Fault Diagnosis of Interconnected Cyber-Physical Systems

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7th oCPS PhD School on Cyber-Physical Systems
Lucca, Italy, 14th June 2017

Presentation Outline

- Motivation for fault diagnosis
- Interconnected cyber-physical systems
- Foundations of fault diagnosis
- Sensor fault diagnosis
- Application example: Smart Buildings
- Concluding Remarks

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The Smart Revolution

- Smart Phones
- Smart Cars
- Smart Grids
- Smart Buildings
- Smart Cities
- Smart Camera Networks
- Smart Water Networks

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→ Smart-X

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Characteristics of Smart-X

HARDWARE

- Sensing & actuation devices
- Embedded computing
- Wide area connectivity

SOFTWARE

- Data management
- Decision making algorithms
- Learning algorithms
- Optimization and control

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Smart-X vs Smart-ready-X

- Digital advances provide the ICT infrastructure not the INTELLIGENCE (so far)
- Infrastructure will be further enhanced via the IoT
- Smart-X   vs. Smart-ready-X

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- Infrastructure will be further enhanced via the IoT
- Smart-X   vs. Smart-ready-X

→ Control systems and machine learning are at the heart of transforming Smart-ready-X to Smart-X

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Control Systems in the Smart-X Era

- More proactive, more planning ahead
- More discrete-event, more event-triggered
- More machine learning, handling of larger volume of data, more heterogeneous data
- Handling of more uncertainty, fault tolerance
- Handling of human-machine interaction

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Fragility

The technological trend is towards:

- more complex and large-scale systems
- more interconnected systems
- more automation and autonomy

However if the data is faulty/inconsistent/missing, this may lead to:

- wrong decisions or escalation to a catastrophic failure
- fault propagation from one subsystem to another
- Unreliable and untrustworthy automation procedures

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The technological trend is towards:

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→ more FRAGILE

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Fragility of Interconnected Systems

Fragility is a crucial issue in an interconnected cyber-physical-social world

Fault Monitoring and Fault Tolerance are necessary components of Smart-X architectures

Black Swan Theory – Nassim Nicholas Taleb

metaphor that describes an event that comes as a surprise, has a major effect, and is often inappropriately rationalized after the fact with the benefit of hindsight (extreme outliers)

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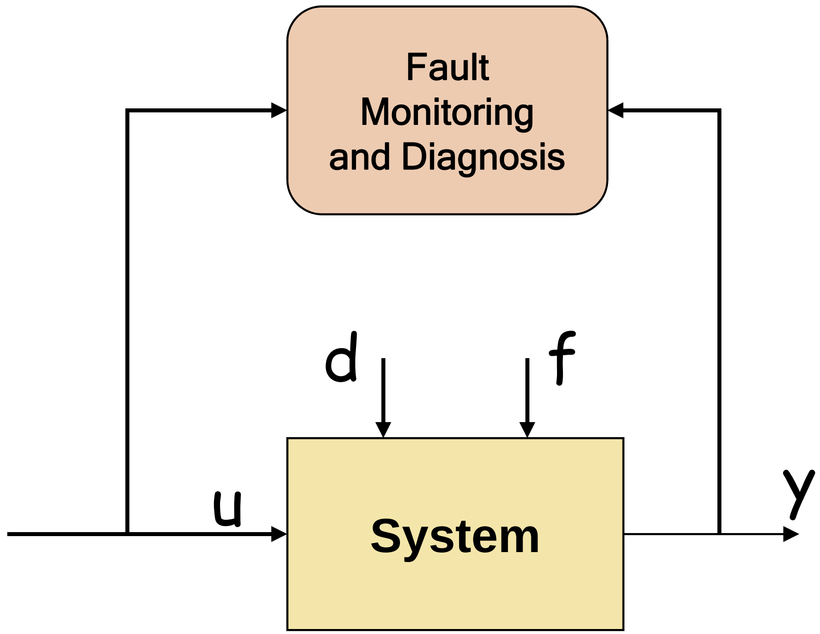
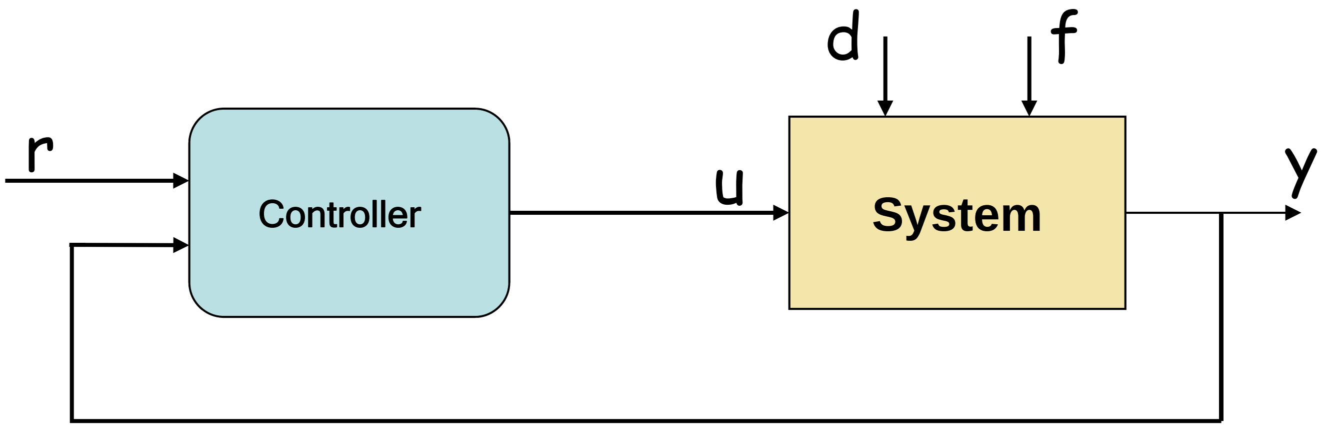
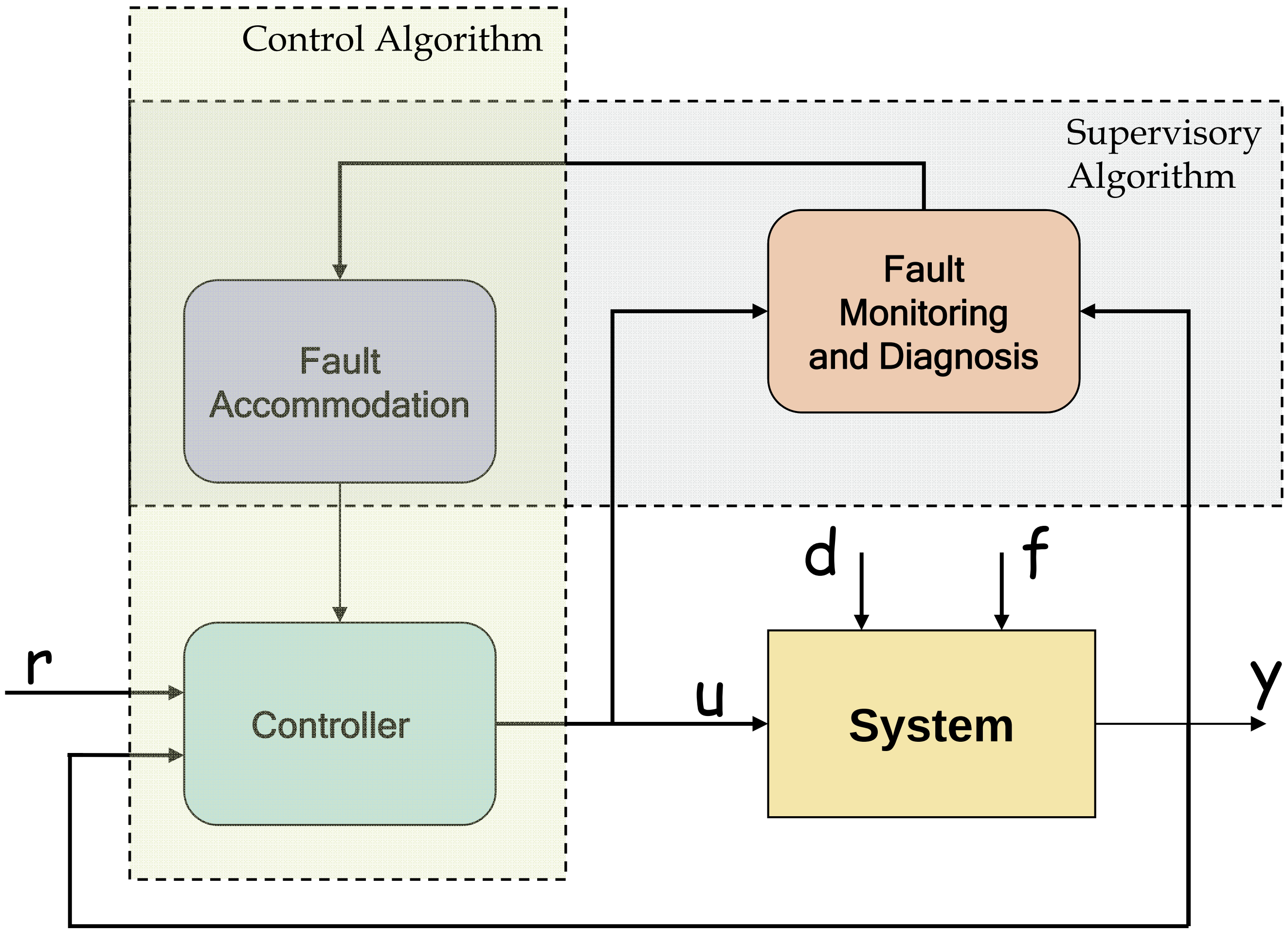
Monitoring and Control



Monitoring and **Control**

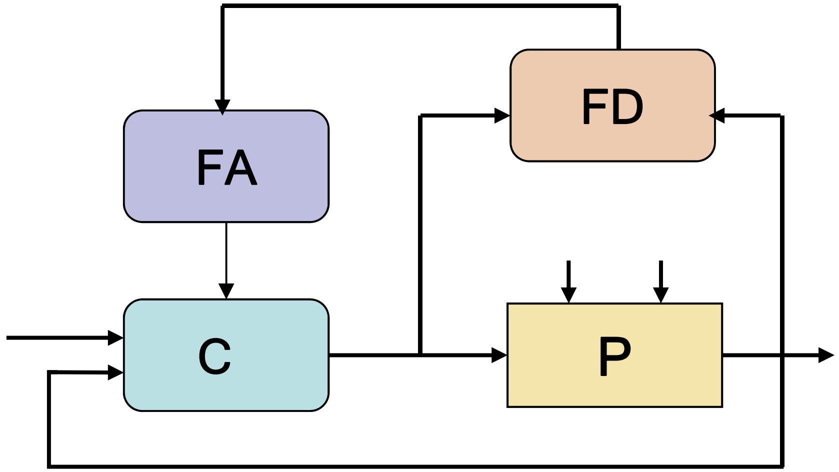


Monitoring and Control



Fault Scenarios

- System/Process Faults
- Actuator Faults
- Sensor Faults
- Communication Faults
- Controller Faults
- Environment Faults
- Malicious Attacks (cyber-security)



Fault Diagnosis Steps

- fault detection
- fault isolation
- fault identification and risk assessment
- fault accommodation

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Key Challenges for Fault Diagnosis

- distinguish between faults and modeling uncertainty or measurement noise
- exploit spatial and temporal correlations between variables
- handle multiple faults
- isolate faults in a large-scale system (needle in a haystack)
- prevent "small" faults from escalating into a major failure
- accommodate the fault – what to do in the presence of information about a fault?

→ Design smart SOFTWARE to handle faulty HARDWARE

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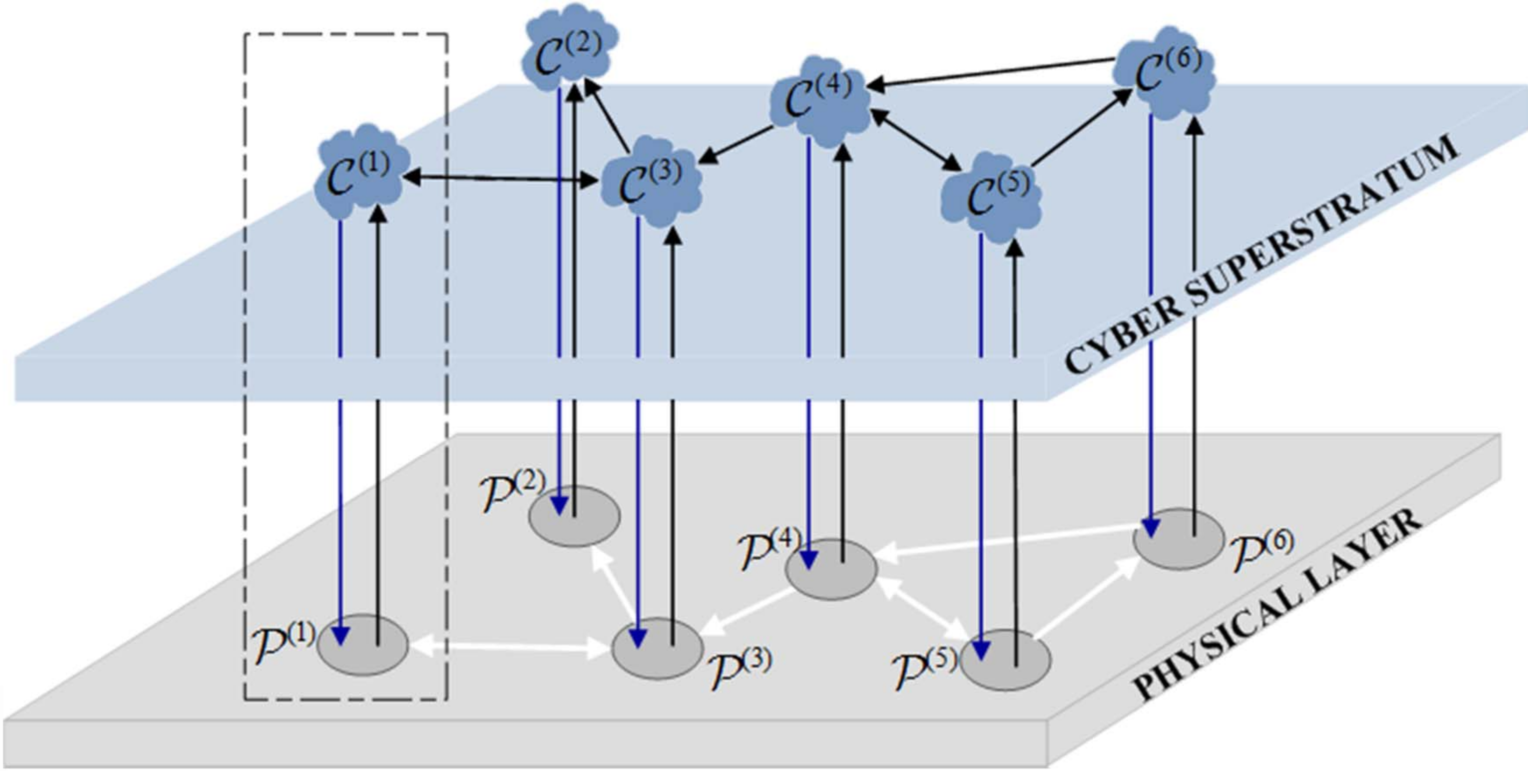
Key Books on Fault Diagnosis

- J. Gertler. Fault Detection and Diagnosis in Engineering Systems. CRC Press, 1998.
- J. Chen and R. J. Patton. Robust Model-based Fault Diagnosis for Dynamic Systems. Kluwer Academic Publishers, 1999.
- R. Isermann. Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Tolerance. Springer Verlag, 2006.
- S. X. Ding. Model-based Fault Diagnosis Techniques: Design Schemes, Algorithms, and Tools. Springer-Verlag London, 2008.
- M. Blanke, M. Kinnaert, J. Lunze, and M. Staroswiecki. Diagnosis and Fault-Tolerant Control. Springer-Verlag Berlin Heidelberg, 2016.

Interconnected CPS

- *N* interconnected CPS.
- *I*-th CPS: described by the pair $\left(\mathcal{P}^{(I)}, \mathcal{C}^{(I)}\right)$
  - $\mathcal{P}^{(I)}$: physical part of the *I*-th CPS,
  - $\mathcal{C}^{(I)}$: cyber part of the *I*-th CPS.



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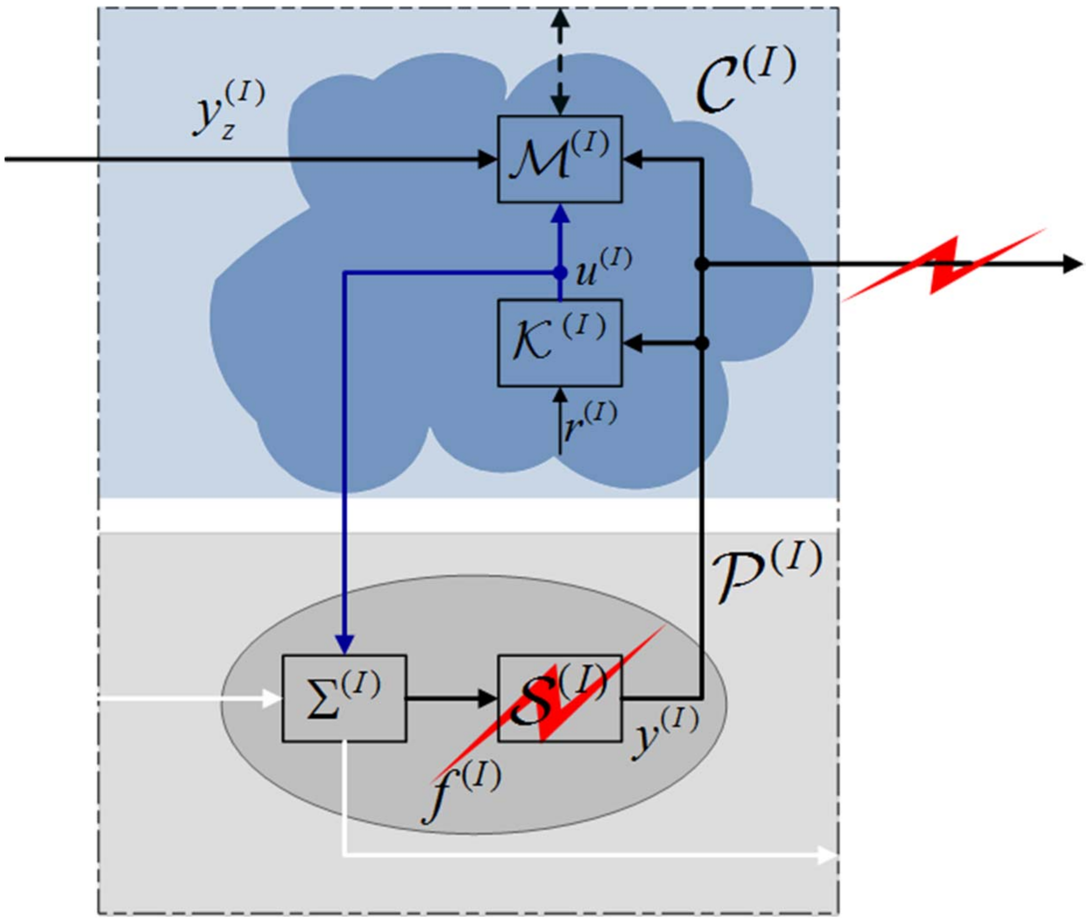
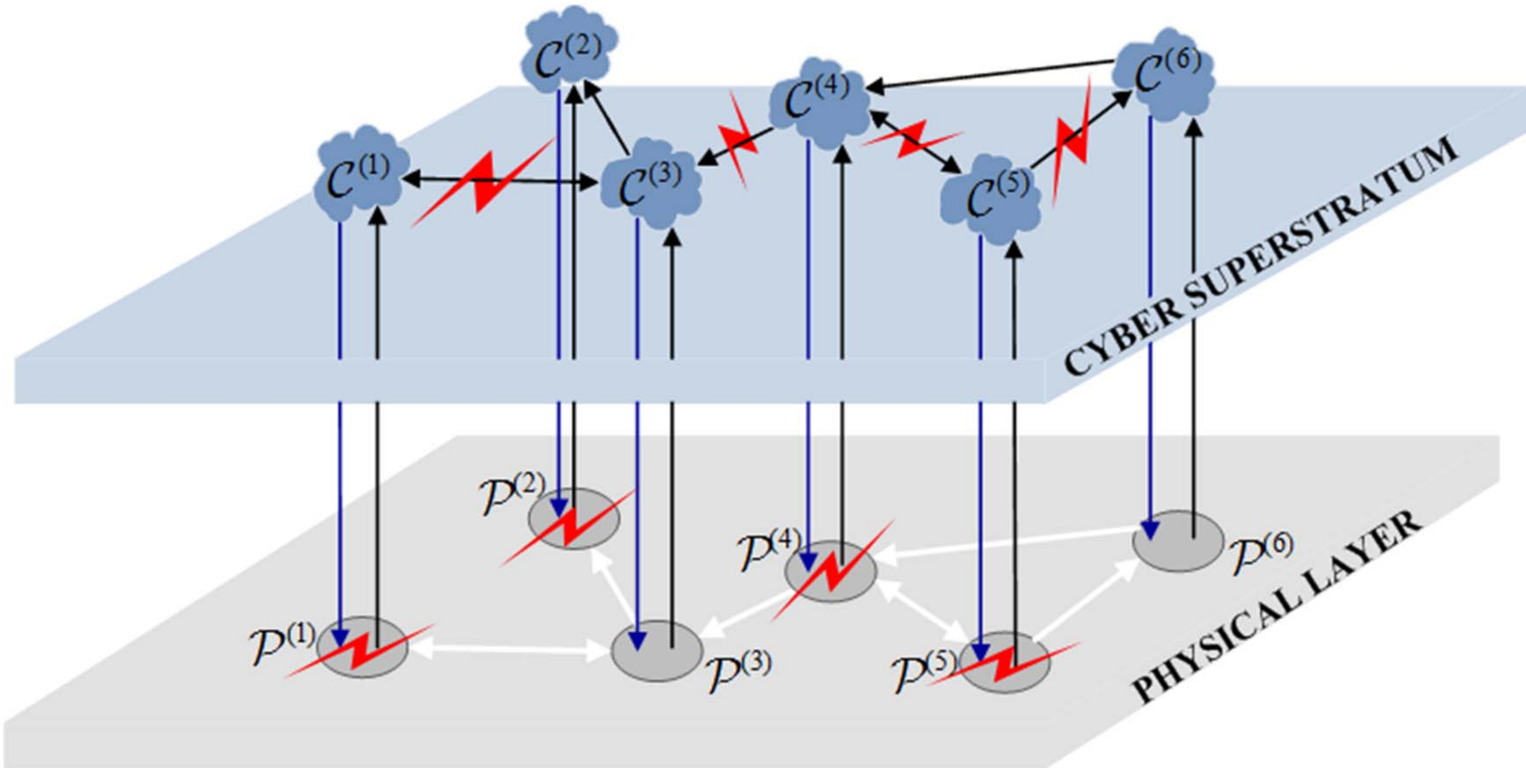
Interconnected CPS – Single Agent



Interconnected CPS



Objective: ***Detect and isolate multiple faults that may occur in one or more CPS***

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Problem Formulation

$$\dot{x}_i = \phi_i(x_i, u_i) + \eta_i(x_i, u_i, t) + \mathcal{B}_i(t - T_0) f_i(x_i, u_i) + \sum_{j \in \mathcal{J}} h_{ij}(x_j)$$

where:

$x \in \Re^n$: state vector

$u \in \Re^m$: input vector

$\phi : \Re^n \times \Re^m \mapsto \Re^n$: Nominal state dynamics

$\eta : \Re^n \times \Re^m \times \Re^+ \mapsto \Re^n$: Modeling uncertainty

$f : \Re^n \times \Re^m \mapsto \Re^n$: Change in the system due to fault

$\mathcal{B}(t - T_0)$: Time profile of the fault

$h_{ij}(x_j)$: Interconnection dynamics

Modeling Uncertainty

The modeling uncertainty η includes external disturbances as well as modeling errors.

$$|\eta_i(x,u,t)| \le \bar{\eta}_i(x,u,t), \qquad \forall\,(x,u) \in \bar{\mathcal{D}}, \quad \forall\, t \ge 0,$$

where for each i = 1, …., n, the bounding function $\bar{\eta}_i(x,u,t) > 0$ is known, integrable and bounded for all (x, u) in some compact region of interest $\bar{\mathcal{D}} \supseteq \mathcal{D}$

The handling of the modeling uncertainty is a key design issue in fault diagnosis architectures:
- need to distinguish between faults and modeling uncertainty
- structured vs. unstructured modeling uncertainty
- trade-off between false alarms and conservative fault detection schemes

Fault Modeling

The term $\mathcal{B}(t-T_0)f(x,u)$ represents the deviations in the dynamics of the system due to a fault.

- $f(x,u)$ is the fault function
- The matrix $\mathcal{B}(t-T_0)$ characterizes the time profile of a fault which occurs at some unknown time T_0

$$\mathcal{B}(t-T_0) = \text{diag}\,[\beta_1(t-T_0), \cdots, \beta_n(t-T_0)]$$

$$\beta_i(t-T_0) = \begin{cases} 0 & \text{if} \quad t < T_0 \\ 1 & \text{if} \quad t \geq T_0 \end{cases} \qquad \text{abrupt}$$

$$\beta_i(t-T_0) = \begin{cases} 0 & \text{if } t < T_0 \\ 1 - e^{-\alpha_i(t-T_0)} & \text{if } t \geq T_0 \end{cases} \qquad \text{incipient}$$

where $\alpha_i > 0$ denotes the unknown fault evolution rate.

