Optimal and Secured Control using V2V Information: from Powertrain to Multiple Autonomous Vehicles

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Hong Wang's Brief Background Information

https://www.ornl.gov/staff-profile/hong-wang-0

- Hong Wang (Fellow of IEE (now IET), Fellow of InstMC, Fellow of IEEE and Fellow of AAIA) received the master's and Ph.D. degrees from the Huazhong University of Science and Technology, Wuhan, China, in 1984 and 1987, respectively. He was a Research Fellow with Salford University, Salford, U.K., Brunel University, Uxbridge, U.K., and Southampton University, Southampton, U.K., before joining the University of Manchester Institute of Science and Technology (UMIST), Manchester, U.K., in 1992. He was a Chair Professor in process control of complex industrial systems with the University of Manchester, U.K., from 2002 to 2016, where he was the Deputy Head of the Paper Science Department, the Director of the UMIST Control Systems Centre from 2004 to 2007, which is the birthplace of Modern Control Theory established in 1966. He was a University Senate member and a member of general assembly during his time in Manchester.
- From 2016 to 2018, he was with the Pacific Northwest National Laboratory (PNNL), Richland, WA, USA, as a Laboratory Fellow and Chief Scientist, and was the Co-Leader and the Chief Scientist for the Control of Complex Systems Initiative. He joined the Oak Ridge National Laboratory in January 2019 as a senior distinguished scientist at corporate fellow grade, US Department of Energy. His research focuses on stochastic distribution control, fault diagnosis and tolerant control, and intelligent controls with applications to transportation system area, and has published more than 200 journal papers and 6 books.
- He was an Associate Editor of the IEEE Transactions on Automatic Control, the IEEE Transactions on Control Systems Technology, and the IEEE Transactions on Automation Science and Engineering. He is also a member for three Technical Committees of International Federation of Automatic Control (IFAC). He is now an associate editor for the IEEE Transactions on Neural Networks and Learning Systems since 2022.

Acknowledgements

- ❑ Work on V2V for Powertrain optimization was performed when Hong Wang was with PNNL under US DoE ARPA – E NextCar program

- ❑ Collaborative fault tolerant control theory was developed at the University of Manchester between 2005 – 2015, application to CAVs was performed at PNNL

- ❑ Thanks to the following collaborators

Dr Wanshi Hong (LBL) **Dr Indrasis Chakraborty (LLNL)** **Professor Gang Tao (UV)**

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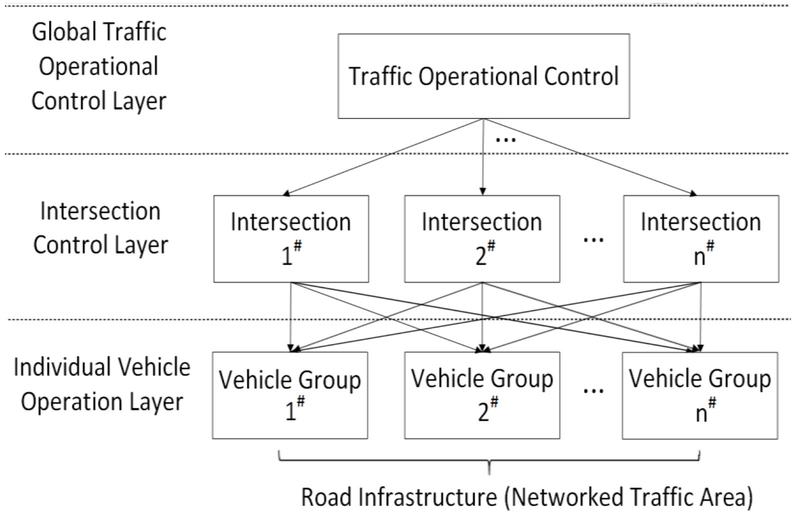
3 – Layered Operational Structure for Transportation Systems [1] – [2]



- ❑ Information flow
- ❑ Mass flow
- ❑ Energy flow [1]

Figure 5

Available data:

- ❑ Data from fixed sensors such as probe detectors, intersection camera images
- ❑ Moving data such as the data provided by individual vehicles

Intersection operational control – non-signalized approach with 100% CAVs

Using the V2V communication capabilities, signal infrastructure can be omitted as the CAVs can manage themselves in passing through each intersection

[1] H Wang, M Zhu, W Hong, G Tao and Y Wang, Optimizing Signal Timing Control for Large Urban Traffic Networks Using an Adaptive Linear Quadratic Regulator Control Strategy, ***IEEE Transactions on Intelligent Transportation Systems*** , 2020 .
[2] H Wang, S Patil, H Aziz and S Young , Modeling and Control Using Stochastic Distribution Control Theory for Intersection Traffic Flow, ***IEEE Transactions on Intelligent Transportation Systems***, 2020,

V2X Overview - How Can It Benefit Transportation Systems – to Vehicle Control and to System Control?

- V2X links vehicles with vehicles and/or infrastructure
- They increases the observability and safety
- Provide new measurements for vehicle control and transportation system control and optimization
- Enables cheap intersectional infrastructure as vehicles can manage themselves when passing through intersections without the need of traffic signals

V2X Overview - How It Can Benefit Transportation Systems – to Vehicle Control and to System Control

In this talk, I will do the following

1. V2V for powertrain control

2. V2V enabled fault tolerant control for a group of vehicles passing through non-signalized intersections.

3. Future perspectives of using V2X

V2V Supports Powertrain Control for Energy Saving

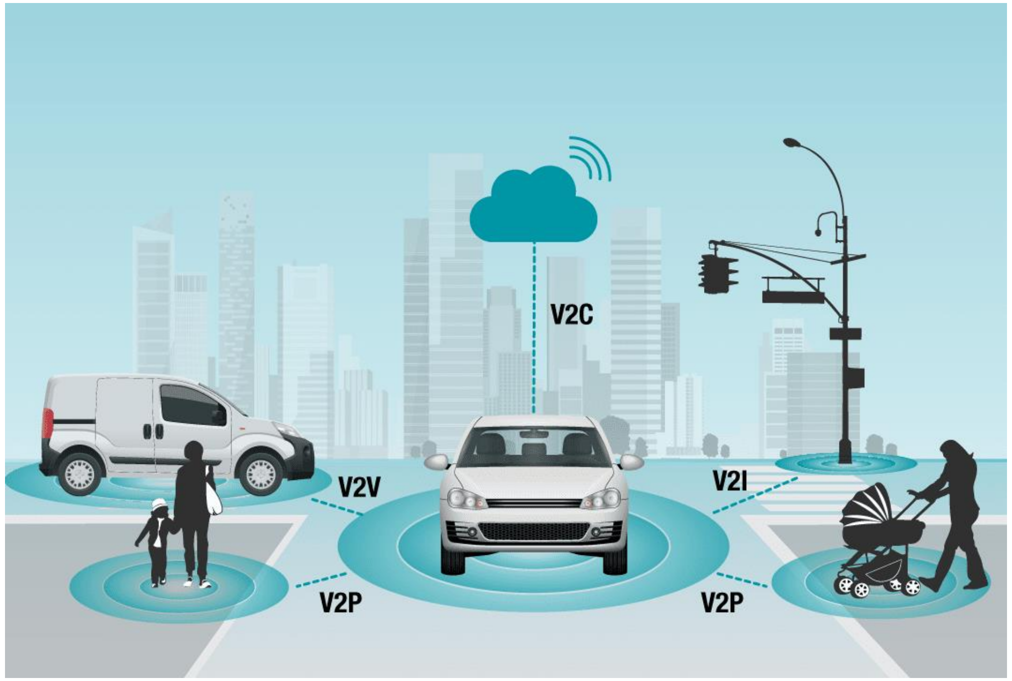
- ❑ **Research Background**
- ❑ **HEV System Modeling**
- ❑ **Control Design**
- ❑ **Simulation Results**
- ❑ **Summary and Discussion**

Acknowledgment: This part is based upon the following publication:

Wanshi Hong; Indrasis Chakraborty; Hong Wang; Gang Tao, Co-Optimization Scheme for the Powertrain and Exhaust Emission Control System of Hybrid Electric Vehicles Using Future Speed Prediction, ***IEEE Transactions on Intelligent Vehicles***, Vol. 6, pp. 533 – 545, 2021.

