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Modeling, Fault Diagnosis and Control Reconfiguration for Live-Stock Building Ventilation Systems

Outline

- Modeling for the live-stock buildings

-Fault diagnosis

-Fault tolerant

-Conclusion

Outline of Modeling Part

- Background on climate control and modeling for the live-stock buildings

-Model description

- **Inlet *Model***
- ***Outlet Model***
- ***Stable Heating Model***
- ***Modeling Climate Dynamics***
- ***Piecewise Affine Systems***

-Parameter Estimation

-Experiments Outline

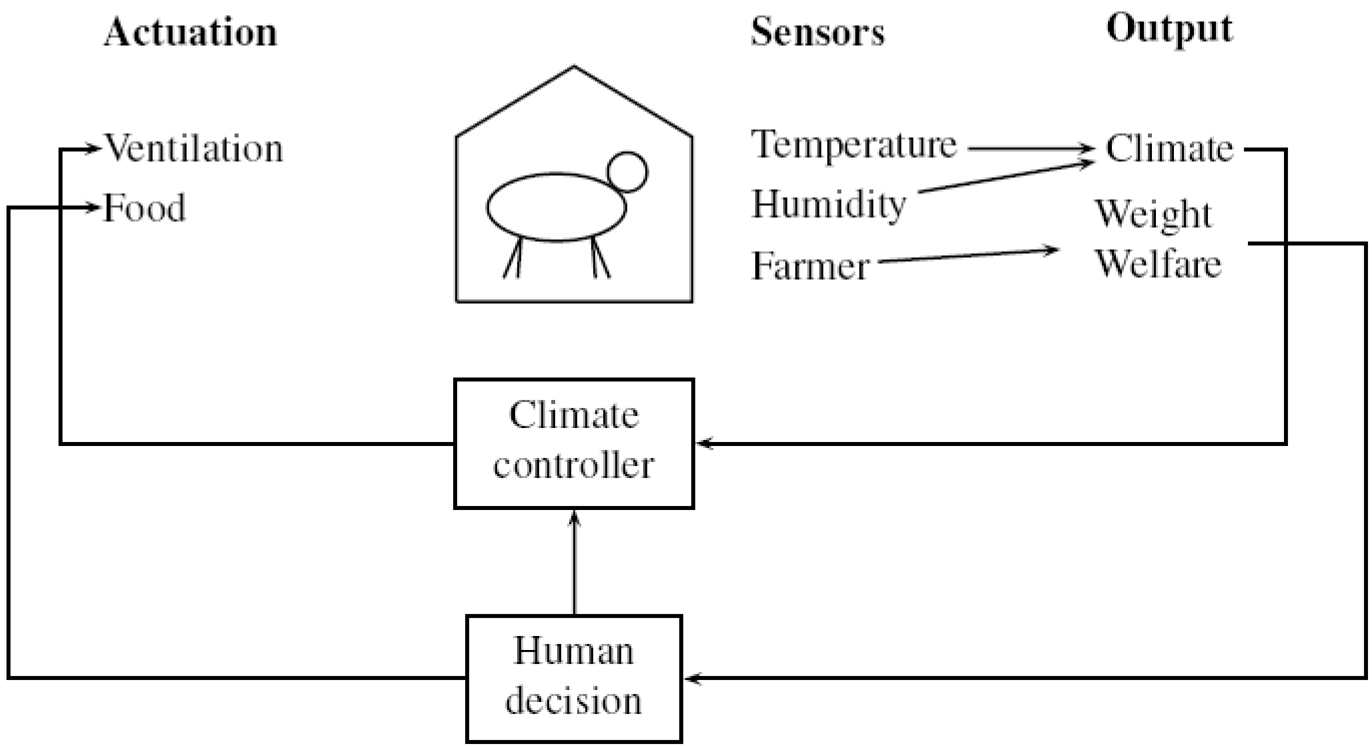
-Results and discussion

- **EKF Estimation**
- ***Model Validation***

-Conclusion

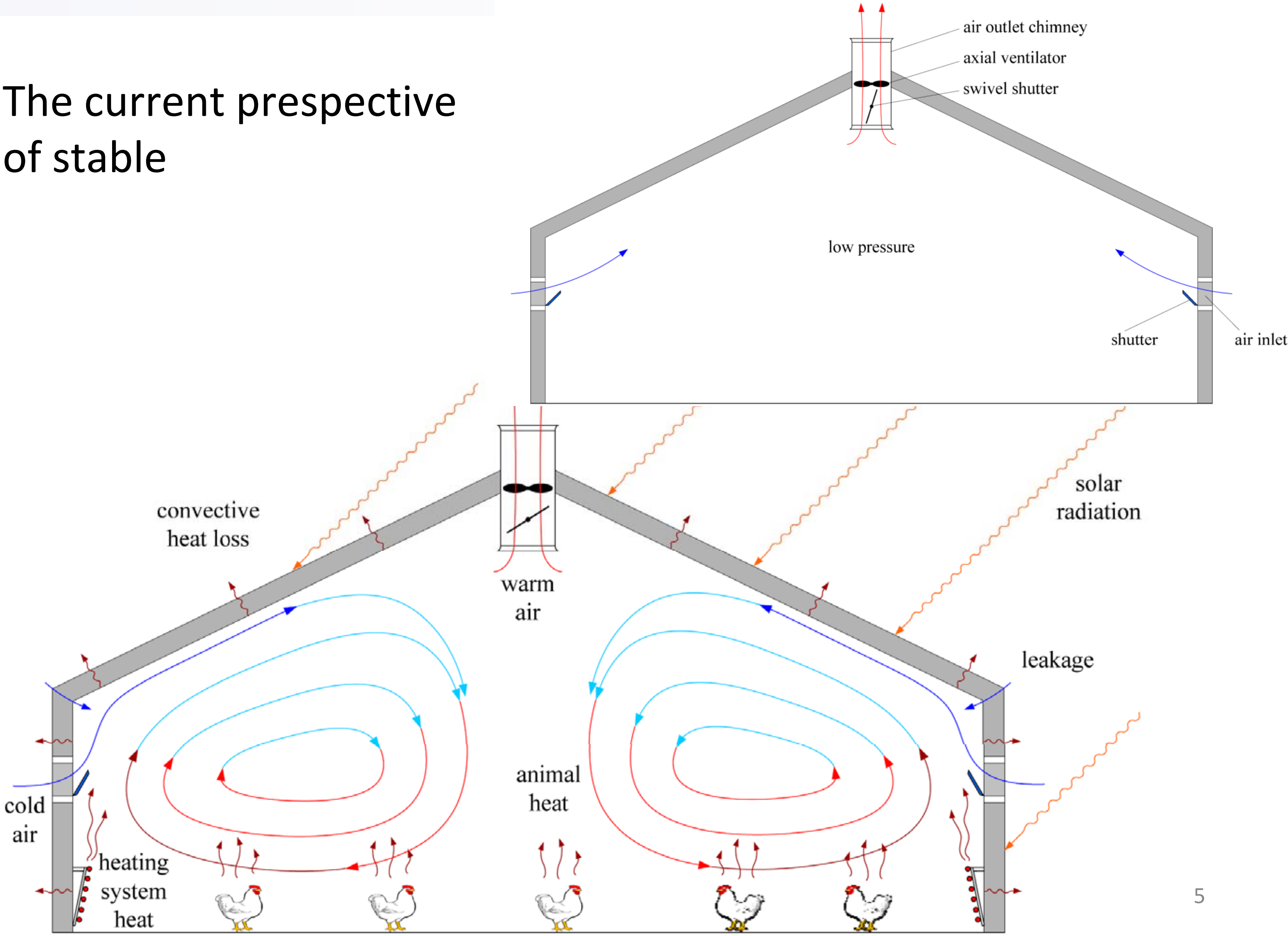
Background on climate control and modeling for the live-stock buildings

Control of Indoor climate of livestock buildings



Background on climate control and modeling for the live-stock buildings

The current prespective of stable



Mathematical Modeling

Inlet model

$$q_i^{in} = k_i(\alpha + leak)\Delta P_{inlet}$$

$$\Delta P_{inlet} = 0.5 C_P \rho V_{ref}^2 - P_i + \rho_o g \left(1 - {}^{T_o}/_{T_i}\right)(H_{NLP} - H_{inlet})$$

Outlet model

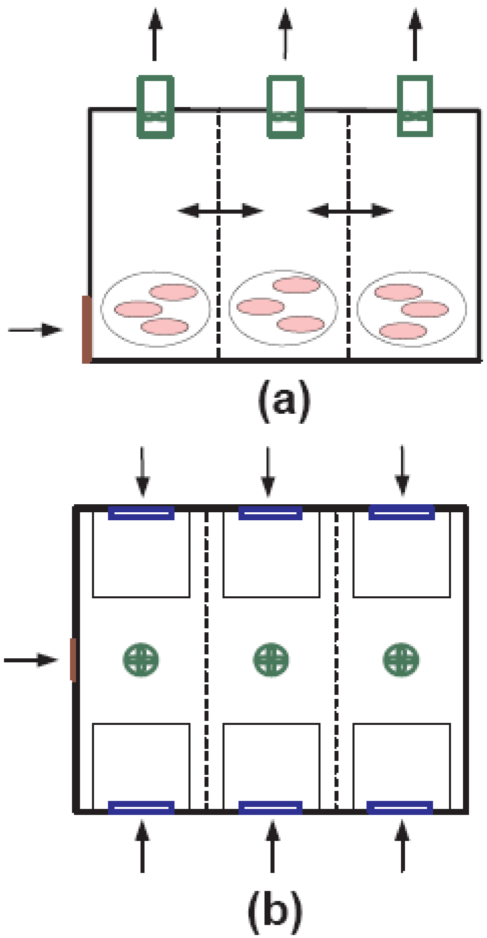
$$q_i^{fan} = u_i c_i - d_i \Delta P_{out\,let}$$