Fault Influence for Distributed Systems

- **Local Faults**
- **Distributed Faults**
- **Distributed Faults with Overlapping Signature**
- **Propagating Faults**

Fault Isolation

Types of FAULT ISOLATION:

- **identify the type of fault that has occurred**
- **identify the physical location of the fault**

Class of fault functions f :

$$f(x,u) \in \mathcal{F} = \left\{ f^1(x,u), \ldots, f^N(x,u) \right\}$$

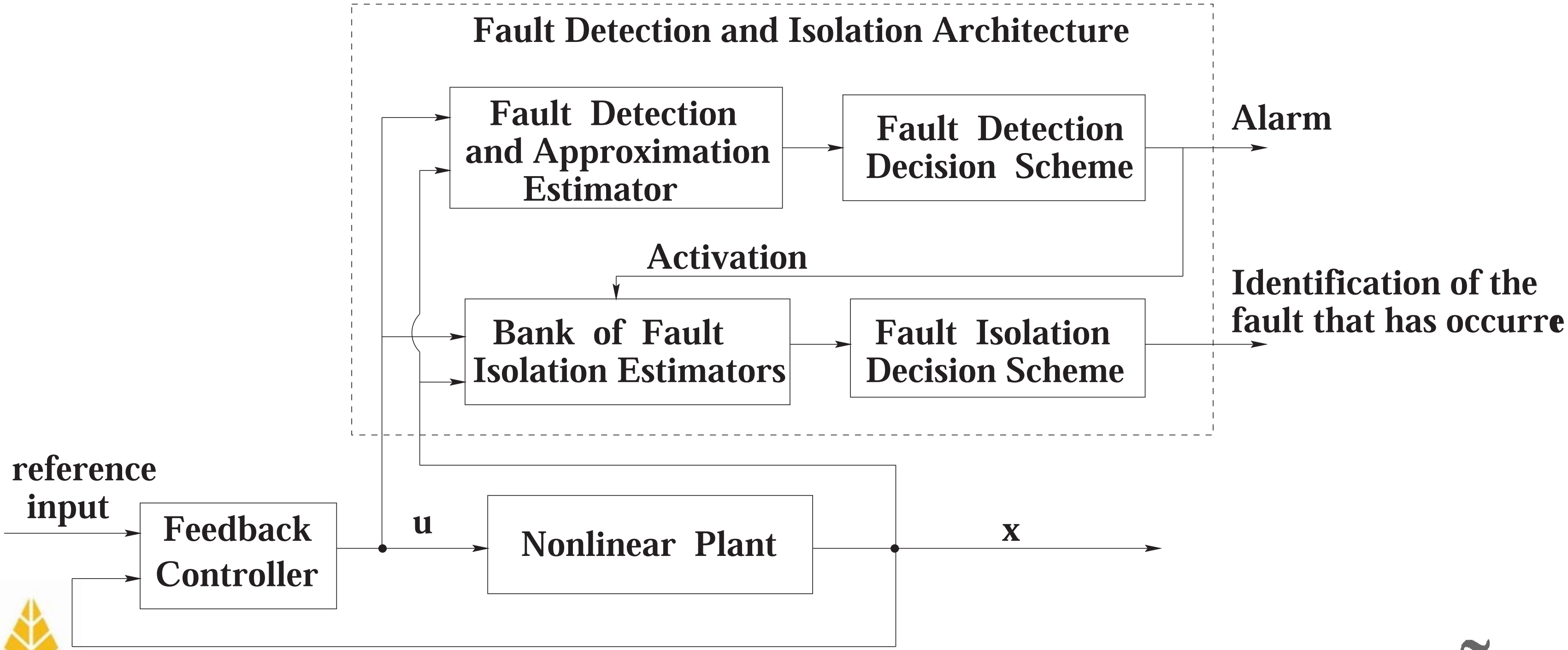
$$f^s(x,u) = \left[(\theta_1^s)^\top g_1^s(x,u), \cdots, (\theta_n^s)^\top g_n^s(x,u) \right]^\top$$

where:

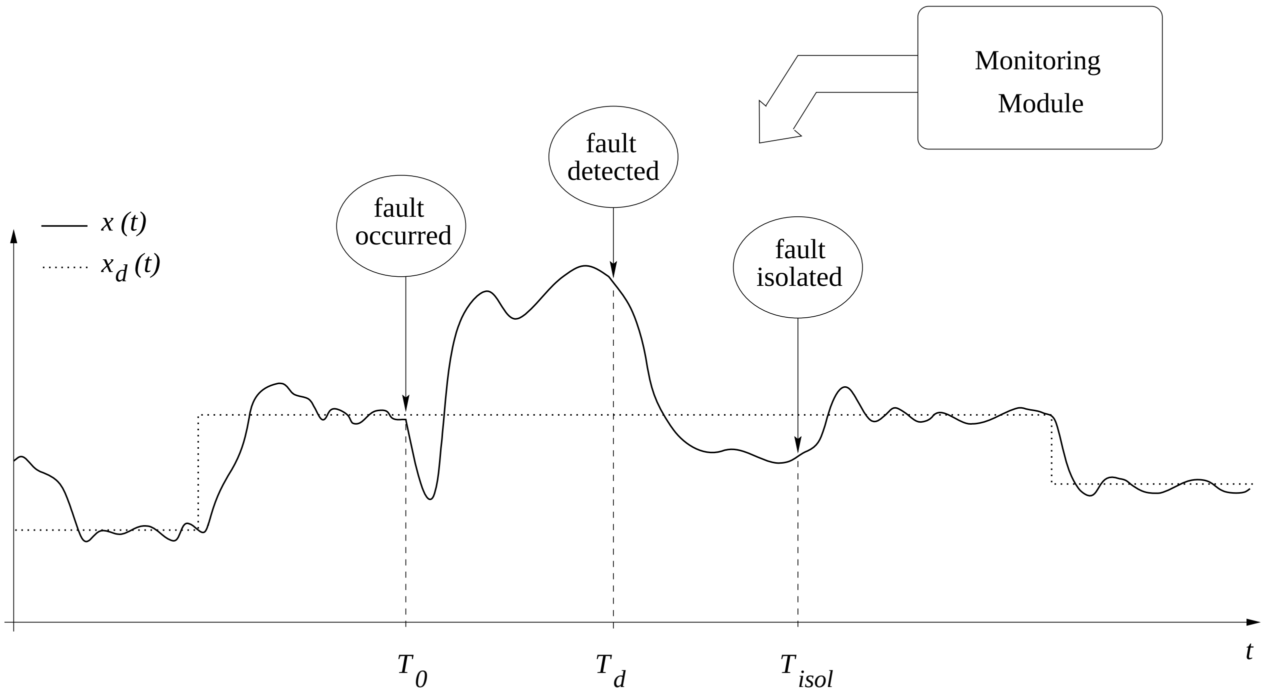
- $\theta_i^s,\ i = 1, \cdots, n$ is an unknown parameter vector, which is assumed to belong to a known compact set
- $g_i^s\colon\ \Re^n \times \Re^m \mapsto \Re^{q_i^s}$ is a known smooth vector field

Fault Diagnosis Architecture

- There are N+1 Nonlinear Adaptive Estimators (NAEs)
- One of the NAEs is used for detecting and approximating faults
- The remaining N NAEs are isolation estimators used only after a fault has been detected for the purpose of fault isolation.



Fault Handling



- $0 < t < T_0$: system is operating in a healthy condition.
- $T_0 < t < T_d$: period in which there is a fault, which however has not yet been detected.
- $T_d < t < T_{isol}$: period during which the fault has been detected, but it is not yet known which particular fault has occurred.
- $t > T_{isol}$: the fault has been isolated.

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Fault Detection and Approximation Estimator

$$\dot{\hat{x}}^0 = -\Lambda^0(\hat{x}^0 - x) + \phi(x,u) + \hat{f}(x,u,\hat{\theta}^0)$$

where:

$\hat{x}^0 \in \Re^n$: estimated state vector

$\hat{f} : \Re^n \times \Re^m \times \Re^p \mapsto \Re^n$: Adaptive approximation model

$\hat{\theta}^0 \in \Re^p$: adjustable weights of the on-line neural approximator

$\Lambda^0 = \mathrm{diag}(\lambda_1^0, \cdots, \lambda_n^0)$: estimation poles

- The initial weight vector $\hat{\theta}^0(0)$ is chosen such that

$$\hat{f}(x,u,\hat{\theta}^0(0)) = 0, \quad \forall (x,u) \in \mathcal{D}$$ (healthy situation)

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Adaptive Approximation Model

- Nonlinear approximation model with adjustable parameters (e.g., neural networks)
- Linearly parameterized vs. nonlinearly parameterized
- It provides the adaptive structure for approximating on-line:
  - Local modeling errors
  - interconnection dynamics
  - unknown fault functions

$$\dot{\hat{\theta}}^0 = \mathcal{P}_{\Theta^0}\left\{\Gamma^0 Z^\top D[\epsilon^0]\right\}$$

where:

$\epsilon^0 = x - \hat{x}^0$: state estimation error

The projection operator $\mathcal{P}_{\Theta^0}$ restricts the parameter estimation vector to a predefined compact and convex region.

$Z = \dfrac{\partial \hat{f}(x,u,\hat{\theta}^0)}{\partial \hat{\theta}^0}$: regressor matrix

$\Gamma^0 = {\Gamma^0}^\top \in \Re^{p\times p}$: Positive definite learning rate matrix

$$D[\epsilon^0(t)] = \begin{cases} 0 & \text{if } \quad |\epsilon_i^0(t)| \le \bar{\epsilon}_i^0(t),\ i = 1,\ldots,n \\ \epsilon^0(t) & \text{otherwise} \end{cases}$$

Dead-zone operator

Detection Threshold

$$\left|\epsilon_i^0(t)\right| = \left|\int_0^t e^{-\lambda_i^0(t-\tau)}\eta_i(x(\tau),u(\tau),\tau)d\tau\right|$$
$$\leq \int_0^t e^{-\lambda_i^0(t-\tau)}\bar{\eta}_i(x(\tau),u(\tau),\tau)d\tau = \bar{\epsilon}_i^0(t)\,.$$

Robustness of the fault detection scheme is the ability to avoid false alarms. The above threshold make the FD scheme robust.

- In the special case of a uniform bound on the modeling uncertainty the detection threshold becomes:

$$\bar{\epsilon}_i^0(t) = \frac{\bar{\eta}_i}{\lambda_i^0}\left(1 - e^{-\lambda_i^0 t}\right)$$

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Detectability Conditions

If there exists an interval of time $[t_1, t_2]$ such that at least one component $f_i(x,u)$ of the fault vector satisfies the condition

$$\left| \int_{t_1}^{t_2} e^{-\lambda_i^0 (t_2-\tau)} \left(1 - e^{-\alpha_i(\tau - T_0)}\right) f_i(x(\tau), u(\tau)) d\tau \right| > \frac{2\bar{\eta}_i}{\lambda_i^0},$$

then a fault will be detected.

- Result holds for the special case of constant bound on the modeling uncertainty.
- We are also able to obtain more simplified detectability conditions, but they are more conservative.
- In general there is an inherent trade-off between robustness and fault detectability.

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Fault Isolation Estimators

N NAEs are activated for isolation (isolation estimators) after the detection of a fault

$$\dot{\hat{x}}^s = -\Lambda^s(\hat{x}^s - x) + \phi(x,u) + \hat{f}^s(x,u,\hat{\theta}^s)$$

$$\hat{f}^s(x,u,\hat{\theta}^s) = [(\hat{\theta}_1^s)^\top g_1^s(x,u), \;\cdots,\; (\hat{\theta}_n^s)^\top g_n^s(x,u)]^\top$$

$$s = 1,\cdots,N,$$

Learning Algorithm

$$\dot{\hat{\theta}}_i^s = \mathcal{P}_{\Theta_i^s}\{\Gamma_i^s g_i^s(x,u)\epsilon_i^s\}$$

- Each isolation estimator corresponds to one of the possible types of parametric faults
- Adaptive threshold are designed based on the available information, similar to the concept of a matching filter
- isolation is achieved if every threshold is exceeded, except one (the one corresponding to the fault)

Intuitively, fault are easier to isolate if they are sufficiently "mutually different" in terms of a suitable measure

$$h_i^{sr}(t) = (1 - e^{-\alpha_i (t - T_0)})(\theta_i^s)^\top g_i^s(x(t), u(t)) - (\hat{\theta}_i^r(t))^\top g_i^r(x(t), u(t)), \quad r, s = 1, \ldots, n, \; r \neq s$$

Fault Mismatch Function

The difference between the actual fault function and the estimated fault function associated with any isolation estimator

Fault isolability condition

$$\left| \int_{T_d}^{t^r} e^{-\lambda_i (t^r - \tau)} h_i^{sr}(\tau)\, d\tau \right| > 2\, |\epsilon_i^r(T_d)|\, e^{-\lambda_i (t^r - T_d)} + \int_{T_d}^{t^r} e^{-\lambda_i (t^r - \tau)} \Big[\Big(\kappa_i^r(\tau) + e^{-\bar{\alpha}_i (\tau - T_d)} |\hat{\theta}_i^r(\tau)| \Big) \cdot |g_i^r(x(\tau), u(\tau))| + 2\, \bar{\eta}_i(x(\tau), u(\tau), \tau) \Big] d\tau \,.$$

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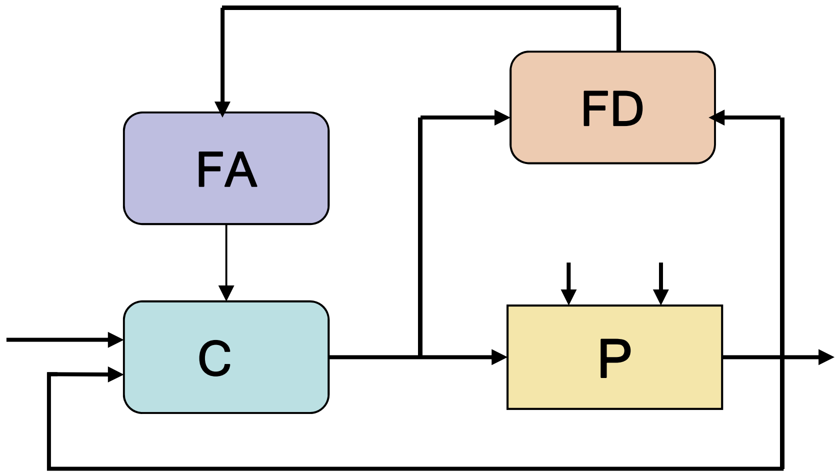
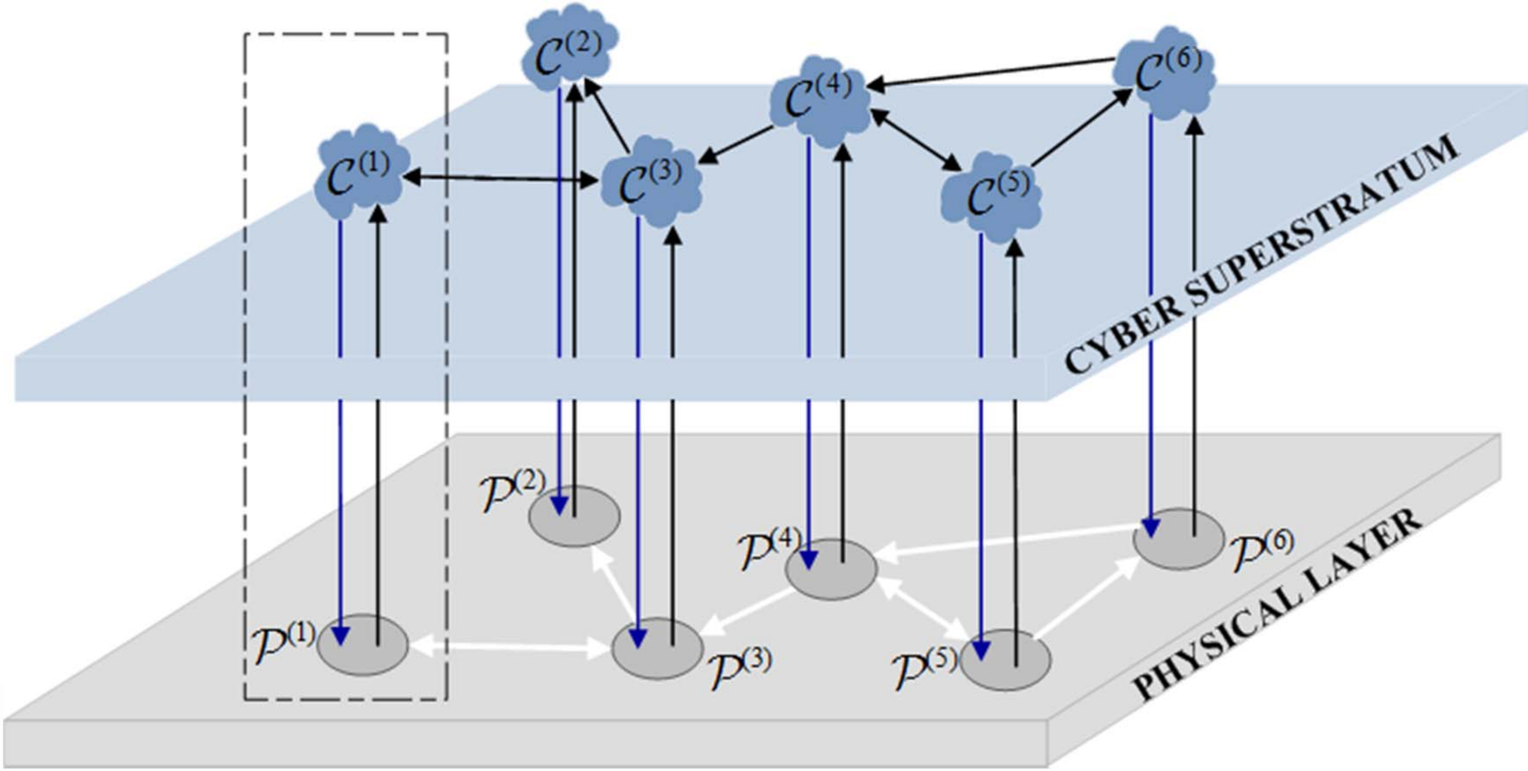
Sensor Fault Diagnosis

- System/Process Faults
- Actuator Faults
- Sensor Faults
- Communication Faults
- Controller Faults
- Environment Faults
- Malicious Attacks (cyber-security)

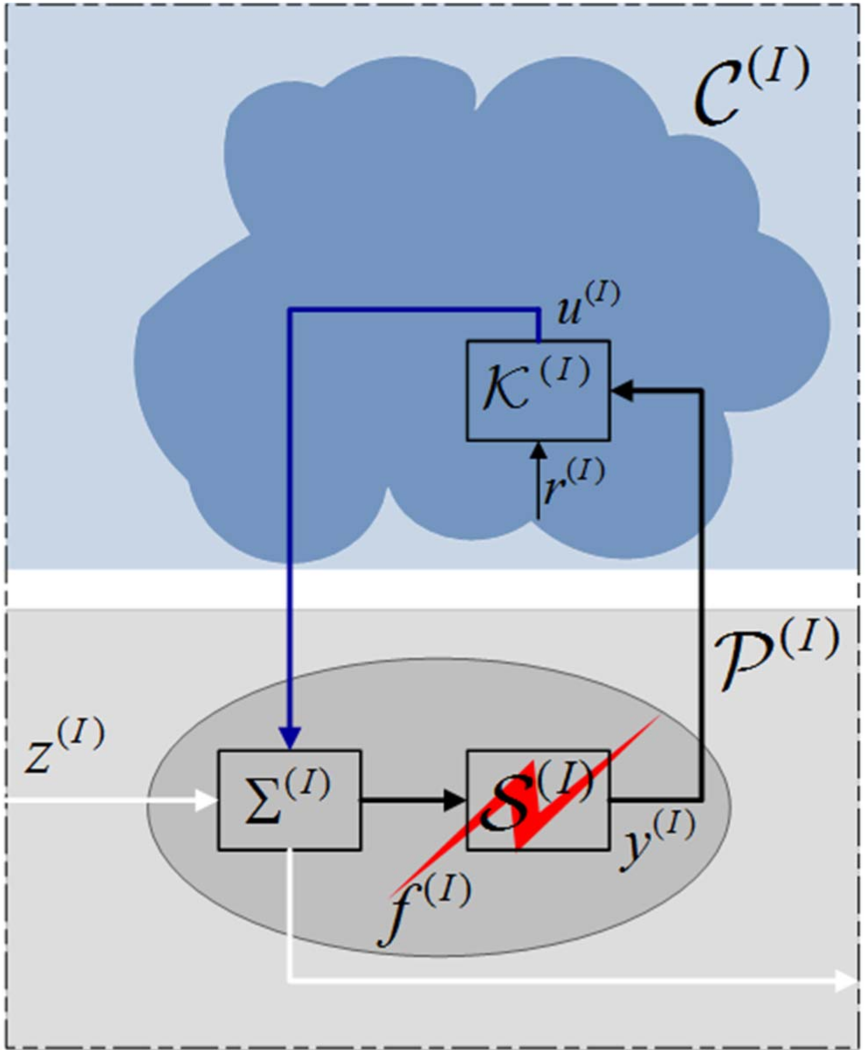


Interconnected CPS

- *N* interconnected CPS.
- *I*-th CPS: described by the pair $\left(\mathcal{P}^{(I)}, \mathcal{C}^{(I)}\right)$
  - $\mathcal{P}^{(I)}$: physical part of the *I*-th CPS,
  - $\mathcal{C}^{(I)}$: cyber part of the *I*-th CPS.



Interconnected CPS

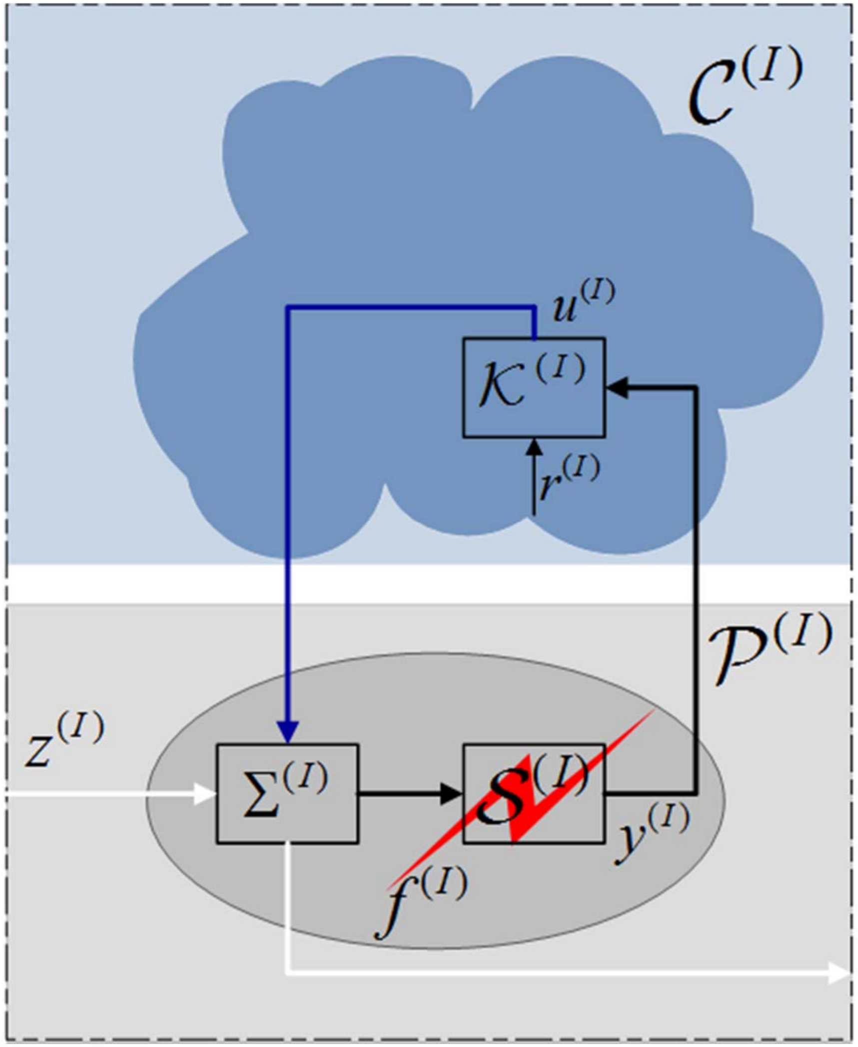


- $\mathcal{P}^{(I)}$ (physical part)
  - a nonlinear system $\Sigma^{(I)}$

$$\dot{x}^{(I)} = \underbrace{A^{(I)}x^{(I)} + \gamma^{(I)}(x^{(I)}, u^{(I)})}_{\text{known local dynamics}} + \underbrace{h^{(I)}(x^{(I)}, u^{(I)}, C_z^{(I)}z^{(I)})}_{\text{known interconnection dynamics}} + \underbrace{\eta^{(I)}(x^{(I)}, u^{(I)}, t)}_{\text{modeling uncertainty}}$$

- $x^{(I)}$: local state vector
- $u^{(I)}$: local input vector generated by a feedback control agent $\mathcal{K}^{(I)}$ using $r^{(I)}$
- $z^{(I)}$: interconnection vector

Interconnected CPS

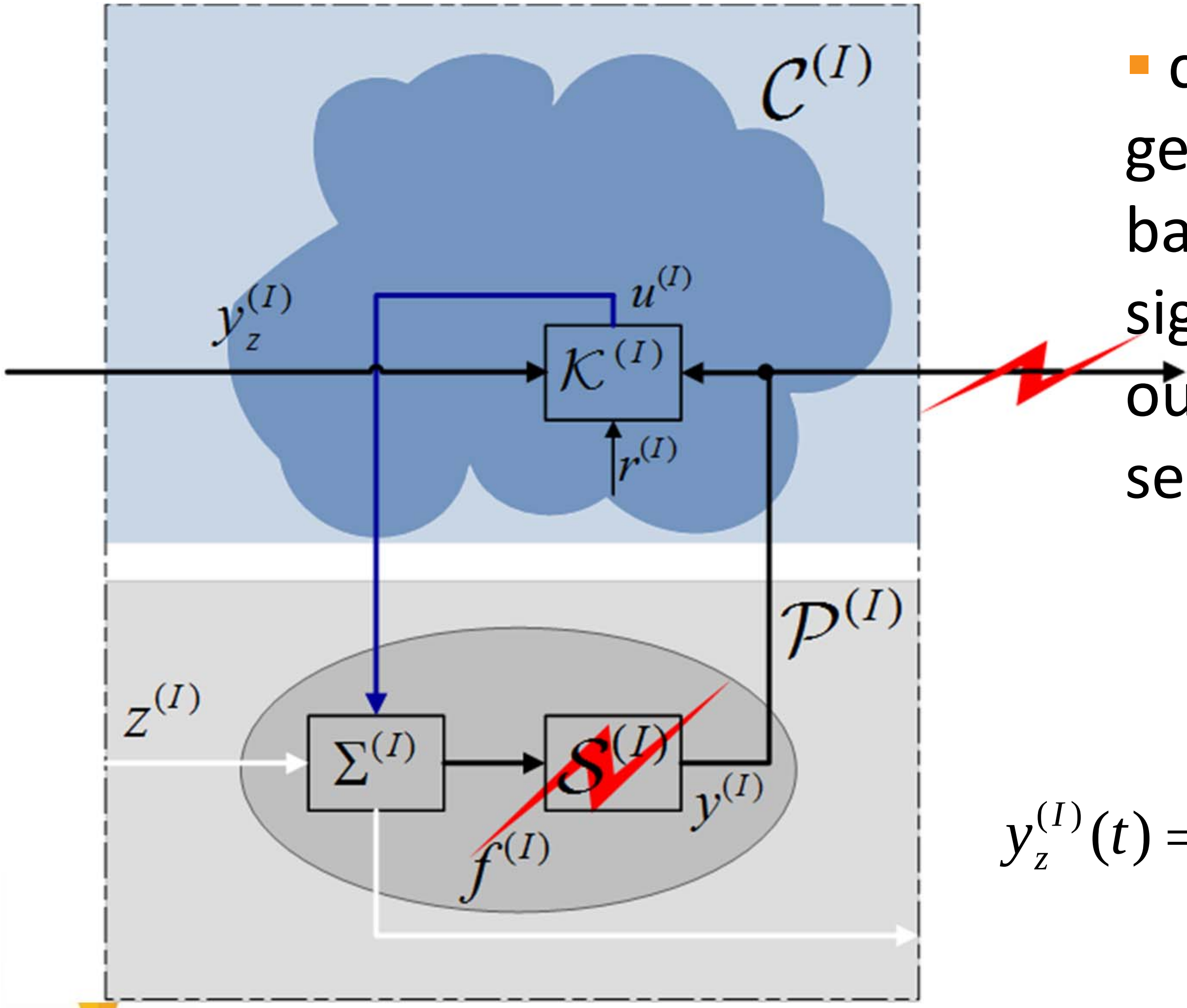


- $\mathcal{P}^{(I)}$ (physical part)
  - Sensor set $\mathcal{S}^{(I)}$ used for measuring the linear combination of states $C^{(I)}x^{(I)}$

$$y^{(I)}(t) = C^{(I)}x^{(I)}(t) + d^{(I)}(t) + f^{(I)}(t)$$

- $y^{(I)}$: local output vector
- $d^{(I)}$: measurement noise
- $f^{(I)}$: fault vector

