Modelling and Tracker for Unknown Nonlinear Stochastic Delay Systems with Positive Input Constraints

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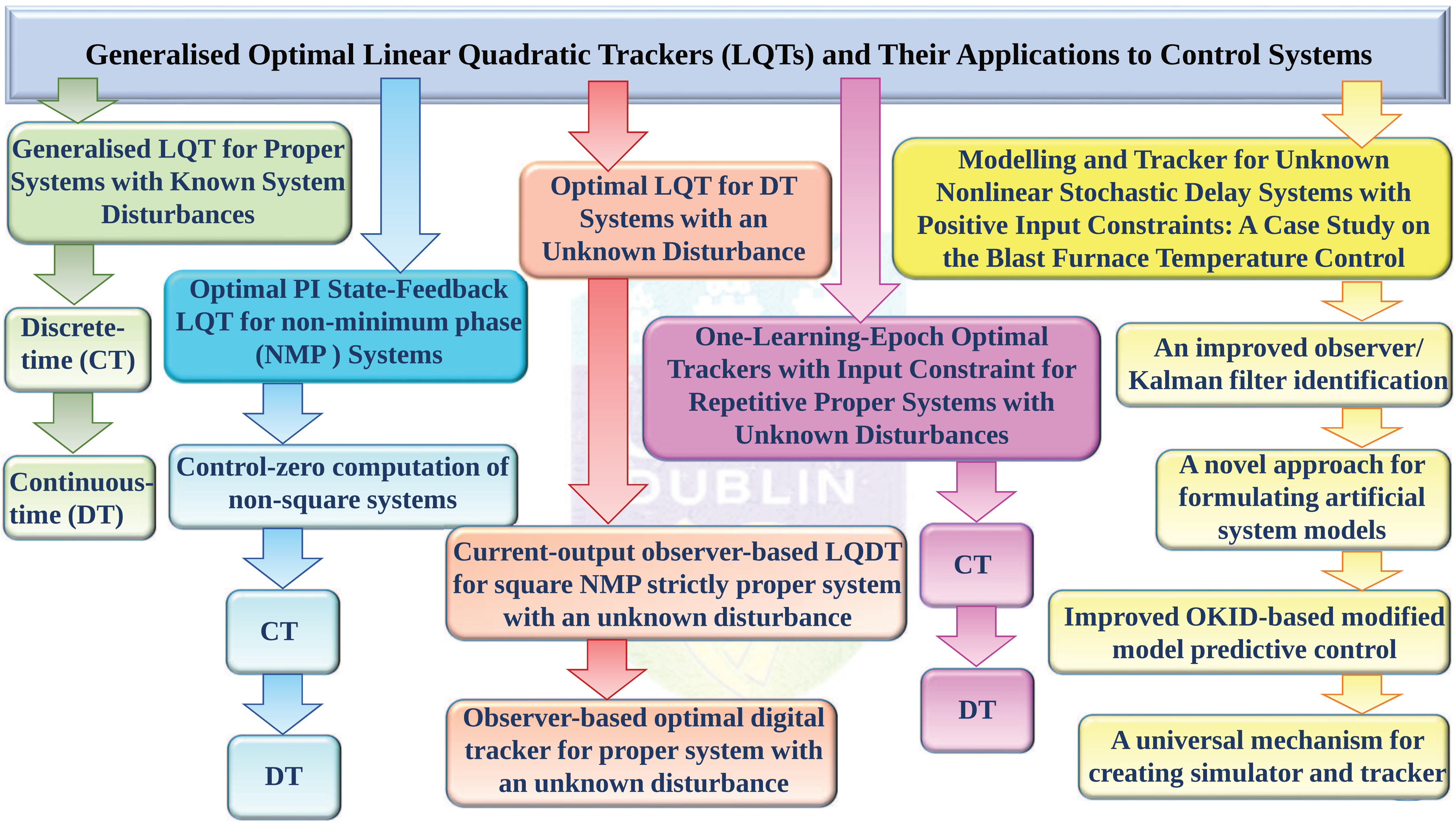
Content

Brief Overview of my Research Background


Generalised Optimal Linear Quadratic Trackers (LQTs) and Their Applications to Control Systems
Generalised LQT for Proper Systems with Known System Disturbances
Discrete-time (CT)
Continuous-time (DT)
Optimal PI State-Feedback LQT for non-minimum phase (NMP) Systems
Control-zero computation of non-square systems
CT
DT
Optimal LQT for DT Systems with an Unknown Disturbance
Current-output observer-based LQDT for square NMP strictly proper system with an unknown disturbance
Observer-based optimal digital tracker for proper system with an unknown disturbance
One-Learning-Epoch Optimal Trackers with Input Constraint for Repetitive Proper Systems with Unknown Disturbances
CT
DT
Modelling and Tracker for Unknown Nonlinear Stochastic Delay Systems with Positive Input Constraints: A Case Study on the Blast Furnace Temperature Control
An improved observer/ Kalman filter identification
A novel approach for formulating artificial system models
Improved OKID-based modified model predictive control
A universal mechanism for creating simulator and tracker

Our Research Strategy

Modelling and Tracker for Unknown Nonlinear Stochastic Delay Systems with Positive Input Constraints: A Case Study on the Blast Furnace Temperature Control [1]

An improved observer/Kalman filter identification

A novel approach for formulating artificial system model

Improved OKID-based modified model predictive control

A universal mechanism for creating simulator and tracker

A case study on the blast furnace temperature control

[1] Jason Sheng-Hong Tsai, **Faezeh Ebrahimzadeh**, Wen-Teng Hsu, Joseph Wei Tann, Shu-Mei Guo, Leang-San Shieh, Jose I. Canelon, Li Wang, "Modelling and tracker design for unknown nonlinear stochastic delay systems with positive input constraints," ***Applied Mathematical Modeling***. Vol. 40(23-24), pp. 10447–10479, 2016.

