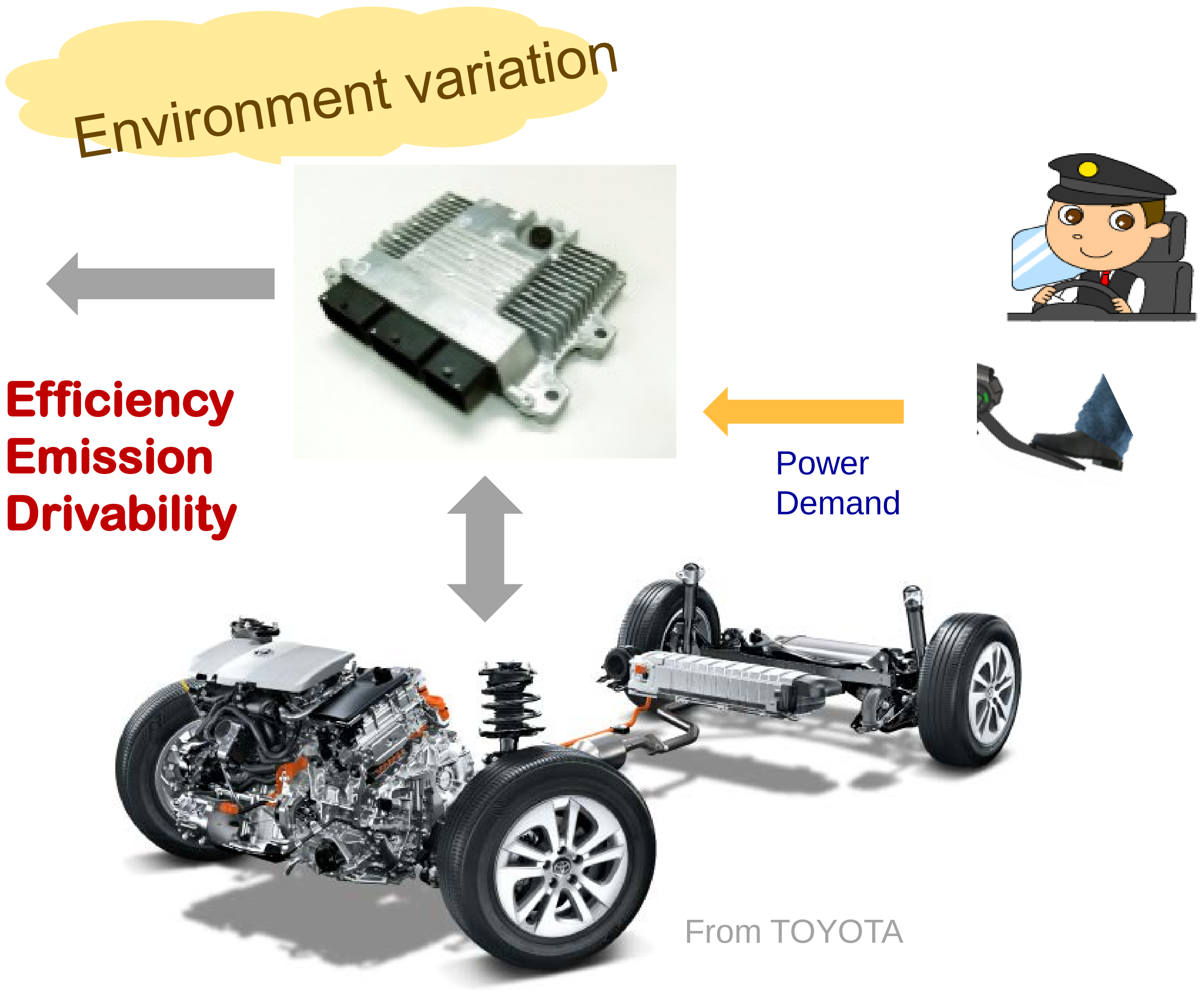
Automotive Powertrain Control: On-line Learning and Optimization

Tielong Shen (申鉄龍)
Sophia University, Tokyo

Powertrain Control and Challenges

- Constraint for control:
  Diver's demanded power
  unknown….

- Modelability
- Stochasticity/Randomness
- Uncertainties
  (Environment and physics)
- Nonlinearity
- Variation
  (aging, environment-depend)



History of Power Sources and Future Direction

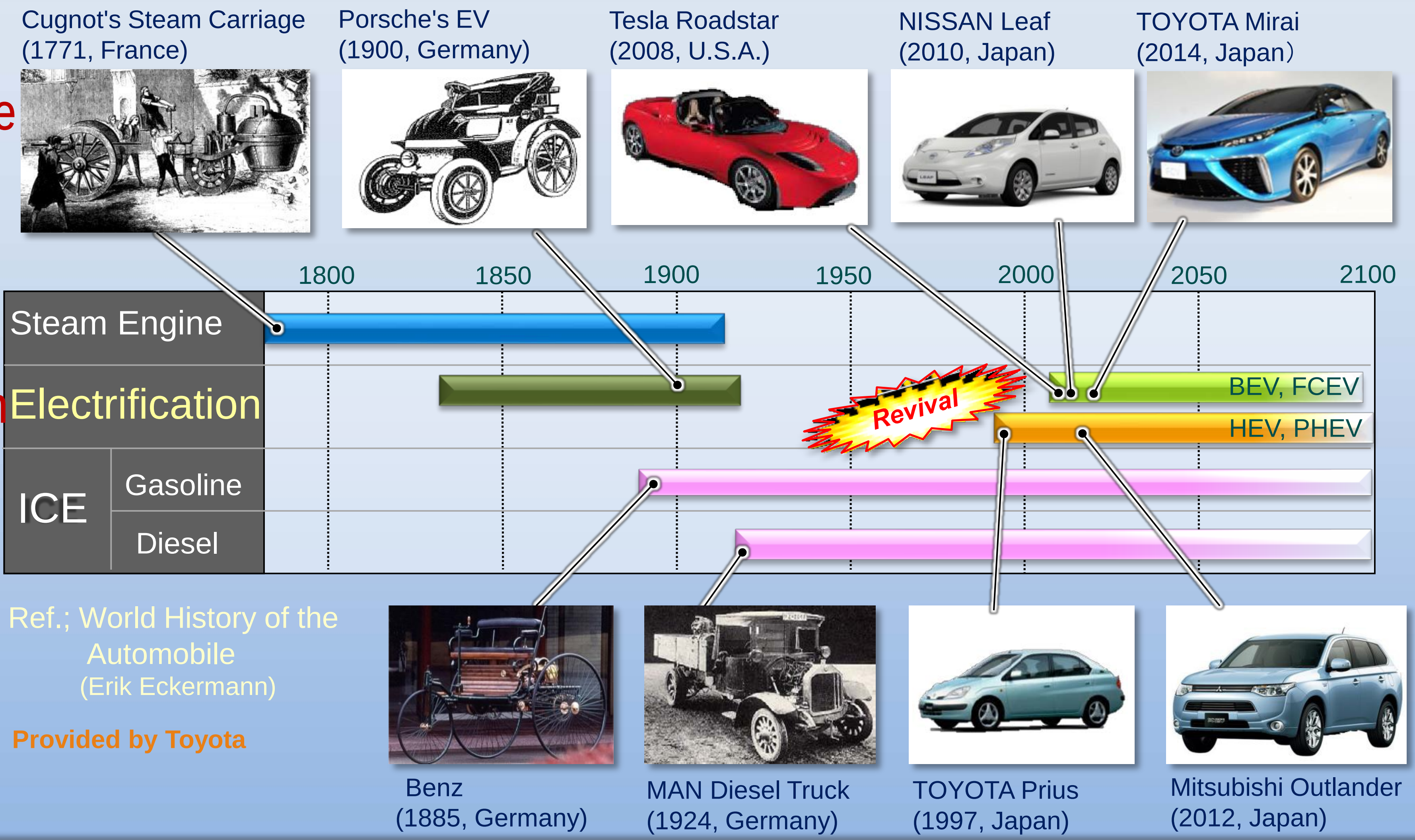
Diversified Power Source

Increasing actuators

Strengthening regulation

Complicity of system

⇒ Needs to Control

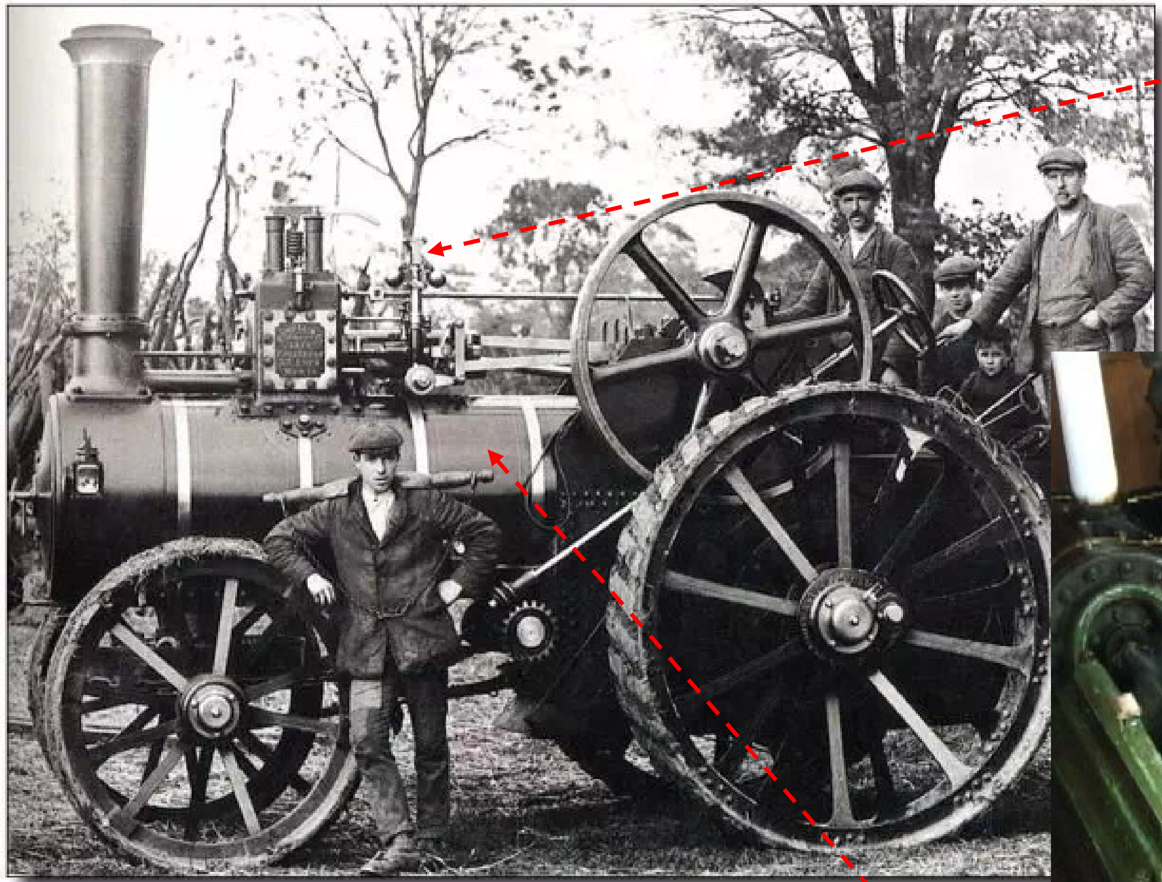


Ref.; World History of the Automobile (Erik Eckermann)

Provided by Toyota

Electrification of powertrain has been revived through the increasing requirement toward zero CO_2 and zero emissions.

Powertrain & Control: at Early Stage



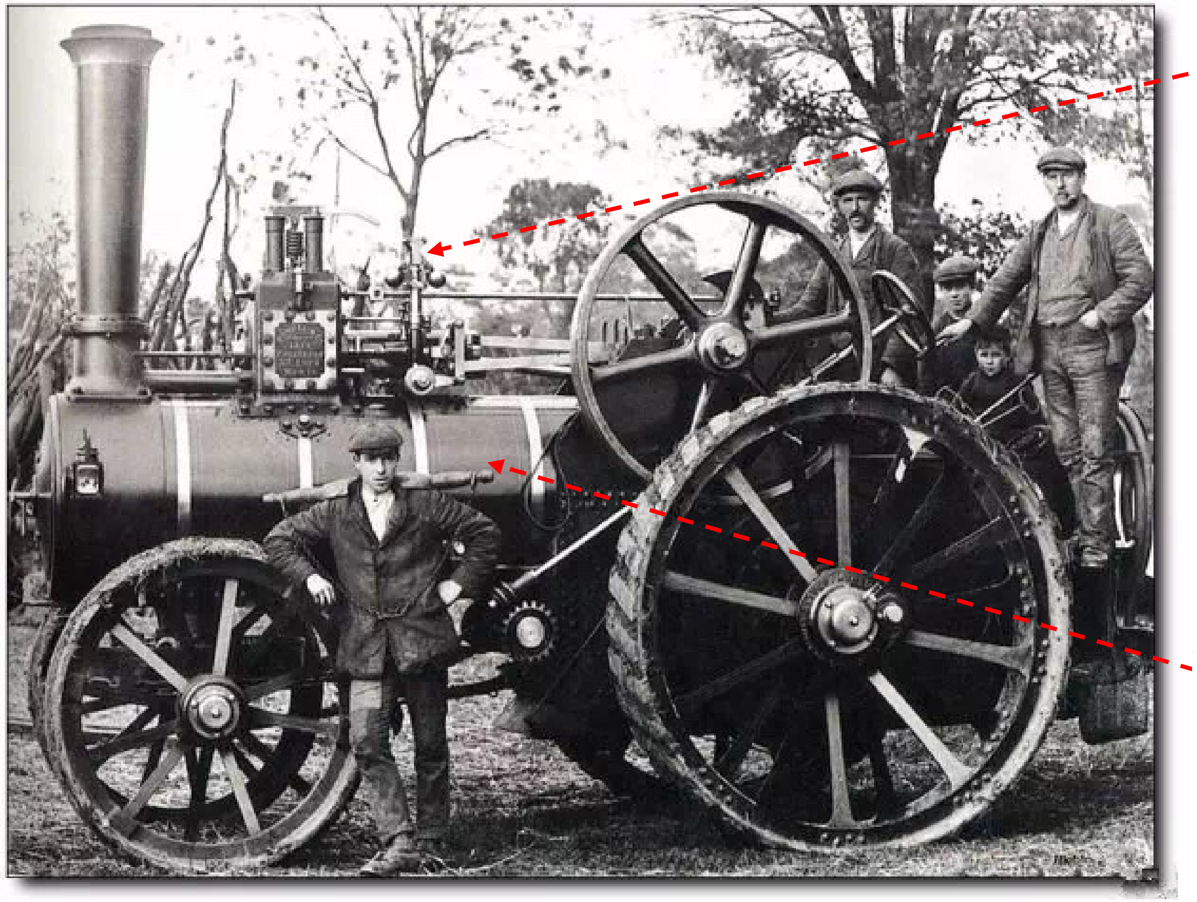
Governor:
Mechanical Control

Feedback

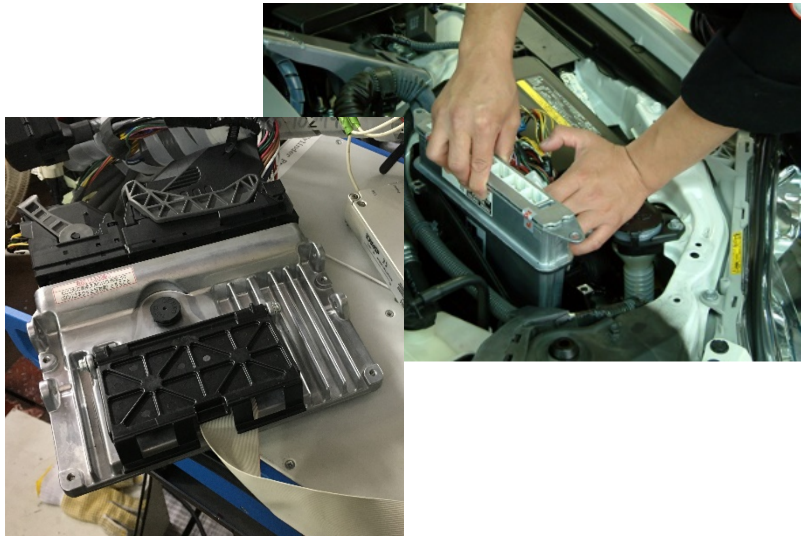
Ballarat (Australia)

Power Source:
Steam engine

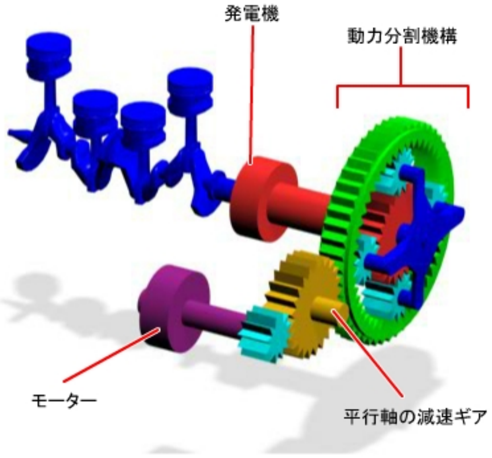
Powertrain: "Computerized Machine"



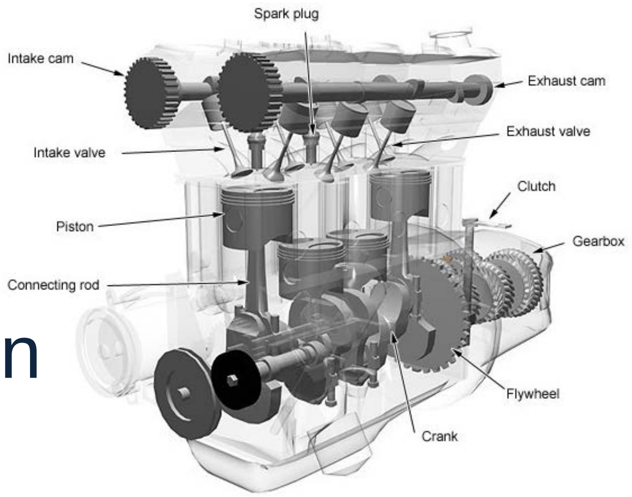
Electrical Control Units



Electric Motor



Combustion Engine



ECU Performance forced by Increasing Actuators

Additional Systems, Sensors, Actuators

- Exhaust Gas Recirculation
- Turbo Charger

New System

- Lean Burn
- Variable Compression

Advanced Controllers

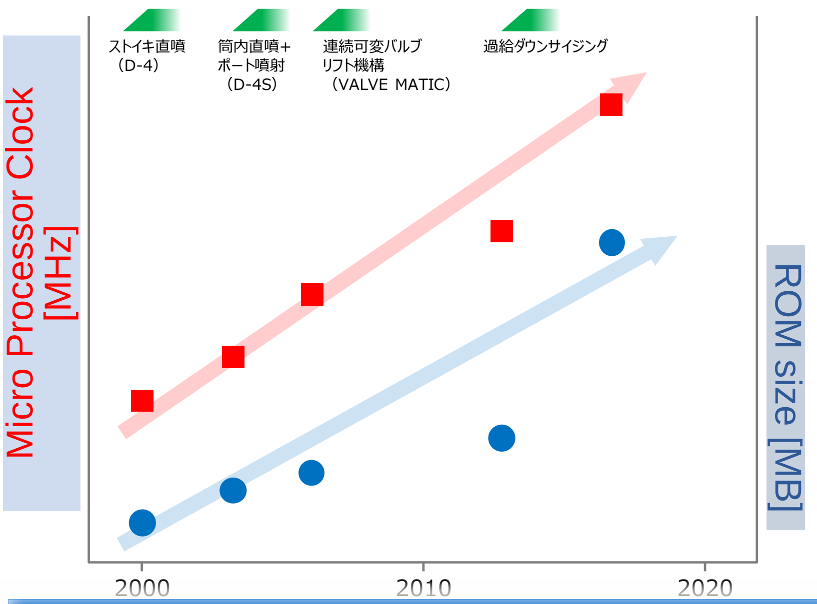
- Online optimization
- Model Predictive Control

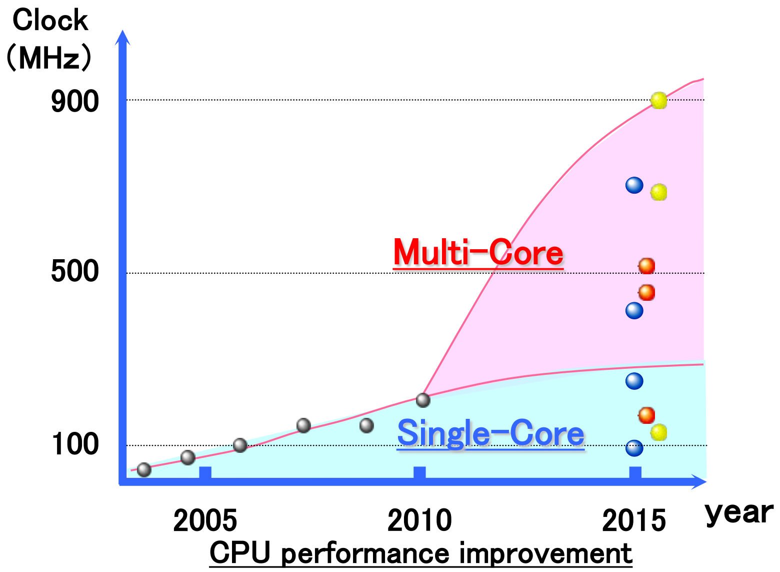
complication

Heavy computation load

ECU
(Electronic Control Unit)

To achieve high performance for New system→ECUperformance





New system+advanced control algorithm → complication

Improving Efficiency: Approach from Control

Once you get the physics right, the rest is mathematics.

--Rudolf E. Kalman

Energy Efficiency

Synthesis

Analysis

Getting Physics and Behavior Description

Model-based?   Model-free?

$$\dot{x} = f(x,u)? \qquad \dot{x} \in F(x,u)?$$

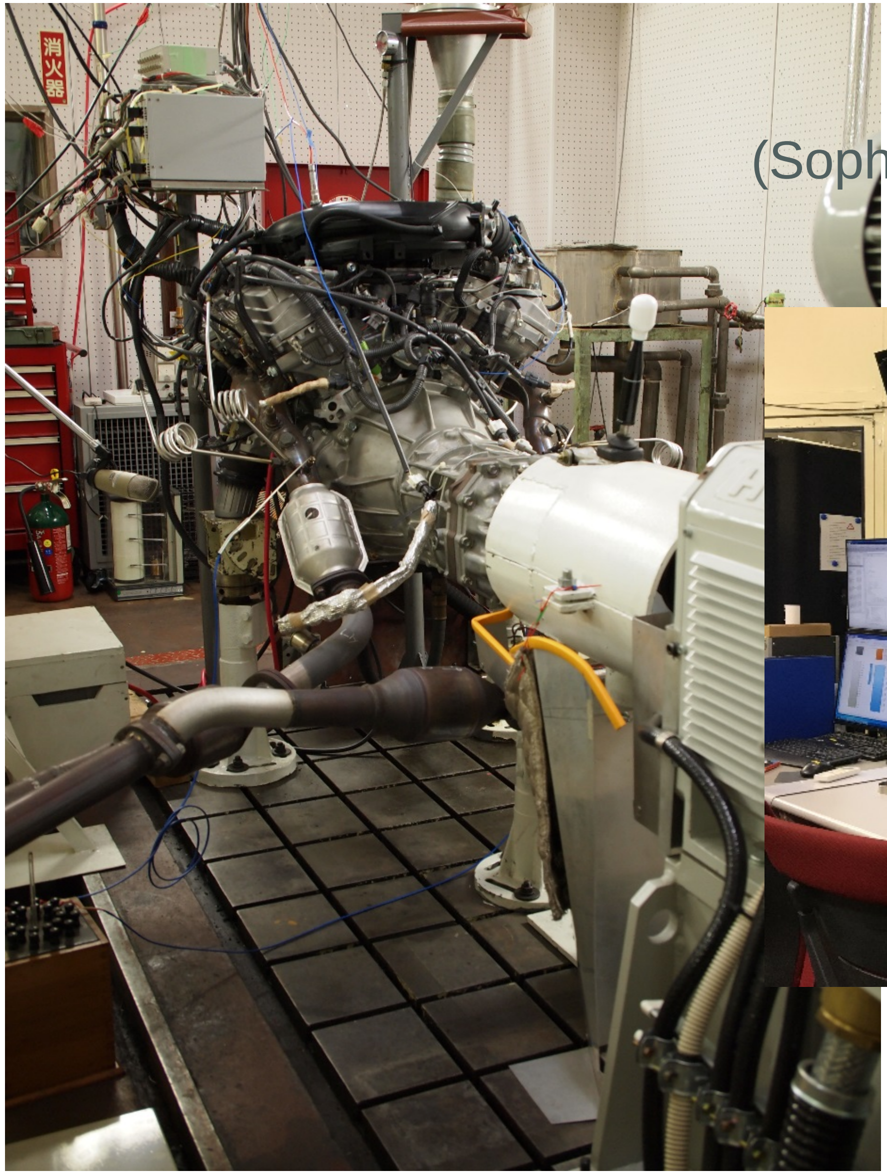
$$p(x_{k+1}) \in \Omega(x_k, u_k)?$$

$$\dot{V} < -x^2? \qquad \min E(x,u)?$$

★Simplify, modify, developing…

★Experimental validation….

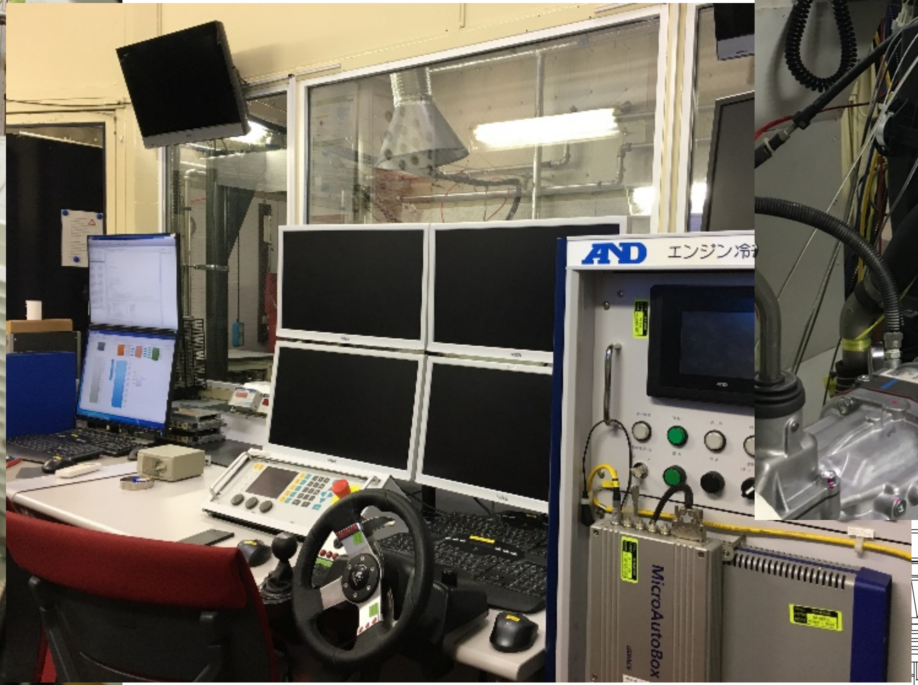
To get the physics

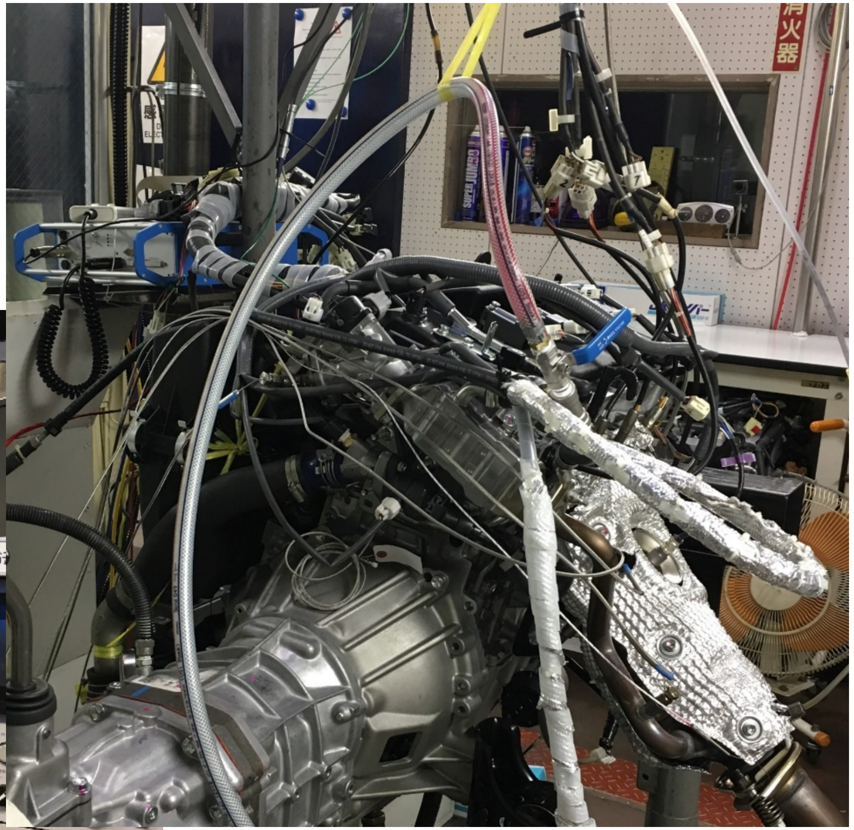


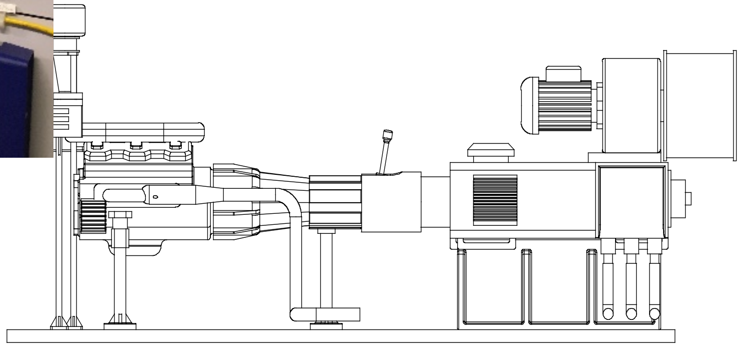
Full-scaled Engine Test Bench

(Sophia University, SHEN Lab.)

