Towards Safe and Reliable CPS: a Learning-based Distributed Fault-Diagnosis Approach

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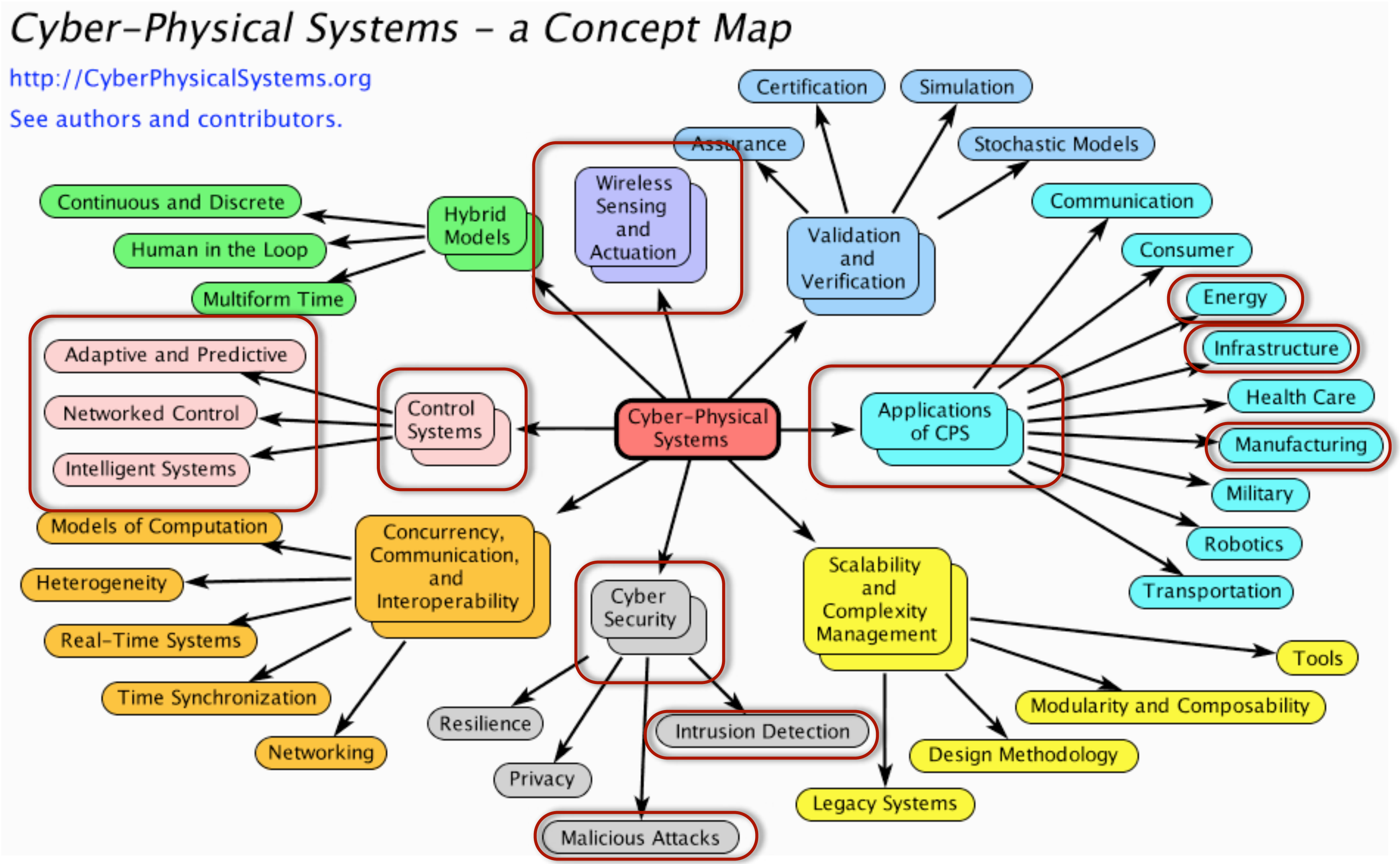
A few definitions from the literature

- CPS are engineered systems whose operations are monitored, coordinated, controlled, and integrated by a computing and communication core embedded in all types of objects and structures in the physical environment
- CPS usually comprise a network of physically distributed embedded sensors and actuators equipped with computing and communicating capabilities. Although each individual device is fairly inept at monitoring or regulating the physical substratum, the coordinated action of the individual network nodes has the potential for unprecedented capabilities
- CPSs refer to the next generation of engineered systems that require tight integration of computing, communication, and control technologies to achieve stability, performance, reliability, dependability, fault-tolerance, robustness, and efficiency in dealing with physical systems of many application domains

CPSs


Cyber–Physical Systems – a Concept Map
http://CyberPhysicalSystems.org
See authors and contributors.
Certification
Simulation
Assurance
Stochastic Models
Continuous and Discrete
Hybrid Models
Human in the Loop
Multiform Time
Wireless Sensing and Actuation
Validation and Verification
Communication
Consumer
Energy
Infrastructure
Health Care
Manufacturing
Military
Robotics
Transportation
Adaptive and Predictive
Networked Control
Intelligent Systems
Control Systems
Cyber-Physical Systems
Applications of CPS
Models of Computation
Heterogeneity
Real-Time Systems
Time Synchronization
Networking
Concurrency, Communication, and Interoperability
Cyber Security
Resilience
Privacy
Intrusion Detection
Malicious Attacks
Scalability and Complexity Management
Tools
Modularity and Composability
Design Methodology
Legacy Systems