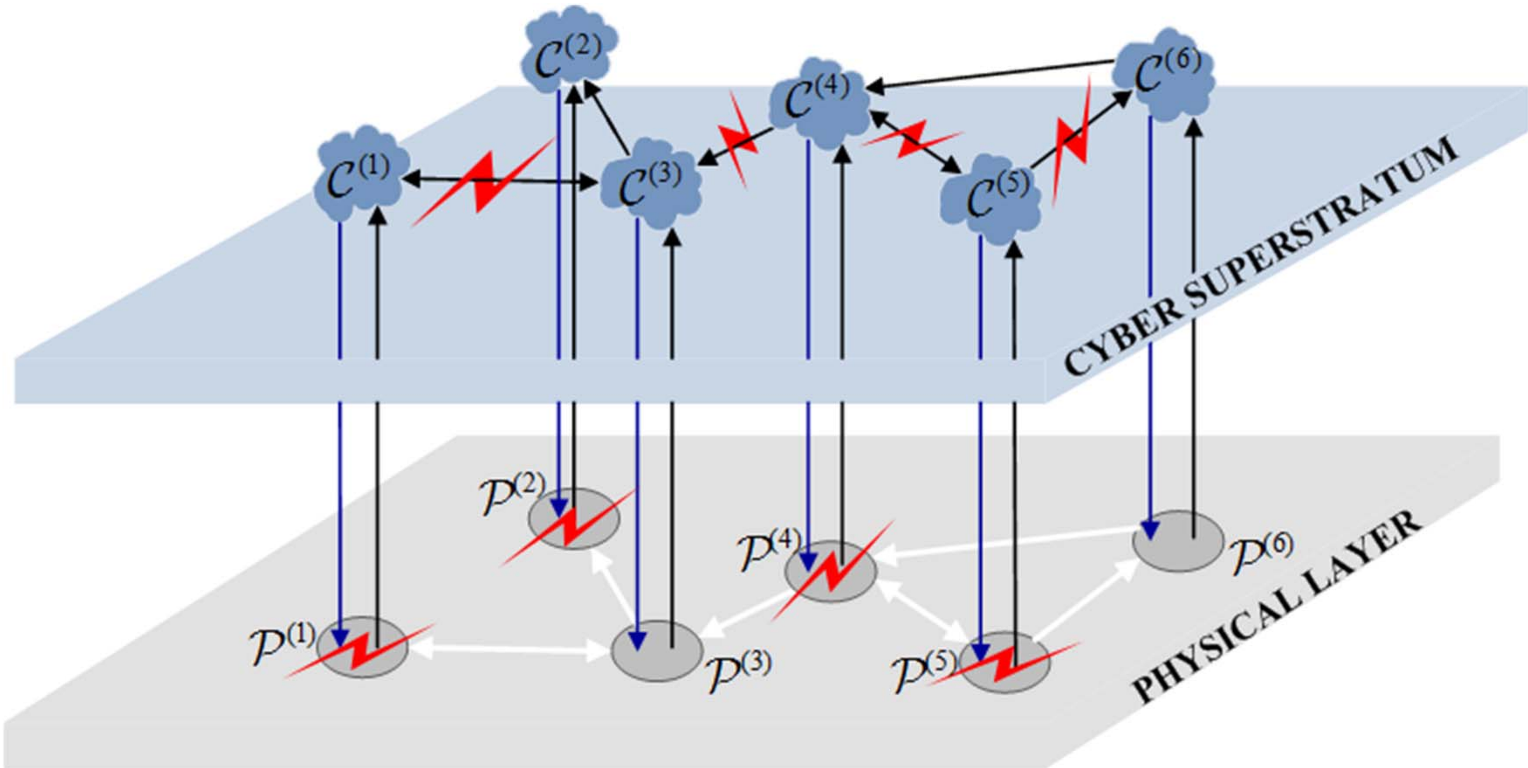
Interconnected CPS



- $\mathcal{C}^{(I)}$ (cyber part)
  - control agent $\mathcal{K}^{(I)}$ that generates the input $u^{(I)}$ based on some reference signal $r^{(I)}$, the measured output and the transmitted sensor information $\mathcal{S}_z^{(I)}$

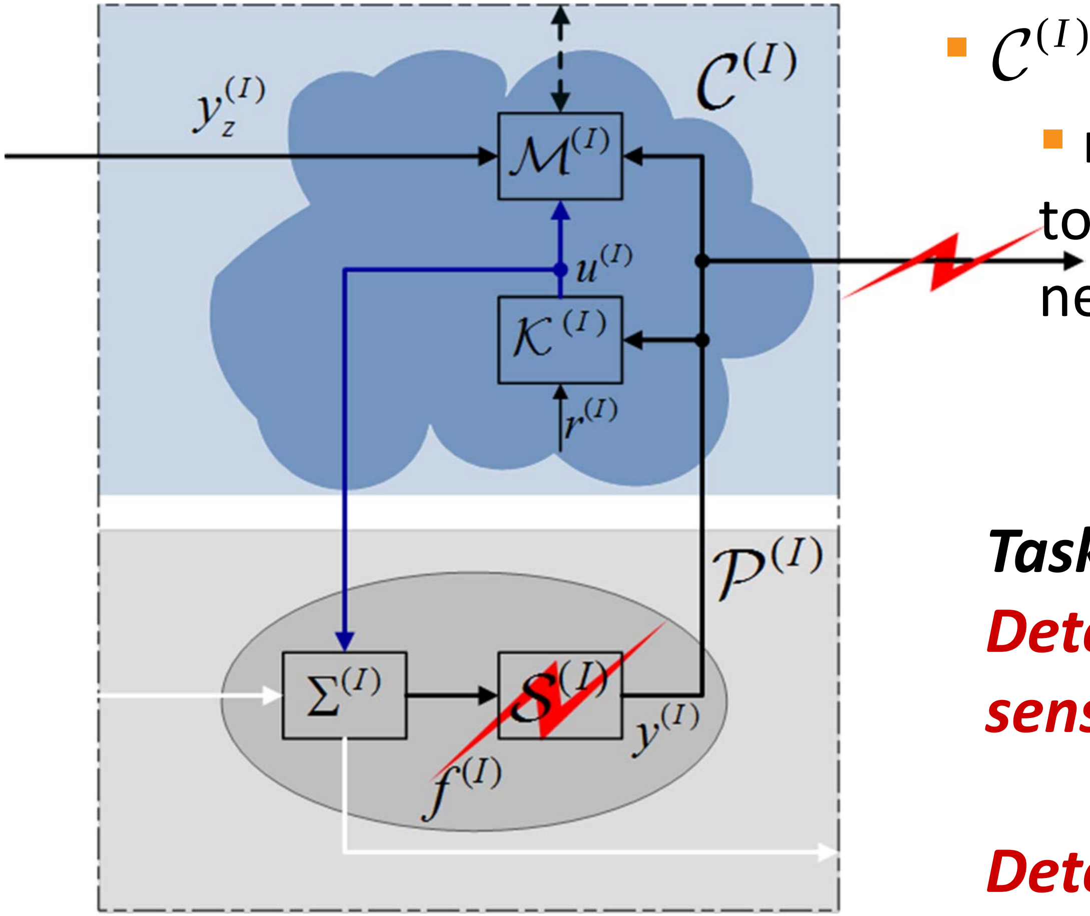
$$y_z^{(I)}(t) = C_z^{(I)} z^{(I)}(t) + d_z^{(I)}(t) + f_z^{(I)}(t)$$

Interconnected CPS



Objective: ***Detect and isolate multiple sensor faults that may occur in one or more CPS***

Distributed Sensor Fault Diagnosis Architecture



- $\mathcal{C}^{(I)}$ (cyber part)
  - monitoring agent $\mathcal{M}^{(I)}$ allowed to exchange information with the neighboring agents $\mathcal{S}_z^{(I)}$

Task:

Detection & isolation of multiple sensor faults in $\mathcal{S}^{(I)}$

Detection of propagated sensor faults in $\mathcal{S}_z^{(I)}$

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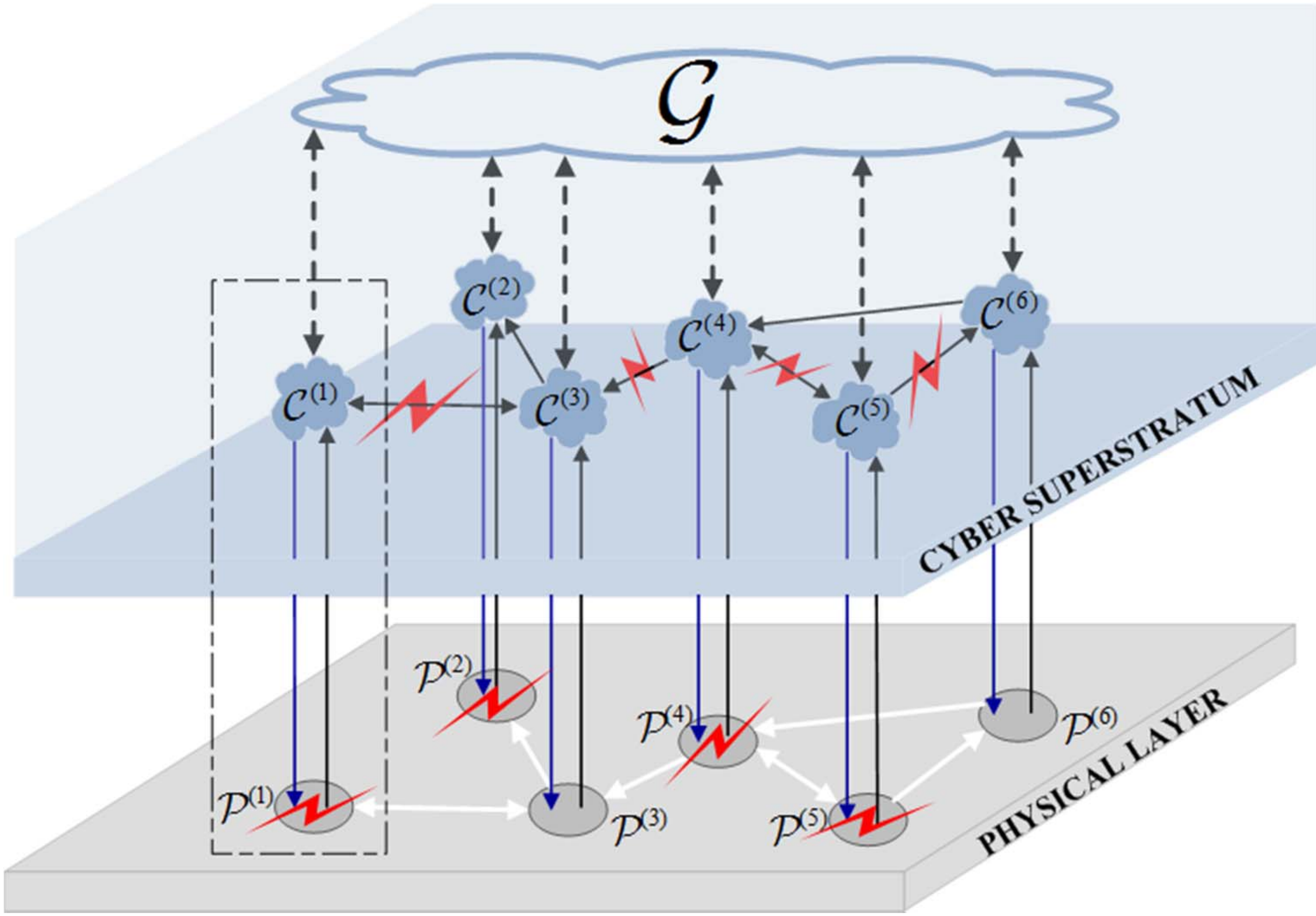
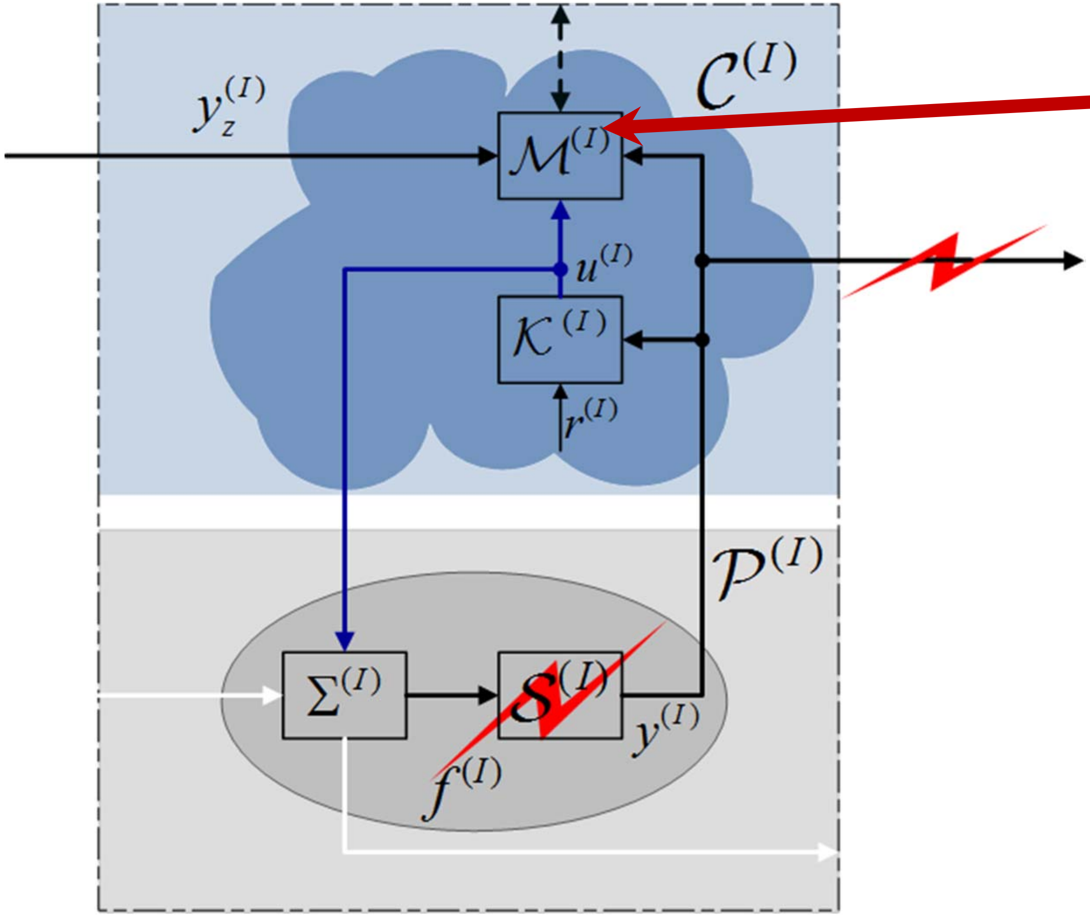
Distributed Sensor Fault Diagnosis Architecture

- $\mathcal{G}$: global decision logic
  - collects and processes combinatorially the decisions of the monitoring agents

***Task**: Isolation of sensor faults propagated in the cyber layer due to the information exchange between monitoring agents*



Monitoring Agent



monitoring agent $\mathcal{M}^{(I)}$

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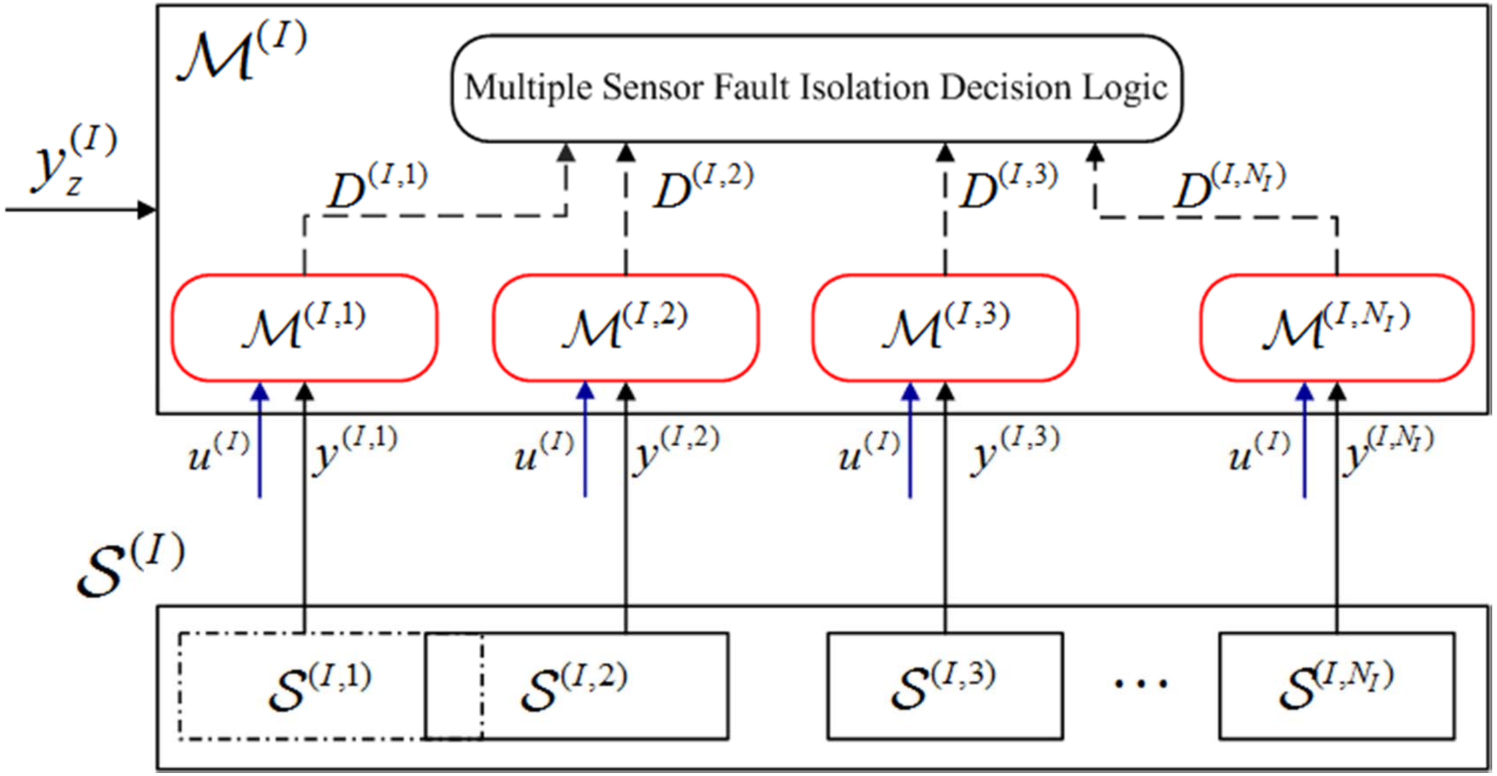
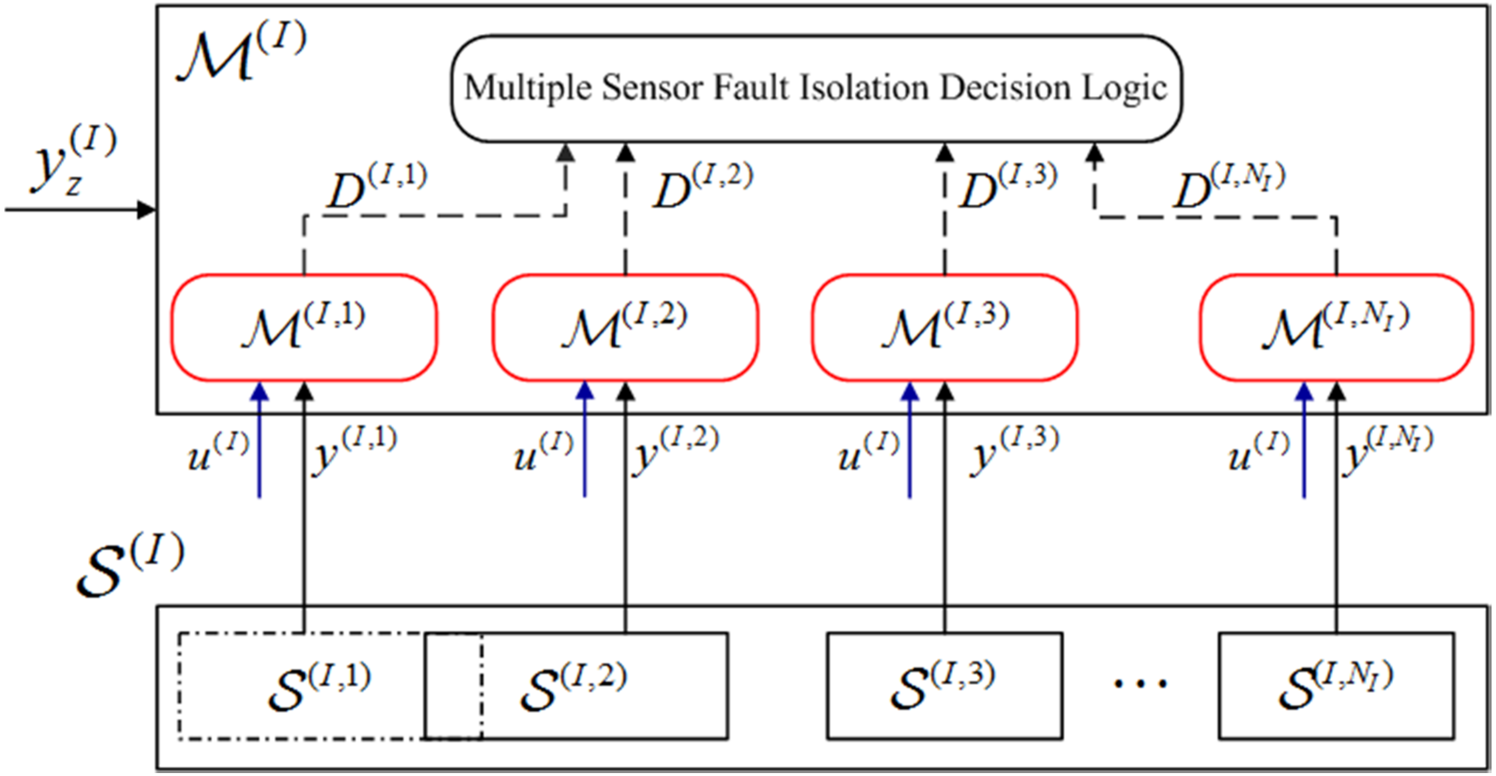
Monitoring Agent



- The monitoring of the local sensor set $\mathcal{S}^{(I)}$ is decomposed into N_I modules
- The module $\mathcal{M}^{(I,q)}$ monitors the group of sensors $\mathcal{S}^{(I,q)}$

$$\mathcal{S}^{(I,q)}: \quad y^{(I,q)} = C^{(I,q)} x^{(I)} + d^{(I,q)} + f^{(I,q)}$$