Our Contributions

An improved observer/Kalman filter identification

Well-performed output estimator

- Collect input-output data
- Clean the input-output data
- Select training data set

Traditional OKID method

Input-output data → $\{G,\ H,\ C,\ F_t\}$

Well-performed output estimator

$$\hat{x}_d(k \mid k) = G\hat{x}_d(k-1 \mid k-1) + Hu(k-1) + K(k)[y(k) - C(G\hat{x}_d(k-1 \mid k-1) + Hu(k-1))]$$

$$\hat{y}_d(k \mid k) = C\hat{x}_d(k \mid k), \quad \hat{x}_d(0 \mid 0) = C^{\dagger}E[y_d(0)]$$

$$P(k \mid k-1) = GP(k-1 \mid k-1)G^T + R_1$$

$$K(k) = P(k \mid k-1)C^T(R_2 + CP(k \mid k-1)C^T)^{-1}$$

$$P(k \mid k) = P(k \mid k-1) - K(k)CP(k \mid k-1)$$

$$K(0) = -F_t, \; P(0 \mid 0) = R_0$$

A novel approach for formulating artificial system model

Well-perfor output estin | **Artificial system model**

Artificial system model

$$x_{a,d}(k) = Gx_{a,d}(k-1) + Hu_{a,d}(k-1) + K_{ss}e_{sys}(k)$$

$$y_{a,d}(k) = Cx_{a,d}(k) + e_{out}(k), \qquad x_{a,d}(0) = \hat{x}_d(k_{ss} \mid k_{ss})$$

$$K_{ss} = K(k_{ss})$$

$$e_{out}(k) = y(k) - \hat{y}_d(k \mid k)$$

$$e_{sys}(k \mid k-1) = y(k) - [y(k) - C(G\hat{x}_d(k-1 \mid k-1) + Hu(k-1))]$$

Improved OKID-based modified model predictive control

Well-perfor output estin | Artificial system model | Iterative MPC with input constraint | Current output-based OKID method / Optimal control law / Input-constraint model predictive control

Current output-based OKID method

$$\hat{x}_{a,d}(k) = G_d \hat{x}_{a,d}(k-1) + H_d u_{a,d}(k-1) - F y_{a,d}(k)$$

$$y_{a,d}(k) = C\hat{x}_{a,d}(k) + e_{out}(k), \quad x_{a,d}(0) = \hat{x}_d(k_{ss} | k_{ss})$$

$$F = -(\tilde{G} P \tilde{\tilde{C}}^T)(\tilde{\tilde{C}} P \tilde{\tilde{C}}^T + R_o)^{-1}$$

$$\tilde{C} = CG, \; \tilde{G} = G/\alpha, \; G_d = (I + FC)G, \; H_d = (I + FC)H, \; 0 < \alpha \le 1$$

Optimal control law

$$u_{a,d}(k) = -K_d \hat{x}_{a,d}(k) + E_d r(k+1)$$

$$K_d = (H^T P H + R_c)^{-1} H^T P G$$

$$E_d = (H^T P H + R_c)^{-1} H^T [I - (G - HK_d)^T]^{-1} C^T Q_c$$

Improved OKID-based modified model predictive control (Cont.)

Improved OKID-based modified MPC with positive input constraint

$$U(k)=\left(\bar{\Phi}_o^T Q_c \bar{\Phi}_o + R_c + M^T W(k) M\right)^{-1}\left[\bar{\Phi}_o^T Q_c\left(R_S(k)-\bar{F}_o\hat{x}(k)\right)+M^T W(k)\bar{N}\right]+U_E$$

$$\bar{N}=\begin{bmatrix}-(U^{\min}-U_E)\\ U^{\max}-U_E\end{bmatrix},\; M=\begin{bmatrix}I_{mN_C}\\ -I_{mN_C}\end{bmatrix},\; N=\begin{bmatrix}U^{\max}\\ -U^{\min}\end{bmatrix},\;\; \Delta U=U-U_E,\; U_E=E[U],\; U(k)=[u(k)\;\; u(k+1)\;\; u(k+2)\ldots u(k+N_C-1)]^T$$

$$\bar{F}_o=\left(I_{pN_P\times pN_P}+\Gamma_o\right)^{-1}F_o,\qquad \bar{\Phi}_o=\left(I_{pN_P\times pN_P}+\Gamma_o\right)^{-1}\Phi_o,\qquad F_o=\left[C_dG_d\;\; C_dG_d^2\;\; C_dG_d^3\;\ldots\; C_dG_d^{N_P}\right]^T$$