Research Background

- Development of Hybrid Electric Vehicle
- Research trend in connected vehicle techniques



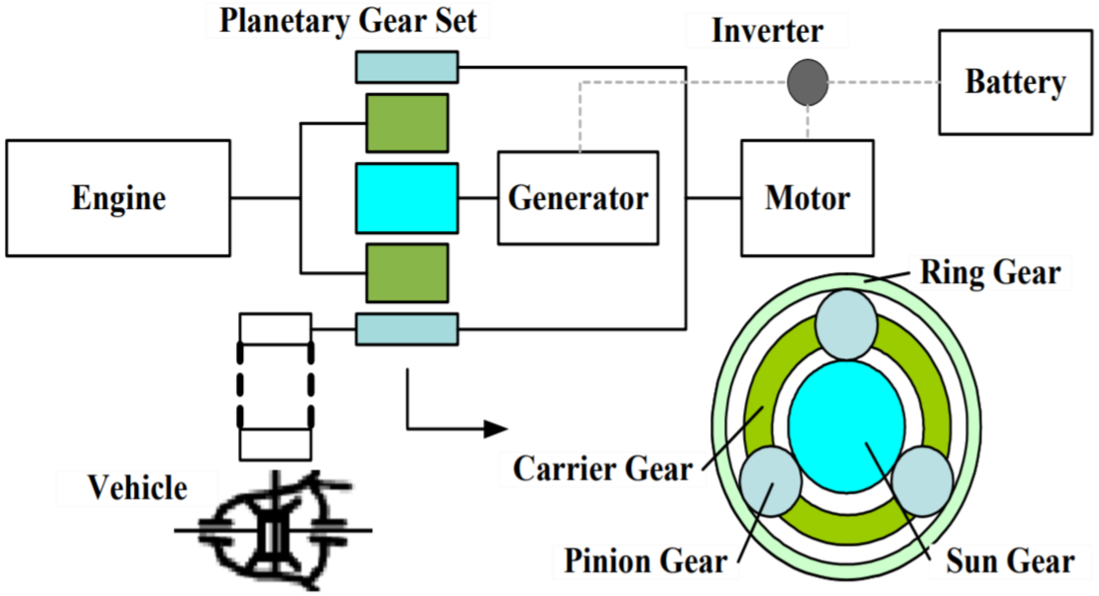
Cite: https://e2e.ti.com/blogs_/b/behind_the_wheel/archive/2019/08/30/how-connected-vehicles-leverage-data

Problem Statement

- **Motivations:**
  - ➢HEV powertrain: integrated nonlinear models – difficult to identify
  - ➢Controller parameters sensitive to fuel consumption
  - ➢Potential improvement on fuel saving using V2V/V2I information
  - ➢Trade-off between fuel saving and harmful gas emissions
- **Research Goals:**
  - ➢Design controller parameter tuning based co-optimization schemes
    - ✓Achieve fuel saving
    - ✓Control harmful gas emission

➡ Fuel co-optimization for connected HEVs

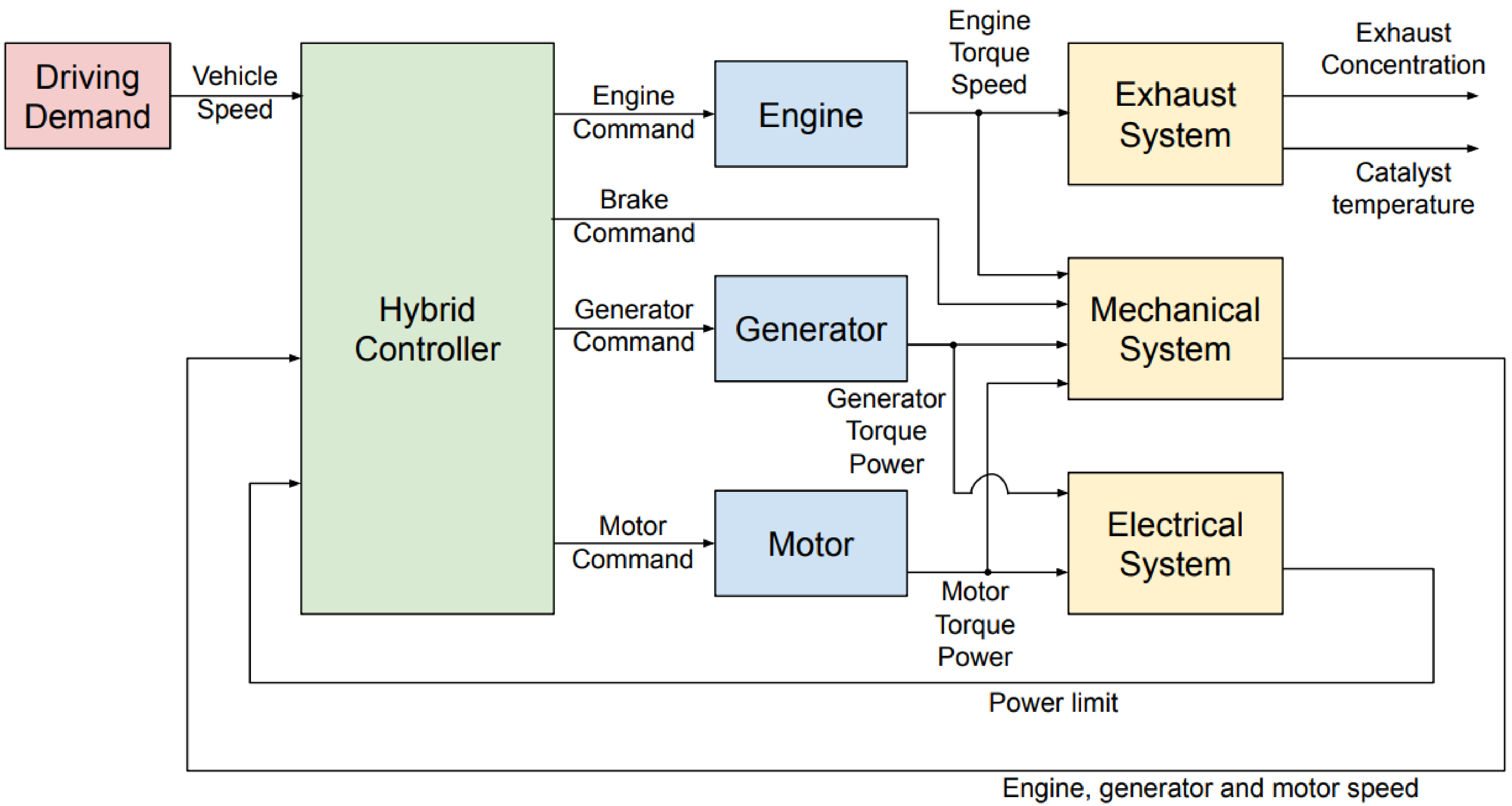
HEV System Dynamic Model



$$
\begin{aligned}
(I_s + I_{MG1})\dot{\omega}_{MG1} &= FS - T_{MG1} \\
(I_c + I_e)\dot{\omega}_e &= T_e = FR - FS \\
\left(\frac{R_{tire}}{K}m + I_{MG2}K + I_r K\right)\dot{\omega}_r &= (T_{MG2} + FR)K \\
&\quad - T_f - mgf_r R_{tire} \\
&\quad - 0.5\rho A C_d\left(\frac{\omega_r}{K}\right)^2 R_{tire}^3 \\
S\dot{O}C &= -V_o - \sqrt{\frac{-V_o^2 - 4P_b R_b}{2R_b Q_{max}}}
\end{aligned}
$$

- T_{MG1}, T_{MG2}, T_e: MG1/MG2 torques and engine torques
- I_r, I_s, I_c: inertias of the ring gear, sun gear, and carrier gear
- I_{MG1}, I_{MG2}, I_e: inertias of the power sources
- P_b: Battery power

HEV System Simulation Model



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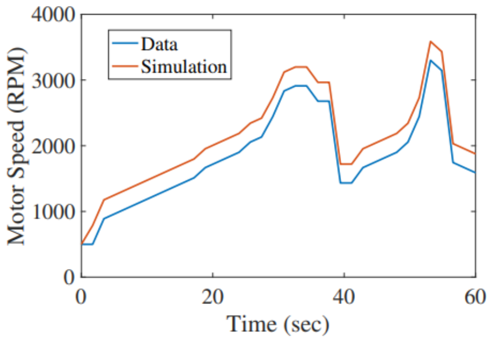
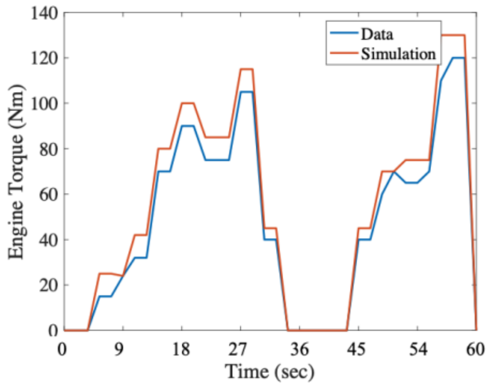
Simulation Model Validation