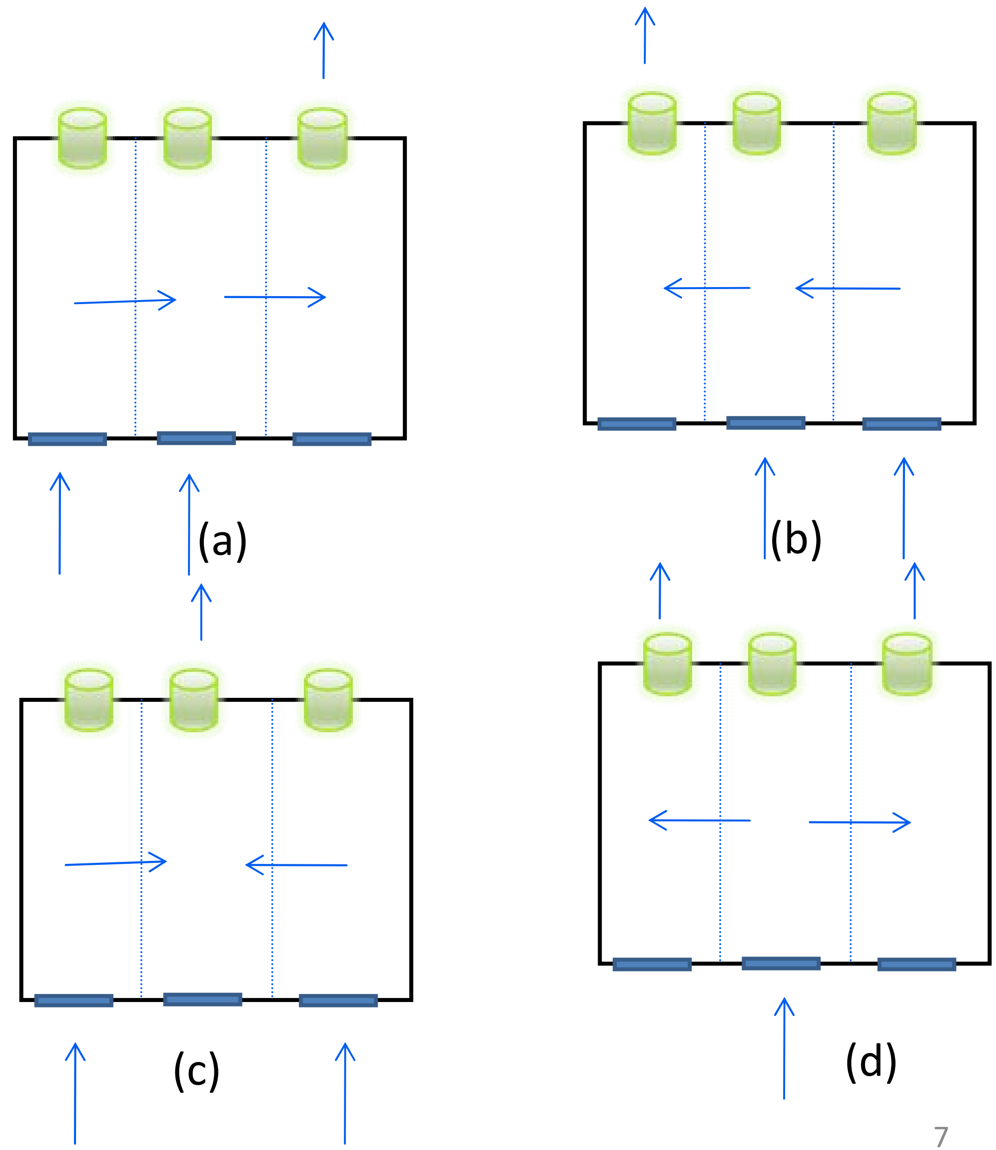
$$\Delta P_{outlet} = \tfrac{1}{2}\rho C_{Poutlet} V_{ref}^2 - P_i + \rho g \frac{T_{out} - T_i}{T_i}\left(H_{nlp} - H_{outlet}\right)$$

$$\sum q_{in}\rho_o \frac{\Delta P}{|\Delta P|} + \sum q_{out}\rho_i = 0$$

Mathematical Modeling

Schematic diagram of the test stable





Mathematical Modeling

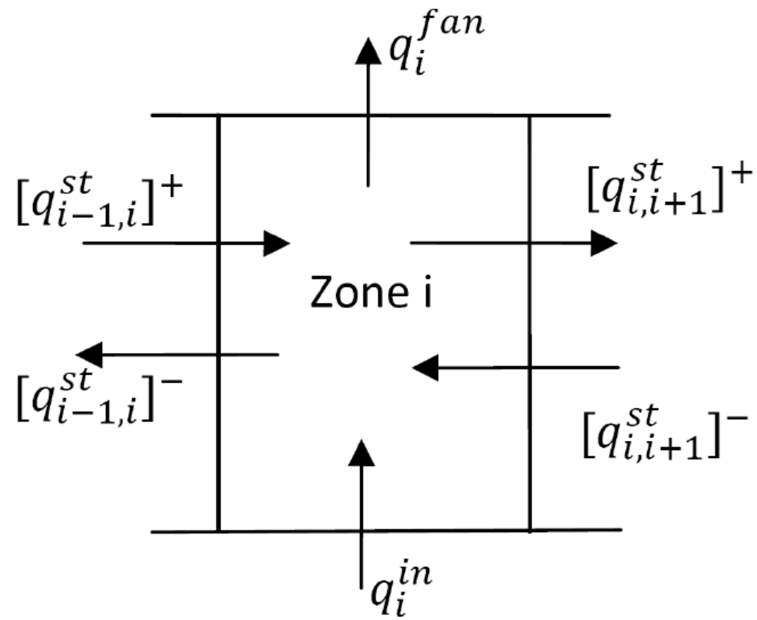
Multizone Concept

$$q_{i-1,i}^{st} = m_1(P_{i-1} - P_i)$$

$$q_{i,i+1}^{st} = m_2(P_i - P_{i+1})$$

$$\left[q_{i-1,i}^{st}\right]^+ = \max(0, q_{i-1,i}^{st})$$

$$[q_{i-1,i}^{st}]^- = \min(0, q_{i-1,i}^{st})$$



$$\sum q_{in} \rho_o \frac{\Delta P}{|\Delta P|} + \sum q_{out} \rho_i = 0$$

Mathematical Modeling

Climate Dynamic Modeling

Stable Heating Model

$$\dot{Q}_{heater} = C_1 (T_{in} - T_{win}) C_2$$

$$C_1 = \dot{m}_{heater}\, c_{pwater}$$

$$C_2 = exp\left[\frac{-U_{heater}\, A_{pipe}}{\dot{m}_{heater}\, c_{pwater}}\right] - 1$$

Temperature Model

$$M_i c_{P,i} \frac{dT_i}{dt} = Q_{i-1,i} + Q_{i,i-1} + Q_{i,i+1} + Q_{i+1,i} + Q_{in,i}$$
$$Q_{out,i} + Q_{conv,i} + Q_{source,i}$$

$$Q = \dot{m}.\, c_p .\, T_i$$
$$Q_{i-1,i} = \left[q^{st}_{i-1,i}\right]^{+} .\, \rho .\, c_p .\, T_{i-1},$$
$$Q_{i,i-1} = \left[q^{st}_{i-1,i}\right]^{-} .\, \rho .\, c_p .\, T_i$$

Piecewise Affine Systems

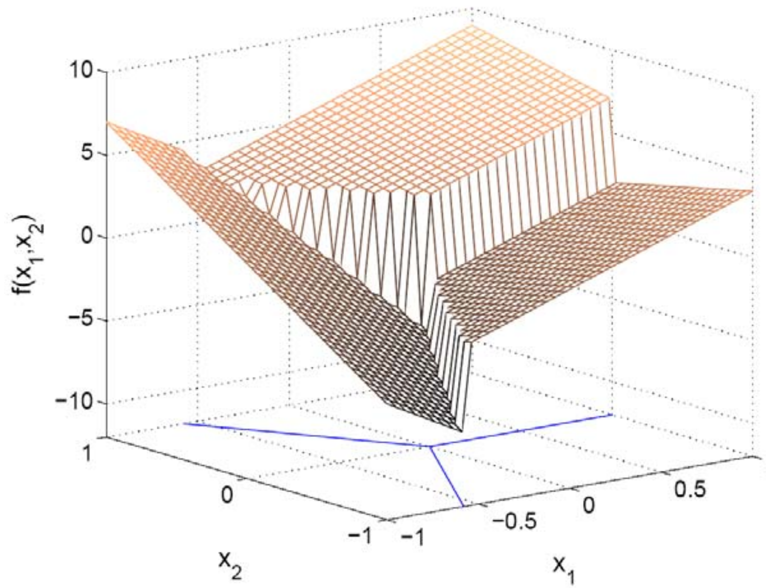
- The state space is partitioned into polyhedral regions
- Each region is associated with a different affine state-update equation

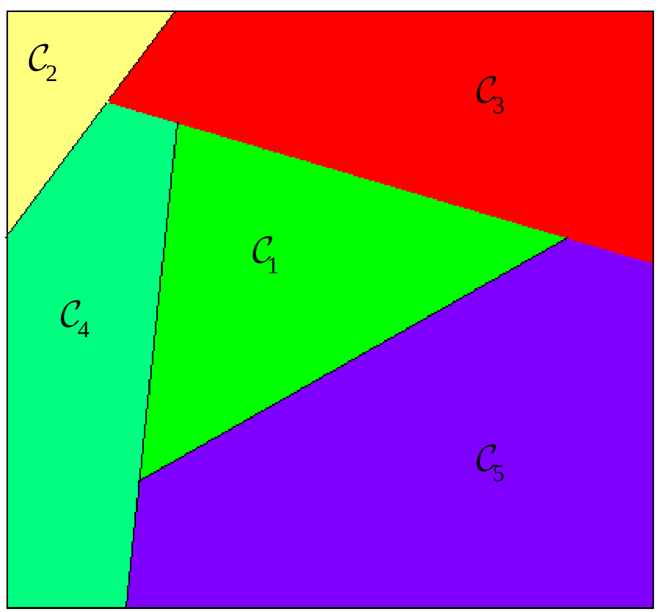
$$\mathbf{x}_{k+1} = A_{i(k)}\mathbf{x}_k + B_{i(k)}\mathbf{u}_k + \mathbf{b}_{i(k)}$$

$$\mathbf{y}_{k+1} = C_{i(k)}\mathbf{x}_k + D_{i(k)}\mathbf{u}_k + \mathbf{d}_{i(k)}$$

$$i(k) = i^* \quad \text{if} \quad (x_k, u_k) \in \mathcal{C}_i,\; i = 1, 2, \ldots., s$$