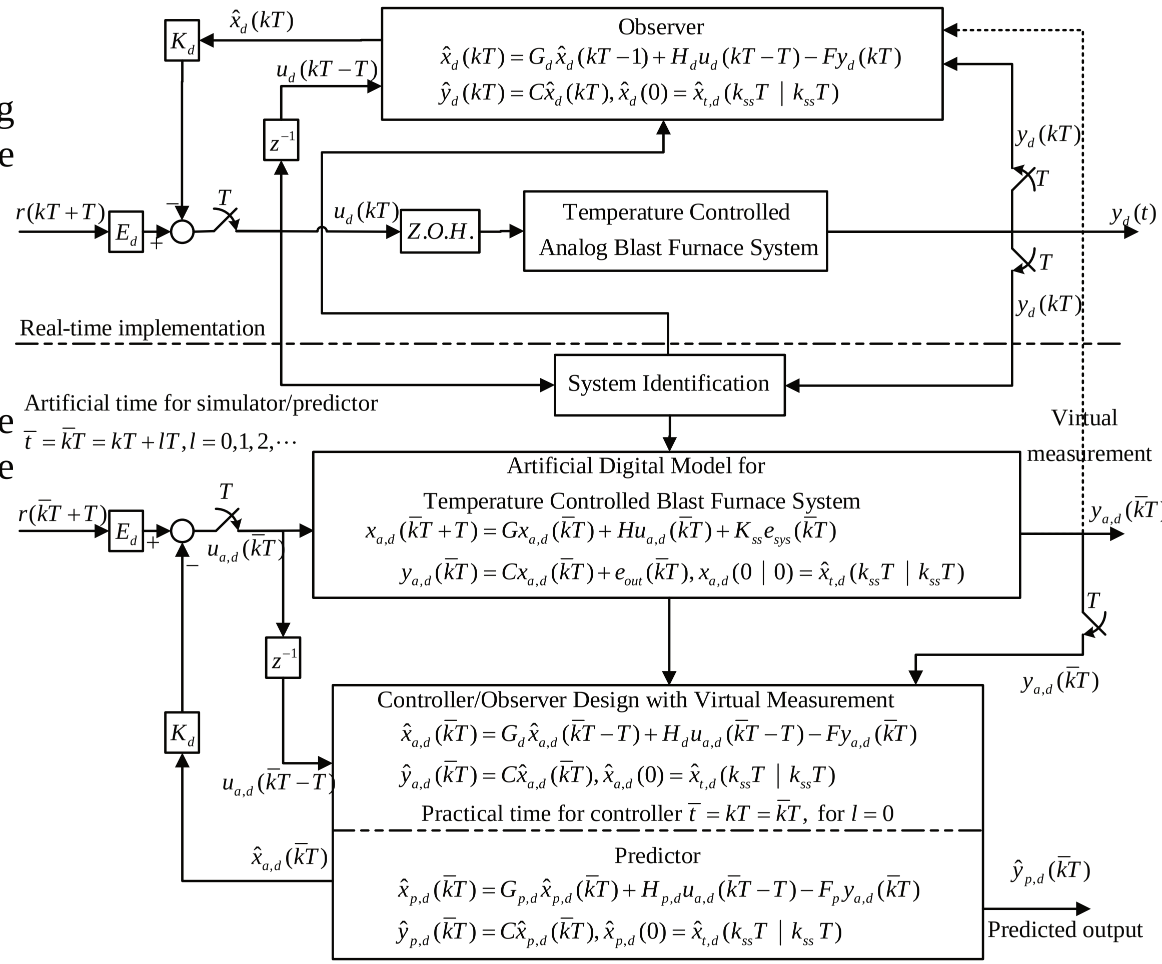
$$\Phi_o=\begin{bmatrix}C_dH_d & 0_{p\times m} & 0_{p\times m} & \cdots & 0_{p\times m}\\ C_dG_dH_d & C_dH_d & 0_{p\times m} & \cdots & 0_{p\times m}\\ C_dG_d^2H_d & C_dG_dH_d & C_dH_d & \cdots & 0_{p\times m}\\ \vdots & \vdots & \vdots & \cdots & \ddots\\ C_dG_d^{N_P-1}H_d & C_dG_d^{N_P-2}H_d & C_dG_d^{N_P-3}H_d & \cdots & C_dG_d^{N_P-N_C}H_d\end{bmatrix},\qquad \Gamma_o=\begin{bmatrix}C_dL_d & 0_{p\times p} & 0_{p\times p} & \cdots & 0_{p\times p}\\ C_dG_dL_d & C_dL_d & 0_{p\times p} & \cdots & 0_{p\times p}\\ C_dG_d^2L_d & C_dG_dL_d & C_dL_d & \cdots & 0_{p\times p}\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ C_dG_d^{N_P-1}L_d & C_dG_d^{N_P-2}L_d & C_dG_d^{N_P-3}L_d & \cdots & C_dL_d\end{bmatrix}$$

Schematic diagram of the proposed control system

- Check the performance is obtained during the pre-study phase, implement the controller to the blast furnace

- Infill those lost and/or not reasonable practical output measurements during the operation phase

- Predict future control parameters and output performance



A case study on the blast furnace hot metal temperature control

The operating conditions

$u_1(kT)$ (Blast volume): $4,300 \sim 5,300$ (Nm^3/min)

$u_2(kT)$ (Blast pressure): 1.9~3.6 (pounds per square inch)

$u_3(kT)$ (Blast temperature): $1,000 \sim 1,180\ ^o$

$u_4(kT)$ (Blast moisture): 15~33 (g / Nm^3)

$u_5(kT)$ (Oxygen enrichment): 0.1~3.5 (precentage)

$u_6(kT)$ (Pulverized coal injection): 60~180 (g / Nm^3)

$u_7(kT)$ (Ore/Coke): 3.6~5.0

$u_8(kT)$ (Coke rate): 330~430 (kg / thm);