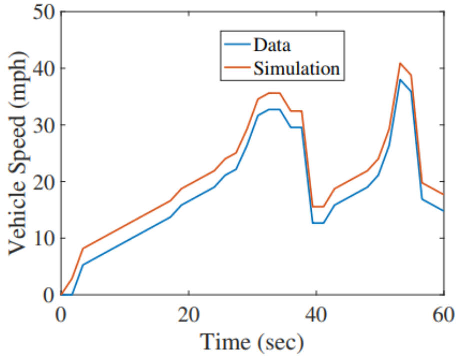
- Powertrain System Validation



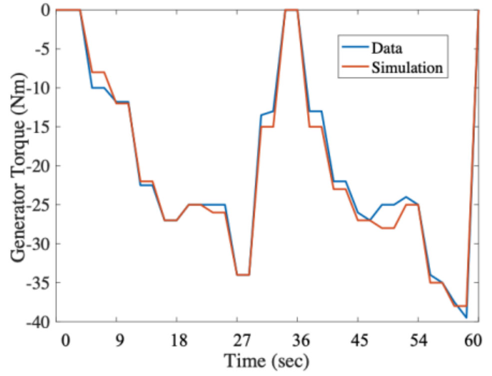
(a) Validation of motor speed



(b) Validation of engine torque

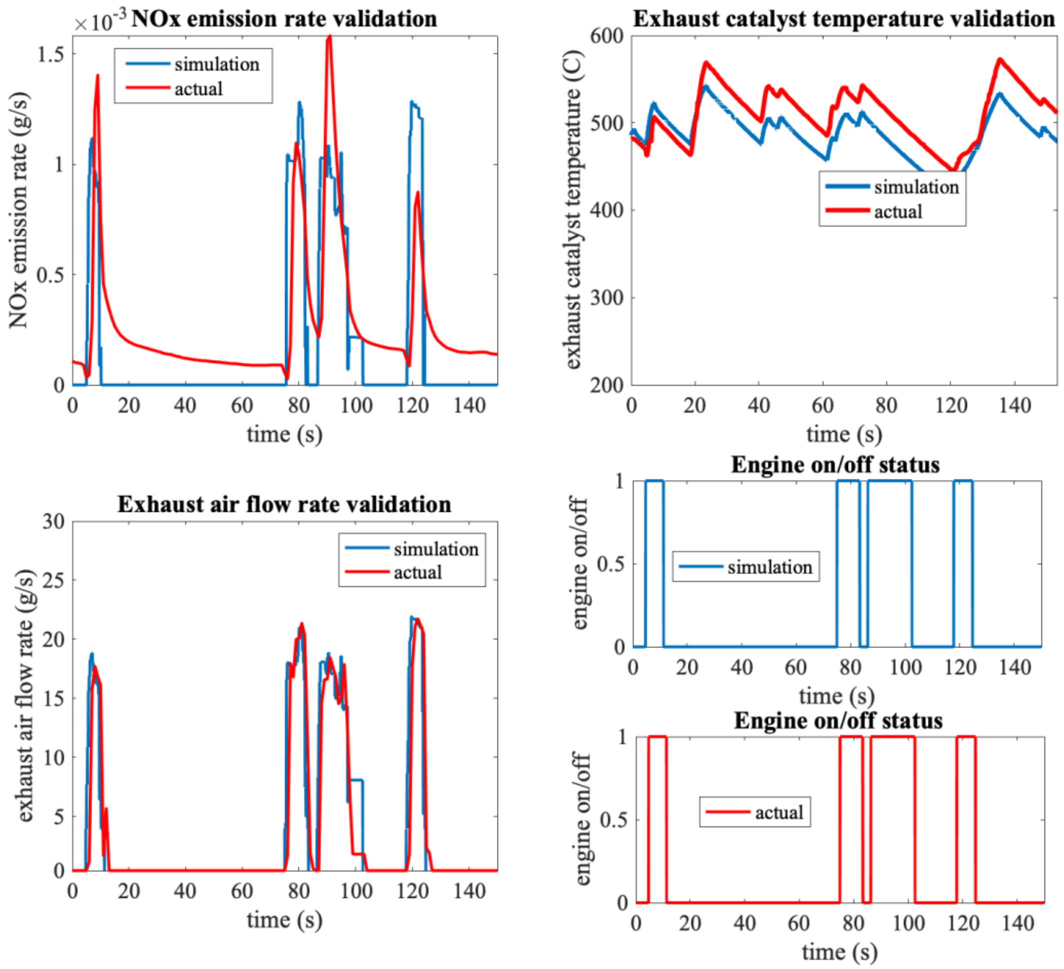


(c) Validation of vehicle speed



(d) Validation of generator torque

- Exhaust System Validation



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Key Optimization Inputs Identification

Based on sensitivity studies, identifies the key system parameter from HEV system that are sensitive to fuel consumptions:

- MG1 generator speed controller:

$$u_{MG1}(t) = \theta_1(\omega^*(t) - \omega_{MG1}(t)) + \theta_2 \int_0^t (\omega^*(\tau) - \omega_{MG1}(\tau))d\tau$$

- Battery charging controller

$$u_p(t) = \begin{cases} u_{p1}(t), u_{p1}(t) < u_{pmax} \\ u_{pmax}, u_{p1}(t) \geq u_{pmax} \end{cases}, u_{p1}(t) = \theta_3(SOC^*(t) - SOC(t))$$

- Pratical parameter ranges:

  $\theta_1 \in [0.5, 1]$, $\theta_2 \in [0.0001, 0.05]$, $\theta_3 \in [13000, 17000]$

- Nominal values:

  $\theta_1 = 0.9$, $\theta_2 = 0.005$, $\theta_3 = 15000$

- Co-optimization: decide the optimal values for θ_1,θ_2 and θ_3

Motivation of Neural Network Estimation

Difficult to directly derive optimization scheme based on powertrain dynamics

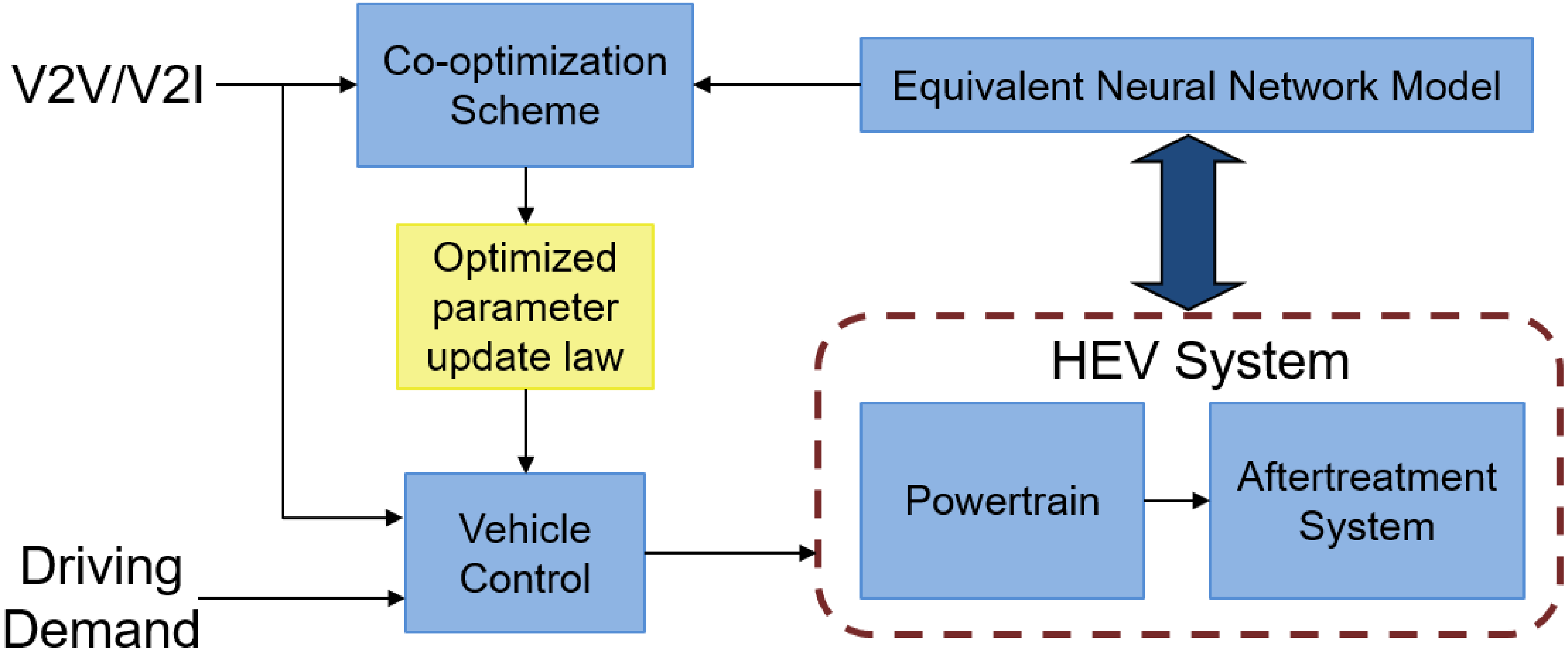
↓

Estimate the direct input-output model to represent the dynamic between fuel consumption and the optimization inputs

↓

Design an equivalent NN model to estimate the direct input-output model

Co-optimization Scheme Design



- Maximize fuel saving with future driving condition taken into account
- Guarantee the catalyst temperature higher than the light-off temperature

Co-Optimization Problem Formulation

- Cost Function:

$$J = fuel(nT) = \sum_{k=1}^{n} \Delta f(\theta(k), cyc(k)).$$

$\theta = [\theta_1, \theta_2, \theta_3]$

$cyc(k) = [v_f(k+1), \ldots, v_f(k+k_{max})]$ - future vehicle speed

$\Delta f(\theta(k), cyc(k))$: fuel consumption (g) at k step

- State Constraints

$$x(k+1) = g(x(k), \theta(k), cyc(k)), \; x = [T_e, T_g, T_m, \omega_e, \omega_g, \omega_m]^T$$

- Exhaust Constraints

$$T_{cat}(k+1) = h(T_{cat}(k), z(k), \theta(k), cyc(k)), \; z = [T_e, \omega_e, C_{on}, r_{air}, T_{cool}]^T$$

$$T_{cat} > T_{lightoff}$$

T_{cat}: Catalyst temperature

System Identification Using Neural Network

Neural network model:

$$y_{NN}(k) = w_2\phi(k) + b_2$$
$$\phi(k) = L(\psi(k))$$
$$\psi(k) = w_1 x(k) + b_1$$

Fuel consumption model:

- input: $\theta(k), cyc(k)$, output: $\Delta f(k)$

State dynamic model:

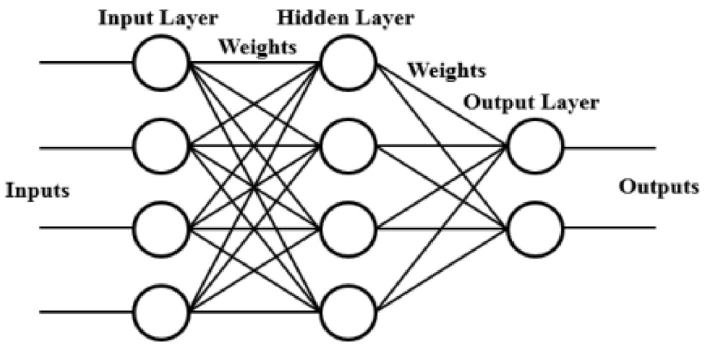
- input: $\theta(k), x(k), cyc(k)$
- output: $x(k+1)$

