



EA 4353

# $H^\infty$ Predictive Control Design for Networked Control Systems

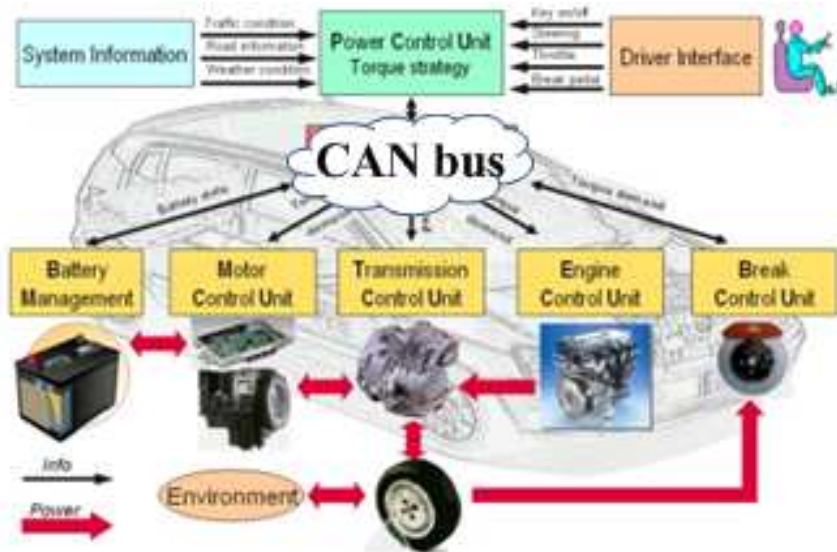
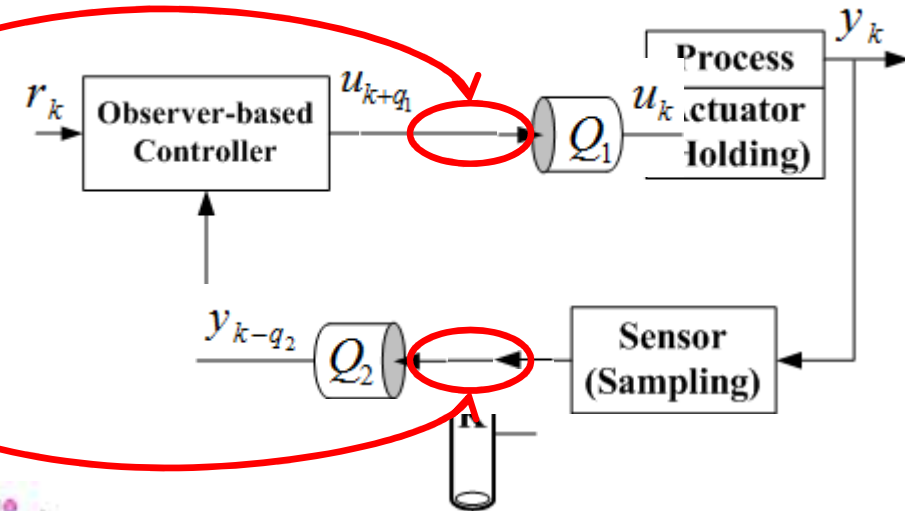
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# Énoncé du Problème

- Network-induced Delay
- Packet dropout or out-of-order
- Process noise



## Combustion Engine for Range Extended Electric Vehicle

- Engine control unit  
(An electromagnetic Valve)
- Battery Management Unit  
(Battery State-of-Charge)



## Objective

- 1, Proposed GPC controller
- 2, Extended  $H^\infty$ -GPC algorithm regarding robust issue
- 3, Parameter tuning
- 4, GPC application in an academic model
- 5, Relative study of network-faced state estimation
- 6, Battery state-of-charge estimation problem

# Introduction to Generalized Predictive Controller

## □ CARIMA Model :

$$A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t-1) + \frac{e(t)}{\Delta}$$

## □ Cost Function :

$$J = \sum_{j=N_1}^N \delta(j) [\hat{y}(t+j|t) - r(t+j)]^2 + \sum_{j=1}^{N_u} \lambda_u(j) [\Delta u(t+j-1)]^2$$