Monitoring and fault diagnosis of CPSs

Motivations

- Huge recent interest in research and applications into reliable methods for diagnosing faults in complex systems
- High levels of safety, performance, reliability, dependability, and availability are needed in several application domains
- Faults: off-specification production, increased operating costs, chance of line shutdown, danger for humans, detrimental environmental impact, ...
- System errors, component faults and abnormal system operation should be detected promptly and the source and severity of each malfunction should be diagnosed (corrective actions)
- The simultaneous presence of a physical substratum and of a cyber substratum imposes additional challenges in safety-critical applications

Basic definitions and concepts

Fault Undesired change in the system that tends to degrade overall performance (a fault not necessarily represents a failure of a physical component)

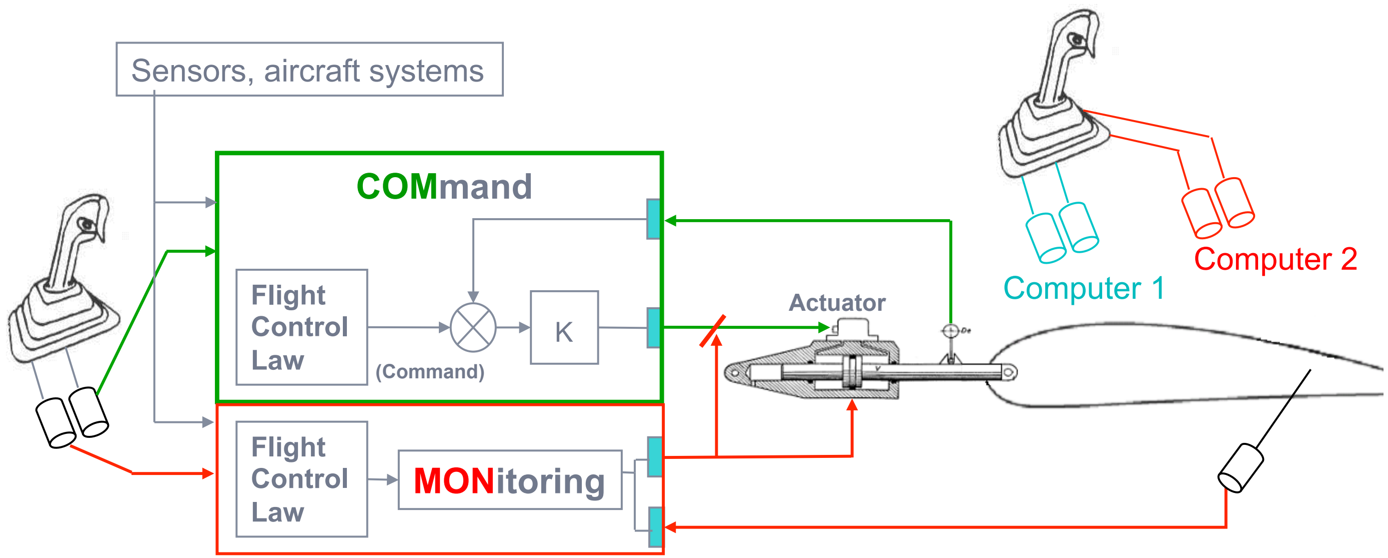
Fault detection Binary decision: "either something has gone wrong or everything is fine"

Fault isolation Determination of the source/type of the fault

Fault diagnosis system Procedure used to detect and isolate faults and possibly assess their significance/severity

Safety & Fault-tolerance: a step beyond HW redundancy only

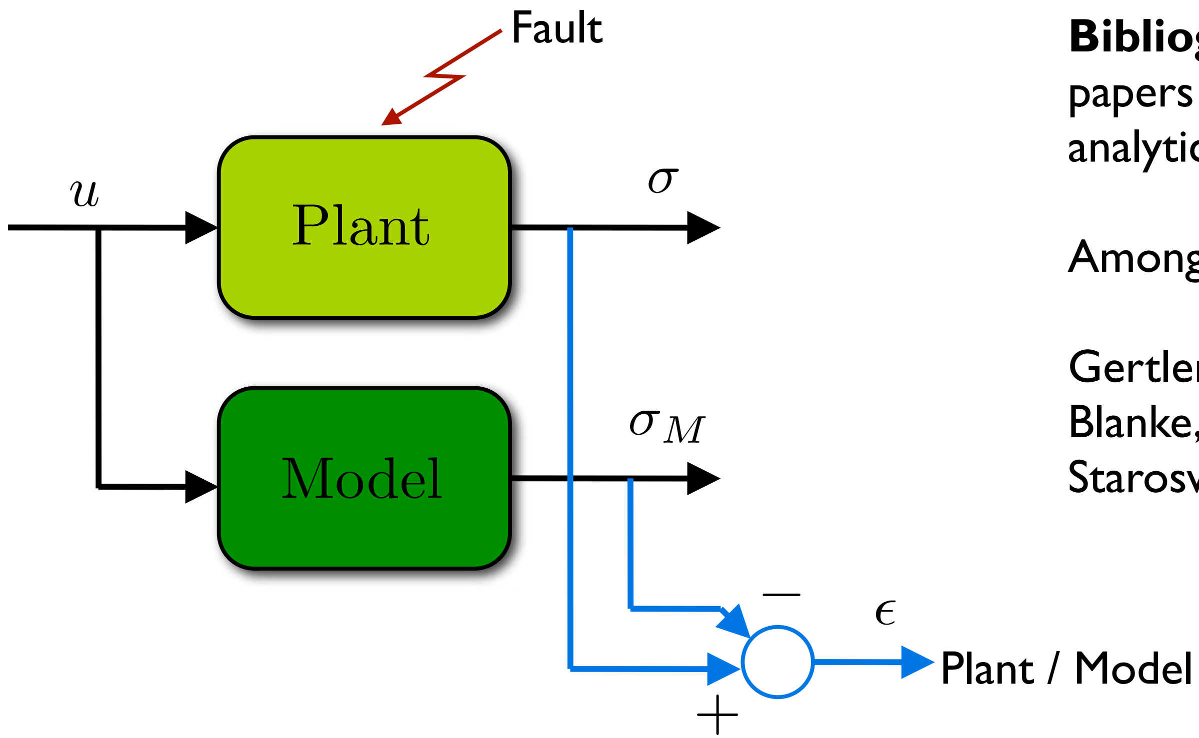
Flight Control Computer COM/MOM Airbus Architecture