Exhaust system model

- input: $T_{cat}(k), z(k), \theta(k), cyc(k)$
- output: $T_{cat}(k+1)$

Gradient based adaptation:

$$w_N^{i+1} = w_N^i + \Delta w_N^i$$
$$b_N^{i+1} = b_N^i + \Delta b_N^i$$
$$\Delta w_N^i = -\alpha \frac{\partial E(k)}{\partial w_N^i}$$
$$\Delta b_N^i = -\alpha \frac{\partial E(k)}{\partial b_N^i}, \quad N = 1,2$$
$$E(k) = \frac{1}{2}(y_{NN}(k) - y(k))^2$$



Equivalent Co-Optimization Problem

Solve θ to minimize fuel consumption given by

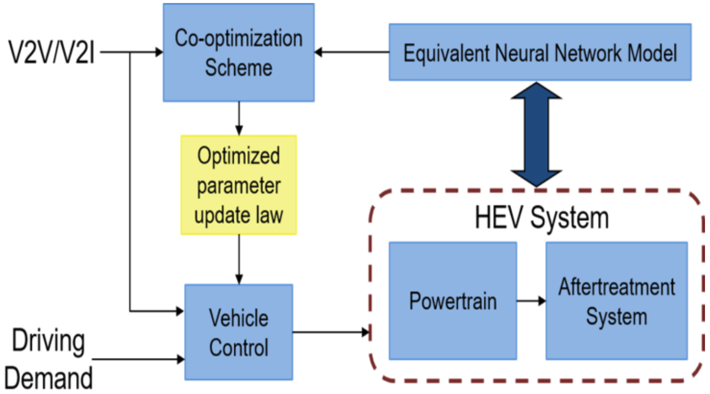
$$\hat{J} = \sum_{i=1}^{n} \Delta\hat{f}(\theta(k), cyc(k)),$$

and satisfy the following constraints:

$$x(k+1) = \hat{g}(x(k), \theta(k), cyc(k)) + \epsilon_1$$
$$T_{lightoff} \leq \hat{h}(T_{cat}(k), z(k), \theta(k), cyc(k)) + \epsilon_2$$

$\Delta\hat{f}$, $\hat{g}$, $\hat{h}$: NN estimate of Δf, g, h

Co-optimization task: find $\theta(k)$ to minimize $\hat{J}$



Parameter Tuning Strategy

Parameter tuning law: solve the optimization problem:

$$\frac{\partial \hat{J}}{\partial \theta(k)} = 0$$

$$x(k+1) = \hat{g}(x(k), \theta(k), cyc(k)) + \epsilon_1$$

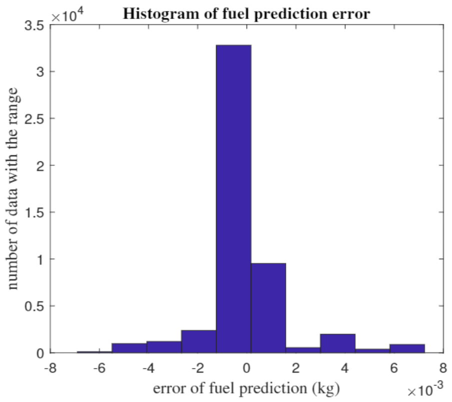
$$T_{lightoff} \leq \hat{h}(T_{cat}(k), z(k), \theta(k), cyc(k)) + \epsilon_2$$

$$\theta(k) = S(x(k), z(k), cyc(k))$$

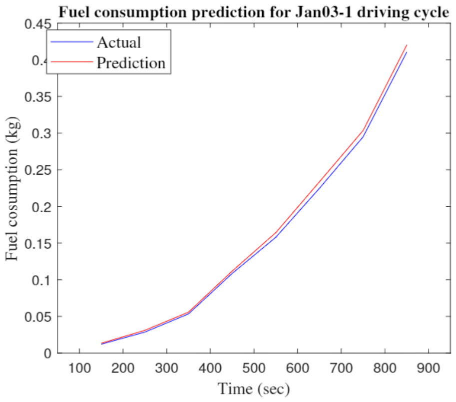
Parameter tuning law depends on powertrain states, exhaust states, and future driving condition.