## □ Control Signal :

$$u = (G^T G + \lambda I)^{-1} G^T (y_d - f)$$

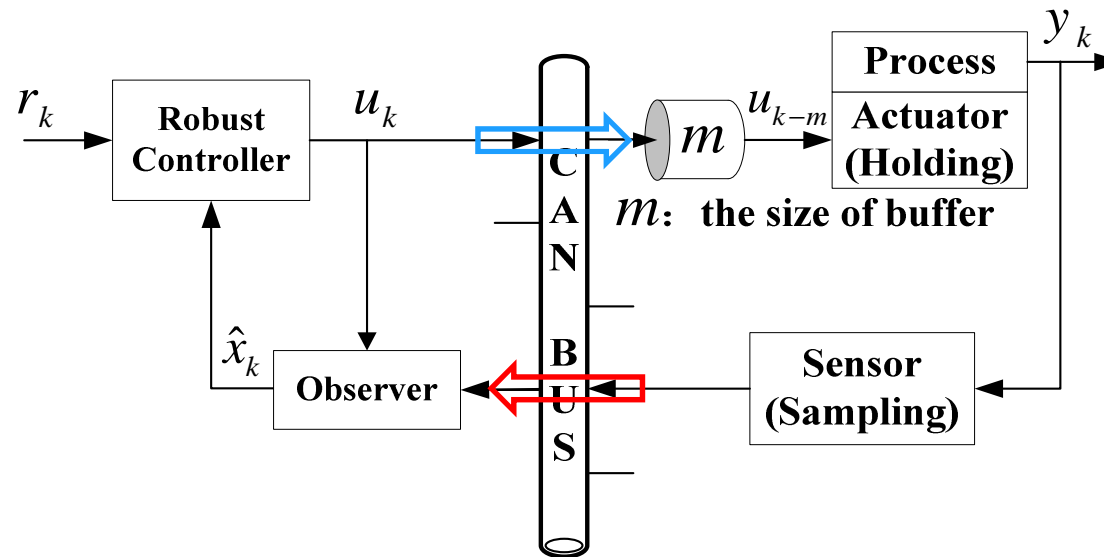


## Main Problems of GPC

- 1, Solution to Network-induced problems
- 2, State-space-model-based system
- 3, Robustness against process noise and model uncertainties
- 4, GPC Parameter computation and tuning
- 5, System stability

## Solution to Network-induced problems

The structure of the networked control system :



- Buffering technique for fixing time-delays ⇨ control channel
- State estimation in NCS ⇨ feedback channel
- The maximal value of a consequent packet losses event:  $S$
- The maximal controller-to-actuator delay:  $T$

# State-space-model-based System

Incremental state-space model :

$$\begin{cases} x_{k+1} = \Phi x_k + \Gamma u_{k-m} + E \omega_k \\ z_k = C x_k \\ y_k = z_k + v_k \end{cases}$$
$$x_k = \Phi x_{k-1} + \Gamma u_{k-m-1} + E \omega_{k-1}$$

$$\Delta \omega_k = \omega_k - \omega_{k-1}$$

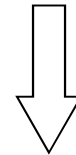
$$\Delta u_{k-m} = u_{k-m} - u_{k-m-1}$$

$$\begin{cases} x_{k+1} = (\Phi + I) x_k - \Phi x_{k-1} + \Gamma \Delta u_{k-m} + E \Delta \omega_k \\ z_k = C x_k \\ y_k = z_k + v_k \end{cases}$$

# GPC Design

- The  $j$ -step predictive output estimation :

$$\hat{y}_{k+j|k} = \sum_{i=1}^{j-m+1} C\Phi^{i-1} \text{Exp}[x_{k+m}] - \sum_{i=2}^{j-m+1} C\Phi^{i-1} \text{Exp}[x_{k+m-1}] + \sum_{h=2}^{j-m+1} \sum_{i=2}^h C\Phi^{h-i} \Gamma \Delta u_{k+j+1-h|k}$$



- Vector form :

$$\hat{Y}_k = G\Delta U_k + T_k$$

$$\Delta U_k = \left\{ \Delta u_{k|k}^T, \Delta u_{k+1|k}^T, \dots, \Delta u_{k+N_u-1|k}^T \right\}^T$$

$$T_k = M_1 \hat{x}_{k+m|k} - M_2 \hat{x}_{k+m-1|k}$$

$$\hat{Y}_k = \left[ \hat{y}_{k+m+1|k}^T, \hat{y}_{k+m+2|k}^T, \dots, \hat{y}_{k+N|k}^T \right]^T$$



# GPC Design

- The GPC cost function :

$$J(k, \Delta U_k) = \text{Exp} \left\{ \sum_{j=m+1}^N (y_{k+j|k} - \gamma_{k+j})^2 + \sum_{j=1}^{N_u} \lambda_j (\Delta u_{k+j-1|k})^2 \right\}$$

- Vector form :

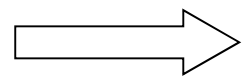
$$J(k, \Delta U_k) = [\hat{Y}_k - R_k]^T [\hat{Y}_k - R_k] + \Delta U_k^T \lambda \Delta U_k$$

$$\lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \lambda_{N_u} \end{bmatrix}$$

$$R_k = [\gamma_{k+m+1}^T, \gamma_{k+m+2}^T, \dots, \gamma_{k+N}^T]^T$$

- Calculating control law sequence :

$$\min_{\Delta U_k} J(N)$$



$$\Delta U_k = H (I - A_b) G^T \bullet \left[ A_a \gamma_k - (I - A_b) M_1 \hat{x}_{k+m|k} + (I - A_b) M_2 \hat{x}_{k+m-1|k} \right]$$

