Research and Innovation Center of Excellence

Intelligent Monitoring and Control of Interconnected Cyber-Physical Systems

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International AI Doctoral Academy (AIDA)
7 December 2021

Funded by:

The Smart Revolution!!

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

The Smart Revolution!!

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

→ ***Smart-X***

Characteristics of Smart-X

HARDWARE

- Sensing devices
- Actuation devices
- Embedded computing
- Wide area connectivity

SOFTWARE

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

From Smart-ready-X to Smart-X

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

From Smart-ready-X to Smart-X

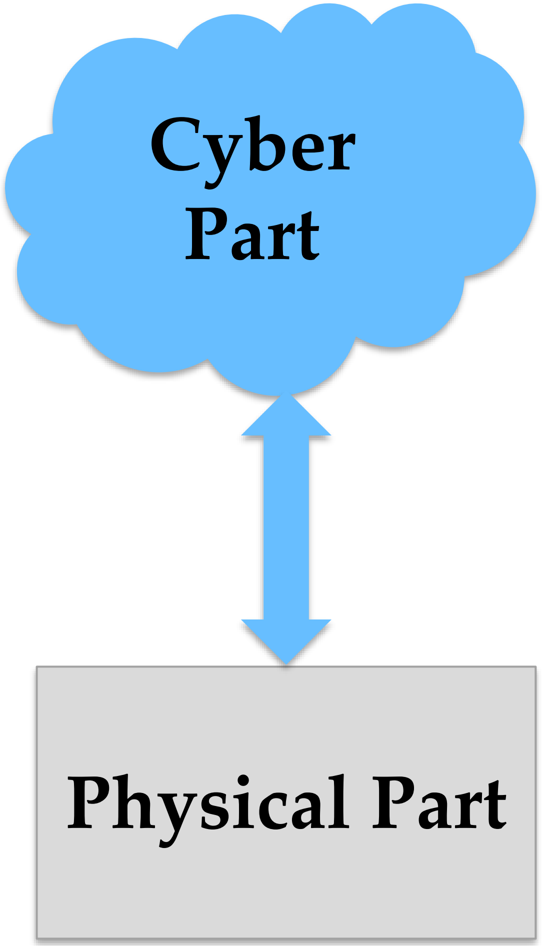
- Digital advances provide the ICT infrastructure not the INTELLIGENCE (so far)
- Infrastructure will be further enhanced via the IoT
- From Smart-ready-X to Smart-X

→ **Machine Learning and Feedback Control Systems are at the heart of transforming Smart-ready-X to Smart-X**

Cyber-Physical Systems (CPS)

- **physical part**: physical, biological or engineered systems that are usually large-scale & complex

- **cyber part**: communication networks & computational resources for **monitoring**, **controlling** & **coordinating** the physical part



P. J. Antsaklis, B. Goodwine, V. Gupta, M. J. McCourt, Y. Wang, P. Wu, M. Xia, H. Yu, and F. Zhu, “Control of cyber-physical systems using passivity and dissipativity based methods,” *European Journal of Control*, vol. 19, no. 5, pp. 379 – 388, 2013.

From Traditional Systems to CPS

- **Sensor technology**
  - wealth of sensors
  - new generation sensors

Pebble Smart Watch

Google Smart Glasses

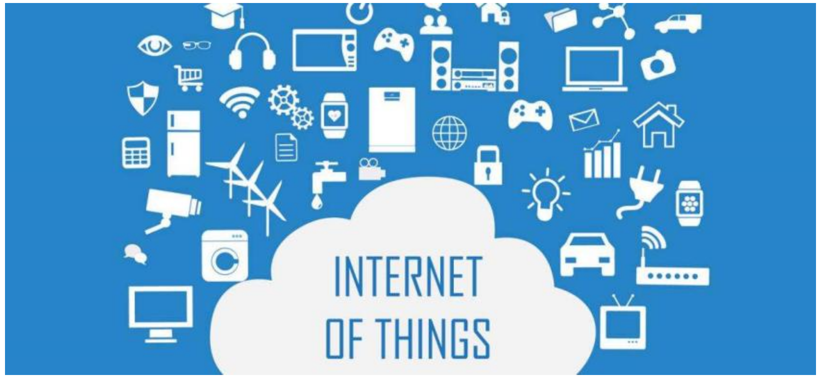
Sonitus in the Mouth Hearing Aid

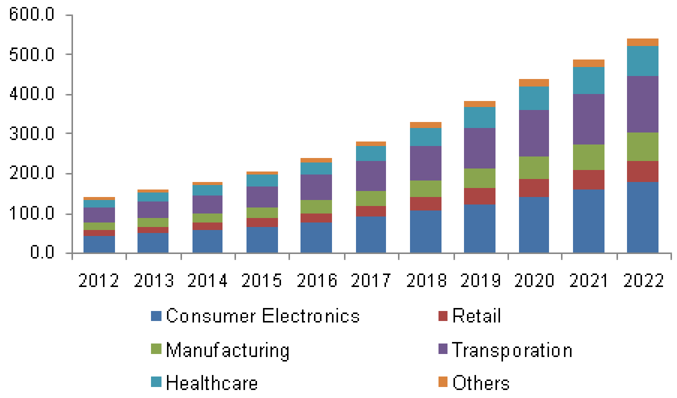
- **Information & Communication Technology (ICT)**
  - store, process and transmit data **collected by sensors**

From Traditional Systems to CPS

- **Internet of Things**

  sensor enabled devices connected to the internet and able to communicate with each other

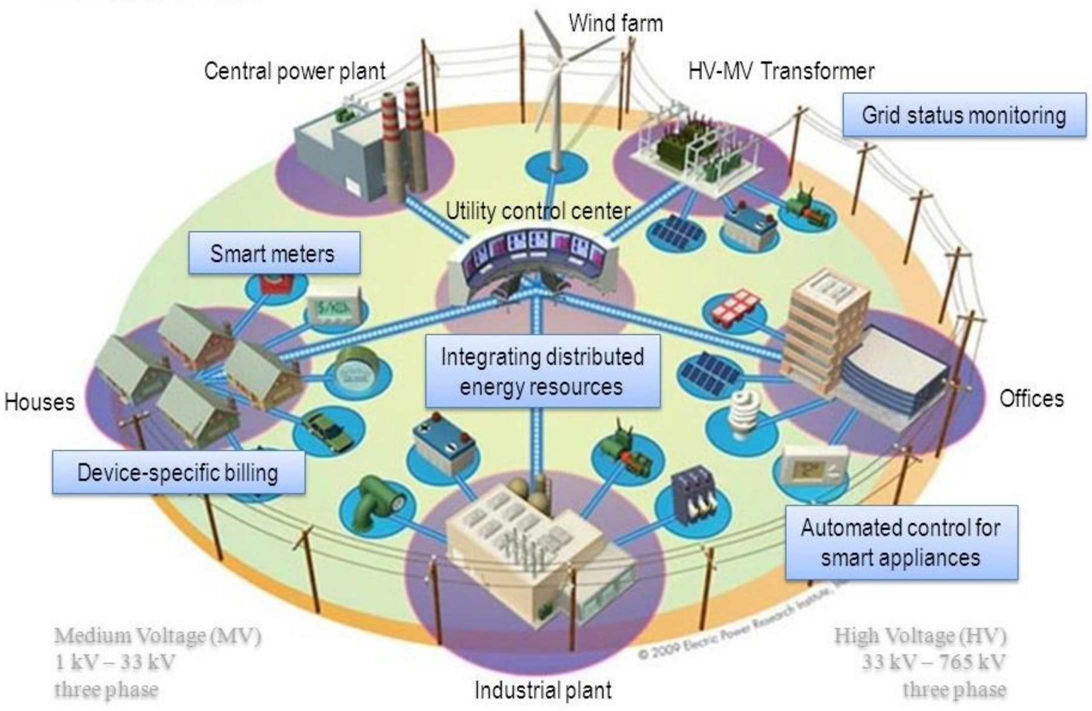


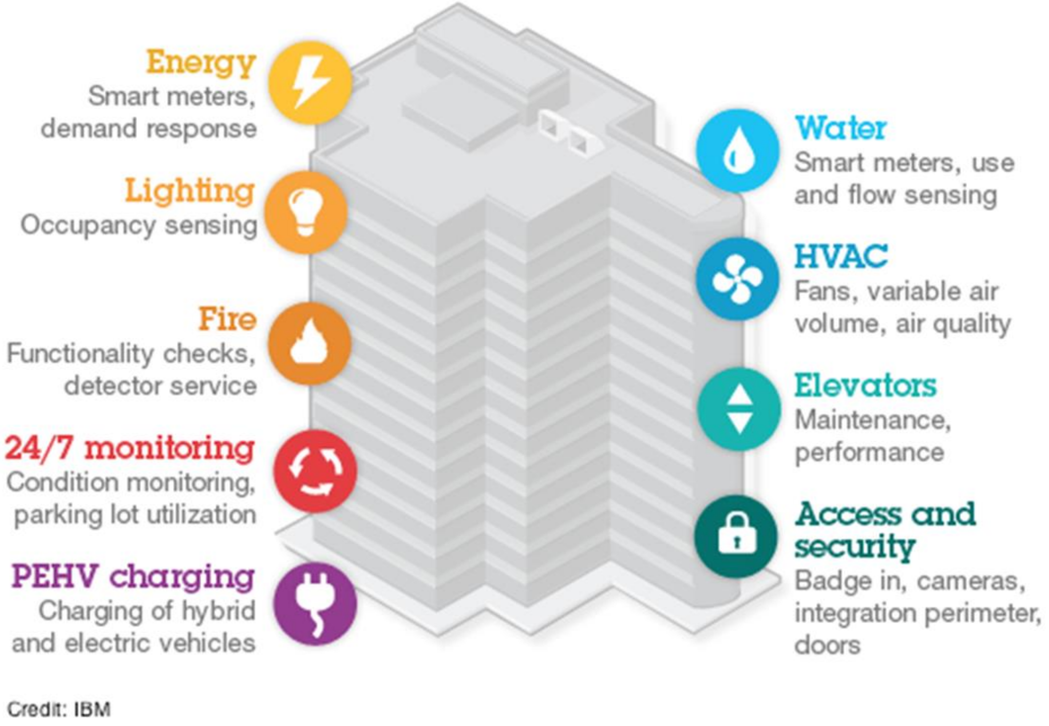


Big Data

- **sensor technology** and ICT enabled the collection of extremely large data sets
- contribute to the better perception of complex systems

Examples of CPS

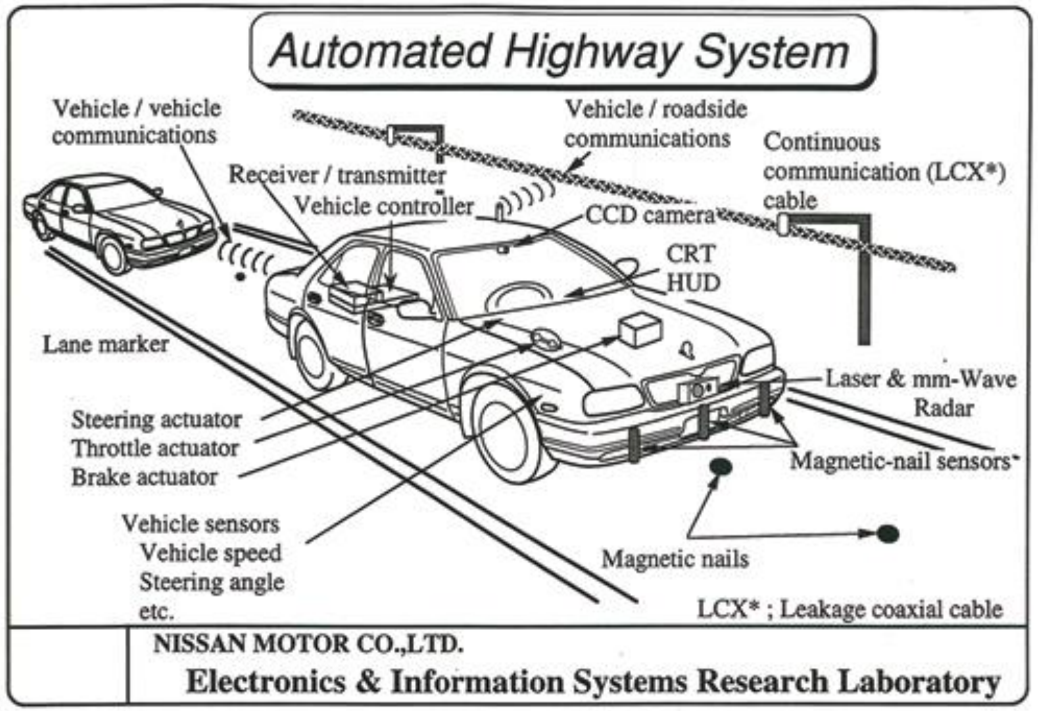




Smart Grid

Smart Buildings

Examples of CPS



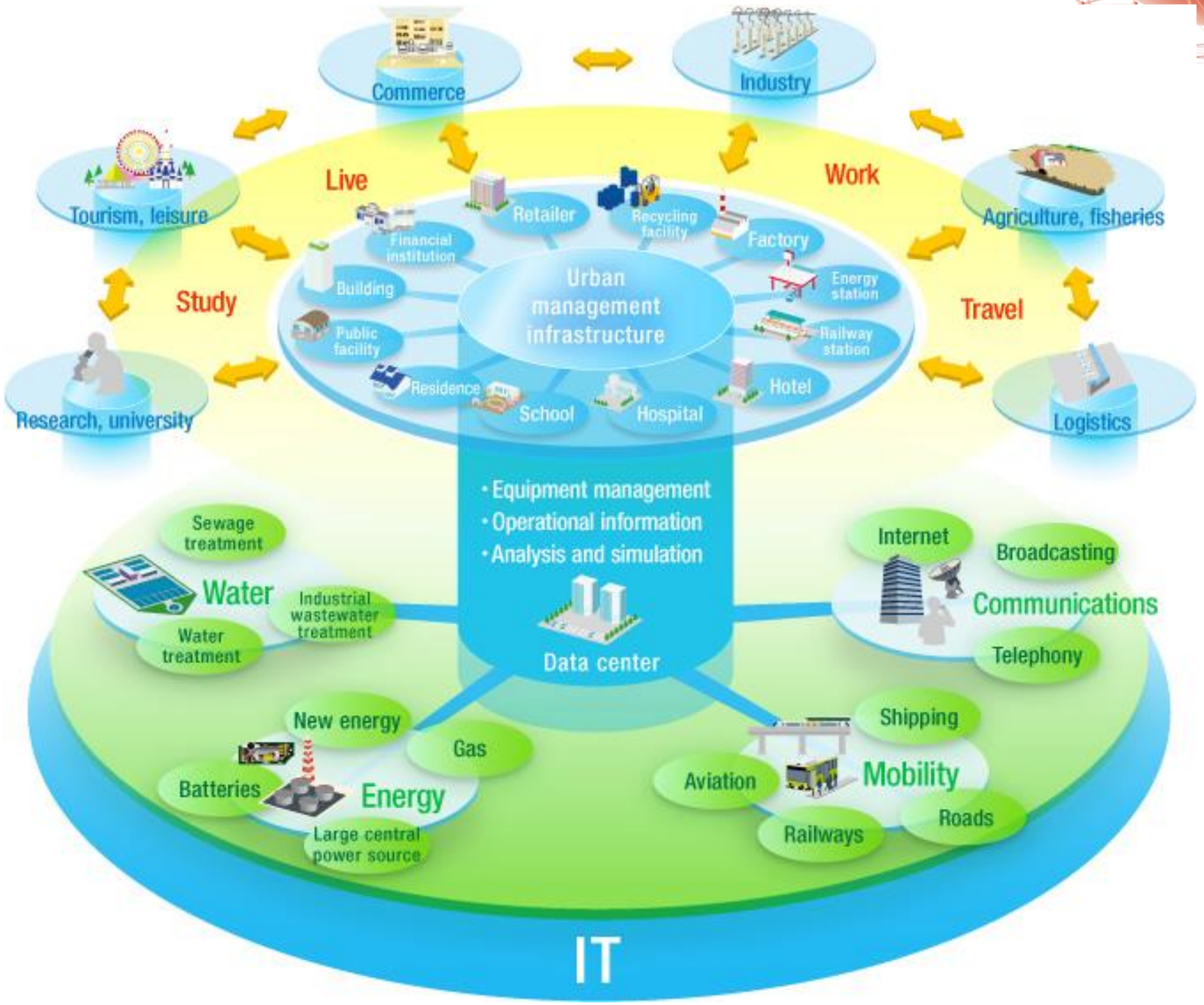
Intelligent Transportation

Multi-robot formation

Examples of CPS

Smart Cities: a network of interconnected CPS

- Physical Interconnections
- Cyber Interconnections
- Interdependencies



The Future of Jobs

World Economic Forum:

By 2025, **85 million jobs** will be displaced and **97 million new** professional positions will be created

Some key areas of futures jobs:
AI, Big-Data analytics, IoT, Machine Learning, Robotics, cloud computing

Fault Tolerant Systems

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

Fault Tolerant Systems

The technological trend is towards:

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

more FRAGILE

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

- wrong decisions or escalation to a catastrophic failure
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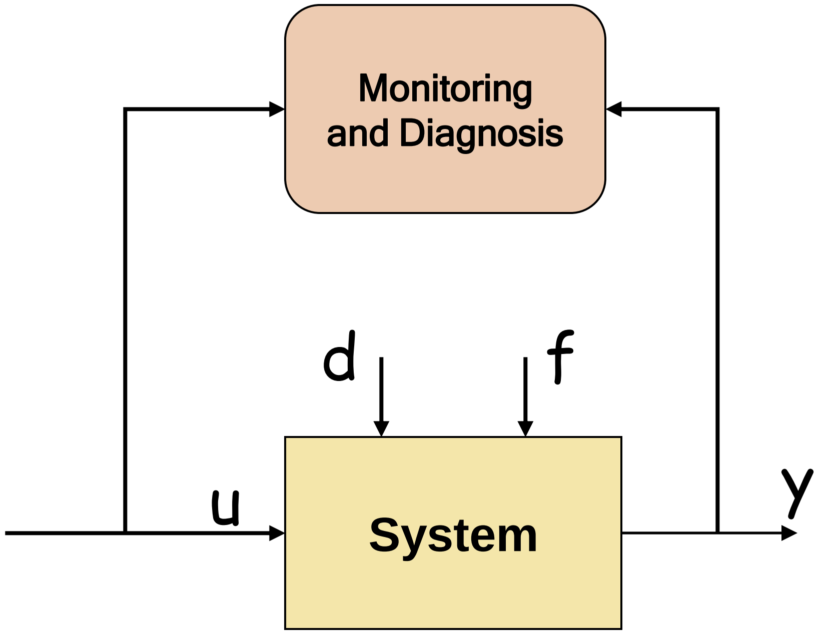
- Unreliable and untrustworthy automation procedures

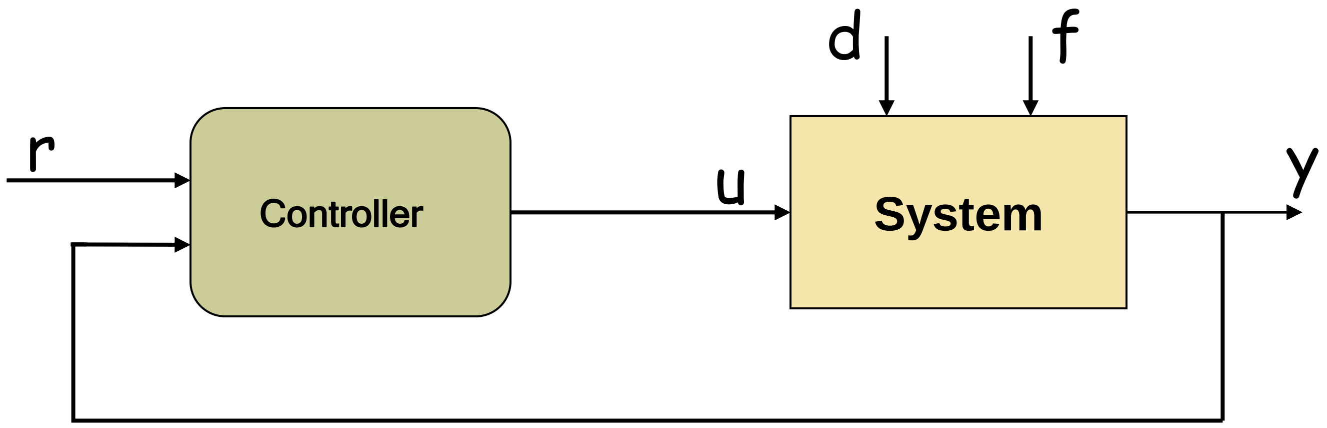
Lifelong Intelligent Condition Monitoring

- Monitor the condition of a system during its lifetime
- Using learning to improve condition monitoring
- Use cooperation to improve condition monitoring
- Consider more realistic events, slowly developing faults, cybersecurity attacks, etc.

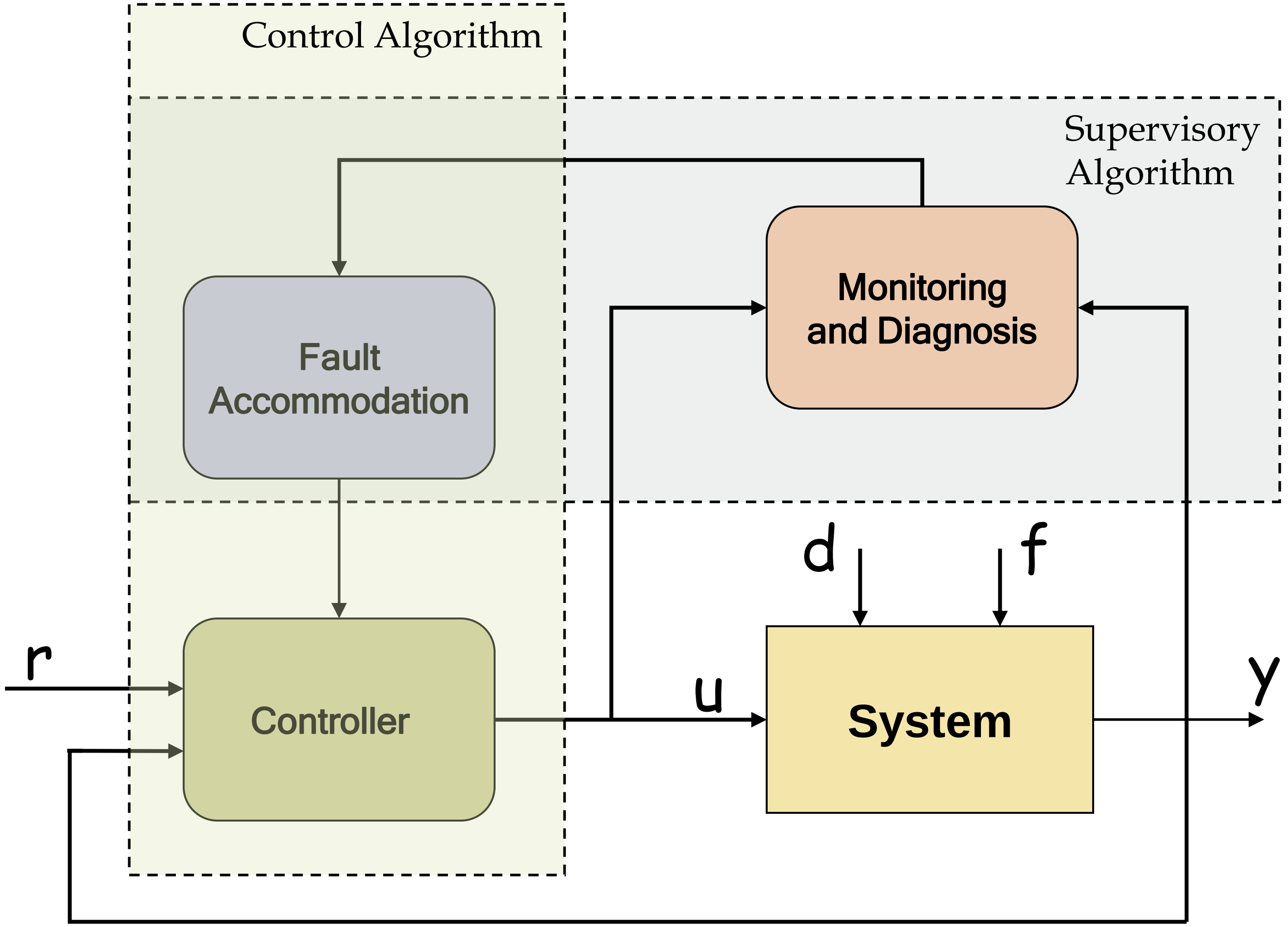
Monitoring and Control



Monitoring and Control

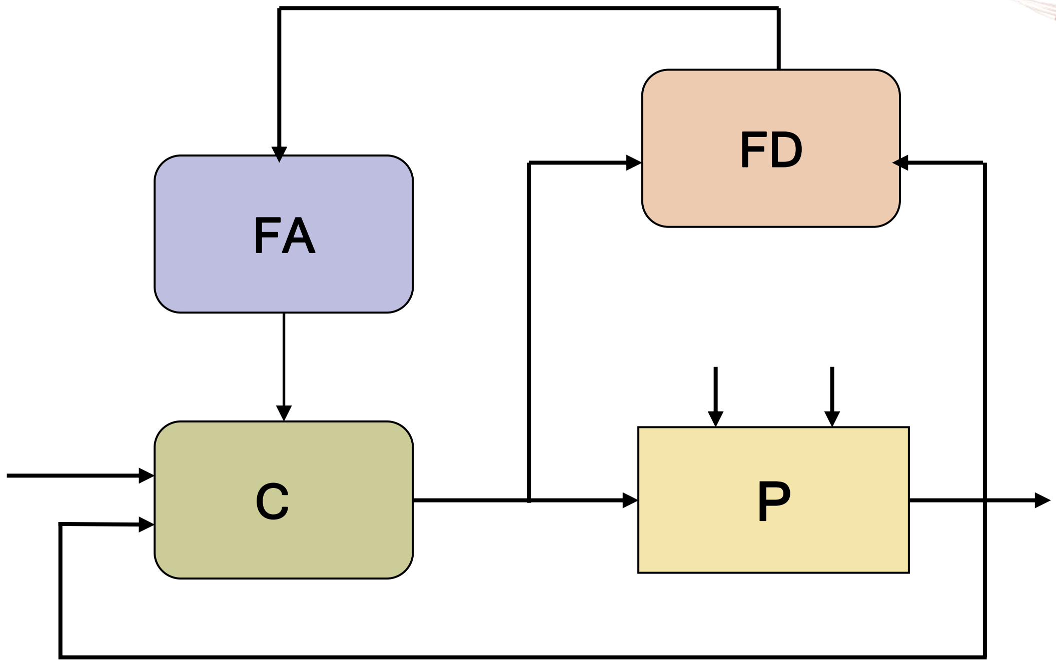


Monitoring and Control



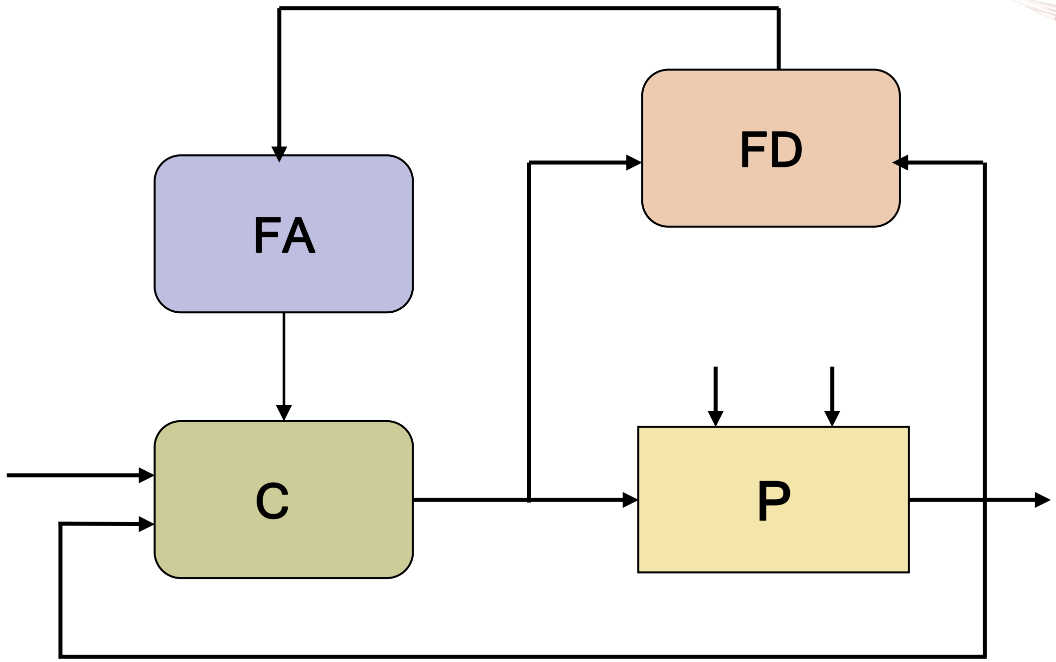
Fault Scenarios

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



Diagnostic Steps

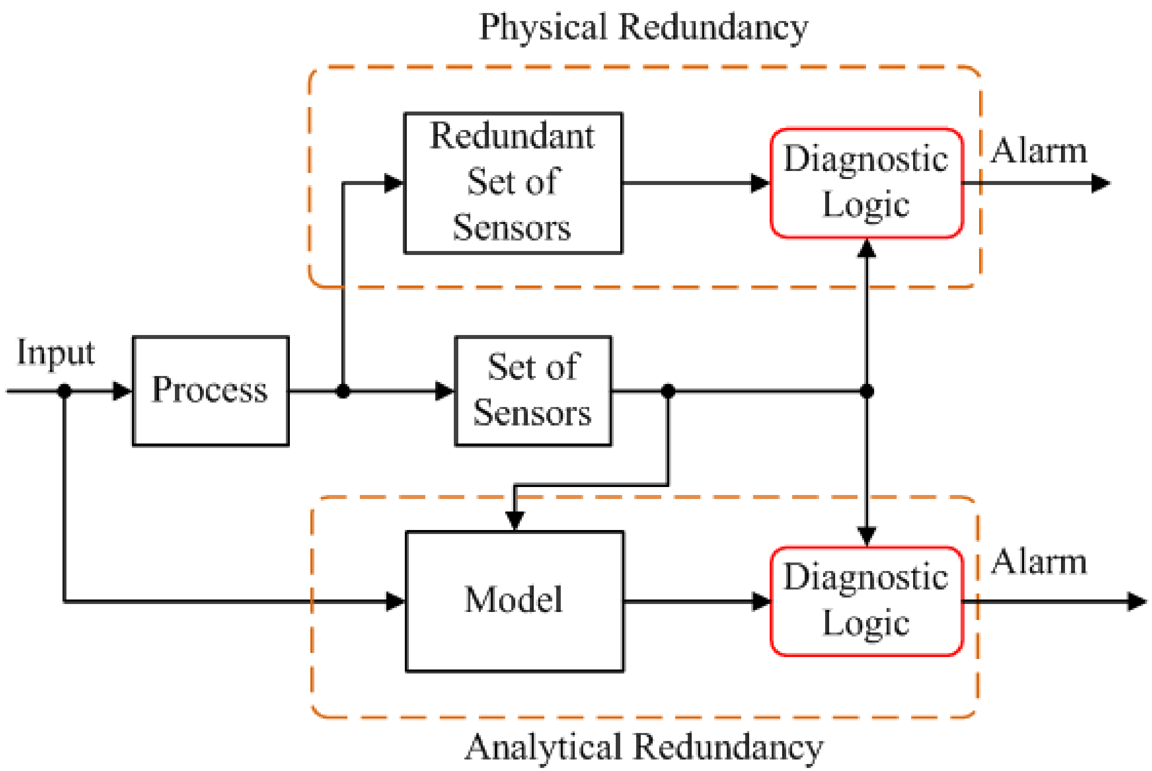
- Event detection
- Event isolation
- Risk assessment
- Accommodation