Model Estimation Performance

Cost function estimation

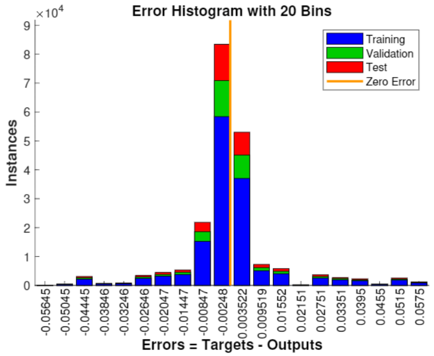


(a) error histogram

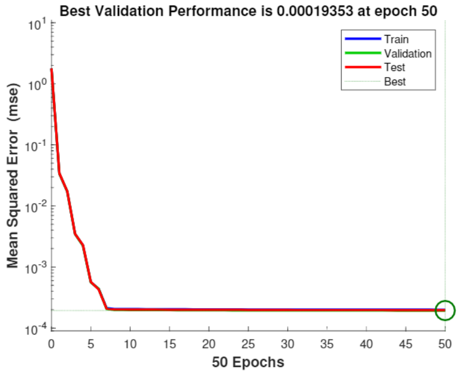


(b) fuel consumption prediction for Jan03-1 driving cycle

Training performance

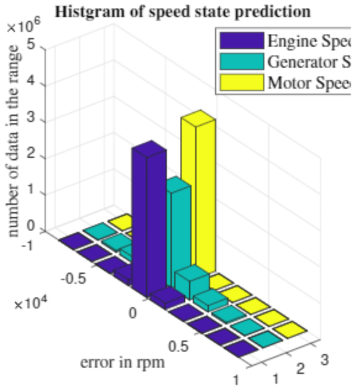


(a) error histogram

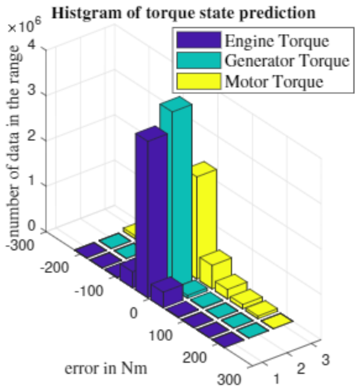


(b) validation performance

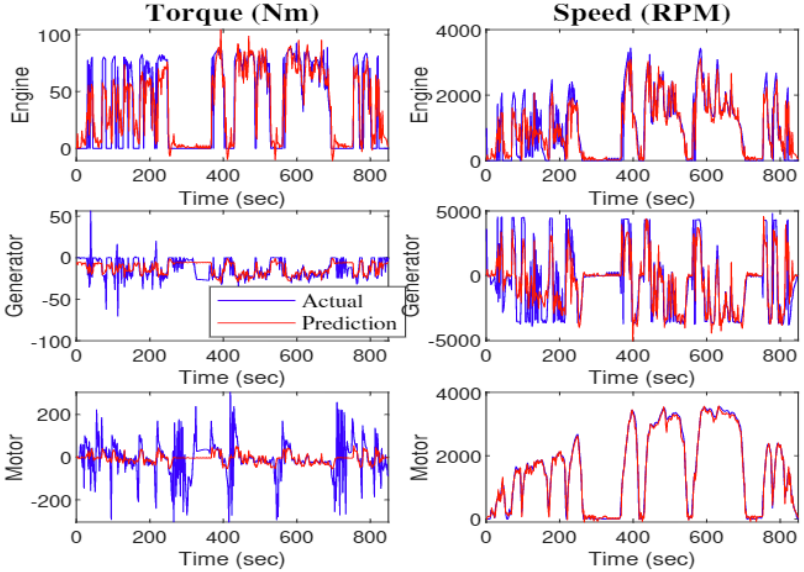
State constraint estimation



(a) error histogram for speed states



(b) error histogram for torque states



(c) state prediction

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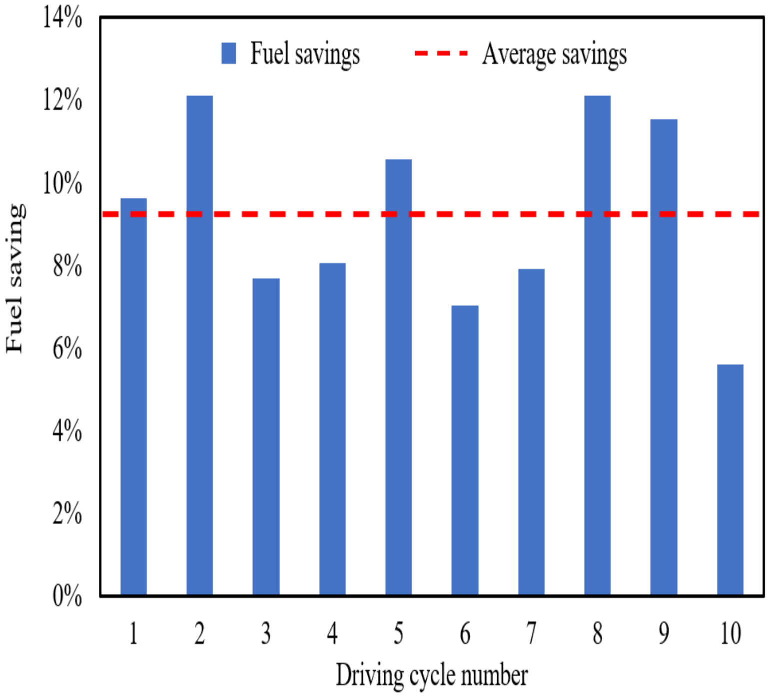
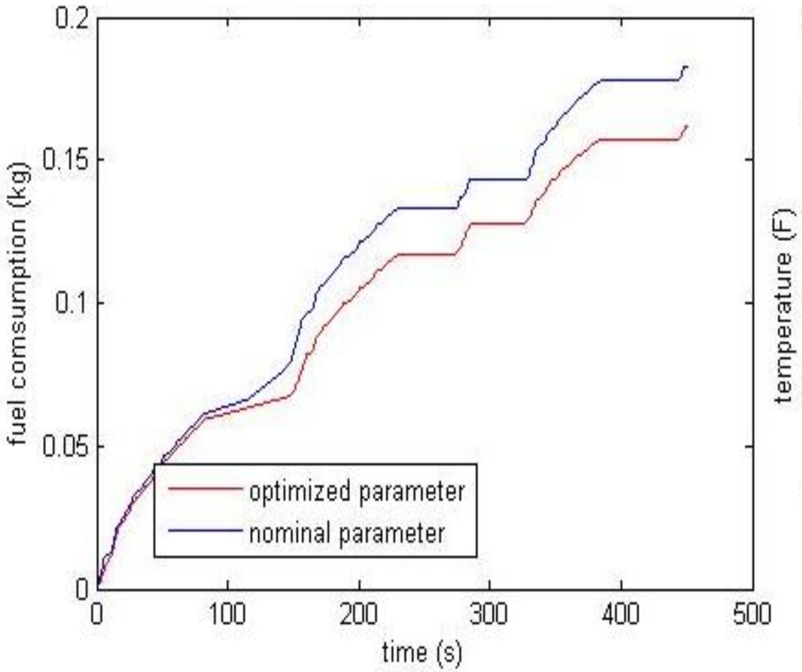
Fuel Saving Results

