, LSCC) (ammonia coverage ratios were equivalent at the 155th second in the cycle)

<table>
<thead>
<tr>
<th>155-600 sec.</th>
<th>NO\textsubscript{x} Before SCRs</th>
<th>NO\textsubscript{x} After SCRs</th>
<th>Inj. NH\textsubscript{3}</th>
<th>NH\textsubscript{3} After SCRs</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASDC</td>
<td>12.94 g</td>
<td>0.78 g</td>
<td>10.68 g</td>
<td>0.19 g</td>
</tr>
<tr>
<td>LSCC</td>
<td>13.26 g</td>
<td>1.82 g</td>
<td>9.82 g</td>
<td>0.73 g</td>
</tr>
<tr>
<td>ASDC/LSCC</td>
<td>97.6%</td>
<td>42.9%</td>
<td>108.8%</td>
<td>26.1%</td>
</tr>
</tbody>
</table>
Concluding Remarks

- Substantially elevated vehicle system complexities require more and more sophisticated estimation and control systems in order to meet the ever-growing demands on energy efficiency, emissions, and safety.

- Control systems are becoming increasingly important and oftentimes central for future ground vehicles and transportation.

- Innovative and systematic combinations of physical insight into the vehicle systems with estimation and control theories may offer effective means to tackle the challenges, as illustrated by the examples.

- Many intriguing future research directions to be investigated.
Acknowledgements

Thanks the financial support from
- National Science Foundation; Office of Naval Research; U.S. Department of Energy (DOE); ORAU; General Motors Global R&D; Ford Motor Company; Honda R&D Americas; Eaton Corporation; Tenneco Inc.; OSU-CAR Industrial Consortium; Honda-OSU Partnership Program; OSU-Transportation Research Endowment Program; OSU-Dept. of Mechanical and Aerospace Engineering

Thanks the current and former students
- Prof. F. Yan; Prof. R. Wang; Prof. H. Zhang, Dr. M.-F. Hsieh; Dr. Y. Chen; Dr. X. Huang; Mr. P. Chen; Mr. J. Zhao; Mr. S. Schnelle; Mr. X. Zeng; Mr. G. Zhang; Mr. Z. Yu; Mr. C. Wiet; Mr. B. Haber
Questions?

Thanks for your attention!