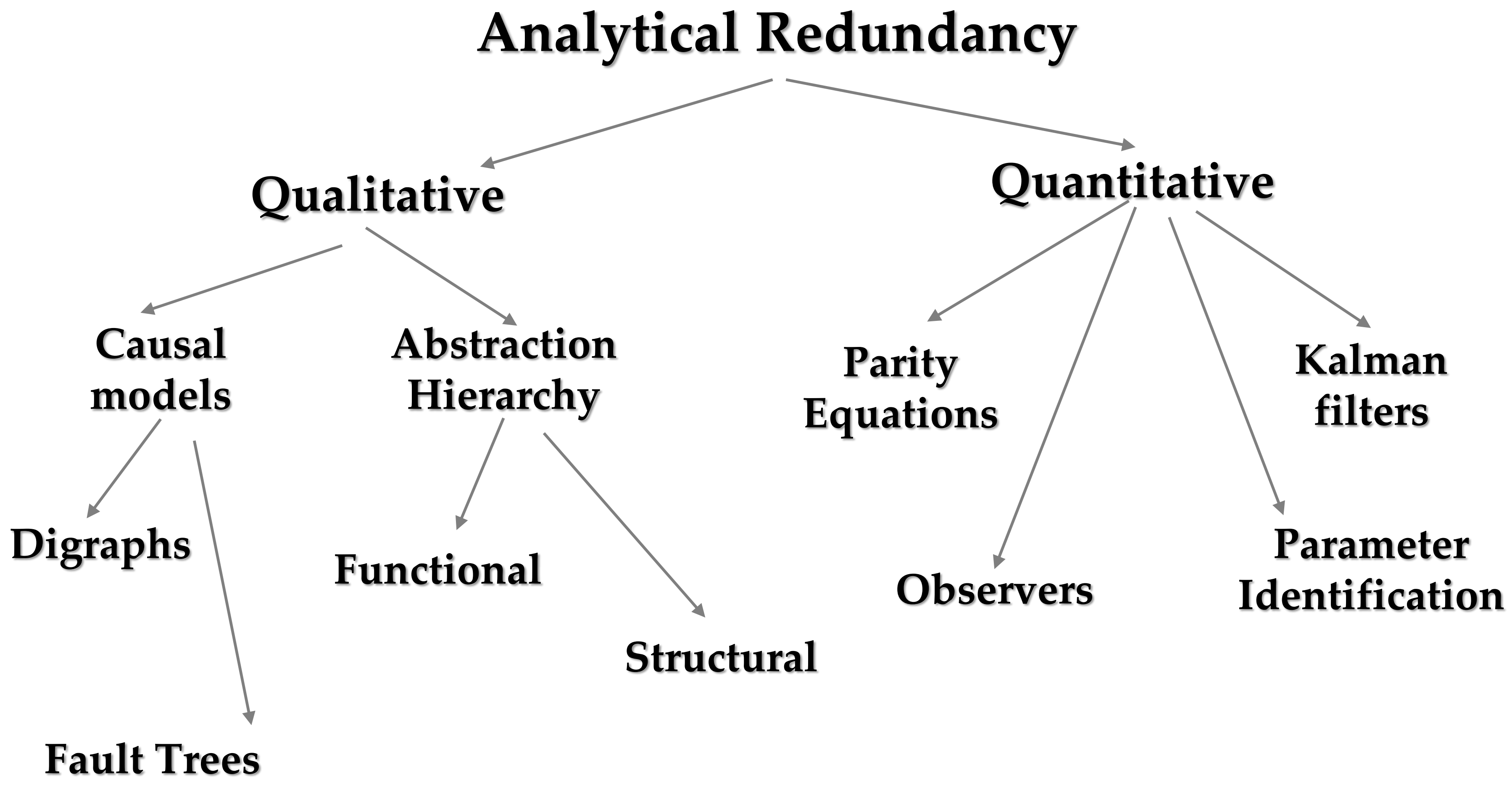
Diagnostic Methods

Physical redundancy based: use of redundant physical components

Analytical redundancy based: use of models describing the system, i.e. analytical mathematical expressions or symbolic /qualitative system representations



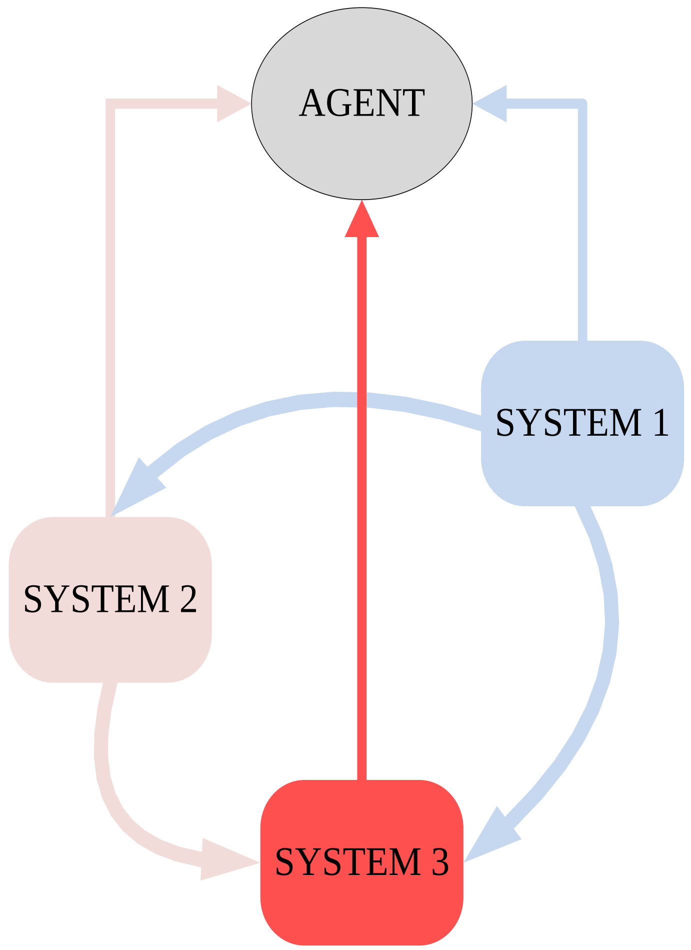
Analytical Redundancy Diagnostic Methods



Large-scale Interconnected Systems

Centralized architectures: less suitable for large-scale, interconnected systems

- increased computational complexity of the FD algorithms using global models
- reduced isolability of multiple faults
- increased communication due to the transmission of information to a central point
- vulnerability of the central cyber core to security threats (single-point of failure)
- reduced scalability of model-based FD in case of system expansion

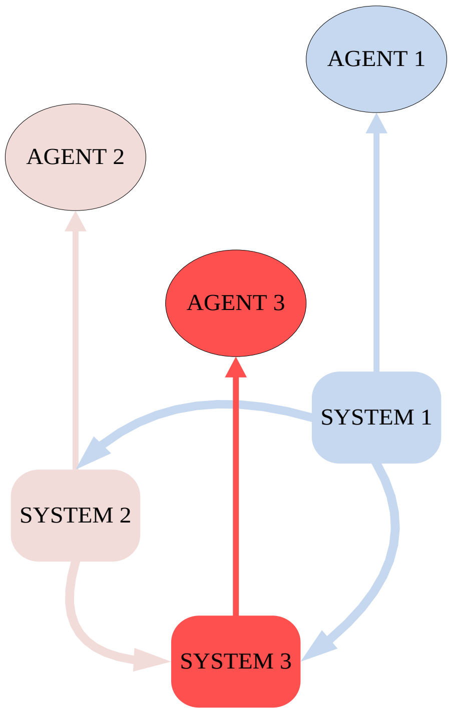


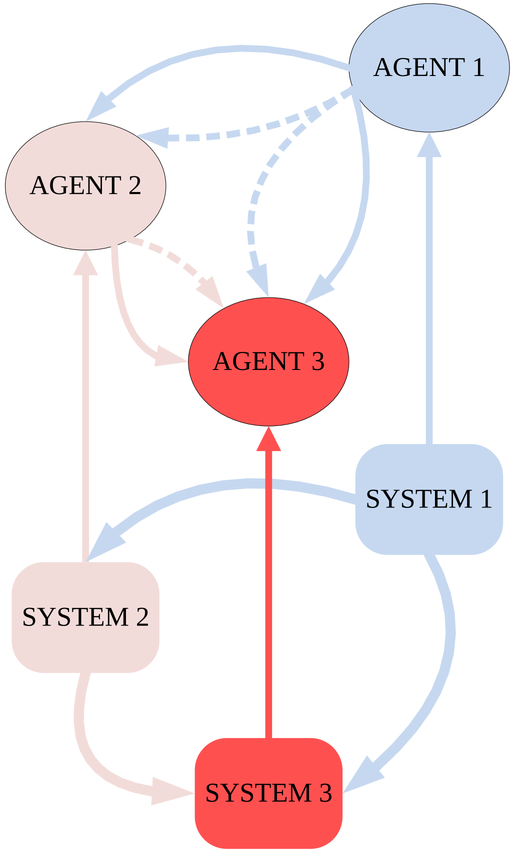
Large-scale Interconnected Systems

Common features of non-centralized architectures:

- deployment of several FD agents
- every agent performs FD based on local models

Decentralized Architecture

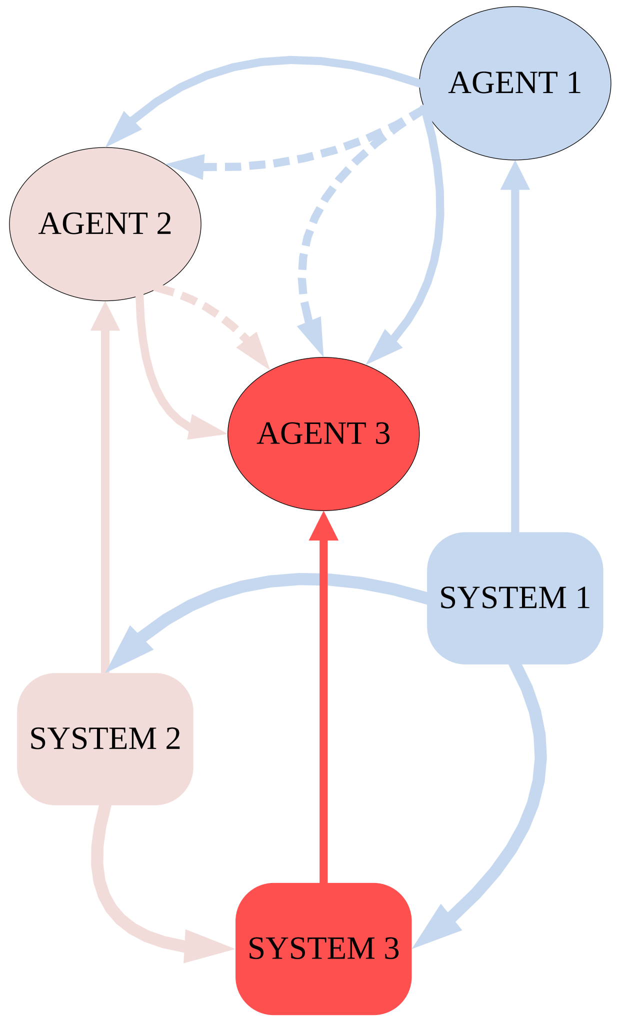




Distributed Architecture

Distributed Fault Diagnostic Methods

- **Classification based on**
  - type of system interconnections
    - physical
    - cyber
  - type of exchanged information
    - input & output data
    - estimations of interconnected subsystems’ states
    - fault signatures
    - decisions
  - type of communication
    - continuous
    - sporadic
    - event-driven