[Sontag, 1996]





Parameter Estimation

Extension of the state space model by parameter variation dynamics:

$$\begin{cases} \dot{X} = \begin{bmatrix} \dot{T} \\ \dot{C} \end{bmatrix} = \begin{bmatrix} f_i(T,u,q) + v \\ 0_{l\times 1} \end{bmatrix} \\ q = h_{3i}(X,P,u) \qquad i = 1, \dots 4 \\ h_2(P,X,u) = 0, \\ z = h_1 X + w, \end{cases}$$

In the EKF the nonlinear equations are aproximated to linear ones, using first order Taylor series expansion:

$$X_k \cong f(X_{k-1}(-)) + \varphi_{X-1}\left(X_{k-1} - X_{k-1}(-)\right)$$

$$\varphi_X = \frac{\partial f\,(X,u,q)}{\partial X} = f_X(X,u,q)\frac{\partial X}{\partial X} + f_q(X,u,q)\frac{\partial q\,(X,u,P)}{\partial X}$$

$$\frac{\partial q\,(X,u,P)}{\partial X} = h_{3x}(X,u,P)\frac{\partial X}{\partial X} + h_{3P}(X,u,P)\frac{\partial P}{\partial X}$$

According to

$$\frac{\partial h_2(X,u,P)}{\partial X} = 0 = h_2p(X,u,P)\frac{\partial P}{\partial X} + h_2x(X,u,P)\frac{\partial X}{\partial X}$$

$$\Rightarrow h_2p(X,u,P)\frac{\partial P}{\partial X} = -h_2x(X,u,P)$$

The extended kalman filter consists of two steps:

Prediction stage:

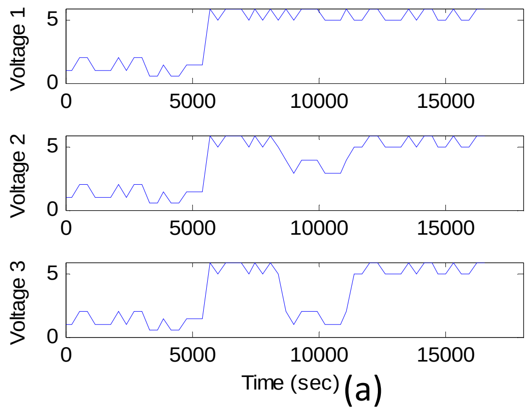
$$\hat{X}_k(-) = f_{k-1}\left(\hat{X}_{k-1}(+)\right)$$
$$P_k(-) = \varphi_{k-1}P_{k-1}(+)\varphi_{k-1}^T + Q_{k-1}$$

Update stage

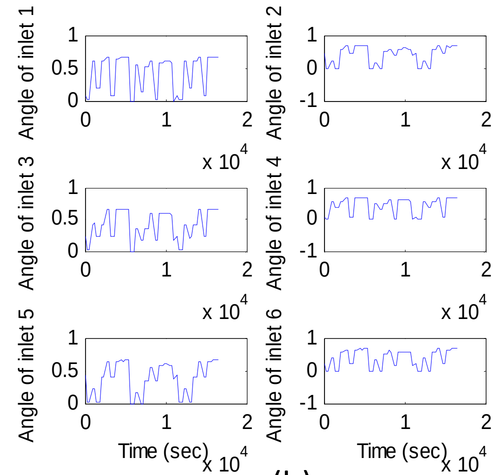
$$\overline{K}_k = P_k(-)H_k^T[H_kP_k(-)H_k^T + R_k]^{-1}$$
$$\hat{X}_k(+) = \hat{X}_k(-) + \overline{K}_k(y_k - \hat{y}_k)$$
$$P_k(+) = \{1 - \overline{K}_kH_k\}P_k(-)$$

Experiments Outline

(a) voltage of fan, (b) the angle of inlets

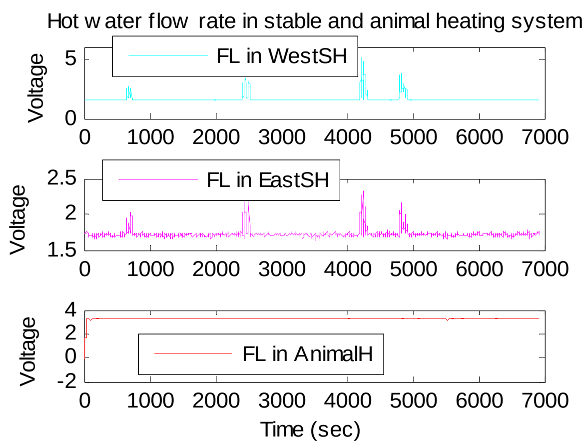


(a)

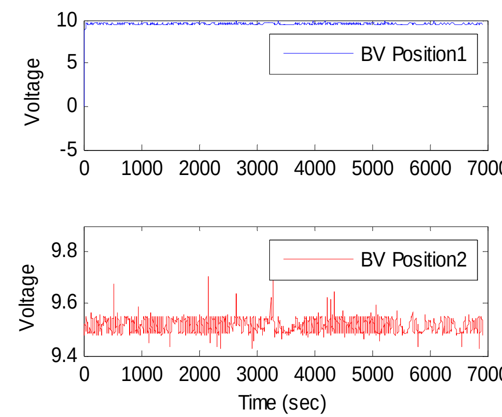


(b)

(c) Ball-valve position for animal and stable heating systems, (d) Hot water flow rate in stable and animal heating system



(c)



(d)

Results and Discussions

Extended Kalman Filter (EKF)

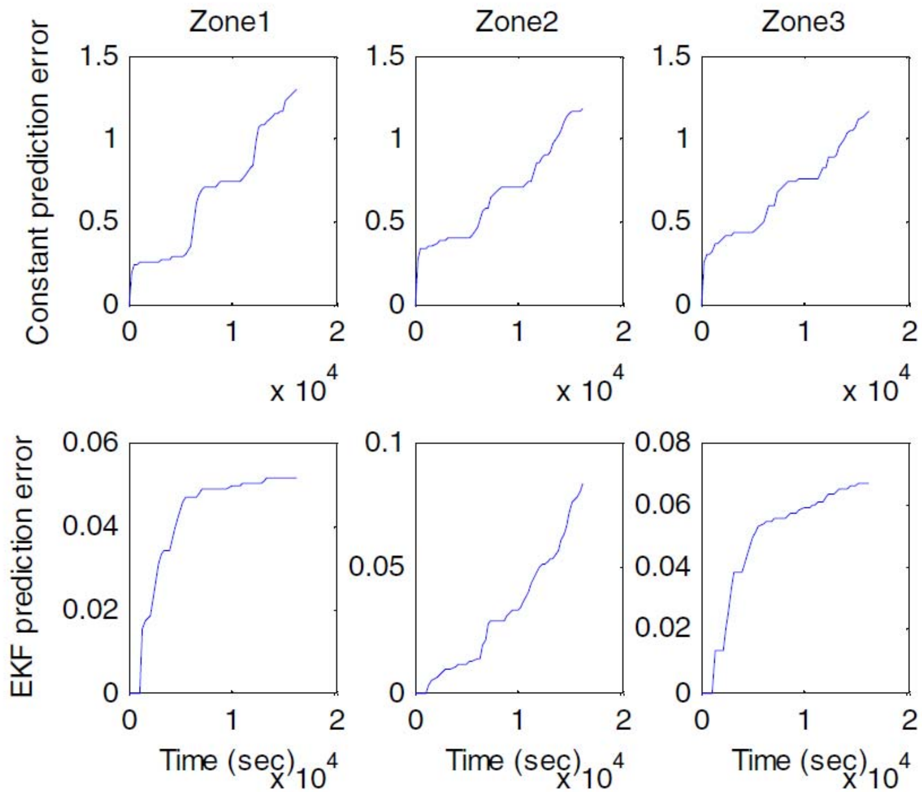
EKF estimation

$$x = [T_1, T_2, T_3, m_1, m_2, UA_{wall1}, UA_{wall2}, UA_{wall3}, k_{11}, k_{12}, k_{13}, C_{11}, C_{12}, C_{13}, V_1, V_2, V_3]$$

$$Z = [T_1, T_2, T_3, Q_{out1}, Q_{out2}, Q_{out3}, \Delta P_{in1}, \Delta P_{in2}, \Delta P_{in3}]$$

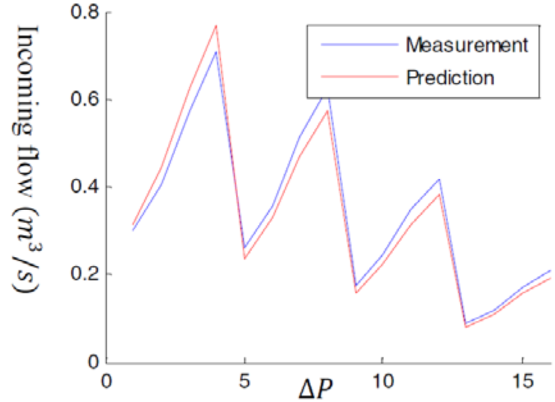
$$\varepsilon_{CP} = \sqrt{\sum (y_{k-1} - y_k)^2}$$