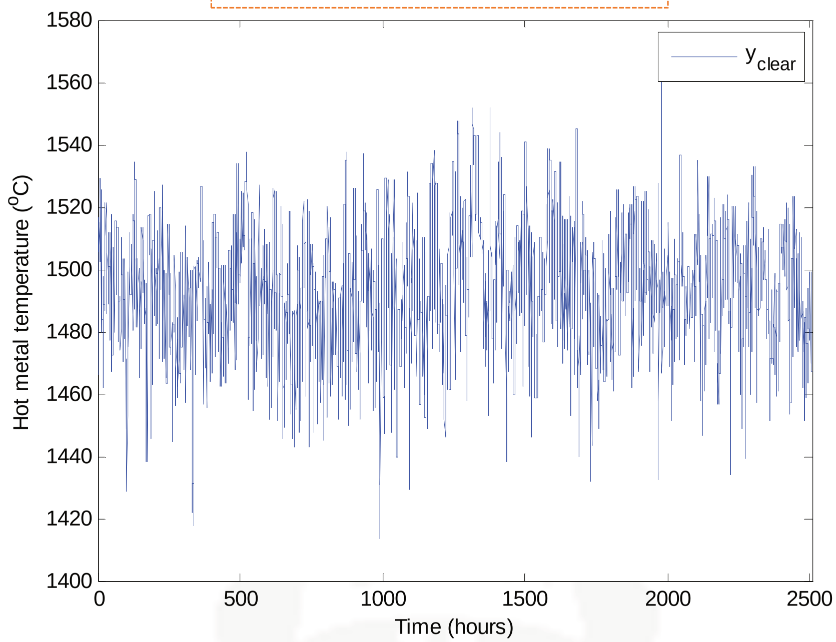
$y(kT)$ (Blast furnace liquid-iron temperature): 1,400~1,600 ^{o}C

Design objective:

The output of the controlled system remains at the reference temperature $r(kT) = 1,500\ ^oC$