- Self-checking computers
- Computer switching in case of fault detection

Courtesy: *Philip Goupil* AIRBUS

Model-based analytical redundancy: the very basic idea



Bibliography - several books and papers available on FD based on analytical redundancy concept.

Among others:

Gertler 1988; Patton and Chen, 2001; Blanke, Kinnaert, Lunze and Staroswiecki, 2003; Isermann, 2006

Key design issues:

- Effects of modelling uncertainties
- Non-conservative diagnosis thresholds

Large-scale CPSs: why distributed?

Mainly because of constraints on:

- Computation power needed to handle the global dynamic model (model-based approach)
- Communications resources needed to convey the information on all the state variables to a single location

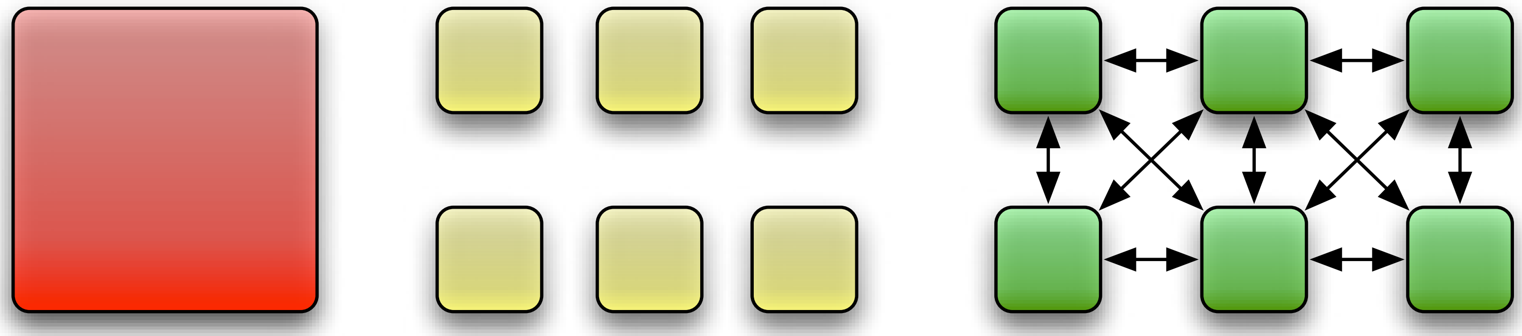
Moreover:

- FDI task running on a single computation node is not fault tolerant itself, nor a single node for this task can always be identified
- The physical substratum may be spatially distributed: the notion of locality induced by the physical substratum is not necessarily compatible with the notion of locality induced by the network of sensors (*Tabuada, 2006*)