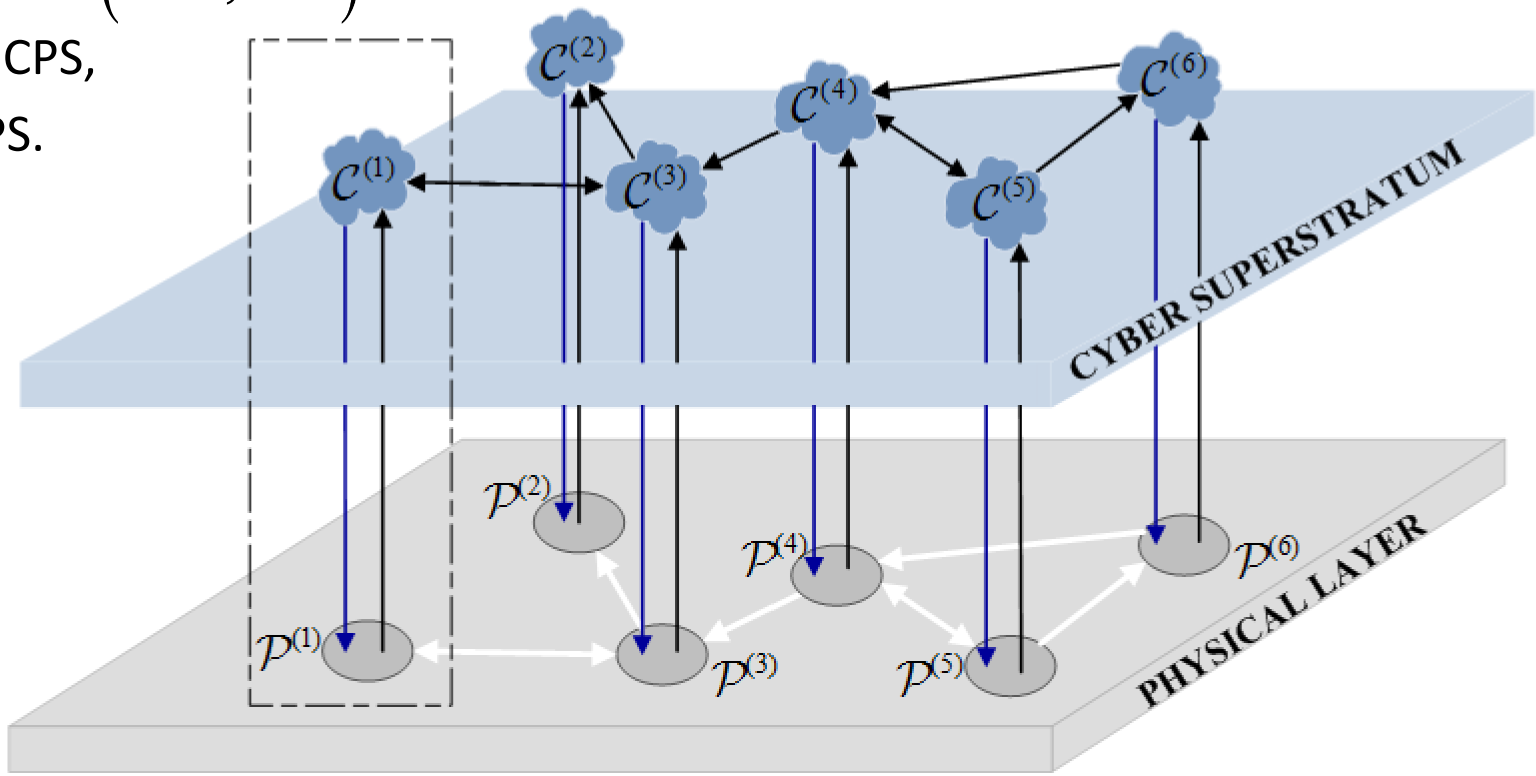


Motivation for Distributed Fault Diagnosis

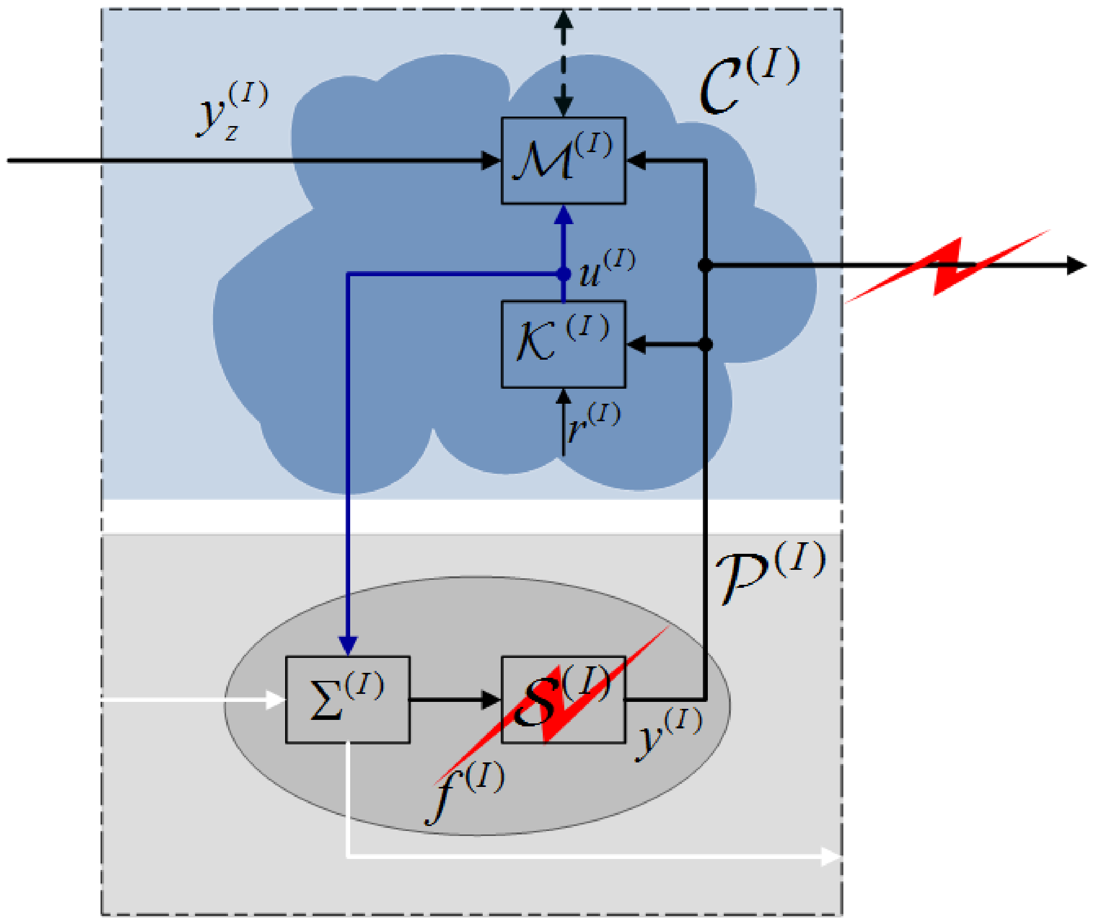
- Handling of large-scale systems
- More natural as systems become more interconnected
- Scalability of fault diagnosis
- Makes it easier to isolate faults
- Matches with distributed control; allows for fault accommodation

Interconnected CPS

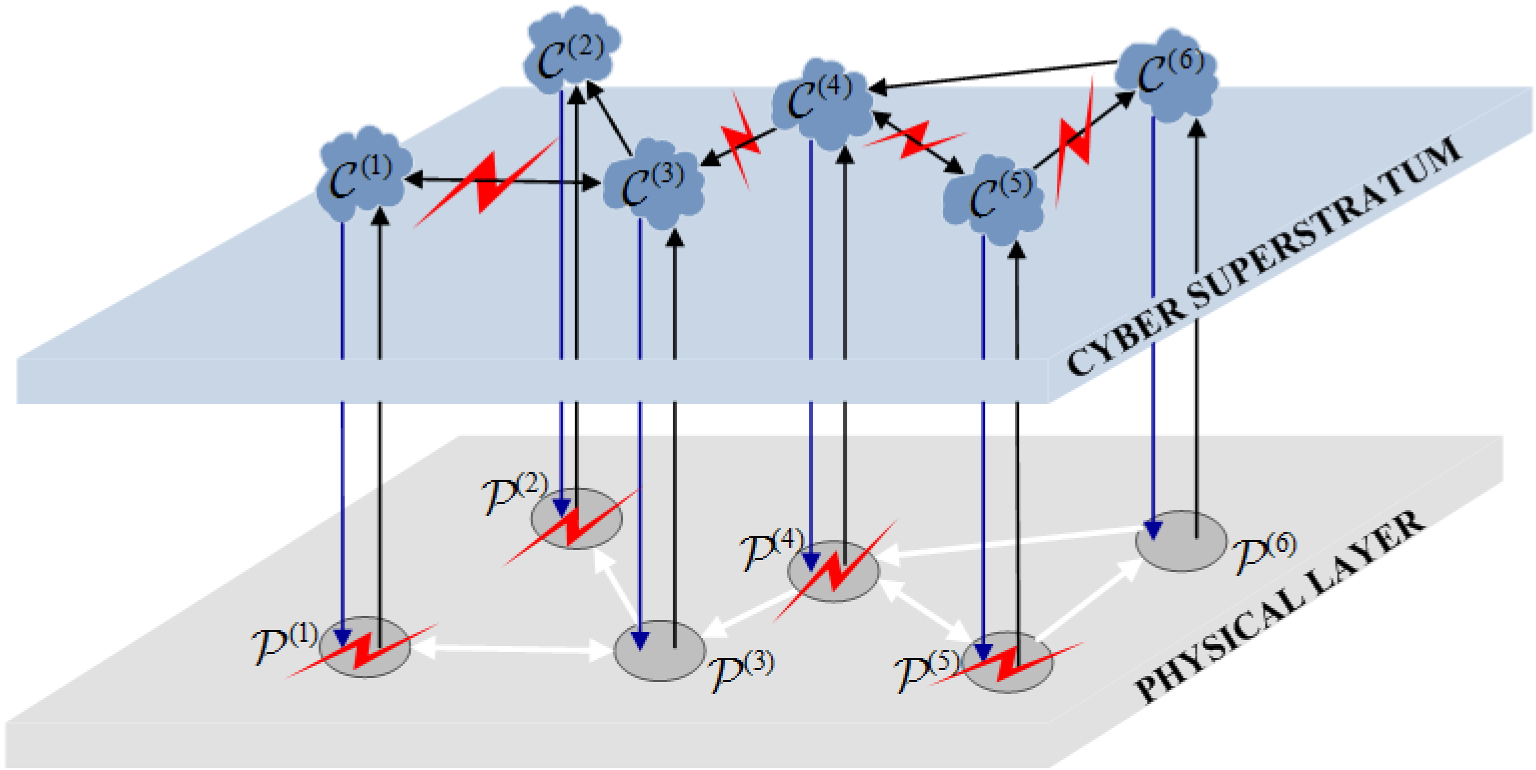
- *N* interconnected CPS.
- *I*-th CPS: described by the pair $\left(\mathcal{P}^{(I)}, \mathcal{C}^{(I)}\right)$
  - $\mathcal{P}^{(I)}$: physical part of the *I*-th CPS,
  - $\mathcal{C}^{(I)}$: cyber part of the *I*-th CPS.



Interconnected CPS – Single Agent

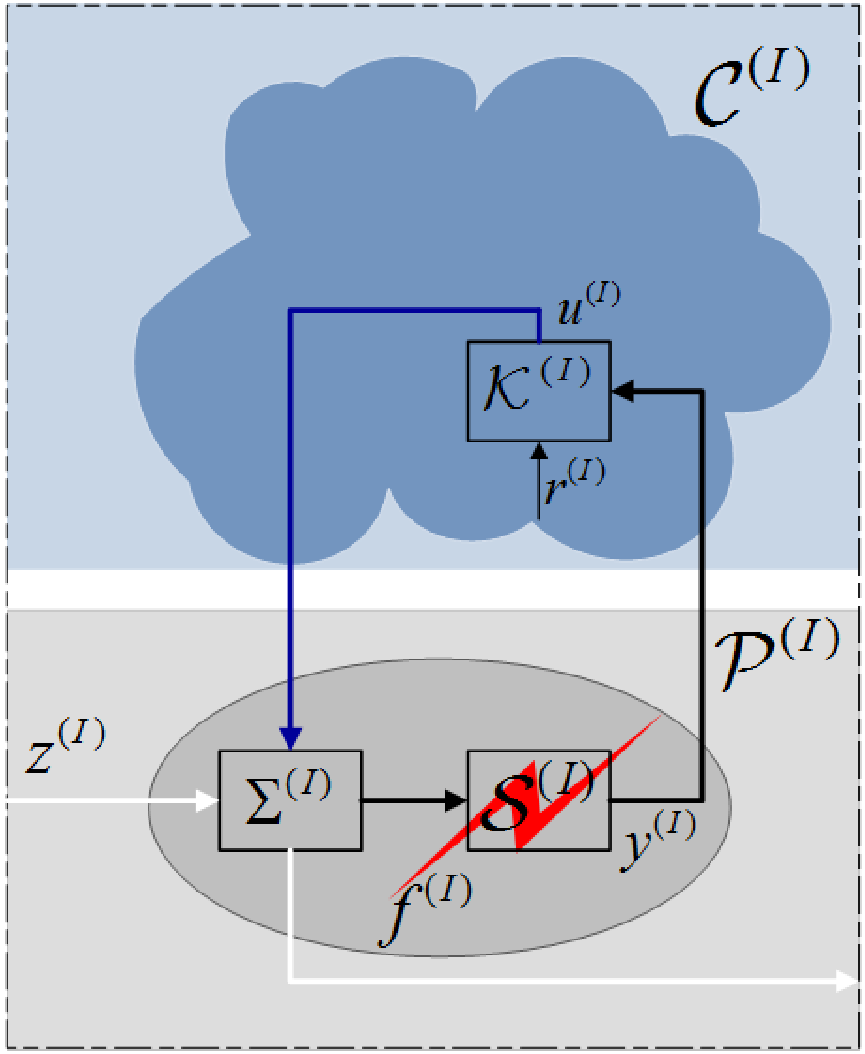


Interconnected CPS



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

Interconnected CPS

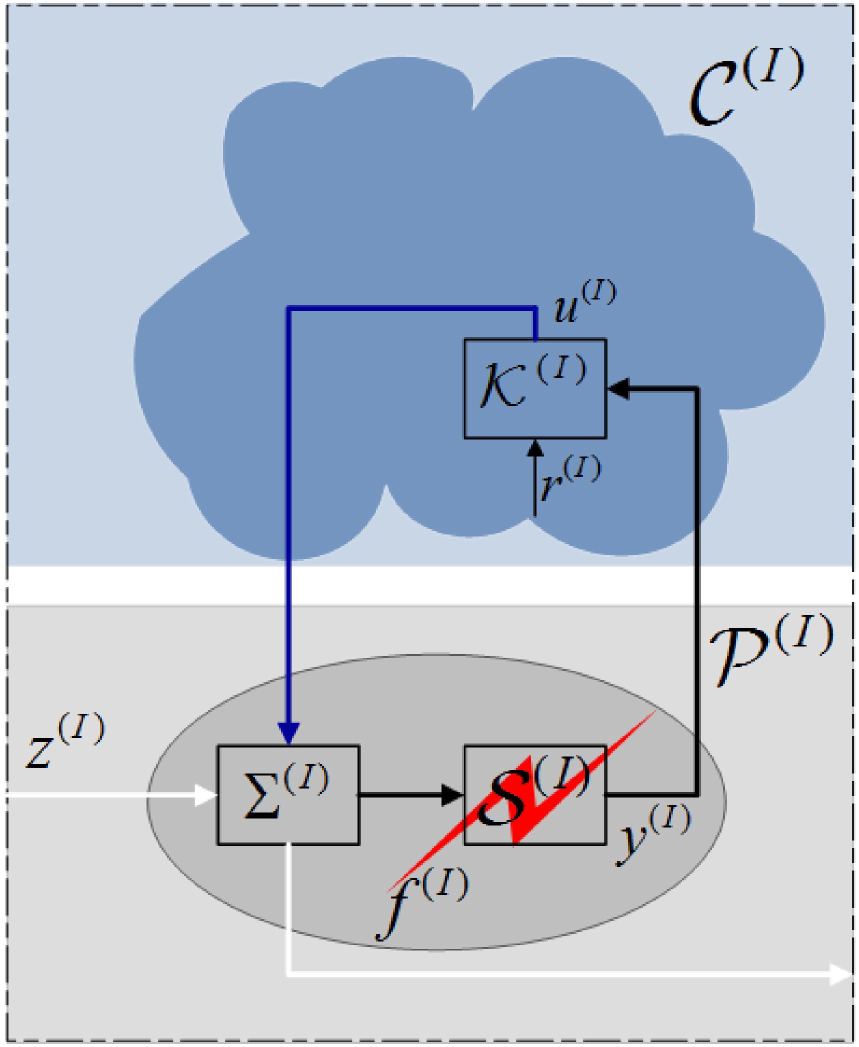


- $\mathcal{P}^{(I)}$ (physical part)
  - a nonlinear system $\Sigma^{(I)}$

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

- $x^{(I)}$: 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

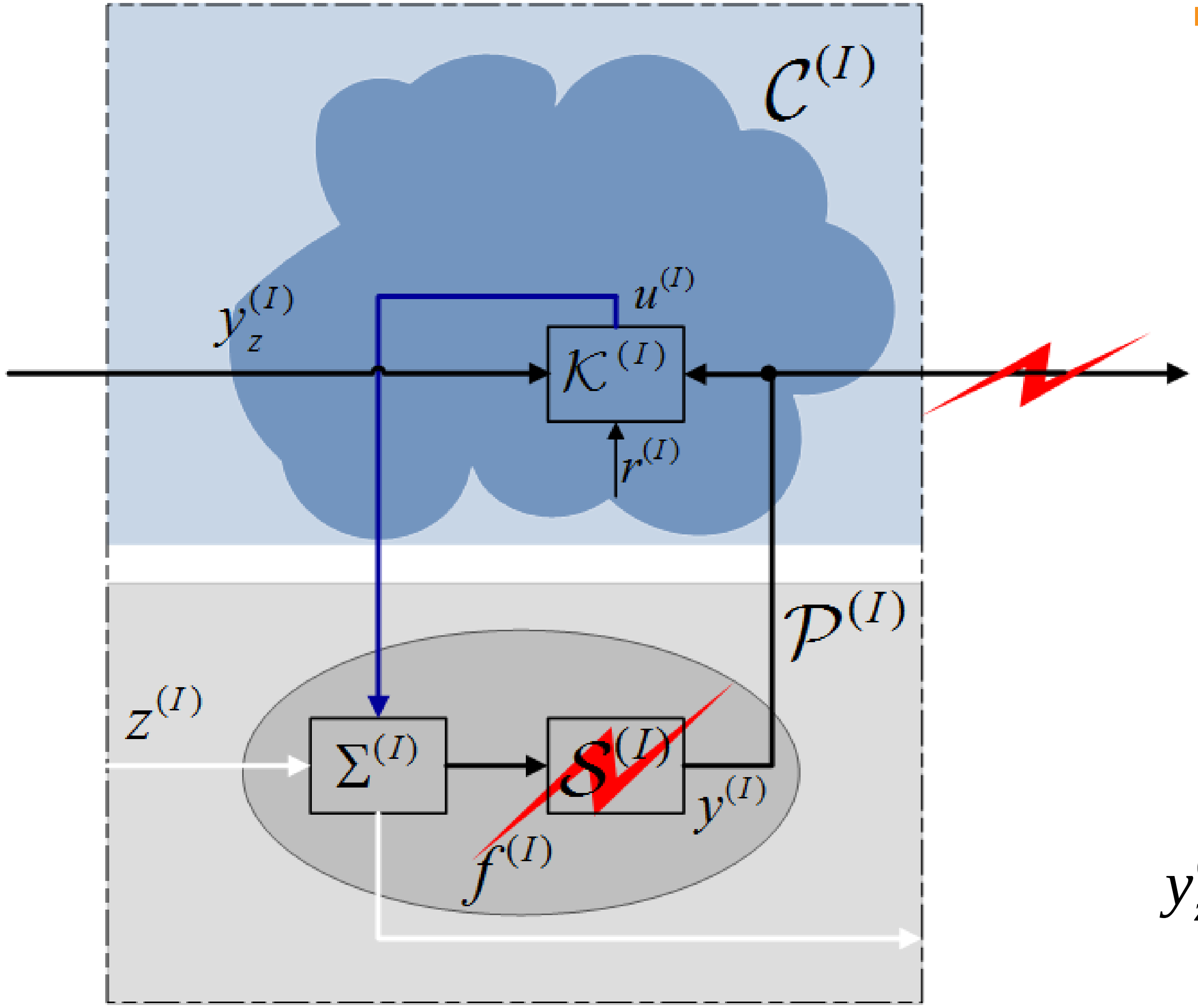


- $\mathcal{P}^{(I)}$ (physical part)
  - Sensor set $\mathcal{S}^{(I)}$ used for measuring the linear combination of states $C^{(I)}x^{(I)}$