Cleaned data

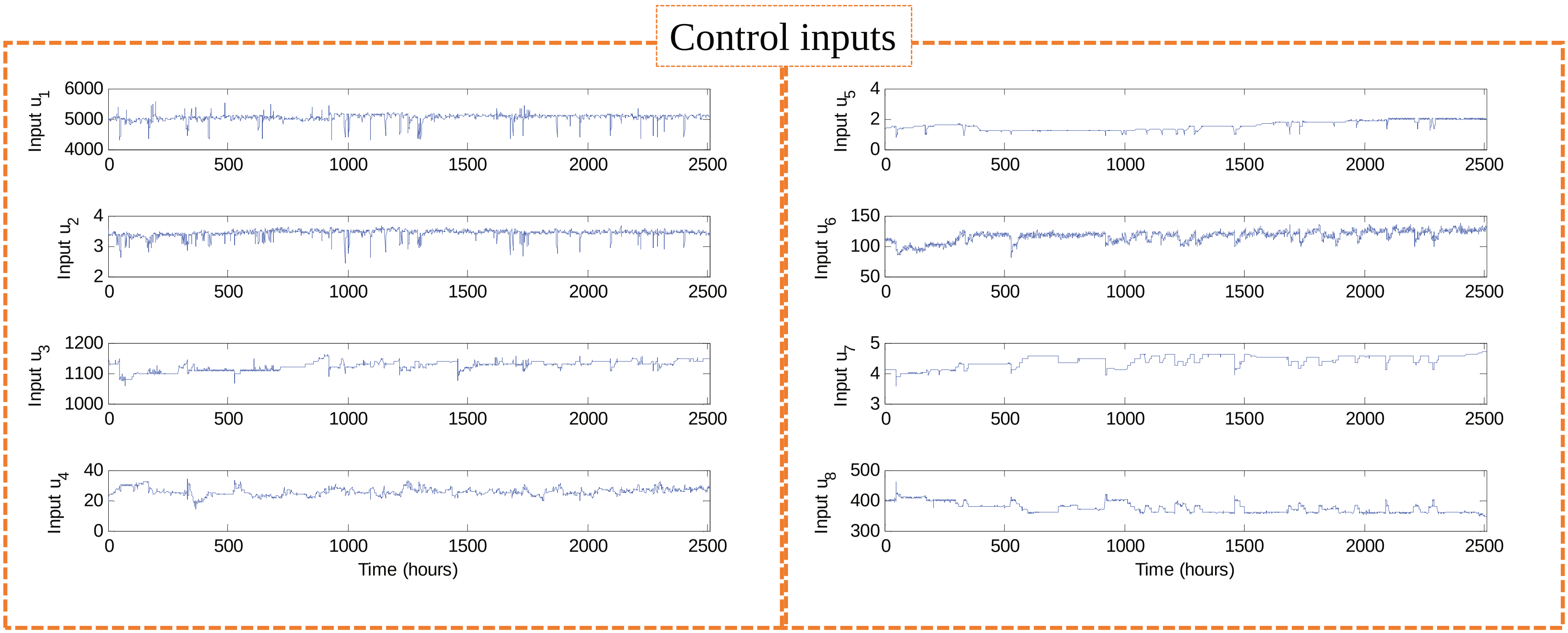
Hot metal temperature



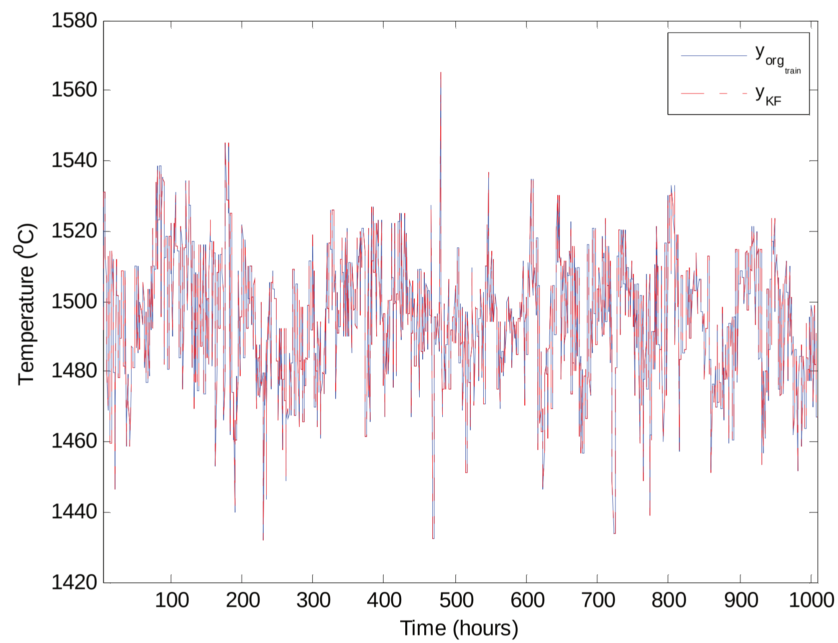
Hot metal temperature $y(kT)$

mean 1,494.504 ^{o}C and
standard deviation 19.668

Cleaned data



Comparison between training data and output estimator

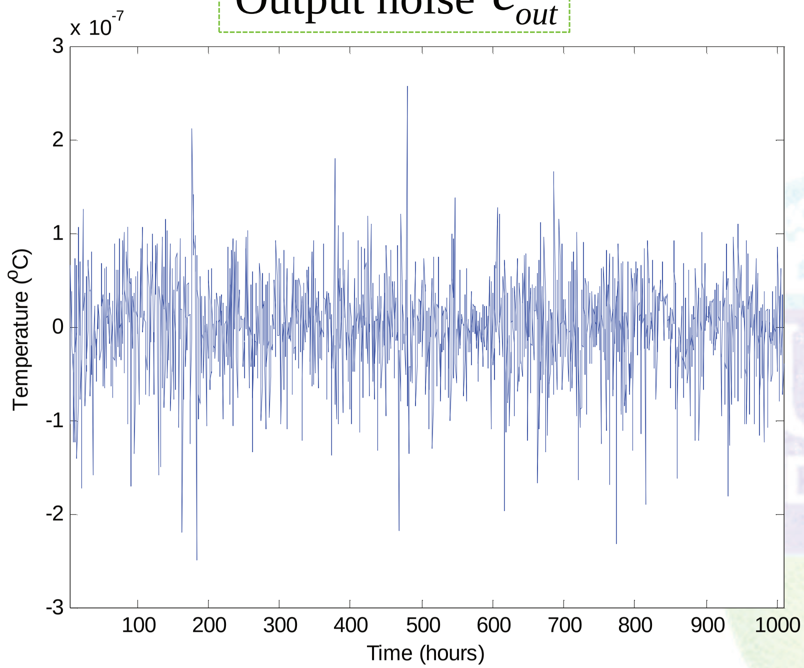


Training data
mean: 1,494.9149
standard deviation: 18.42159

Output estimator
mean: 1,494.9149
standard deviation: 18.42159

Quantification of the dynamic characteristic

Output noise e_{out}



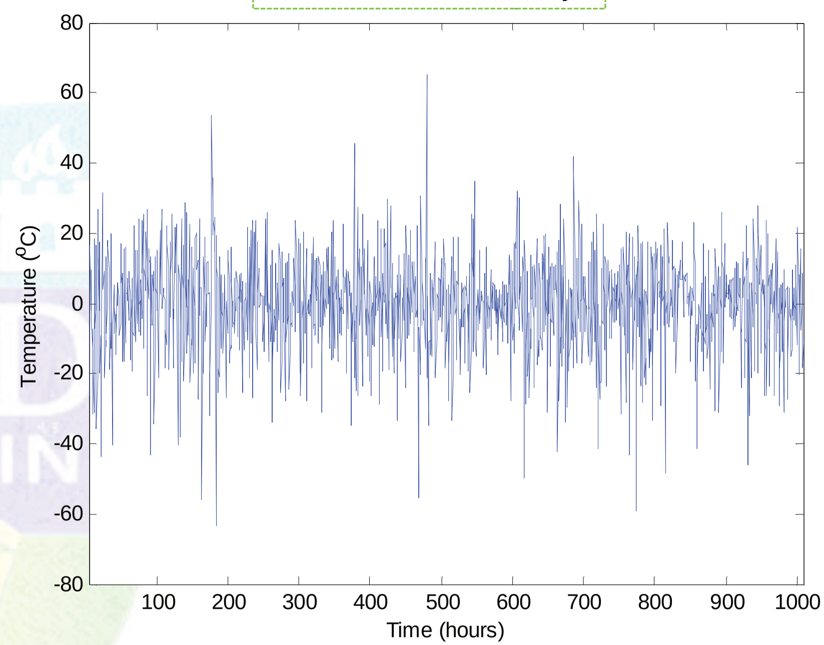
Mean: 2.24108×10^{-11}

Standard deviation: 4.8598×10^{-8}

Probability between $[-\sigma, \sigma]$: 72.3245%