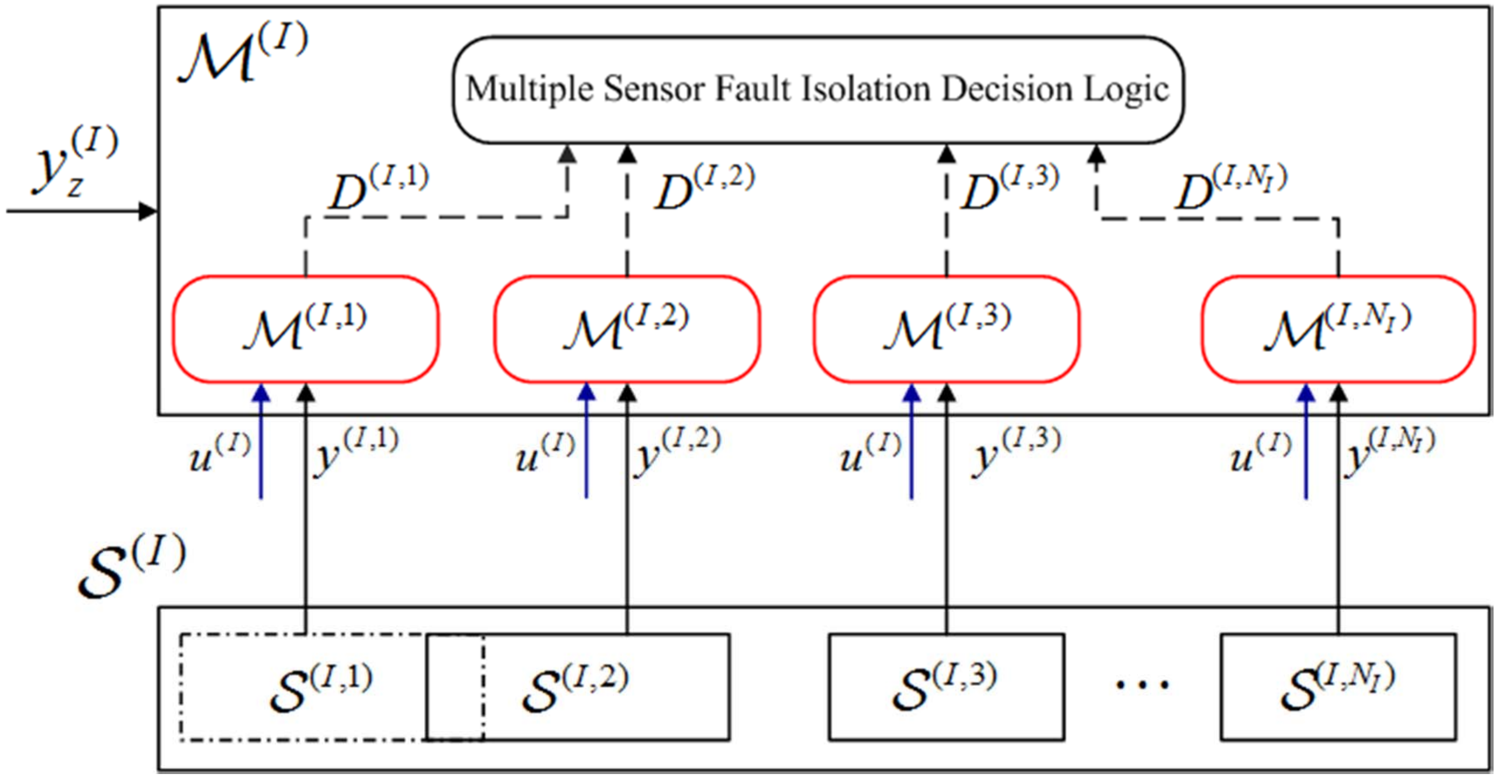
Monitoring Agent



- $\mathcal{M}^{(I,q)}$: *q*-th module of the *I*-th monitoring agent

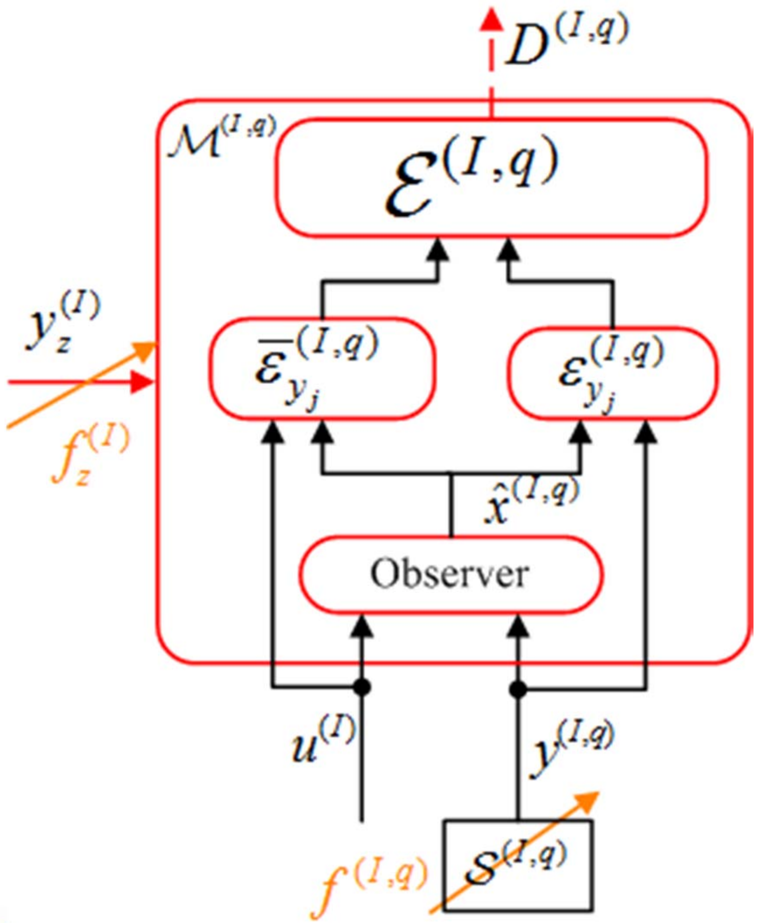
***Task**: Detection of sensor faults in $\mathcal{S}^{(I,q)}$ and/or $\mathcal{S}_z^{(I)}$*

Monitoring Agent



The decisions of the N_I modules are aggregated and processed combinatorially for isolating the combination of multiple sensor faults that have occurred and inferring the presence of propagated sensor faults

Monitoring Module



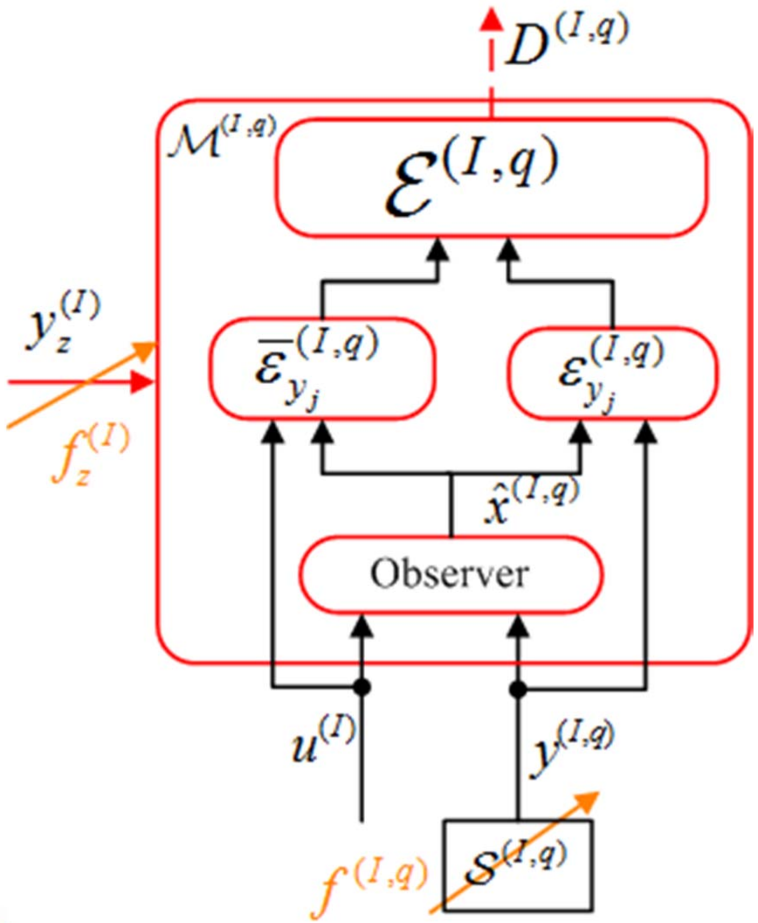
j-th residual, $\varepsilon_{y_j}^{(I,q)}$

$$\varepsilon_{y_j}^{(I,q)} = y_j^{(I)} - C_j^{(I)} \hat{x}^{(I,q)}, \ j \in \mathcal{J}^{(I,q)} \quad \textbf{(1)}$$

- $\hat{x}^{(I,q)}$: estimation model based on the nonlinear observer

$$\dot{\hat{x}}^{(I,q)} = A^{(I)} \hat{x}^{(I,q)} + \gamma^{(I)}(\hat{x}^{(I,q)}, u^{(I)}) + h^{(I)}(\hat{x}^{(I,q)}, u^{(I)}, y_z^{(I)}) + L^{(I,q)}\left(y^{(I,q)} - C^{(I,q)} \hat{x}^{(I,q)}\right) \quad \textbf{(2)}$$

Monitoring Module



- The j-th adaptive threshold $\bar{\varepsilon}_{y_j}^{(I,q)}(t)$ is designed to bound the j-th residual $\varepsilon_{y_{jH}}^{(I,q)}(t)$ under healthy conditions

$$\left|\varepsilon_{y_{jH}}^{(I,q)}(t)\right| \le \bar{\varepsilon}_{y_j}^{(I,q)}(t)$$

Adaptive Threshold Computation

- The j-th adaptive threshold can be implemented using linear filters

$$\bar{\varepsilon}_{y_j}^{(I,q)}(t) = H(s)\left[\bar{\eta}(\hat{x}^{(I,q)}(t), u^{(I)}(t), t) + \Lambda_I Z^{(I,q)}(t)\right] + Y_j^{(I,q)}(t)$$

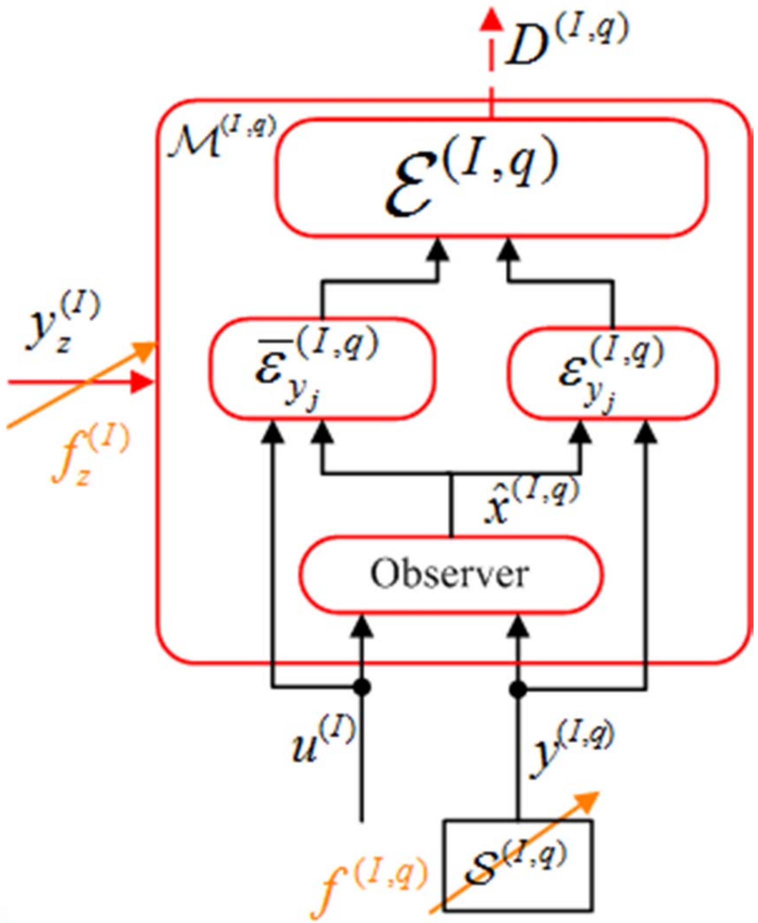
$$Z^{(I,q)}(t) = E^{(I,q)}(t) + H_1(s)\left[E^{(I,q)}(t)\right]$$

$$E^{(I,q)}(t) = H_2(s)\left[\bar{\eta}(\hat{x}^{(I,q)}(t), u^{(I)}(t), t)\right] + E_B^{(I,q)}(t),$$

$$H(s) = \frac{\alpha_j^{(I,q)}}{s + \zeta_j^{(I,q)}}, H_1(s) = \frac{\rho^{(I,q)}\Lambda_I}{s + \left(\xi^{(I,q)} - \rho^{(I,q)}\Lambda_I\right)}, H_2(s) = \frac{\rho^{(I,q)}}{s + \xi^{(I,q)}}$$

$$\Lambda_I = \lambda_{\gamma_I} + \lambda_{h_I} + \lambda_{\eta_I}$$

Monitoring Module



Decision Logic based on a set of **Analytical Redundancy Relations** (ARRs)

$$\mathcal{E}^{(I,q)} : \bigcup_{j \in \mathcal{J}^{(I,q)}} \mathcal{E}_j^{(I,q)}$$

$$\mathcal{E}_j^{(I,q)} : \left|\varepsilon_{y_j}^{(I,q)}(t)\right| - \bar{\varepsilon}_{y_j}^{(I,q)}(t) \leq 0,$$

residual adaptive threshold

Under healthy conditions, $\mathcal{E}^{(I,q)}$ is always satisfied

Robustness and Structured Fault Sensitivity

Theorem: The distributed sensor fault diagnosis design guarantees that:

(a) **Robustness:** If neither the local sensor set $\mathcal{S}^{(I,q)}$ nor the transmitted sensor information $y_z^{(I)}$ are affected by sensor faults, then the set of ARRs $\mathcal{E}^{(I,q)}$ is always satisfied.

(b) **Structured fault sensitivity:** If there is a time instant at which $\mathcal{E}^{(I,q)}$ is not satisfied, then the occurrence of at least one sensor fault in $\mathcal{S}^{(I,q)} \bigcup \mathcal{S}_z^{(I)}$ is guaranteed.

V. Reppa, M. Polycarpou and C. Panayiotou, "Distributed Sensor Fault Diagnosis for a Network of Interconnected Cyber-Physical Systems," *IEEE Transactions on Control of Network Systems*, vol 2, no. 1, pp. 11-23, March 2015.

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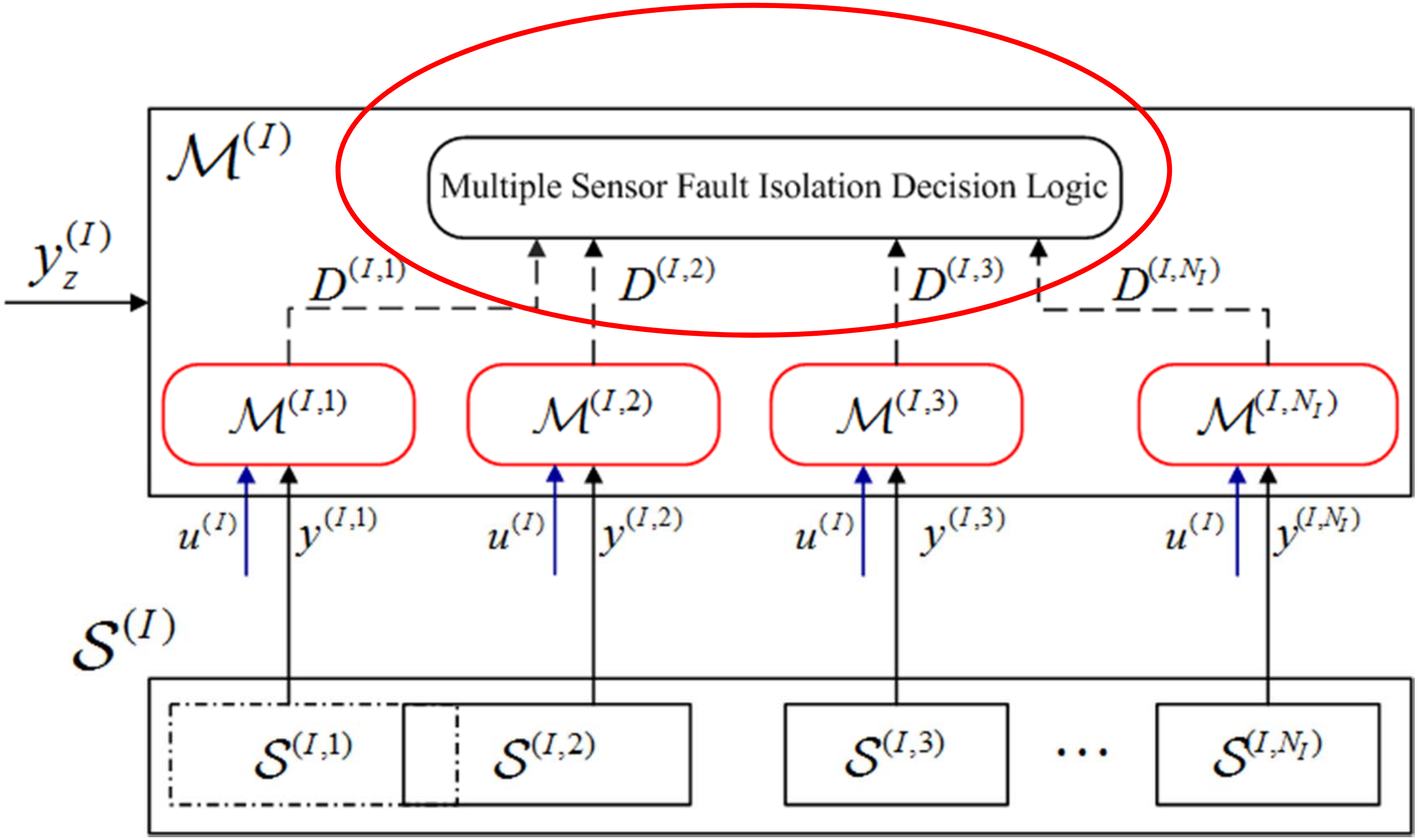
Monitoring Agent



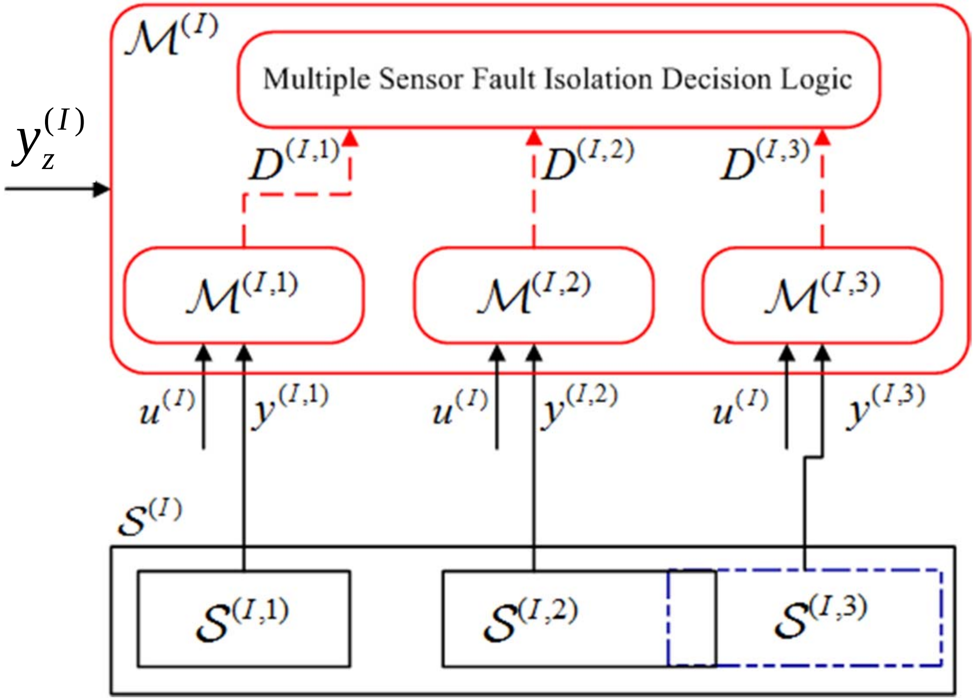
Local Multiple Sensor Fault Isolation

Example:

$$\mathcal{S}^{(I,1)} = \left\{ \mathcal{S}^{(I)}\{1\} \right\},$$

$$\mathcal{S}^{(I,2)} = \left\{ \mathcal{S}^{(I)}\{2\}, \mathcal{S}^{(I)}\{3\} \right\}$$

$$\mathcal{S}^{(I,3)} = \left\{ \mathcal{S}^{(I)}\{3\} \right\}$$



	$f_1^{(I)}$	$f_2^{(I)}$	$f_3^{(I)}$	$\{f_1^{(I)}, f_2^{(I)}\}$	$\{f_1^{(I)}, f_3^{(I)}\}$	$\{f_2^{(I)}, f_3^{(I)}\}$	$\{f_1^{(I)}, f_2^{(I)}, f_3^{(I)}\}$	$f_z^{(I)}$	$\{f_z^{(I)}, \mathcal{F}_c^{(I)}\}$
$\mathcal{E}^{(I,1)}$	1	0	0	1	1	0	1	1	1
$\mathcal{E}^{(I,2)}$	0	1	1	1	1	1	1	1	1
$\mathcal{E}^{(I,3)}$	0	0	1	0	1	1	1	1	1

Local Multiple Sensor Fault Isolation

	$f_1^{(I)}$	$f_2^{(I)}$	$f_3^{(I)}$	$\{f_1^{(I)}, f_2^{(I)}\}$	$\{f_1^{(I)}, f_3^{(I)}\}$	$\{f_2^{(I)}, f_3^{(I)}\}$	$\{f_1^{(I)}, f_2^{(I)}, f_3^{(I)}\}$	$f_z^{(I)}$	$\{f_z^{(I)}, \mathcal{F}_c^{(I)}\}$
$\mathcal{E}^{(I,1)}$	1	0	0	1	1	0	1	1	1
$\mathcal{E}^{(I,2)}$	0	1	1	1	1	1	1	1	1
$\mathcal{E}^{(I,3)}$	0	0	1	0	1	1	1	1	1

$$D^{(I)}(t) = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

Diagnosis Set: $\mathcal{D}_s^{(I)}(t) = \left\{ \left\{ f_1^{(I)}, f_2^{(I)} \right\} \right\}$

Decision on the presence of sensor faults in $y_z^{(I)}$

$$D_z^{(I)}(t) = \begin{cases} 0, & f_z^{(I)} \notin \mathcal{D}_s^{(I)}(t) \\ 1, & f_z^{(I)} \in \mathcal{D}_s^{(I)}(t) \end{cases}$$

Local Multiple Sensor Fault Isolation

	$f_1^{(I)}$	$f_2^{(I)}$	$f_3^{(I)}$	$\{f_1^{(I)}, f_2^{(I)}\}$	$\{f_1^{(I)}, f_3^{(I)}\}$	$\{f_2^{(I)}, f_3^{(I)}\}$	$\{f_1^{(I)}, f_2^{(I)}, f_3^{(I)}\}$	$f_z^{(I)}$	$\{f_z^{(I)}, \mathcal{F}_c^{(I)}\}$
$\mathcal{E}^{(I,1)}$	1	0	0	1	1	0	1	1	1
$\mathcal{E}^{(I,2)}$	0	1	1	1	1	1	1	1	1
$\mathcal{E}^{(I,3)}$	0	0	1	0	1	1	1	1	1

$$D^{(I)}(t) = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

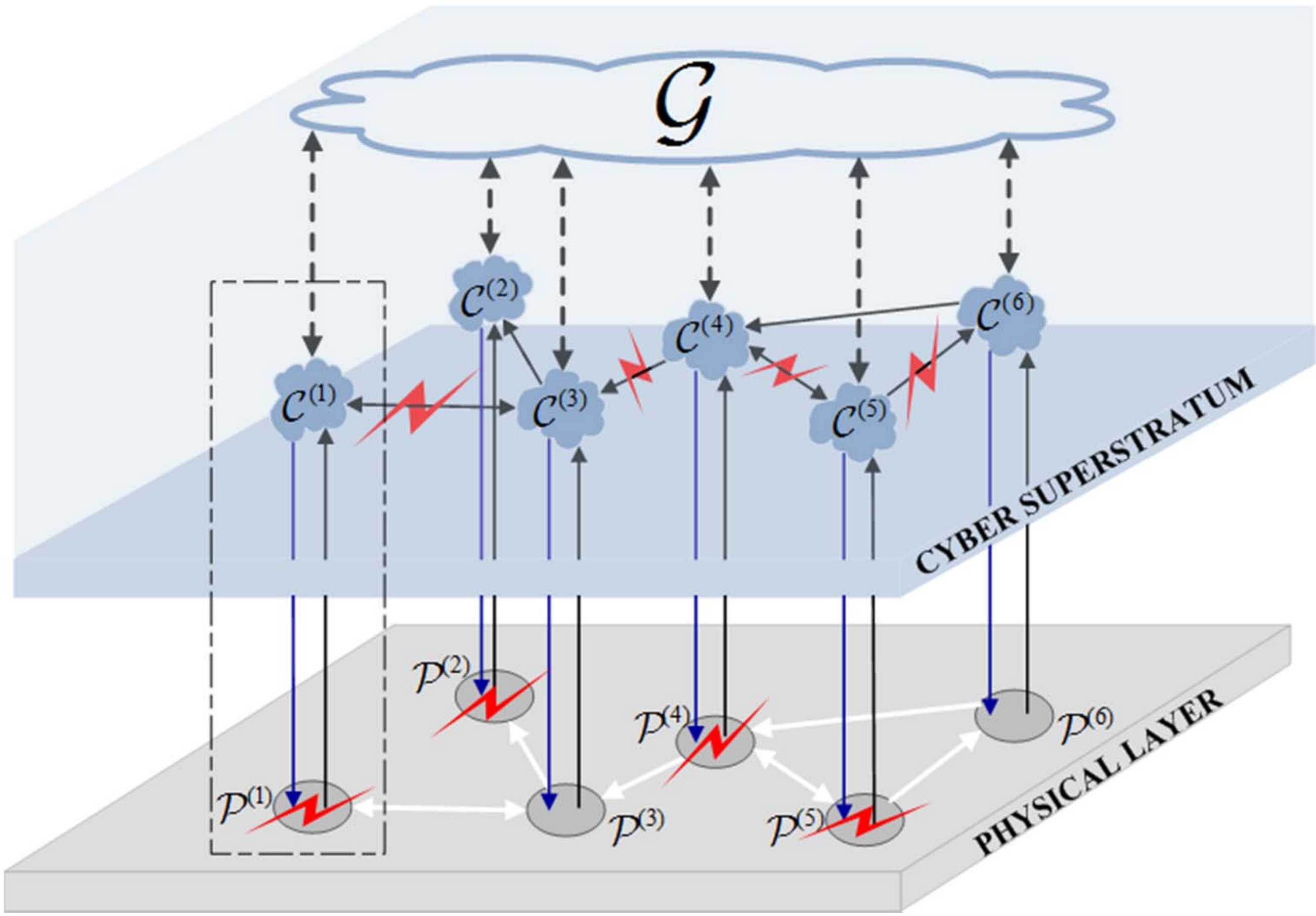
Diagnosis Set:

$$\mathcal{D}_s^{(I)}(t) = \left\{ \left\{ f_1^{(I)}, f_3^{(I)} \right\}, \left\{ f_1^{(I)}, f_2^{(I)}, f_3^{(I)} \right\}, f_z^{(I)}, \left\{ f_z^{(I)}, \mathcal{F}_c^{(I)} \right\} \right\}$$

Decision on the presence of sensor faults in $y_z^{(I)}$

$$D_z^{(I)}(t) = \begin{cases} 0, & f_z^{(I)} \notin \mathcal{D}_s^{(I)}(t) \\ 1, & f_z^{(I)} \in \mathcal{D}_s^{(I)}(t) \end{cases}$$

Global Multiple Sensor Fault Isolation



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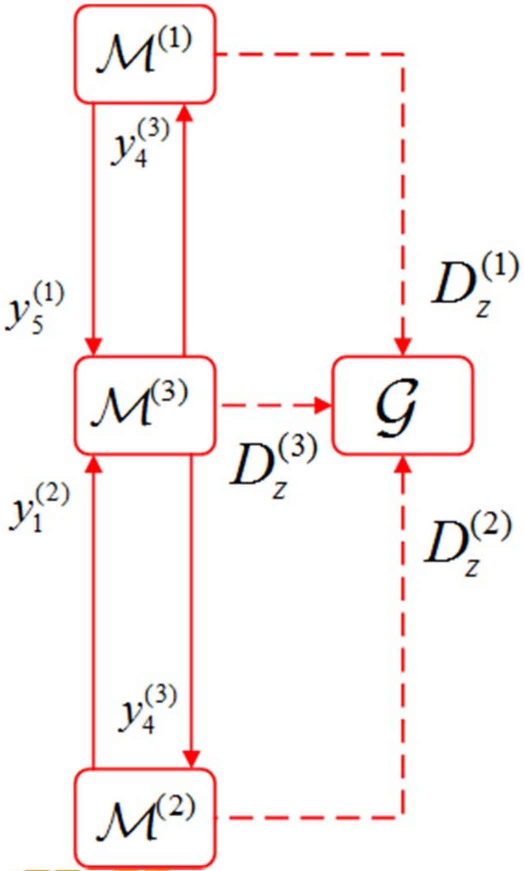
Global Multiple Sensor Fault Isolation

Observed pattern of sensor faults in transmitted sensor information: $D_z(t) = \left[D_z^{(1)}(t) \quad D_z^{(2)}(t) \quad \cdots \quad D_z^{(N)}(t) \right]^\top$



	$f_5^{(1)}$	$f_1^{(2)}$	$f_4^{(3)}$	$\{f_5^{(1)}, f_1^{(2)}\}$	$\{f_5^{(1)}, f_4^{(3)}\}$	$\{f_1^{(2)}, f_4^{(3)}\}$	$\{f_5^{(1)}, f_1^{(2)}, f_4^{(3)}\}$
$\mathcal{E}^{(1)}$	1	0	*	1	1	*	1
$\mathcal{E}^{(2)}$	0	1	*	1	*	1	1
$\mathcal{E}^{(3)}$	*	*	1	*	1	1	1

Semantics of '*': the sensor fault involved in the ARR can explain why the ARR is violated, while the ARR may be satisfied although the corresponding fault has occurred

Learning Approaches for Fault Diagnosis

- Reduce adaptive thresholds by reducing the bound of the modeling uncertainty using learning techniques.
- Design and analysis of an adaptive approximation methodology to learn the modeling uncertainty

V. Reppa, M. Polycarpou and C. Panayiotou, "Adaptive approximation for multiple sensor fault detection and isolation of nonlinear uncertain," *IEEE Transactions on Neural Networks and Learning Systems*, vol 25, no. 1, pp. 137-153, January 2014.