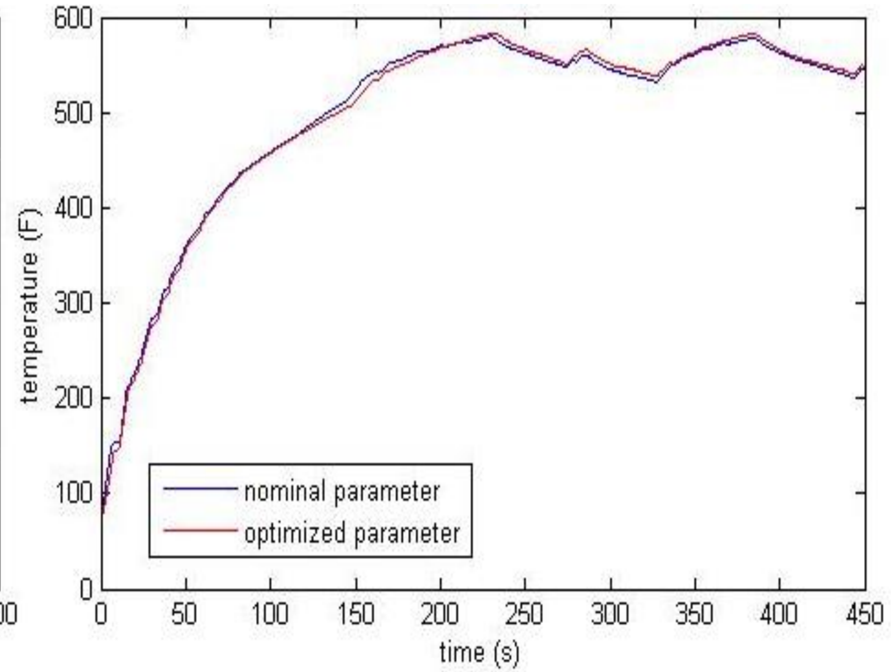
Average fuel saving plot



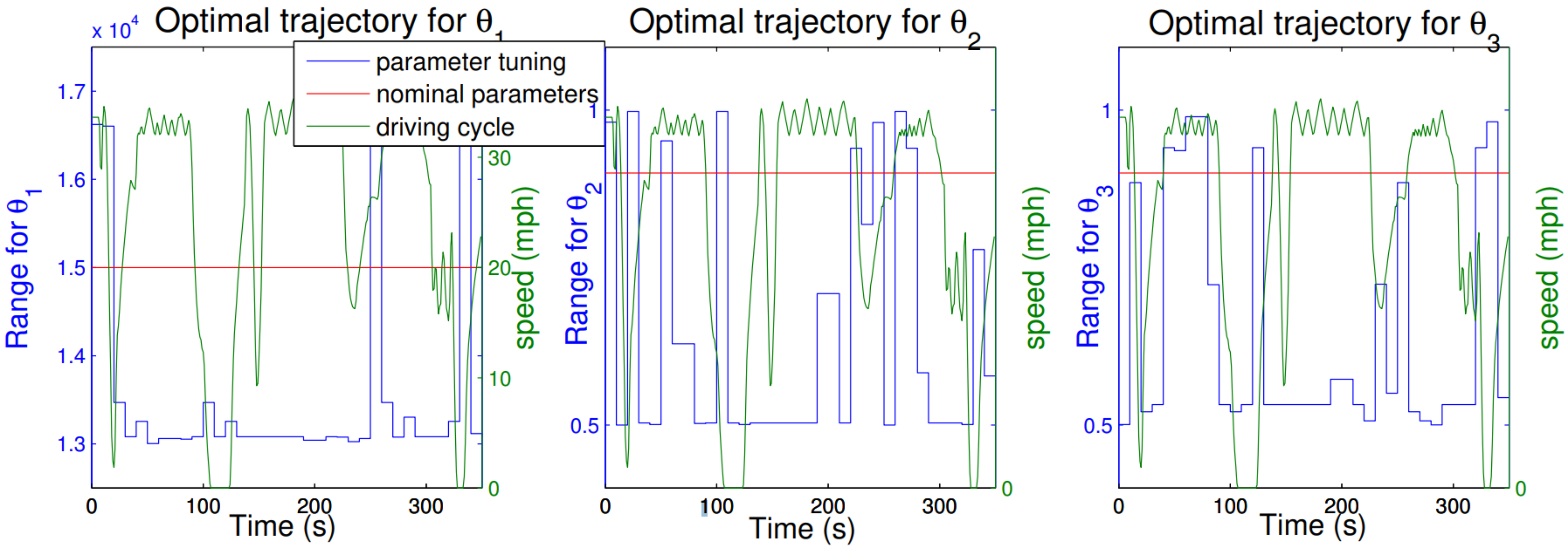
Fuel consumption plot



Catalyst temperature plot

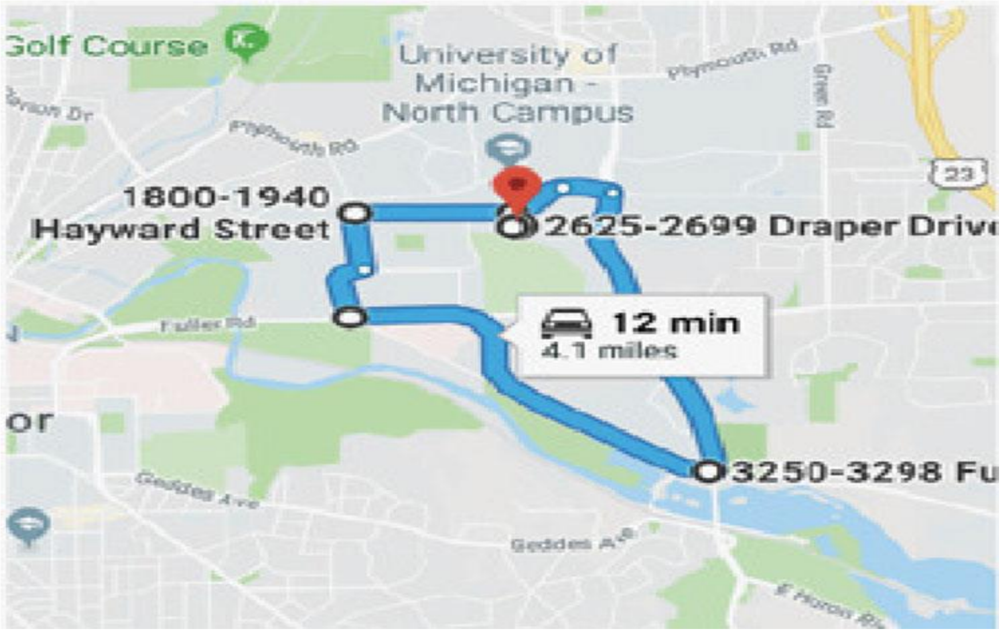


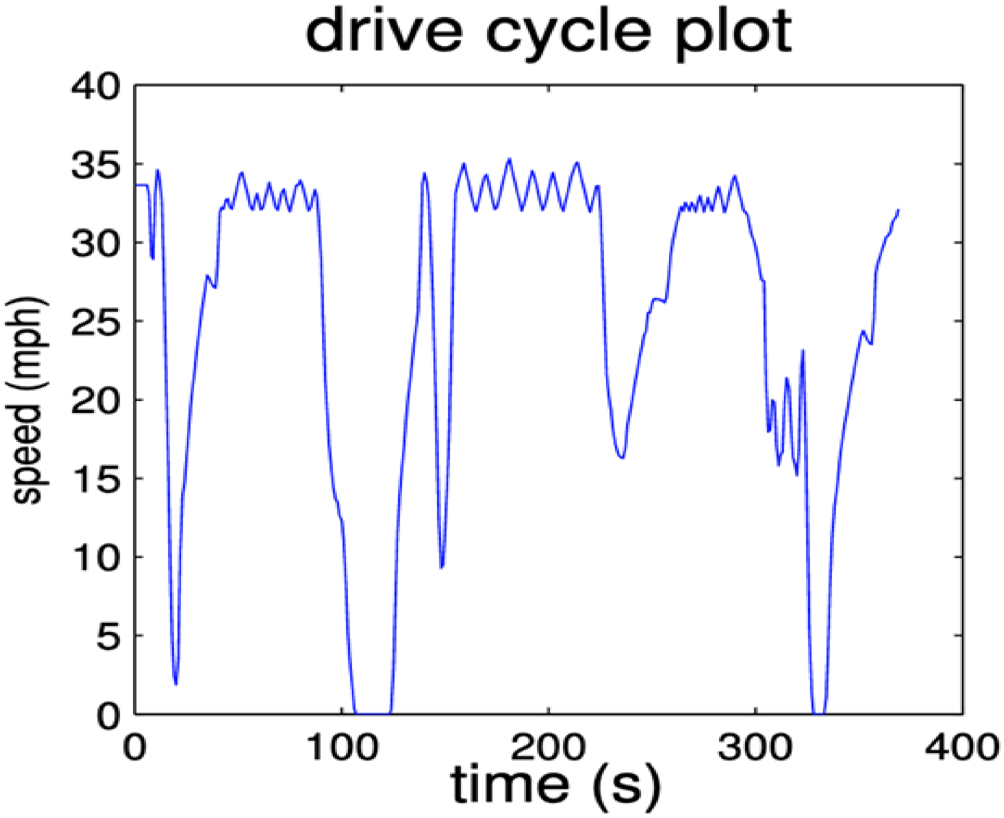
Optimal Parameter Trajectory



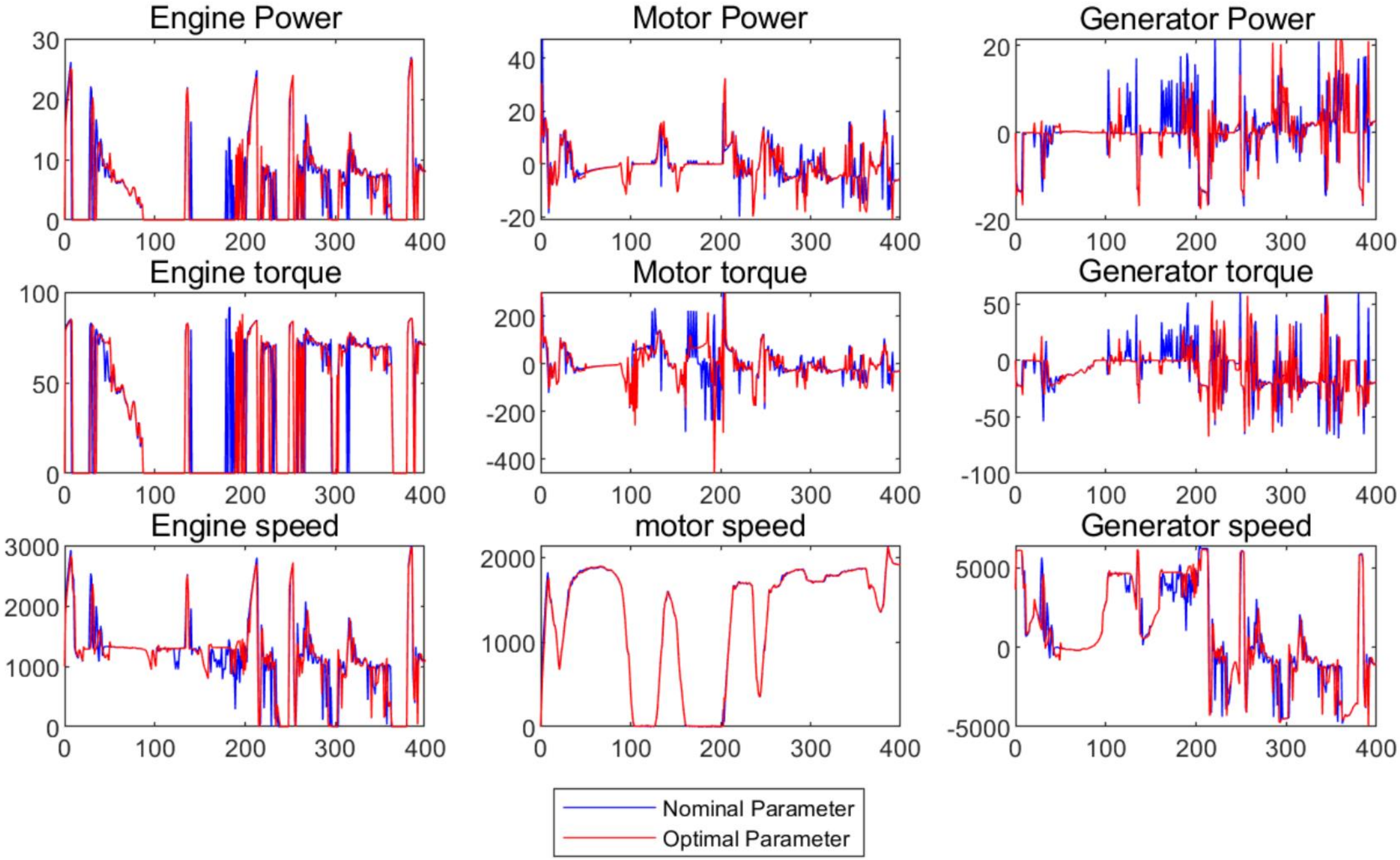
Powertrain State Change with Optimization

Driving Cycle for the Data Collection and Powertrain Optimization





Powertrain State Change with Optimization



V2V Supports the Collaborative Fault Tolerant Control of Non-Signalized Intersections for Connected and Autonomous Vehicles

- With the potential of increased penetration of connected and autonomous vehicles (CAVs), intersectional signal control faces new challenges in terms of its operation and implementation.

- One possibility is to fully make use of the communication capabilities of CAVs so that intersectional signal control can be realized by CAVs alone – this leads to non-signalized intersection operation for traffic networks.

- The collaborative fault tolerant functionality at CAVs operational level in response to possible individual vehicle faults, where detailed modelling used with a multi-agent based approach, will be described together with the construction of fast fault diagnosis and tolerant control algorithms.

V2V supports Level-4 vehicles to pass through non-signalized intersections safely when faults occur - Challenges

In this context, intersectional signal control faces the following new challenges in terms of its operation and implementation:

1) How the communication capabilities of CAVs can be leveraged to develop control strategies that allow the CAVs to manage and control themselves when passing through non-signalized intersections;

2) If a CAV has a fault how other CAVs can autonomously control themselves in a fault tolerant way so that they can still pass through the intersections safely with a smooth speed profile.

Intersection control Layer

- With 100% CAVs, V2V communications allows vehicles to pass through smoothly with appropriate safety constraints
- Modelling and control for interactive CAVs movement is required
- Collaborative fault tolerant control is required to ensure safety in virtually all operating conditions.

Figure 6.

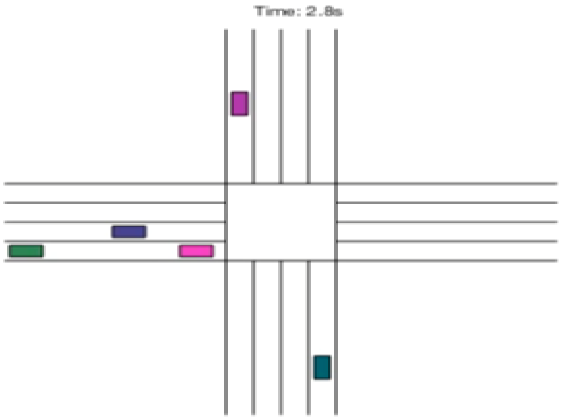


Figure 7

Video from ppt of the paper by C Liu et al at ACC2018 titled *Improving Efficiency of Autonomous Vehicles by V2V Communication*

Modelling at Vehicle Level Taking into Account V2V Communications

<u>Modelling</u>: Model the vehicle dynamics while accounting for V2V information in terms of speed and position

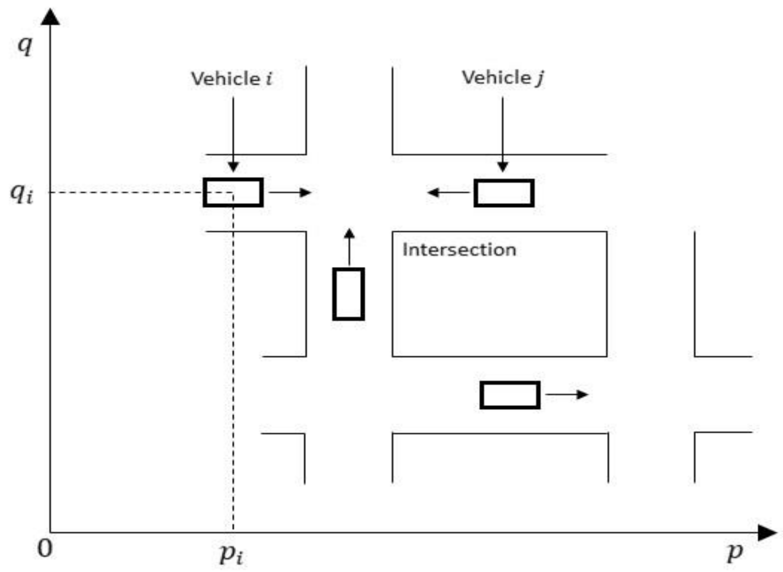


Figure 8

- We consider a number N of CAVs approaching an intersection, as shown in Figure 4
- Assume that the dynamics of the ith CAV is a self-closed loop system whose position and speed is denoted in a 2D plane shown in Figure 4 as

$$x_i = \begin{bmatrix} p_i \\ q_i \end{bmatrix}; \frac{dx_i}{dt} = \dot{x}_i = \begin{bmatrix} \frac{dp_i}{dt} \\ \frac{dq_i}{dt} \end{bmatrix}; (i = 1, 2, \dots, N)$$

where p_i stands for the longitude movement and q_i represents the latitude movement (i.e., lane changes) of the ith CAV in Figure 4.