→ Layer of networked local monitoring modules

De/centralised, distributed system

System: entity to be monitored against faults



Centralised

Possibly large # of
sub-systems with
global interaction

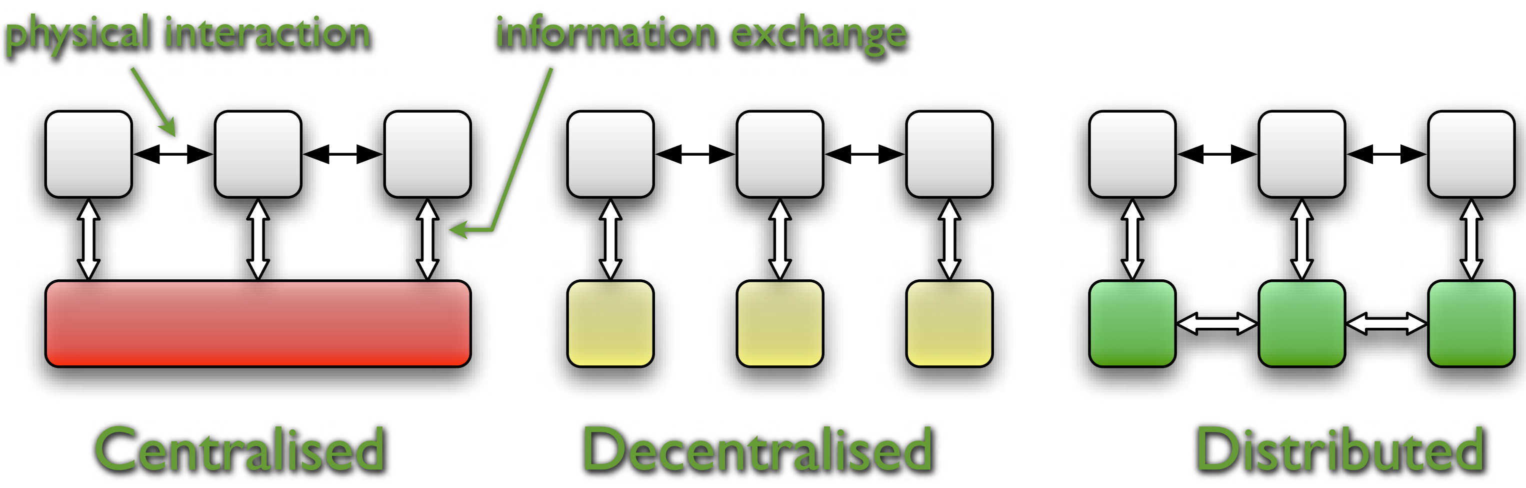
Decentralised

Non-interacting
sub-systems

Distributed

Sub-systems with
local interaction

De/centralised, distributed FD architecture



All information conveyed to a single diagnostic system	No information exchange among the local diagnosers mirroring the physical interactions	The information exchange mirrors the local physical interactions

Distributed FDI: *divide et impera*

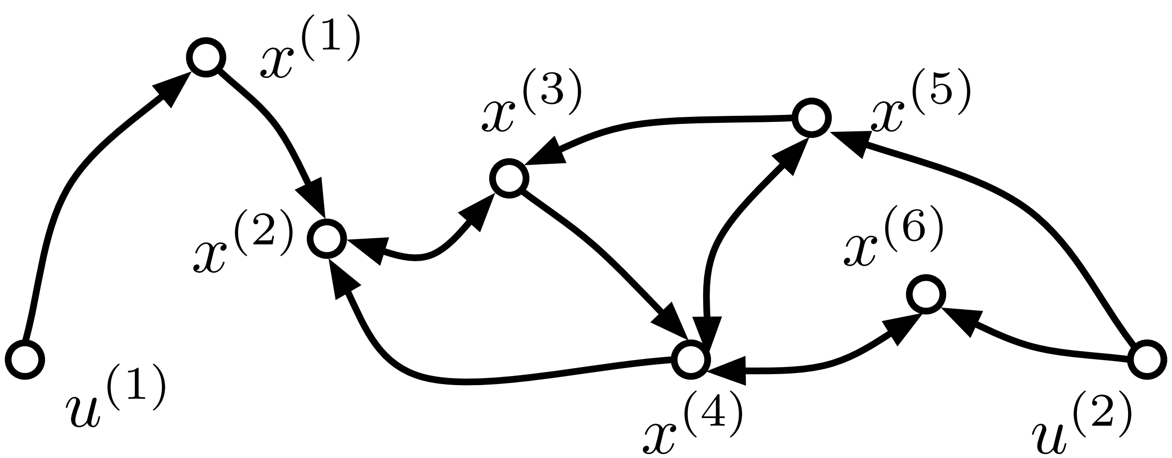
- Convenient to decompose the FDI task in smaller sub-tasks that can run in parallel on different local diagnosers
- Use of directed graphs to match the decomposition structure
- FDI task decomposition follows from a decomposition of the monolithic system structural graph and model
- Consensus techniques used to monitor overlapping parts
- Adaptive approximators used to learn on-line uncertain parts of the model (typically, the interconnection between subsystems)

A simple structural graph

$$\mathcal{G} \triangleq \{\mathcal{N}_{\mathcal{G}}, \mathcal{E}_{\mathcal{G}}\}$$

- Nodes represent state or input components of the monolithic system
- Two nodes are connected if the first one appears in the state equation of the second one

$$\mathcal{E}_{\mathcal{G}} \triangleq \left\{(x^{(i)}, x^{(j)}) : \text{"}x^{(i)} \text{ acts on } x^{(j)}\text{"}\right\} \cup \left\{(u^{(i)}, x^{(j)}) : \text{"}u^{(i)} \text{ acts on } x^{(j)}\text{"}\right\}$$