2005~

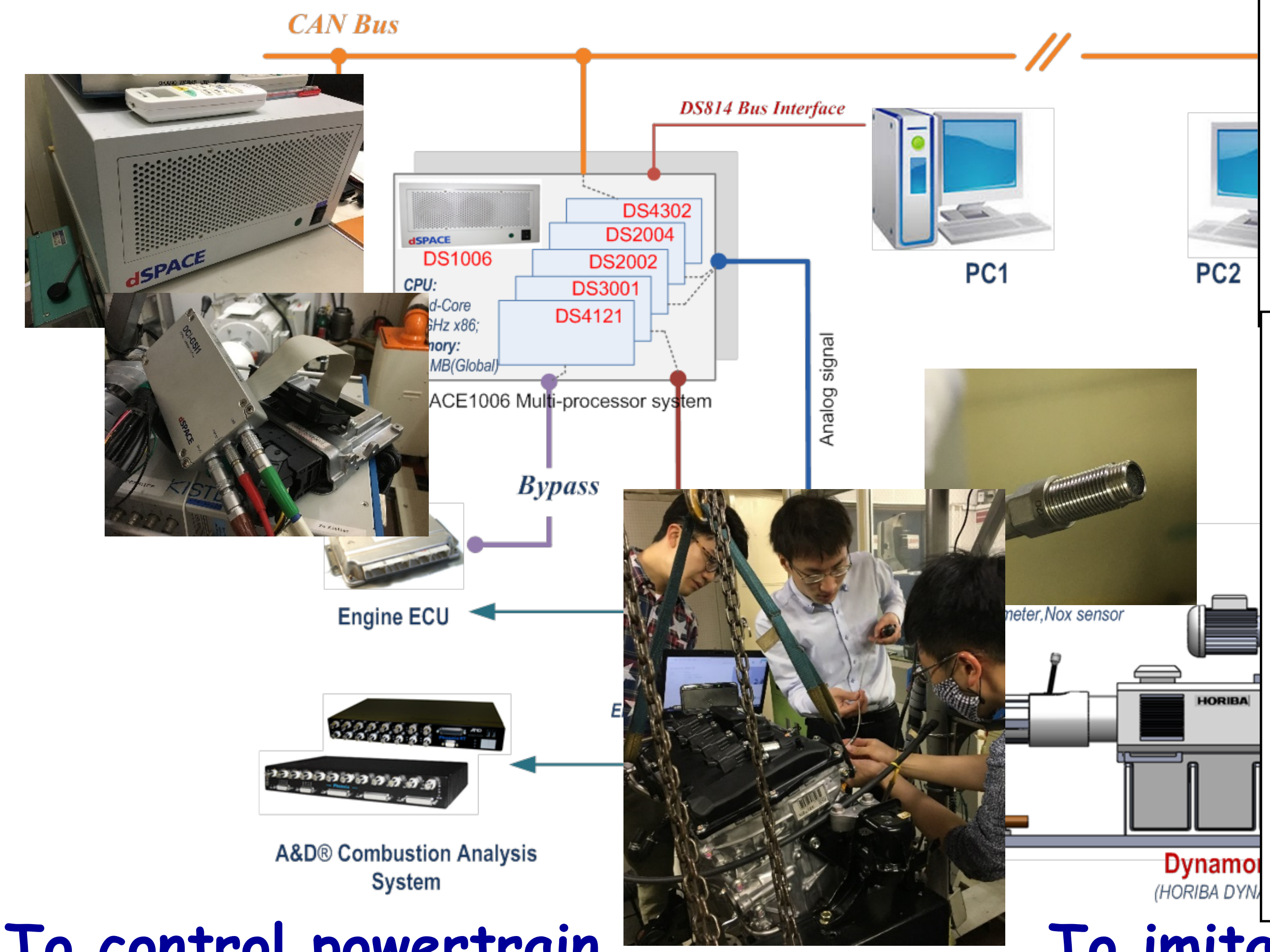






Supported by TOYOTA

To validate real-time control

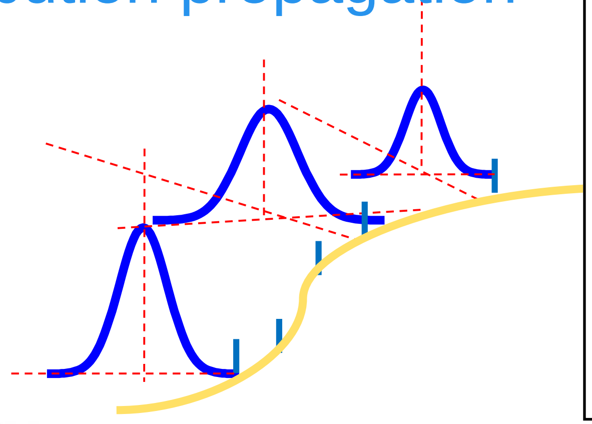


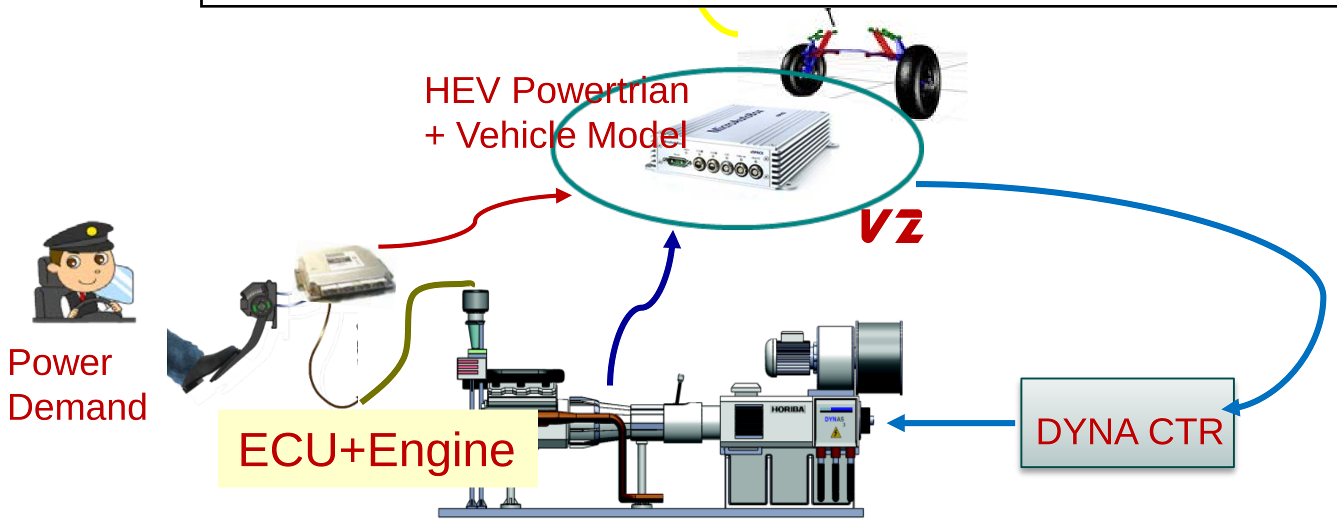
To control powertrain

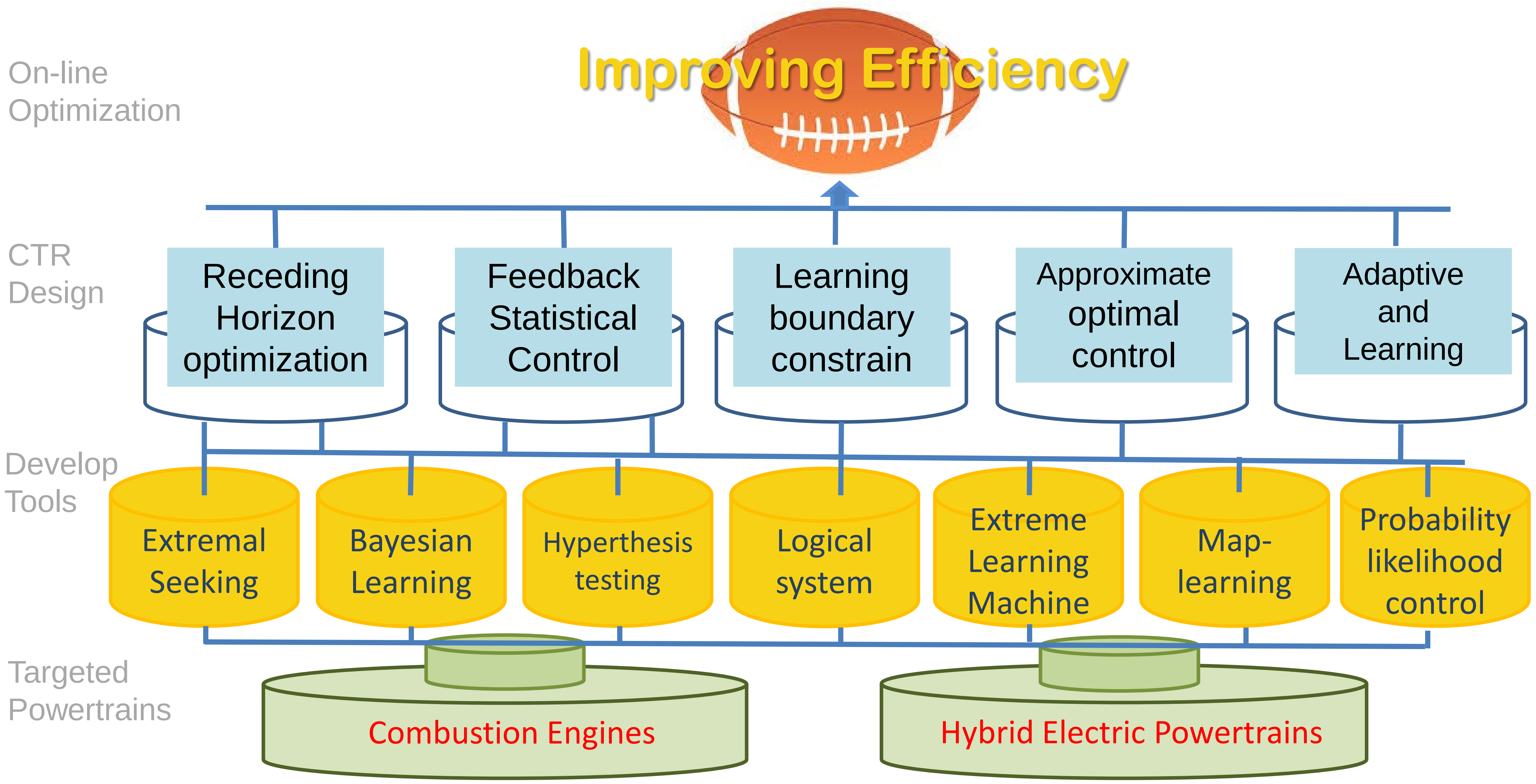
To imitate demand and environment

Engine-in-the-loop for random traffic scenario

⇒ Traffic-in-the-loop
⇒ Route-Traffic scenario
⇒ P-distribution propagation






On-line Optimization
Improving Efficiency
CTR Design
Receding Horizon optimization
Feedback Statistical Control
Learning boundary constrain
Approximate optimal control
Adaptive and Learning
Develop Tools
Extremal Seeking
Bayesian Learning
Hyperthesis testing
Logical system
Extreme Learning Machine
Map-learning
Probability likelihood control
Targeted Powertrains
Combustion Engines
Hybrid Electric Powertrains

Special Thanks to

TOYOTA

"Control technology for the next generation engine"

科研費 KAKENHI

Grants-in-Aid for Scientific Research B

"Optimization of automotive engines with traffic information"

JST

SIP 革新的燃焼技術
Innovative Combustion Technology
bridging to....

Cross-ministerial Strategic Innovation Program

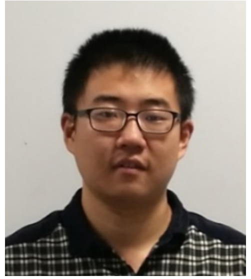
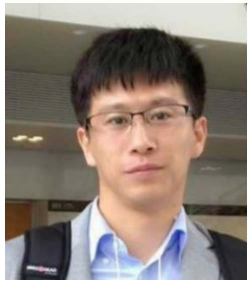
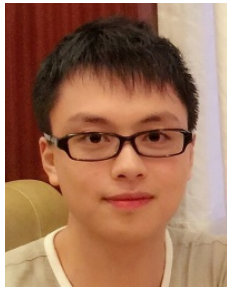
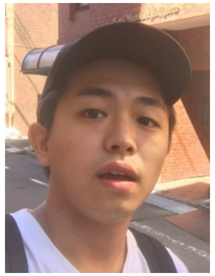
"On-board optimization algorithm for super lean burn engines"

AICE

The Research association of **A**utomotive **I**nternal **C**ombustion **E**ngines

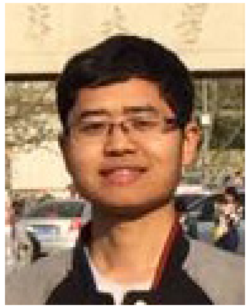
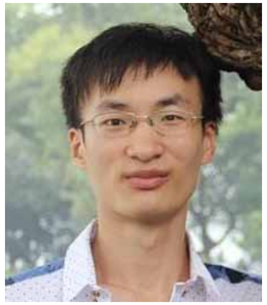
"Control Technologies for Combustion Engine"

Research Team

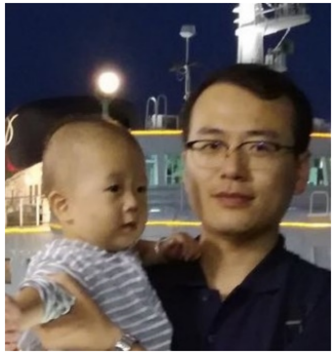
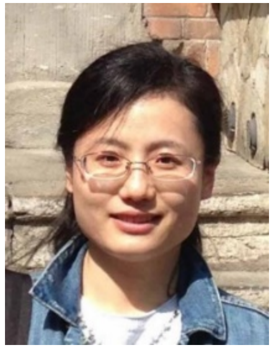
H. Di *F. Xu* *Z. Xu* *Y. Nishio* *B. Zhang* *H. Shi* *K. Zhao* *Z. Xu* *S. Inutsuka*

PhD Candidates

W. Jiang *Y. Zhang*

PD Fellow

M. Kang *J. Gao* *Y. Wu* *M. Toyoda* *J. Zhang*

Visiting faculty Member (Former PhD, PD)

- Background
- Combustion Engine Control
- Hybrid Electric Powertrain Control
- Prospect: Further Research

Combustion Engine Control

-- Thermal Efficiency

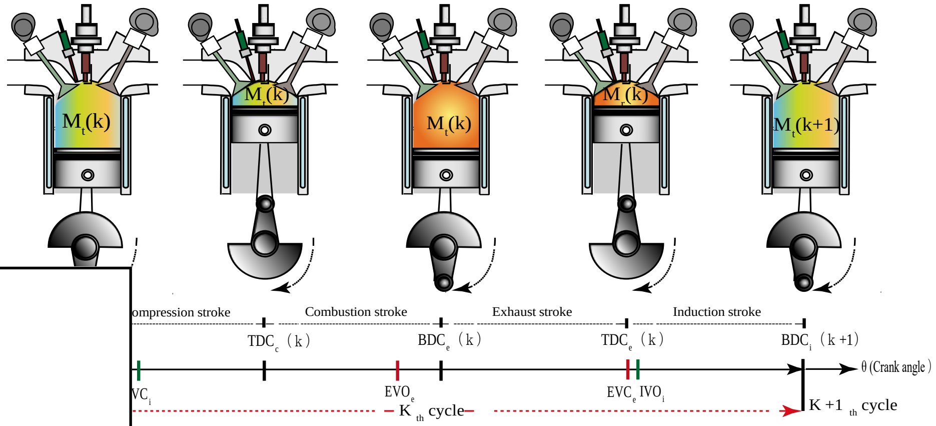
-- Knock probability

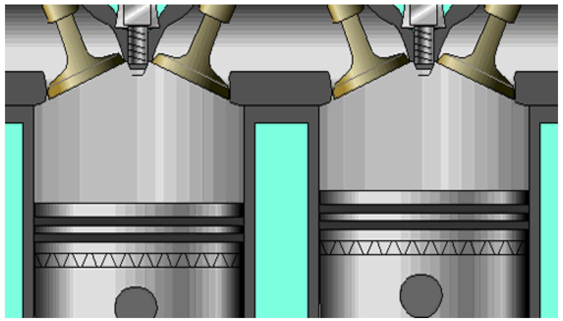
-- Combustion Quality

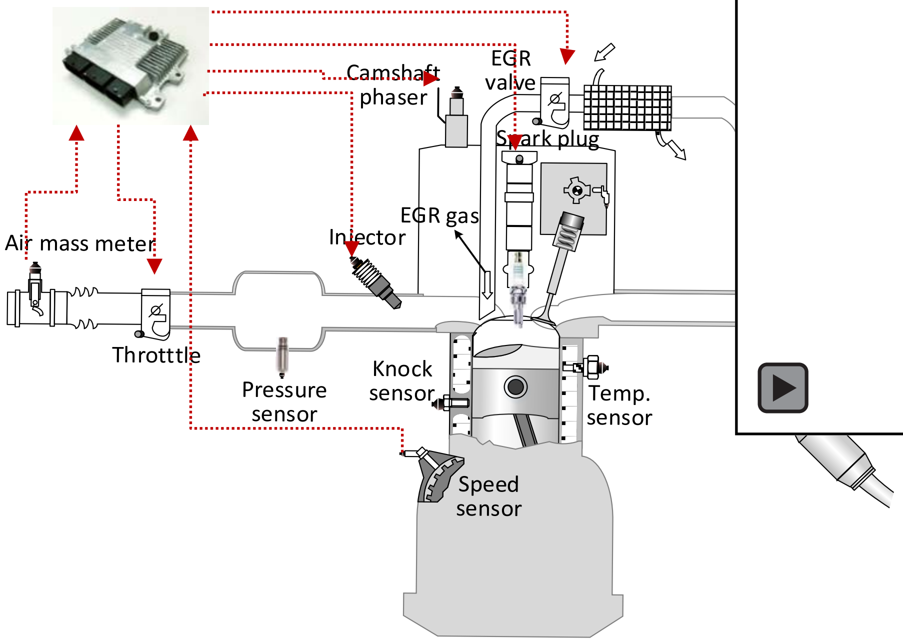
-- Rejecting Variation

Controlling Combustion

- Abnormal combustion
  - --Misfire
  - --Knock
- Heat-release profile
  - --thermal efficiency







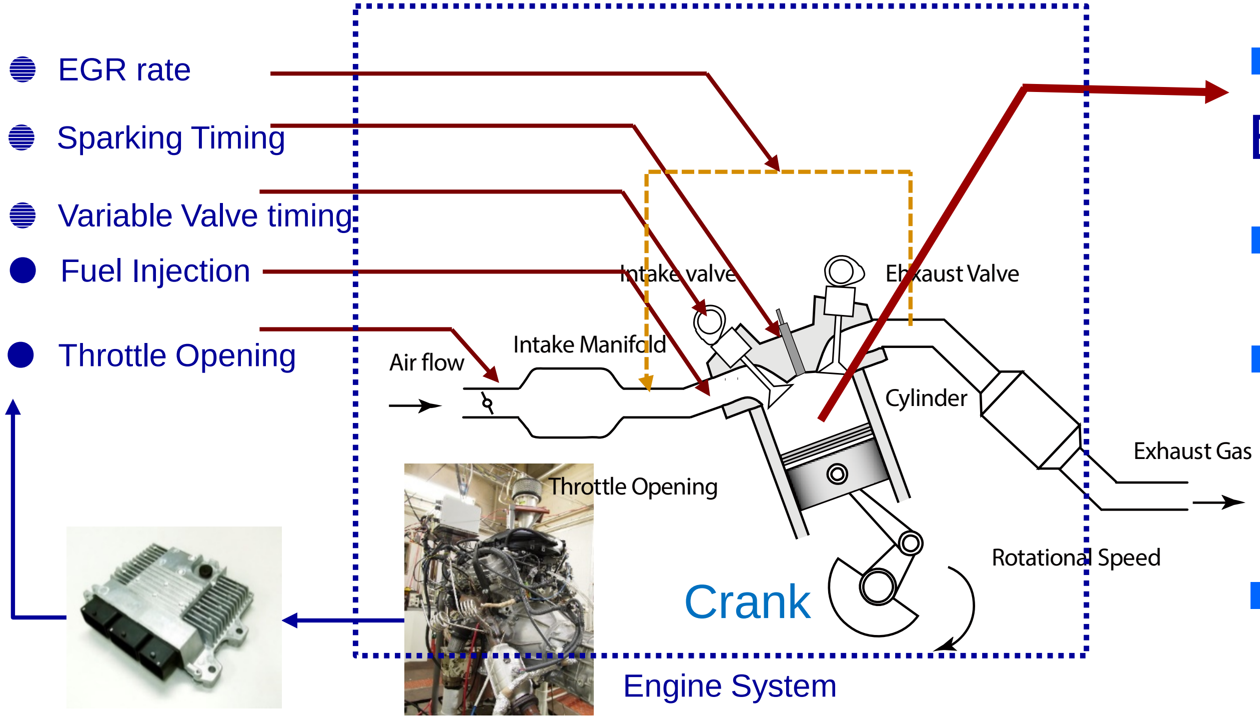
Challenges in Combustion Control

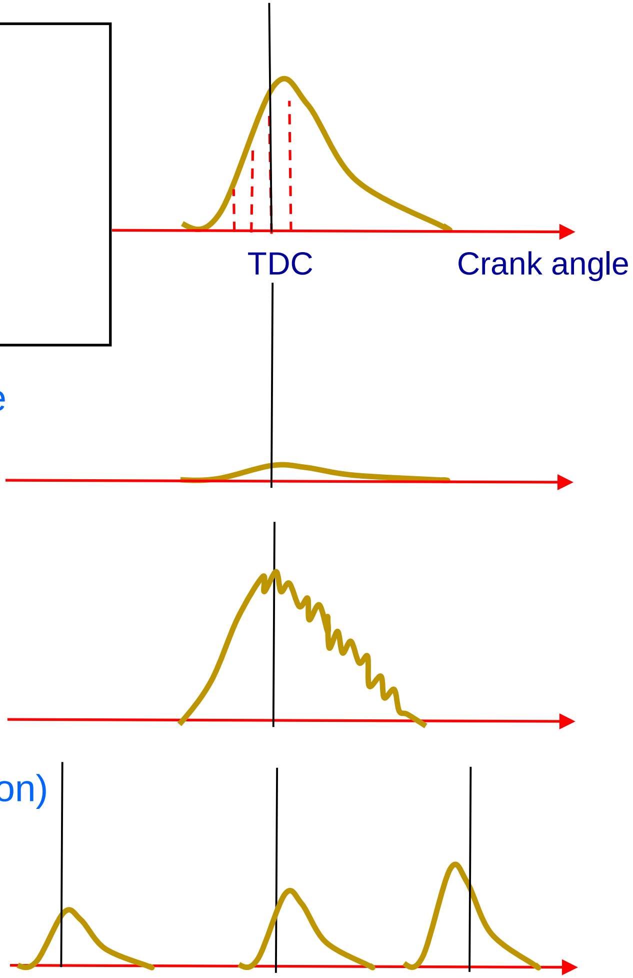
max *Thermal Efficiency*

Control s.t.

probability of abnormal combustion < B

(Combustion quality > A)



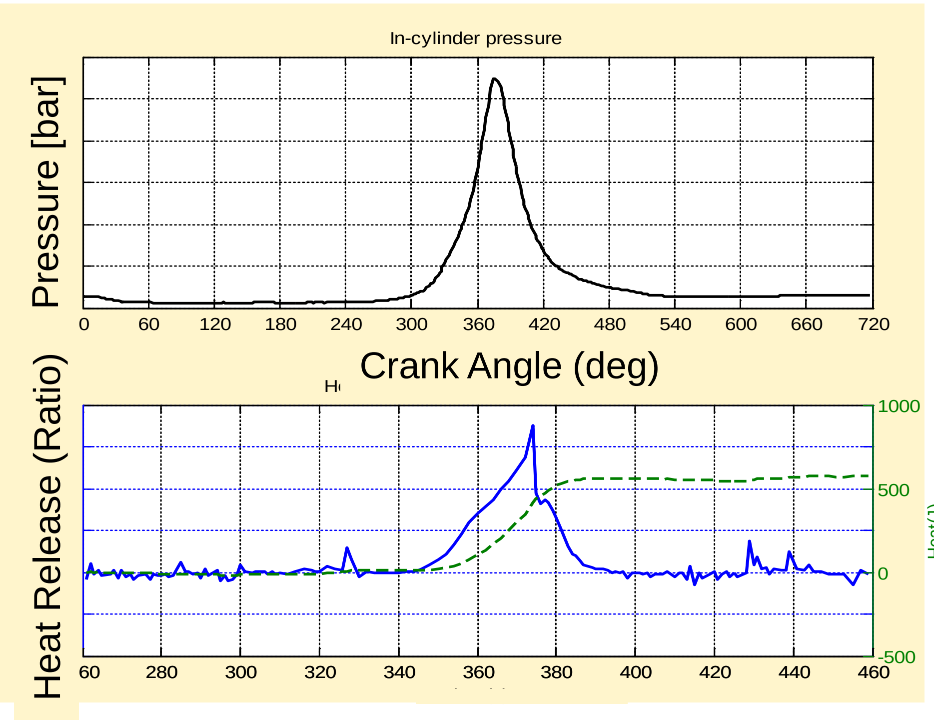


- Heat Release Rate
- Misfire

Efficiency

- knock
- Imbalance (Variation)
- Residual gas fraction

Measuring Combustion



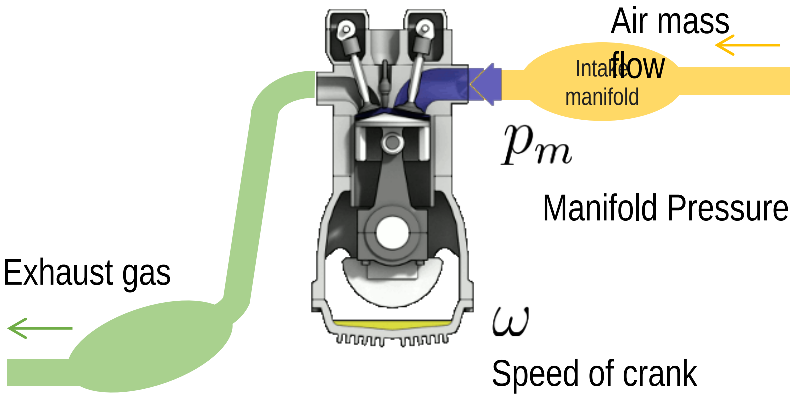
In-Cylinder Pressure Measurement

Model-based calculation

$$\delta Q_{ch,net} = dU + \delta W$$

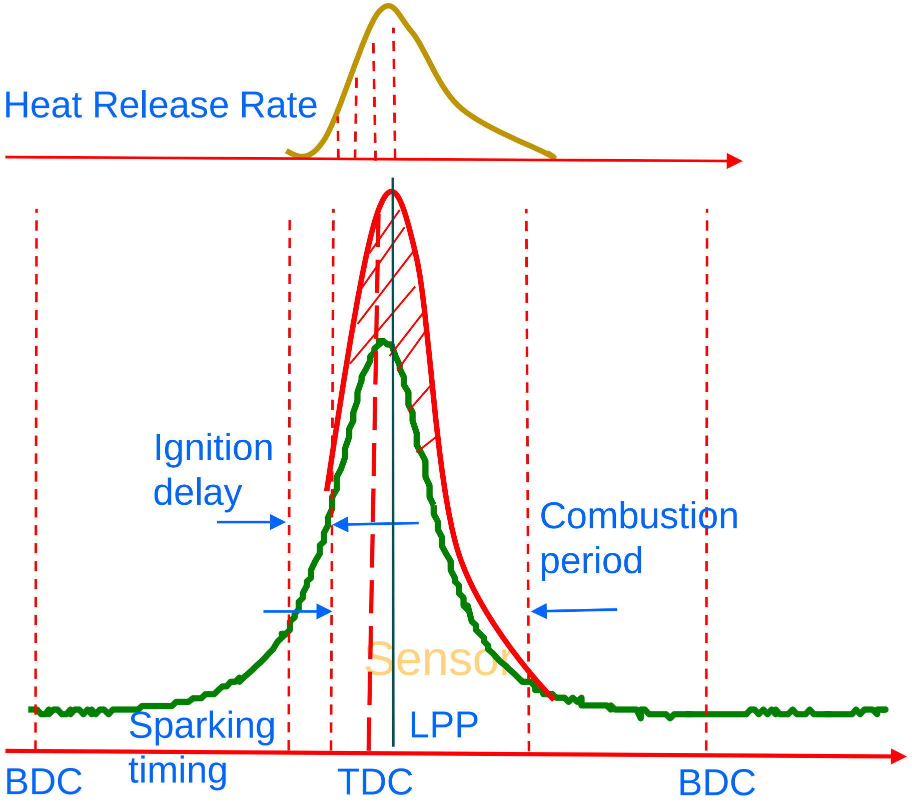
Energy Balancing

$$\frac{dQ_{ch,net}}{d\theta} = \left(\frac{\gamma}{\gamma - 1}\right) p \frac{dV}{d\theta} + \left(\frac{1}{\gamma - 1}\right) V \frac{dp}{d\theta}$$