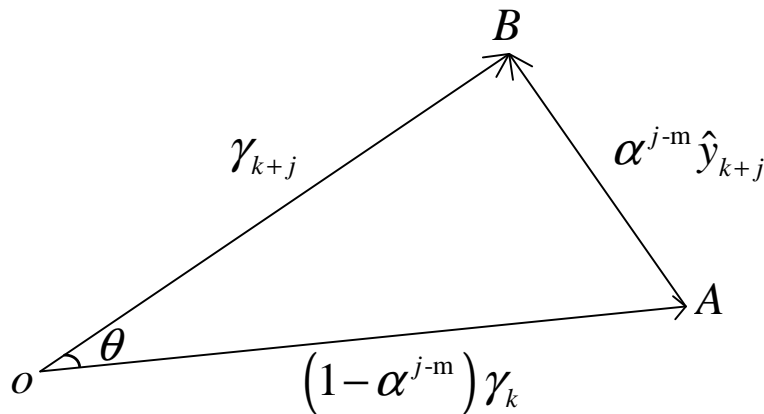
## The Future Reference Trajectory

- The Multi-step rule of reference :

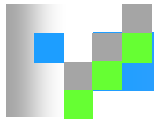
$$\gamma_{k+m+1} = \alpha \hat{y}_{k+m+1} + (1-\alpha) \gamma_k$$

$$\gamma_{k+j} = \alpha^{j-m} \hat{y}_{k+j} + (1-\alpha^{j-m}) \gamma_k, \quad j \geq m+2$$

- The vector structure diagram of the future reference :



$$R_k = \underbrace{\begin{bmatrix} \alpha & 0 & \dots & 0 \\ 0 & \alpha^2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \alpha^{N-m} \end{bmatrix}}_{A_b} \hat{Y}_k + \underbrace{\begin{bmatrix} 1-\alpha \\ 1-\alpha^2 \\ \vdots \\ 1-\alpha^{N-m} \end{bmatrix}}_{A_a} \gamma_k$$



## Robustness against Process Noise and Model Uncertainties

- State space model with incremental control law :

$$x_{k+1} = \underbrace{\left[ \Phi + I - \Gamma \beta_1 H (I - A_b) G^T (I - A_b) M_1 \right]}_M x_k - \underbrace{\left[ \Phi - \Gamma \beta_1 H (I - A_b) G^T (I - A_b) M_2 \right]}_N x_{k-1} + E \Delta \omega_k$$

- We define  $H^\infty$  control performance index with a positive scalar  $r$ . The system under the incremental control law should satisfy: if (1) is satisfied for  $\Delta \omega_k \in \ell_2[0, \infty)$ , the system is  $H^\infty$  norm stable.

$$\|Cx_k\|_2 \leq r \|\Delta \omega_k\|_2 \quad (1)$$



$$\Lambda = \sum_{k=0}^{\infty} \left[ x_k^T C^T C x_k - r^2 \Delta \omega_k^T \Delta \omega_k \right] \leq 0$$

## System stability

- Lyapunov function :

$$V_k = x_k^T P x_k + x_{k-1}^T Q x_{k-1} > 0$$

- Proof :

$$\Delta \leq \Delta + V_k = \sum_{k=0}^{\infty} [\Delta V_k + z_k^T z_k - r^2 \Delta \omega_k^T \Delta \omega_k] < 0$$

$$= \sum_{k=0}^{\infty} \left\{ \begin{bmatrix} x_k \\ x_{k-1} \\ \Delta \omega_k \end{bmatrix}^T \left( \begin{bmatrix} M^T \\ N^T \\ E^T \end{bmatrix} P [\times] + \begin{bmatrix} Q - P + C^T C & 0 & 0 \\ 0 & -Q & 0 \\ 0 & 0 & -r^2 \end{bmatrix} \begin{bmatrix} x_k \\ x_{k-1} \\ \Delta \omega_k \end{bmatrix} \right) \right\} < 0$$

$$\begin{bmatrix} M^T \\ N^T \\ E^T \end{bmatrix} P [\times] + \begin{bmatrix} Q - P + C^T C & 0 & 0 \\ 0 & -Q & 0 \\ 0 & 0 & -r^2 \end{bmatrix} < 0 \Rightarrow \begin{bmatrix} Q - P + C^T C & 0 & 0 & * \\ 0 & -Q & 0 & * \\ 0 & 0 & -r^2 & * \\ PM & PN & PE & -P \end{bmatrix} < 0$$

## Theorem

For a given  $r > 0$ , if there exist symmetric positive definite matrices  $P$  and  $Q$  such that the LMI is solvable, then the system is  $H_\infty$  norm stable.

$$\begin{bmatrix} Q - P + C^T C & 0 & 0 & * \\ 0 & -Q & 0 & * \\ 0 & 0 & -r^2 I & * \\ P\Phi + P - X(I - A_b)G^T(I - A_b)M_1 & X(I - A_b)G^T(I - A_b)M_2 - P\Phi & PE & -P \end{bmatrix} < 0$$

where  $X = P\Gamma\beta_1 H$

## Parameter Computation and Tuning

- Computation of the control-weighting parameter :

$$\lambda_1 = \frac{1}{\Gamma^T K K^T \Gamma} \left[ \Gamma^T \Gamma \beta_1 K^T \Gamma - \Gamma^T K (I - A_b) G^T (I - A_b) G K^T \Gamma \right]_{K=P^{-1}X}$$

- Parameter tuning (a rule aiming to adapt the control-weighting parameter with respect to the smooth parameter change):

$\alpha$	$\alpha_1$	$\alpha_2$	$\alpha_3$
$\lambda$	$\lambda_1$	$\lambda_2$	$\lambda_3$

- ❑ a function adapting the control-weighting parameter in real-time when a large reference drop or rise is detected.
- ❑ a table between the control-weighting parameter and the smooth parameter with respect to any specific maximal controller-to-actuator delay like the above Table.