Fault Diagnosis and Cybersecurity

- Targeted faults
- Early detection is crucial
- Sensor placement is a key issue
- Need to consider the impact dynamics

Application Example: Smart Buildings

Credit: IBM

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How critical are buildings?

- 48% of energy consumption is for buildings (27% for transportation; 25% for factories)
- 76% of electricity consumption is for buildings (23% for factories; 1% for transportation)
- 87% of our time is spent indoors

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How critical are buildings?

- 48% of energy consumption is for buildings (27% for transportation; 25% for factories)
- 76% of electricity consumption is for buildings (23% for factories; 1% for transportation)
- 87% of our time is spent indoors
- 6% in automobiles and public transportation
- 7% outdoors

The Transformation of Buildings

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The Transformation of Buildings

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The Electronic Transformation Inside

- **Sensors** (more self-aware)
- **Actuators** (more automation)
- **Intelligent decision making** (energy efficiency, safety and security, fault diagnosis, etc.)
- **Communication devices** (building to user; user to building; building to building; etc.)

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The Electronic Transformation Inside

- Sensors (more self-aware)
- Actuators (more automation)
- Intelligent decision making (energy efficiency, safety and security, fault diagnosis, etc.)
- Communication devices (building to user; user to building; building to building; etc.)

→ Internet of Things (IoT)

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Motivation for Smart Buildings

- Need to monitor and control:
  - indoor living conditions and safety of the occupants
  - energy consumption of large-scale buildings
- The technology is available (smart-ready):
  - building automation is well established
  - Cyber-physical systems for smart buildings
  - sensing and actuation devices are widely available

→ Need to develop smart software to enable the coordination and scheduling of actions for handling dynamic and uncertain environments

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Topics pursued at KIOS Research Center

- KIOS Research Center for Intelligent Systems and Networks was founded in 2008
- Currently about 50 researchers working on Monitoring, Control and Security of Critical Infrastructure Systems
- Awarded a TEAMING project from H2020 to upgrade to a Center of Excellence for Research and Innovation (more than €40M)

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Smart Buildings Topics pursued at KIOS

- Distributed fault diagnosis and control of HVAC systems
- Contamination event detection and isolation in large-scale buildings
- Security surveillance using smart camera networks
- Cognitive agents for on-line reconfiguration of in smart buildings

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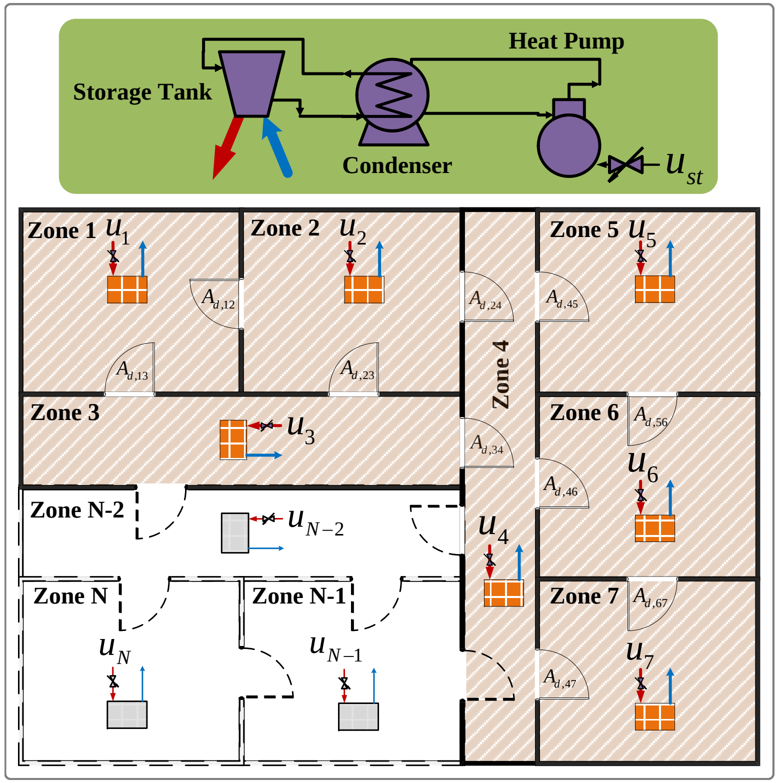
Topics pursued at KIOS Research Center

- **Distributed control and fault diagnosis of large-scale HVAC systems**

- V. Reppa, P. Papadopoulos, M. Polycarpou and C. Panayiotou, "A Distributed Architecture for HVAC Sensor Fault Detection and Isolation," *IEEE Transactions on Control Systems Technology*, vol. 23, pp. 1323-1337, July 2015.
- V. Reppa, P. Papadopoulos, M. Polycarpou, and C. Panayiotou, "A Distributed Virtual Sensor Scheme for Smart Buildings based on Adaptive Aproximation," *Proceedings of the International Joint Conference on Neural Networks, World Congress on Computational Intelligence (IJCNN 2014)*, pp. 99-106, July 2014.



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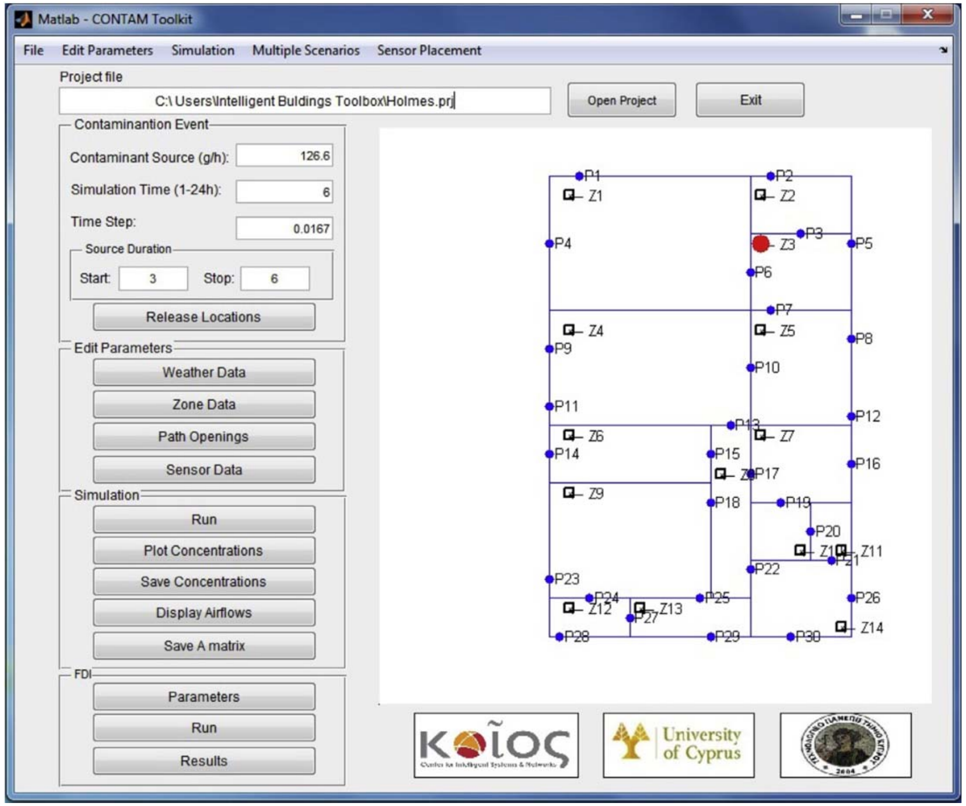
Topics pursued at KIOS Research Center

• Contamination event detection and isolation in large-scale buildings

- M. Michaelides, V. Reppa, M. Christodoulou, C. Panayiotou and M. Polycarpou, “Contaminant Event Monitoring in Multi-zone Buildings Using the State-Space Method,” *Building and Environment*, vol. 71, pp. 140-152, January 2014. *(2014 Best Paper Award).*
- D. Eliades, M. P. Michaelides, C. Panayiotou and M. Polycarpou, “Security-Oriented Sensor Placement in Intelligent Buildings”, *Building and Environment*, vol. 63, pp. 114-121, March 2013.



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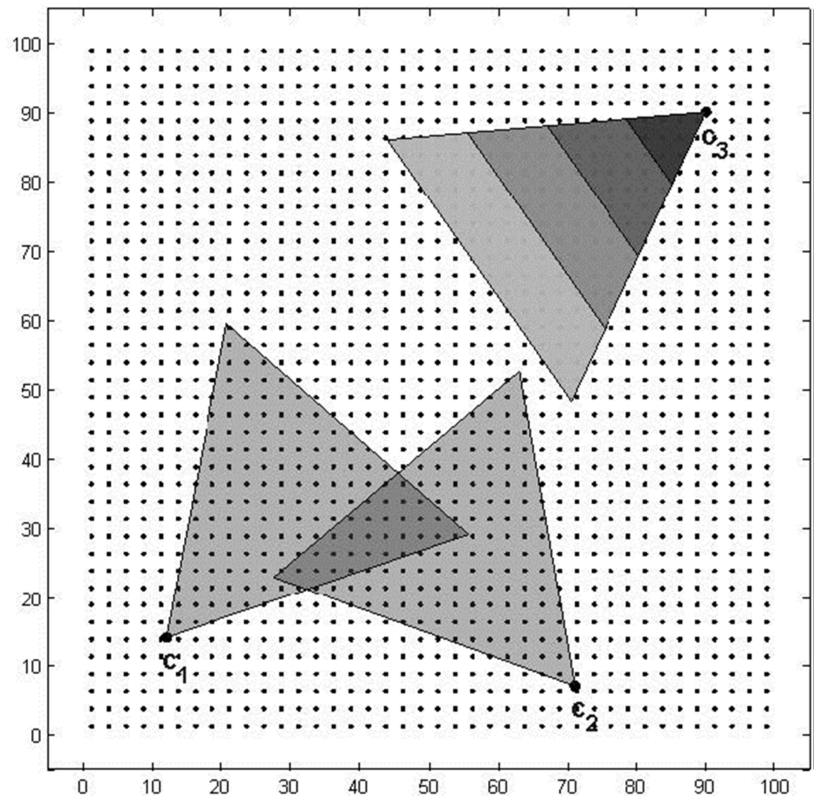
Topics pursued at KIOS Research Center

• Security surveillance using smart camera networks

- C. Laoudias, P. Tsangaridis, M. Polycarpou, C. Panayiotou, C. Kyrkou and T. Theocharides, “'Cooperative Fault-Tolerant Target Tracking in Camera Sensor Networks," *Proceedings of the IEEE International Conference on Communications (ICC’2015),* June 2015.
- C. Kyrkou, C. Laoudias, T. Theocharides, C. Panayiotou and M. Polycarpou, "Adaptive Energy-Oriented Multi-Task Allocation in Smart Camera Networks", IEEE Embedded Systems Letters, vol. 8, no. 2, pp. 37-40, June 2016.



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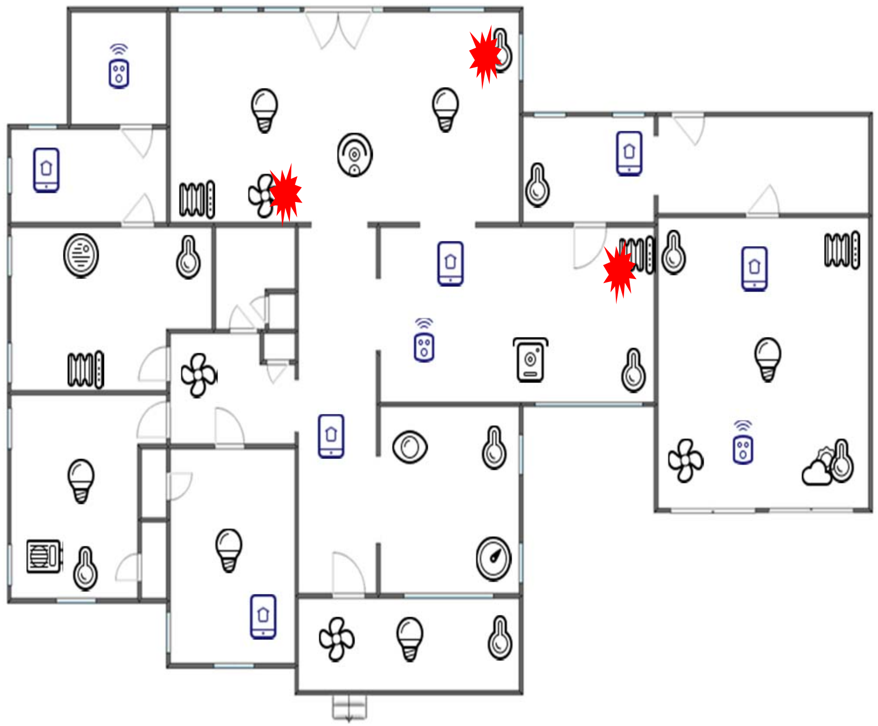
Topics pursued at KIOS Research Center

- **Cognitive agent for on-line reconfiguration in smart buildings**

- G. Milis, D. Eliades, C.G. Panayiotou and M. Polycarpou, “A Cognitive Fault-Detection Design Architecture,” in Proceedings of IEEE World Congress on Computational Intelligence (WCCI’2016), July 2016.
- G. Milis, C.G. Panayiotou and M. Polycarpou, “Semantically-Enhanced Online Configuration of Feedback Control Schemes,” IEEE Transactions on Cybernetics, 2017 (to appear).



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Topics pursued at KIOS Research Center

- Distributed fault diagnosis and control of HVAC systems
- Contamination event detection and isolation in large-scale buildings
- Security surveillance using smart camera networks
- Cognitive agent for on-line reconfiguration of in smart buildings

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HVAC Description

- HVAC systems consist of:
  - A number of electrical and mechanical components for
    - Heating (i.e., boilers, heating coils, heat pump)
    - Cooling (i.e., cooling towers, chillers, cooling coils)
    - Ventilating (i.e., fans, supply/return ducts, mixing boxes)
  - A number of building zones (i.e., interconnected or not)
    - the dynamics of a zone in the building are affected by the dynamics of their neighbouring zones

- Types of faults in HVAC systems:
  - actuator/process faults (i.e., fouled heat exchangers, stuck dampers, leaking valves, broken fans)
  - sensor faults (i.e., drifting, stuck-at-zero),
  - communication faults (i.e., wire break).

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Faulty Situations in HVAC Systems

- The recovery of faulty situations in HVAC systems:
  - shutting down the operation of the system (inconvenient and possibly ineffective from the viewpoint of energy)
  - reconfiguring the controller(s) via a fault tolerant control scheme, using the outcome of a fault detection and isolation mechanism

- Early diagnosis and accommodation of faults is critical since local faults effects may propagate from a local subsystem to neighbouring subsystems
  - the physical interconnections
  - the distributed control scheme (local controllers may use information transmitted from neighbouring controllers to achieve the best possible tracking performance)

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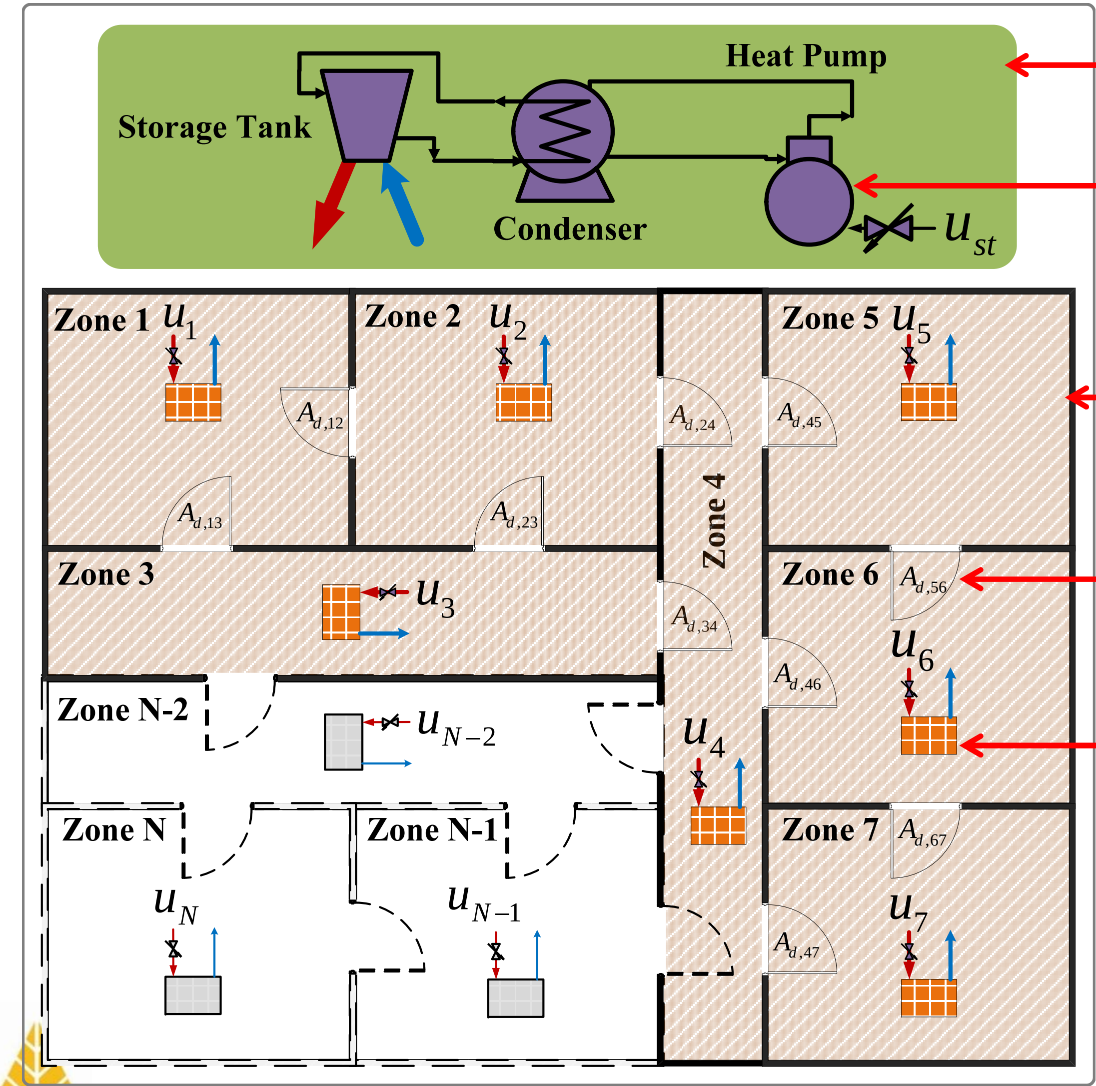
HVAC System Description



Electromechanical part

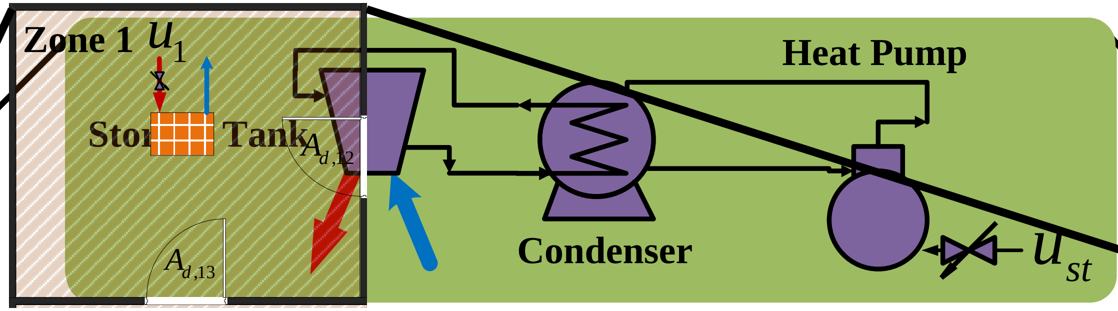
For cooling operation:
Replace Heat pump
with Chiller

Building Zones

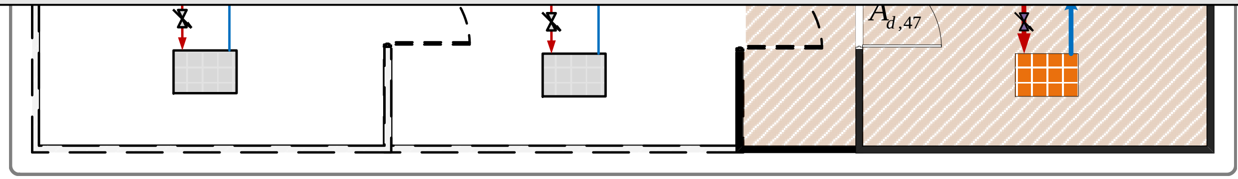
Door

Fan-coil unit

HVAC System Description



$$
\begin{aligned}
\frac{dT_{z_i}(t)}{dt} = {} & \frac{U_{i,max} a_{sz}}{C_{z_i}} \left(T_{st}(t) - T_{z_i}(t)\right) u_i(t) - \frac{a_{z_i}}{C_{z_i}} \left(T_{z_i}(t) - T_{amb}(t)\right) \\
& + \frac{hA_{w_i}}{C_{z_i}} \left(T_{i1}(t) - T_{z_i}(t)\right) + \frac{1}{C_{z_i}} \sum_{j \in \mathcal{K}_i} a_{z_{ij}} \left(T_{z_i}(t) - T_{z_j}(t)\right) + \frac{a_{z_i}}{C_{z_i}} \tilde{T}_{z_i}(t) \\
& + \frac{\rho_{air} C_p}{C_{z_i}} \sum_{j \in \mathcal{K}_i} sgn\left(T_{z_j}(t) - T_{z_i}(t)\right) \\
& \times A_{d_{ij}} \max\left(T_{z_i}(t), T_{z_j}(t)\right) \sqrt{2(C_p - C_v) \left| T_{z_j}(t) - T_{z_i}(t) \right|},
\end{aligned}
$$



HVAC System Modelling

Temperature nonlinear dynamics for water in the storage tank:

$$\frac{dT_{st}(t)}{dt}=\frac{U_{st,max}}{C_{st}}P_s(T_{st}(t))u_{st}(t)+\frac{a_{sz}}{C_{st}}\sum_{i\in\mathcal{N}}u_i(t)U_{i,max}(T_{z_i}(t)-T_{st}(t))$$

$$-\frac{a_{st}}{C_{st}}(T_{st}(t)-T_{pl}(t))+\frac{a_{st}}{C_{st}}\tilde{T}_{st}(t), \qquad \mathcal{N}=\{1,\dots,N\}$$

Performance coefficient of the heat pump

$$P_s(T_{st}(t))=\begin{cases}1+p\left(1-\dfrac{T_{st}(t)-T_o(t)}{\Delta T_{max}}\right), & T_{st}(t)-T_o(t)\leq \Delta T_{max}\\ 1, & T_{st}(t)-T_o(t)>\Delta T_{max}\end{cases}$$

$$p = (P_{max} - 1)$$

M. Zaheer-Uddin and R. Patel, “Optimal tracking control of multizone indoor environmental spaces,” *Journal of Dynamic Systems, Measurement and Control*, vol. 117, no. 3, pp. 292–303, 1995.