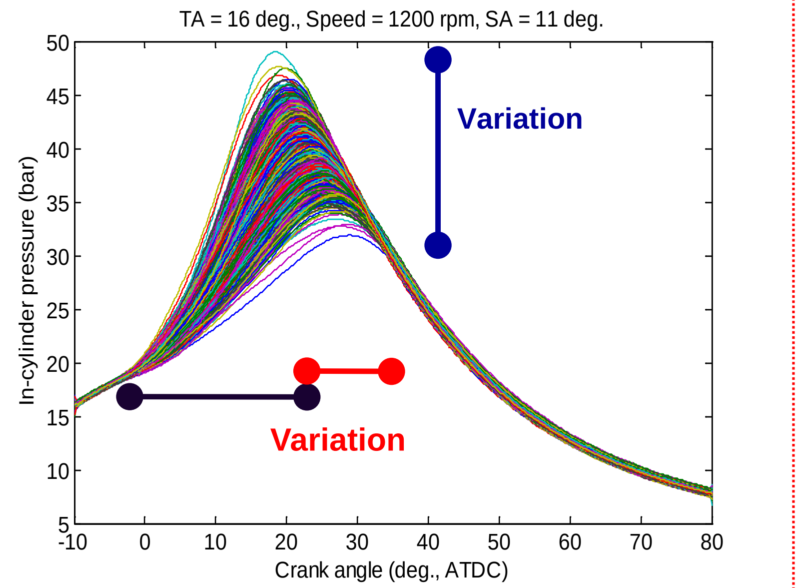


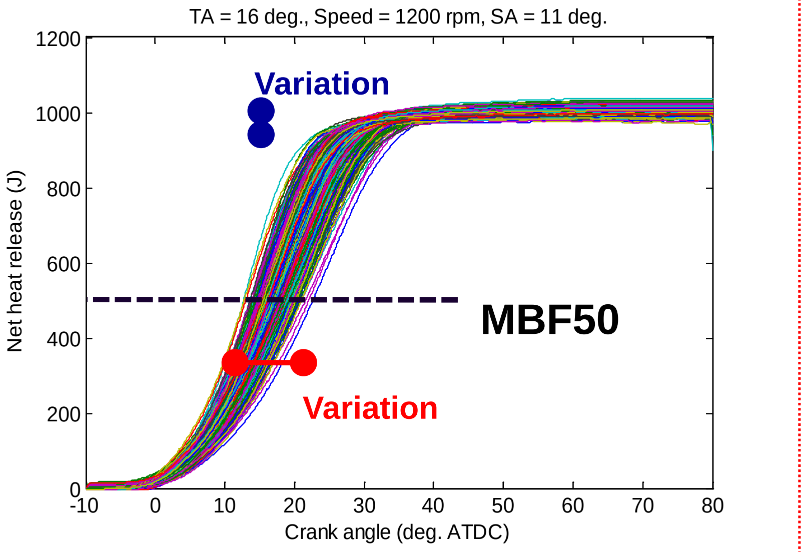
Index of Combustion Quality

- CA50
- CA1090
- Thermal efficiency
- IMEP

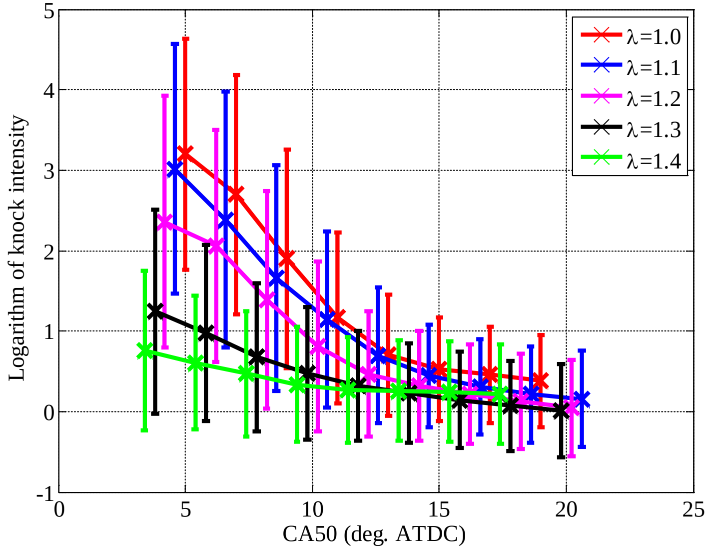


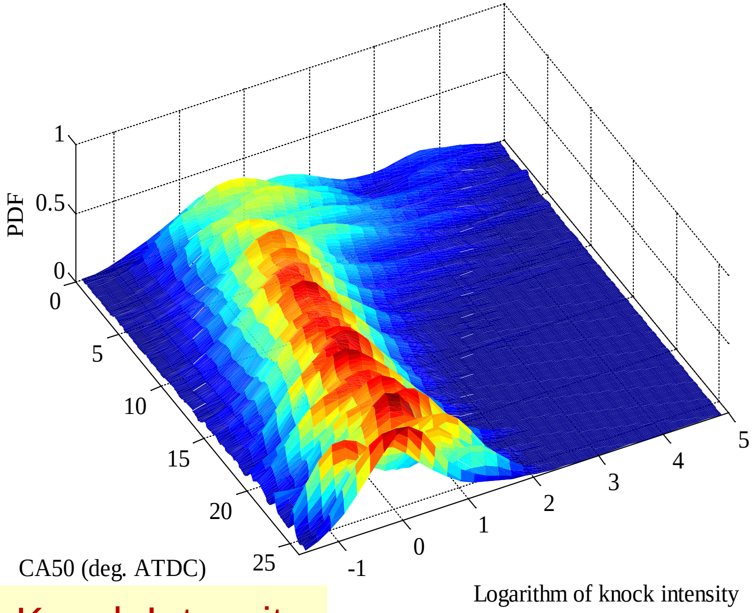
Uncertainty and Stochasticity in Combustion



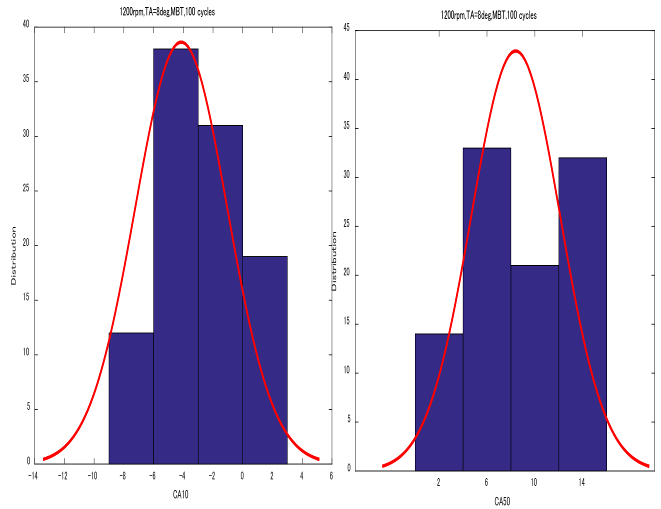


Cyclic Variation

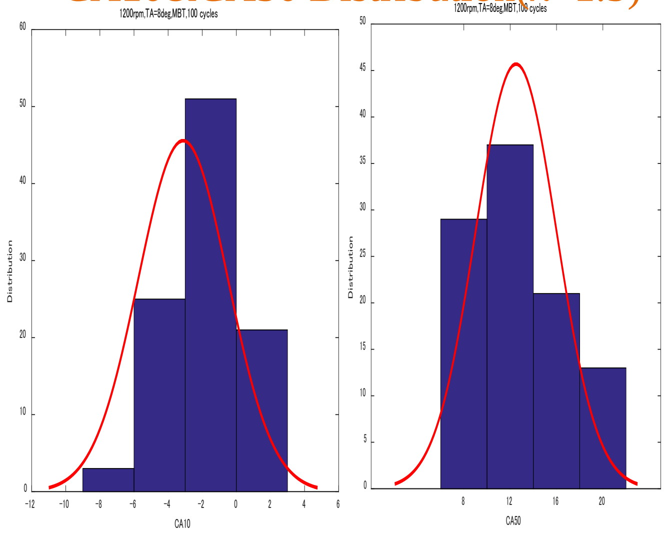




Knock Intensity



CA10&CA50 Distribution(λ=1.5)



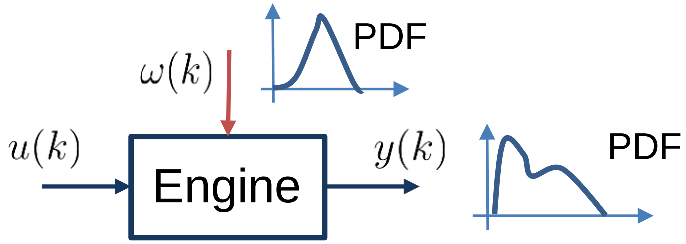
CA10&CA50 Distribution(λ=1.3)

Cyclic Variation

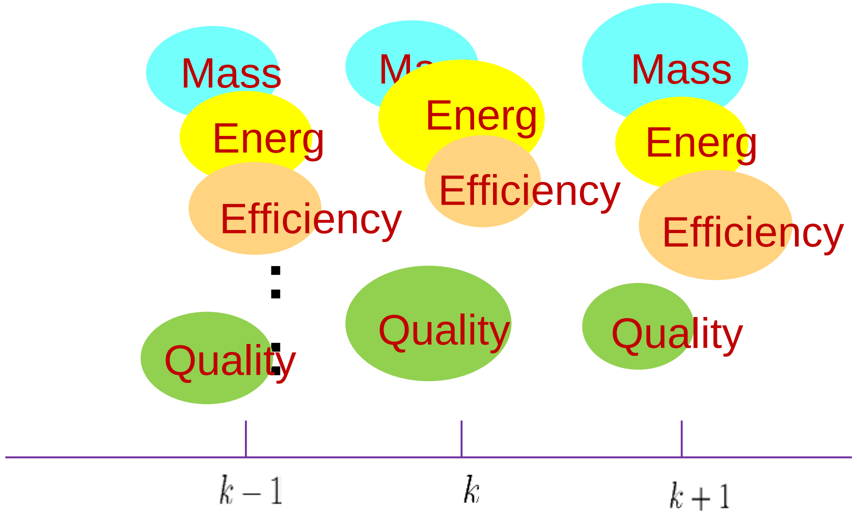
Model-based or Model Free?

- **Dynamic model---Difficult**
- **Stochastic model—**

  Stochastic disturbance propagation?



- **Model-free Control based on Measuring**



Physics:
mass, energy, etc transient cycle-to-cycle

- **Dynamical model**

$$x_{k+1} = f(x_k, u_k, w_k)$$

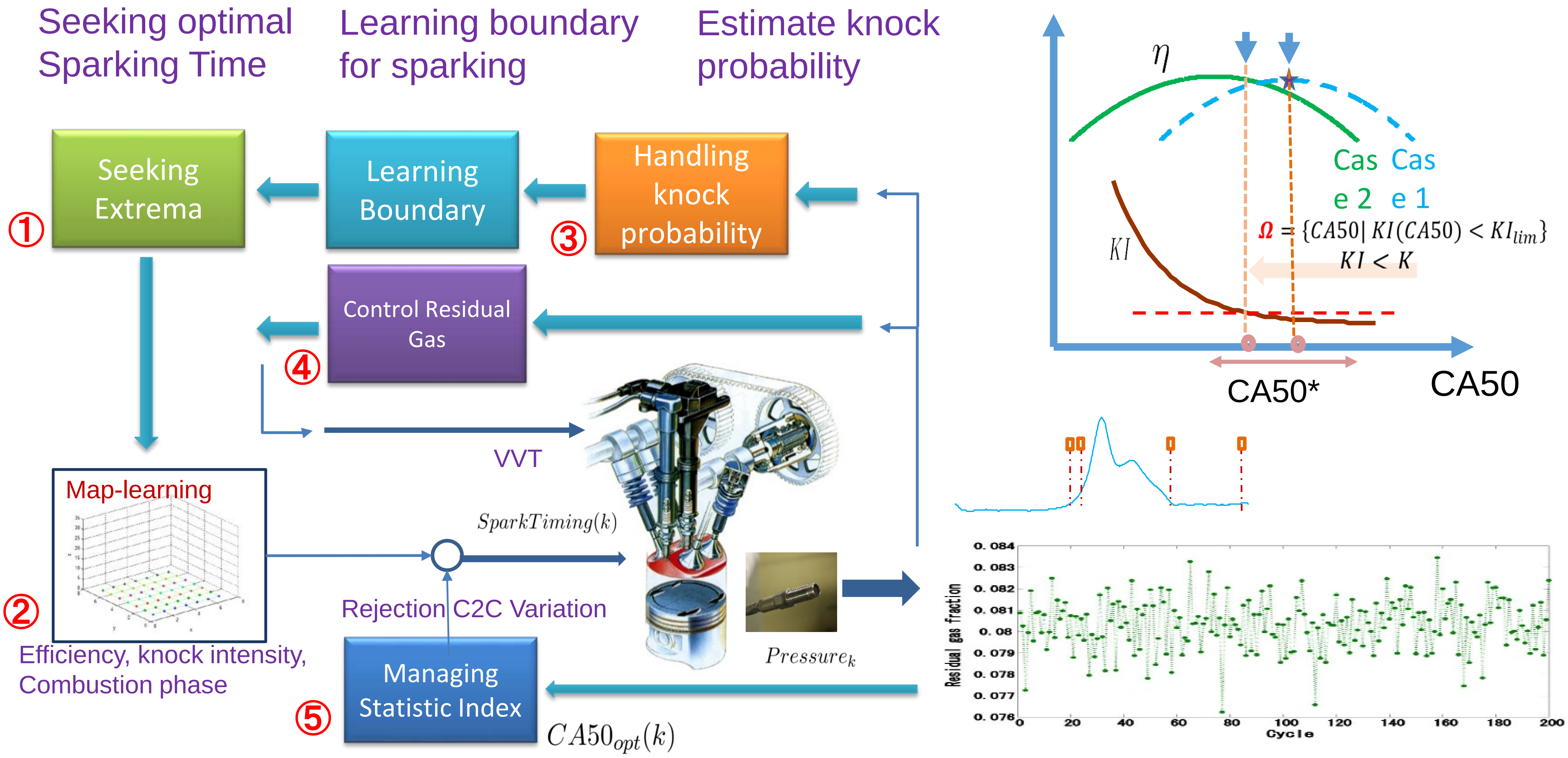
Model-based control theory

- **Statistical Model (Probability transient model)**

$$\Pr\{x_{k+1} = s_j\} = T(x_k, u_k, \omega_k)$$

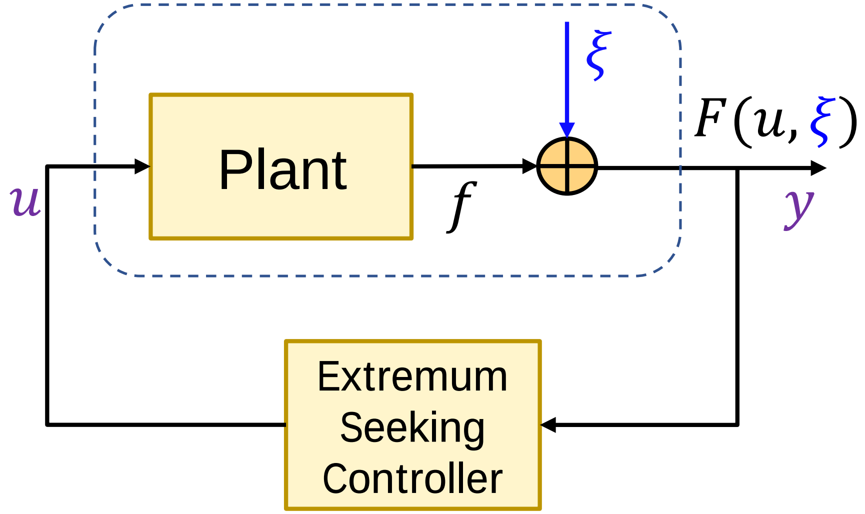
Controlled Markov process, game, decision theory

To improve efficiency by on-board control



1-1. Fundamentals of Extremum Seeking

Let $u \in \boldsymbol{U}$, $\boldsymbol{U}$ is convex, ξ is the disturbance, $f(u)$ is the unknown objective function, measurements: $F(u, \xi) = f(u) + \xi(u)$,



Find the optima which can maximize $f(u)$:

$$u^* = \arg\max_{u \in \boldsymbol{U}} f(u)$$

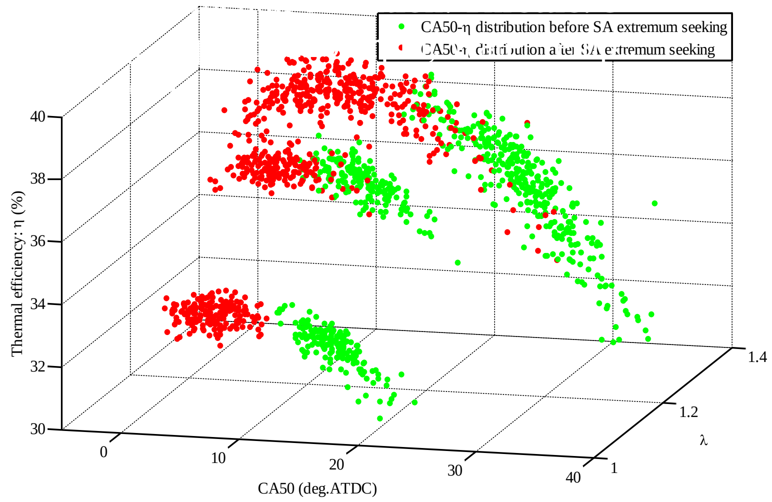
❑ Extremum Seeking

ES is a control system which is used to determine and maintain the extremum value of a function.

- ➢ Stochastic Approximation-based ES
- ➢ Adaptive ES

Tan & Nešić 2006, 2009

Experimental condition: Throttle: 8 deg., Speed: 1200 rpm, Water temp.: 100 °C



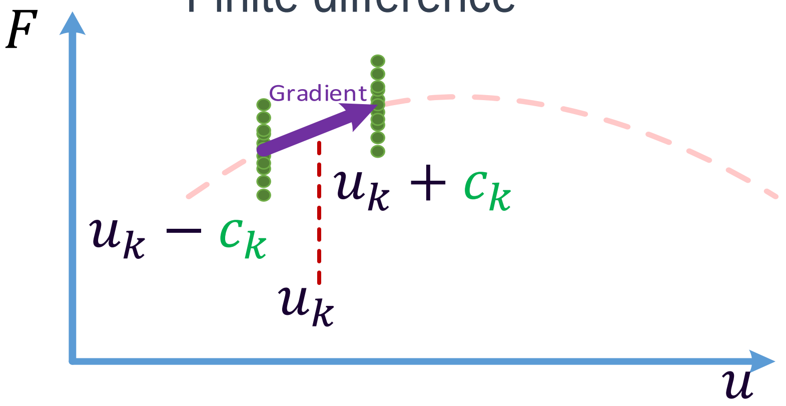
1-2. Stochastic approximation-based Extremum Seeking

- Finite Difference SA (FDSA)
  - ✓ Gradient Descent

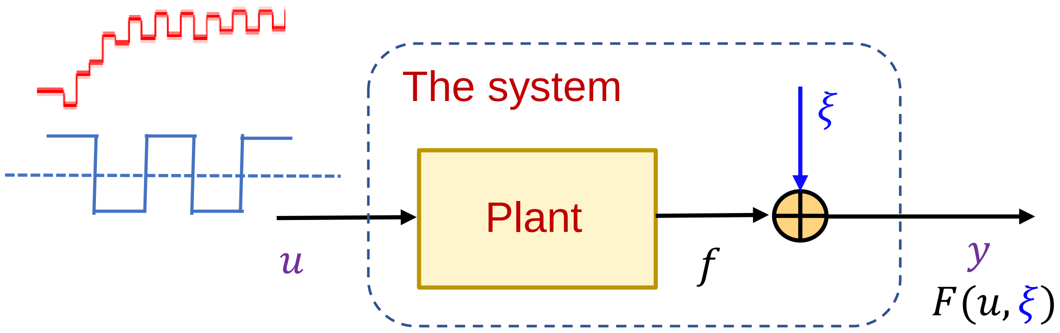
$$u_{k+1} = u_k + a_k \cdot \nabla_u f(u_k) \qquad (1)$$

  - ✓ Gradient Approximation

Finite difference



$$\nabla_u f(u_k) = \frac{F(u_k + c_k, \xi) - F(u_k - c_k, \xi)}{2c_k} \qquad (2)$$



■ Result on convergence

A1. Gain sequence:

$$a_k > 0, \sum_{k=1}^{\infty} a_k = \infty, \sum_{k=1}^{\infty} a_k^2 < \infty, c_k > 0, \sum_{k=1}^{\infty} a_k c_k < \infty, \sum_{k=1}^{\infty} a_k^2 / c_k^2 < \infty$$

A2. Unique minimum u^*

A3. Mean-zero and finite variance noise ξ

A4. Bounded Hessian matrix (if multi-variable)

Suppose that A1-A4 hold. Then, for FDSA according to (1) and (2),

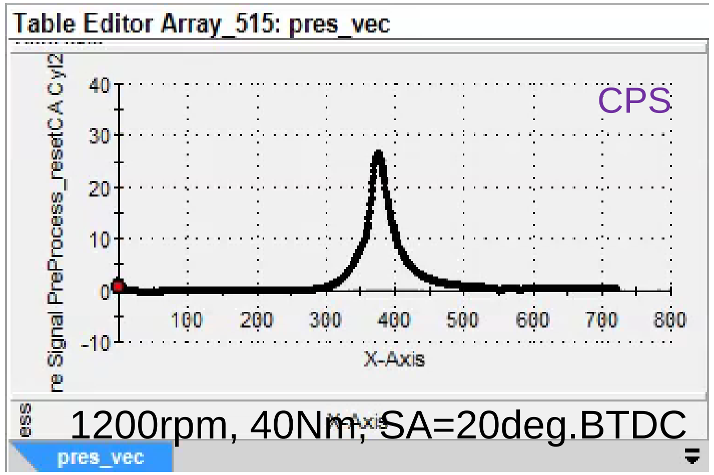
$$u_k \to u^* \text{ a.s. as } k \to \infty$$

James C. Spall, Introduction to stochastic search and optimization: estimation, simulation, and control, 2005

1-3. Seeking Extremal Spark Timing

- Control input (actuator): SA: spark-timing
- Control output: η: thermal efficiency
- Measurement: CA50: crank angle of 50% fuel burnt

Prius 2ZR-FSE engine



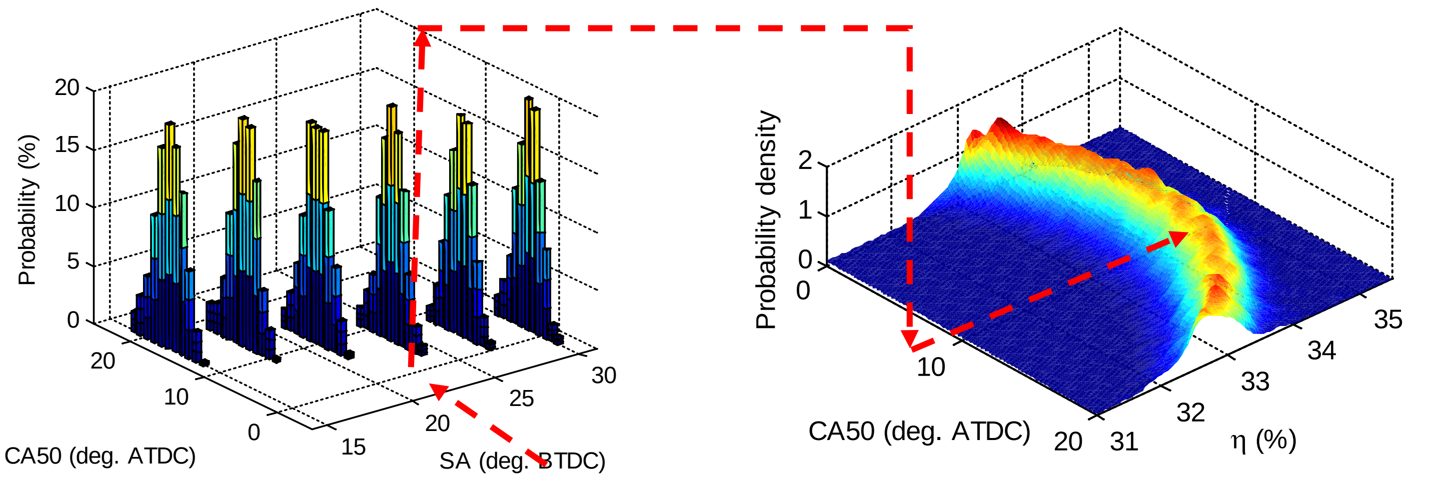
1200rpm, 40Nm, SA=20deg.BTDC

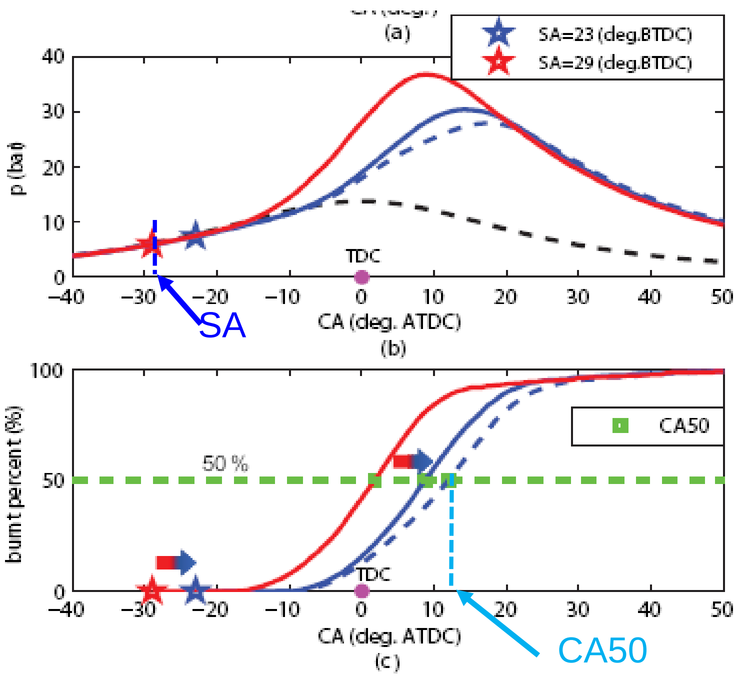
SA-CA50 statistical causality:

$$CA50 = a \cdot SA + b + \zeta$$

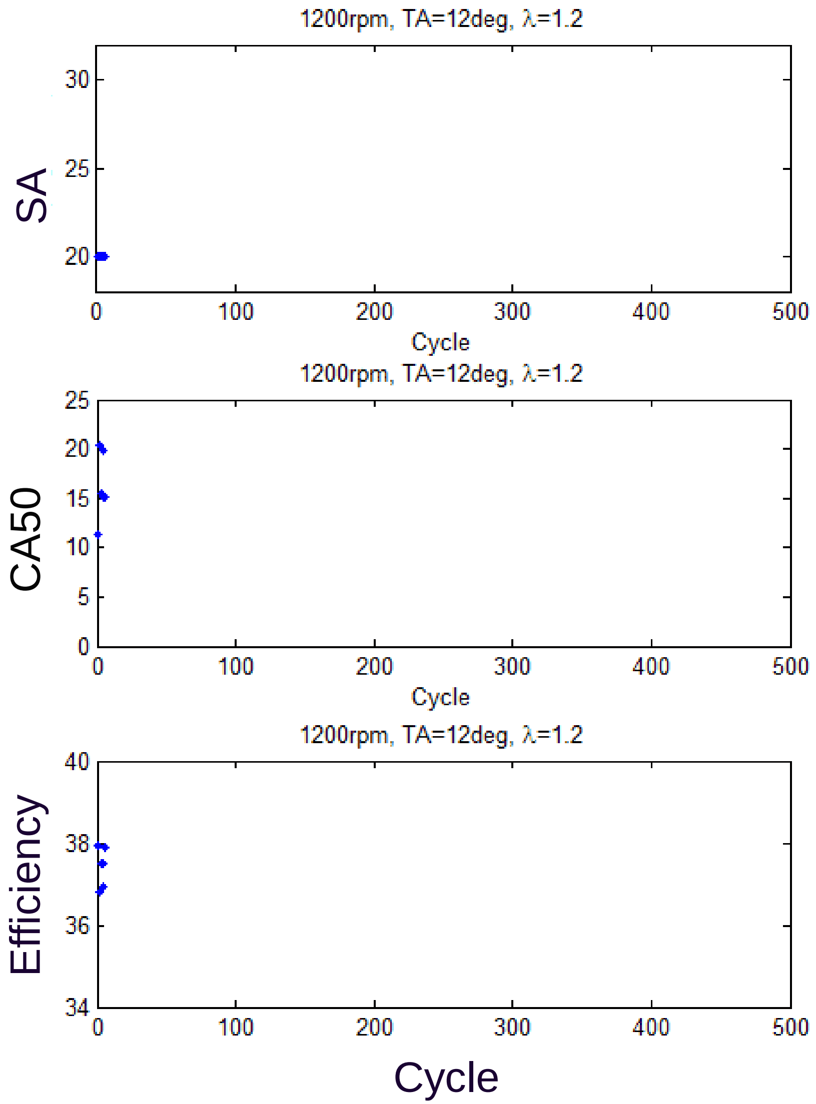
η-CA50 statistical causality:

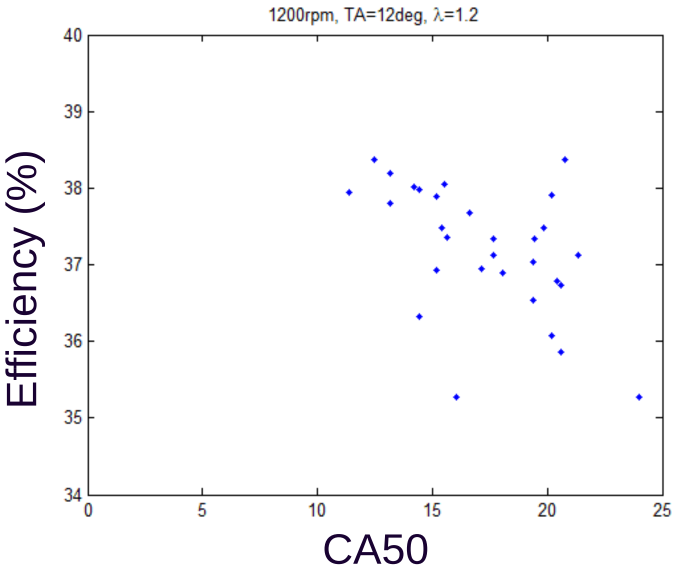
$$\eta = \alpha \cdot CA50^2 + \beta \cdot CA50 + \gamma + \xi$$

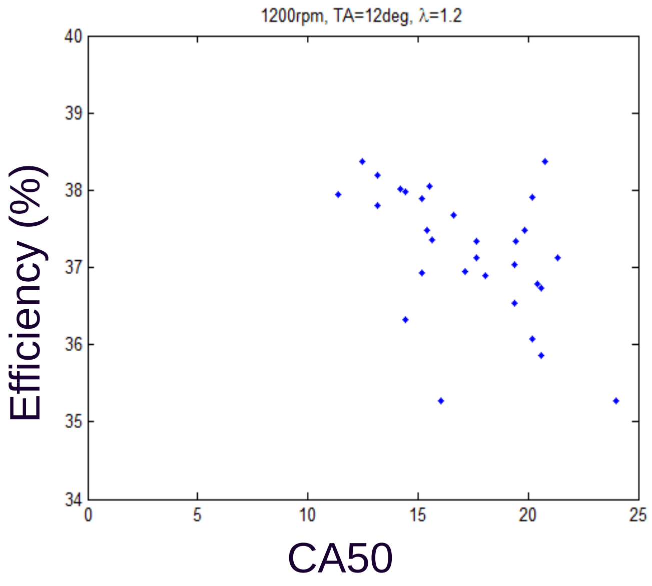




1-4. Experimental Validation







Throttle angle: 12 deg., @1200rpm, ***lean mode***: **lambda=1.2**

--Y. Zhang, J. Gao, T. Shen, Probabilistic Guaranteed Gradient Learning-Based Spark Advance Self-Optimizing Control for Spark-Ignited Engines, IEEE Trans on Neural Networks and Learning Systems, 2018.

--Global Patent with Toyota, 2018

2-1. On-line Map Learning

- Approximation of a continues function with discretized grids
  - o Engine operating state is continues
- Convergence (safety, reliability)

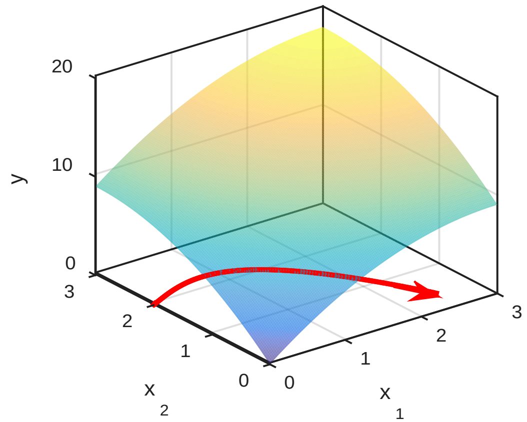
- Interpolation Model: Extensible, Robust, Flexible

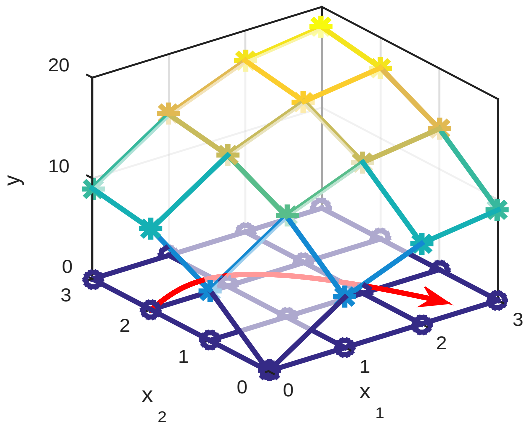
Engineering Problem

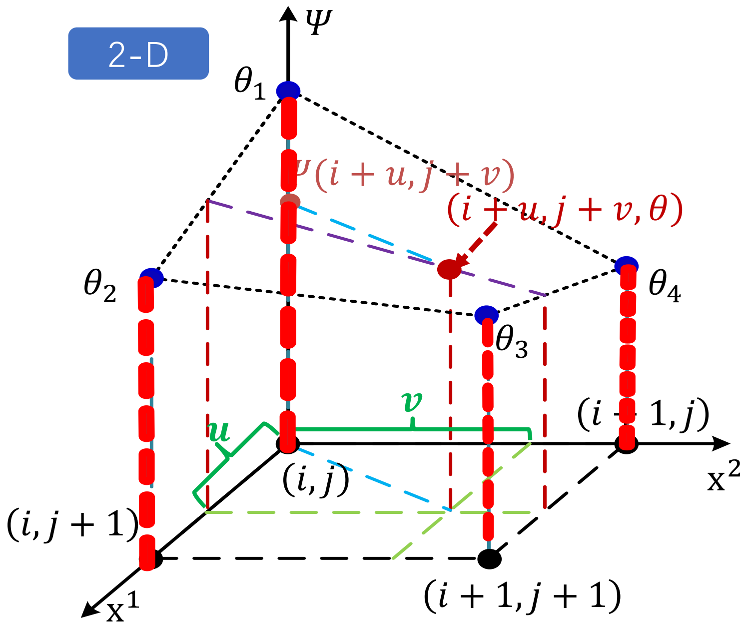
Function Approximation

Model Parameter Estimation

Interpolation Model







Bilinear interpolation

$$\Psi(i+u, j+v) = \phi^{T}(u, v)\,\boldsymbol{\theta}$$

$$= \begin{bmatrix} (1-u)(1-v) \\ u(1-v) \\ uv \\ (1-u)v \end{bmatrix}^{T} \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \end{bmatrix}$$

Extend to n-D

……

……

2-2. Learning Algorithm

Observation: $\{\boldsymbol{x}_k, y_k\},\ k = 1,2,\ldots,N$

Model: $\Psi(\boldsymbol{x}) = \phi^T(\boldsymbol{x}) \cdot \boldsymbol{\theta}$

$\boldsymbol{\theta} = \left[\theta_1, \theta_2, \ldots, \theta_{N^\theta}\right]^T$

Model structure:

$\phi(\boldsymbol{x})$ is a known interpolation model

Unknown model parameter:

$\boldsymbol{\theta}_k = \boldsymbol{\theta}_{k-1} + \Delta_k$ $\Delta = 0$: time-invariant

$\Delta \neq 0$: time-varying

Noise: w_k $y_{k+1} = \phi_k^T(\boldsymbol{x}) \cdot \boldsymbol{\theta}_k + w_{k+1}$

Stochastic Gradient-based Algorithm

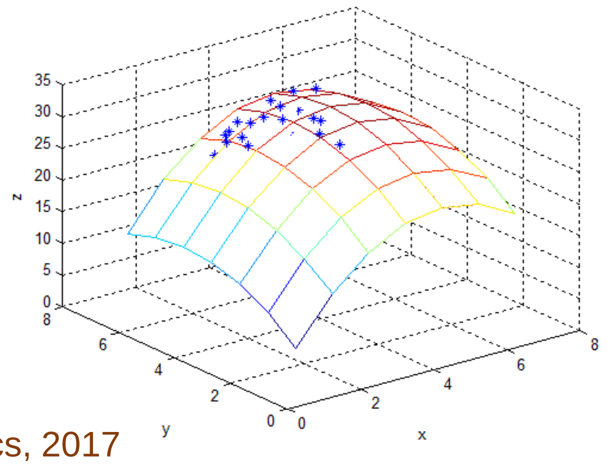
$$\frac{\partial J_k}{\partial \boldsymbol{\theta}} = -\phi_k\left(y_k - \phi_k^T \boldsymbol{\theta}\right)$$

$$\boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k - \gamma \boldsymbol{I}^{N^\theta \times N^\theta} \cdot \frac{\partial J_k}{\partial \boldsymbol{\theta}}$$

Stochastic Gradient-based Algorithm

Target Map: $X \to Y$

Sample: $\boldsymbol{x}_k \to y_k$



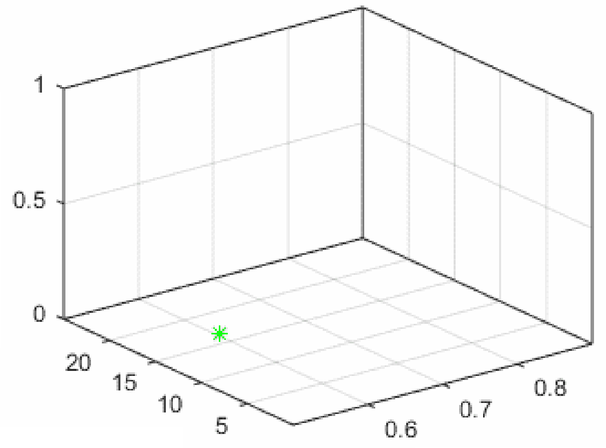
J. Gao, Y. Zhang, T. Shen,
IEEE/ASME Trans on Mechatronics, 2017

Bayesian-based Map Learning of Stochastic Event Probability

Target Map:
$X \to Pr(event)$

Sample: $\boldsymbol{x}_k \to event_k$

Stochastic event: 0,1,2,⋯



Y. Zhang, X. Shen, Y. Wu, T. Shen,
International Journal of Engine Research, 2019

2-3 Learning combustion phase with varying boundary

❑ Knock Probability Constrained Optimal Combustion Control

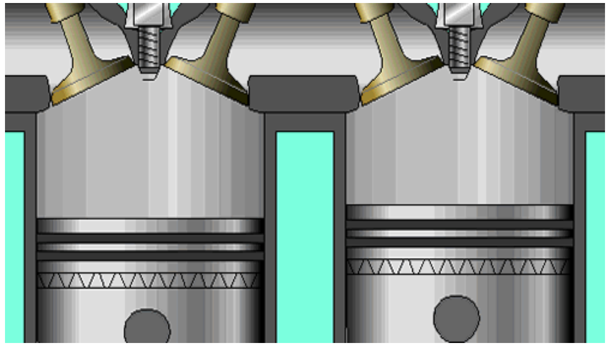
➢ Purpose: combustion quality improvement

- Maximize efficiency
- Satisfy knock risk

$$CA50^* = \arg \max_{CA50 \in \Omega} \eta(CA50)$$

$$\Omega = \{CA50 | \, p < p_{thr}\}$$

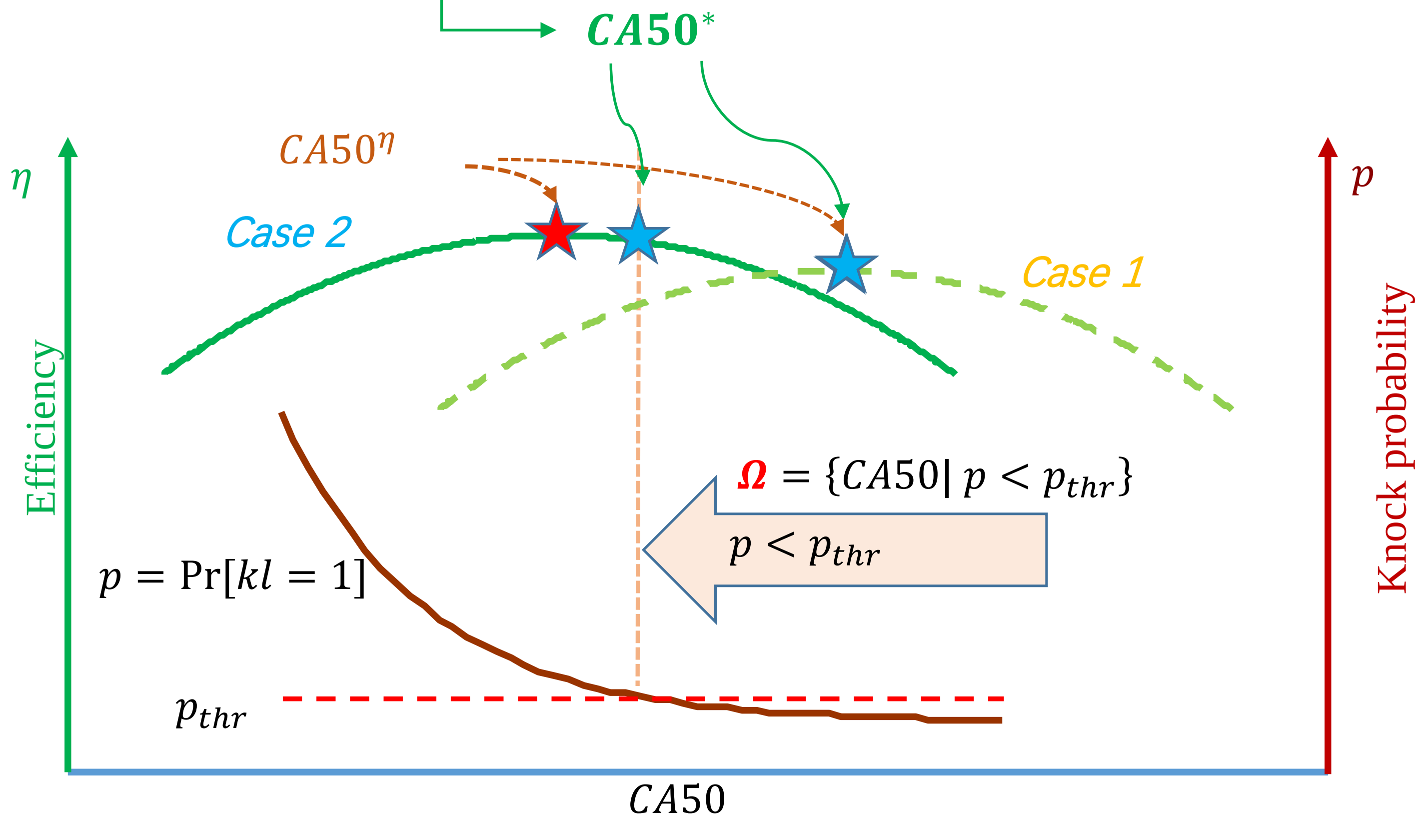
Abnormal combustion: **Knock**



http://info.auto-m.hc360.com/2011/02/160827281195.shtml

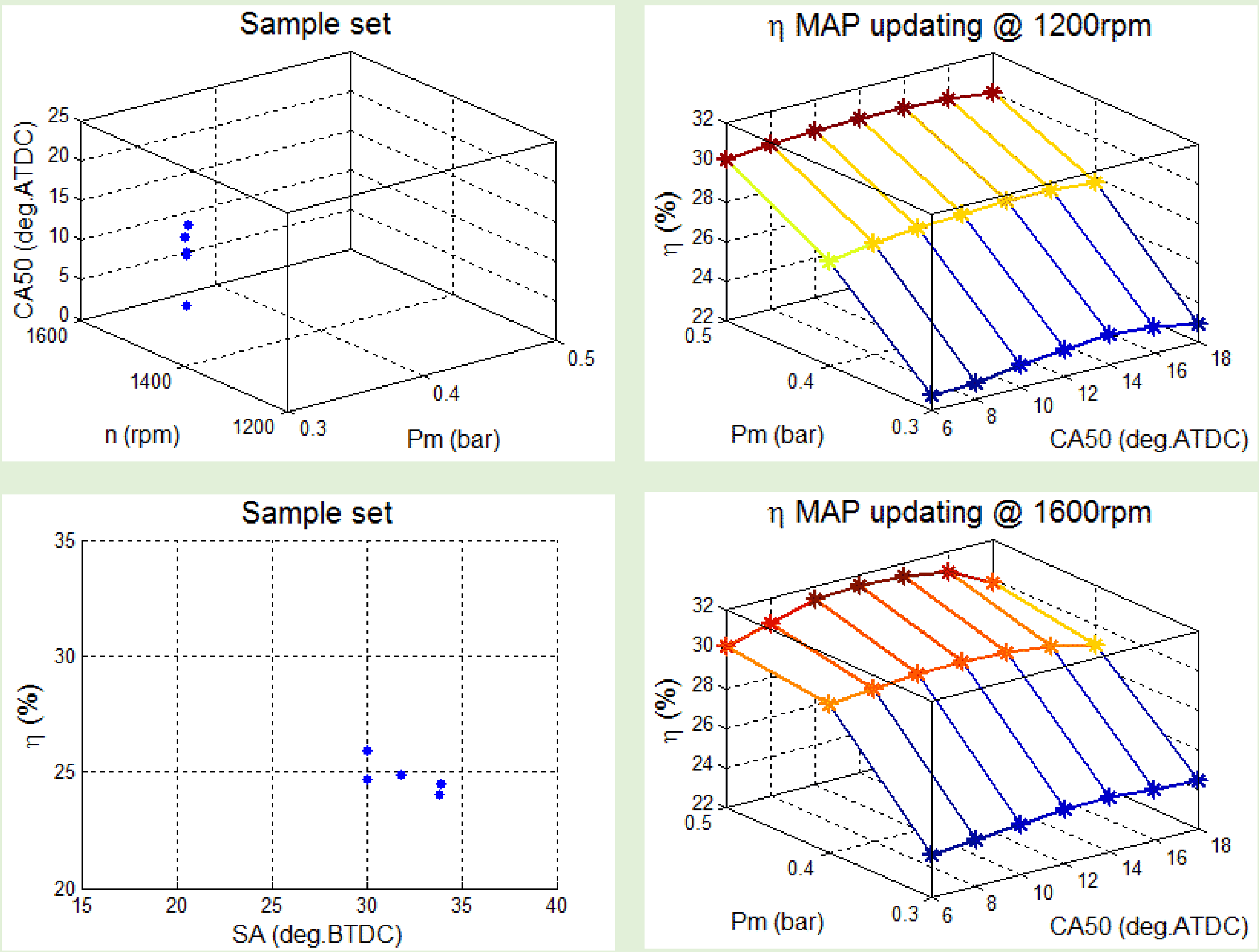
- Challenges: optimal values of controllable variables, and physical constraints change due to different fuel qualities, environment variations, engine aging, etc.

‘Risk for Win’: making tradeoff between benefit and risk

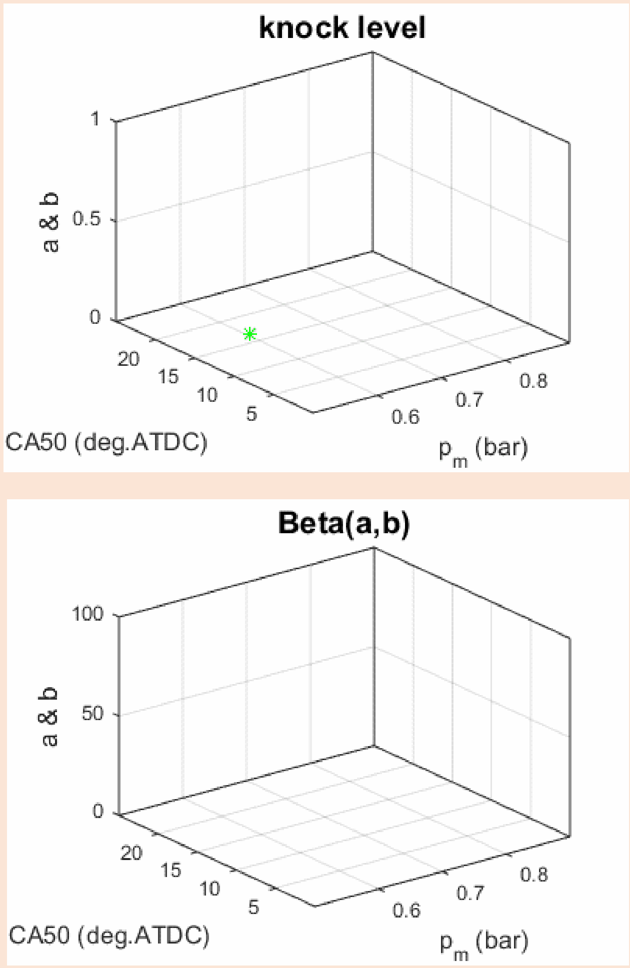


2-3. Experimental Validation

Stochastic Gradient-based Efficiency Map Learning

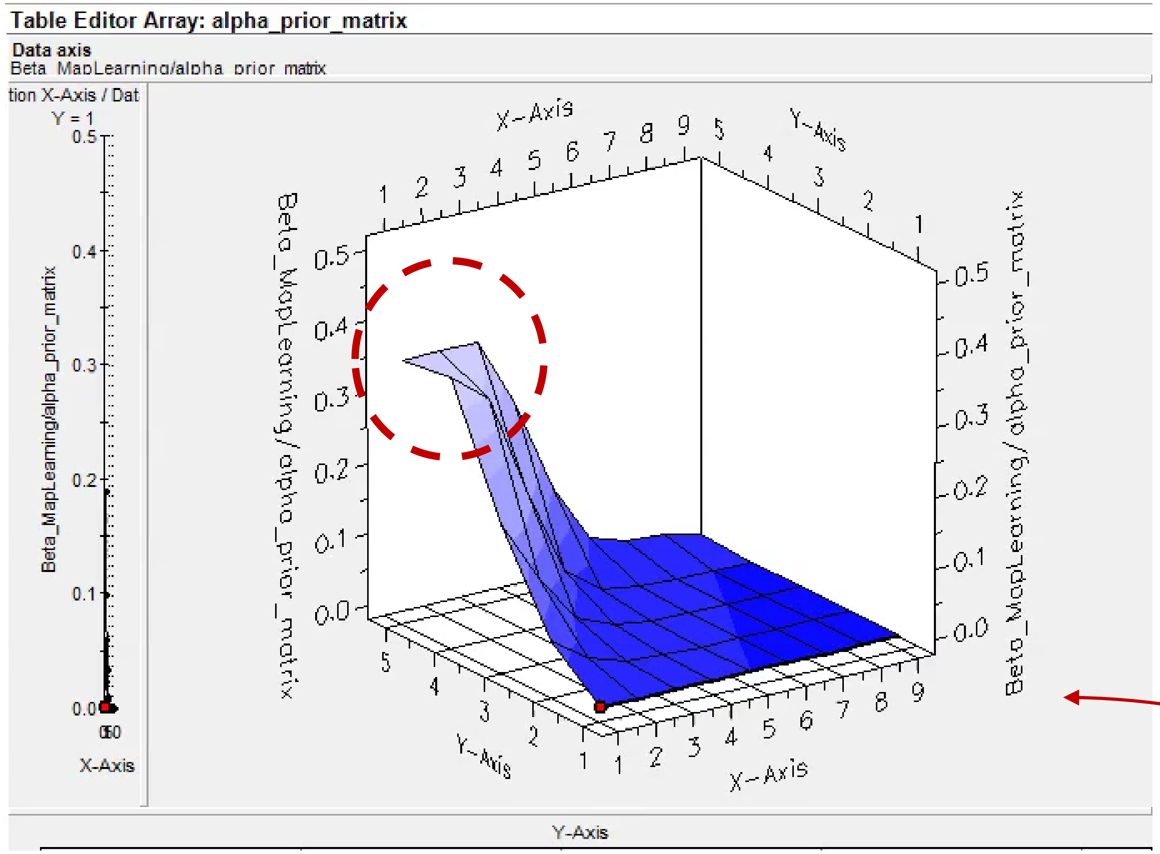


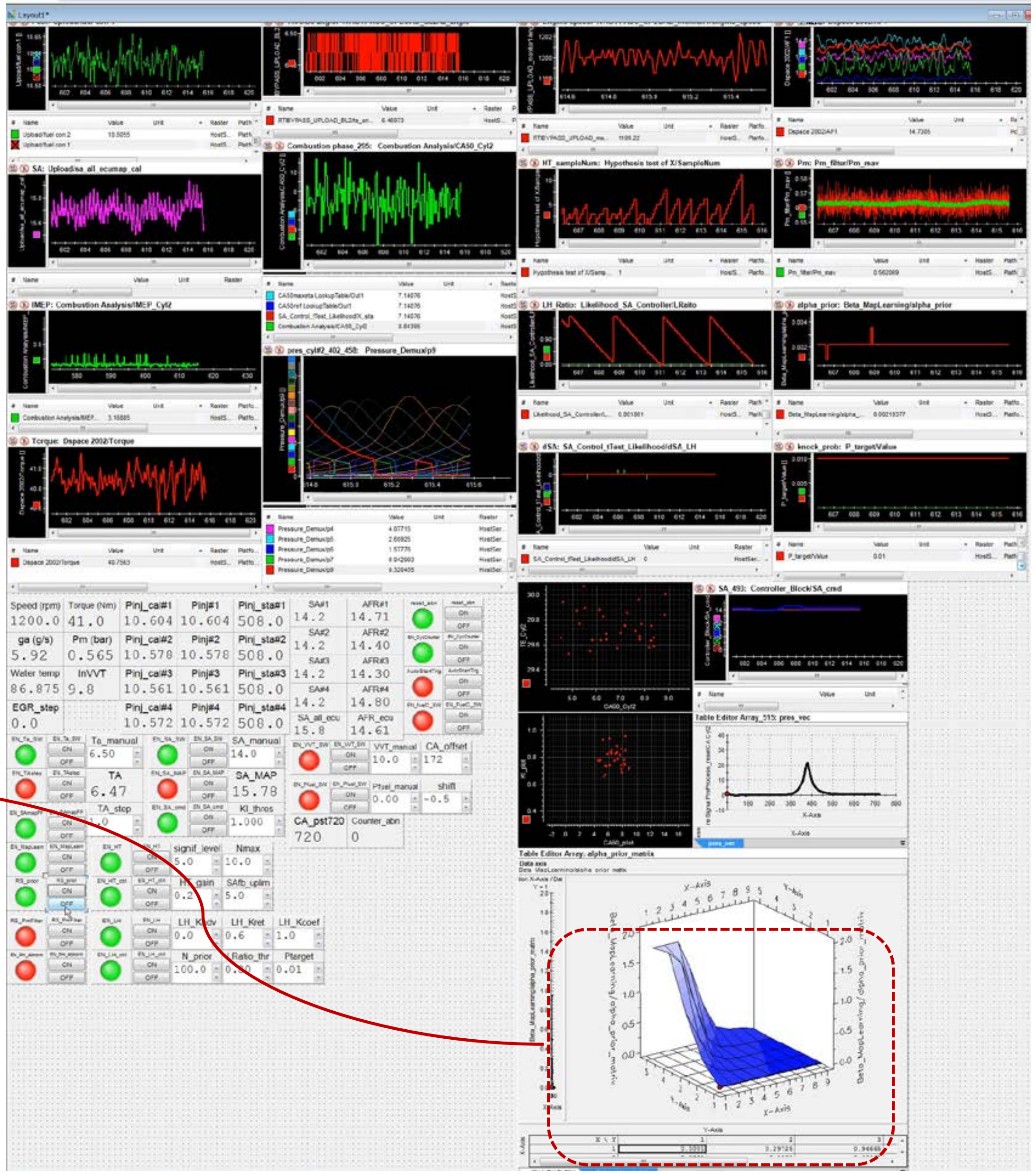
Bayesian-based Map Learning of Knock Event Probability