## Academic Model

- System :  $\Phi = \begin{bmatrix} 1.2 & -0.7 \\ 1 & 0 \end{bmatrix}, \Gamma = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, C = [0.5 \quad 0.1], E = \begin{bmatrix} 0.1 \\ 0.1 \end{bmatrix}$

$$\omega_{kT} \sim N(0, Q) \quad \text{with variance } Q = I_3$$

$$v_{kT} \sim N(0, R) \quad \text{with variance } R = 2.5$$

- GPC and  $H_\infty$  Parameters :  $r=1$   
 $N_u=3$   
 $N=8$

# Simulation 1

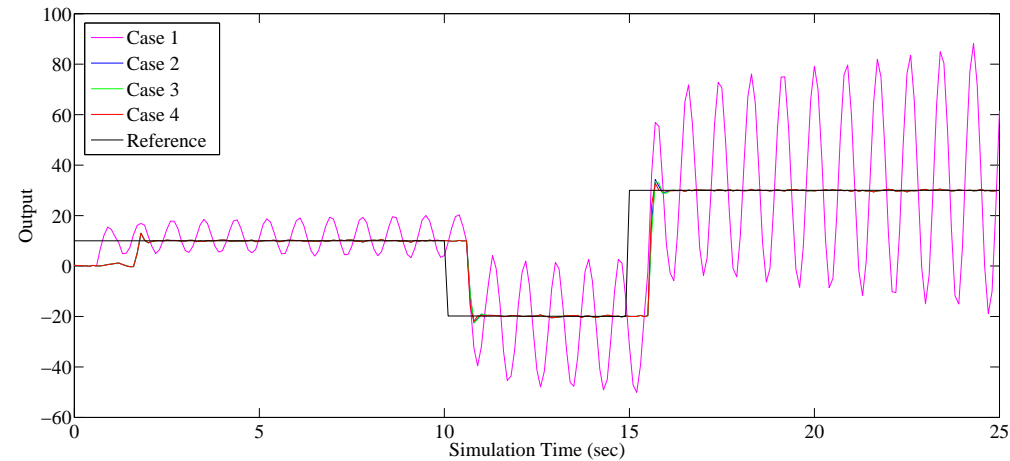
- case 1 with conventional GPC;
- case 2 with the proposed  $H^\infty$  predictive control and a constant parameter;
- case 3 with the proposed  $H^\infty$  predictive control and varying control-weighting parameter;
- case 4 with the proposed  $H^\infty$  predictive control and varying smooth on control-weighting parameters
- Table of parameter tuning (two sudden jumps at time 10s and 15s):

Simulation period/sec	0–10	10–15	15–25
Case 1	$\alpha=0.4, \lambda=0.04$	$\alpha=0.4, \lambda=0.04$	$\alpha=0.4, \lambda=0.04$
Case 2	$\alpha=0.73, \lambda = 0.0024$	$\alpha=0.73, \lambda = 0.0024$	$\alpha=0.73, \lambda = 0.0024$
Case 3	$\alpha=0.73, \lambda = 0.0024$	$\alpha=0.73, \lambda = 0.003$	$\alpha=0.73, \lambda = 0.0043$
Case 4	$\alpha=0.73, \lambda = 0.0024$	$\alpha=0.4, \lambda = 0.003$	$\alpha=0.2, \lambda = 0.0043$

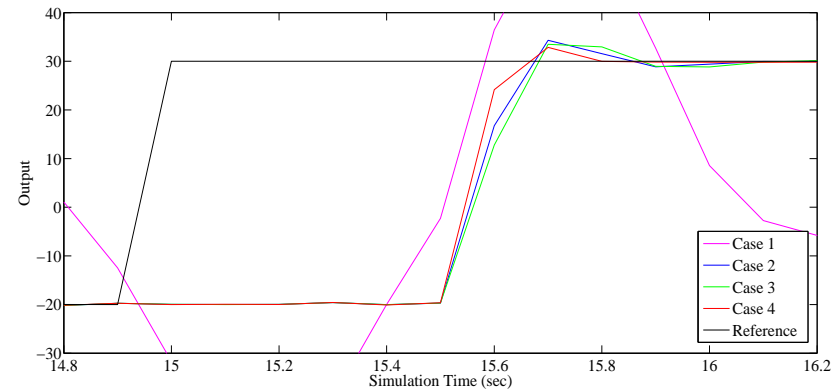
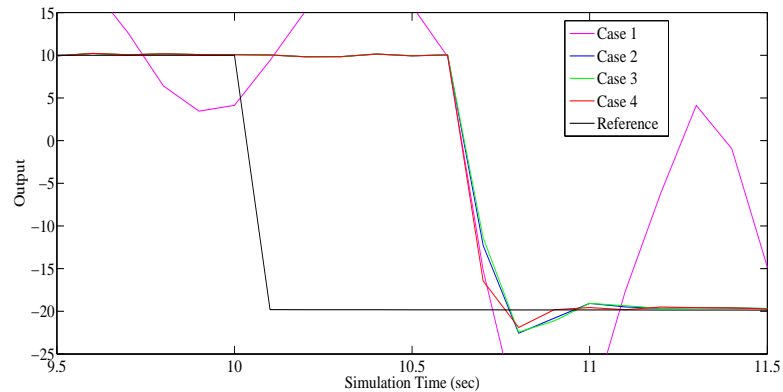