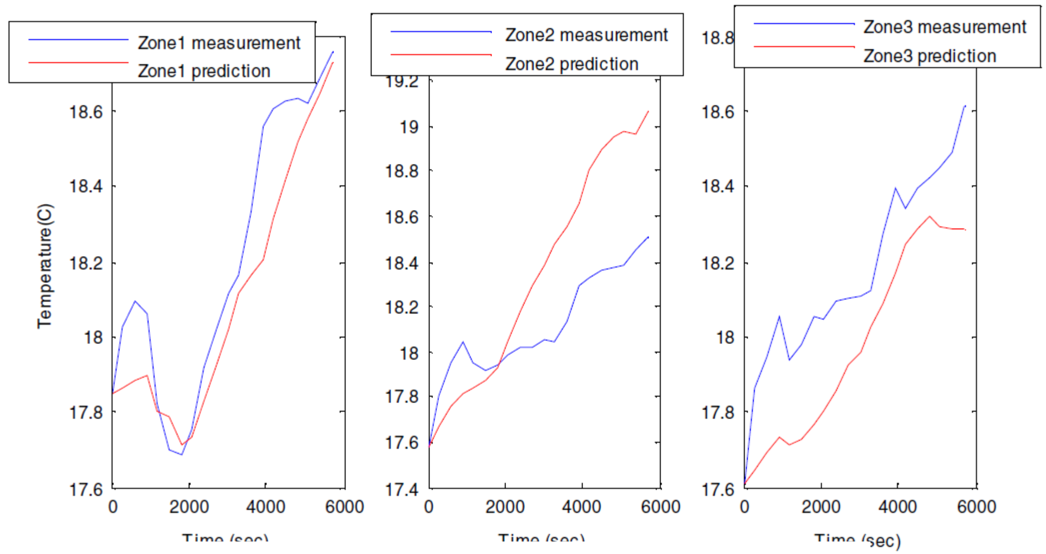
$$\varepsilon_{EKF} = \sqrt{\sum (\hat{y}_k - y_k)^2}$$

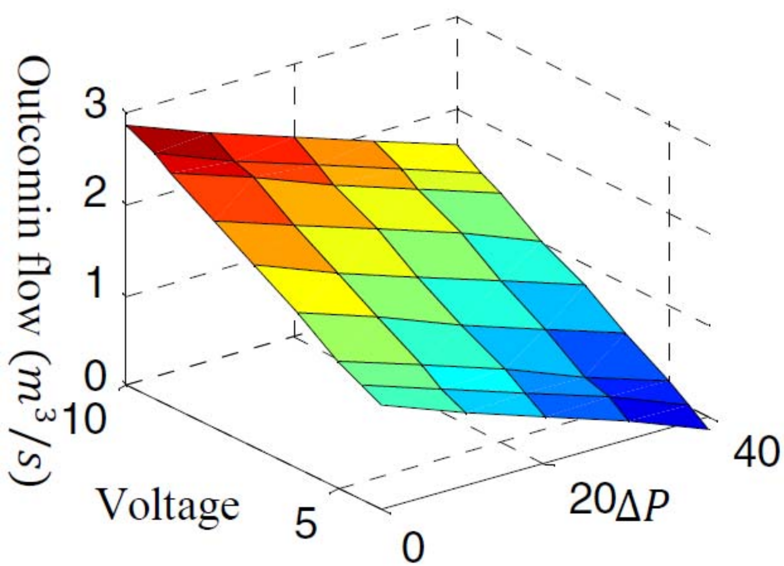


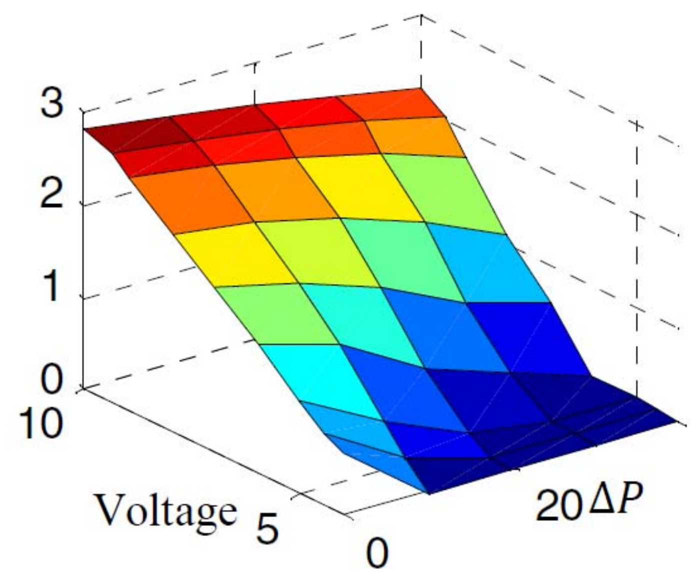
Model Validation

The extended kalman filter consists of two steps:









Conclusion and Future work

Conclusion:

• Deriving multi zone model for the indoor climate of a live-stock building

• Parameter estimation using EKF due to it is able to converge well to the parameters of the nonlinear hybrid models

• The EKF depends on the initial values and tuning factors

• generally the multi-zone model tracks the trace of real data; however, some discrepancy between predicted and measurement values were observed.

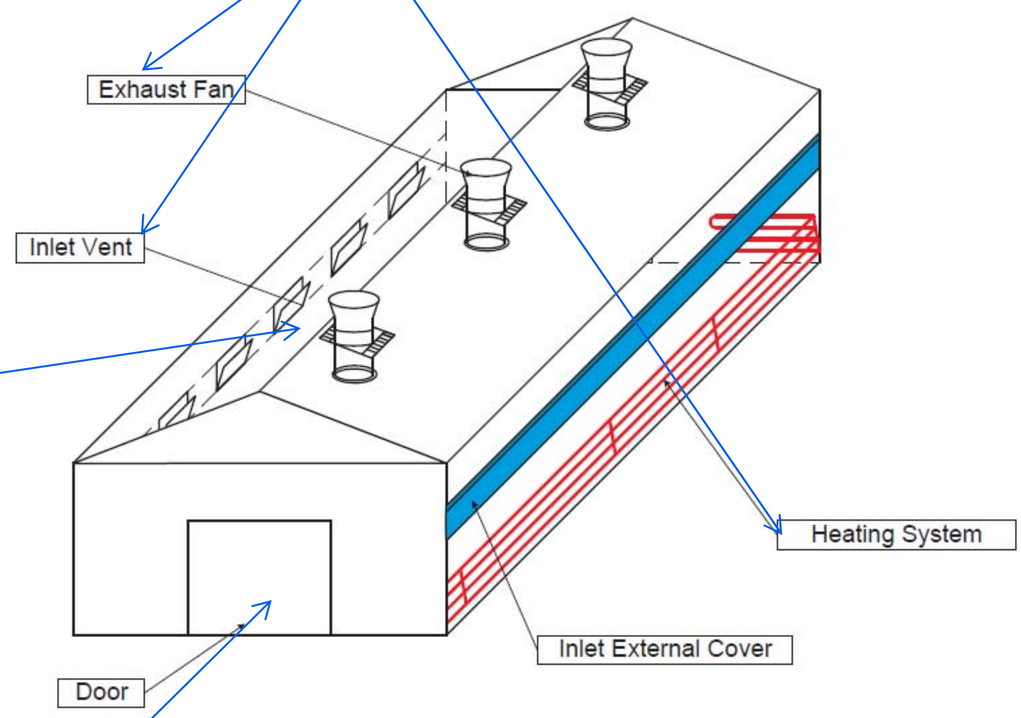
• The model uncertainty is related to undesirable environment disturbances.

• For Future work, it will addressed to open questions for using analytical input-output modeling instead of grey box

Fault Diagnosis

Actuator fault

The different kinds of fault in the system:



Sensor fault

Component fault

Outline of Active Fault Diagnosis

- Passive fault detection versus active fault detection

- Deriving the test input using the sensitivity analysis

-Active fault detection with EKF for the stable

- Active fault detection with new adaptive filter mixed with EKF for the stable

-Discussion and results

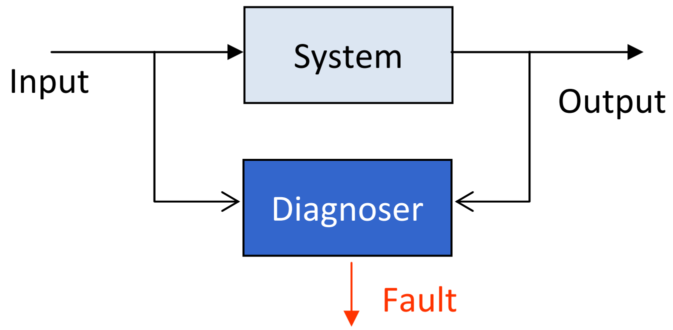
Passive fault detection versus Active fault detection

-Passive

-like all kind of warning lights, fire and smoke alarms

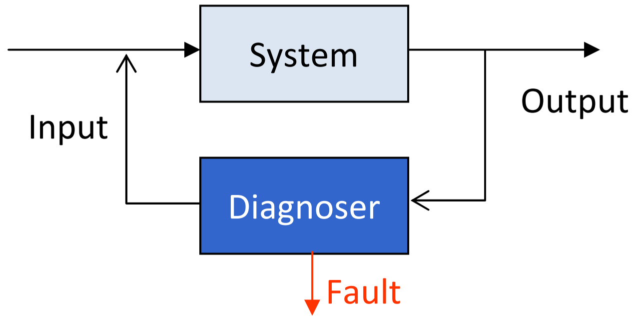
-Diagnoser observes the input and output set of the system and decides if a fault has happend or not

-Most of the available approaches



-Active

-Diagnoser disturb the system from normal operation point with a test signal, in order to observe if there is any hidden fault in the system



Active fault detection

-Test Signal is Optimum :

- -To perturb the system as little as possible
- -Meanwhile it's big enough to make the fault observable from the output of the system

-Advantages:

- - It is possible to observe the fault when normal and faulty systems represent same behaviour
- - Sanity check at the commissioning phase of the operation
- -Faster detection
- -Detection when the faulty behaviour is masked by the controller regulations

Sensitivity Analysis for obtaining the test signal

$$\theta_N = \arg\min_{\theta} P(u_N, y_N, \theta) \qquad P(\theta) = \frac{1}{2N}\sum_{k=1}^{N} \varepsilon^2(k,\theta)$$

$$\varepsilon_P(k,\theta) = y_m(k,\theta) - y_m(k,\theta_N)$$

It is known from (4) that an accurate estimate of a parameter θ_i requires $P(\theta)$ being sensitive to θ_i .
The root mean square of $\varepsilon_P(k,\theta)$ is defined as:

$$\varepsilon_{P,RMS}(\theta) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} \varepsilon_P^2(k,\theta)} \qquad \varepsilon_{P,RMSn} = y_{RMS}^{-1}\varepsilon_{P,RMS}$$

where

$$\theta_r = L^{-1}\theta \qquad L = diag(\theta_N) \qquad y_{RMS} = \sqrt{\frac{1}{N}\sum_{k=1}^{N} y^2(k)}$$