η-MAP is slightly updated

2-4. From the bench panel



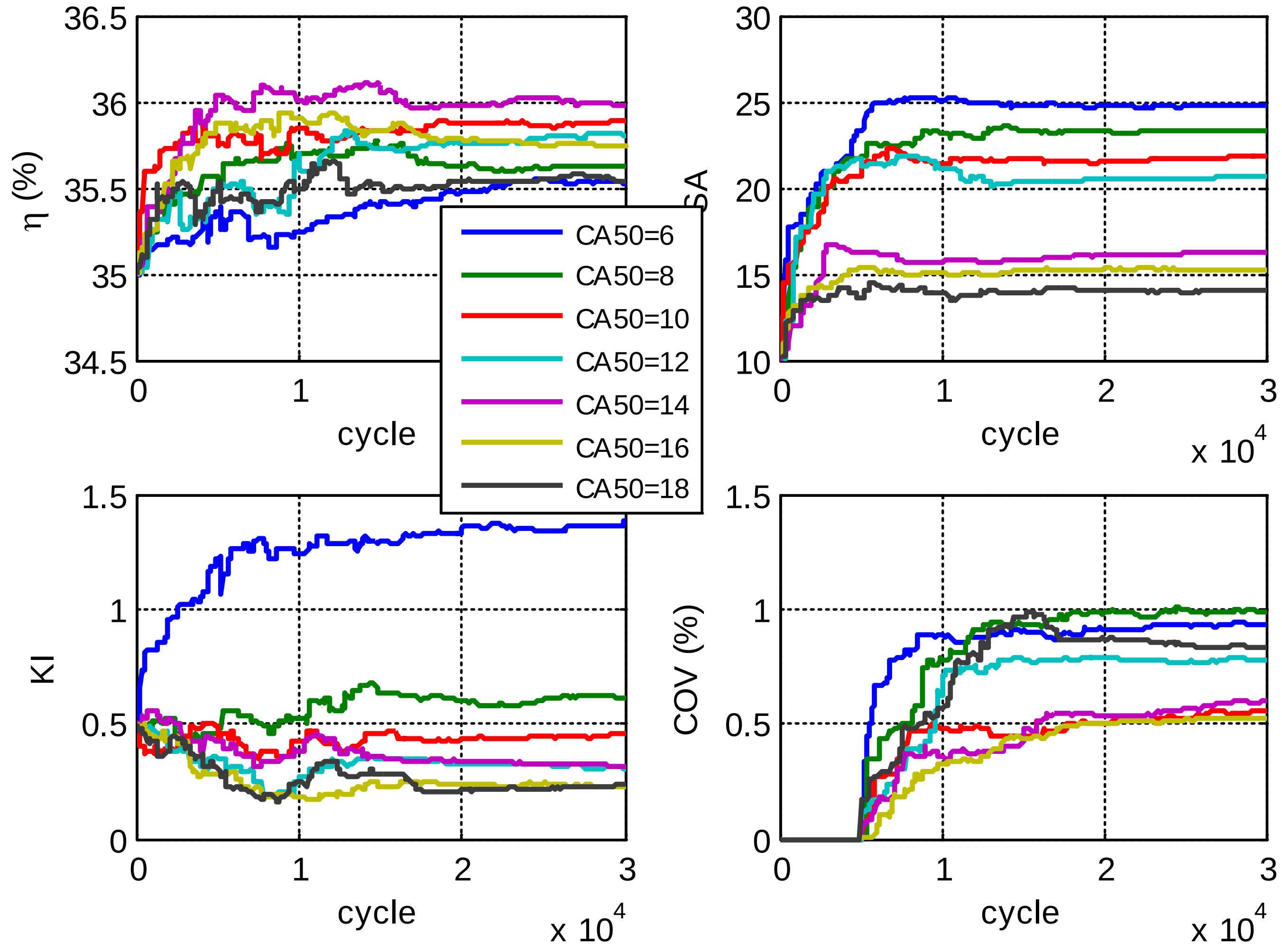


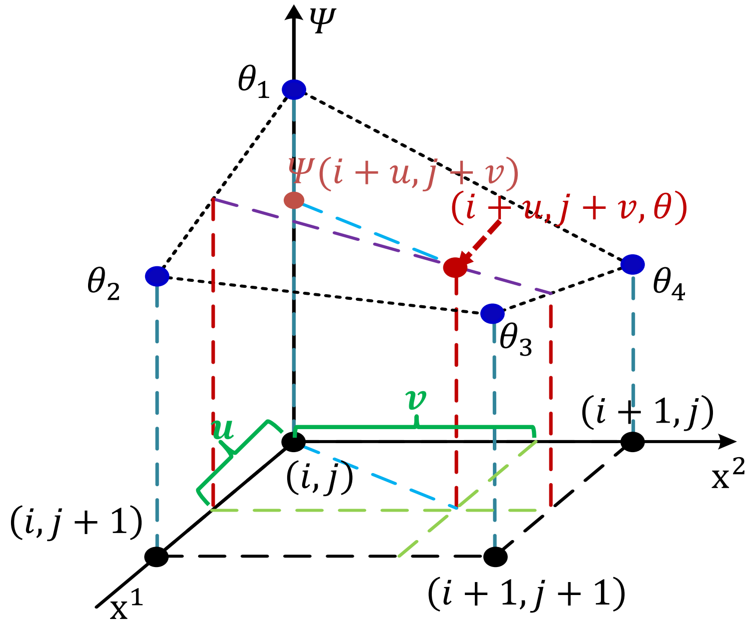
Bayesian-based Map Learning of Knock Event Probability

2-5. Convergence of the learning

Grid: $n = [800,1200,1600,2000]\ rpm$ $\quad p_m = [0.3,0.4,0.5,0.6,0.7,0.8]\ bar$

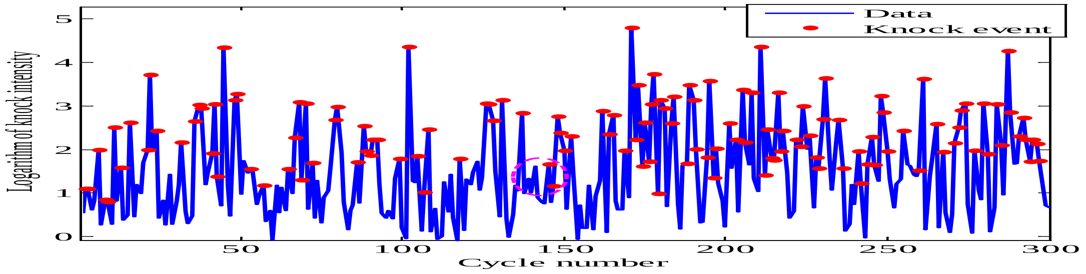
$CA50 = [6,7,8,\ldots,18]\ deg.$ Learning process at gird: 0.7bar, 1200rpm





3-1. Knock probability estimation and control

- Measured by knock intensity (KI)
- knock event and non-knock event can have same KI values



How to detect knock event with knock intensity signal■

→ Mixed Gaussian distribution

→ Global Patent with Toyota, 2018

How to estimate probability of knock■

→ Beta-distribution+Baysian-based learning

→ K. Zhao, Y. wu, T. Shen, IEEE CST, 2019(app), ITE 2019

How to detect boundary■

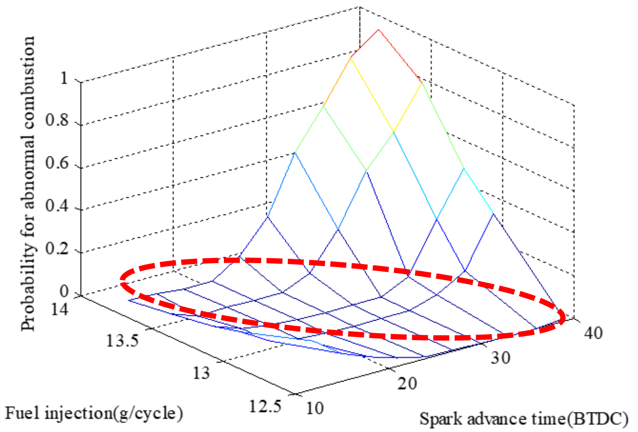
→ Beta-distribution+Baysian

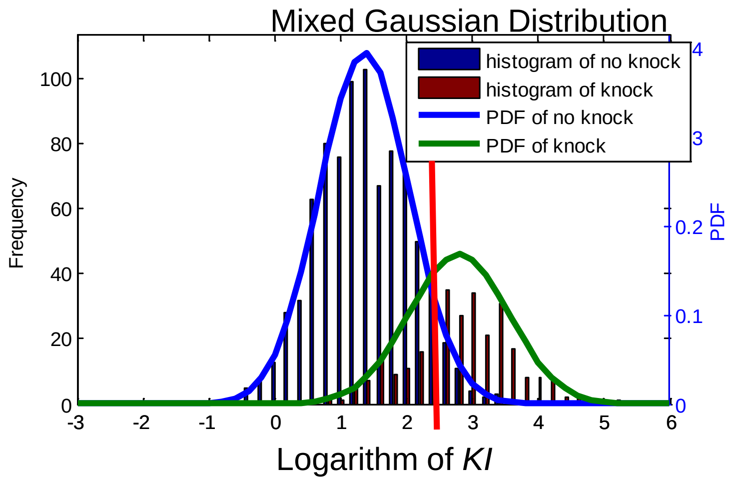
→ Global Patent with Toyota, 2019

How to control know probability■

→ Likelihood control

→ IEEE CST, 2017, 2018





$$\Pr\{Error\} = J(T)$$

$$= \int_T^{\infty} \frac{w_1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-u_1)^2}{2\sigma_1^2}} dx + \int_{-\infty}^{T} \frac{w_2}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(x-u_2)^2}{2\sigma_2^2}} dx$$

3-2. Knock probability estimation and control

Assumption:
Knock probability satisfies Beta-distribution

$$beta(\theta|\alpha,\beta) = \frac{1}{B(\alpha,\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}I_{(0,1)}$$

- where

$$B(\alpha,\beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)},$$

$$\Gamma(\alpha) = \int_0^{+\infty} x^{\alpha-1}e^{-x}dx$$

□ Expectation: $E(\theta) = \frac{\alpha}{\alpha+\beta}$

Knock Probability Estimation Update:

Prior distribution: $Beta(\theta|\alpha,\beta)$
Posterior distribution: $Beta(\theta|k+\alpha,(n-k)+\beta)$

Numerical Estimation, integral are not required

Knock Probability Estimation:

□ Bayesian method

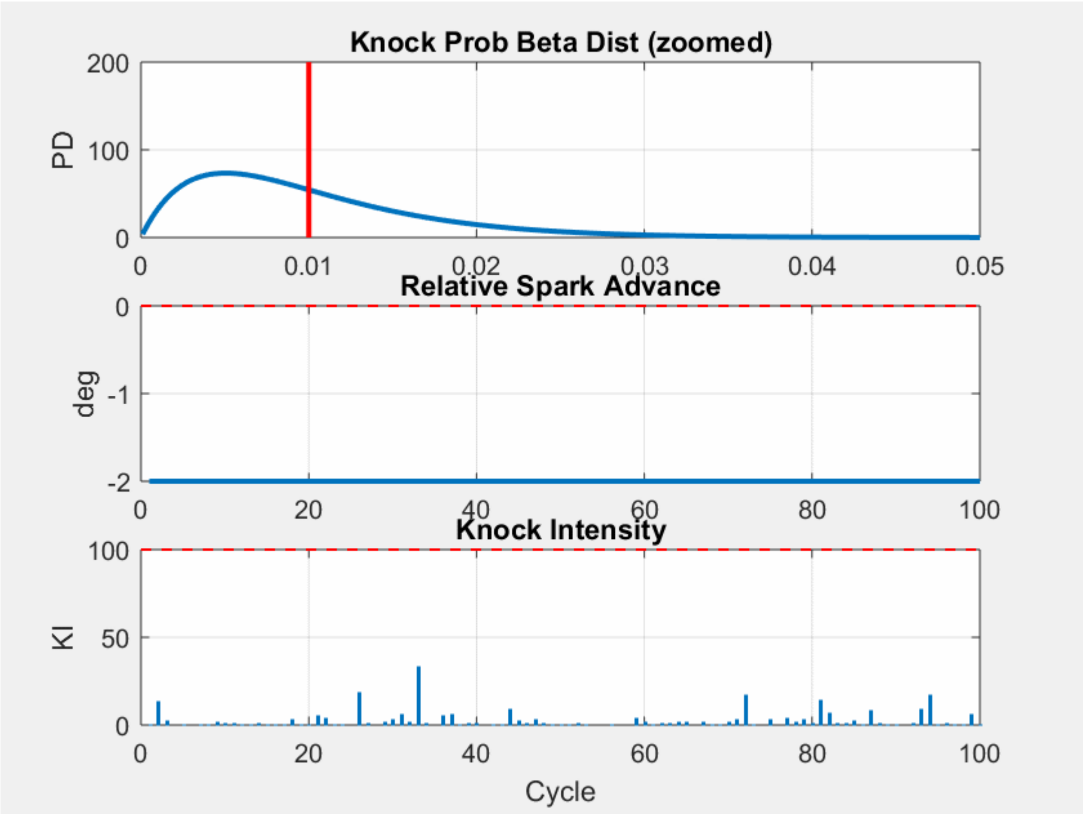
$$p(\theta|X) = \frac{f(X|\theta)p(\theta)}{\int_\Theta f(X|\theta)p(\theta)d\theta}$$

- $p(\theta)$: Prior distribution of θ, $beta(\theta|\alpha,\beta)$
- Likelihood function

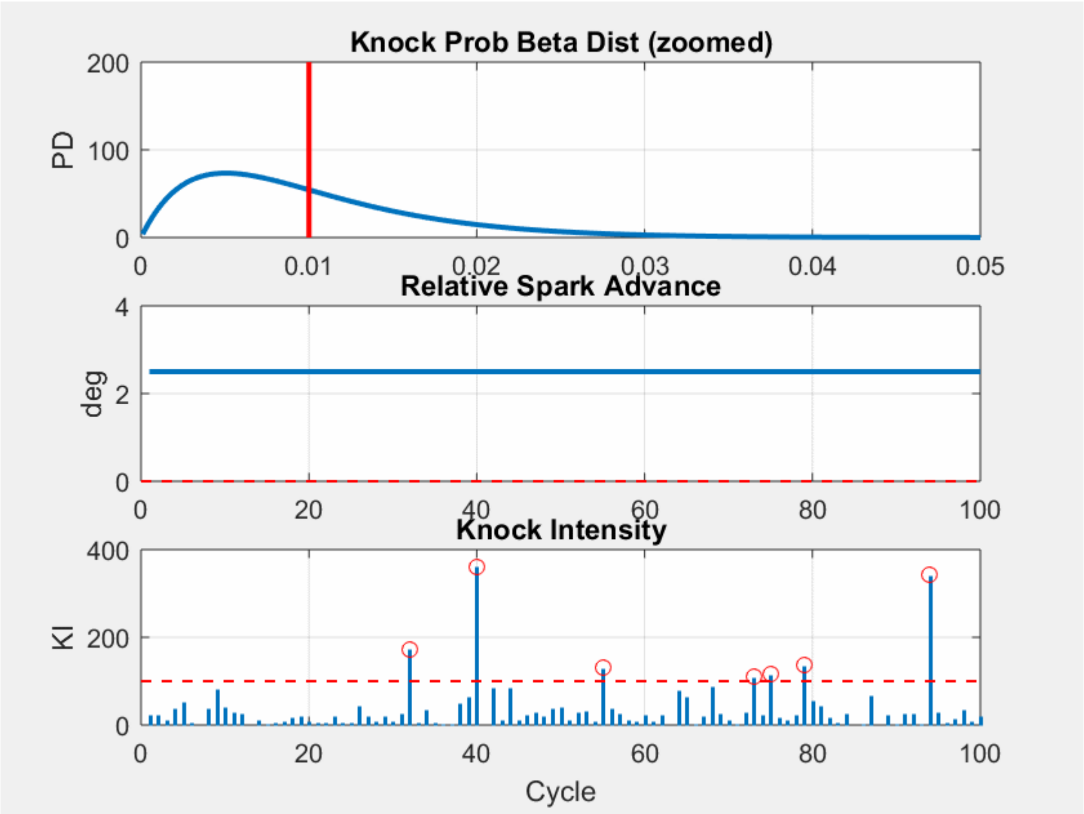
  $$f(X|\theta) = \binom{n}{k}\theta^k(1-\theta)^{n-k}$$

  The observation X, $X = \{x_1,\dots,x_n\}$, $x \in \{0,1\}$
  (k 'knock's in n engine cycles)
- $p(\theta|X)$: Posterior distribution of θ, $Beta(\theta|k+\alpha,(n-k)+\beta)$

3-3. Experimental validation



Overly retarded initial SA



Overly advanced initial SA

- Experiment Conditions: 1200 [rpm] 70[Nm], Toyota L4 SI engine (2ZR-FXE)
- Control is enabled at the 300th cycle
- SA is shown in relative value, $SA = 0\ [deg]$ where knock probability is at $p_{target} = 1\%$

3-2. Control Scheme

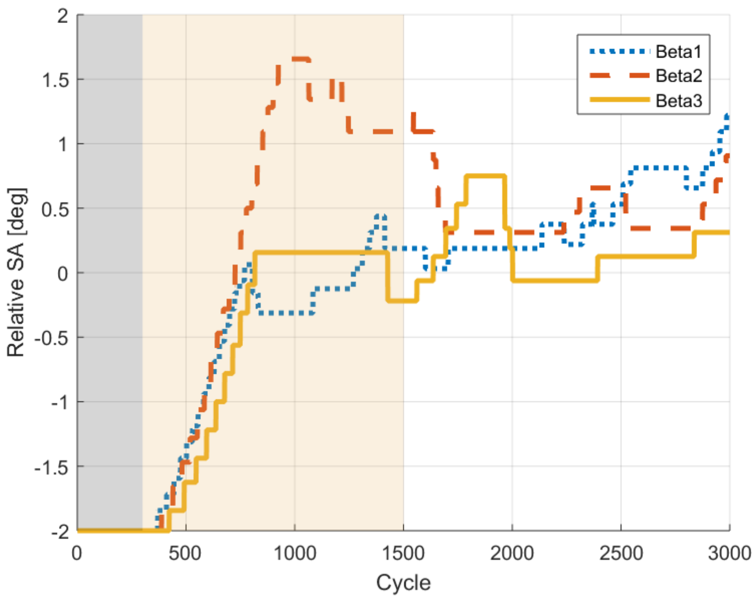
- Step 1:
  Probability Estimation
- Step 2:
  Decision SA
  - Likelihood ratio test

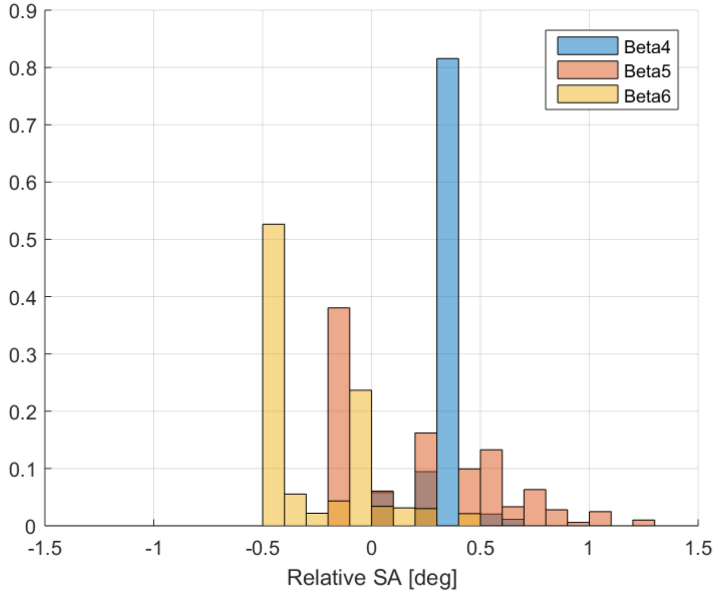
$$\lambda = \frac{p_{tar}^{k}(1-p_{tar})^{n-k}}{p_{est}^{k}(1-p_{est})^{n-k}}$$

  - Given a threshold

$\lambda_T \in (0,1)$ for likelihood ratio λ

- Step 3: SA Adjustment





- SA which leads to 1% knock probability is set as borderline (0 point of Relative SA in histogram)
- Histogram plots SA dispersion from 1500th cycle (white section in left plot)

Operating Condition	
Engine Speed [rpm]	1200
Throttle Angle [degree]	13
Torque [Nm]	70
SA leads to 1% Knock Probability [BTDC]	13.5

Case		Initial SA	Initial α	Initial β	Relative SA Mean	Relative SA Std	Knock Probability
Overly Retarded Start	Beta1	11.5	1	99	0.4267	0.3001	0.0093
	Beta2	11.5	2	198	0.4860	0.2437	0.0093
	Beta3	11.5	4	396	0.1701	0.2667	0.0087

4-1. RGF Control: Stochastic Logical Transient System Theory

■ Logical System

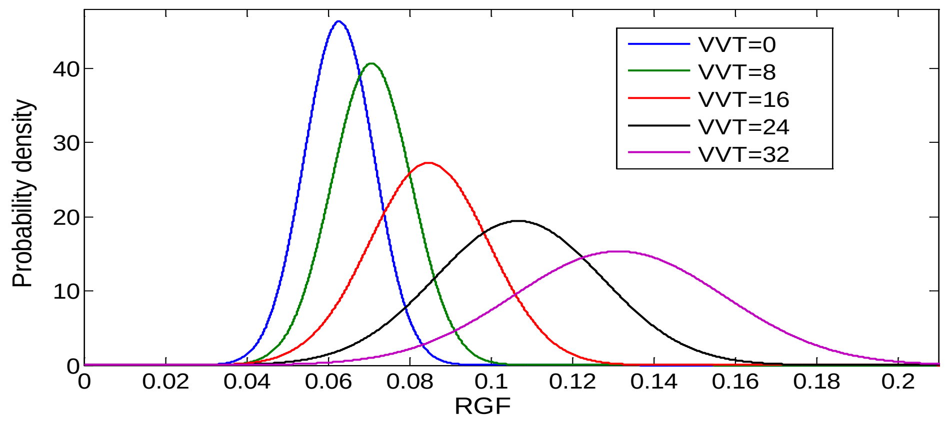
$$\mathrm{Pro}\{x_{k+1}\} = f(x_k, u_k, w_k),$$

$$\mathrm{S}=\{\delta_s^1, \delta_s^2, \cdots, \delta_s^s\} \quad U = \{\delta_r^1, \delta_r^2, \cdots, \delta_r^r\}$$

■ Optimal Control

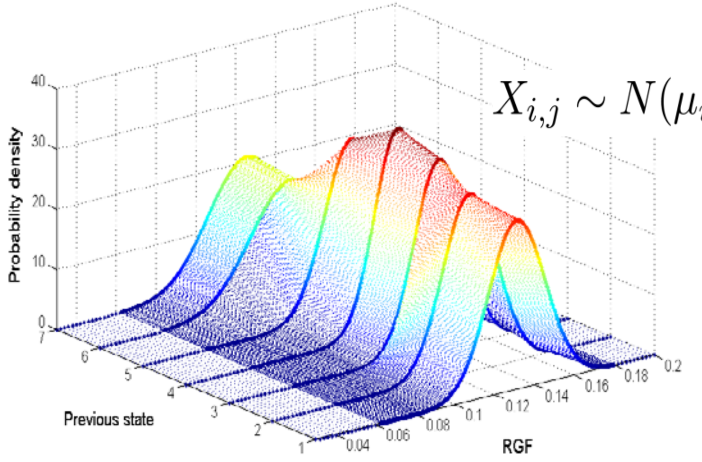
$$J_{\pi^*}(x_0) = J^*(x_0) \triangleq \inf_{\pi\in\Pi} E\left\{\mathcal{K}(x_N) + \sum_{k=0}^{N-1} g(x_k, u_k)\right\}, \quad x_0 \in S,$$

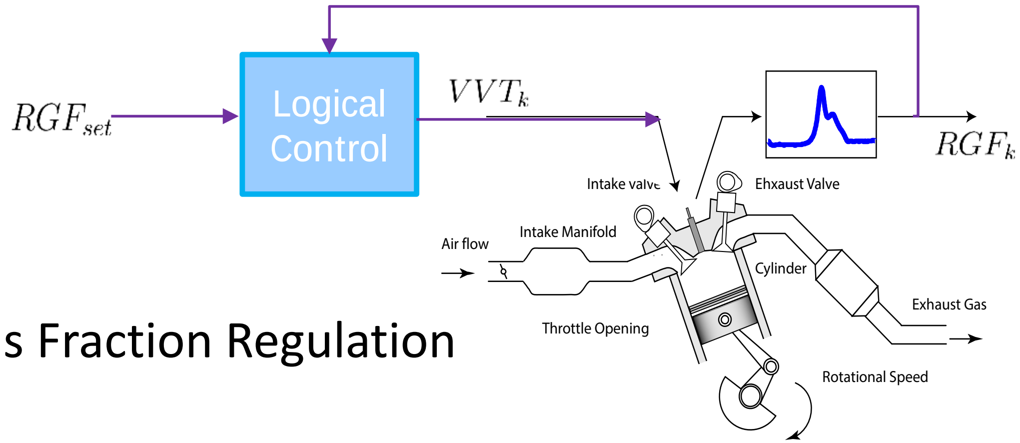
$$\pi = \{\mu_0, \mu_1, \cdots, \mu_{N-1}\}, \qquad \mu_k : S \to U$$



$$P(x_{k+1}|x_k \in A^i, u_k = \delta_5^4)$$

$$X_{i,j} \sim N(\mu_{i,j}, \sigma_{i,j}^2).$$

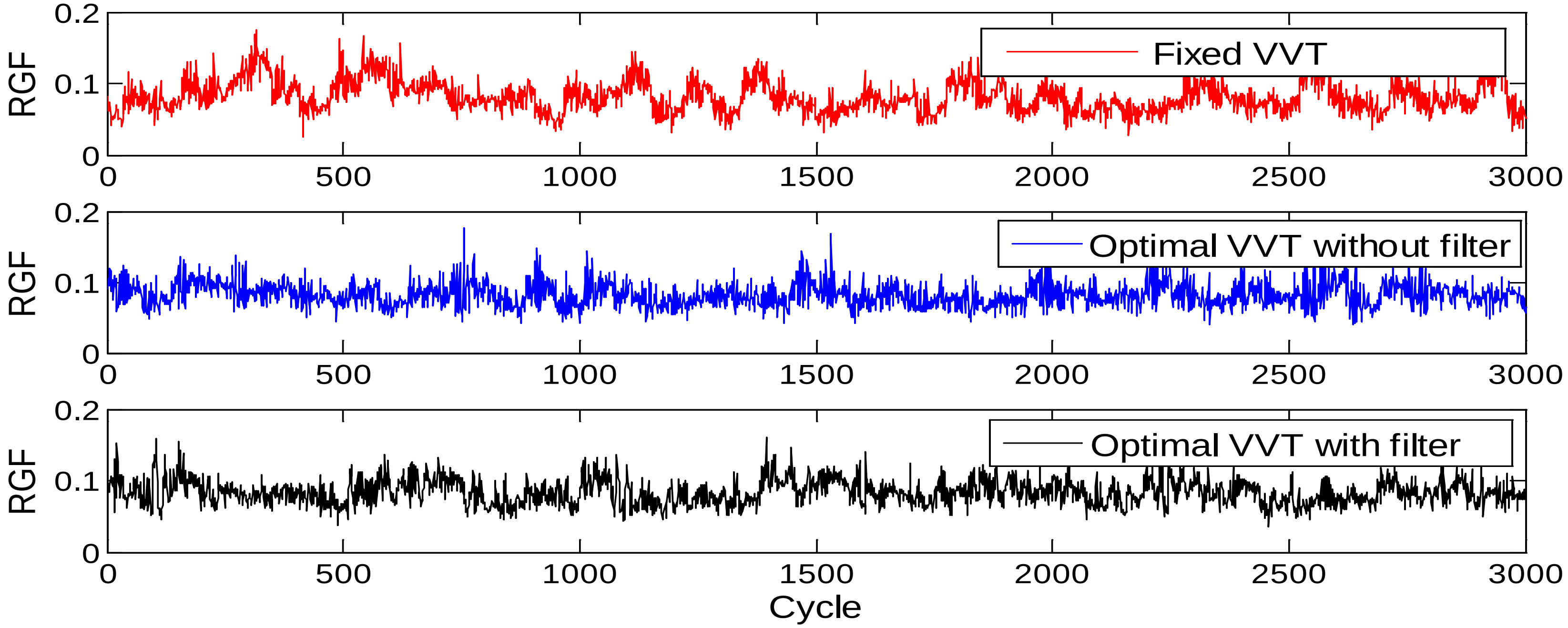


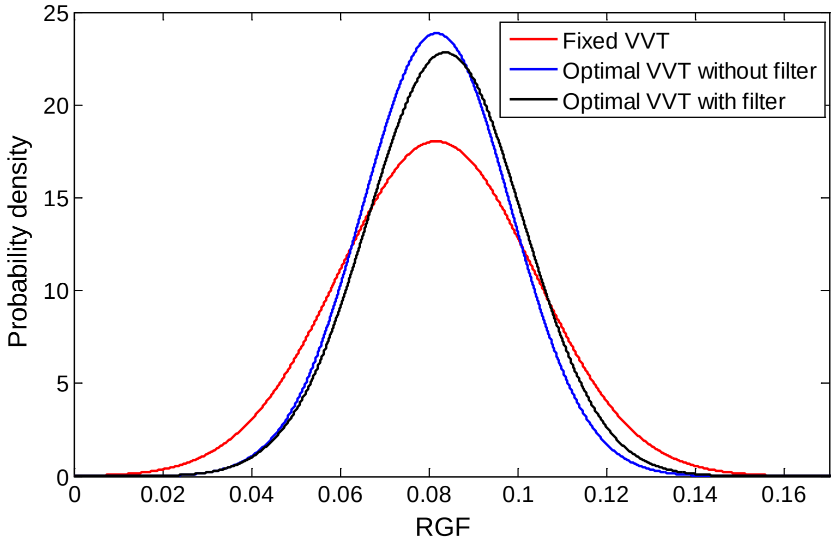


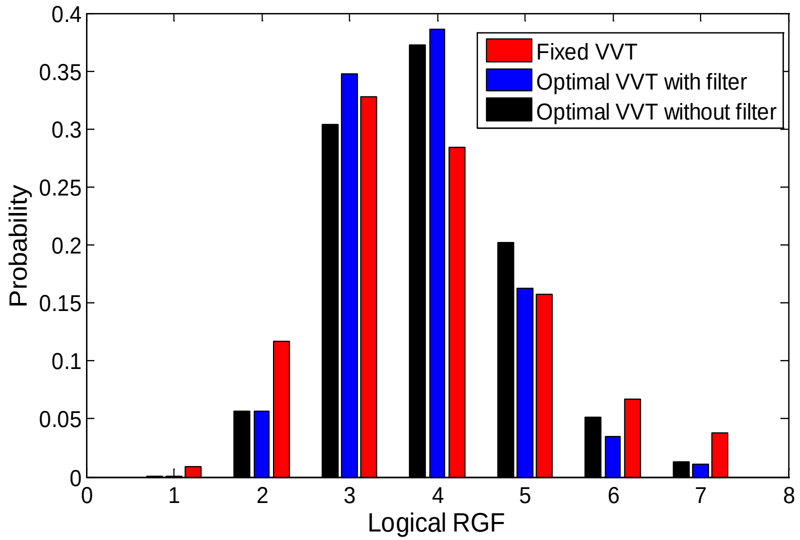
■ Residual Gas Fraction Regulation

Y. Wu, T. Shen, IEEE CST, 2017, Contr. Sys. Lett 2016

4-2. Experimental Result







5-1. Statistical Control：On-line application of Hypothesis Test

- Population of a random variable X has a normal distribution with **unknown** population mean μ and variance σ^2, i.e., $X \sim \mathcal{N}(\mu, \sigma^2)$
- The sample mean $\bar{x}$, variance s^2

$$\bar{x} = \frac{1}{n\sum_{i=1}^{n} x_i},\ s^2 = \frac{\sum(x_i - \bar{x})}{n}$$