# Simulation 2: the adaptive parameter tuning approach

- Outputs and reference of the plant (figure 1):



- Zoom-in (left: figure 2 and right: figure 3) :

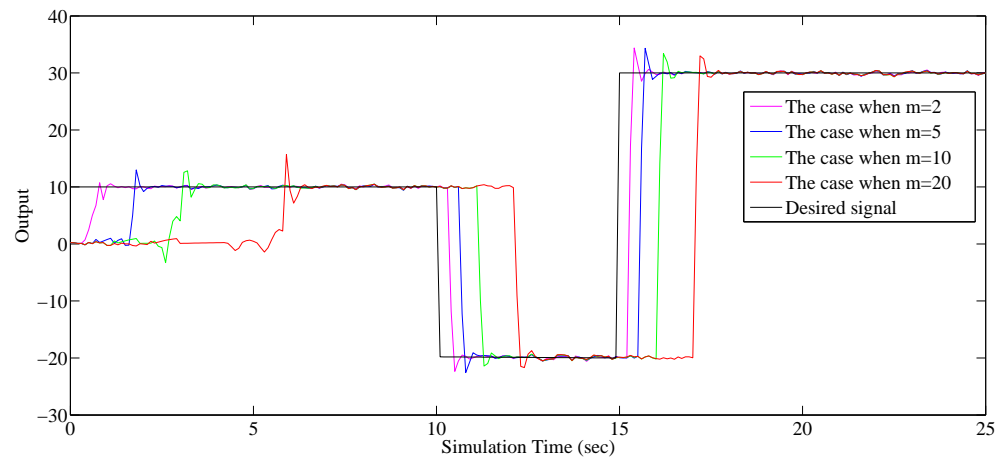


## Simulation 3: the influence of the maximal controller-to-actuator delay on the control performance

- Table of parameter tuning :

Case 4	0–10	10–15	15–25
m=2	$\alpha=0.73, \lambda=0.002$	$\alpha=0.4, \lambda=0.0024$	$\alpha=0.2, \lambda=0.003$
m=5	$\alpha=0.73, \lambda=0.0024$	$\alpha=0.4, \lambda=0.003$	$\alpha=0.2, \lambda=0.0043$
m=10	$\alpha=0.73, \lambda=0.0112$	$\alpha=0.4, \lambda=0.0167$	$\alpha=0.2, \lambda=0.0259$
m=20	$\alpha=0.73, \lambda=0.0174$	$\alpha=0.4, \lambda=0.0224$	$\alpha=0.2, \lambda=0.0321$

- Outputs and reference of the plant :





## Conclusion

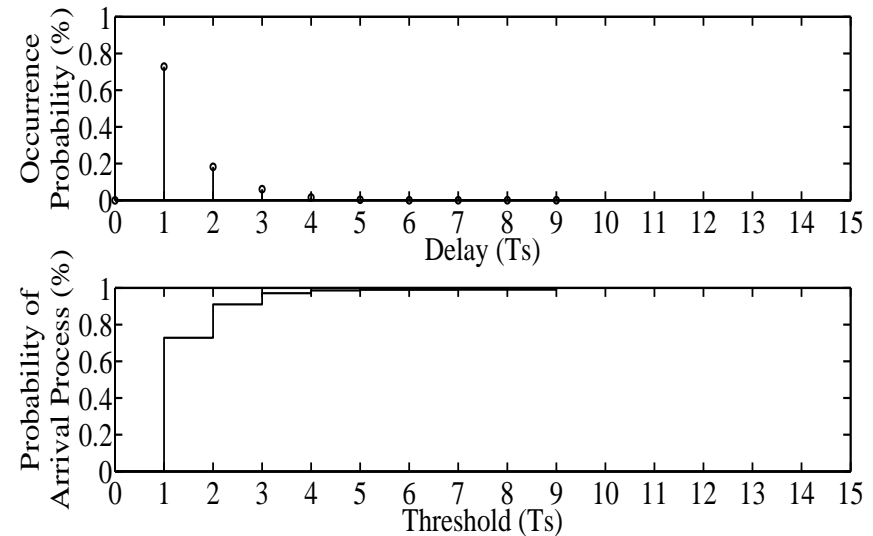
- It achieves the robustness issue of GPC algorithm. The presented  $H_\infty$  performance index compensates for the performance loss caused by process noise, which is not taken into account in GPC.
- The proposed approach also allows the adaptation control for GPC with respect to the adjustable smooth parameter for the reference with sudden jumps, which leads to an additional improvement.