A simple graph decomposition

Local state variables

$$x_1 = [x^{(1)}, x^{(2)}, x^{(3)}]^\top$$

$$x_2 = [x^{(3)}, x^{(4)}, x^{(5)}, x^{(6)}]^\top$$

Local input variables

$$u_1 = u^{(1)}$$

$$u_2 = u^{(2)}$$

Interconnection variables

$$z_1 = [x^{(4)}, x^{(5)}]^\top$$

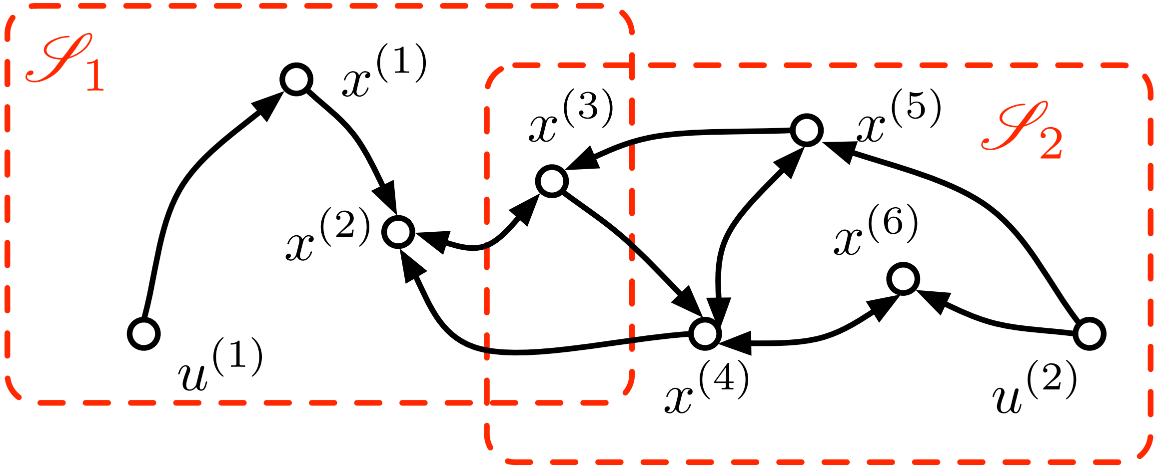
$$z_2 = x^{(2)}$$

Shared variables

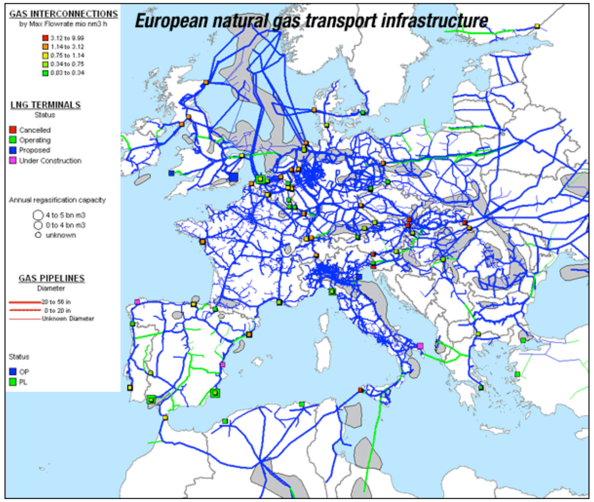
$$x^{(3)} \equiv x_1^{(3)} \equiv x_2^{(1)}$$

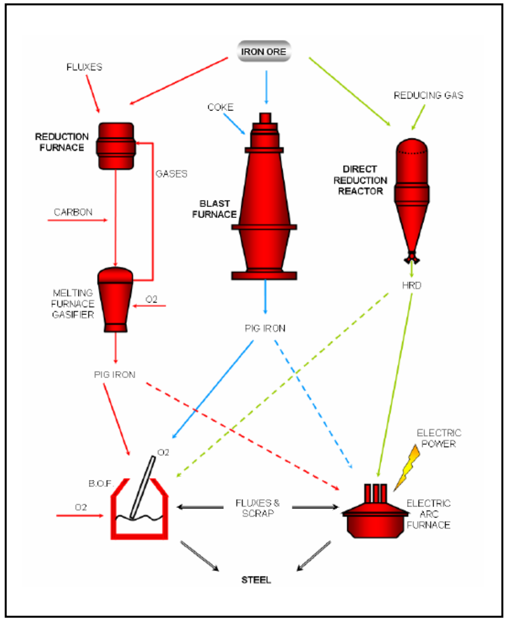
Overlap set

$$\mathcal{O}_3 = \{1, 2\}$$



Large-scale CPS "monolithic" model of physical substratum





Nominal model dynamics (healthy mode)

Modelling uncertainty (plant/model mismatch)

$$x^+ = \phi(x,u) + \eta(x,u,t) + \mathcal{B}(t - T_0) f(x,u)$$

Time-evolution of the fault

Deviation to state equation due to a fault/malfunction. Several failure causes (e.g., component-level, sensors, but ... malicious too)

Decomposition

We **decompose**

$$x^+ = \phi(x,u) + \eta(x,u,t) + \mathcal{B}(t-T_0) f(x,u)$$

as

$$x_I^+ = \phi_I(x_I,u_I) + g_I(x_I,z_I,u_I) + \beta(t-T_0) f_I(x_I,z_I,u_I)$$

Nominal local model dynamics

Interconnection function (includes modelling uncertainty)