Test procedure

- Stating hypothesis,

$$H_0: \mu = \mu_0 \qquad H_1: \mu = \mu_1$$

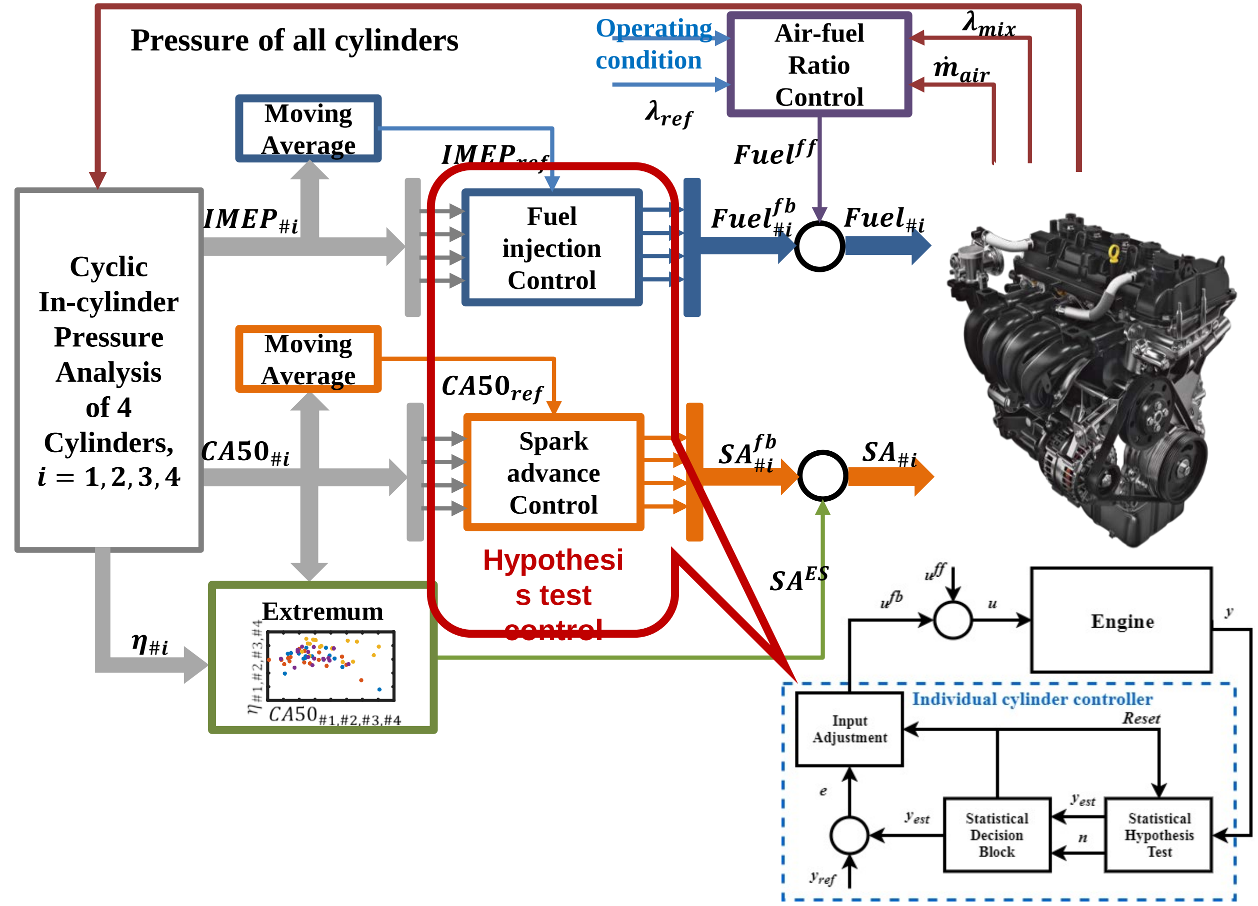
- One sample t statistic,

$$t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \sim t(n-1)$$

- Find P-value:

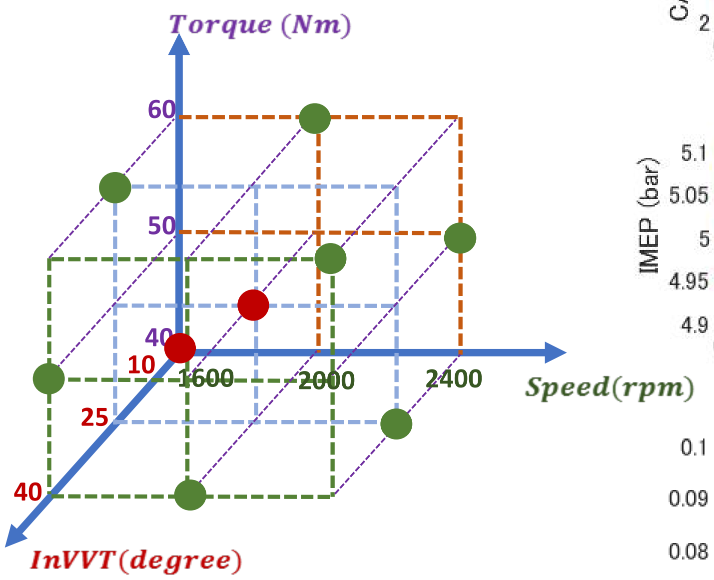
$$P(T \le -t \& T \ge t) = 2P(T \ge |t|)$$

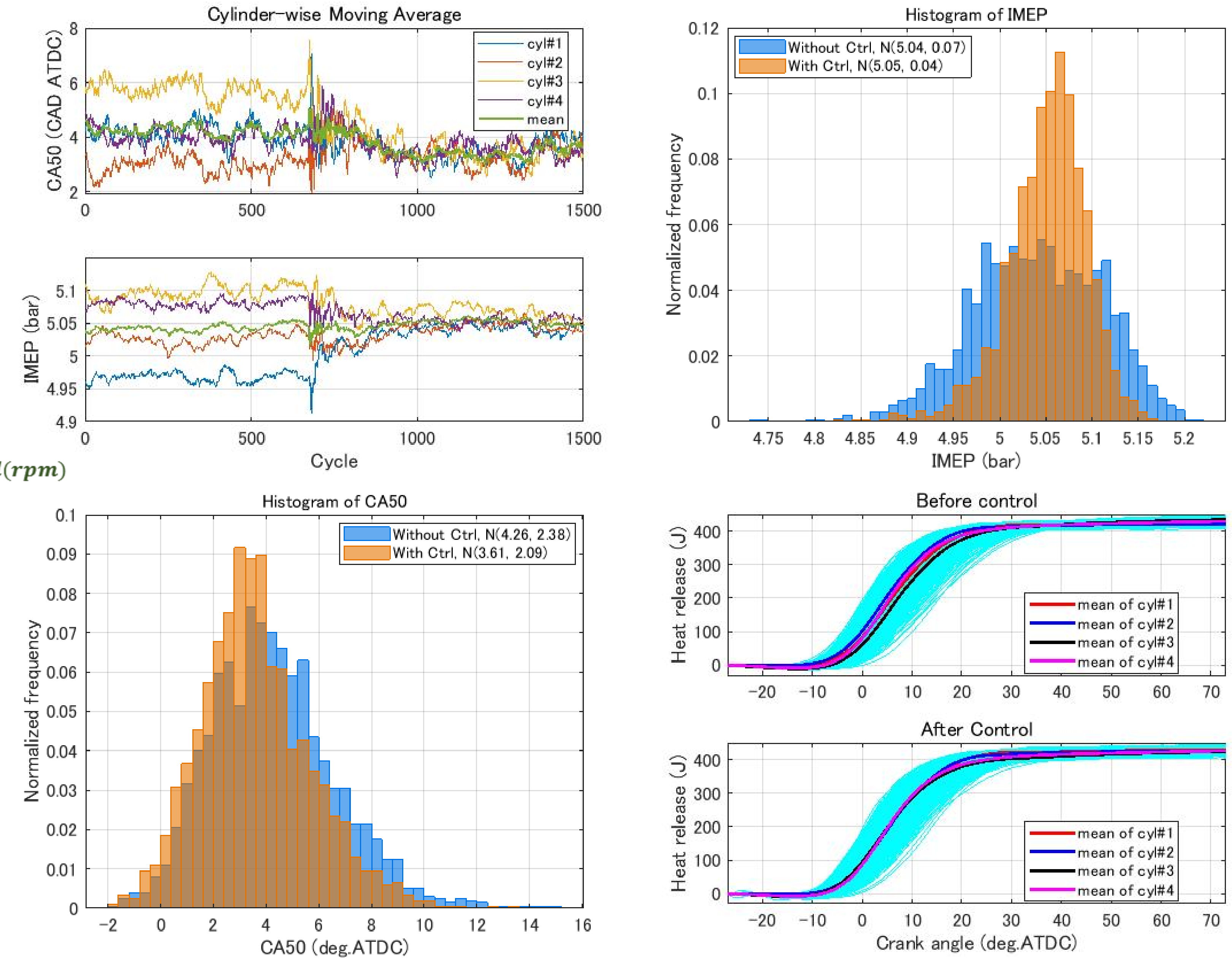
- Decisions (given a significance level α):
  - ✓ If $P \le \alpha$, Reject H_0
  - ✓ If $P \ge \alpha$, Reject H_1



--J. Gao, Y. wu, T. Shen. Mechanical Systems & Signal Processing, 2018
--Global patent woth TOYOTA 2018

5-2. Statistical Control：On-line application of Hypothesis Test





- **Performance evaluations**

Variation restrain evaluation

Point	COV_{IMEP}(%) (With ctrl $\lambda = 1.55$)	COV_{IMEP}(%) (Open loop $\lambda = 1.55$)	r_{COV}	Overall
1	1.80	2.37	0.76	0.7267
2	1.02	1.24	0.82	
3	0.85	1.52	0.56	
4	1.32	1.74	0.76	
5	1.22	1.67	0.73	
6	1.65	1.98	0.83	
7	1.11	1.91	0.58	
8	2.46	2.89	0.85	
9	0.89	1.37	0.65	

Efficiency enhancement evaluation

Point	Baseline η_b(%) (Open loop $\lambda = 1$)	η_o(%) (Open loop $\lambda = 1.55$)	η_c(%) (With control $\lambda = 1.55$)	$\Delta\eta$(%) ($\eta_c - \eta_b$)	Overall $\Delta\eta$ (%)
1	30.16	34.96	35.15	4.99	4.98
2	30.63	35.50	35.56	4.93	
3	33.30	36.63	36.95	3.65	
4	29.59	35.35	35.44	5.85	
5	30.98	36.44	36.51	5.53	
6	33.63	36.82	36.92	3.29	
7	31.02	37.92	37.93	6.91	
8	32.23	37.29	37.42	5.19	
9	34.13	38.56	38.57	4.44	

Hybrid Electric Powertrain Control

-- Real-time Optimization of Consumption

-- Receding Horizon with Demand Prediction

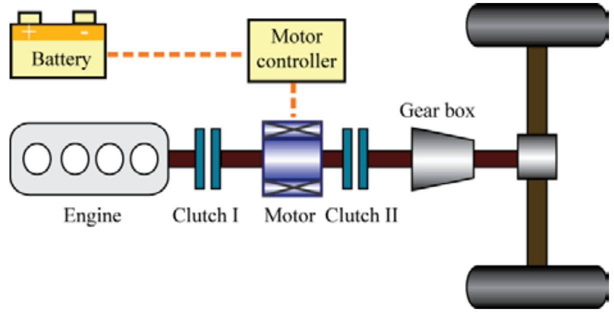
HEV Powertrain Control: Minimizing Energy Consumption

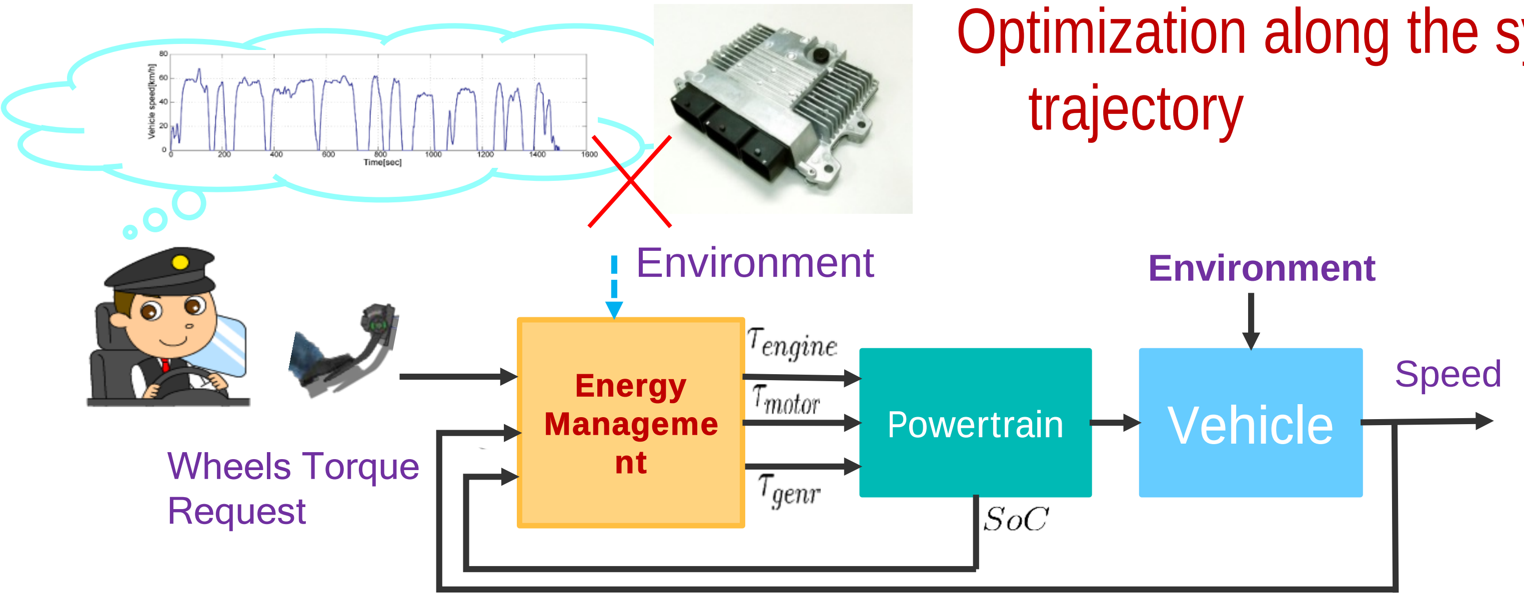
Constraint: Satisfying demanded power is a fateful constraint for powertrain control

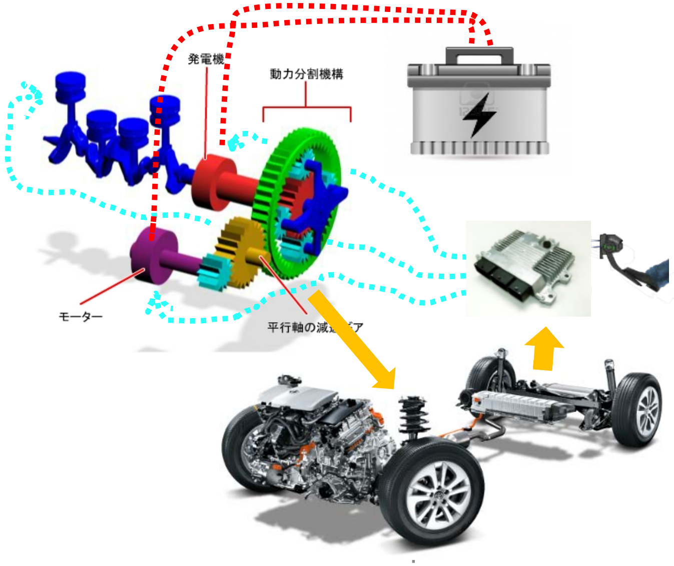
$$\min_{u(t)} J(u, x_0) = \min \int_0^T g(x,u)dt$$

- Predict Vehicle's behavior
- Demanded Power?

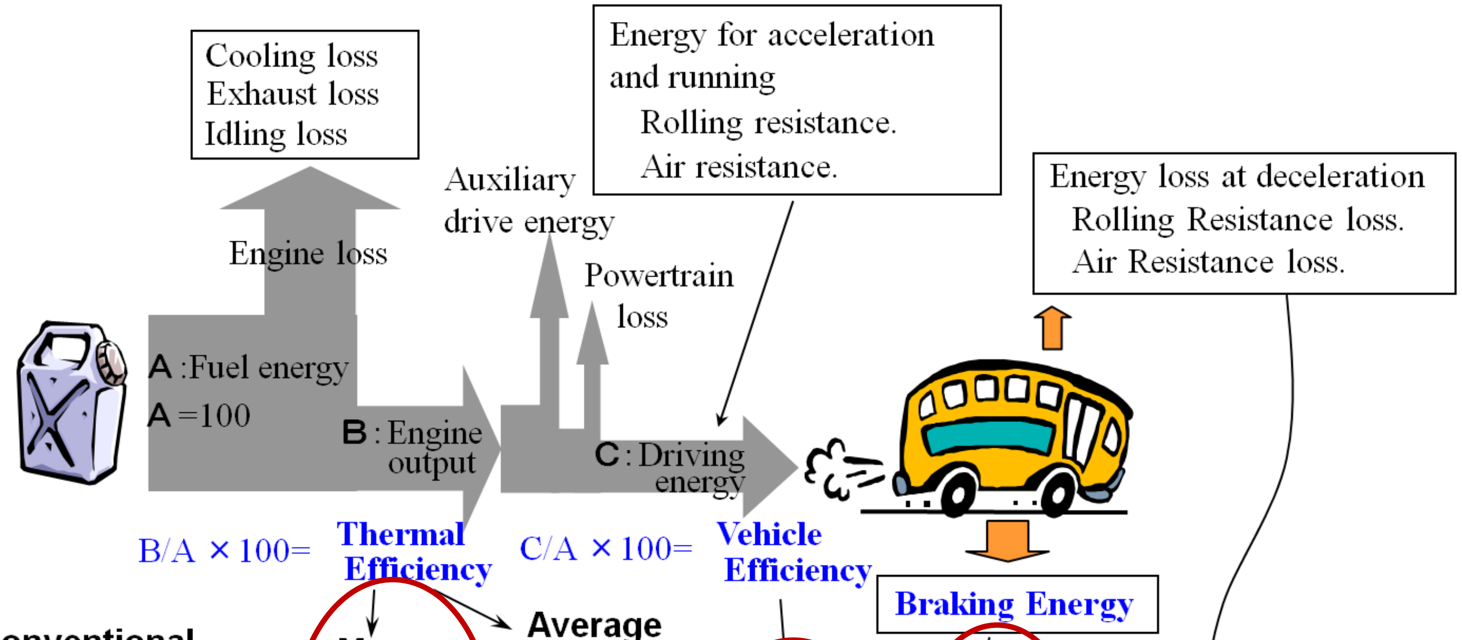
Optimization along the system trajectory



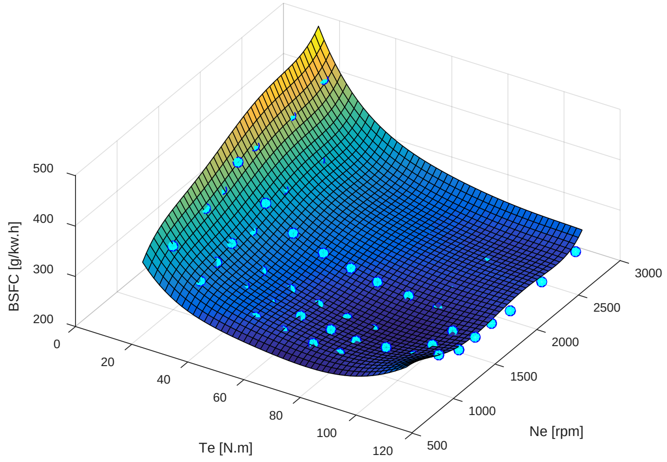




Efficiency in Powertrain



Conventional Engine Vehicles	Max.. Efficiency	Average Efficiency in driving			
Diesel Bus&Truck ;	40%~	~29%~	~21%~	~15%~	~6%~
Gasoline Car ;	~35%~	~18%~	~13%~	~9%~	~4%~
Diesel Bus&Truck ; A=476	190	138	100	70	30
Gasoline Car ; A=769	269	138	100	70	30



From Dr. Sasaki

Parallel hybrid electric powertrain

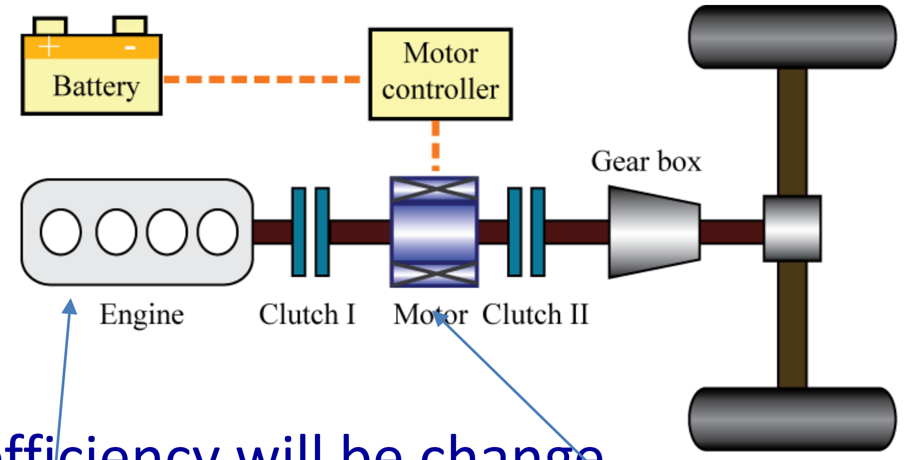
- Total torque must satisfy demand

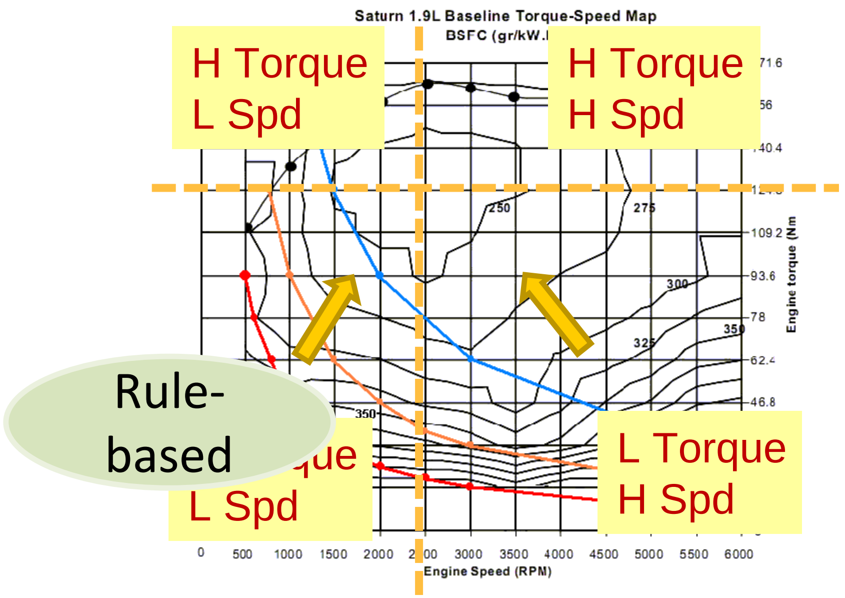
$$T_{drive} = i_g i_0 \eta_f (T_e + T_m)$$

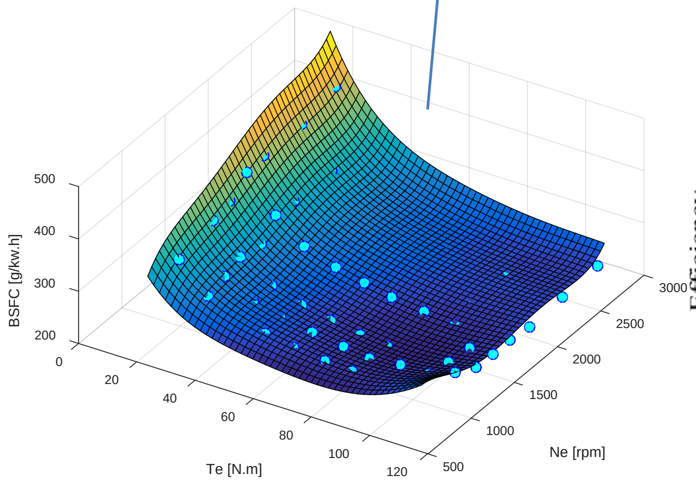
- Rotational speed of engine and motor can be changed by gear ratio

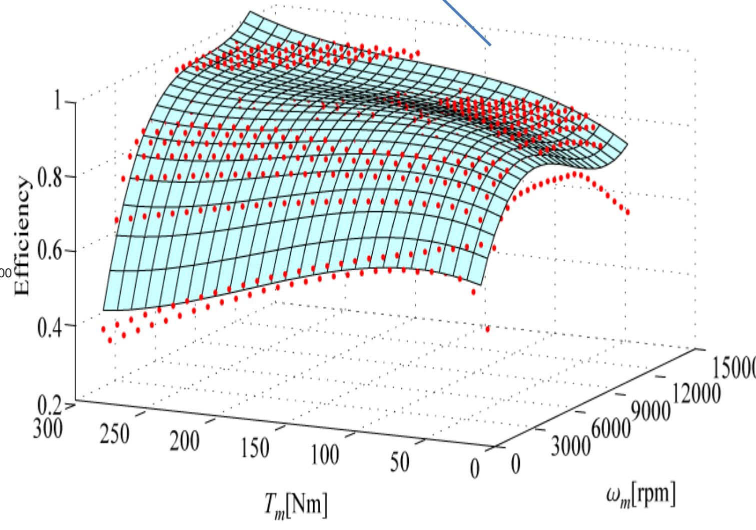
$$i_g i_0 \omega_w = \omega_e = \omega_m$$

- By select one of the torque and gear ratio, the efficiency will be change....