Probability between $[-2\sigma, 2\sigma]$: 95.1717%

System noise e_{sys}



Mean: -0.00730

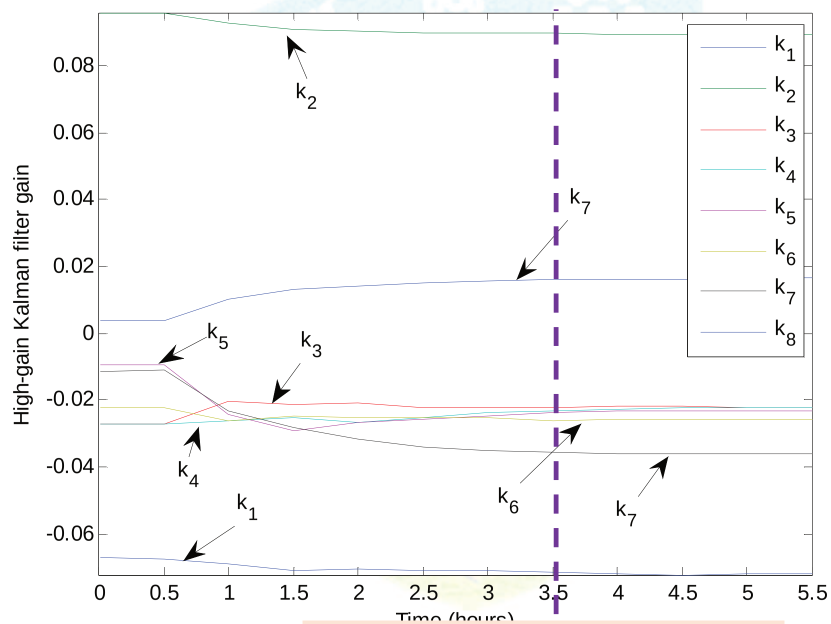
Standard deviation: 13.3067278

Probability between $[-\sigma, \sigma]$: 73.1209%

Probability between $[-2\sigma, 2\sigma]$: 95.2215%

Kalman filter gain

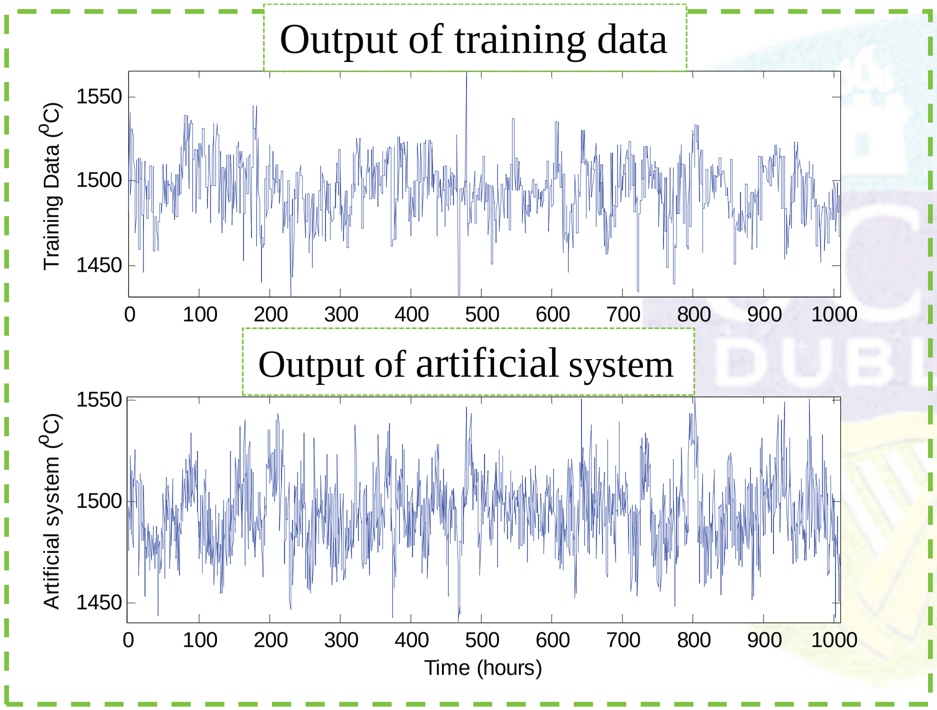
$$\lambda(G - K_{ss}CG) = \{-0.6108, -0.3625 \pm 0.4205i, 0.5607 \pm 0.1641i, 0.0, 0.2074 \pm 0.6353i\}$$



Steady-state index: $k_{ss0} = 8$

Comparison between the training data and the artificial system output

Same stochastic features of the constructed artificial model and of the practical system