Local fault dynamic influence (modelling of faults)

with $I \in \{1,\ldots,N\}$ and

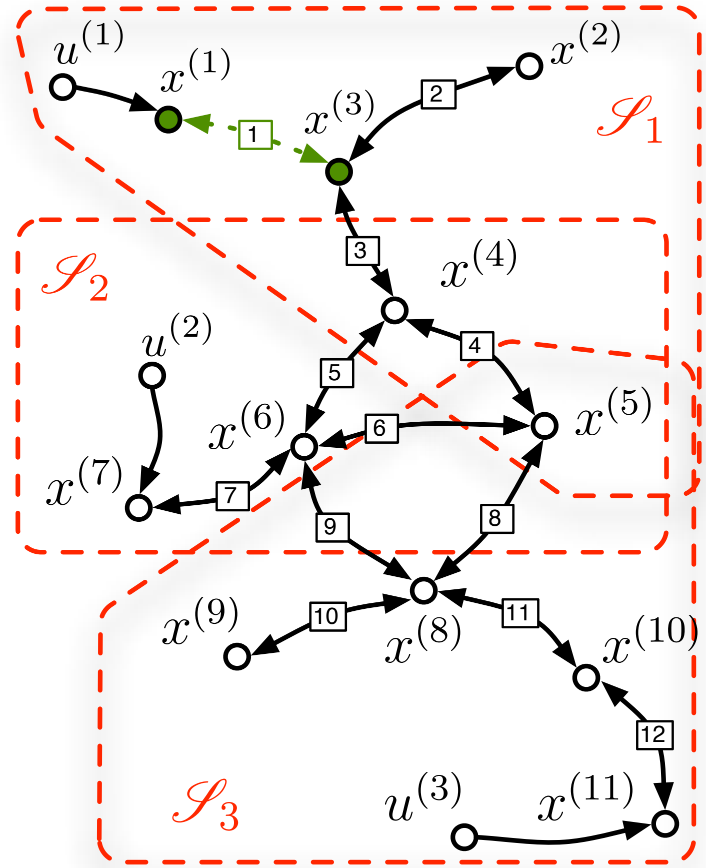
$$f_I(x_I,z_I,u_I) \in \mathcal{F}_I = \{f_I^1(x_I,z_I,u_I),\ldots,f_I^{N_{\mathcal{F}_I}}(x_I,z_I,u_I)\}$$

Types of fault: local

- Example of a local fault
- Green arcs and nodes represent the fault influence
- The influence set is a singleton