On-line optimization: Receding Horizon Control

$$\min_u J = \min \int_t^{t+T} \{\dot{m}_f(x,u,p) + \rho \dot{m}_e(x,u,p)\} * dt'$$

Subject to :

-- Dynamical mod

-- Physical const

-- SoC Management Constraint

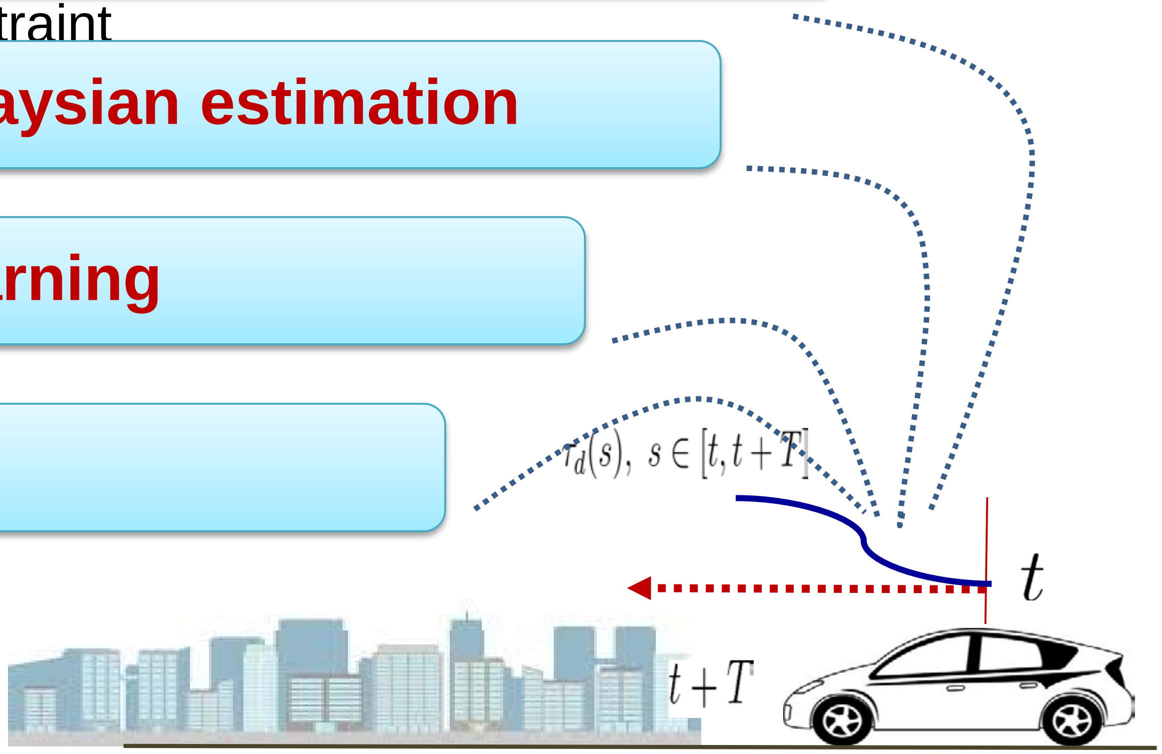
-- External D

ARMA model for prediction

GPR+Baysian estimation

Scenario learning

ELM



Dynamical Model

$$M\dot{v}_s = \frac{T_{drive} - T_{fb}}{R_w} - \underbrace{Mg(\mu_r \cos\theta + \sin\theta)}_{\text{rolling resistance}} - \underbrace{\frac{1}{2}\rho A C_d v_s^2}_{\text{aerodynamic drag}}$$

In this equation, T_{drive} (driving torque) and θ (road slope) are the external inputs to the vehicle system

$$\dot{\text{SoC}} = \frac{-U_{oc}(\text{SoC}) + \sqrt{U_{oc}^2(\text{SoC}) - 4R_b(\text{SoC})P_b}}{2Q_{bmax}R_b(\text{SoC})}$$

Battery power:

Power-split HEV: $P_b = \eta_g^k T_m \omega_m + \eta_m^k T_g \omega_g, \quad k = \begin{cases} -1, & \text{discharging} \\ 1, & \text{charging} \end{cases}$

Parallel HEV: $P_b = \eta_m P_m = \eta_m(T_m, \omega_m) T_m \omega_m$

Solver 1: C/GMRES (on-line solve pontryagin)

Lev Semenovich Pontryagin
1908-1988

- Cost function

$$J(u) = \int_0^T R(x,u)dt + g(x(T))$$

- Constraint condition

$$\dot{x} = f(x,u), \quad x(0) = x_0$$
$$u \in \mathcal{U}$$

- If $u^*(t) \in \mathcal{U}$ is the solution, then

$$\dot{x}^* = \mathcal{H}_p(x^*,p^*,u^*), \quad x^*(0) = x_0$$
$$\dot{p}^* = -\mathcal{H}_x(x^*,p^*,u^*), \quad p^*(T) = g_x(x(T))$$
$$\mathcal{H}(x^*,p^*,u^*) = \max \mathcal{H}(x^*,p^*,u), \quad \forall t \le T$$
$$\text{Mapping}: \quad t \to \mathcal{H}(x^*,p^*,u^*) \quad \text{constant}$$

Hamiltonian

$$\mathcal{H}(x,p,u) = f(x,u)p + R(x,u), \quad x,p \in R^n, \; u \in \mathcal{U}$$

Discretization of the optimality condition (N-steps $N\Delta T = T$)

$$x^*_{k+1}(t) = x^*_k(t) + f[x^*_k(t), u^*_k(t)]\Delta T, \quad x^*_0(t) = x(t)$$
$$\lambda^*_k(t) = \lambda^*_{k+1}(t) + H_x^T\left[x^*_k(t), x_{d_k}(t), u^*_{c_k}(t), \lambda^*_{k+1}(t), \mu^*_k(t)\right]\Delta T,$$
$$H_{u_c}\left[x^*_k(t), x_{d_k}(t), u^*_{c_k}(t), \lambda^*_{k+1}(t), \mu^*_k(t)\right] = 0$$
$$\bar{C}\left[x^*_k(t), u^*_{c_k}(t)\right] = 0 \qquad (k = 0, 1, 2, , N)$$

- Equivalently,

$$F(x,\lambda,U) = 0$$

$$\frac{dF}{dt} = -\sigma F(x,\lambda,U)$$

$$U(t) = [u^T_{c_0}(t) \;\; \mu^T_0(t) \cdots u^T_{c_{N-1}}(t) \;\; \mu^T_{N-1}(t)]^T$$

Solver II: Multiple-shooting

- Single Shooting-based Prediction

$$\min_{u_{k\sim N-1}, s_{k\sim N-1}} J = \min \sum_{i=k}^{k+N} e(s_i, u_i), \qquad x(k) = x_0$$

$$\text{Subject to :}$$

$$\begin{cases} s_k - x_k = 0, \quad x_{k+1} = f(s_k, u_k), \\ s_{k+1} - x_{k+1} = 0, \quad x_{k+2} = f(s_{k+1}, u_{k+1}) \\ \quad \vdots \\ s^x_{k+N-1 k+N-1} = 0, \quad x_{k+N-1} = f(s_{k+N-1}, u_{k+N-1}) \end{cases}$$

$$\Downarrow$$

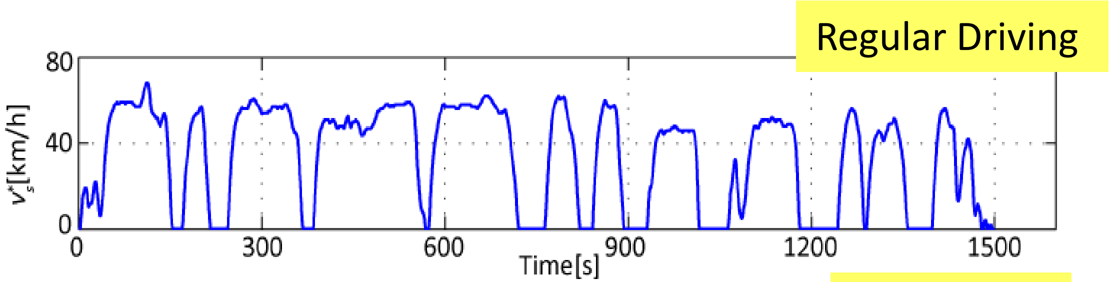
$$\boxed{\min_{u_{k\sim k+N-1}, s_{k\sim k+N-1}} E(x_0, u, s)}$$

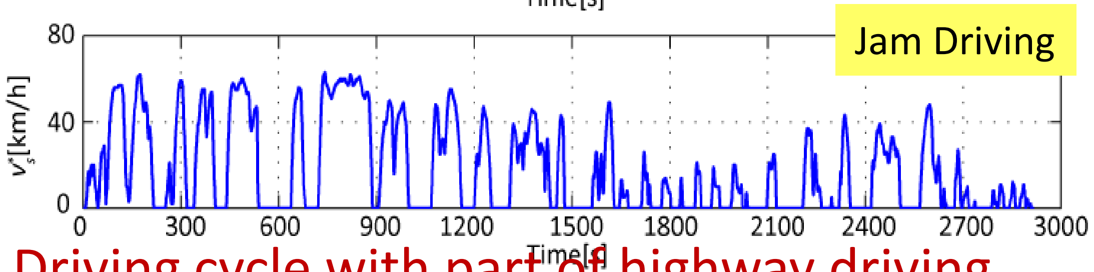
$$\Uparrow$$

Sequential-Quadratic Programing

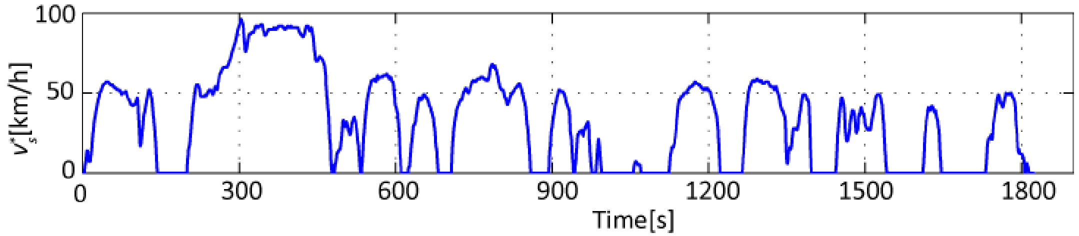
KKT: Karush-Kuhn-Tucker Condition

Validation





Driving cycle with part of highway driving



slope θ=0;

ω_{emax}=4000[rpm], ω_{gmin}=2000[rpm]; SoC(0)=0.9;

SoC^{I}_{min}=0.4, SoC^{II}_{min}=0.5

T=5[s], $\delta\tau$=0.01[s];

J. Zhang, T. Shen, IEEE CST, 2016
Patent with NISSAN, 2015

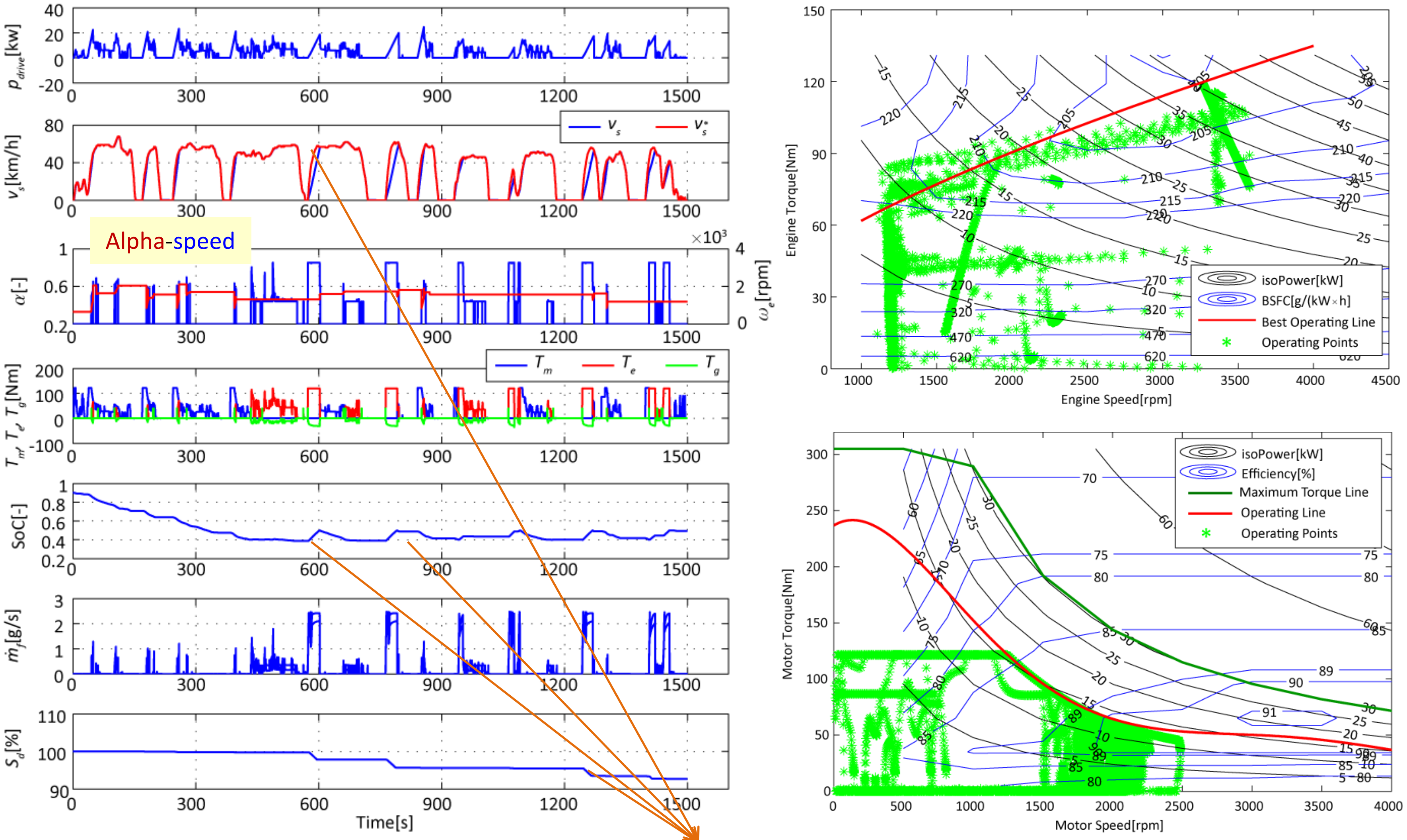
Testing Results on GT-SUIT

	MicroAutoBox II	DS1104
Processor	900 MHz	250MHz
$\delta\tau = 0.01$	real-time execution fail	real-time execution fail
$\delta\tau = 0.02$	real-time execution success; $\|\mathcal{F}\|_{max} = 1.12$	real-time execution fail
$\delta\tau = 0.05$	real-time execution success; $\|\mathcal{F}\|_{max} = 1.85$	real-time execution success; $\|\mathcal{F}\|_{max} = 1.85$

Realtimeness Testing on dSPACE

		Receding Horizon Control Algorithm			Example Algorithm		
		Final SoC[-]	Fuel Consumption[g]	S_d[%]	Final SoC[-]	Fuel Consumption[g]	S_d[%]
Standard City Driving	Regular	0.4942	398.95	92.7	0.5203	570.5	100
	Jam	0.4858	496.78	96.5	0.5066	909.6	
Driving with Highway		0.4709	567.7	91.8	0.5087	764.8	

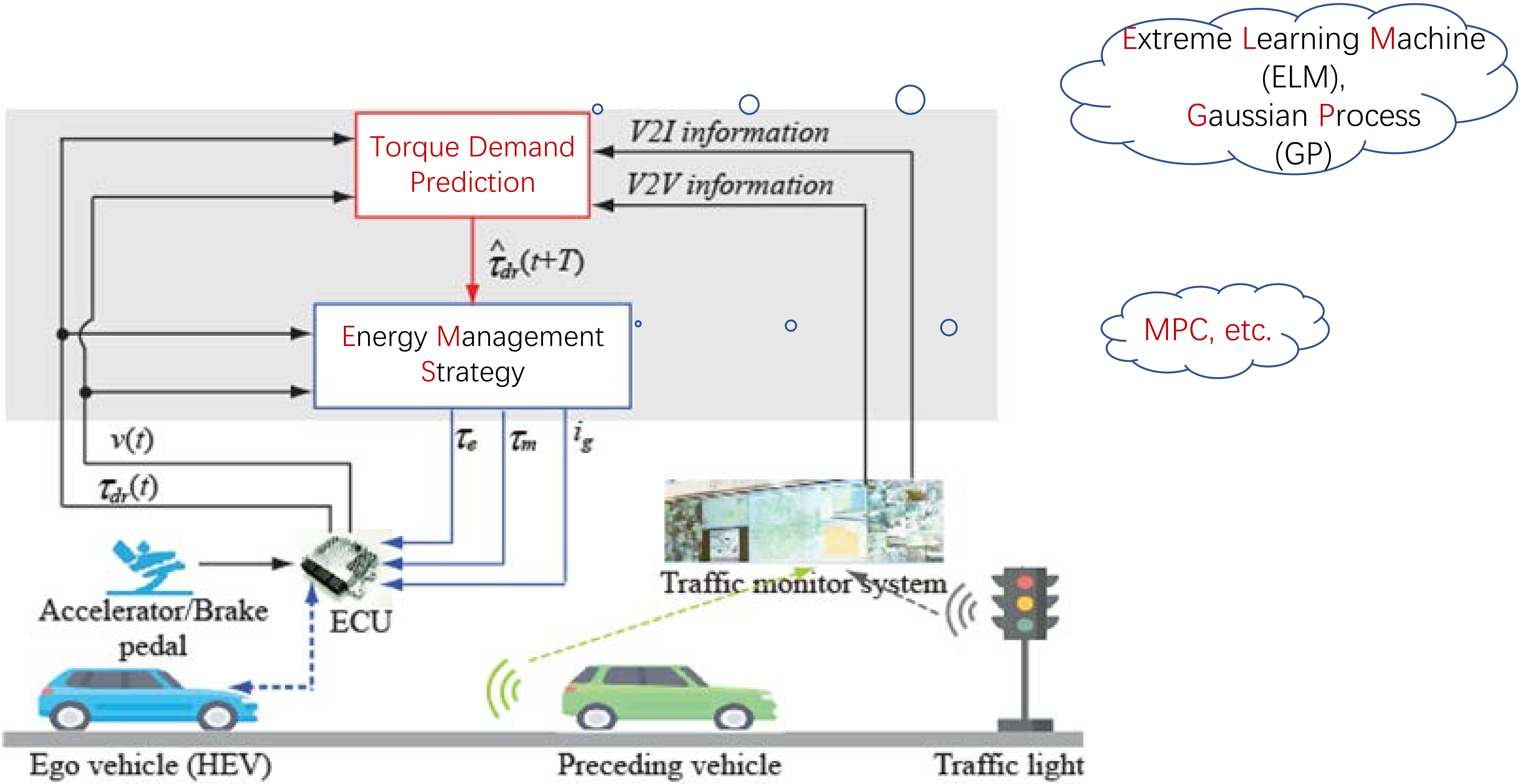
Standard city driving cycle (regular driving)



Acceleration performance is weak due to the limitation of the engine power when the emergency mode is activated

On-line Optimization with Connectivity

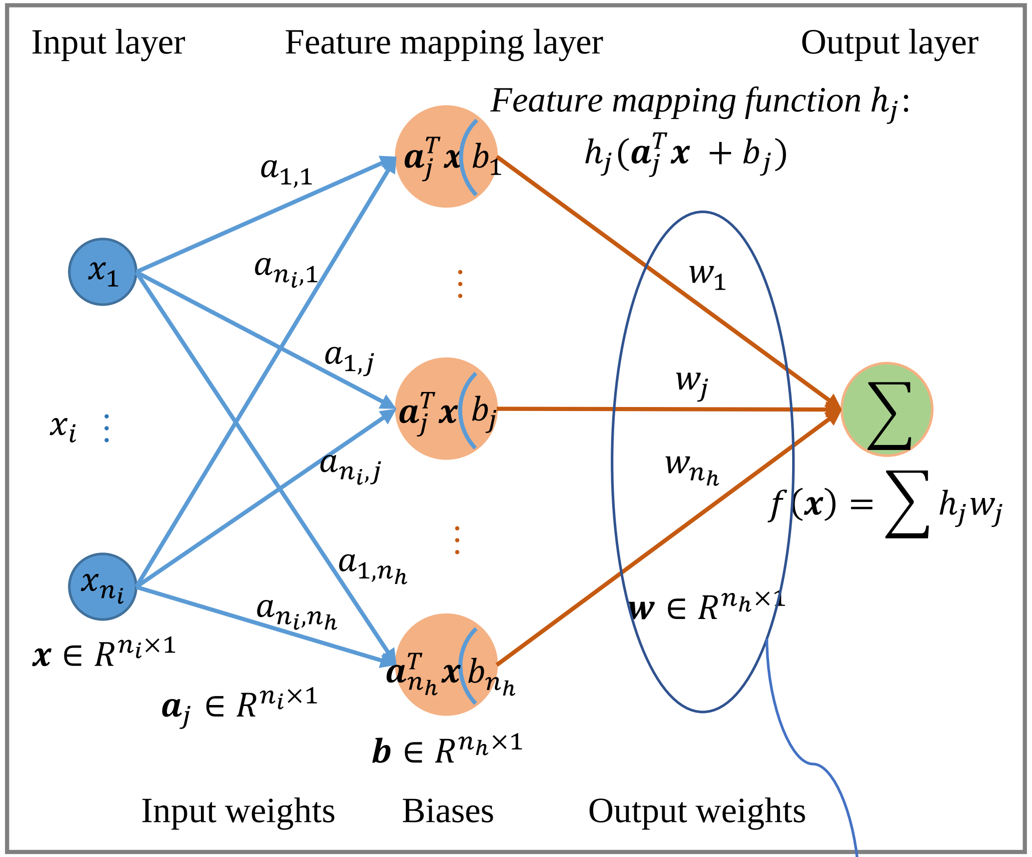
- Framework of V2X-based EMS for Connected HEVs



Zhang, J., Xu, F., Zhang, Y., & Shen, T. ELM-based driver torque demand prediction and real-time optimal energy management strategy for HEVs. *Neural Computing and Applications*, 1-19, 2019

ELM-based Torque Demand Prediction

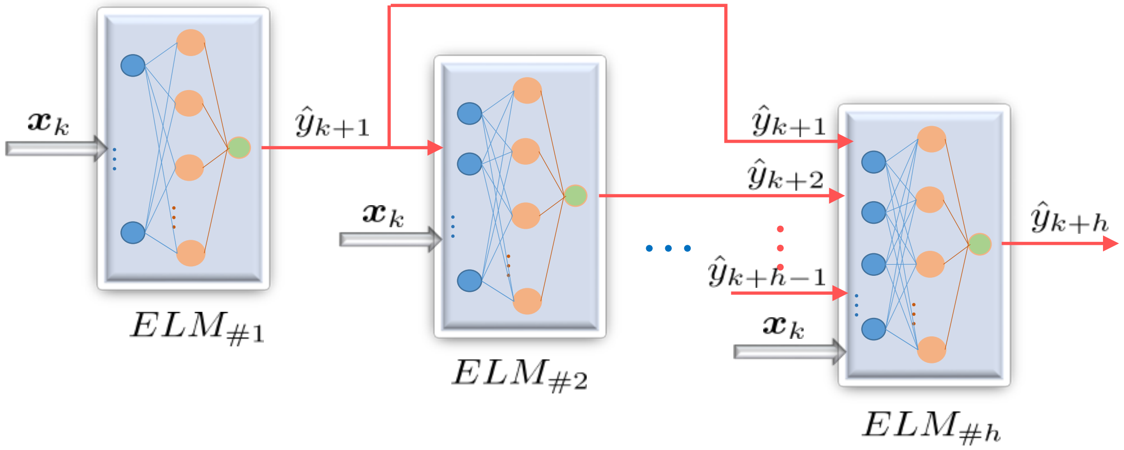
- Basic ELM model structure



The trained parameter: Output weights

Huang, G. B., Zhu, Q. Y., & Siew, C. K. Neurocomputing, 2006.

- Chained ELM for Multi-Step-Ahead Prediction

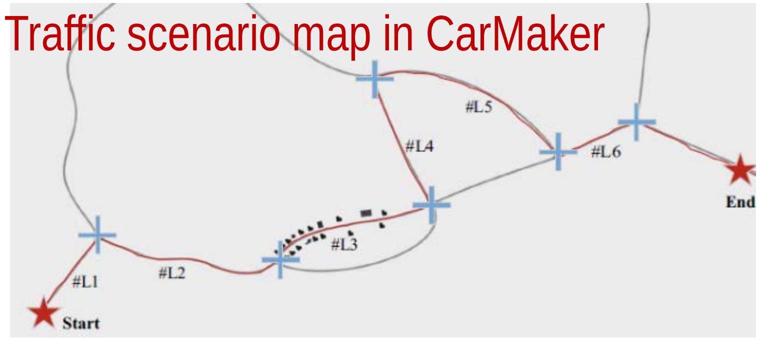


Signal	Vector	Variable	Description	Category
Input	$\mathbf{u}_\tau$	$\tau_{dr(k)}$	Driver torque demand at k step	Ego
		$\tau_{dr(k-1)}$	Driver torque demand at $k-1$ step	Ego
		$\tau_{dr(k-2)}$	Driver torque demand at $k-2$ step	Ego
	$\mathbf{u}_c$	α_g	Gas pedal at k step	Ego
		a_{α_g}	Gas pedal rate at k step	Ego
		α_b	Braking pedal at k step	Ego
		a_{α_b}	Braking pedal rate at k step	Ego
		v_p	Preceding vehicle speed at k step	V2V
		a_{v_p}	Preceding vehicle acceleration at k step	V2V
		s_h	Headway at k step	V2V
		a_v	Ego vehicle acceleration at k step	Ego
		τ	Driving and braking torque at k step	Ego
	$\mathbf{u}_l$	l_s	Next intersection traffic light phase at k step	V2I
		l_t	Next intersection traffic light timing at k step	V2I
	$\mathbf{u}_s$	s_l	Distance to next intersection at k step	V2I
		v	Ego vehicle speed at k step	Ego
Output		$\hat{\tau}_{dr(k+1)}$	Driver torque demand at $k+1$ step	Ego