Parameter Sensitivity

$$R = \frac{S_{\max}}{S_{\min}} \qquad S_i = \frac{\partial \varepsilon_{p,RMSn}}{\partial \theta_{ri}} = \sqrt{h_{rnii}}$$

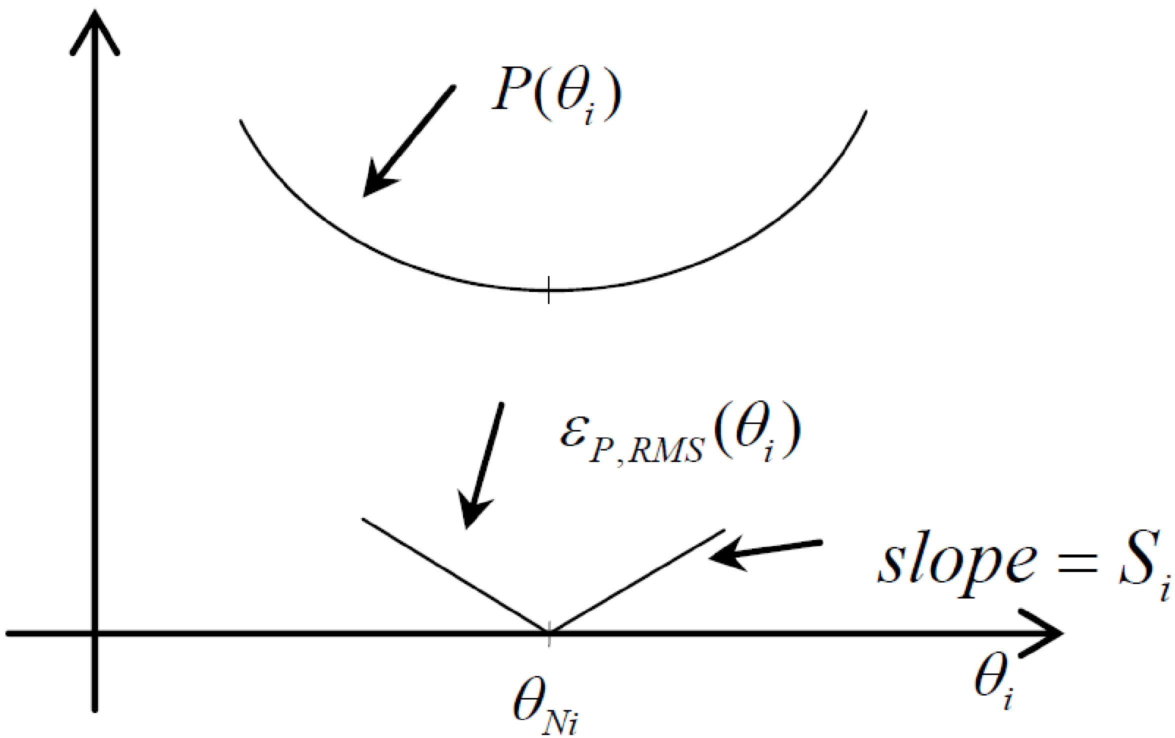


Fig 2. Performance function $P(\theta_i)$ and RMS parameter dependent error $\varepsilon_{P,RMS}(\theta_i)$ as a function of parameter θ_i

Parameter Sensitivity

$$\vec{u} = \vec{a}\sin(2\pi \vec{f} t)$$

$$(\vec{a}, \vec{f}) = \arg\max_{\vec{a}, \vec{f}} S_i \quad i = 1, \ldots l$$

Solved by GA

$s.t.$

Model constraints

$$P_k^- = F_{k-1} P_{k-1}^+ F_{k-1}^T + Q_{k-1}$$

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1}$$

$$\hat{x}_k^- = F_{k-1}\hat{x}_{k-1}^+ + G_{k-1}u_{k-1} = \text{ \textit{a priori} state estimate}$$

$$\hat{x}_k^+ = \hat{x}_k^- + K_k(y_k - H_k\hat{x}_k^-) = \text{ \textit{a posteriori} state estimate}$$

$$\begin{aligned} P_k^+ &= (I - K_k H_k) P_k^- (I - K_k H_k)^T + K_k R_k K_k^T \\ &= \left[(P_k^-)^{-1} + H_k^T R_k^{-1} H_k\right]^{-1} \\ &= (I - K_k H_k) P_k^- \end{aligned}$$

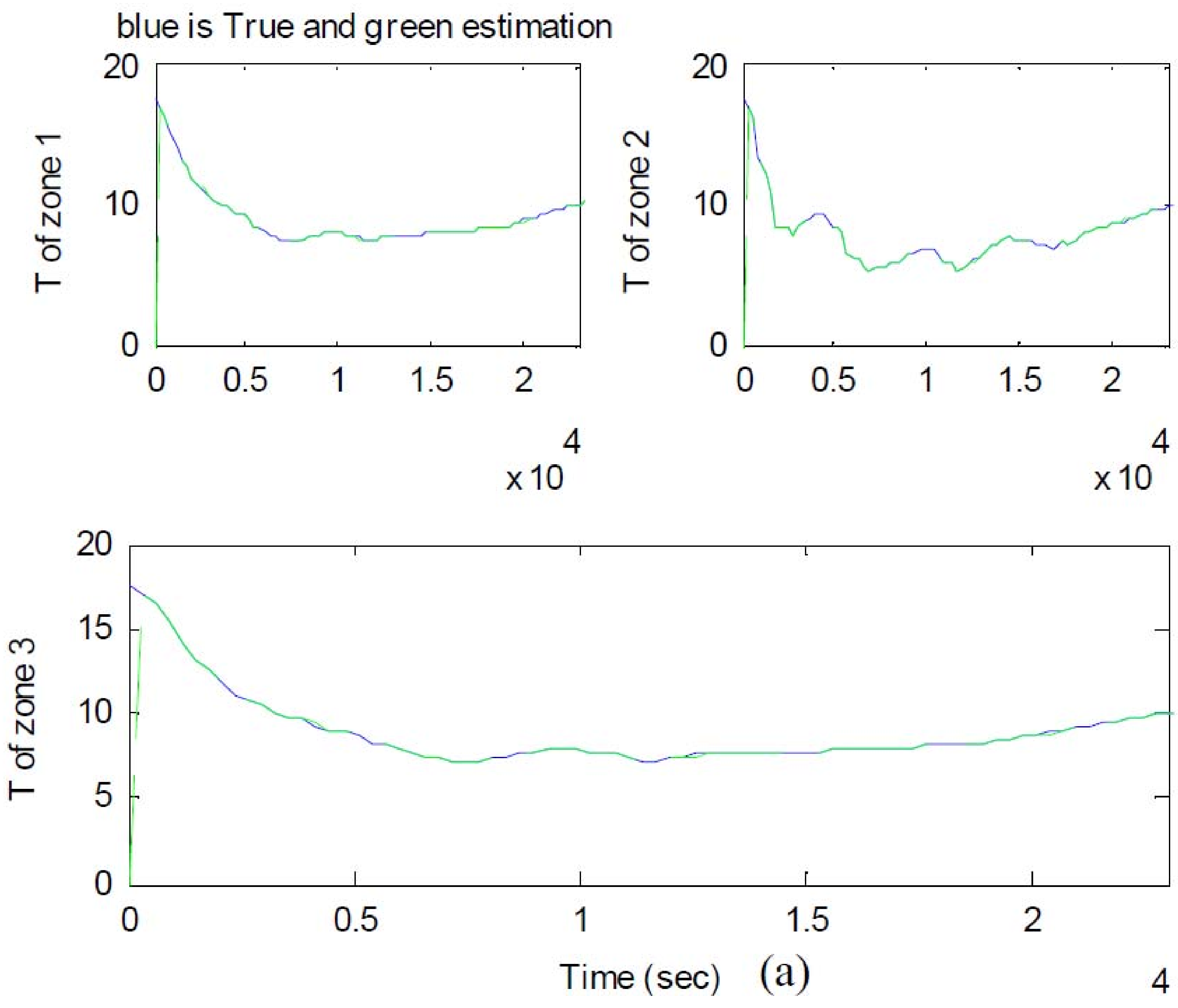
Parameter Sensitivity

In order to use the EKF as an observer and parameter estimator the state space model of the system must be extended as:

$$\begin{cases} \dot{X} = \begin{bmatrix} \dot{x} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} f(x,u,t)+v \\ 0_{l\times 1} \end{bmatrix} \\ y = h(X,u,t)+w, \end{cases}$$

$$\begin{cases} \hat{\theta}_i - \theta_i = r_i \quad i = 0,\ldots l \\ for\ \ i = 0\ to\ l \\ \qquad if\ r_i > \gamma \\ \qquad F = F_i \\ \qquad end\ if \\ end\ \ for \end{cases}$$

Active fault detection with EKF for the stable



(a)