HVAC System Modelling

- Temperature nonlinear dynamics of air in the *i-th* zone

$$
\begin{aligned}
\frac{dT_{z_i}(t)}{dt} = {} & \frac{U_{i,max}\, a_{sz}}{C_{z_i}} (T_{st}(t) - T_{z_i}(t)) u_i(t) - \frac{a_{z_i}}{C_{z_i}} (T_{z_i}(t) - T_{amb}(t)) \\
& + \frac{hA_{w_i}}{C_{z_i}} (T_{i1}(t) - T_{z_i}(t)) + \frac{1}{C_{z_i}} \sum_{j \in \mathcal{K}_i} a_{z_{ij}} (T_{z_i}(t) - T_{z_j}(t)) + \frac{a_{z_i}}{C_{z_i}} \tilde{T}_{z_i}(t) \\
& + \frac{\rho_{air} C_p}{C_{z_i}} \sum_{j \in \mathcal{K}_i} sgn(T_{z_j}(t) - T_{z_i}(t)) \times A_{d_{ij}} T_{z_i}(t) \sqrt{2(C_p - C_v) \left| T_{z_j}(t) - T_{z_i}(t) \right|},
\end{aligned}
$$

$$C_{z_i} = \rho_{air} C_p V_{z_i}$$

air heat capacity

HVAC System with Feedback Control

$$\dot{x}^{(i)}(t) = \underbrace{A^{(i)}x^{(i)}(t) + g^{(i)}(x^{s}(t), x^{(i)}(t))u^{(i)}(t)}_{\text{local linear and nonlinear dynamics}} + \underbrace{h^{(i)}(x^{(i)}(t), x^{(j)}(t))}_{\text{interconnection dynamics}} + \underbrace{\eta^{(i)}(d^{(i)}(t))}_{\text{known disturbances}} + \underbrace{r^{(i)}(t)}_{\text{modeling uncertainty}},$$

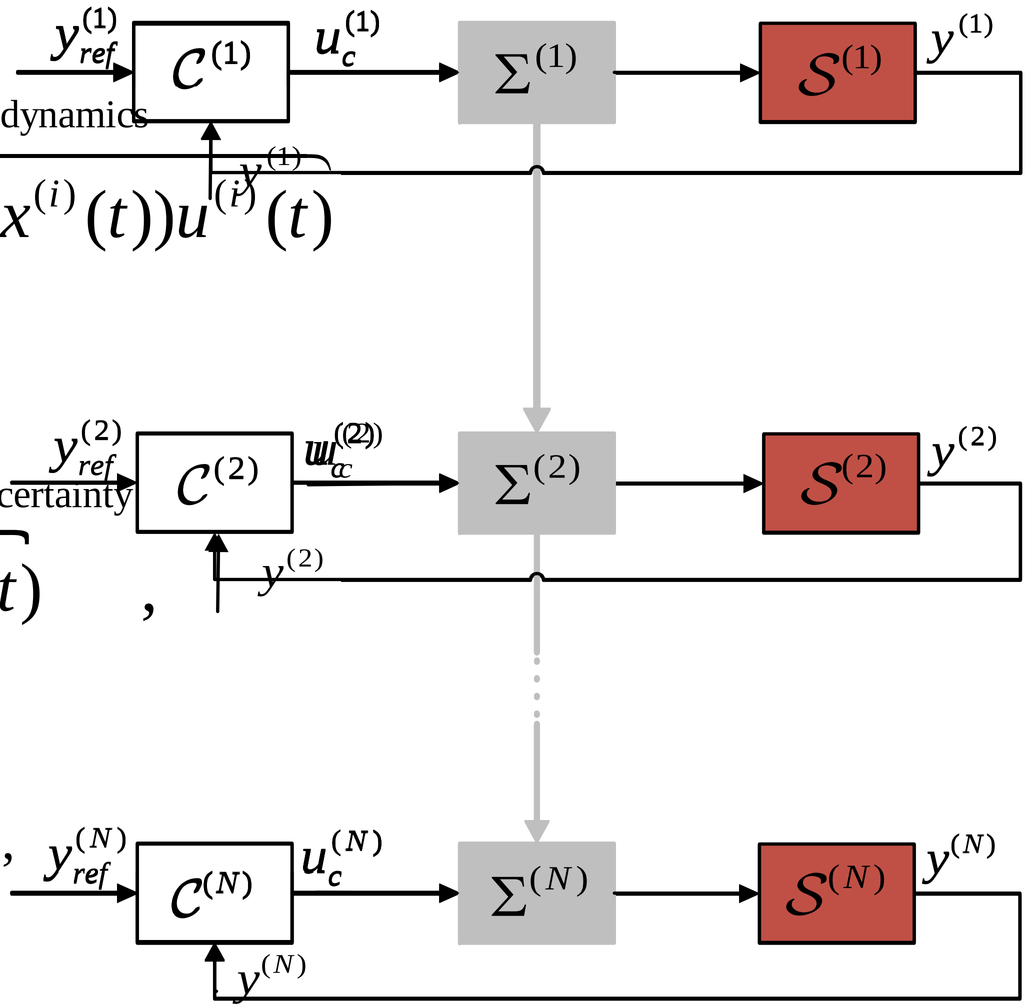
$$u^{(i)}(t) = u_c^{(i)}(t) + \underbrace{f_a^{(i)}(t)}_{\text{permanent actuator fault}},$$

$$\mathcal{S}^{(i)}: y^{(i)}(t) = x^{(i)}(t) + n^{(i)}(t) + \underbrace{f_s^{(i)}(t)}_{\text{permanent sensor fault}},$$

$$u_c^{(i)}(t) = \frac{1}{g^{(is)}(x^{(i)}(t), x_s(t))}\Big[-A^{(i)}x_s^{(i)}(t) - h^{(i)}(x^{(i)}(t), x^{(j)}(t)) - \eta^{(i)}(d^{(i)}(t)) + \dot{y}_{ref}^{(i)}(t) + k^{(i)}\big(\underbrace{y_{ref}^{(i)}(t)}_{\text{reference signal}} - x^{(i)}(t)\big)\Big]$$

$$u^{(i)}(t) = u_c^{(i)}(t) + \underbrace{f_a^{(i)}(t)}_{\text{permanent actuator fault}},$$

$$\mathcal{S}^{s}: y^{s}(t) = x^{s}(t) + n^{s}(t) + f_s^{s}(t),$$



HVAC System Modelling

- HVAC temperature dynamics represented in nonlinear state space form

$$\Sigma^s : \dot{x}^s(t) = \overbrace{A^s x^s(t) + g^s(x^s(t), d^s(t))u^s(t)}^{\text{local linear and nonlinear dynamics}}$$
$$+ \overbrace{h^s(x^s(t), x(t), u(t))}^{\text{interconnection dynamics}} + \overbrace{\eta^s\left(d^s(t)\right)}^{\text{known disturbances}} + \overbrace{r^s(t)}^{\text{modeling uncertainty}},$$

$$\Sigma^{(i)} : \dot{x}^{(i)}(t) = \overbrace{A^{(i)} x^{(i)}(t) + g^{(i)}(x^s(t), x^{(i)}(t))u^{(i)}(t)}^{\text{local linear and nonlinear dynamics}}$$
$$+ \overbrace{h^{(i)}(x^{(i)}(t), x^{(j)}(t))}^{\text{interconnection dynamics}} + \overbrace{\eta^{(i)}(d^{(i)}(t))}^{\text{known disturbances}} + \overbrace{r^{(i)}(t)}^{\text{modeling uncertainty}},$$

Nominal Distributed Control

- Distributed control laws:
  - Control law for Σ^S :

$$u_c^s(t) = \frac{1}{g^s(x^s(t), d^s(t))}\Big[-A^s x^s(t) - h^s(x^s(t), x(t), u(t)) - \eta^s(d^s(t)) + k^s\Big(\underbrace{y_{ref}^s(t)}_{\text{reference signal}} - x^s(t)\Big) + \dot{y}_{ref}^s(t)\Big]$$

  - Control law for $\Sigma^{(i)}$:

$$u_c^{(i)}(t) = \frac{1}{g^{(i)}(x^s(t), x^{(i)}(t))}\Big[-A^{(i)} x^{(i)}(t) - h^{(i)}(x^{(i)}(t), x^{(j)}(t)) - \eta^{(i)}(d^{(i)}(t)) + k^{(i)}\Big(\underbrace{y_{ref}^{(i)}(t)}_{\text{reference signal}} - x^{(i)}(t)\Big) + \dot{y}_{ref}^{(i)}(t)\Big]$$

- Sensor's Structure:

$$\mathcal{S}^s : y^s(t) = x^s(t) + n^s(t) + f_s^s(t),$$

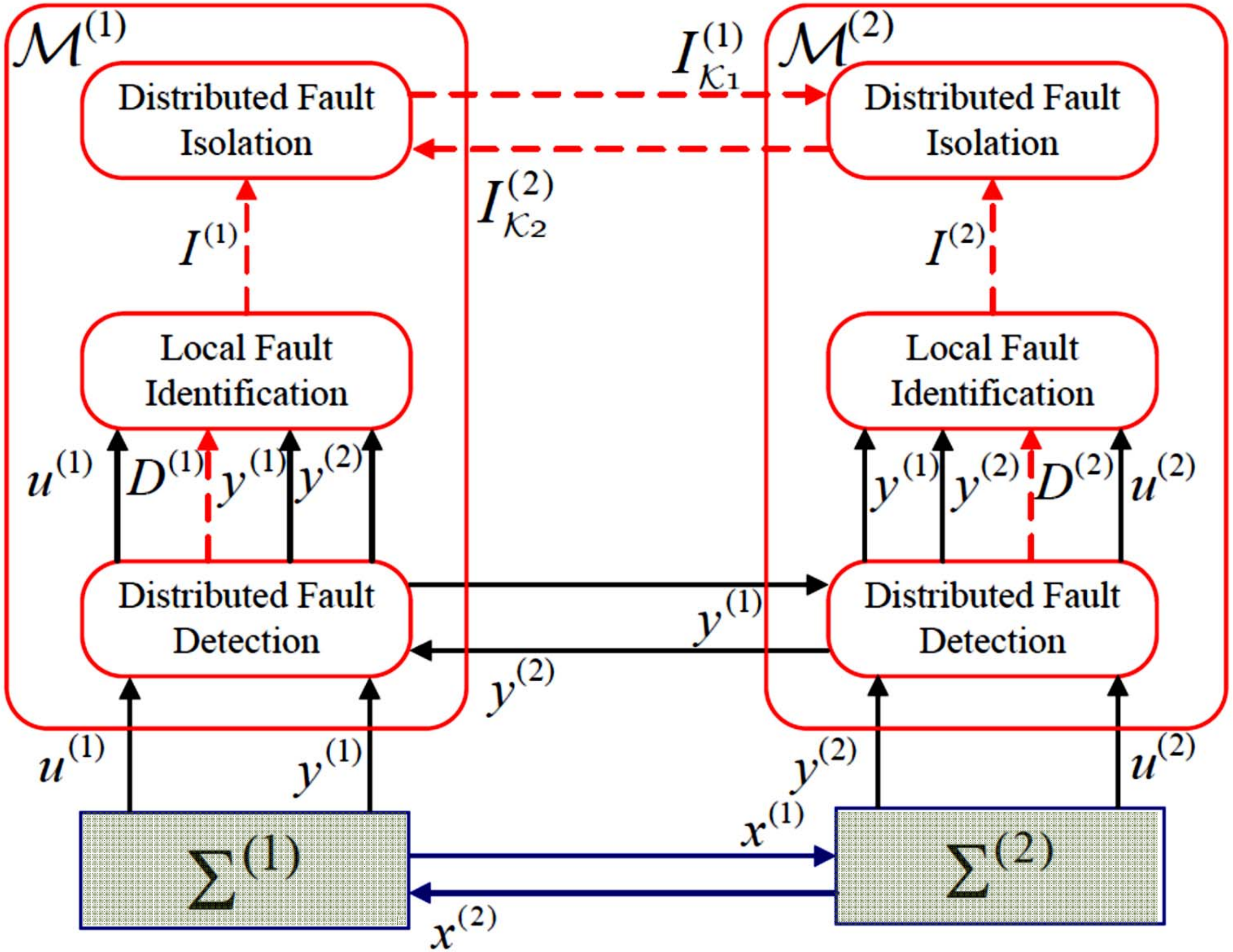
$$\mathcal{S}^{(i)} : y^{(i)}(t) = x^{(i)}(t) + n^{(i)}(t) + \underbrace{f_s^{(i)}(t)}_{\text{permanent sensor fault}},$$

- Faults in Actuators:

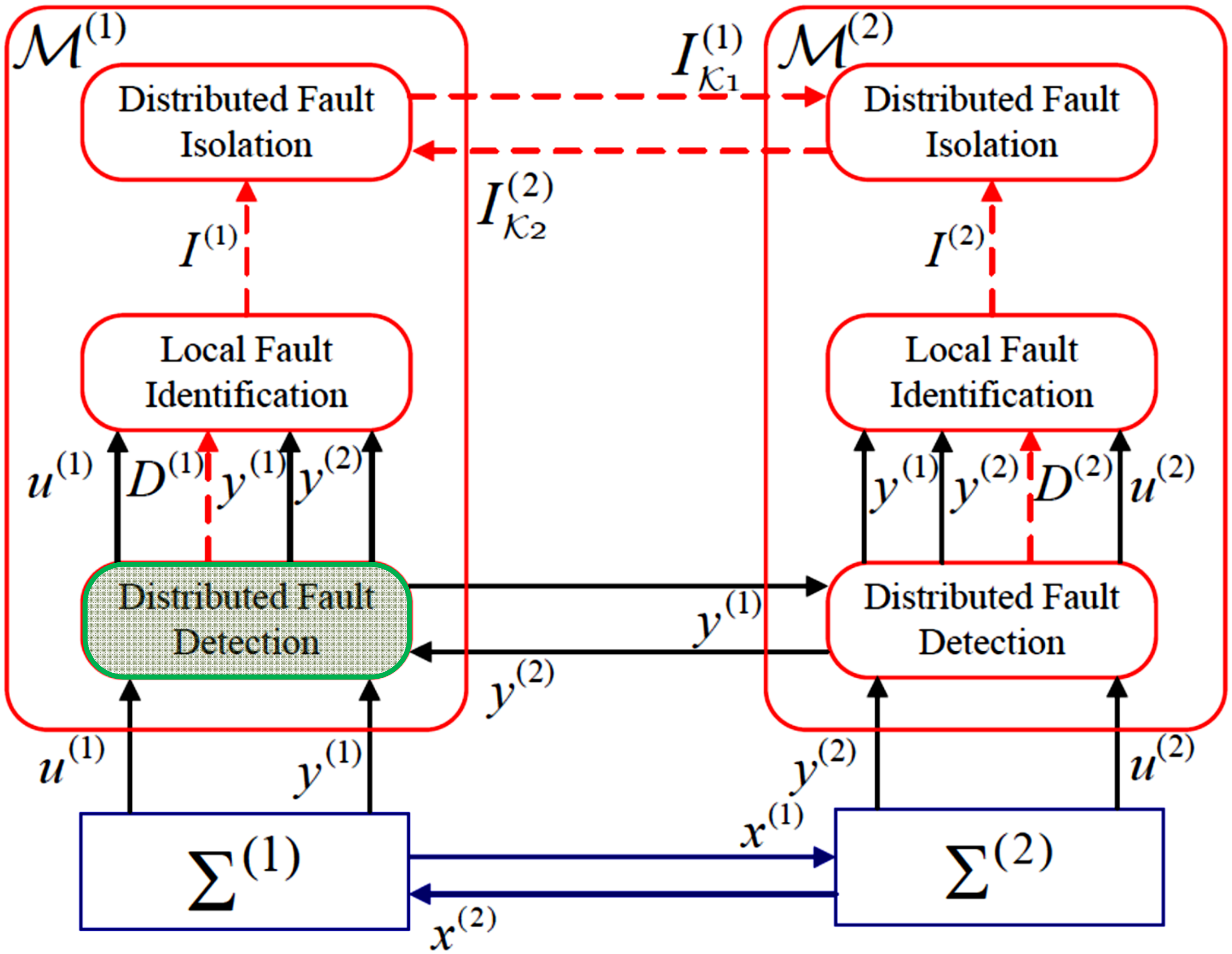
$$u^s(t) = u_c^s(t) + f_a^s(t),$$

$$u^{(i)}(t) = u_c^{(i)}(t) + \underbrace{f_a^{(i)}(t)}_{\text{permanent actuator fault}},$$

Distributed Sensor Fault Diagnosis Scheme



Distributed Sensor Fault Diagnosis Scheme



$|\varepsilon_y^{(i)}(t)| > \bar{\varepsilon}_y^{(i)}(t)\}$

$y^{(i)}(t) - \hat{x}^{(i)}(t)$

$(t))u_c^{(i)}(t)$

$(t))$

Distributed Sensor Fault Diagnosis Scheme

$\mathcal{M}^{(i)}$

- Distributed Fault Detection:
  - Analytical redundancy relation (ARR): $\mathcal{E}^{(i)} : |\varepsilon_y^{(i)}(t)| \leq \overline{\varepsilon}_y^{(i)}(t),$
  - Boolean decision signal:

$$D^{(i)}(t) = \begin{cases} 0, t < t_D^{(i)} \\ 1, t \geq t_D^{(i)} \end{cases}, \qquad t_D^{(i)} \equiv inf\{t \geq 0 : |\varepsilon_y^{(i)}(t)| > \overline{\varepsilon}_y^{(i)}(t)\}$$

  - Residual generation: $\varepsilon_y^{(i)}(t) = y^{(i)}(t) - \hat{x}^{(i)}(t)$

  - Distributed nonlinear estimator:

$$\dot{\hat{x}}^{(i)}(t) = A^{(i)}\hat{x}^{(i)}(t) + g^{(i)}(y^s(t), y^{(i)}(t))u_c^{(i)}(t) + h^{(i)}(y^{(i)}(t), y_{\mathcal{K}_i}(t))$$
$$+\eta^{(i)}(d^{(i)}(t)) + L^{(i)}\left(y^{(i)}(t) - \hat{x}^{(i)}(t)\right),$$
$$y_{\mathcal{K}_i}(t) = \left[y^{(j)}(t) : j \in \mathcal{K}_i\right]^\top,$$

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Distributed Sensor Fault Diagnosis Scheme

- Adaptive threshold:

$$\mathcal{M}^{(i)}$$

$$\bar{\varepsilon}_y^{(i)} = \rho^{(i)} e^{-\lambda^{(i)} t} \bar{x}^{(i)} + \bar{n}^{(i)} + \int_0^t \rho^{(i)} e^{-\lambda^{(i)}(t-\tau)} \Big(\left| L^{(i)} \right| \bar{n}^{(i)} + \bar{r}^{(i)} + \bar{g}^{(i)}(\bar{n}^{(i)}, \bar{n}^s, u_c^{(i)}) + \bar{h}^{(i)}(\bar{n}^{(i)}, \bar{n}_{\mathcal{K}_i}, y^{(i)}, y_{\mathcal{K}_i}) \Big) d\tau,$$

$$|\tilde{g}^{(i)}| \leq \sigma^{(i)} \left(\bar{n}^{(i)} + \bar{n}^s \right) = \bar{g}^{(i)}(\bar{n}^{(i)}, \bar{n}^s),$$

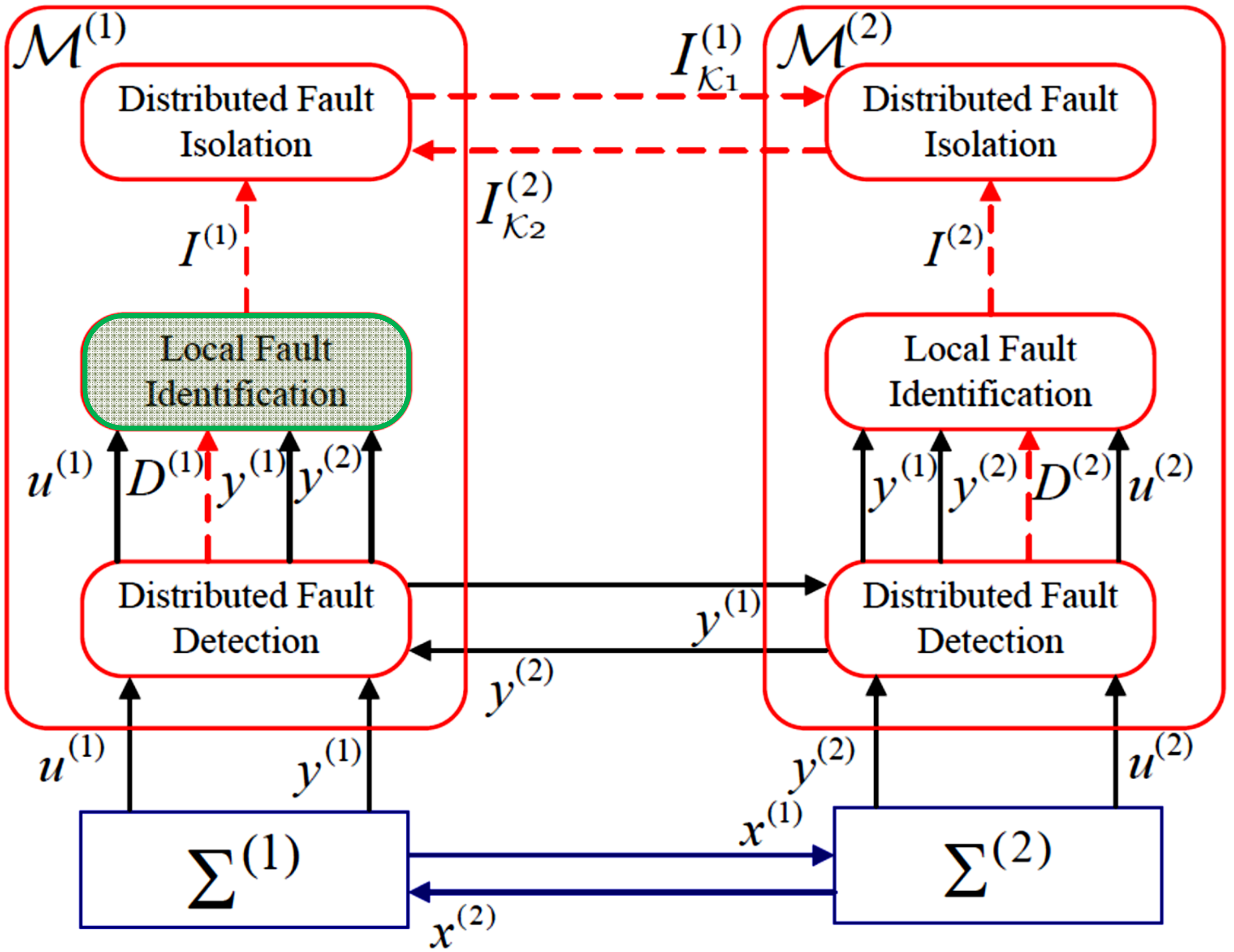
$$|\tilde{h}^{(i)}| \leq p^{(i)} \sum_{j \in \mathcal{K}_i} A_{d_{ij}} \bar{\mu}^{(i)}(y^{(i)}, y^{(j)}) + \frac{1}{C_{z_i}} \sum_{j \in \mathcal{K}_i} a_{z_{ij}} \bar{n}^{(j)} = \bar{h}^{(i)}(\bar{n}^{(i)}, \bar{n}_{\mathcal{K}_i}, y^{(i)}, y_{\mathcal{K}_i})$$

$$\bar{\mu}^{(i)}(y^{(i)}, y^{(j)}) = \bar{n}^{(i)} \frac{\left| 2y^{(j)} - 3y^{(i)} \right|}{2\left| y^{(j)} - y^{(i)} \right|} + \bar{n}^{(j)} \frac{\left| y^{(i)} \right|}{2\left| y^{(j)} - y^{(i)} \right|} + \bar{\mu}_e^{(i)},$$

$$|x^{(i)}(t)| \leq \bar{x}^{(i)}$$

$$|e^{A_L^{(i)} t}| \leq \rho^{(i)} e^{-\lambda^{(i)} t}$$

Distributed Sensor Fault Diagnosis Scheme



Distributed Sensor Fault Diagnosis Scheme

$\mathcal{M}^{(i)}$

- Local Fault Identification:
  - ARR's:

$$E_a^{(i)} : |\varepsilon_{y_a}^{(i)}(t)| \le \bar{\varepsilon}_{y_a}^{(i)}(t),$$

$$E_s^{(i)} : |\varepsilon_{y_s}^{(i)}(t)| \le \bar{\varepsilon}_{y_s}^{(i)}(t),$$

  - Boolean decisions functions:

$$I_a^{(i)}(t) = \begin{cases} 0, t < t_{I_a}^{(i)} \\ 1, t \ge t_{I_a}^{(i)} \end{cases}, \qquad I_s^{(i)}(t) = \begin{cases} 0, t < t_{I_s}^{(i)} \\ 1, t \ge t_{I_s}^{(i)} \end{cases}, \qquad \begin{aligned} t_{I_a}^{(i)} &\equiv inf\{t \ge t_D^{(i)} : |\varepsilon_{y_a}^{(i)}(t)| > \bar{\varepsilon}_{y_a}^{(i)}(t)\} \\ t_{I_s}^{(i)} &\equiv inf\{t \ge t_D^{(i)} : |\varepsilon_{y_s}^{(i)}(t)| > \bar{\varepsilon}_{y_s}^{(i)}(t)\} \end{aligned}$$

  - Residual generation:

$$\varepsilon_{y_a}^{(i)}(t) = y^{(i)}(t) - \hat{x}_a^{(i)}(t),$$

$$\varepsilon_{y_s}^{(i)}(t) = y^{(i)}(t) - \hat{x}_s^{(i)}(t) - \hat{f}_s^{(i)},$$

Distributed Sensor Fault Diagnosis Scheme

$$\mathcal{M}^{(i)}$$

- Local Fault Identification:
  - Distributed adaptive nonlinear estimation scheme:

$$\overbrace{\dot{\hat{x}}_a^{(i)}(t) = A^{(i)}\hat{x}_a^{(i)}(t) + g^{(i)}(y^s(t), y^{(i)}(t))(u_c^{(i)}(t) + \hat{f}_a^{(i)}(t)) + h^{(i)}(y^{(i)}(t), y_{\mathcal{K}_i}(t)) + \eta^{(i)}(d^{(i)}(t))}^{\text{nonlinear estimator}}$$

$$+L_a^{(i)}\varepsilon_{y_a}^{(i)}(t) + \Omega_a^{(i)}(t)\dot{\hat{f}}_a^{(i)}(t),$$