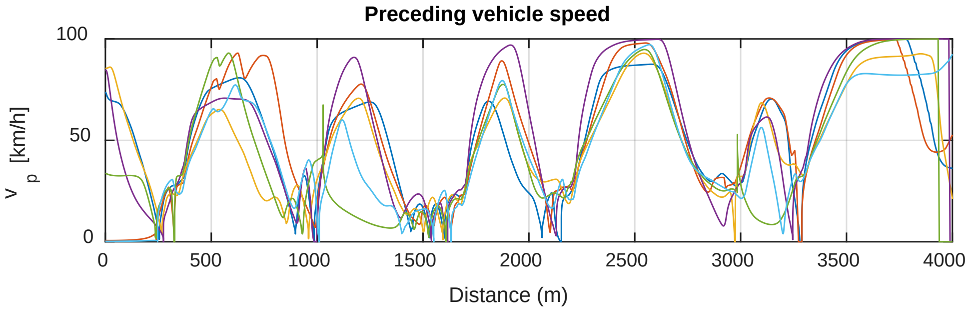
Validation with traffic simulator

➢ Model Training

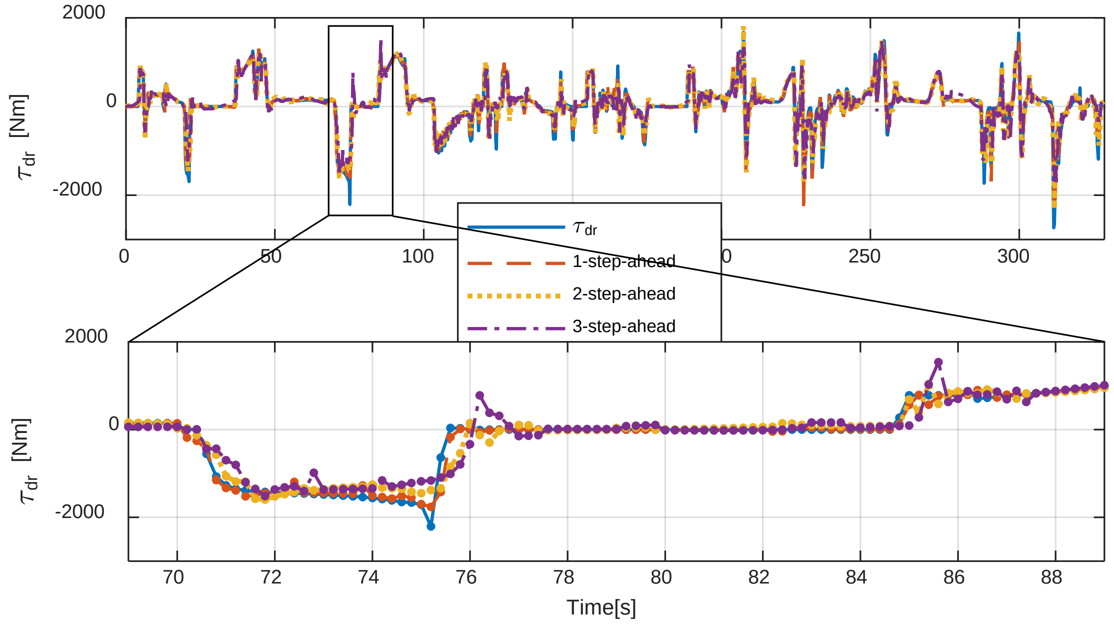
Traffic scenario map in CarMaker

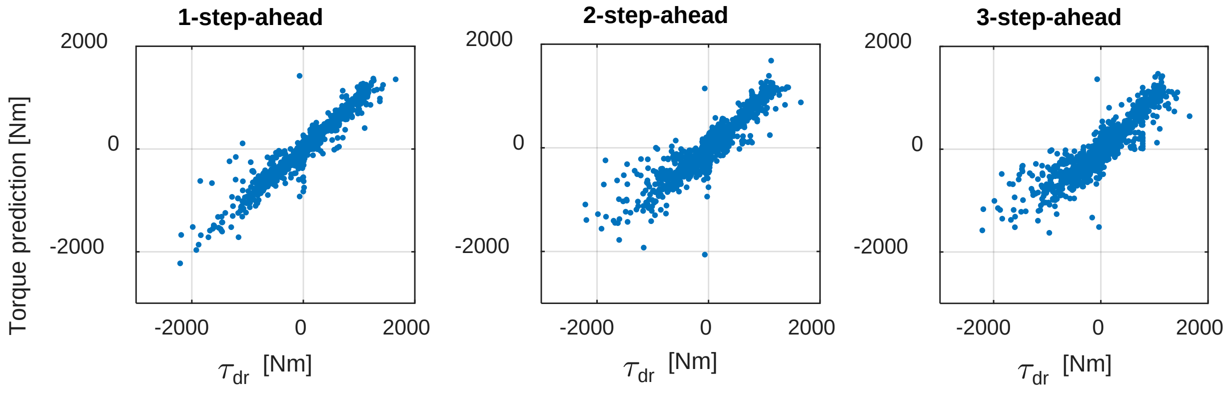


30 groups of scenarios for training and testing



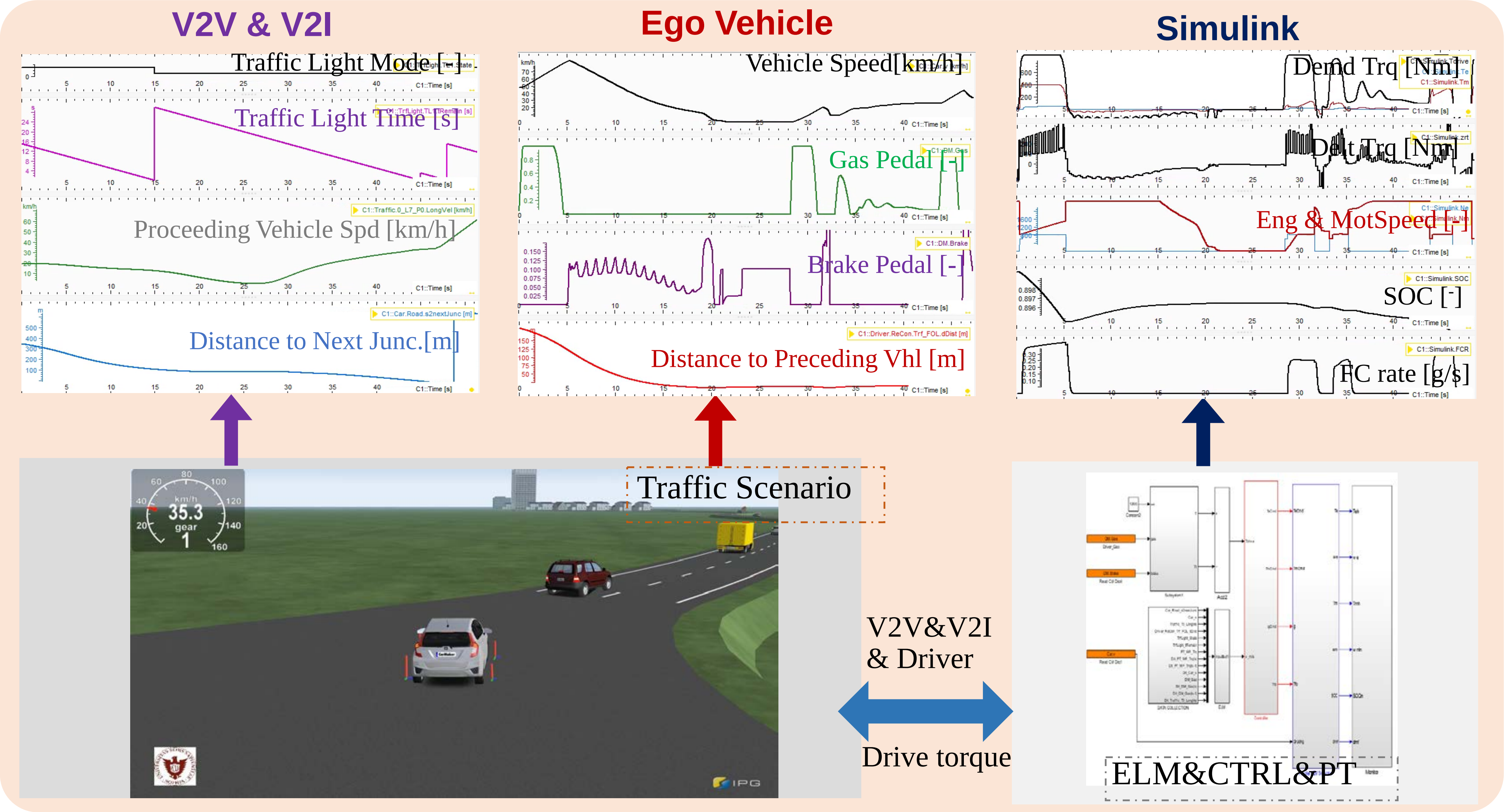
➢ Model Testing





Powertrain Level Optimization in HEVs

- Traffic-in-the-Loop Validation: EMS with ELM-based Torque Demand Prediction



Traffic-in-the-Loop Validation: EMS with ELM-based Torque Demand Prediction

Table 1 Result with one-step ahead torque demand prediction

cases	with predicted $\hat{\tau}_{dr(k+1)}$			$\hat{\tau}_{dr(k+1)} = \tau_{dr(k)}$			fuel economy	efficiency improvement
	fuel /[L]	electricity /[kWh]	efficiency /[¥/MJ]	fuel /[L]	electricity /[kWh]	efficiency /[¥/MJ]		
no.1	1.0137	1.1296	13.1449	1.0154	1.1225	13.1346	+0.17%	-0.08%
no.2	1.0385	1.0258	13.1913	1.0412	1.0169	13.1735	+0.26%	-0.14%
no.3	1.0959	0.9148	12.8154	1.0990	0.9133	12.8055	+0.28%	-0.08%

Table 2 Result with three-step ahead torque demand prediction ($i = 1, 2, 3$)

cases	with predicted $\hat{\tau}_{dr(k+i)}$			$\hat{\tau}_{dr(k+i)} = \tau_{dr(k)}$			fuel economy	efficiency improvement
	fuel /[L]	electricity /[kWh]	efficiency /[¥/MJ]	fuel /[L]	electricity /[kWh]	efficiency /[¥/MJ]		
no.1	1.0022	1.0954	12.9519	1.0072	1.0933	13.0326	+0.50%	+0.62%
no.2	1.0326	1.0232	13.1230	1.0403	1.0168	13.1361	+0.74%	+0.10%
no.3	1.0957	0.9147	12.8128	1.0988	0.9132	12.8143	+0.28%	+0.01%

- With one-step ahead prediction data, the cost efficiency has little improvement;
- The cost efficiency could benefit from a longer prediction horizon by V2X information.

Prospect: Further Research

-- Completely Model-free Learning of Optimal Control

-- Connected Powertrain Control

Learning-based Approximate Optimal

- Control Plant

$$\dot{x} = f(x) + g(x)u$$

- Cost Function

$$J(x) = \int_0^\infty L(x,u)dt$$

- Optimization Problem

$$\min_u J(x) = \min_u \int_0^\infty L(x,u)dt, \quad \text{s. t.}$$

$$\dot{x} = f(x) + g(x)u, \quad x(0) = x_0$$

- Value Function

$$V^*(t_0, \xi) = \min_u \int_{t_0}^\infty L(x,u)dt, \quad x_0 = \xi$$

Fundamental Theorem

Let Quadratic Form on Control Input

$$L(x,u) = Q(x) + \frac{1}{2}u^T R u, \quad R = R^T > 0$$

$V^*(x)$ is value function, iff

$$L_f V^*(x) - \frac{1}{4} L_g V^*(x) R^{-1} L_g^T V^*(x) + Q(x) = 0$$

equivalently,

$$L_f V^*(x) - \frac{1}{4} L_g V^*(x) u^* + Q(x) = 0$$

Furthermore, the optimal control is given by

$$u^*(t) = -R^{-1} L_g^T V^*(x)$$

Approximation: Policy Iteration and Learning

- Policy iteration

$$\nabla V^{i+1}(x)\left(f(x)+g(x)u^i\right)\} = 0$$

$$u^{i+1} = -R^{-1}\{\nabla V^{i+1} g(x)\}^T$$

$V^i(x) \to V^*(x), \quad u^i(x) \to u^*(x) \;\text{ as } i \to \infty, \quad u^0(x)$ **stabilizing controller**

- Neural Network-based Approximation

$$V^i(x) = \sum_{j=1}^{N} w_j^i \sigma_j(x)$$

Residual error

$$E^i(x(t),T) = \int_t^{t+T} L(x,u^i)d\tau + \sum_{j=1}^{N} w_j^i \left(\sigma_j(x(t+T) - \sigma_j(t)\right)$$

- LS algorithm $\quad (w_1^{i*}, w_2^{i*}, \cdots, w_N^{i*}) = \text{argmin}\{E^i\}^2$

- Galerkin spectral approximation method

  --Randal Beard & Saridis, Automatica, '97

- Neural network approximation method

  --Abu Khalaf & Lewis, Automatica, '05

New Challenge: Completely Model-free Solution

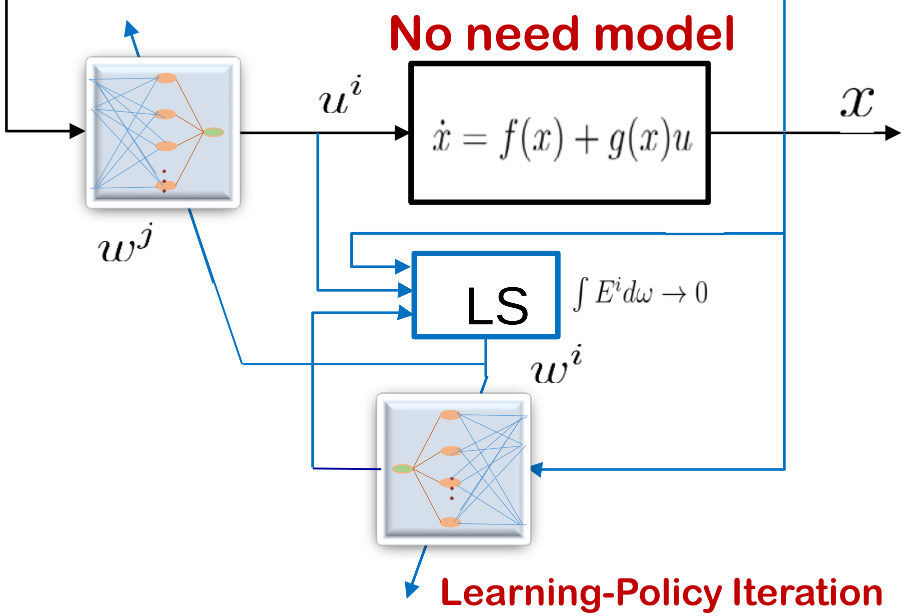
- Model
  - -- Structure: Nonlinear Affine
  - -- Unknown $f(x),\ \ g(x)$
- Policy-Iteration
- Two NN Approximation
- Guaranteed Convergence

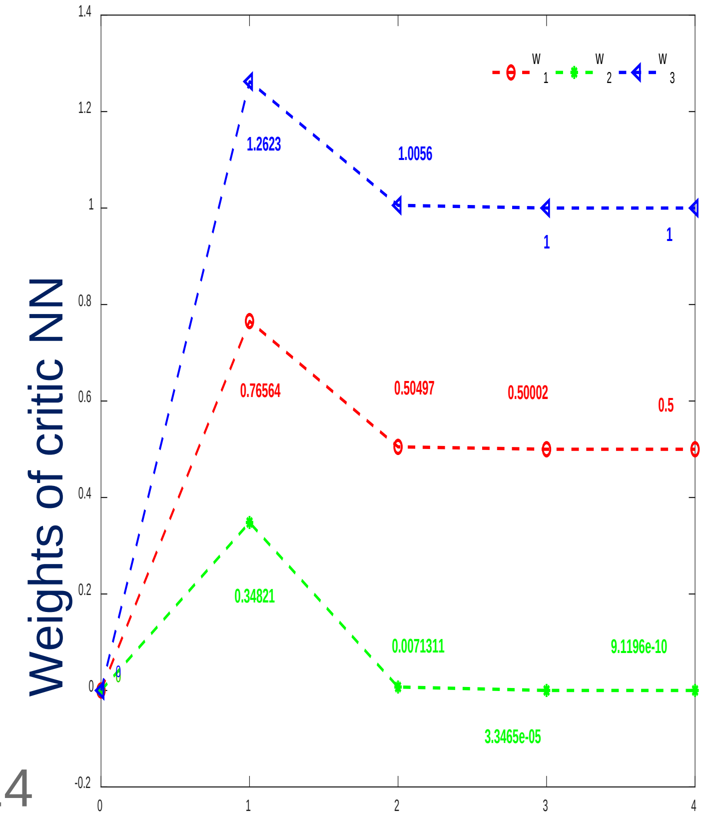
$$\begin{cases} \dot{x}_1 = -x_1 + x_2 \\ \dot{x}_2 = -\dfrac{1}{2}(x_1 + x_2) + \dfrac{1}{2} x_2 \sin^2(x_1) + \sin(x_1)\, u \end{cases}$$

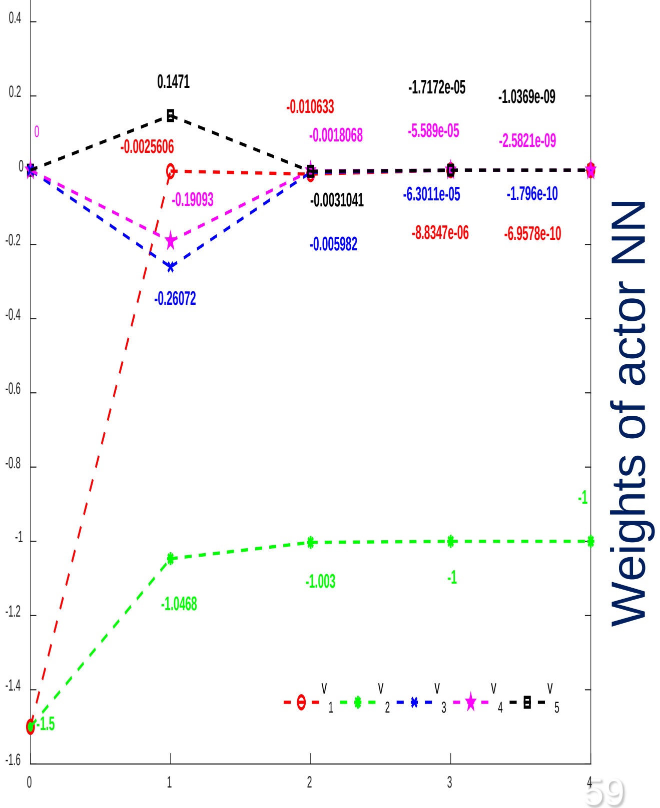
$$J = \int_0^{\infty} (x_1^2 + x_2^2 + u^2) dt$$

$$u^* = -\sin(x_1)\, x_2$$

$$V^* = \frac{1}{2} x_1^2 + x_2^2$$



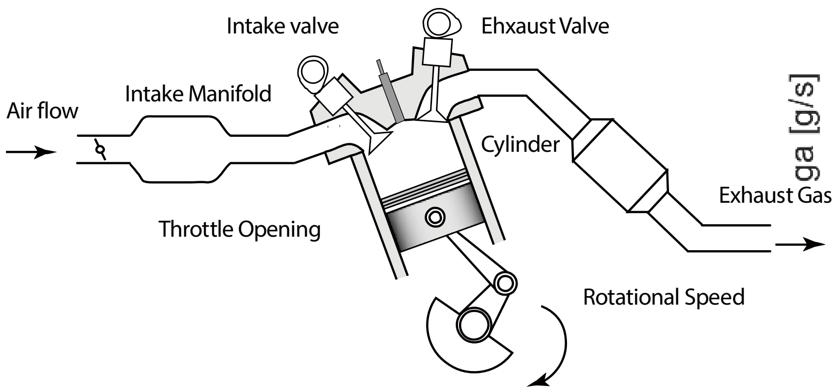


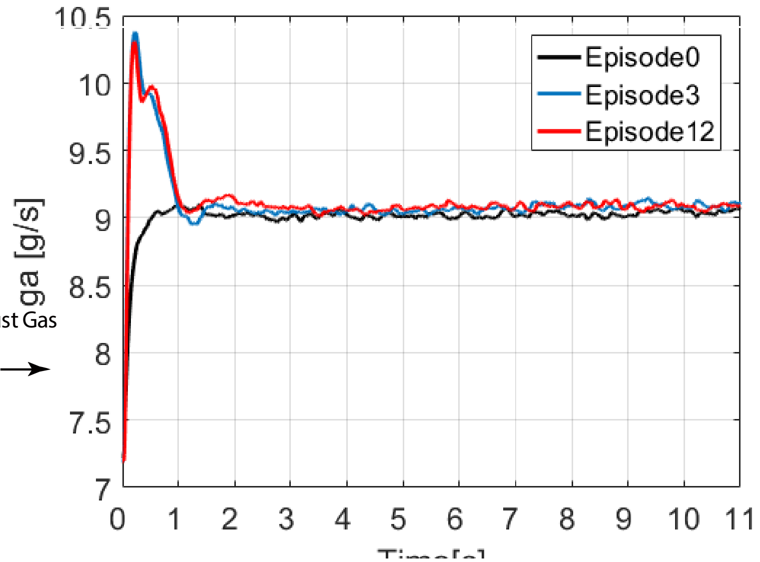


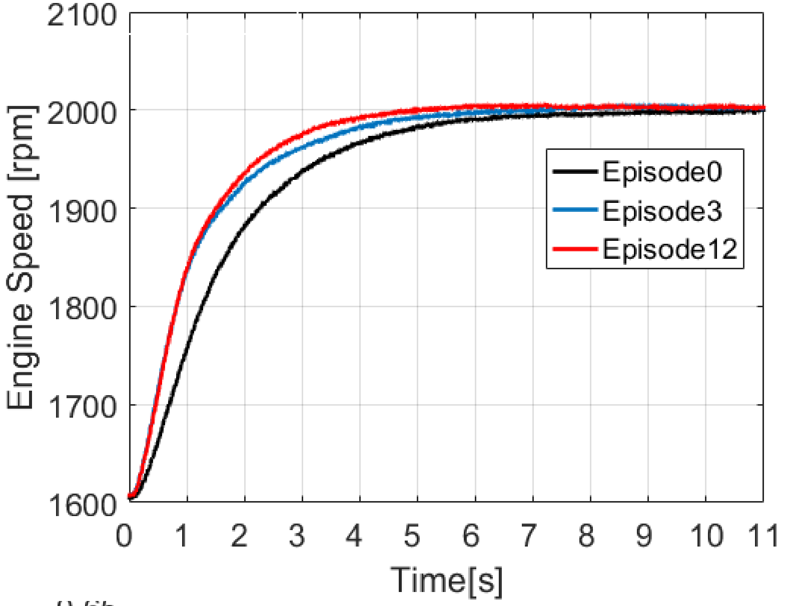
Jiang & Jiang, Automatica, ‘12

Luo & Wu & Huang & Liu,Automatica, ‘14

New Challenge: Completely Model-free Solution



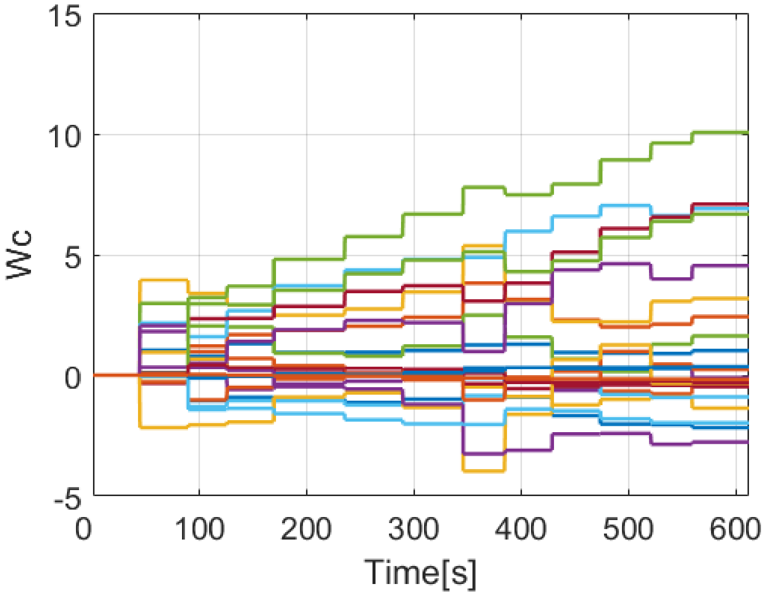


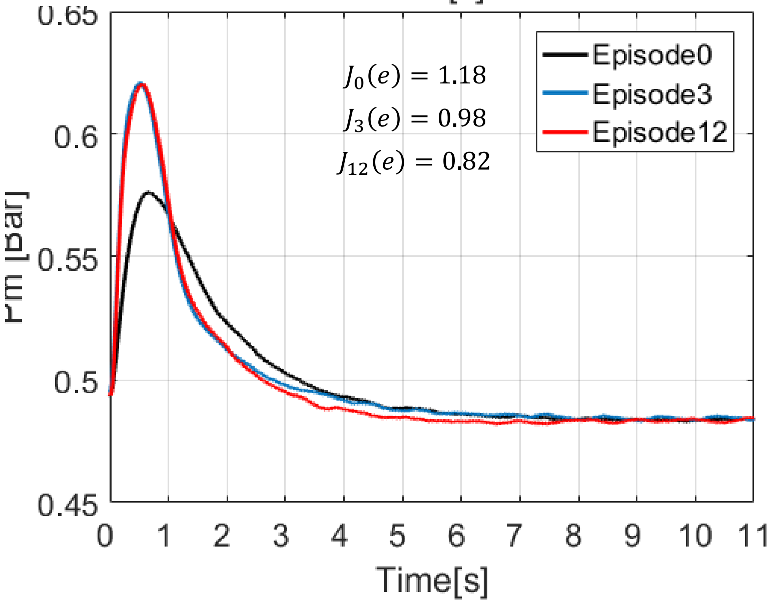


- $\dot{p}_m = \frac{RT_m}{V_m}(\dot{m}_{in} - \dot{m}_{out})$
- $J\dot{\omega} = \tau_e - \tau_f - \tau_l$

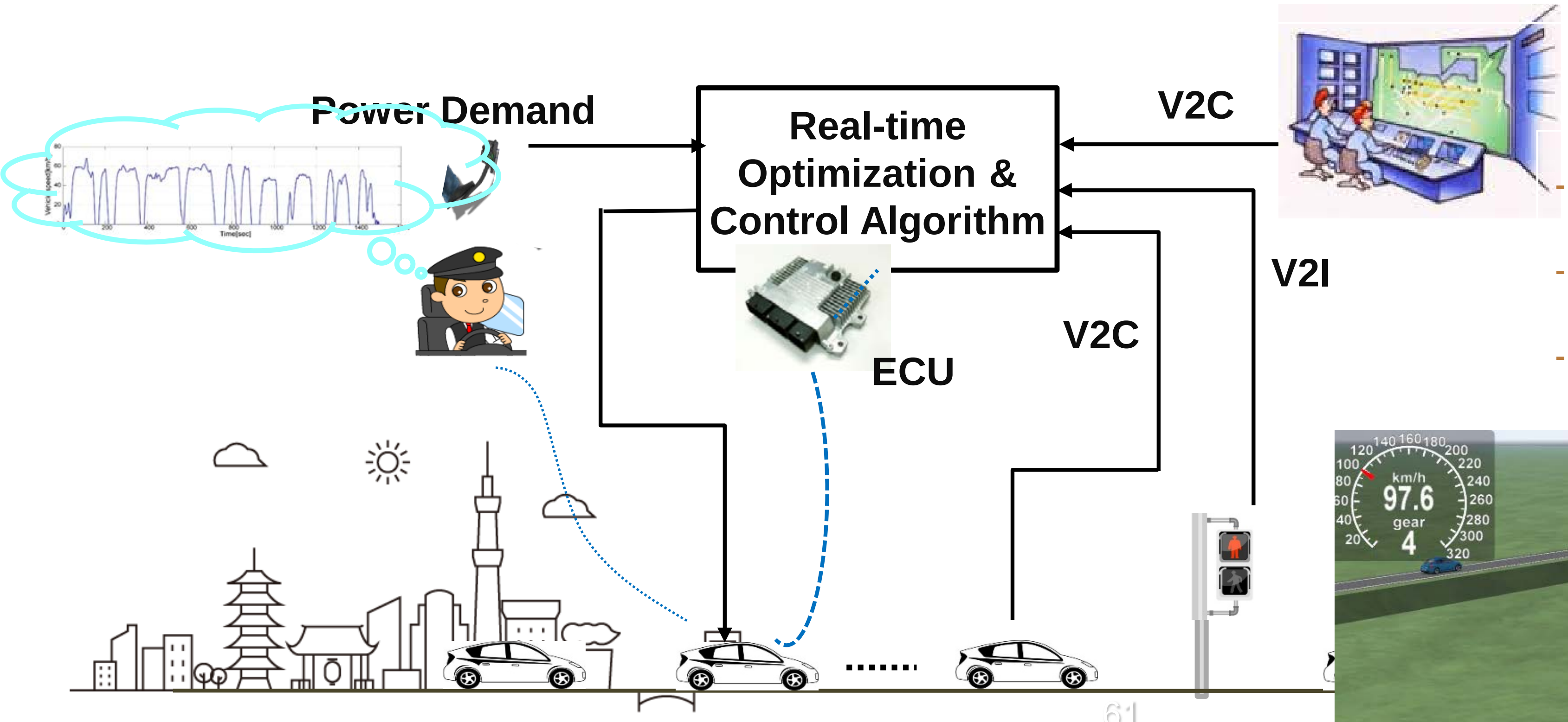
$$\dot{m}_{in} = \text{ga}$$

$$\dot{m}_{out} = \rho_{in}\eta_v(p_m, \omega_e)\frac{V_d}{N}\frac{\omega_e}{2\pi}$$

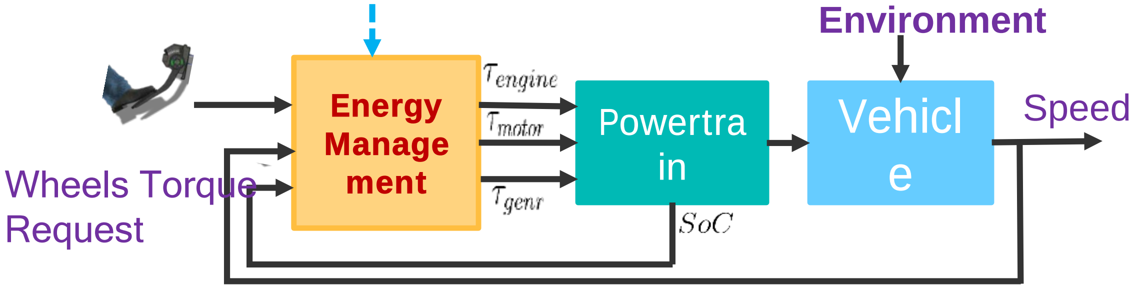




Control Vehicles with Efficiency Consideration



- Fixed Distance, free time,
- fixed end-point
- Saving time and energy




Sophia University, Faculty of Science and Technology,
Department of Engineering and Applied Sciences,

Shen Laboratory

Site Map
Japanese

- Home
- Publications
- Research Projects
- Laboratory
- Activities
- Announcement
- Education
- People
- Access
- Link

上智大学
SOPHIA UNIVERSITY

HOME > English > news > Ph.D Short Course is opened for registration now! > Ph.D Short Course, Nov. 2017

Ph.D Short Course, Nov. 2017

Address: Sophia University, Yotsuya Campus, Tokyo, Japan
Date: November 9-11, 2017

Introduction

This short course aims to introduce several advanced control theories and applications in automotive powertrain system. The topics include numerical solution of optimal control problems, logical dynamic systems, and model predictive control, and their applications in developing advanced automotive powertrain control systems. During the course, an interactive poster session and round table discussion will be organized for the attenders.

Lecturers

Lei Wang, Associate Professor, Dalian University of Technology, China
Thivaharan Albin, Senior Researcher, ETH Zürich, Switzerland
Hongsheng Qi, Associate Professor, Chinese Academy of Sciences, China

please download the flyer here !

Connectivity Provides New Paradise for Control

http://shenlab.jp/en/


Welcome to Tokyo
SICE Annual Conference, 09, 2021
Thank you!
©TCVB