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

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

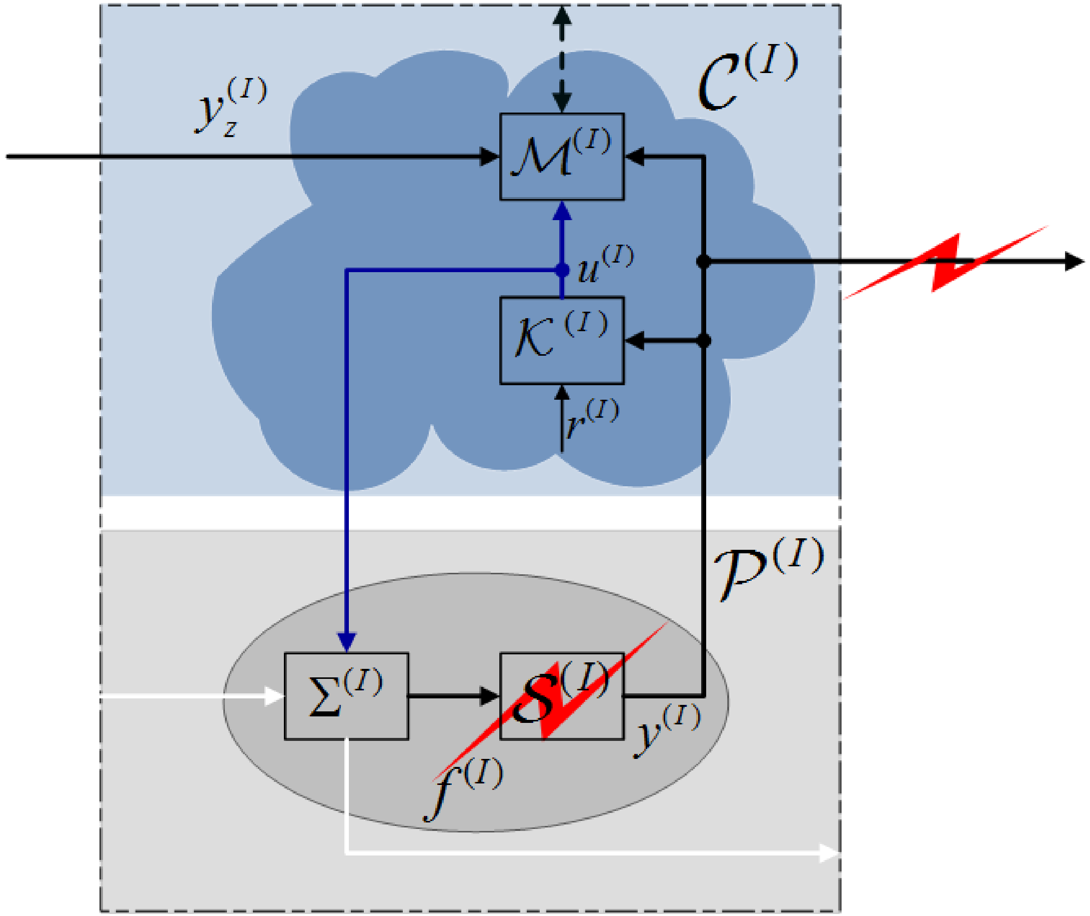
Interconnected CPS



- $\mathcal{C}^{(I)}$ (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 $\mathcal{S}_z^{(I)}$

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

Distributed Sensor Fault Diagnosis Architecture



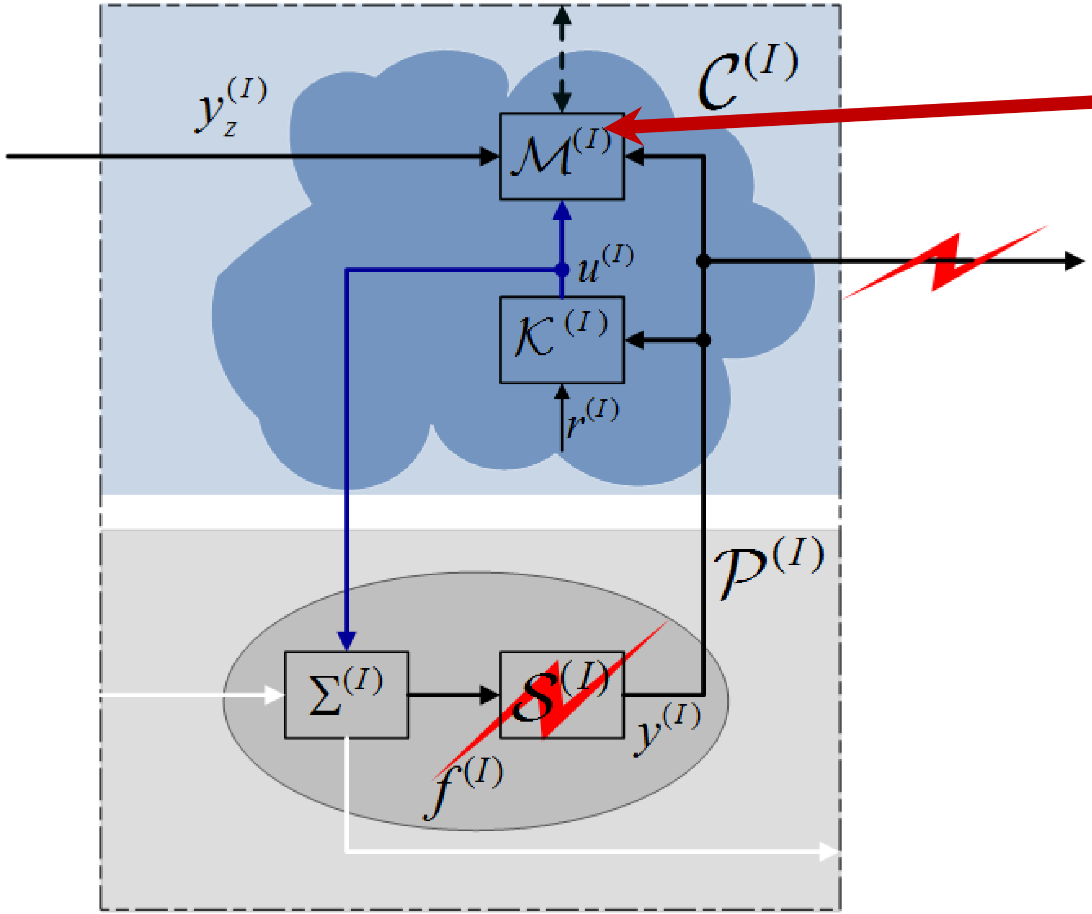
- $\mathcal{C}^{(I)}$ (cyber part)
  - monitoring agent $\mathcal{M}^{(I)}$ allowed to exchange information with the neighboring agents $\mathcal{S}_z^{(I)}$

Task:

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

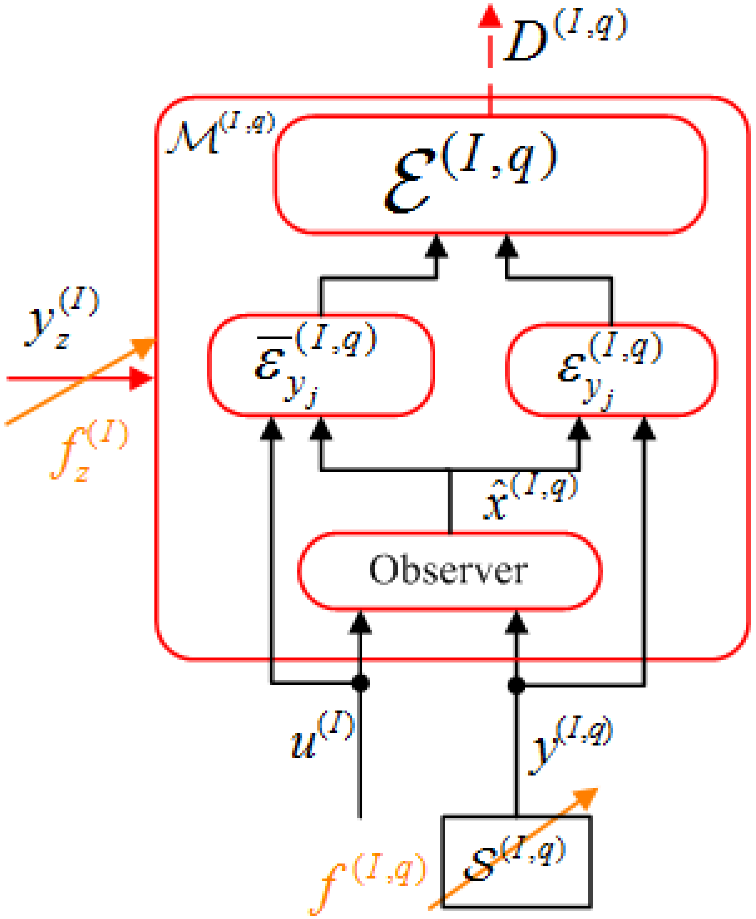
Detection of propagated sensor faults in $\mathcal{S}_z^{(I)}$

Monitoring Agent



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

Monitoring Module



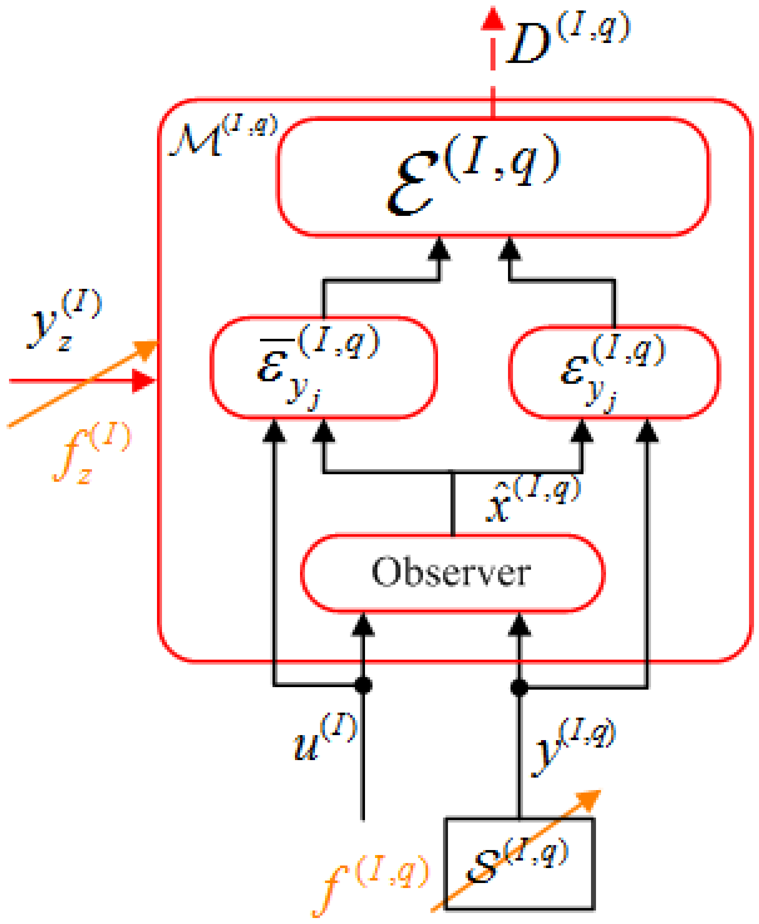
j-th residual, $\varepsilon_{y_j}^{(I,q)}$

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

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

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

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

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

Adaptive Threshold Computation

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

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

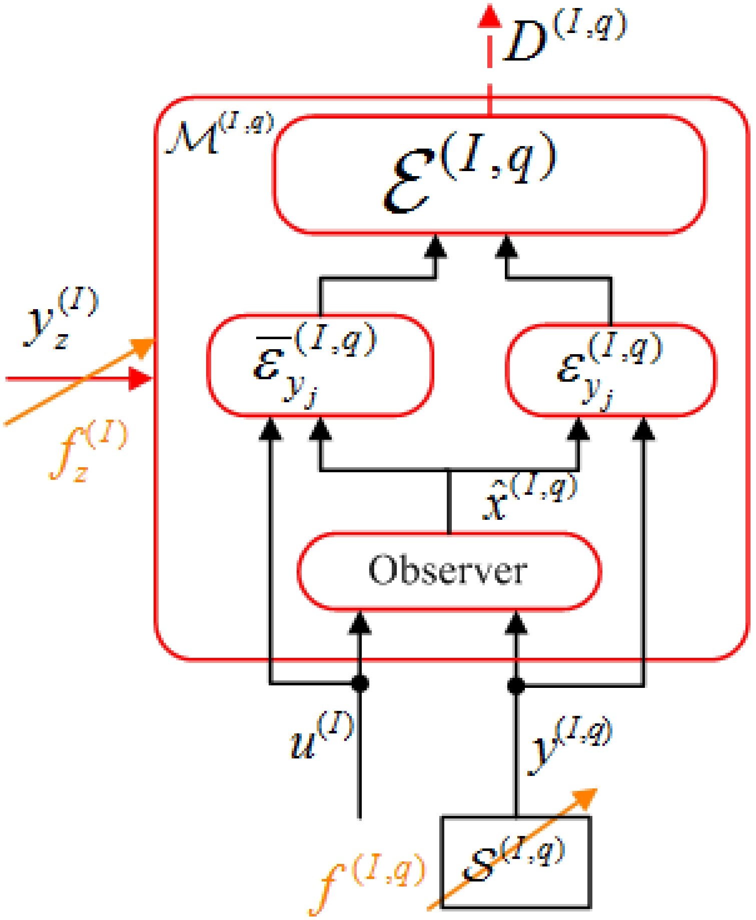
$$Z^{(I,q)}(t) = E^{(I,q)}(t) + H_1(s)\left[E^{(I,q)}(t)\right]$$