# Modeling of Observation Arrival Process

## Bernoulli Process:

$$\gamma_k = \begin{cases} 1, & \text{if packet arrives at time } k \\ 0, & \text{otherwise} \end{cases}$$

## Poisson Distribution:



**Problem 0: Given available measurements  $Y_k = \{\gamma_1 y_1, \dots, \gamma_k y_k\}$ , seek the state estimate  $\hat{x}_k$ , which minimizes  $J_k = E[(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T]$ .**

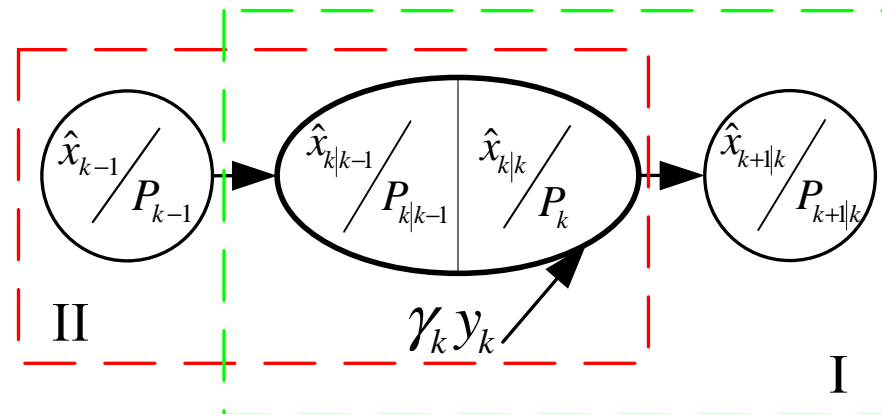
# Generalized State Estimation

**Problem 1:** For observation arrival process  $Y_k = \{\gamma_1 y_1, \dots, \gamma_k y_k\}$ , seek a critical value  $\lambda_c$  for observation arrival probability, which enables state estimation with intermittent observations stable for all initial conditions as  $\lambda > \lambda_c$ .