Modelling at Vehicle Level Taking into Account V2V Communications

The position and speed are the two groups of state variables defined as follows,

$$X_i = \begin{bmatrix} x_i \\ \dot{x}_i \end{bmatrix} \in R^4; \quad (i = 1, 2, \dots, N) \qquad (1)$$

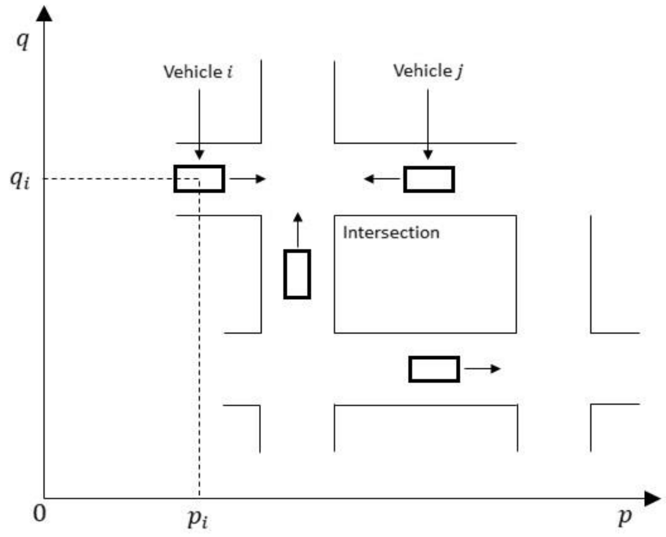


Figure 9.

In this regard, the dynamics of the ith CAV (the ith agent or sub-system) can be expressed in the following form

$$\dot{X}_i = A_i X_i + B_i r_i + \sum_{i \neq j}^{N} C_{ij} X_j + E_i f_i \qquad (2)$$

- ❑ $\{A_i, B_i\}$ are the assumed known parameter matrices that represent the dynamics of the concerned CAV of appropriate dimensions,
- ❑ C_{ij} are the communication coefficient matrices that represent the communication capabilities between the ith and the jth CAV. If there is no communications between the ith and the jth CAV, then $C_{ij} = 0$.
- ❑ f_i is the fault of the ith CAV;
- ❑ r_i is the set-point of the position trajectory of the ith CAV.

Modelling at Vehicle Level Taking into V2V Communications

If we define the whole state vector as

$$x^T = [X_1^T \quad X_2^T \cdots X_{N-1}^T \quad X_N^T] \in R^{1\times 4N} \tag{3}$$

Then

$$\dot{x} = Ax + Br + Ef \tag{4}$$

with the following output equation only for the position of each CAV.

$$y = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} = Fx; \quad F = diag(\aleph, \dots, \aleph); \aleph = [1 \quad 0] \tag{5}$$

Other matrices are

$$A = \begin{bmatrix} A_1 & C_{12} & \cdots & C_{1N} \\ C_{21} & A_2 & \cdots & C_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ C_{N1} & C_{N2} & \cdots & A_N \end{bmatrix} \in R^{4N\times 4N}; \quad B = diag(B_1, \dots, B_N) \in R^{4N\times N}$$

$$E = diag(E_1, E_2, \dots, E_N) \in R^{4N\times N}; f = \begin{bmatrix} f_1 \\ \vdots \\ f_N \end{bmatrix} \in R^{4N}; r = \begin{bmatrix} r_1 \\ \vdots \\ r_N \end{bmatrix} \in R^{4N}$$

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Fault Diagnosis and Collaborative Tolerant Control

Fault detection and diagnosis

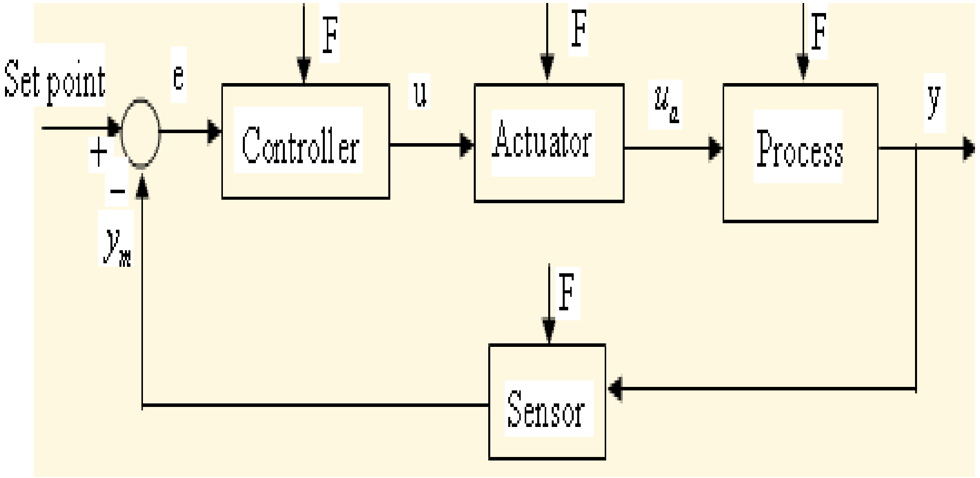


Figure 10

- Faults in a system can be in actuators, sensors, systems and controller
- The purpose of FD is to estimate the fault in the system using available information such as inputs and outputs of the concerned system ([13])

In terms of the algorithm structure, the following figure shows how a fault diagnosis can be implemented in a software perspective [2].

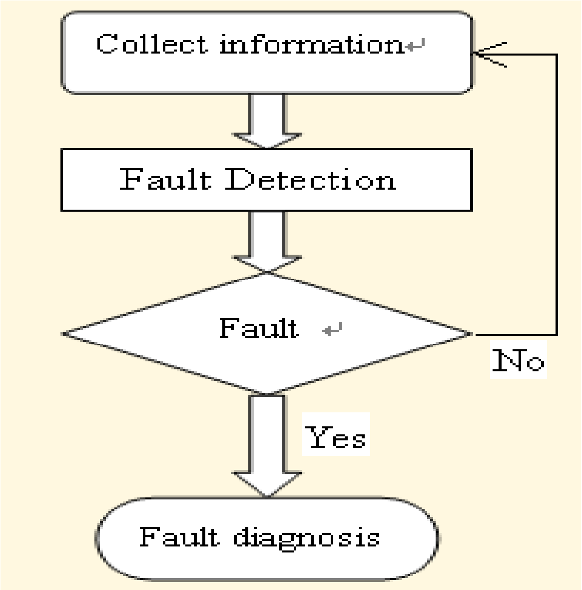


Figure 11

[2] L. Yao and H. Wang, A fault tolerant control scheme for collaborative two sub-systems, Proceedings of the 13th Mediterranean Conference on Control and Automation, Limassol, Cyprus, June, 27 – 29, 2005.

Adaptive Fault Diagnosis Algorithm at Individual CAV Level

For this purpose, the following adaptive diagnostic observer is constructed [3].

$$\dot{\hat{X}}_i = A_i\hat{X}_i + B_i r_i + \sum_{i \neq j}^{N} C_{ij}\hat{X}_j + E_i\hat{f}_i + L(x_i - \hat{x}_i) \quad (10)$$

where $\hat{X}_i$ is the estimate of X_i and $\hat{f}_i$ is the diagnosed (i.e., estimated) result of f_i, L is a gain matrix to be designed. Define the state estimate error and the fault estimation error as

$$\begin{aligned} e_i &= \hat{X}_i - X_i \\ \tilde{f}_i &= \hat{f}_i - f_i \end{aligned} \quad (11)$$

Then the following diagnosis result can be obtained, *where the detailed formulation, including the selection of the gain matrix L, will be given in the final paper using Lyapunov stability theory*.

$$\frac{d\hat{f}_i}{dt} = -(\hat{x}_i - x_i) \quad (12)$$

where $\hat{x}_i$ is the estimate of the unknown x_i due to a fault.

[3] Y. Ren, A. Wang and H. Wang, Fault Diagnosis and Tolerant Control for Discrete Stochastic Distribution Collaborative Systems, IEEE Transactions on Systems, Man and Cybernetics, Part. A, Vol. 45, No. 3, pp. 462 – 471, 2015.

Collaborative Tolerant Control - Objectives

When a fault occurs, the purpose of collaborative fault tolerant control design is to select the set-points of each CAV in the group so that the following multi-objective constrained optimization is achieved.

$$\max_{r} \dot{x}_i; \quad (i = 1, 2, \dots, N) \tag{13a}$$

s.t.

$$\|x_i - x_j\| > \delta; \quad i \neq j \quad \longrightarrow \quad \text{Safety constraints} \tag{13b}$$

$$\|\dot{x}_i\| < M; (i = 1, 2, \dots, N) \quad \longrightarrow \quad \text{Speed constraints} \tag{13c}$$

The problem can be transferred into making the speed of each vehicle to be as close as possible to its maximum allowable speed M with a time interval average. In this case the objective function in the above can be transferred into

$$\underset{r}{\mathrm{Mim}} \frac{1}{T_2 - T_1} \int_{T_1}^{T_2} (M - \dot{x}_i)^2 \, dt \qquad i = 1, 2, \dots, N \tag{14}$$

Collaborative Tolerant Control - Objectives

As a result, to ensure an optimal passing through of all the CAVs near the concerned intersection with guaranteed safety margin, one needs to select the set-points of each vehicle so that the following optimization problem is solved

$$\min_{r} J = \min_{r} \int_{T_1}^{T_2} [(\tilde{M} - Hv)^T (\tilde{M} - Hv) + \rho \dot{r}^2] dt \tag{15}$$

Subjected to constraints (13b) and (13c), where $\rho > 0$ is a pre-specified weighting coefficient.