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

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

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

Monitoring Module



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

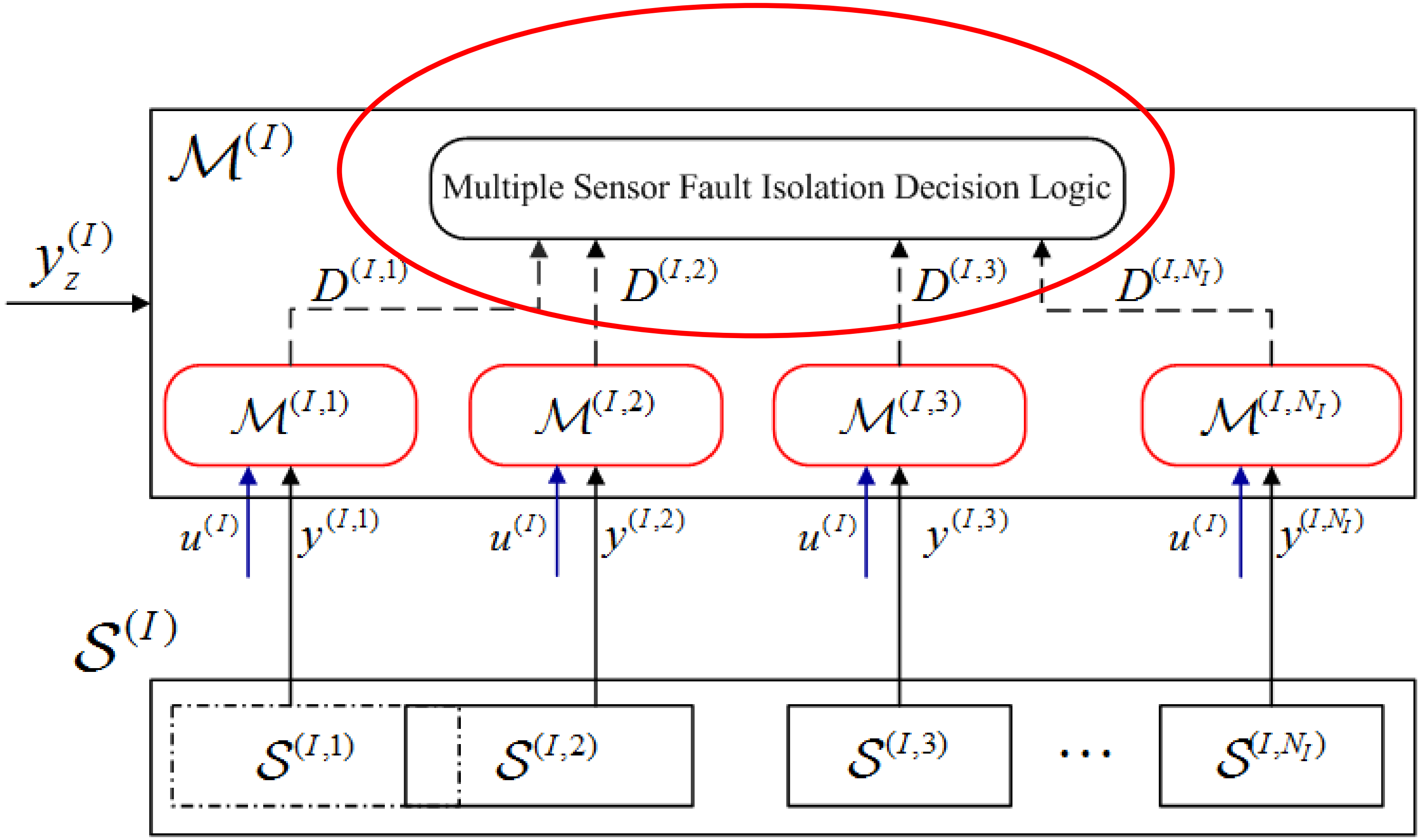
$$\mathcal{E}^{(I,q)} : \bigcup_{j \in \mathcal{J}^{(I,q)}} \mathcal{E}_j^{(I,q)}$$

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

residual   adaptive threshold

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

Monitoring Agent



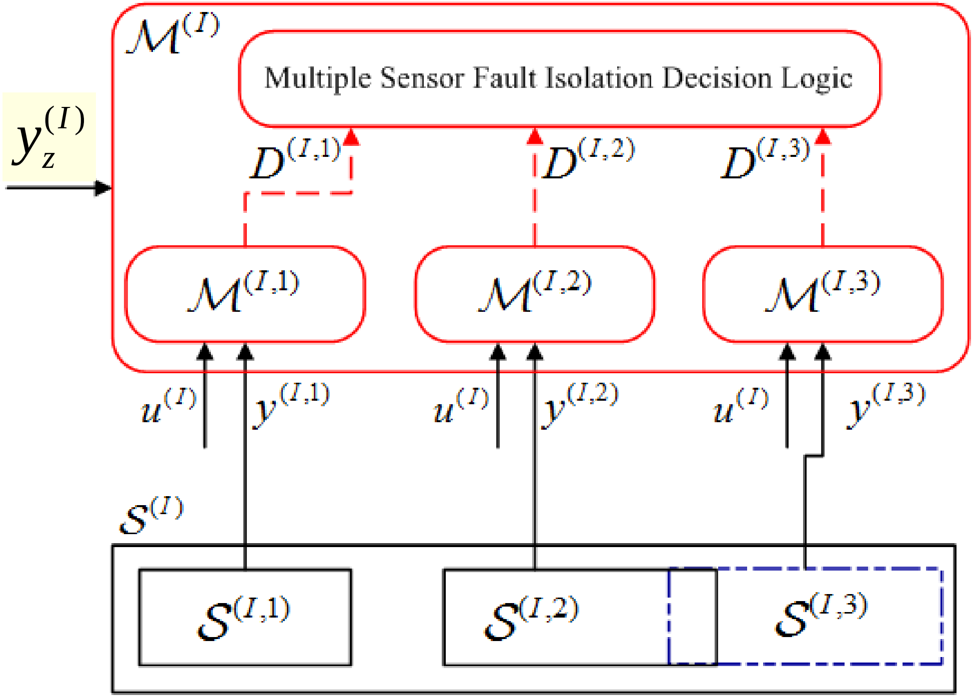
Local Multiple Sensor Fault Isolation

Example:

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

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

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



	$f_1^{(I)}$	$f_2^{(I)}$	$f_3^{(I)}$	$\left\{f_1^{(I)}, f_2^{(I)}\right\}$	$\left\{f_1^{(I)}, f_3^{(I)}\right\}$	$\left\{f_2^{(I)}, f_3^{(I)}\right\}$	$\left\{f_1^{(I)}, f_2^{(I)}, f_3^{(I)}\right\}$	$f_z^{(I)}$	$\left\{f_z^{(I)}, \mathcal{F}_c^{(I)}\right\}$
$\mathcal{E}^{(I,1)}$	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

	$f_1^{(I)}$	$f_2^{(I)}$	$f_3^{(I)}$	$\{f_1^{(I)}, f_2^{(I)}\}$	$\{f_1^{(I)}, f_3^{(I)}\}$	$\{f_2^{(I)}, f_3^{(I)}\}$	$\{f_1^{(I)}, f_2^{(I)}, f_3^{(I)}\}$	$f_z^{(I)}$	$\{f_z^{(I)}, \mathcal{F}_c^{(I)}\}$
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$$D^{(I)}(t) = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

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

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

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

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.

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**
- **Learn from previous monitoring experience and from other agents**

- 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.
- C. Keliris, M. Polycarpou and T. Parisini, “An Integrated Learning and Filtering Approach for Fault Diagnosis of a Class of Nonlinear Dynamical Systems", *IEEE Transactions on Neural Networks and Learning Systems*, vol. 28, no. 4, pp. 988-1004, April 2017.

Fault Diagnosis and Cyber-Physical Security

- **Similar formulation for detection, isolation and risk assessment**
- **How do we distinguish between faults and cyber-physical attacks (compare to robust fault diagnosis)**
- **Early detection of a cyber-physical attack is crucial**
- **Sensor placement is a key issue**

Applications pursued at KIOS Center of Excellence

- Monitoring of water distribution networks for water leakages and detection of water contamination
- Distributed fault diagnosis and fault-tolerant control of HVAC systems
- Contamination event detection and isolation in large-scale buildings
- Fault diagnosis and accommodation in transportation systems
- Security surveillance using smart camera networks
- Monitoring of electric grid side converters

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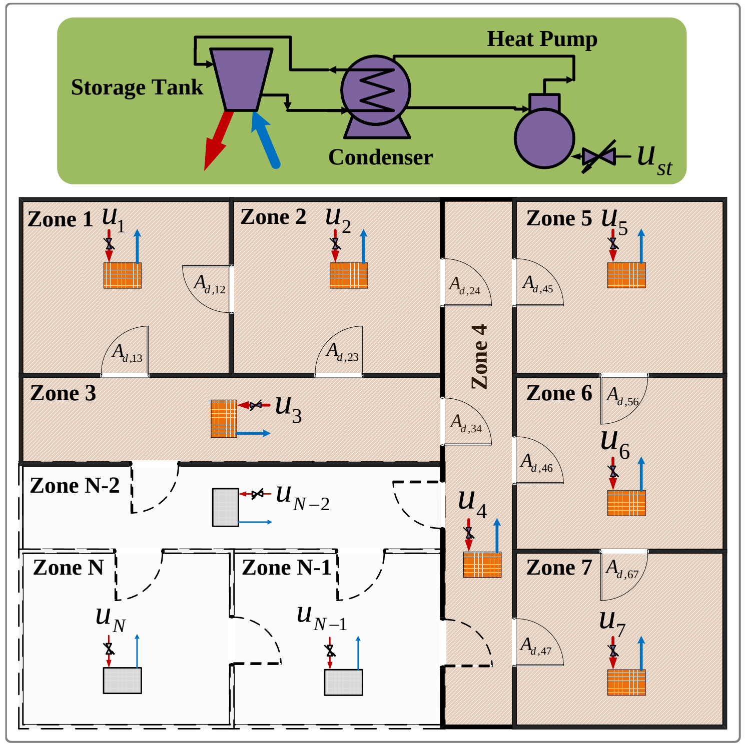
Simulation Results

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

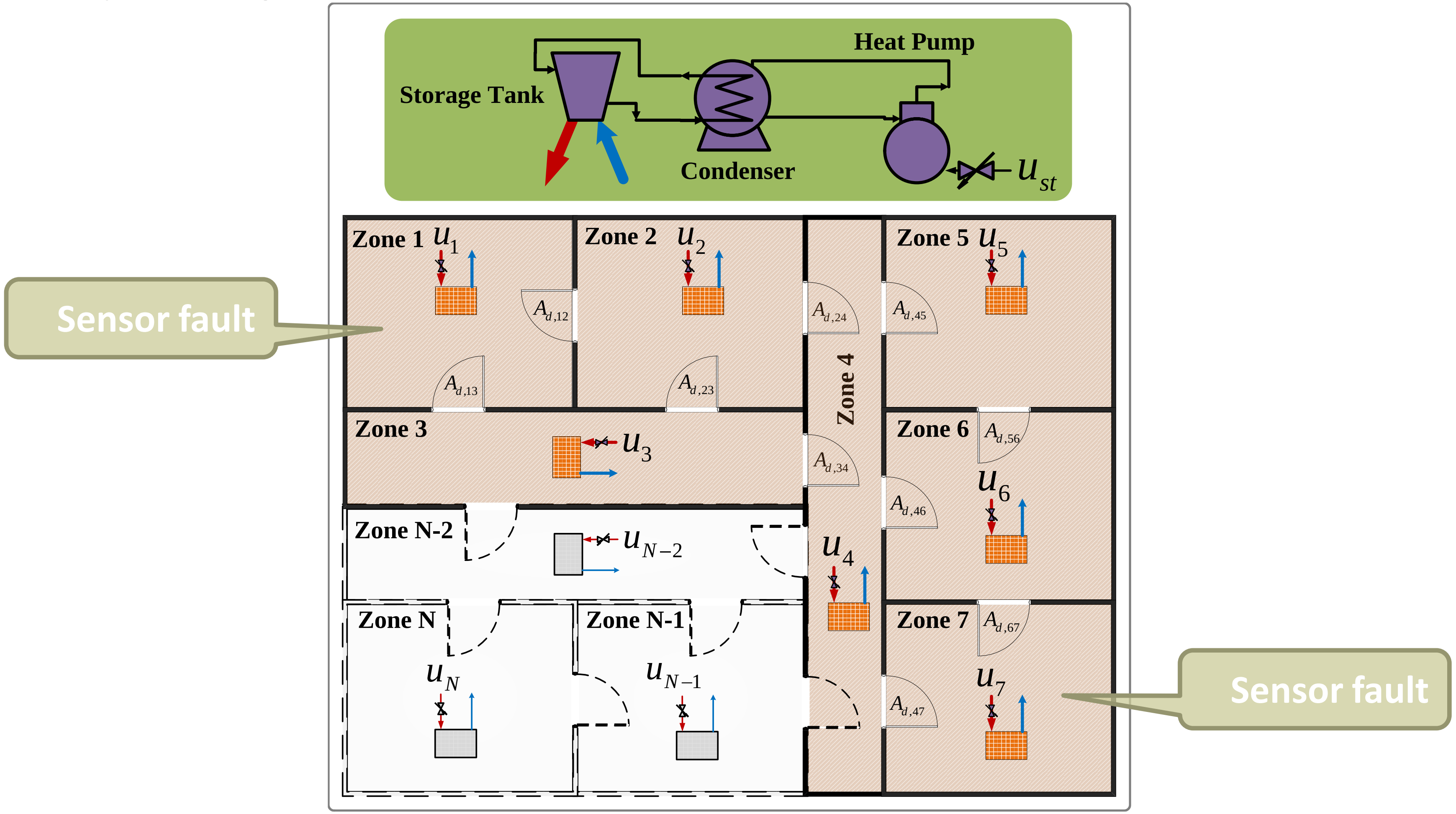


PARAMETERS OF THE SEVEN-ZONE HVAC SYSTEM

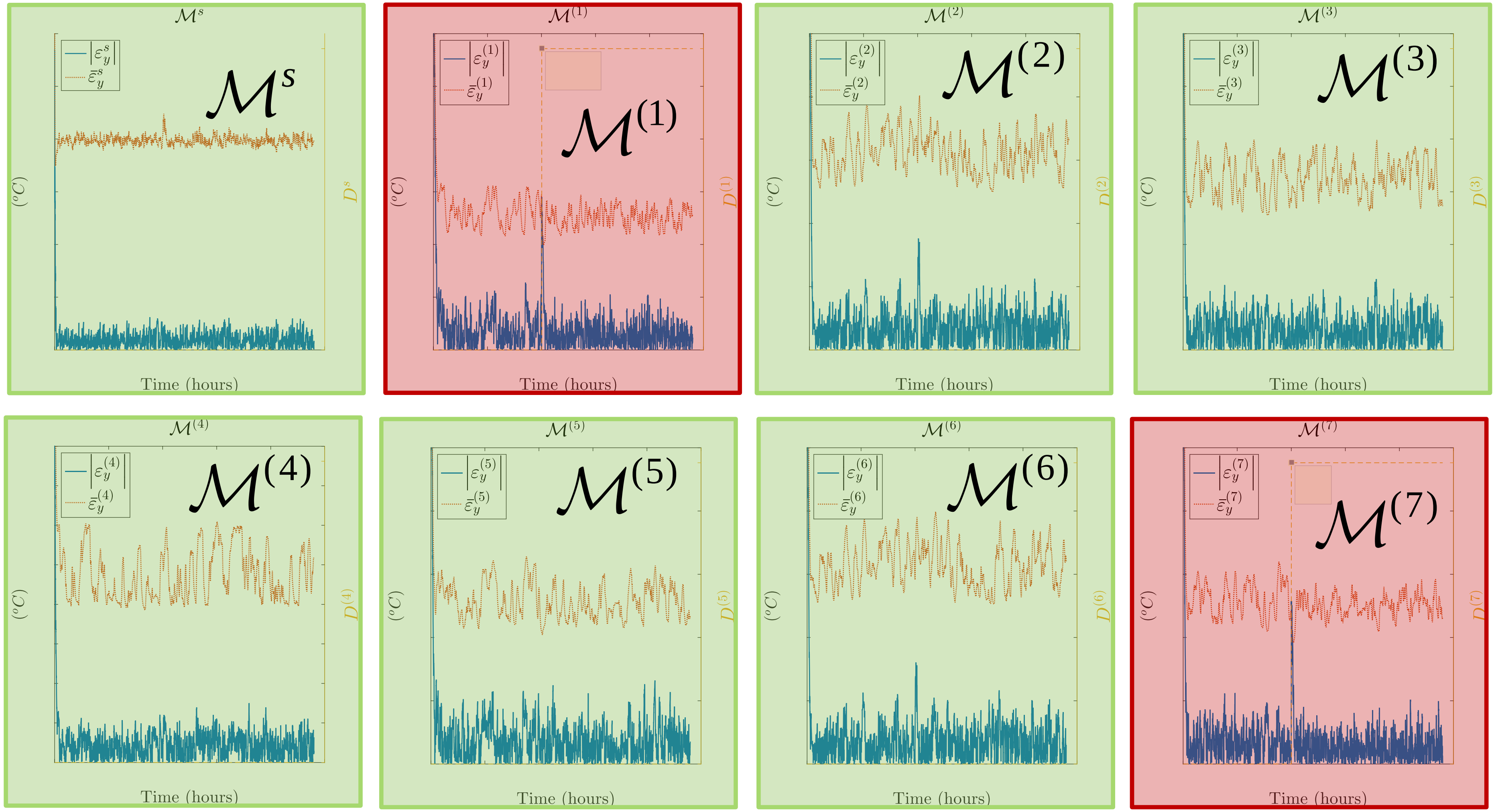
Symbol	Value	Units
a_{z_i}, $i \in \{1, 2, 3, 4, 5, 6, 7\}$	740	kJ/h^{o}C
$a_{z_{12}}$, $a_{z_{13}}$, $a_{z_{24}}$, $a_{z_{34}}$, $a_{z_{45}}$, $a_{z_{46}}$, $a_{z_{47}}$, $a_{z_{56}}$, $a_{z_{67}}$	50	kJ/h^{o}C
a_{st}	12	kJ/kg^{o}C
a_{sz}	0.6	kJ/kg^{o}C
C_{st}	837	kJ/^{o}C
C_p	1.004	kJ/kg^{o}C
C_v	0.717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