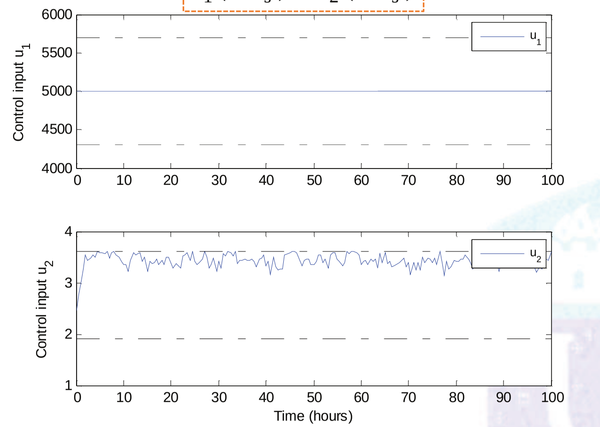


Training data mean: 1,494.9149
Training data standard deviation: 18.42159

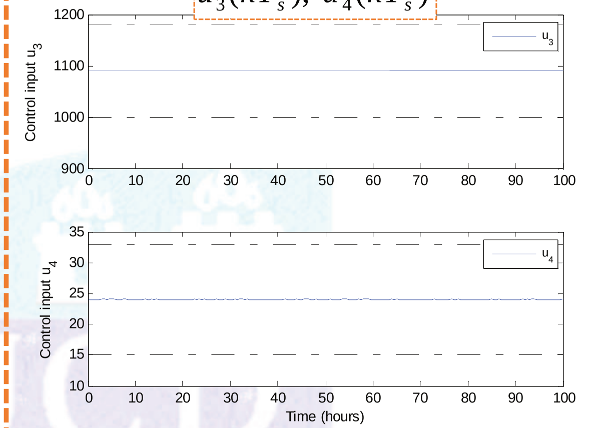
Mean: 1,495.1304
Standard deviation: 18.2517
Probability between $[-\sigma, \sigma]$: 68.6819 %
Probability between $[-2\sigma, 2\sigma]$: 95.6888 %

The predicted control inputs for the next 100 hours

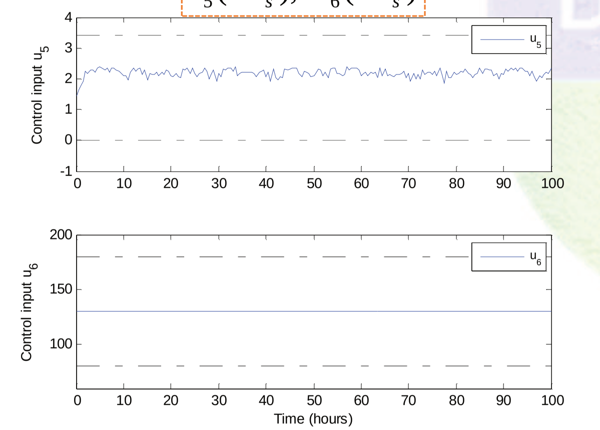
$u_1(\bar{k}T_s),\ u_2(\bar{k}T_s)$



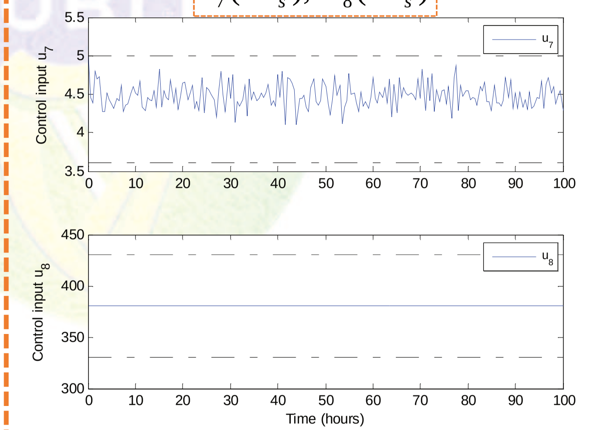
$u_3(\bar{k}T_s),\ u_4(\bar{k}T_s)$



$u_5(\bar{k}T_s),\ u_6(\bar{k}T_s)$



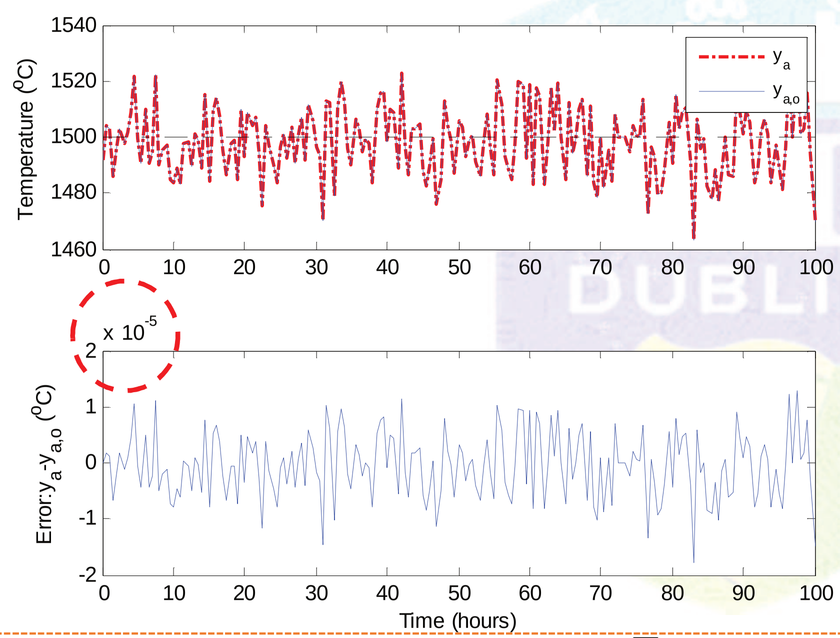
$u_7(\bar{k}T_s),\ u_8(\bar{k}T_s)$



Comparison between controlled output/virtual measurement and predicted output

Satisfactory prediction performance for the outputs over the next 100 hours

Controlled output/virtual measurement $y_d(k\bar{T})$



Predicted output $\hat{y}_d(k\bar{T})$

Controlled output/virtual measurement
mean: 1,499.6489
standard deviation: 10.984