Active fault detection with EKF for the stable

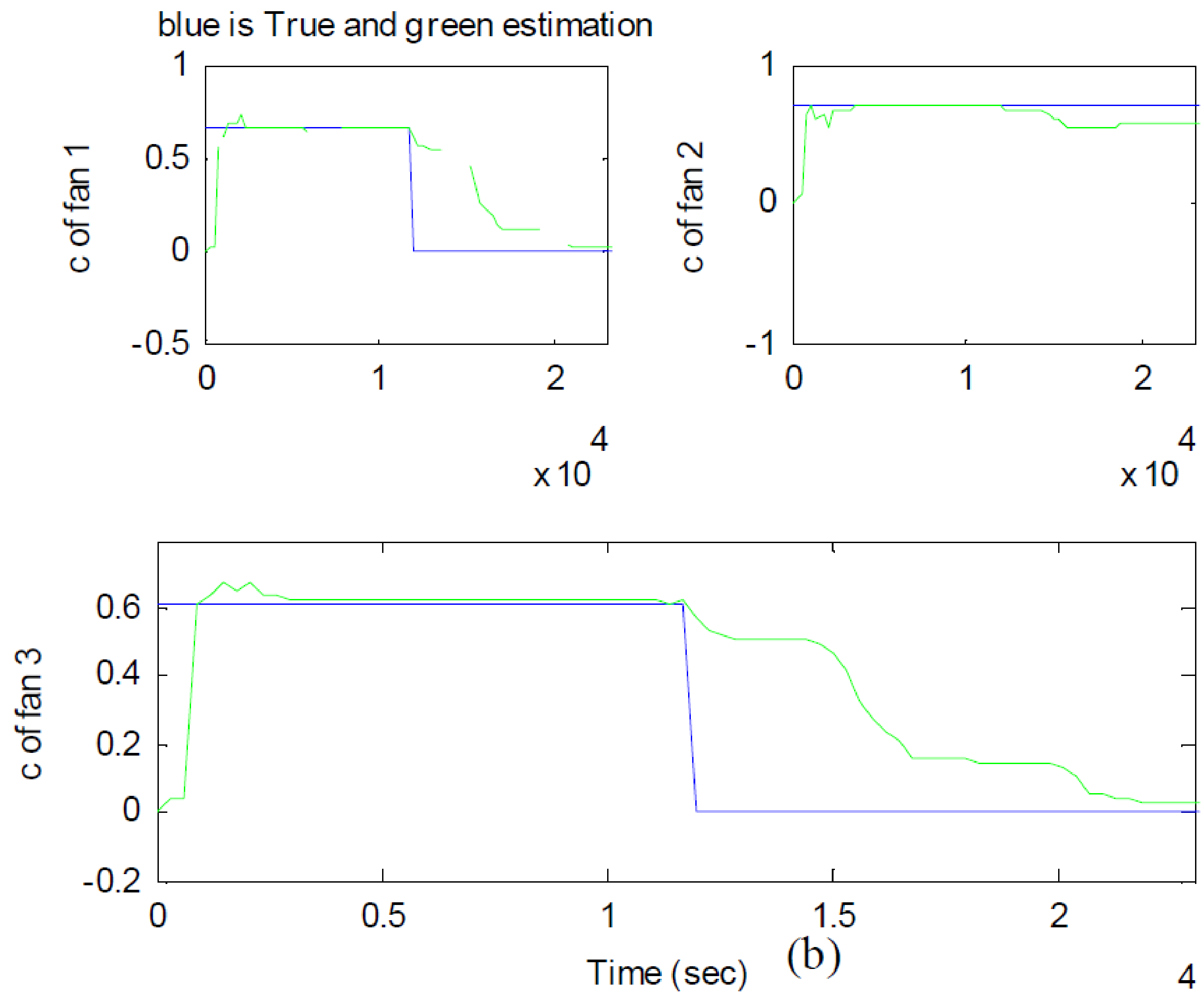


Fig. 4. (a) shows the real and estimated value of the indoor temperature of each zone. (b) shows the parameter of the each fan

Active fault detection with EKF for the stable

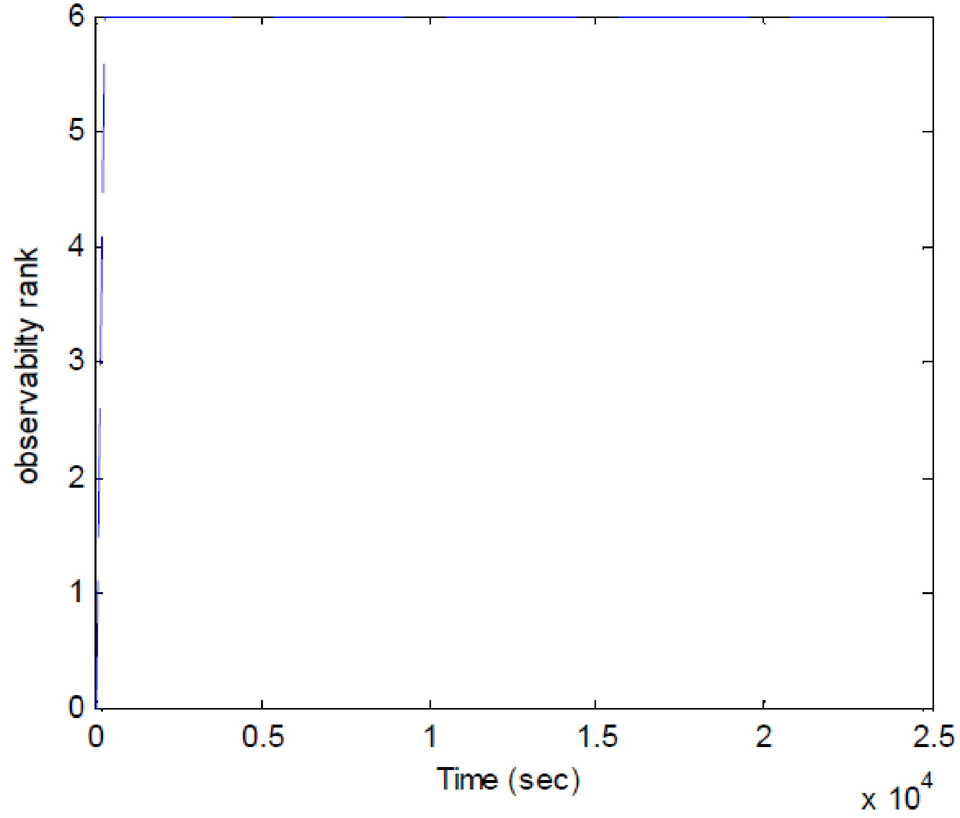
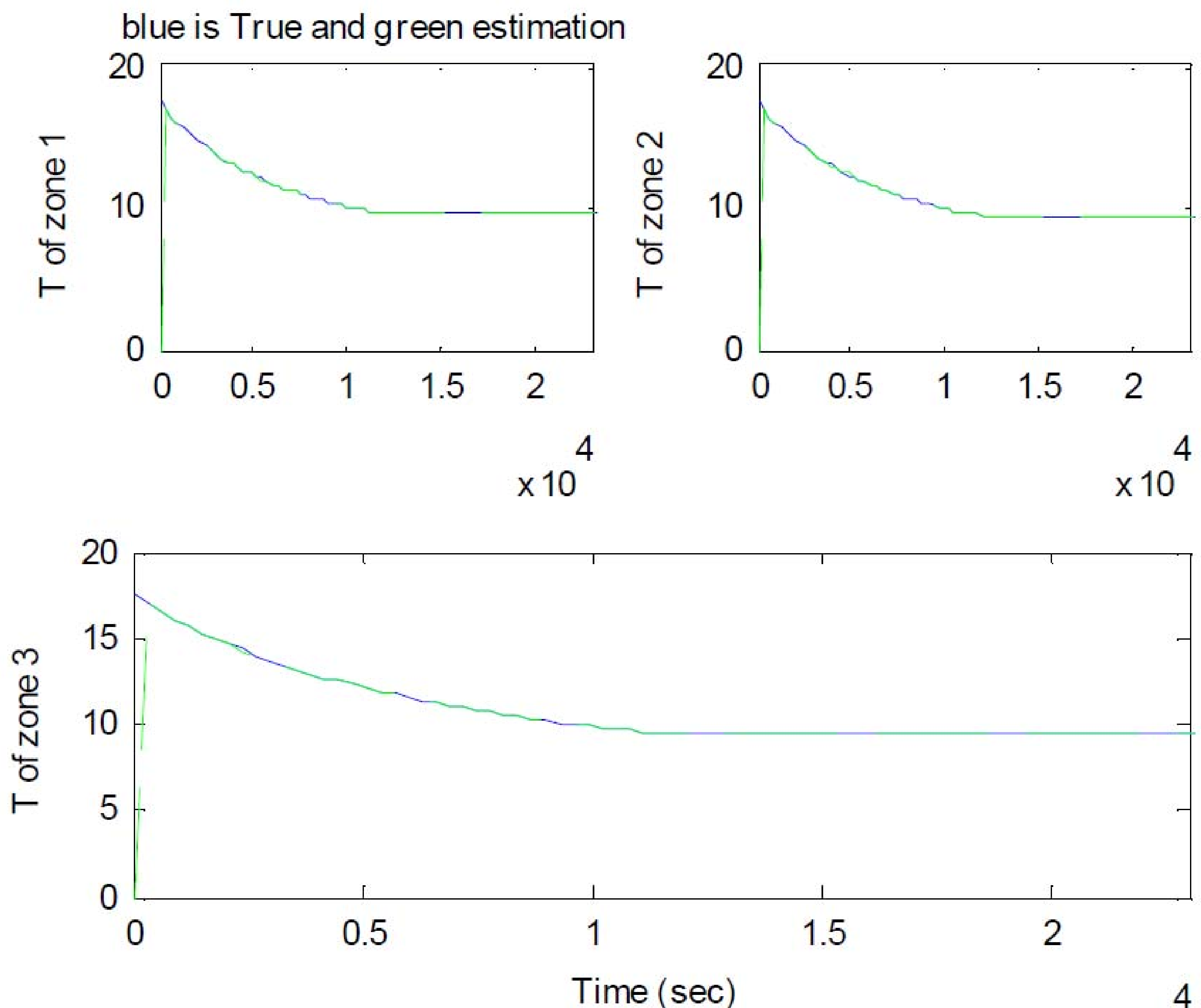