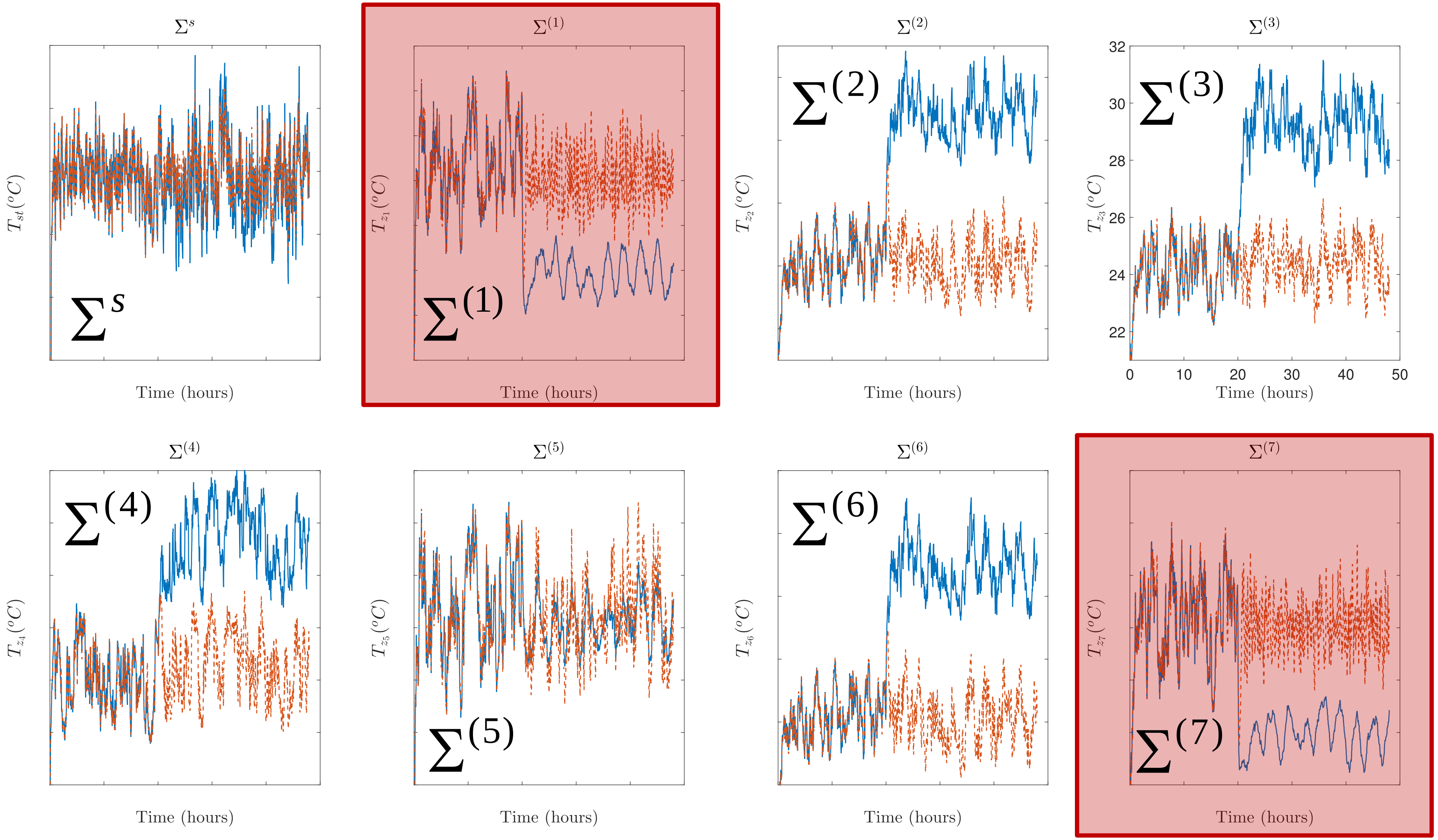
Consider a seven-zone HVAC system where the architectural arrangement of the seven zones is presented by the diagram



Simulation Results

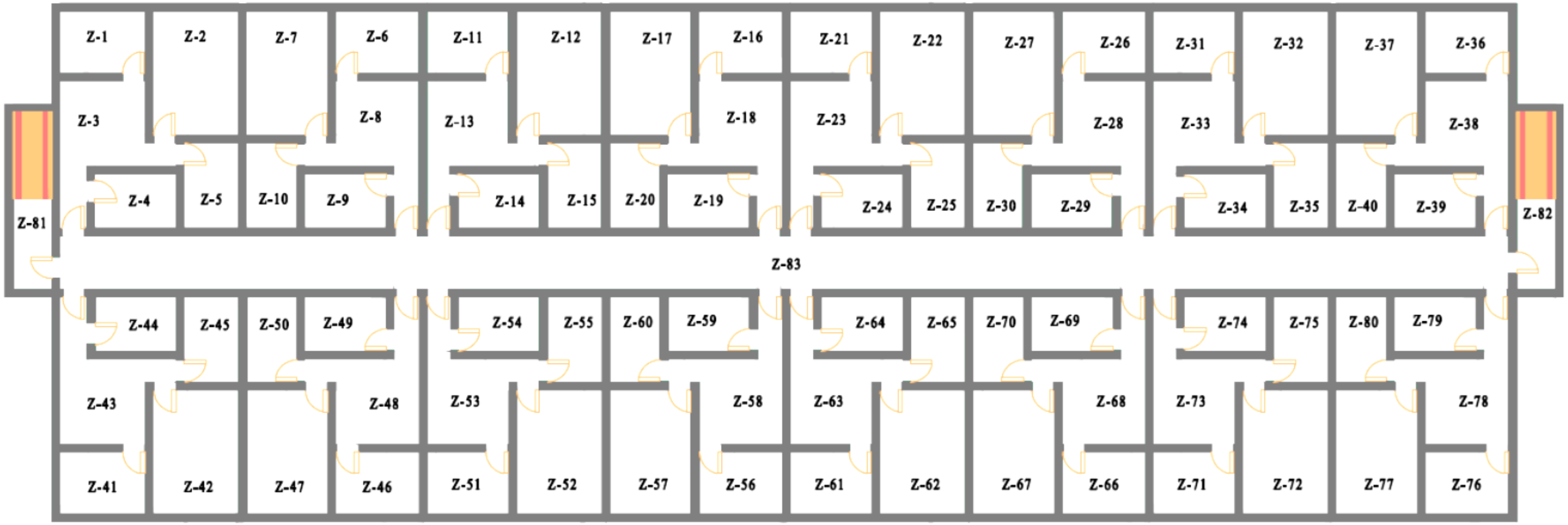


Simulation Results



Simulation Results

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

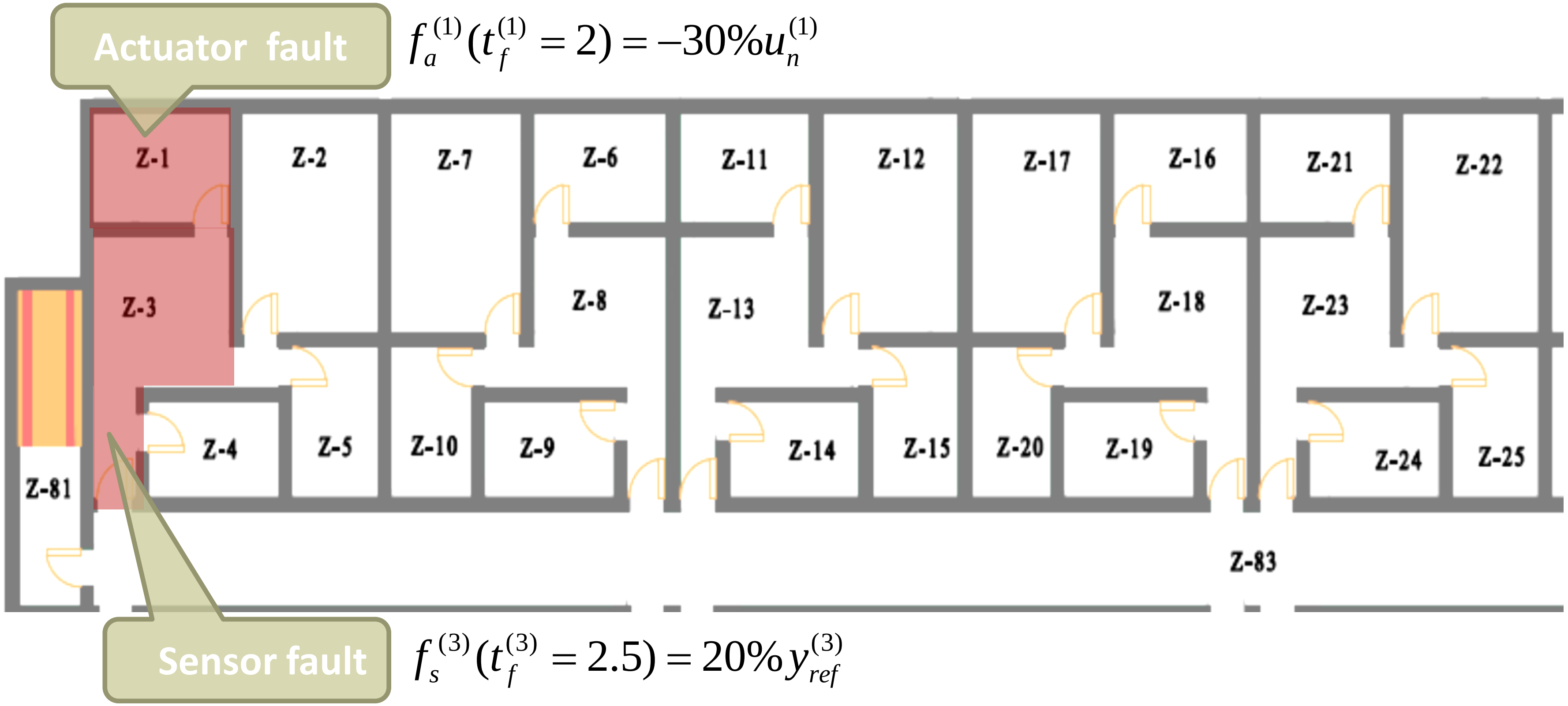


Papadopoulos M. P., Reppa V., Polycarpou M. M., Panayiotou C., “Distributed Diagnosis of Actuator and Sensor Faults in HVAC systems,” IFAC *World Congress,* July 2017.

Simulation Results

- Multiple Faults occurring consecutively

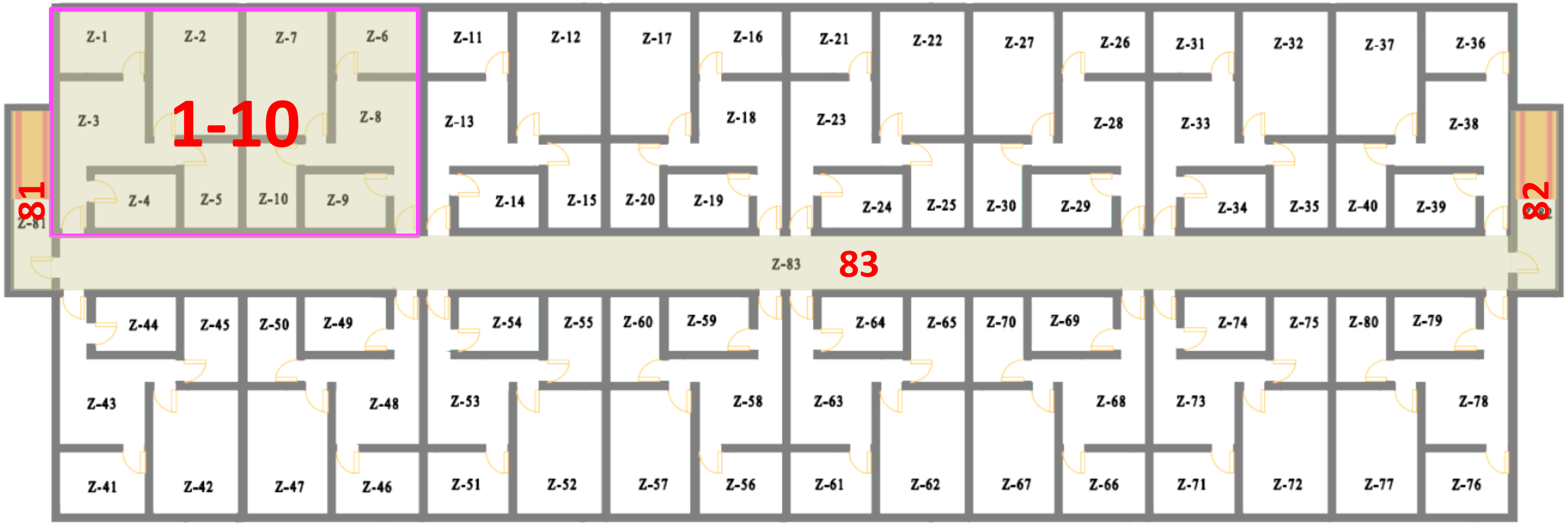
$$f_a^{(1)}(t_f^{(1)} = 2) = -30\% u_n^{(1)}$$