The second term in the index is the penalty onto the rates of change of the set-points so as to minimize unnecessary energy consumption.

Subjected ALSO to the safety constraints

Collaborative Tolerant Control – Set-point Tuning for CAVs

Assuming that the i_*th CAV has developed a fault, then the collaborative fault tolerant control for other healthy CAVs would be to tune their set-point slightly to ensure a safe movement in line with the optimization given by equations (13b) – (13c).

This will lead to the following form

$$r_{j\neq i_*} = r^*_{j\neq i_*} + \Delta r_{j\neq i_*} \tag{16}$$

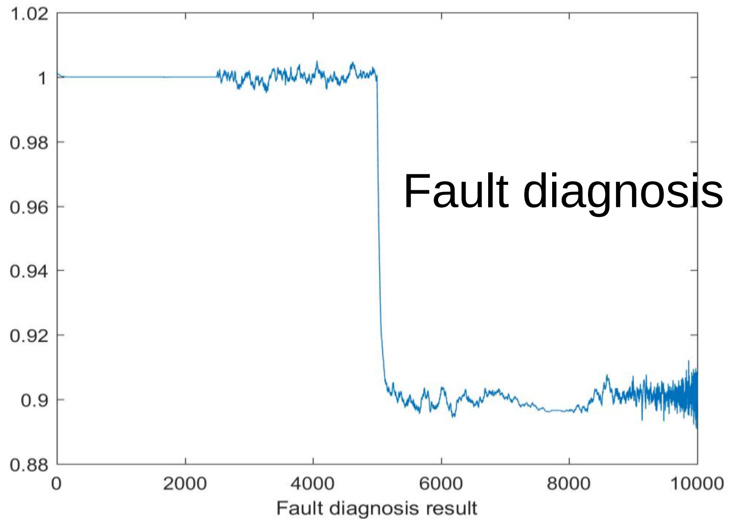
where the incremental change of set-point represented as $\Delta r_{j\neq i_*}$ is given by [4]

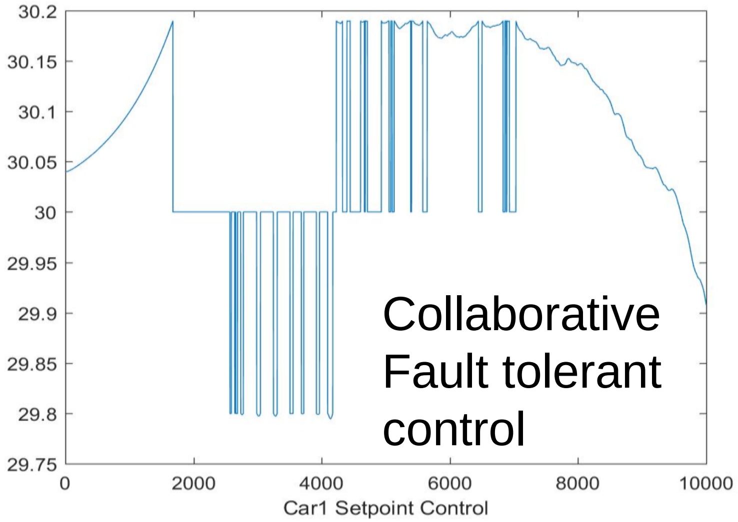
$$\Delta r_{j\neq i_*} = \sum_{j\neq i_*} \theta_j X_j \tag{17}$$

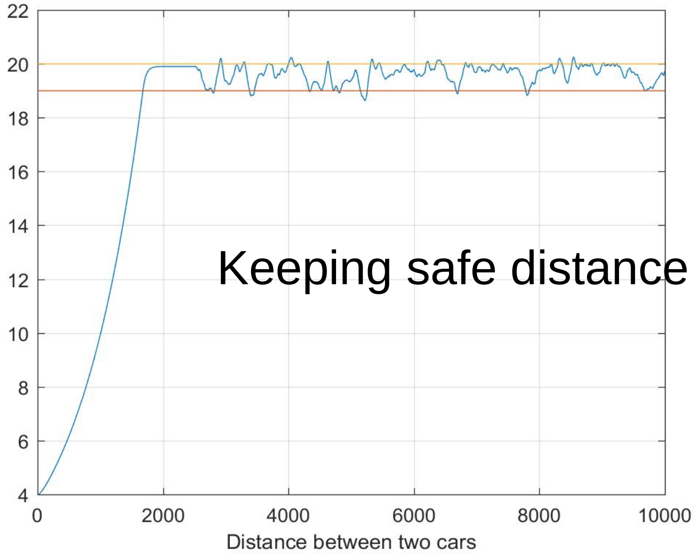
where θ_j represents feedback gain matrices.

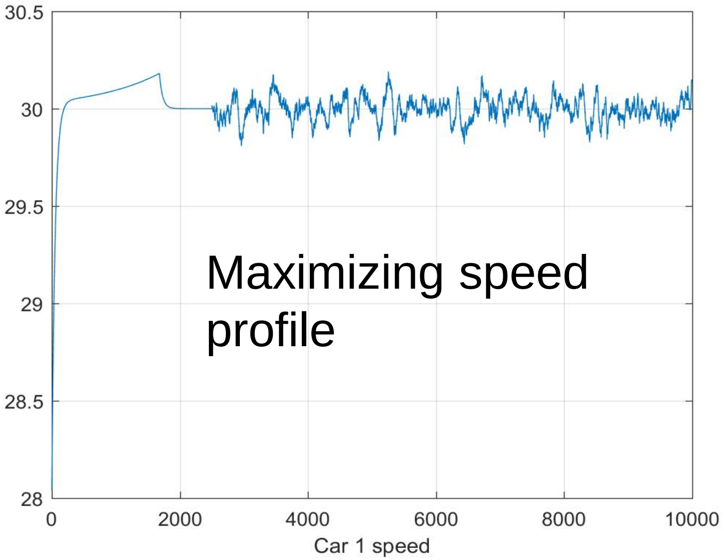
[4] Y. Ren, A. Wang and H. Wang, Fault Diagnosis and Tolerant Control for Discrete Stochastic Distribution Collaborative Systems, IEEE Transactions on Systems, Man and Cybernetics, Part. A, Vol. 45, No. 3, pp. 462 – 471, 2015.

Collaborative Tolerant Control – Simulation

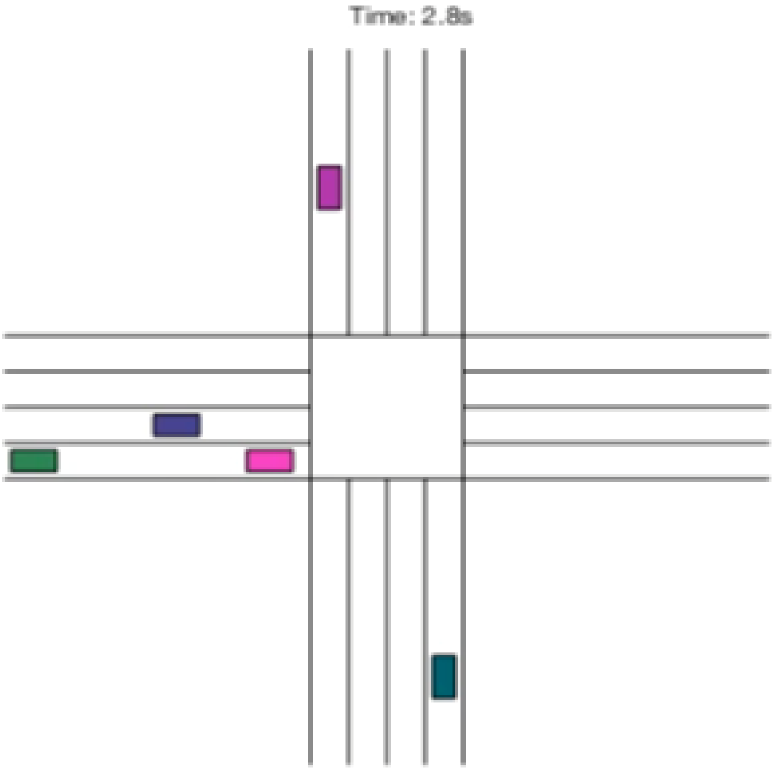








Collaborative Tolerant Control – Simulation



Video from ppt of the paper by C Liu et al at ACC2018 titled *Improving Efficiency of Autonomous Vehicles by V2V Communication*

Conclusions

A 3-layered operational structure has been discussed, powertrain system and non-signalized intersection modelling have been established taking account of V2V capabilities

- V2V helps to improve the powertrain operational efficiency
- Fault diagnosis algorithm at vehicle (CAV) level has been developed using adaptive observers with guaranteed convergence and stability
- Objective functions and constraints are defined to obtain collaborative fault tolerant tuning of the set points to all CAVs
- Simulation results have been obtained to show encouraging powertrain and fault tolerant control effects.
- V2V plays a key role in future transportation system operation

Thank you!