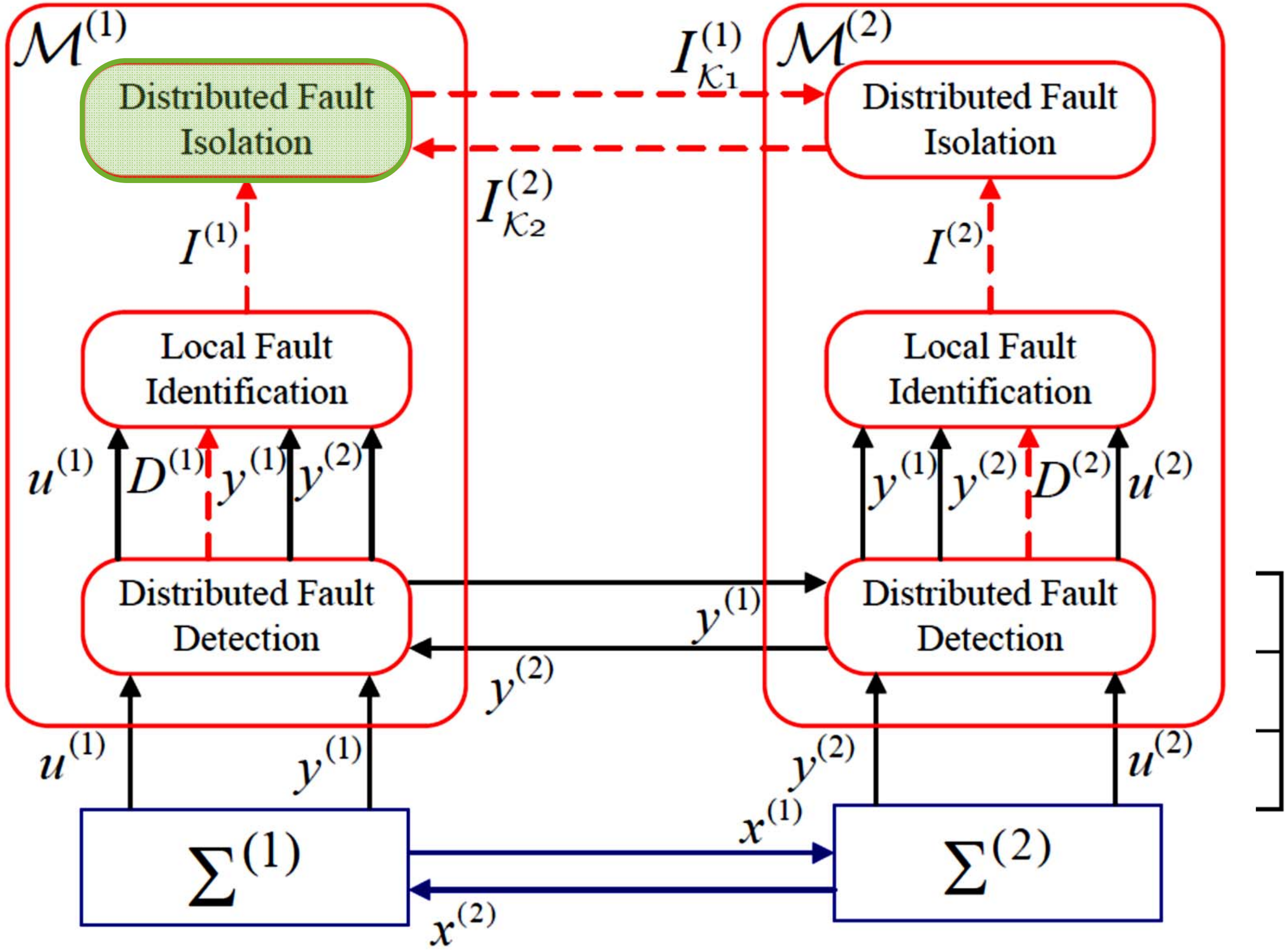
$$\overbrace{\dot{\Omega}_a^{(i)}(t) = A_L^{(i)}\Omega_a^{(i)}(t) + g^{(i)}(y^s(t), y^{(i)}(t))}^{\text{adaptive filter}}, \quad \overbrace{\dot{\hat{f}}_a^{(i)}(t) = \gamma_a^{(i)}\Omega_a^{(i)}(t)D^{(i)}\left[\varepsilon_{y_a}^{(i)}(t)\right]}^{\text{adaptive law}},$$

$$\overbrace{\dot{\hat{x}}_s^{(i)}(t) = A^{(i)}\hat{x}_s^{(i)}(t) + g^{(i)}(y^s(t), y^{(i)}(t) - \hat{f}_s^{(i)}(t))u_c^{(i)}(t) + h^{(i)}(y^{(i)}(t) - \hat{f}_s^{(i)}(t), y_{\mathcal{K}_i}(t)) + \eta^{(i)}(d^{(i)}(t))}^{\text{nonlinear estimator}}$$

$$+L_s^{(i)}\varepsilon_{y_s}^{(i)}(t) + \Omega_s^{(i)}(t)\dot{\hat{f}}^{(i)}(t),$$

$$\overbrace{\dot{\Omega}_s^{(i)}(t) = A_L^{(i)}\Omega_s^{(i)}(t) - L_s^{(i)} + \sigma^{(i)}u_c^{(i)}(t) - p^{(i)}\sum_{j\in K_i} A_{d_{ij}}\frac{\partial \mu^{(i)}}{x^{(i)}}\left(y^{(i)} - \hat{f}_s^{(i)}, y^{(j)}\right)}^{\text{adaptive filter}}, \quad \overbrace{\dot{\hat{f}}_s^{(i)}(t) = \gamma_s^{(i)}(\Omega_s^{(i)}(t) + 1)D^{(i)}\left[\varepsilon_{y_s}^{(i)}(t)\right]}^{\text{adaptive law}},$$

Distributed Sensor Fault Diagnosis Scheme



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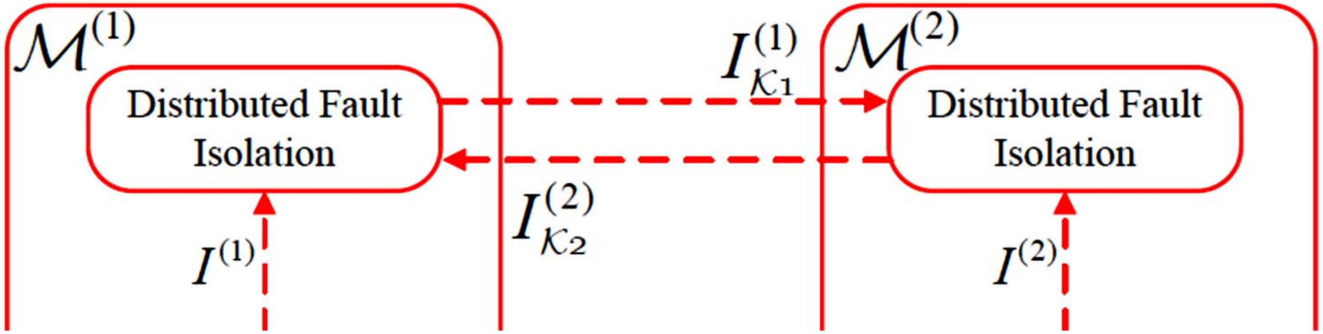
Distributed Sensor Fault Diagnosis Scheme



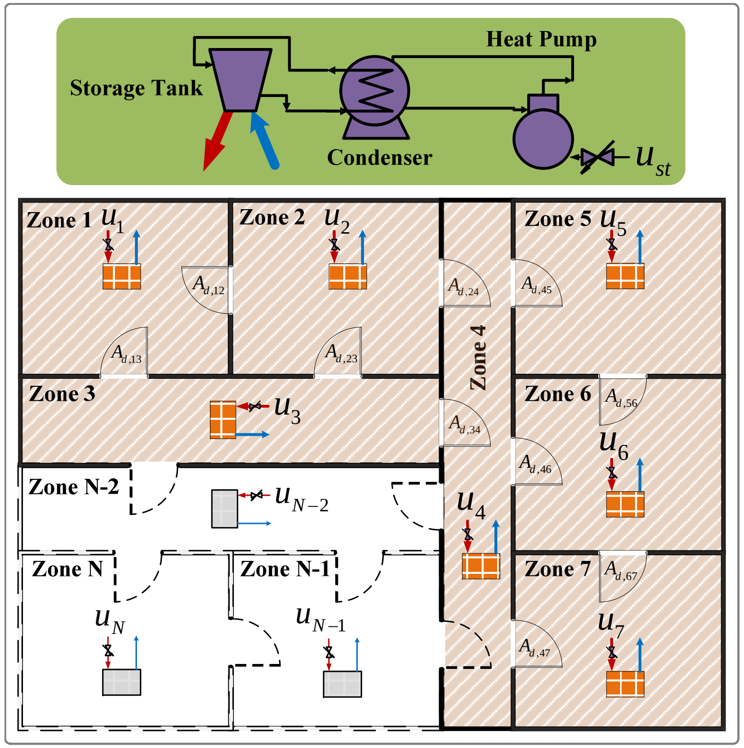
- Distributed Fault Isolation:
  - Observed fault pattern of **propagated sensor** faults: $I_{K_i}(t) = \left[I^{(j)}_{K_j}(t) : j \in K_i \cup \{i\} \right]^\top$
  - Fault isolation signature matrix $F^{(i)}_{\mathcal{K}_i}$

	$f_s^{(1)}$	$f_s^{(2)}$	$f_s^{(3)}$	$f_s^{(1,2)}$	$f_s^{(1,3)}$	$f_s^{(2,3)}$	$f_s^{(1,2,3)}$
$\mathcal{E}_{\mathcal{K}_1}$	1	*	*	1	1	*	1
$\mathcal{E}_{\mathcal{K}_2}$	*	1	*	1	*	1	1
$\mathcal{E}_{\mathcal{K}_3}$	*	*	1	*	1	1	1

$$f_s^{(1,2)} = \left\{ f_s^{(1)}, f_s^{(2)} \right\} \quad f_s^{(1,3)} = \left\{ f_s^{(1)}, f_s^{(3)} \right\} \quad f_s^{(2,3)} = \left\{ f_s^{(2)}, f_s^{(3)} \right\} \quad f_s^{(1,2,3)} = \left\{ f_s^{(1)}, f_s^{(2)}, f_s^{(3)} \right\}$$

Simulation Results

- Consider a seven-zone HVAC system where the architectural arrangement of the seven zones is presented by the diagram

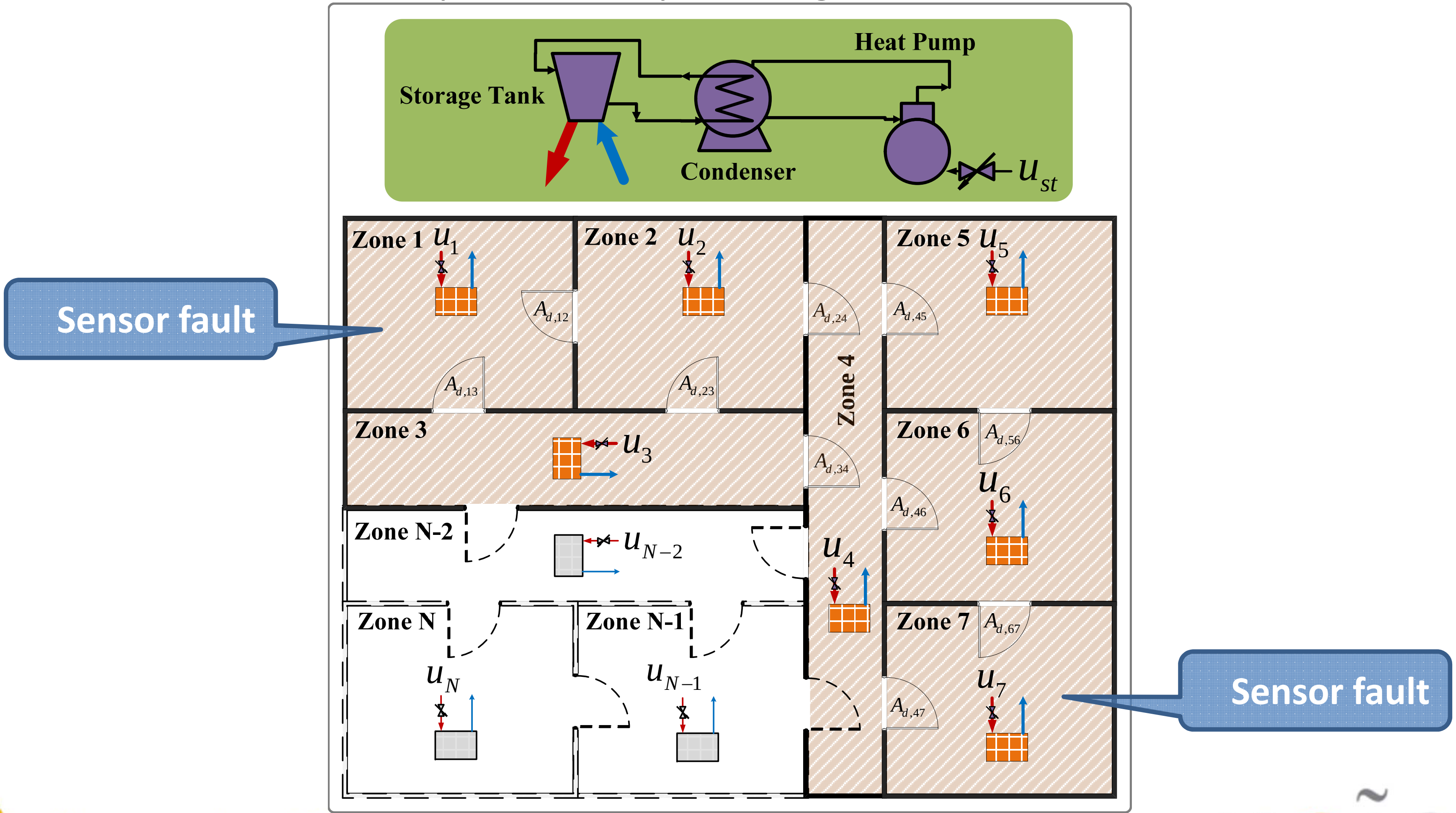


PARAMETERS OF THE SEVEN-ZONE HVAC SYSTEM

Symbol	Value	Units
$a_{z_i},\ i \in \{1,2,3,4,5,6,7\}$	740	kJ/h°C
$a_{z_{12}}, a_{z_{13}}, a_{z_{24}}, a_{z_{34}}, a_{z_{45}}, a_{z_{46}}, a_{z_{47}}, a_{z_{56}}, a_{z_{67}}$	50	kJ/h°C
a_{st}	12	kJ/kg°C
a_{sz}	0.6	kJ/kg°C
C_{st}	837	kJ/°C
C_p	1.004	kJ/kg°C
C_v	0.717	kJ/kg°C
r_{air}	1.225	kg/m^3
$C_{z_i},\ i \in \{1,2,3,4,5,6,7\}$	370	kJ/°C
$U_{i,max},\ i \in \{1,2,3,4,5,6,7\}$	3700	kg/h
$U_{st,max}$	27.36×10^4	kJ/h
P_{max}	3.5	
DT_{max}	45	°C
$A_{w,i},\ i \in \{1,2,3,4,5,6,7\}$	120	m^2
h	8.29	W/m°C
$A_{d,12}, A_{d,13}, A_{d,24}, A_{d,34}$	2.60	m^2
$A_{d,45}, A_{d,46}, A_{d,47}, A_{d,56}, A_{d,67}$	2.60	m^2

Simulation Results

- Consider a seven-zone HVAC system where the architectural arrangement of the seven zones is presented by the diagram



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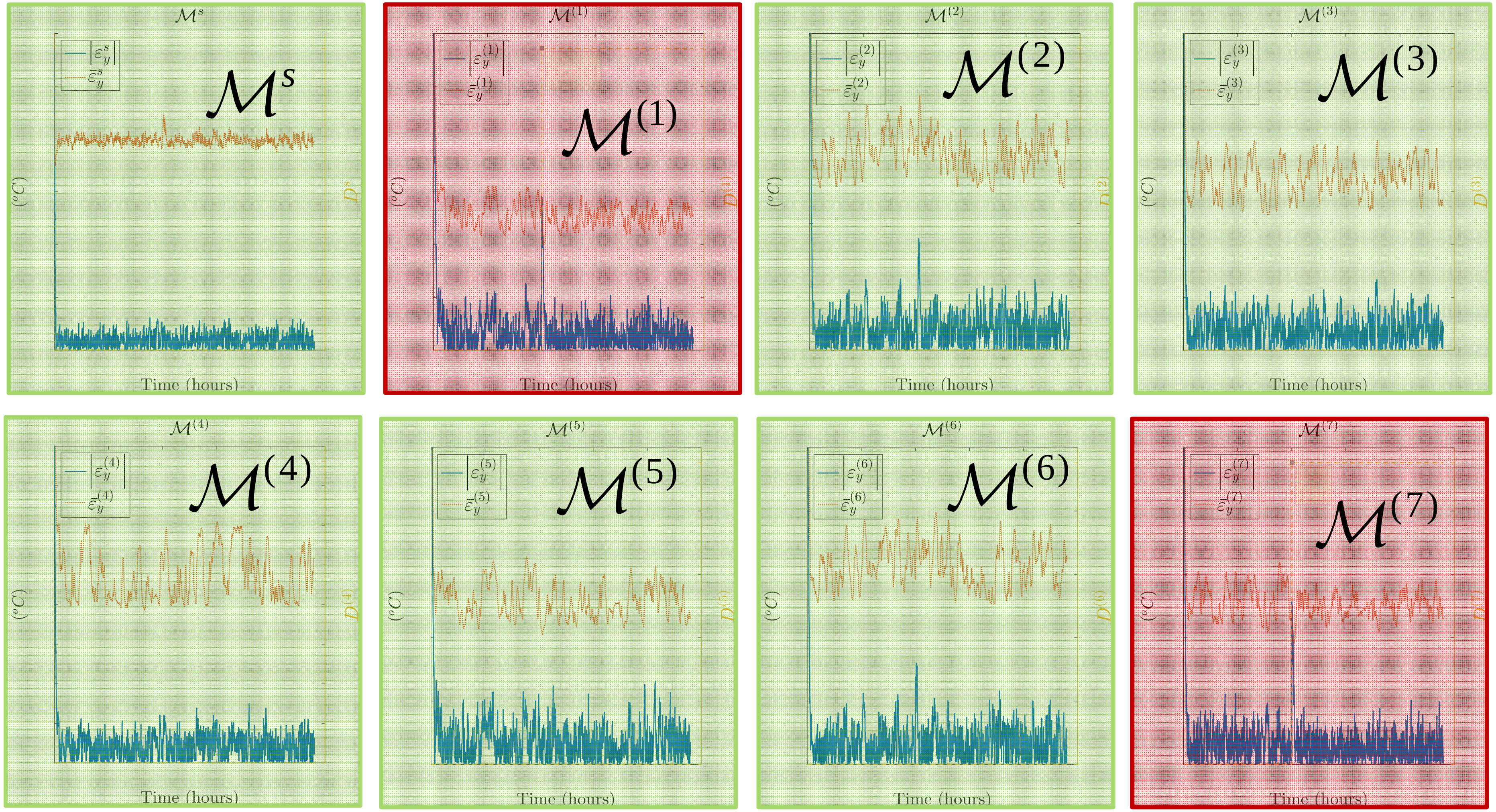
Simulation Results



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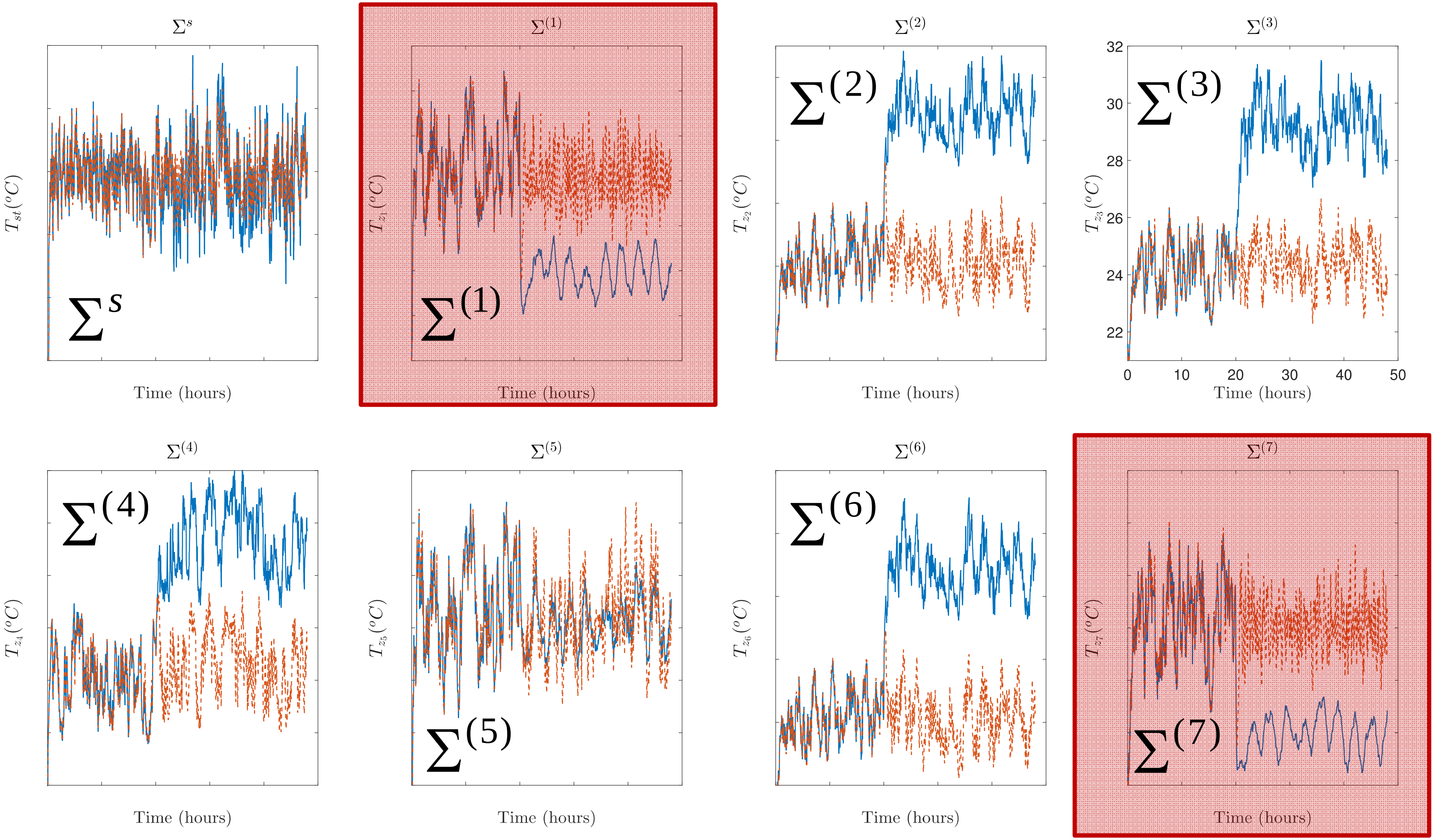
Simulation Results



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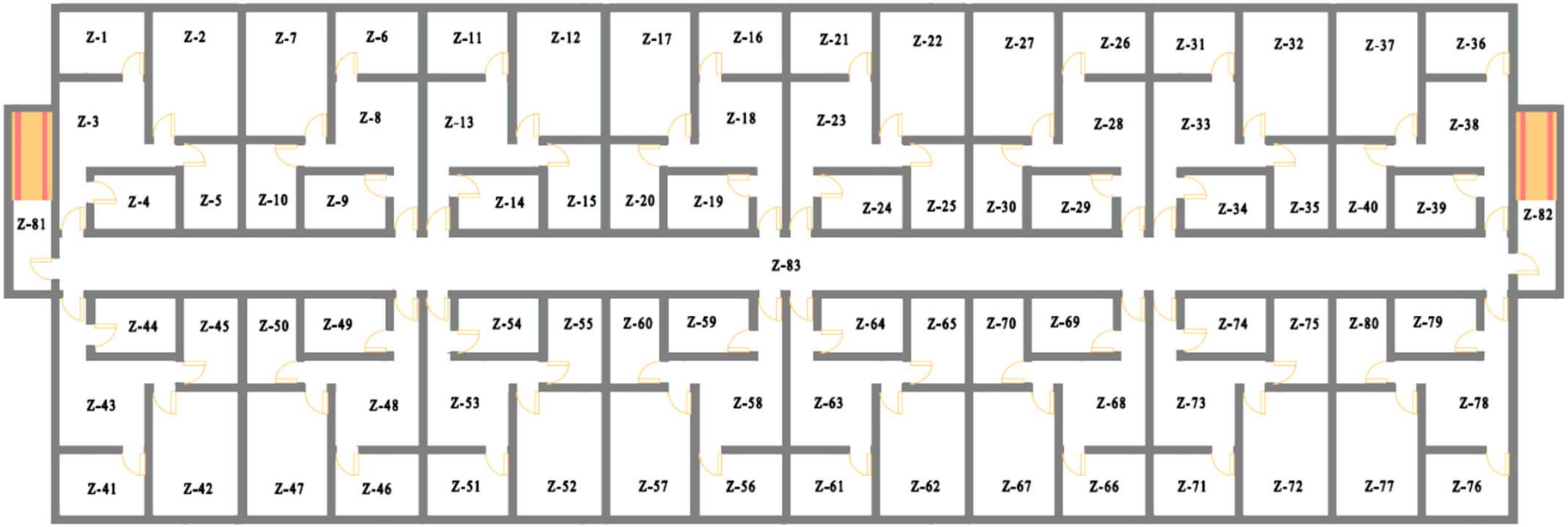
Simulation Results

- Consider a 83-zone HVAC system where the architectural arrangement of the 83 zones is presented by the diagram



Papadopoulos M. P., Reppa V., Polycarpou M. M., Panayiotou C., “Distributed Diagnosis of Actuator and Sensor Faults in HVAC systems,” IFAC *World Congress* 2017.