Fig. 5. The rank of the Grammian matrix

Active fault detection with EKF for the stable with different Inputs



Active fault detection with EKF for two tank example

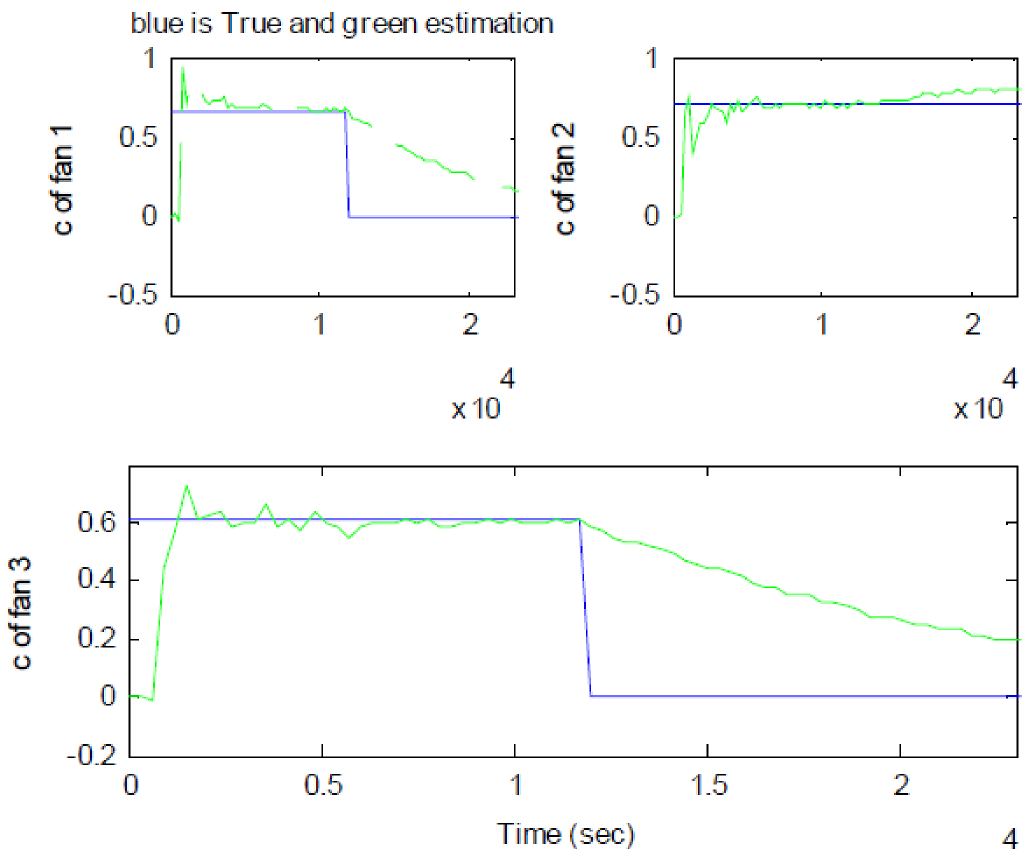


Fig. 6. (a) shows the real and estimated value of the indoor temperature of each zone. (b) shows the parameter of the each fan

Active fault detection with new adaptive filter mixed with Kalman filter for The stable

$$\begin{aligned}\dot{x}(t) &= A(t,u,y)x(t) + B(t,u,y)u(t) + \Psi(t,u,y)\theta + \varphi(t,u,y)\\ y(t) &= C(t,u,y)x(t) + D(t,u,y)u(t)\end{aligned}$$

$$\dot{\hat{x}}(t) = A(t)\hat{x}(t) + B(t)u(t) + \Psi(t)\hat{\theta}(t) + \left[K(t) + \Upsilon(t)\Gamma\Upsilon^T(t)C^T\Sigma(t)\right]\left[y(t) - C(t)\hat{x}(t)\right] \quad (10a)$$

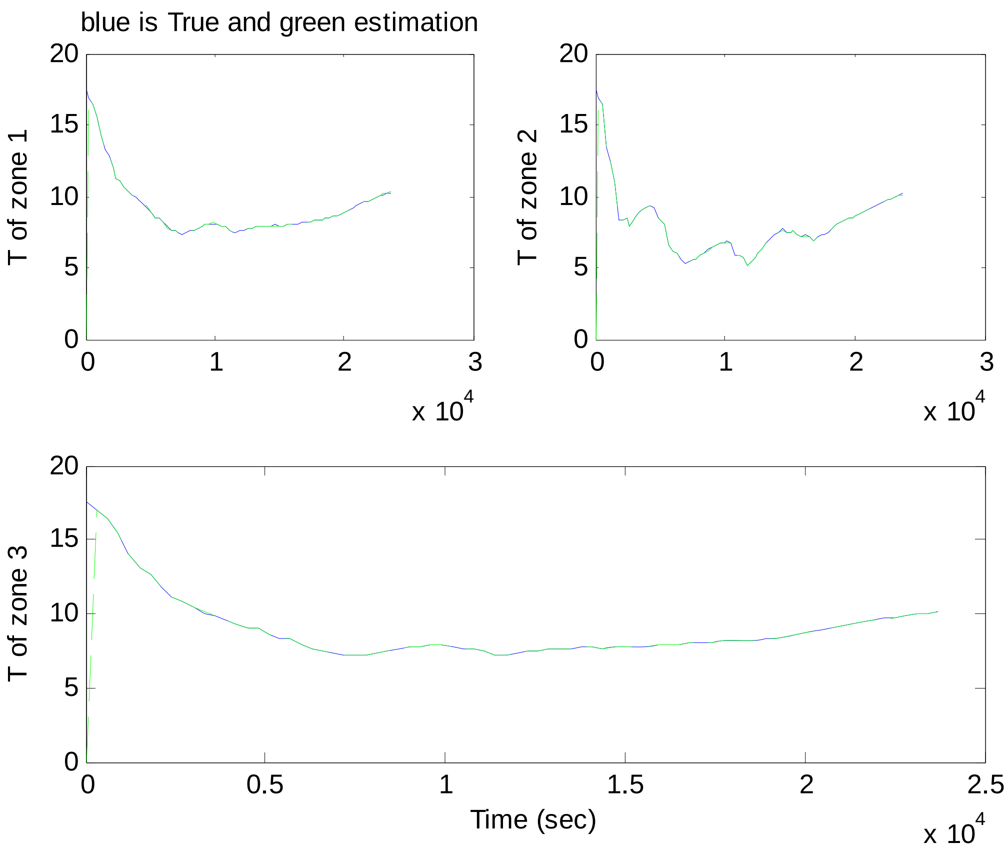
$$\dot{\hat{\theta}}(t) = \Gamma\Upsilon^T(t)C^T(t)\Sigma(t)\left[y(t) - C(t)\hat{x}(t)\right] \quad (10b)$$

$$\dot{\eta}(t) = [A(t) - K(t)C(t)]\eta(t)$$

$$\dot{\Upsilon}(t) = [A(t) - K(t)C(t)]\Upsilon(t) + \Psi(t)$$

$$\int_t^{t+T} \Upsilon^T(\tau)C^T(t)\Sigma(t)C(t)\Upsilon(\tau)d\tau \geq \delta I$$

Active fault detection with new adaptive filter mixed with EKF for the stable



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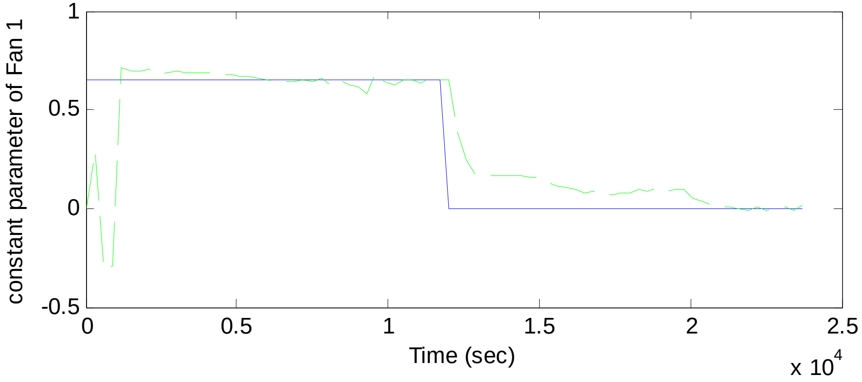
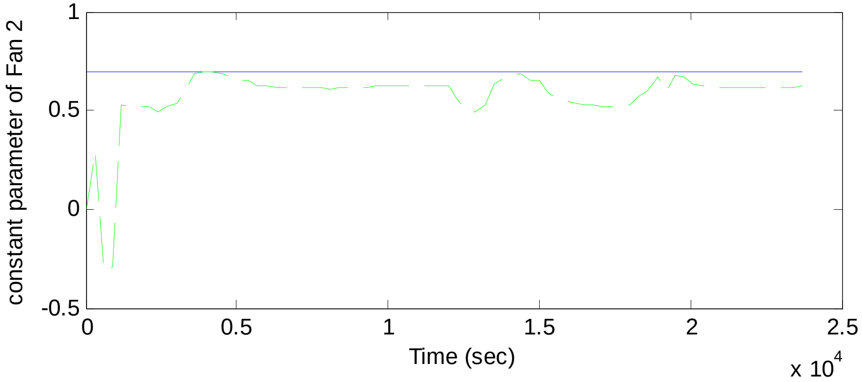
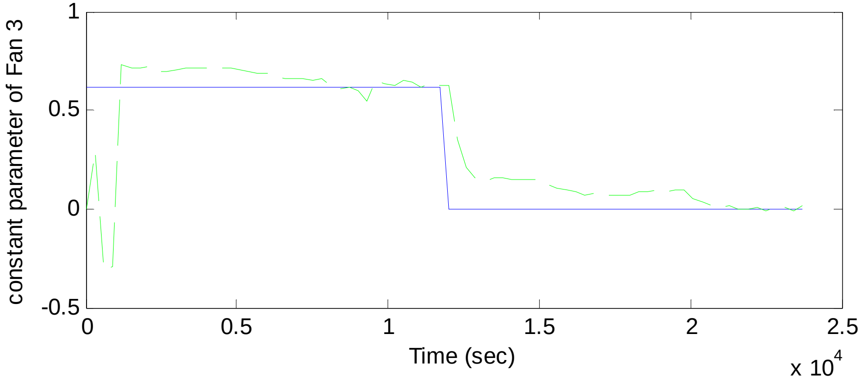
Active fault detection with new adaptive filter mixed with EKF for the stable