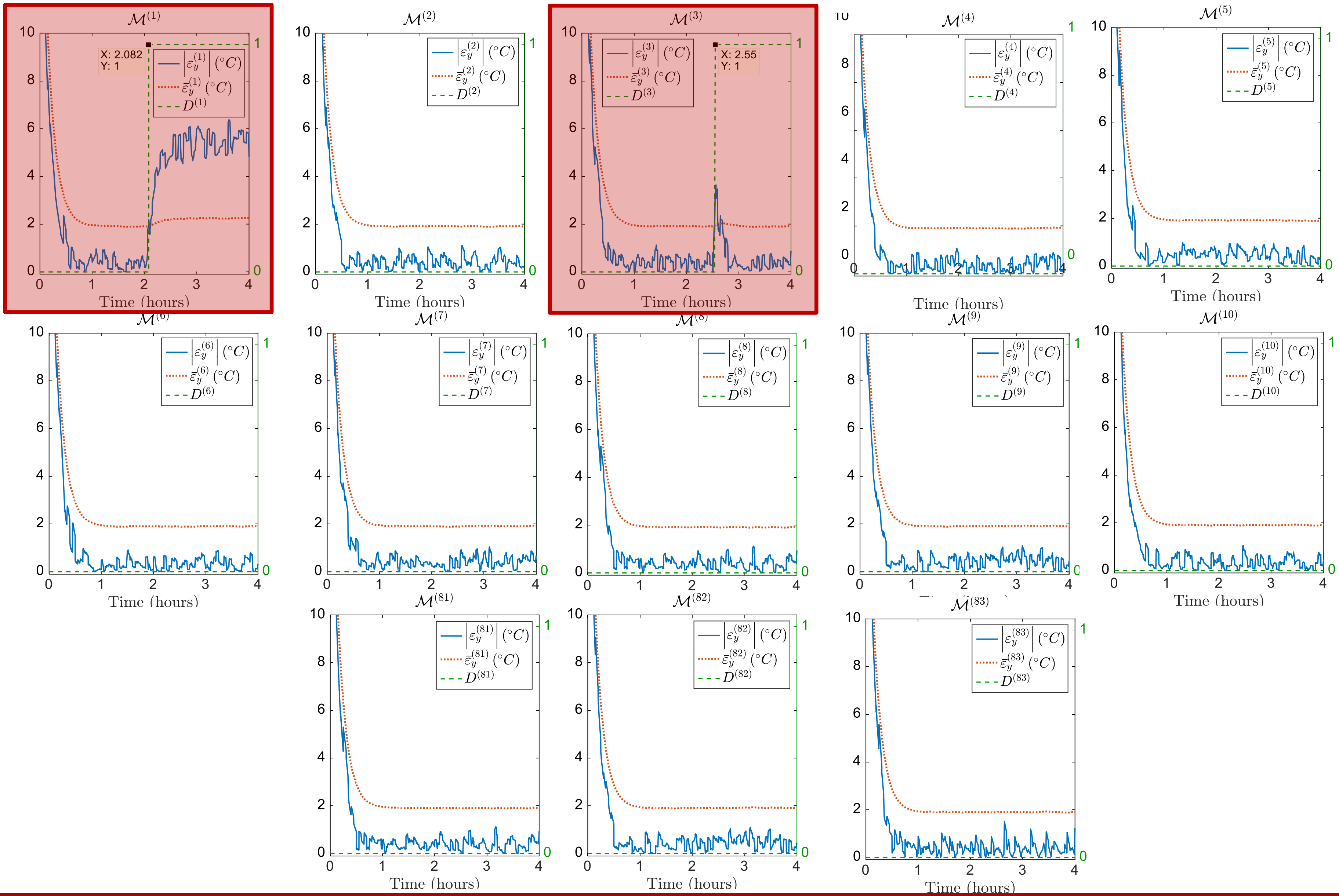
$$f_s^{(3)}(t_f^{(3)} = 2.5) = 20\% y_{ref}^{(3)}$$

Simulation Results

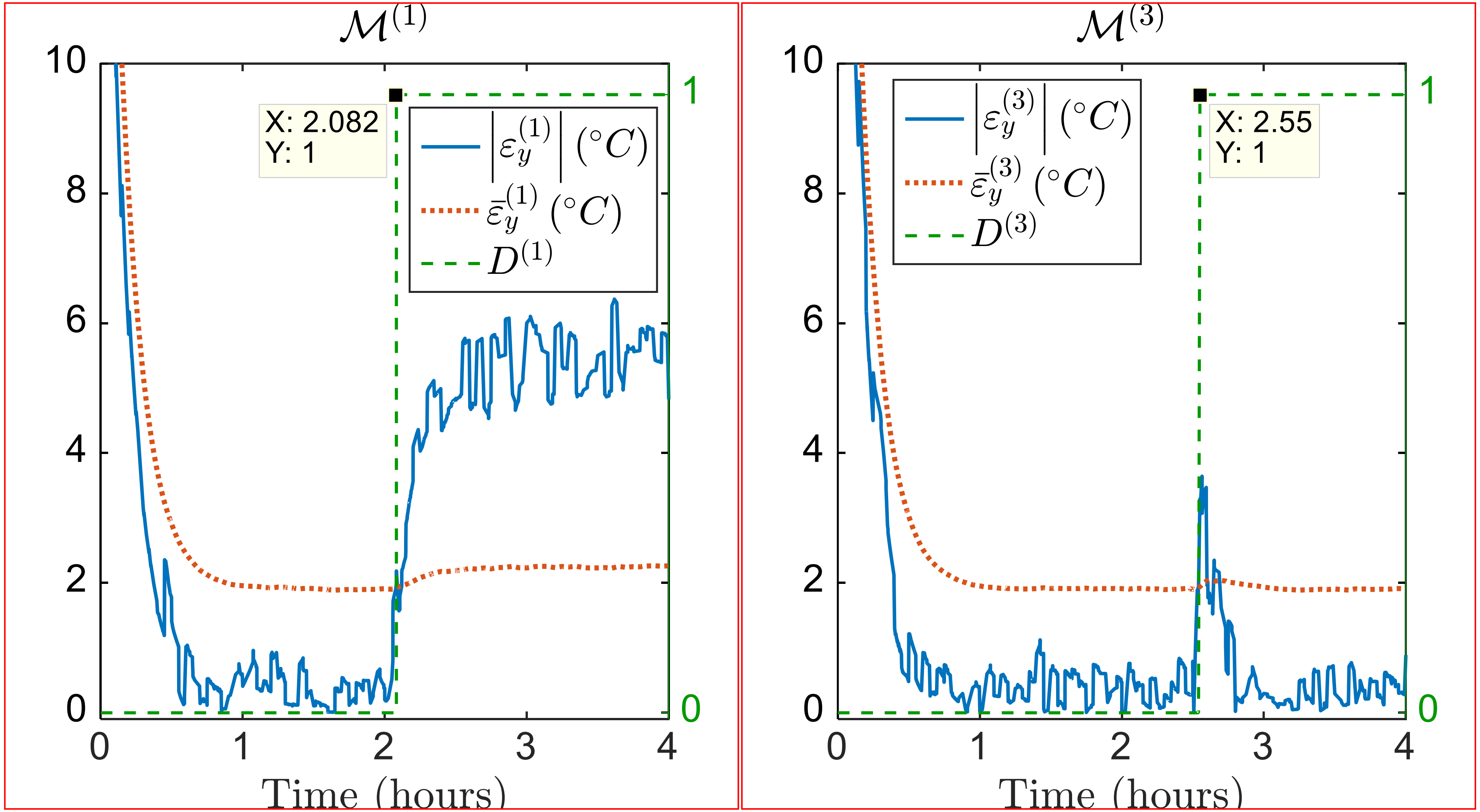
Have a look at the distributed **monitoring** agents located at Zones { 1-10, 81, 82, 83}



Simulation Results

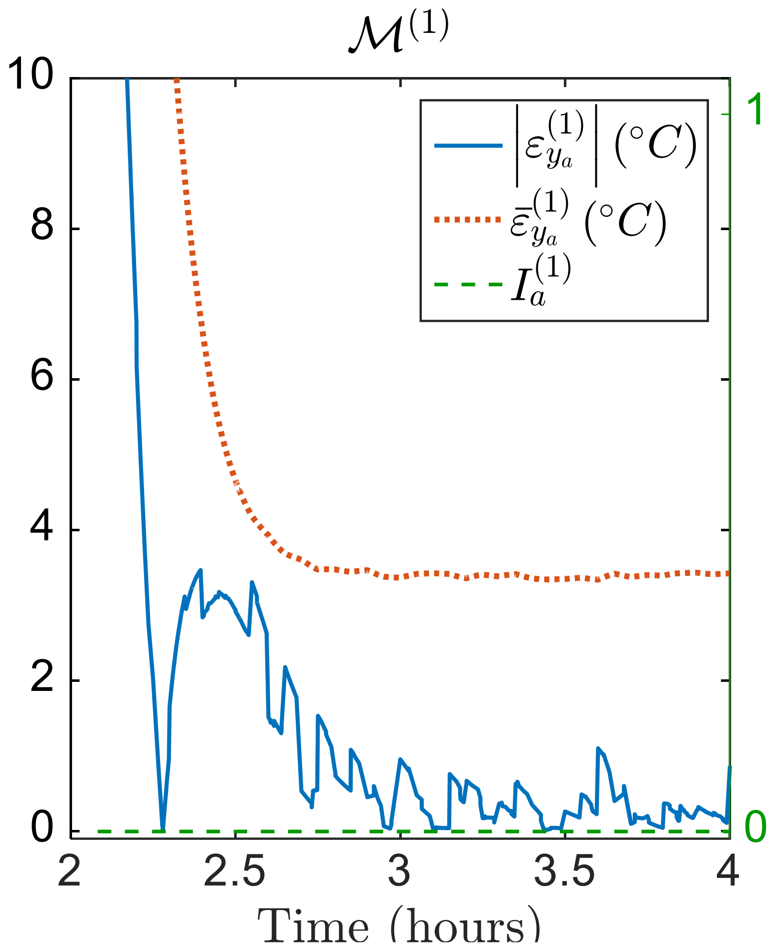


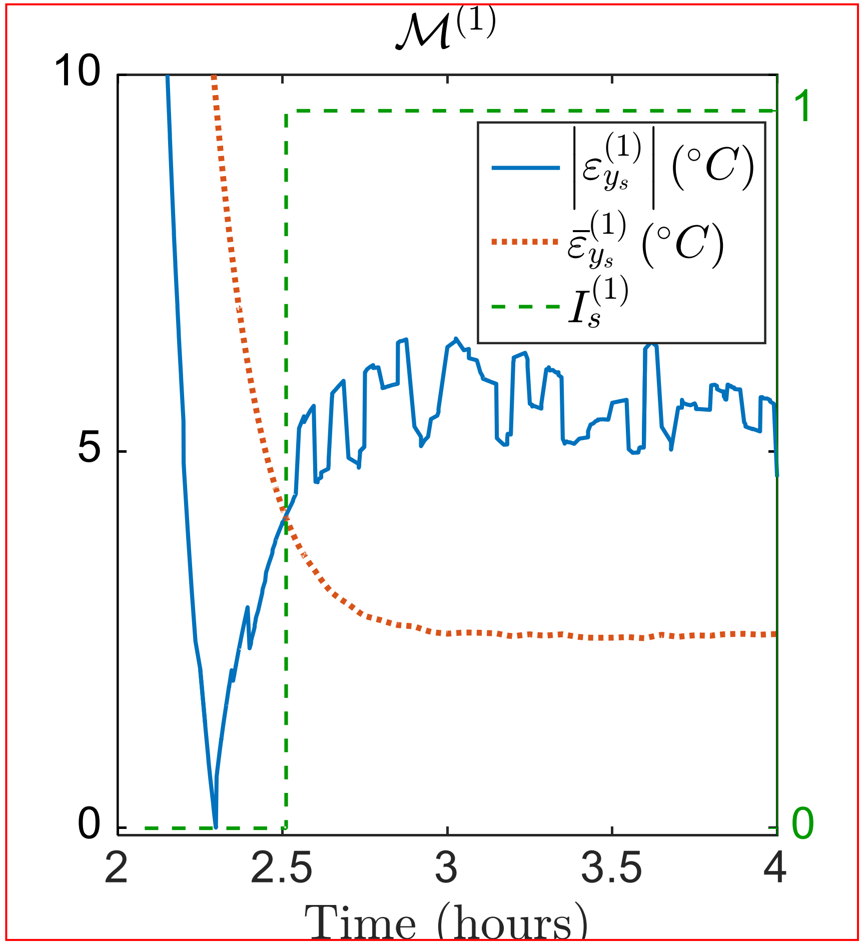
Simulation Results



Simulation Results

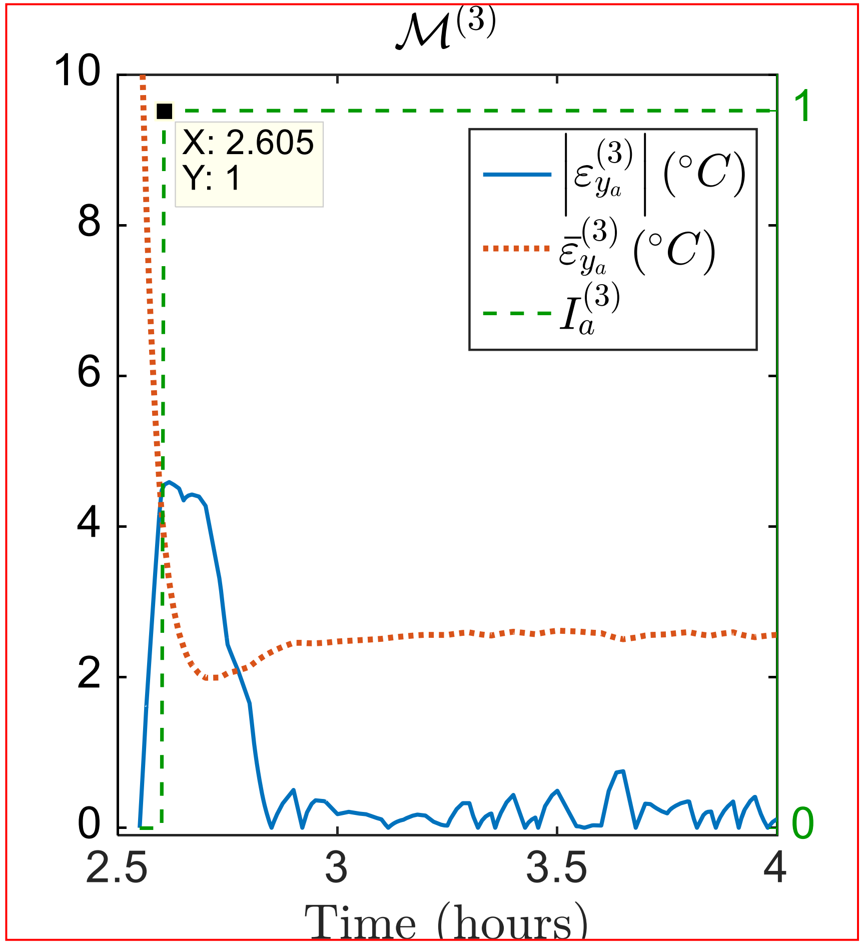
- Local Fault **Identification in Zone 1**:

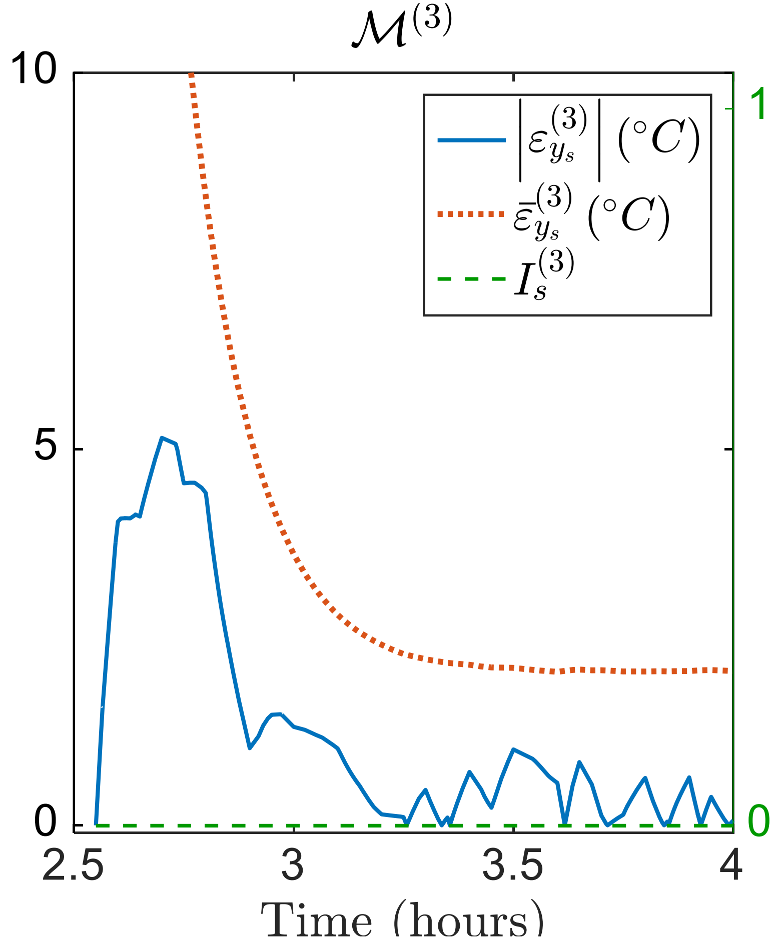




Simulation Results

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





Some recent relevant references

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Where is intelligent monitoring and control heading?

- **More distributed**
- **More cooperation**
- **More data → more machine learning**
- **More heterogeneous data**
- **More interaction between monitoring and control**
- **More interaction between fault diagnosis and cyber-physical security**
- ***Safety of machine learning (Safe AI)***

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Thank you!

Questions?