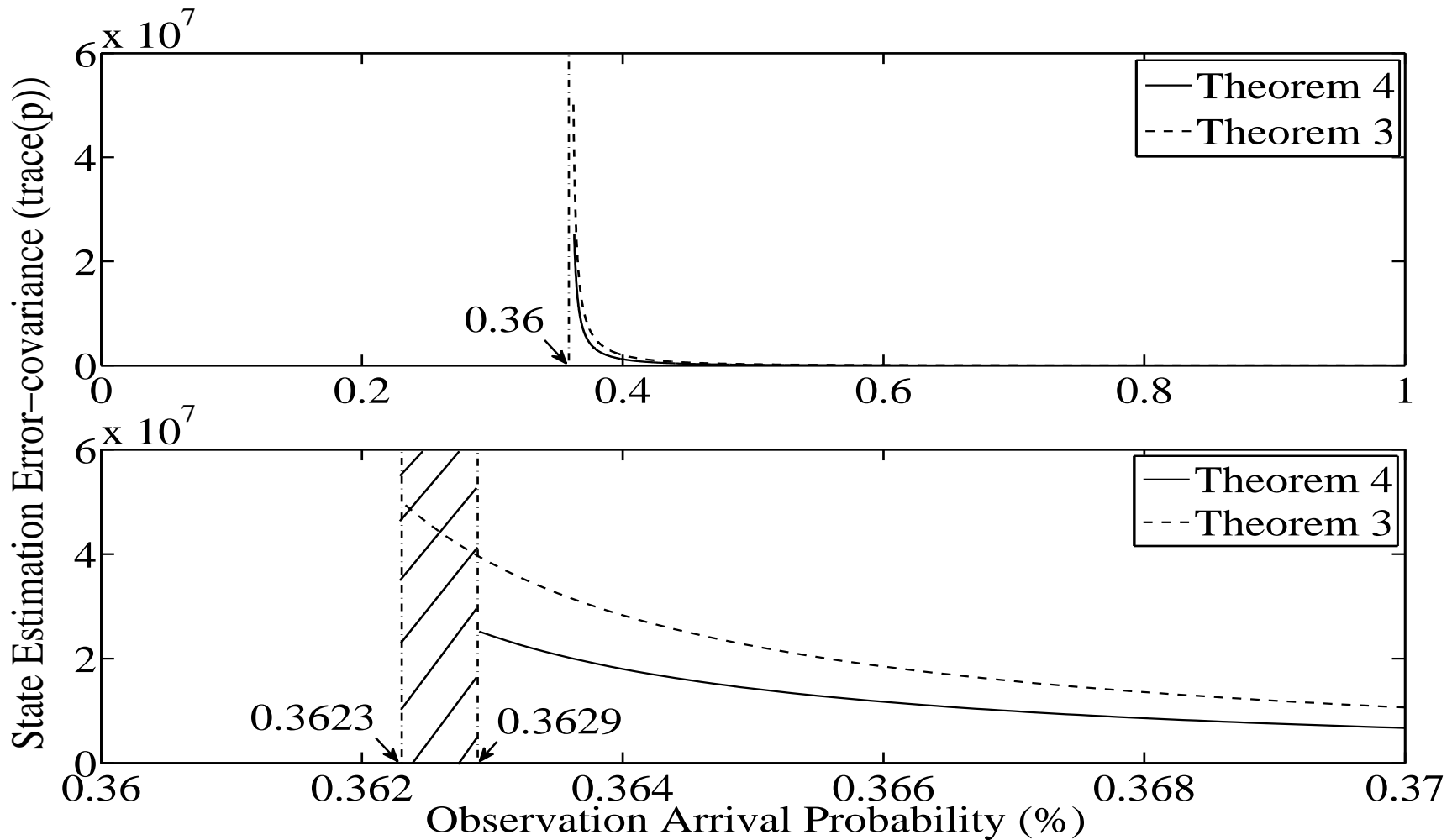
**State-space model with noise:**

$$\begin{cases} x_{k+1} = \Phi x_k + \Gamma u_k + \omega_k \\ y_k = C x_k + D u_k + v_k \end{cases}, k \geq 1 \quad (6)$$

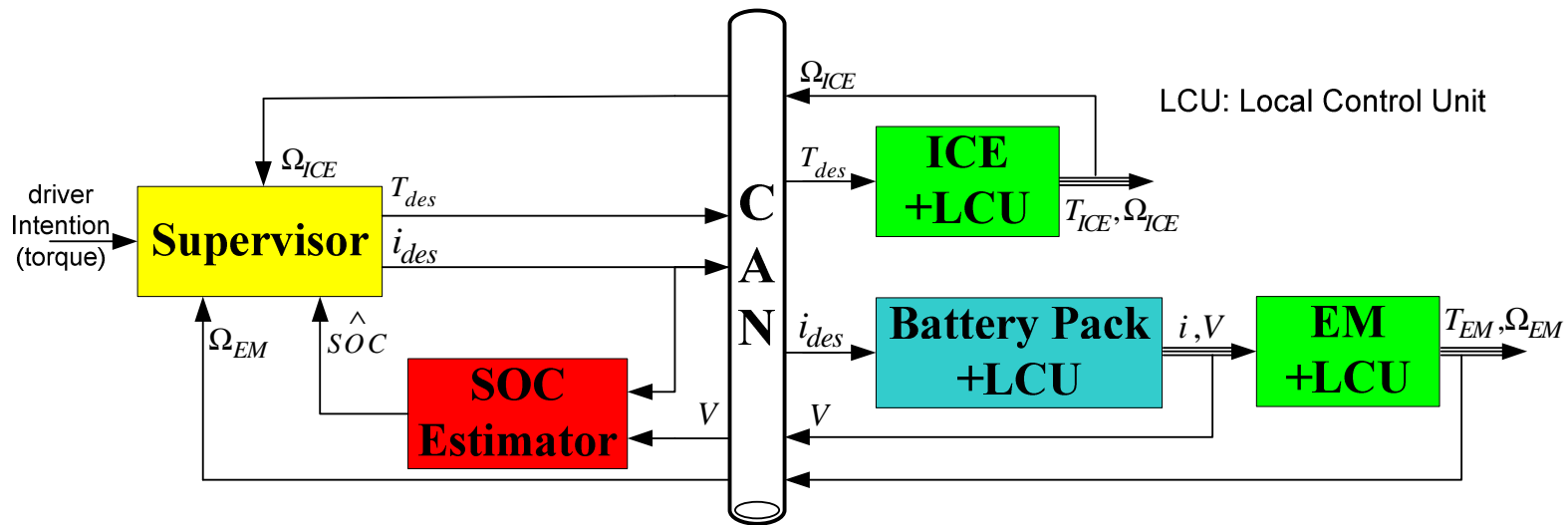
**Transition model with respect to observation arrival process:**



# Generalized Convergence Condition Subject to Observation Arrival Probability



# Battery State-of-Charge Estimation



ICE – Internal Combustion Engine;  
EM – Electric Motor.