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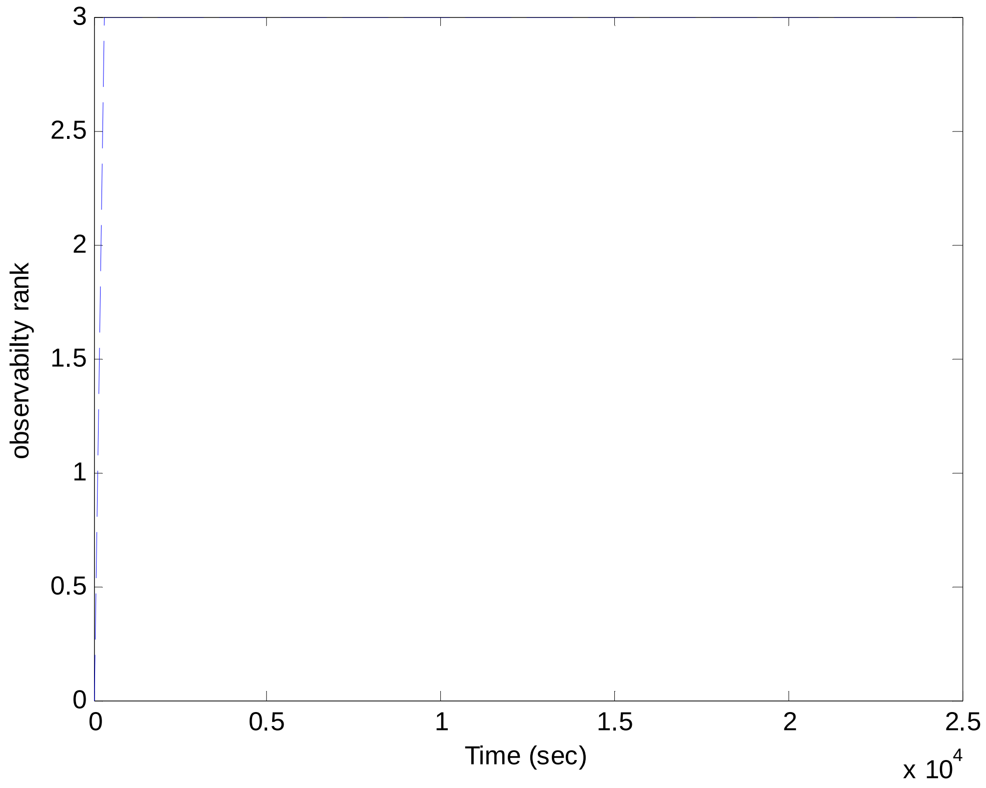
Active fault detection with new adaptive filter mixed with EKF for the stable



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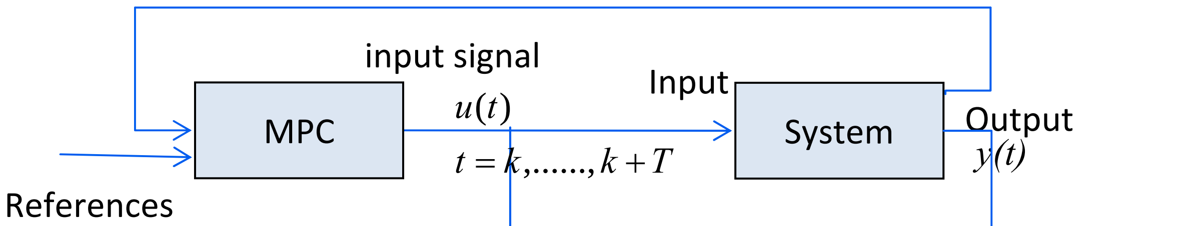
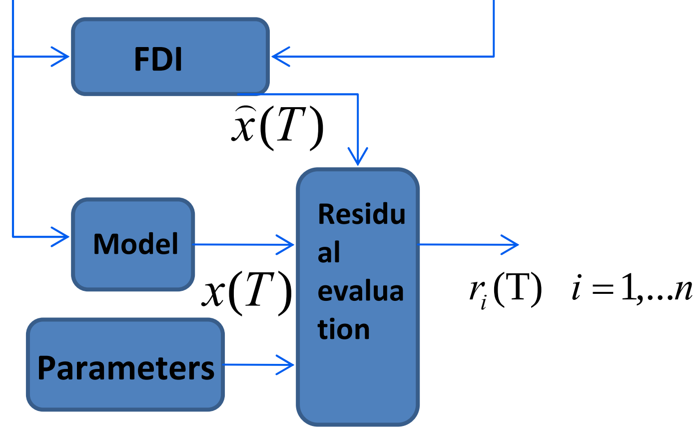
Active fault detection and isolation

$$\dot{\hat{x}} = f(x,u) + Md(t)$$
$$y = C\hat{x}$$

The system is hybrid





$$u(f,a,t) = \arg\min \sum_{t=k}^{k+h-1} [\hat{u}(t) - u_r] Q [\hat{u}(t) - u_r] +$$
$$[\hat{y}(t) - y_r] R [\hat{y}(t) - y_r]$$
$$s.t.$$
$$\dot{\hat{x}}(t) = f(x(t), u(t)) + Md(t)$$

model constraints

sensitivity boundary

persistent excitation criteria

$$x = T_1, T_2, T_3, C_{din1}, C_{din2}, C_{din3}, c_{out1}, c_{out2}, c_{out3}, C_{heater}$$

Controller reconfiguration

fault-tolerant control against actuator fault

Passive fault-tolerant control of discrete time piecewise Affine systems

the state feedback controller is designed to tolerate the actuator faults

$$x_{k+1} = A_i x_k + B_i u_k + a_i, \ \text{for} \ \begin{bmatrix} x_k \\ u_k \end{bmatrix} \in \chi_i$$

$$\chi_i := \left\{ \left[\, x^T \ u^T \, \right]^T \ \text{such that} \ F_i^x x \geq f_i^x \ \text{and} \ F_i^u u \geq f_i^u \right\}.$$

$$S := \{(i,j) | [x^T(k) \ \ u^T(k)]^T \in \chi_i, [x^T(k+1) \ \ u^T(k+1)]^T \in \chi_j\}$$

Fault Model

$$u_j^F = (1 - \alpha_j) u_j, \quad 0 \leq \alpha_j \leq \alpha_{M_j},$$

Then

$$\alpha = diag\{\alpha_1, \alpha_2, \ldots, \alpha_m\}.$$

$$\mathbf{u}^F = \Gamma \mathbf{u}, \qquad \Gamma = (I - \alpha).$$

Controller Reconfiguration

Passive fault-tolerant control of discrete time piecewise Affine systems

the state feedback controller is designed to tolerate the actuator faults

The PWA model of the system with the loss of gain in actuators is:

$$x(k+1) = A_i x(k) + B_i \Gamma_i u(k) + a_i \quad \text{for } \left[x^T(k) \;\; u^T(k)\right]^T \in \chi_i \qquad (1)$$

State feedback design for PWA systems:

$$u(k) = K_i x(k) \quad for \left[x^T(k) \;\; u^T(k)\right]^T \in \chi_i \qquad (2)$$

Such that the closed loop piecewise affine system is:

$$x(k+1) = \mathrm{A}_i x(k) + a_i \quad for \left[x^T(k) \;\; u^T(k)\right]^T \in \chi_i$$

Where

$$\mathrm{A}_i = A_i + B_i \Gamma_i K_i$$

Fault Tolerant Control

Passive fault-tolerant control of discrete time piecewise Affine systems

the state feedback controller is designed to tolerate the actuator faults

The quadratic cost function associated with the system is:

$$J = \sum_{k=0}^{\infty} x^T(k)Qx(k) + u^T(k)Ru(k), \qquad (3)$$

Where

$Q \geq 0$ *and* $R \geq 0$ are given weighting matrices of appropriate dimensions.

- **Passive fault tolerant control**

A piecewise affine control law of the form (2) is a passive fault-tolerant guaranteed cost control for the system (1) and performance function (3) if the following inequality is satisfied:

$$(A_j + B_j\Gamma_j K_j)^T P_i (A_j + B_j\Gamma_j K_j) - P_j + Q + K_j^T \Gamma_j^T R \Gamma_j K_j < 0, \quad \forall (i,j) \in \mathcal{S}.$$

The performance function satisfies:

$$J \leq x^T(0) P_{i_0} x(0).$$

Fault Tolerant Control

$$V(x(k)) = x^T(k)P_i x(k), \forall x \in \mathcal{X}_i \qquad V(x(k+1)) - V(x(k)) < 0.$$

$$\begin{bmatrix} -\epsilon_j I & \alpha_j Y_j & 0 & 0 & 0 \\ Y_j^T \alpha_j & Z_j - G_j - G_j^T & G_j^T & Y_j^T & (A_j G_j + B_j Y_j)^T \\ 0 & G_j & Q^{-1} & 0 & 0 \\ 0 & Y_j & 0 & R^{-1} + \epsilon_j I & \epsilon_j B_j^T \\ 0 & (A_j G_j + B_j Y_j) & 0 & \epsilon_j B_j & Z_i + \epsilon_j B_j^T B_j \end{bmatrix} < 0, \quad \forall (i,j) \in \mathcal{S}$$

$$K_i = Y_i G_i^{-1} \qquad J \leq x^T(0) Z_{i_0}^{-1} x(0)$$

$$E(J) \leq E(tr(P_{i_0} x(0) x^T(0))) \leq \sum_{i \in \mathcal{I}} \sigma_i tr(P_i L_i),$$

$$L_i = E(x(0)x^T(0)) \qquad i \in \mathcal{I} = \{1, \cdots, s\}$$

$$\min_{Z_i, Y_i, G_i, V_i, \epsilon_i} \sum_{i \in \mathcal{I}} \sigma_i tr(V_i L_i)$$

$$s.t. \begin{cases} \begin{bmatrix} V_i & I \\ I & Z_i \end{bmatrix} \geq 0, \; i \in \mathcal{I} \\ Z_i = Z_i^T > 0, \; i \in \mathcal{I} \\ V_i = V_i^T > 0, \; i \in \mathcal{I} \end{cases}$$

It can be solved by YALMIP/LMILAB (Free software)

Conclusion and Open issues

- Passive fault-tolerant control of discrete time piecewise Affine systems
- Using piecewise quadratic Lyapunov function and piecewise linear state feedback
- Existence of the controller is reformulated as the feasibility of a set of LMIs.
- The performance cost is minimized using a convex minimization problem with LMI constraints.

Open issues

How to fulfil the different input constraints as a LMI

Relaxation of polytope constraint of each region to ellipsoid and integrating with the following LMI for the path tracking problem

A summary of the current research

Piecewise nonlinear modeling for the live-stock buildings

- **Parameter estimation using EKF**

Active Fault diagnosis

- **Using sensitivity analysis to derive the test signal**
- **Using EKF for fault diagnosis**
- **Using an adaptive filter mixed with EKF for fault diagnosis**

Fault tolerant control

- **Converting the piecewise nonlinear model to PWAmodel**
- **At first assuming actuator fault**
- **Desiging state feedback controller for fault tolerancy, usin a convex minimization problem with LMI constraints**

Thank you !