$$\mathcal{U} = \{1\}$$

- Only one LFD (the first one) is needed to detect and isolate the fault



Types of fault: distributed

- This is an example of a distributed fault, the fault influence set is

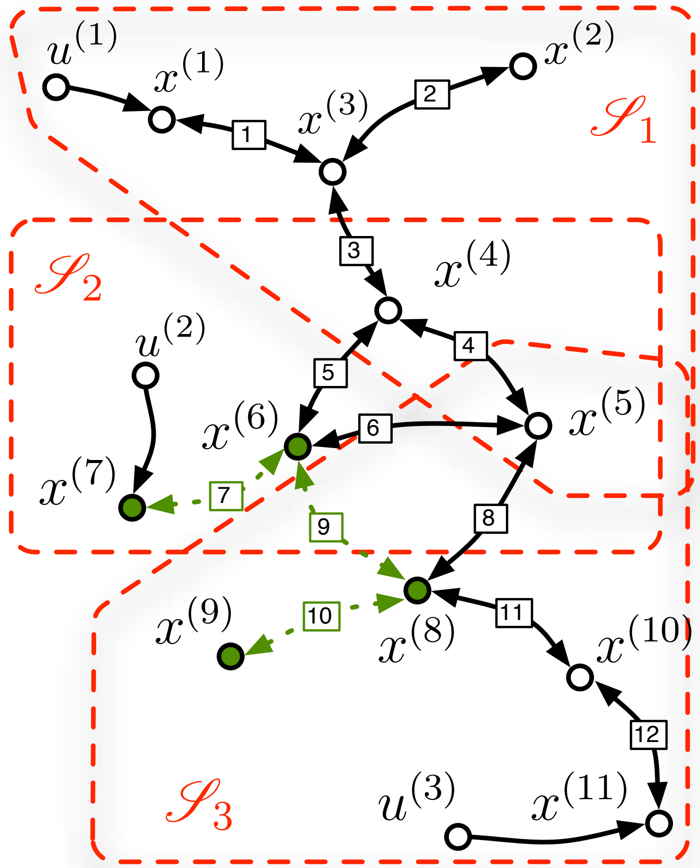
$$\mathcal{U} = \{2, 3\}$$

- The fault is detected as soon as any LFD locally detects it

- After detection every LFD starts the isolation procedure

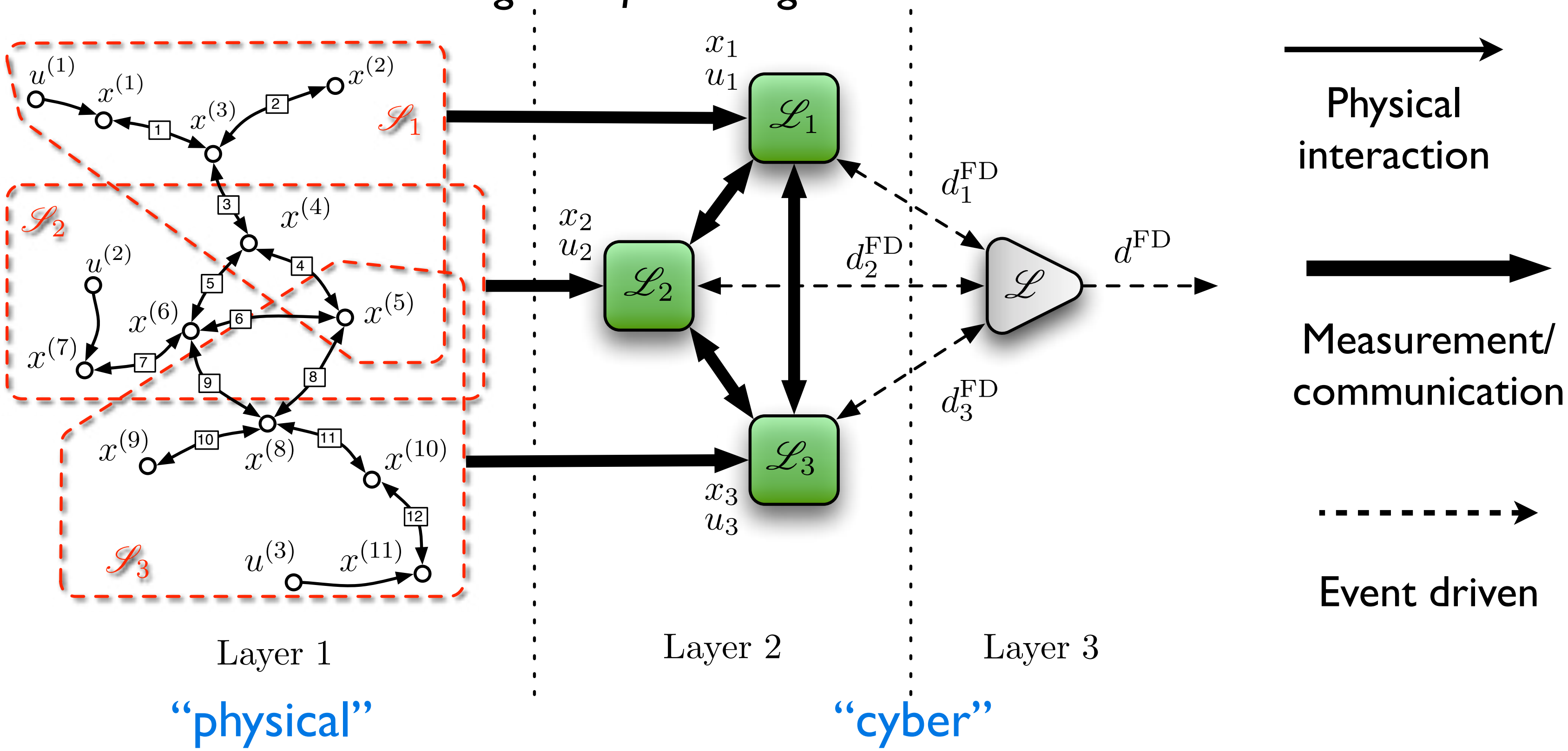
- The fault is isolated only if all the LFD belonging to $\mathcal{U}$ succeed in isolating their local component of the fault