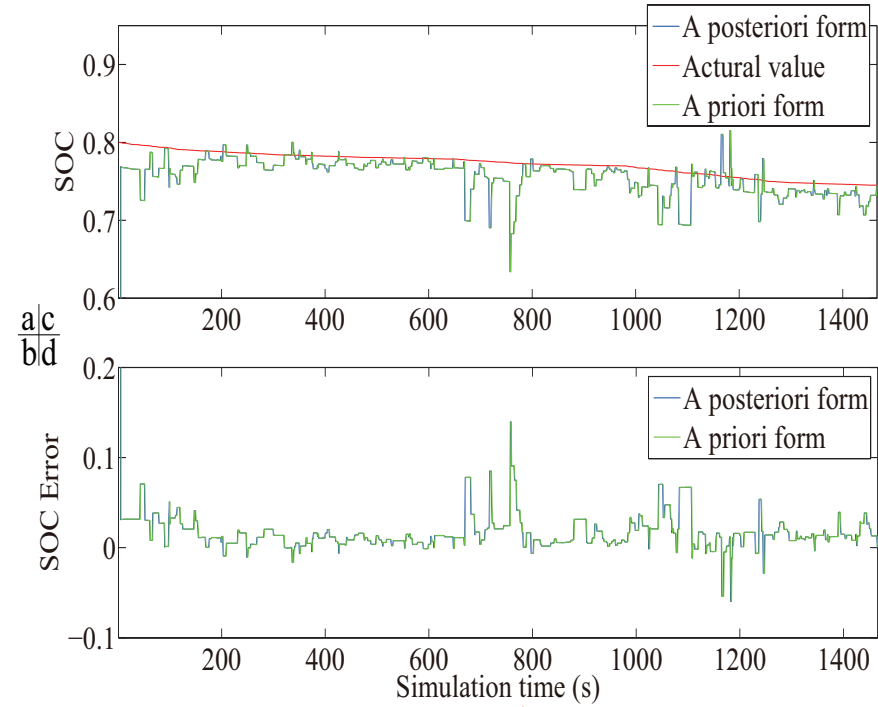
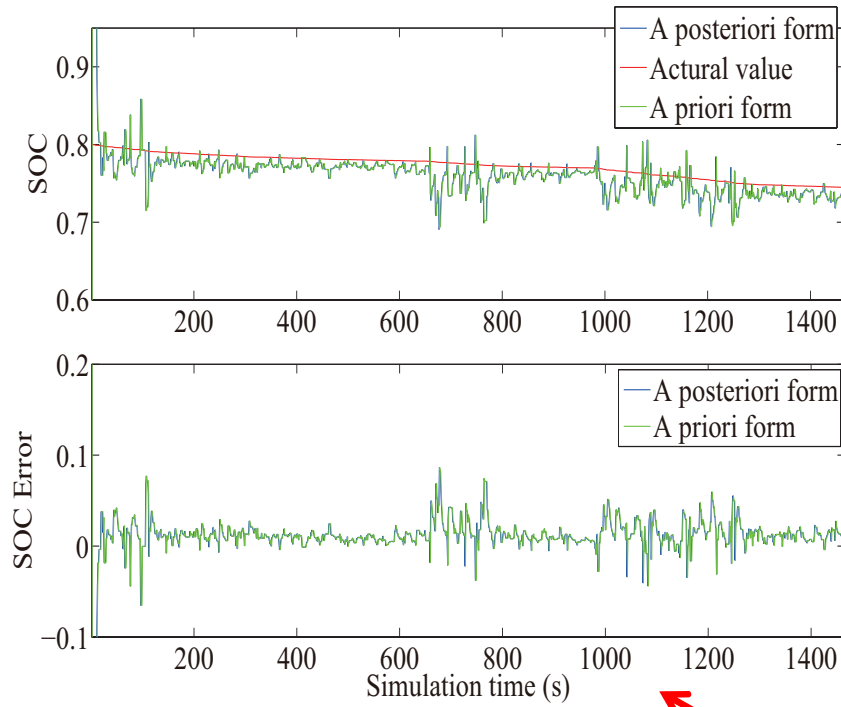


Table1. Comparison of Mean Absolute Estimation Errors

	$\lambda_c = 0.6016$	$\lambda_c = 0.1851$
$Ave_{pre}$	0.0934	0.9761
$Ave_{post}$	0.0049	0.8876



## Perspectives et travaux futurs

(i). The convergence subject to state estimation error-covariance is limited by a critical boundary of observation arrival probability.

(i). if it is possible to directly or non-directly identify the intensity of system noise online, it would develop an adaptive buffering strategy based on this work so as to always keep the filter working with a lower error-covariance.



## Publications

- **Y.M. ZHANG, V. SIRCOULOMB, N. LANGLOIS.** "Observer Design for Discrete-time Systems Subject to Long Time-delays". IEEE Chinese Control & Decision Conference 24th, Taiyuan, China, pp. 2949-2954, May 23-25, 2012.
- **Y.M. ZHANG, V. SIRCOULOMB, N. LANGLOIS.** "Stable Observer-based Control for Long Network-induced Delays". IEEE Chinese Control & Decision Conference 24th, Taiyuan, China, pp. 2966-2971, May 23-25, 2012.
- **Y.M. ZHANG, V. SIRCOULOMB, N. LANGLOIS.** "Kalman Filtering for Discrete-time Networked Control Systems with Incomplete Observations: A Dropping Over-delayed Packets Approach". IFAC SSSC joint conference, Grenoble, France, February 4-6, 2013.
- **Y.M. ZHANG, V. SIRCOULOMB, N. LANGLOIS,** "Robust Linear Estimator for Networked Control Systems with Incomplete Observations: A Dropping Over-delayed Packets Approach". IEEE ISIE joint conference, Taipei, Taiwan, May 28-31, 2013.
- **Y.M. ZHANG, V. SIRCOULOMB, N. LANGLOIS.** "Predictive Control Design for Discrete-Time Networked Control Systems", 11th IFAC International Workshop on Adaptation and Learning in Control and Signal Processing, Caen, France, July 3-5, 2013.
- **ZHANG Y., SIRCOULOMB V., LANGLOIS N.,** Robust Optimal Estimation with Lossy Network: A Probabilistic Approach. Application to Battery State of Charge Estimation, accepted at International Journal of Robust and Nonlinear Control, October 2013.

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