Predicted output
mean: 1,499.6489
standard deviation: 10.984

Comparison between our proposed approach-based output and training data

Tracking performance improvement

40.374% of standard deviation improvement

Predicted output	Training data
mean: 1,499.6489	mean: 1,494.9149
standard deviation: 10.984	standard deviation: 18.42159

Conclusions and Future Direction

Development of an improved OKID method, which uses the current output measurement to estimate the current state,

Constructing a well-performed system output estimator based on the current output-based Kalman filter

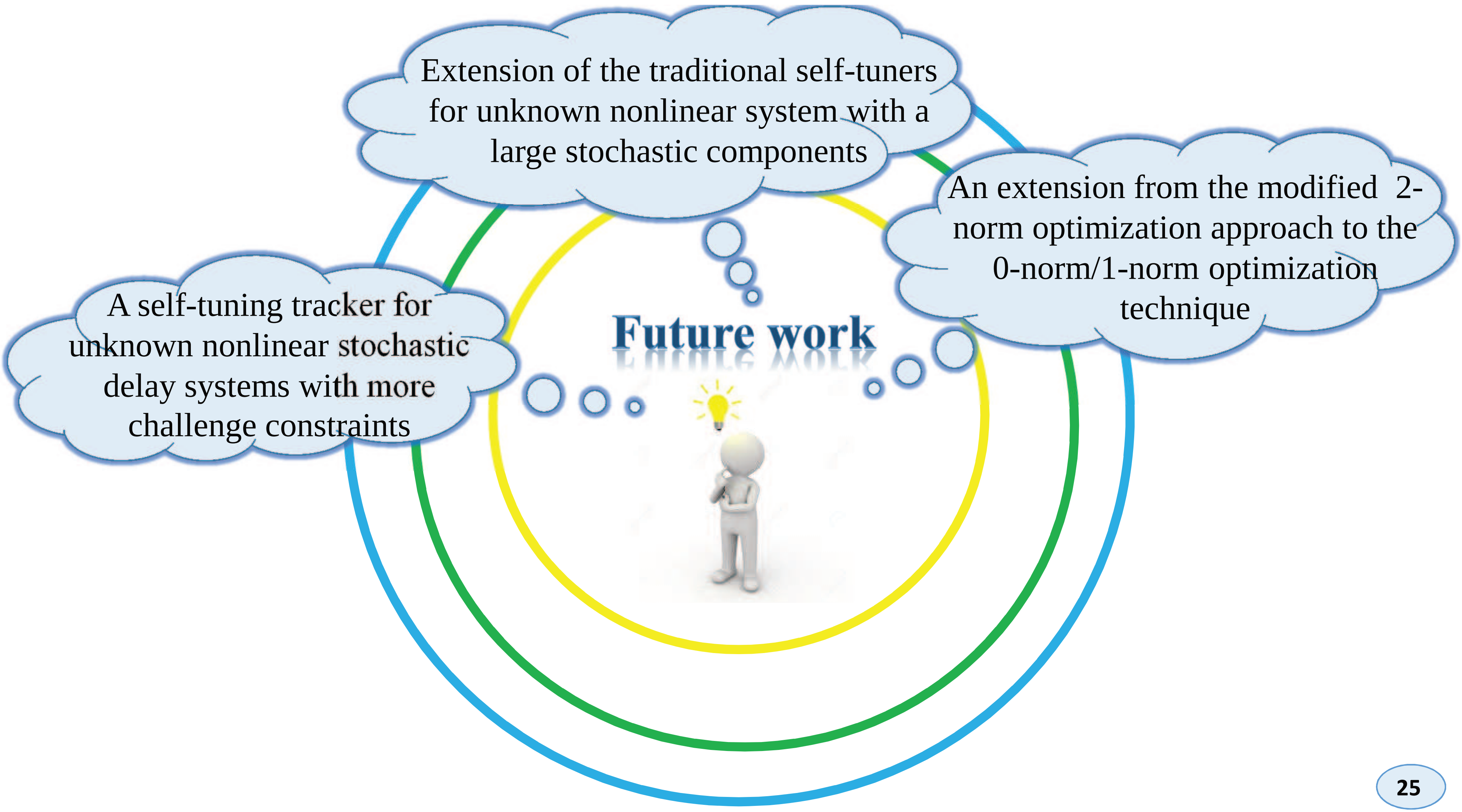
Formulating a universal approach for artificial system models, based the current output-based Kalman filter

Conduction of quantitative analysis to determine the stochastic and deterministic components of the system of interest

Development of a modified observer-based MPC with positive input constraint for the unknown nonlinear time-delay stochastic system with input constraints

Development of a universal mechanism for creating simulator and tracker design for positive input-constrained unknown nonlinear input time-delay stochastic sampled-data systems

Studying the operation of a temperature controlled real nonlinear input time-delay blast furnace process


Extension of the traditional self-tuners for unknown nonlinear system with a large stochastic components
An extension from the modified 2-norm optimization approach to the 0-norm/1-norm optimization technique
A self-tuning tracker for unknown nonlinear stochastic delay systems with more challenge constraints
Future work

THANKS FOR YOUR ATTENTION