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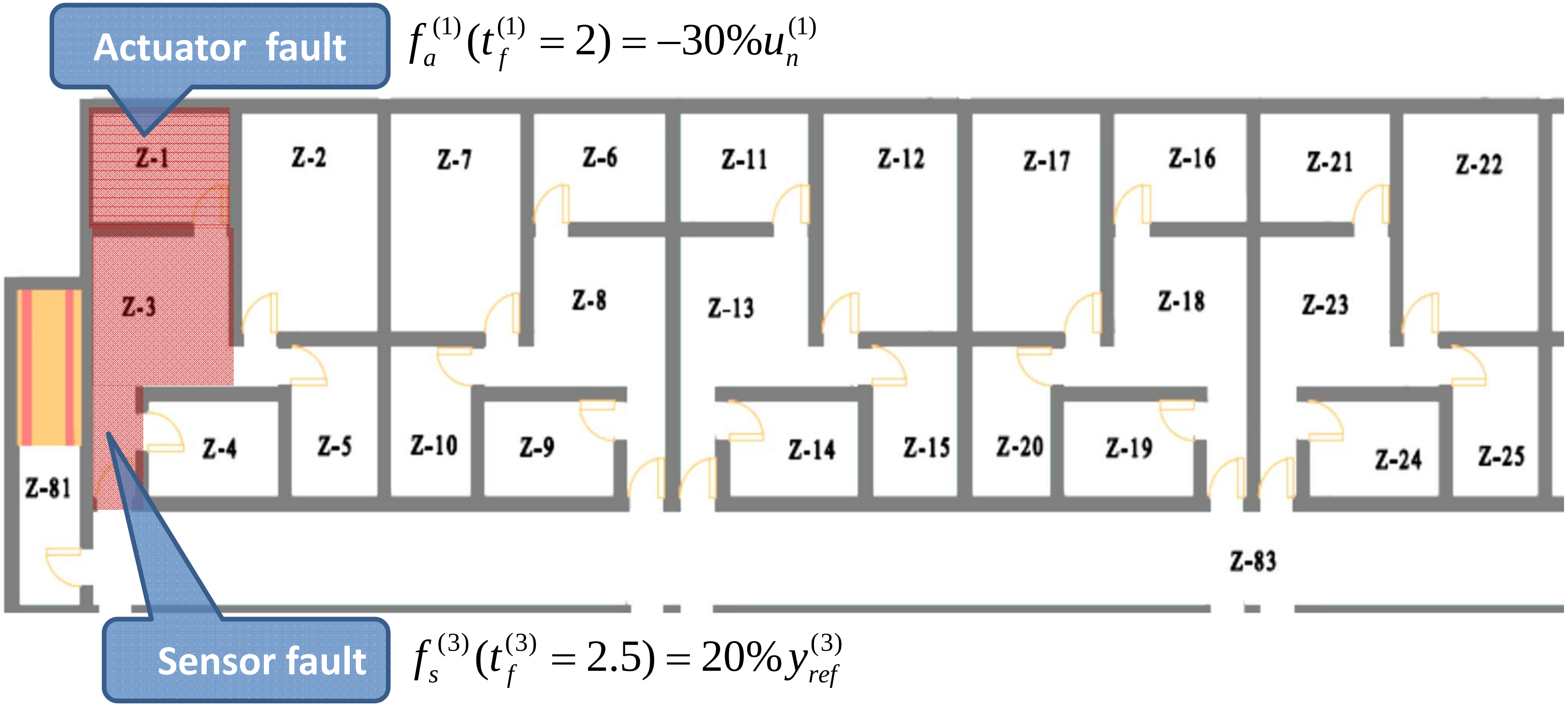
Simulation Results

- Multiple Faults occurring consecutively

$$f_a^{(1)}(t_f^{(1)} = 2) = -30\% u_n^{(1)}$$



$$f_s^{(3)}(t_f^{(3)} = 2.5) = 20\% y_{ref}^{(3)}$$

Simulation Results

- Multiple Fault Scenario

  - Actuator fault in $\Sigma^{(1)}$: $f_a^{(1)}(t_f^{(1)}=2)=-30\% u_n^{(1)}$
  - Sensor fault in $\mathcal{S}^{(3)}$: $f_s^{(3)}(t_f^{(3)}=2.5)=20\% y_{ref}^{(3)}$

  - The parameters of each subsystem are:

$$a_{z_i}=740, i\in\{1,\ldots,N\}, a_{z_{ij}}=50, a_{st}=12, a_{sz}=0.6, C_{st}=83700, C_p=1.004,$$

$$C_v=0.717, \rho_{air}=1.22, C_{z_i}=370, U_{i,max}=3700, i\in\{1,\ldots,N\}, U_{st,max}=27.36\times 10^5, p=2.5,$$

$$\Delta T_{max}=45, A_{w_i}=120, i\in\{1,\ldots,N\}, h=8.29, A_{d_{ij}}=1.95, i\in\{1,\ldots,N\}, j\in\mathcal{K}_i$$

  - It is assumed that the exogenous uncontrollable signals are constant

$$d_1^s=10^o C, d_2^s=5^o C, d_1^{(i)}=5^o C, d_2^{(i)}=10^o C, i\in\{1,\ldots,N\}$$

  - The modeling uncertainty in each subsystem $r^s=10\% d_1^s \sin(0.1t),$

$$r^{(i)}=10\% d_1^{(i)} \sin(0.1t)$$

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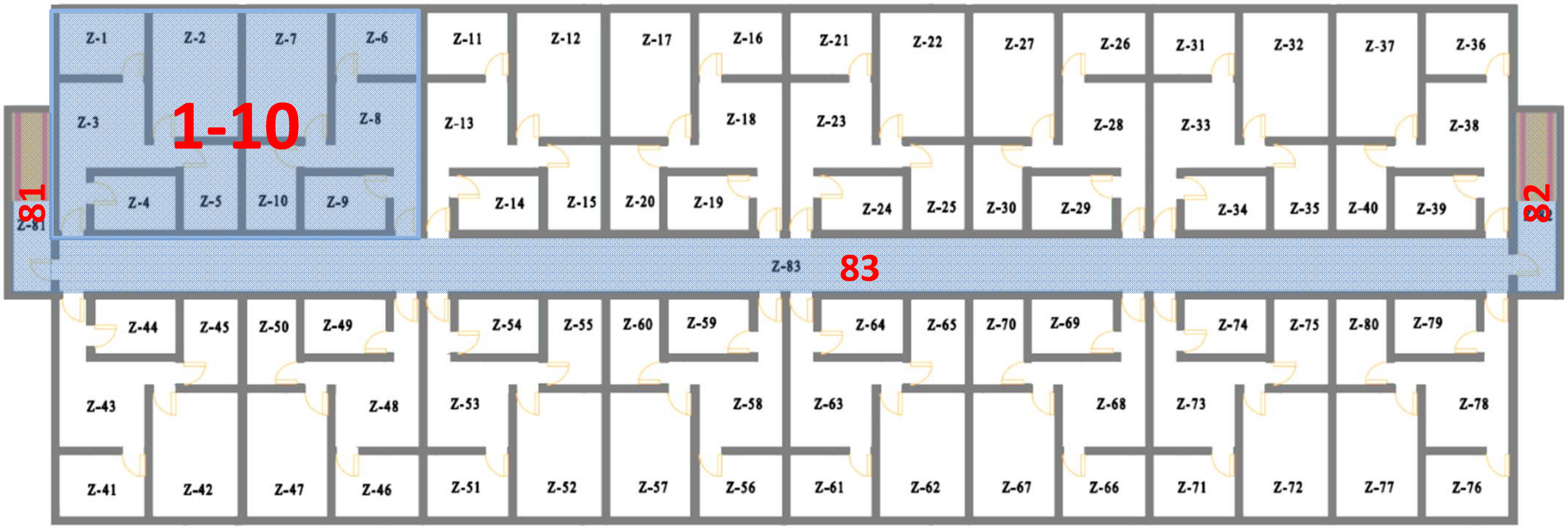
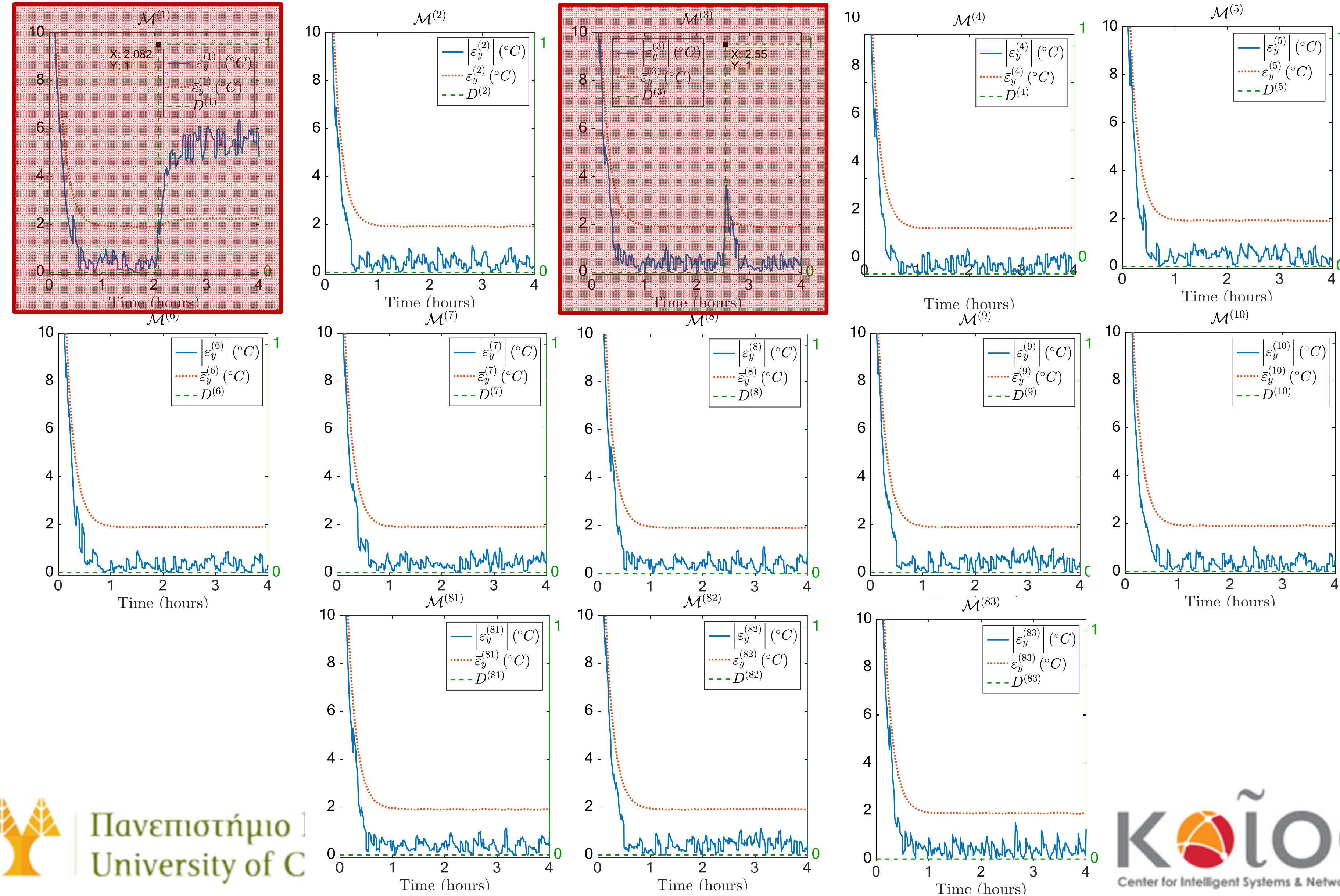
Simulation Results

- Have a look at the distributed **monitoring** agents located at:

Zones { 1-10, 81, 82, 83}



Simulation Results



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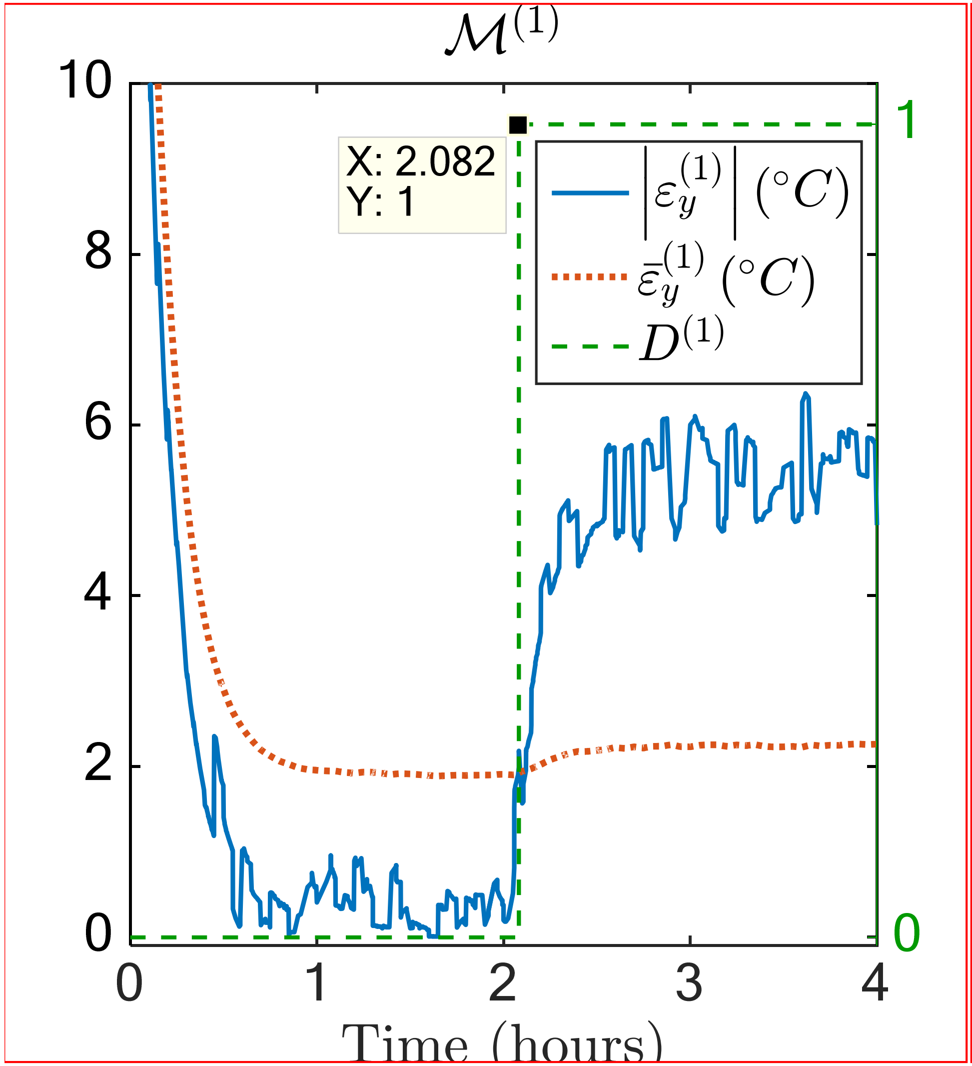
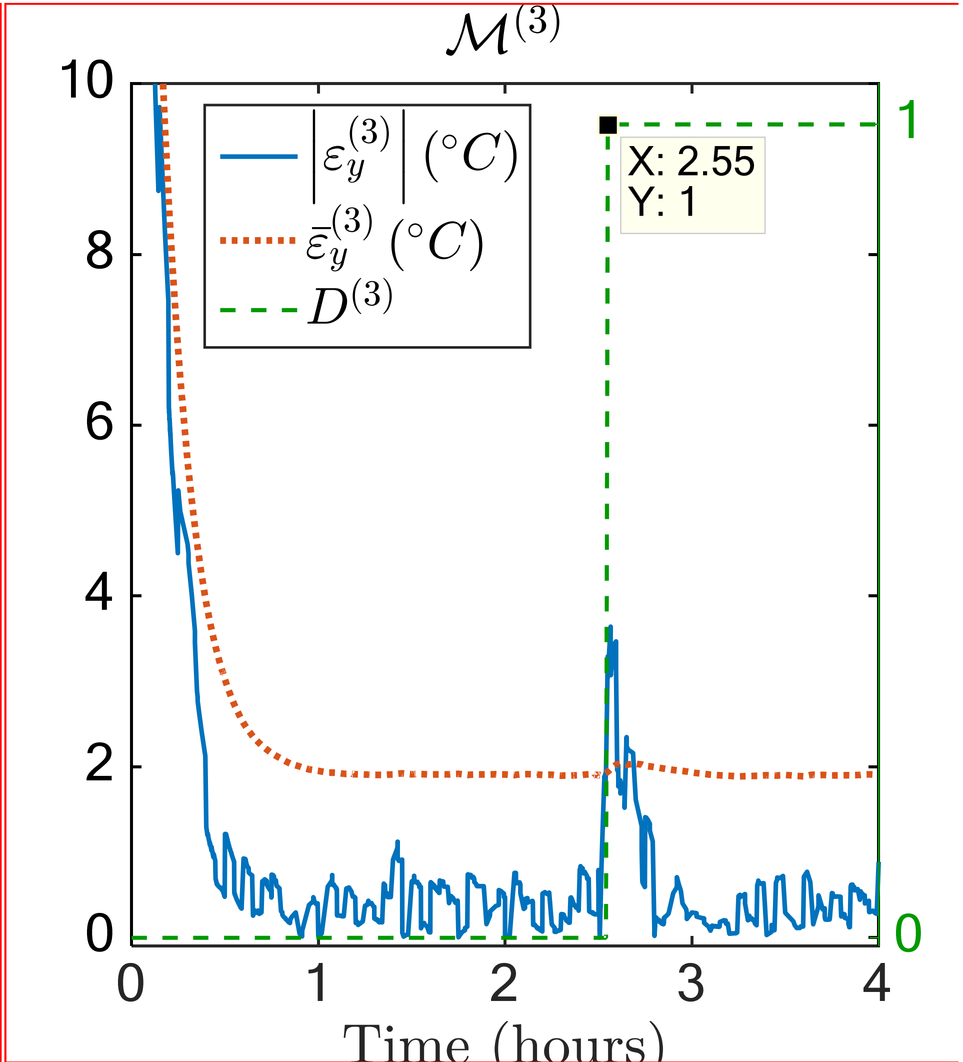
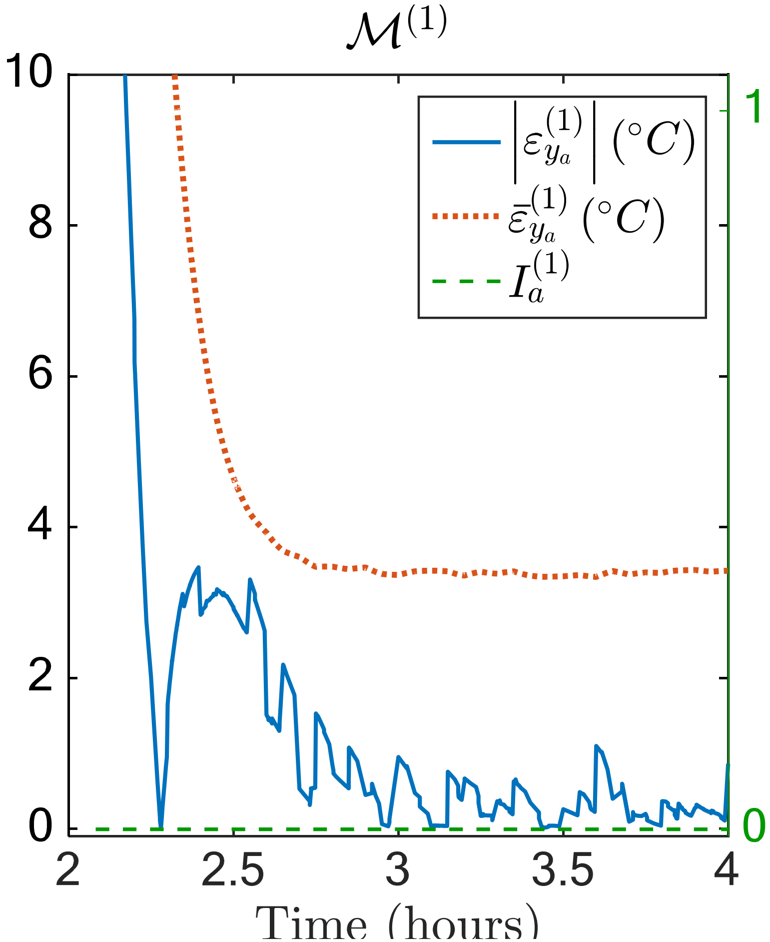
Simulation Results

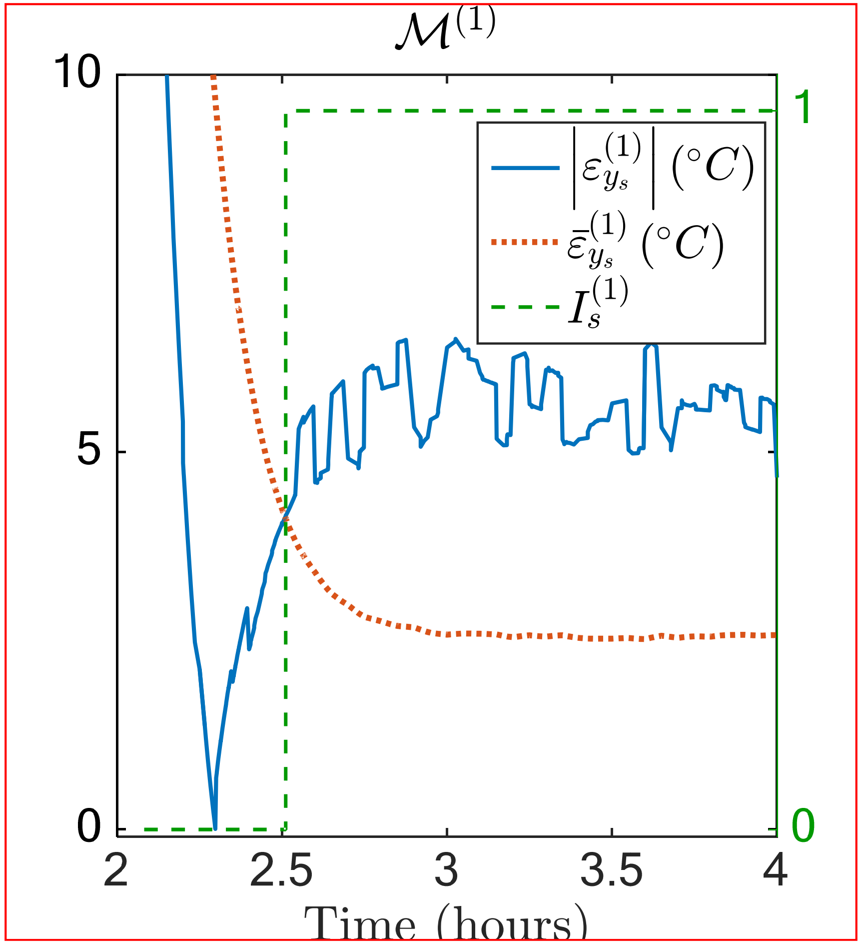




Simulation Results

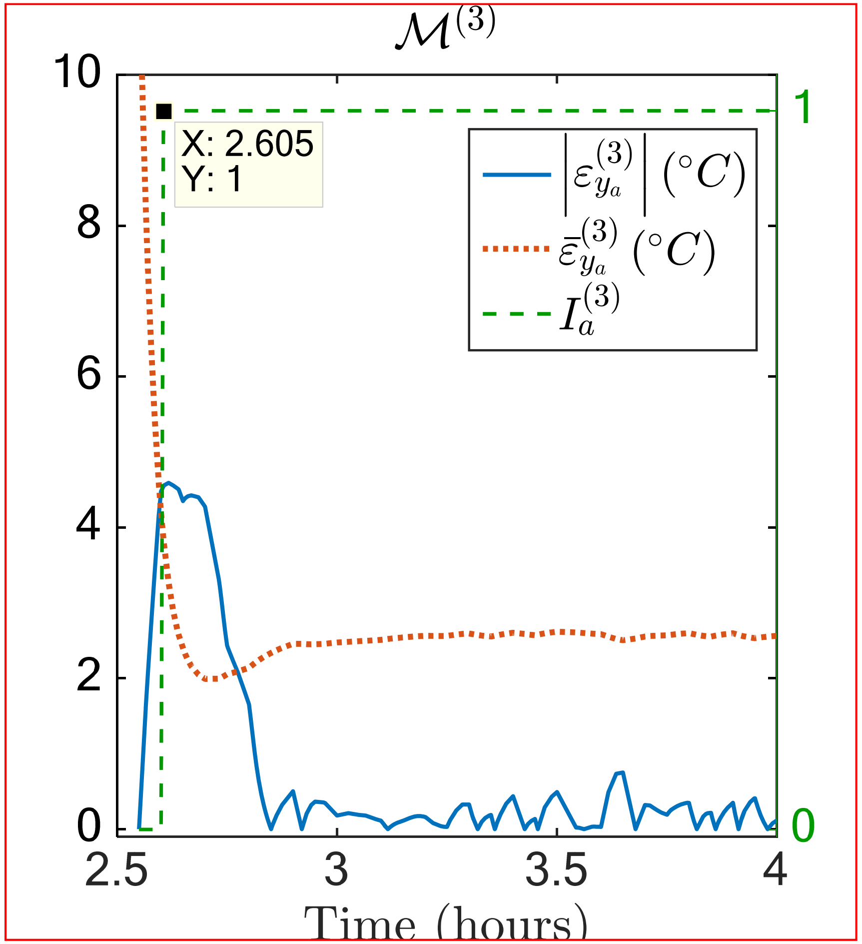
- Local Fault **Identification in Zone 1**:

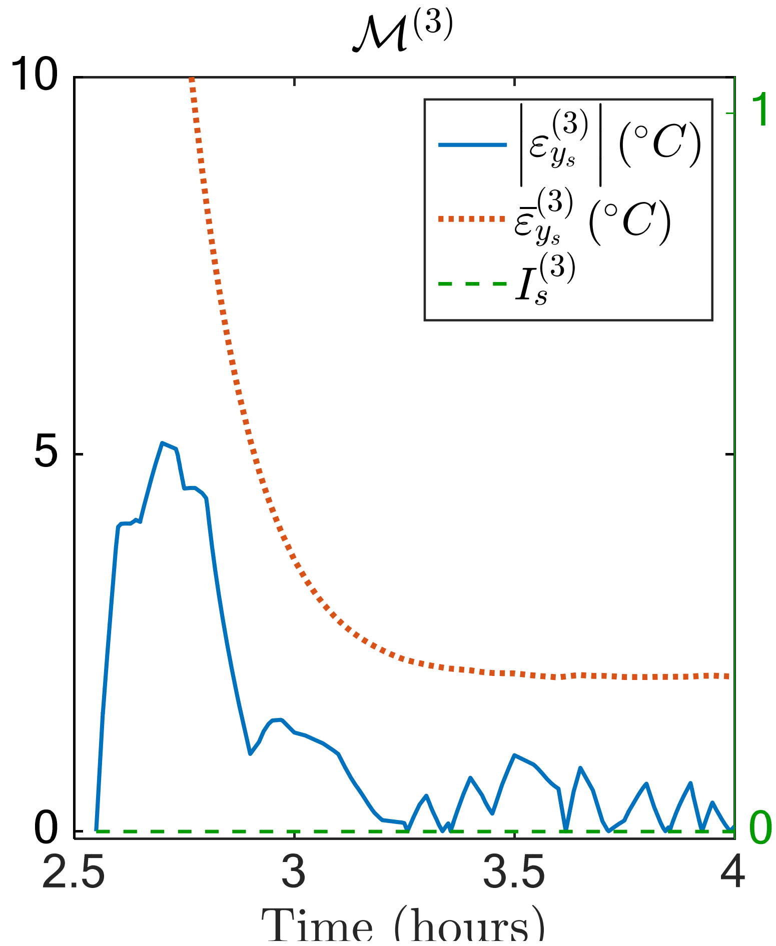




Simulation Results

- Local Fault **Identification in Zone 3**:





Remarks on Fault Diagnosis for HVAC Systems

- A distributed fault diagnosis (FD)methodology for isolating actuator and sensor faults in a multi-zone HVAC system is presented.
- The proposed architecture relies on the deployment of several distributed monitoring agents, which are allowed to exchange information.
- Every agent is designed to detect the presence of faults, identify the type and infer the number and location (local or propagated faults).

Concluding Remarks

- Monitoring and security of interconnected cyber-physical systems is a key area of growth
- Fault diagnosis will play a key role in big data computing and Internet of Things (IoT)
- Trend towards more sensors but cheaper sensors → more susceptible to faults
- Need for smart software to address faulty behavior of hardware

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Acknowledgements

- Colleagues and Graduate Students: Vasso Reppa, Christos Panayiotou, Thomas Parisini, Xiaodong Zhang, Panayiotis Papadopoulos, Demetris Eliades, Michalis Michaelides, Chris Keliris, Stelios Timotheou, Riccardo Ferrari.

- This work is funded by the European Research Council Advanced Grant FAULT-ADAPTIVE (ERC-AdG-291508)

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