  The global isolation is possible thanks to the GFD

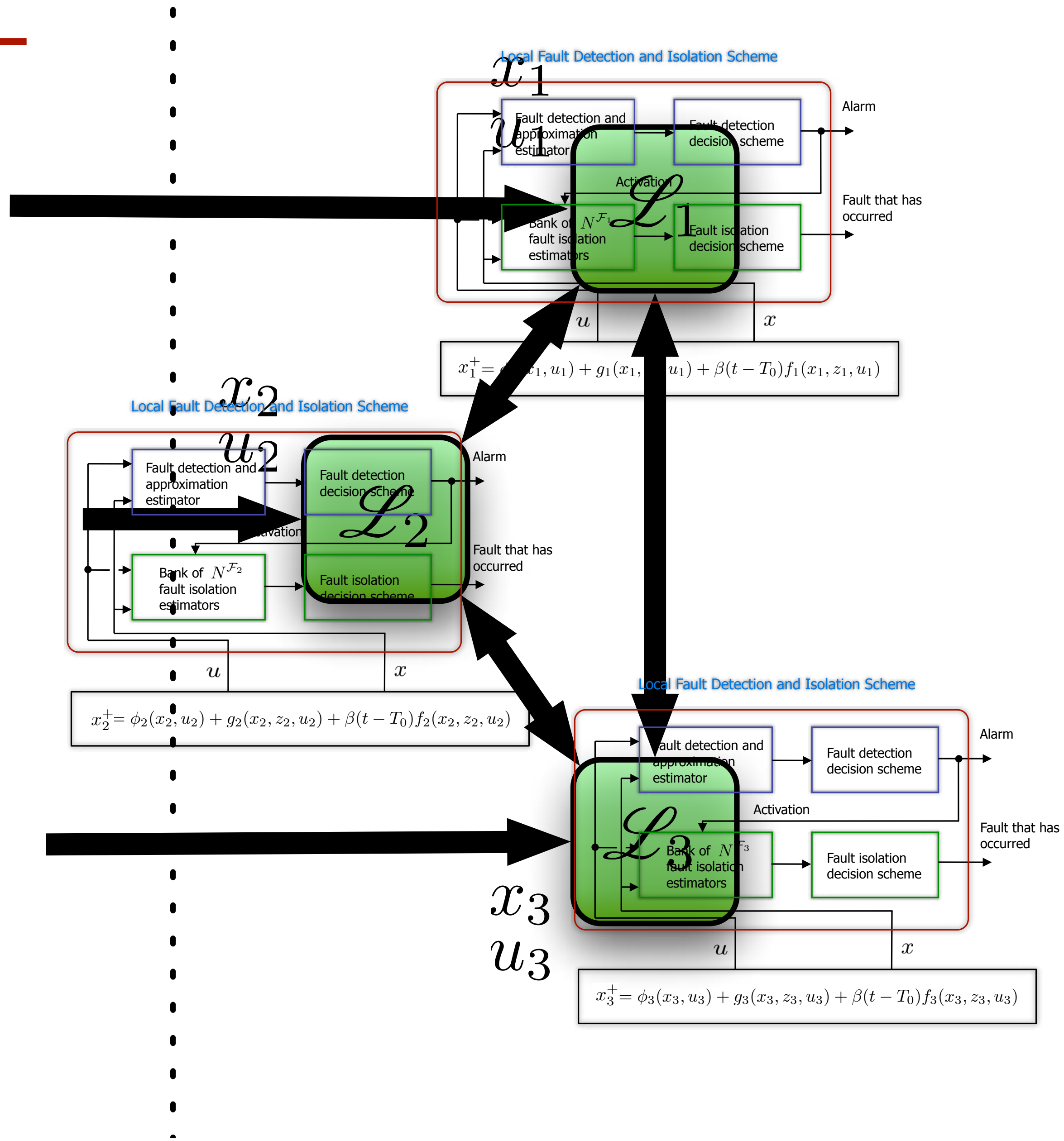


Distributed FDI Architecture

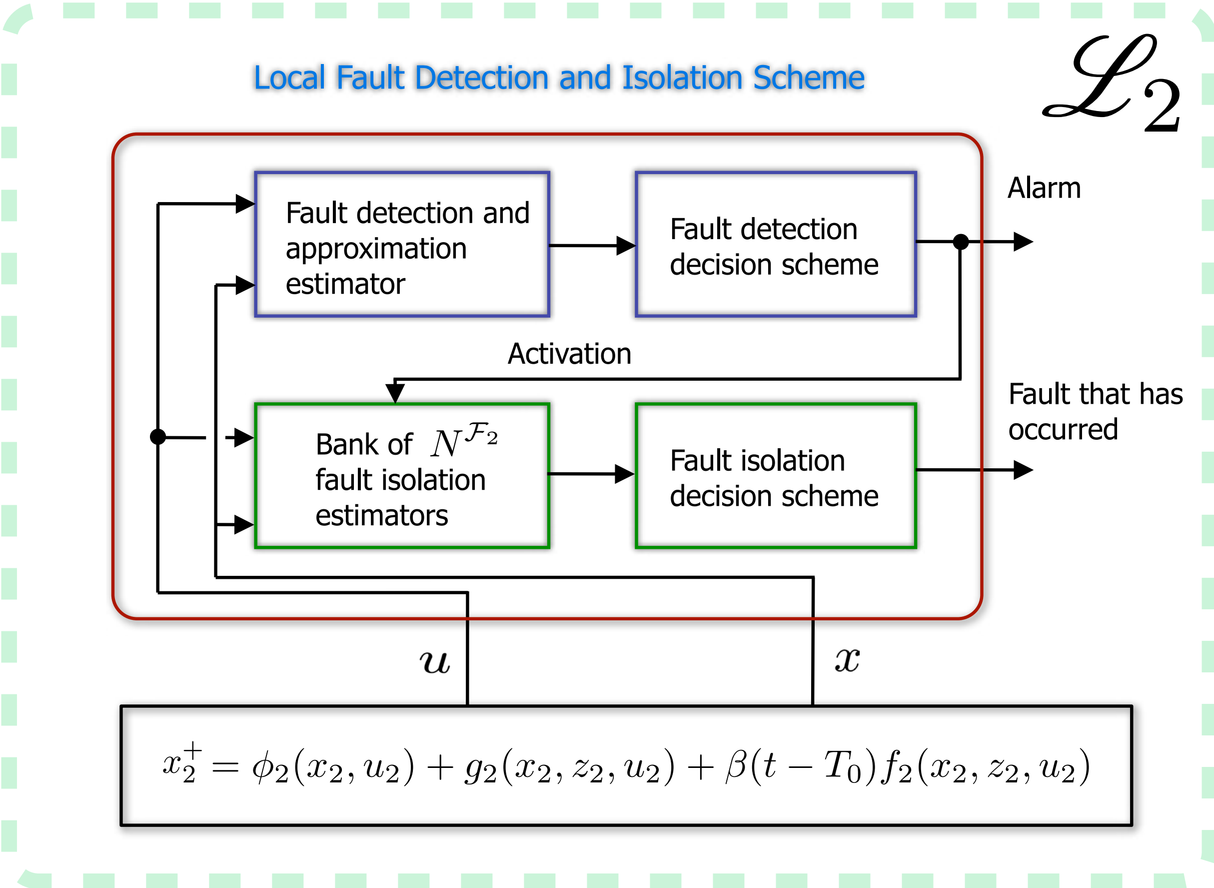
- **Layer 1**: physical subsystems
- **Layer 2**: a Local Fault Diagnoser (LFD) for each subsystem, using *local measurements* and *exchanging information* with neighbors
- **Layer 3**: a Global Fault Diagnoser (GFD) exploiting local fault decisions from LFDs in order to reach a *global fault diagnosis* decision



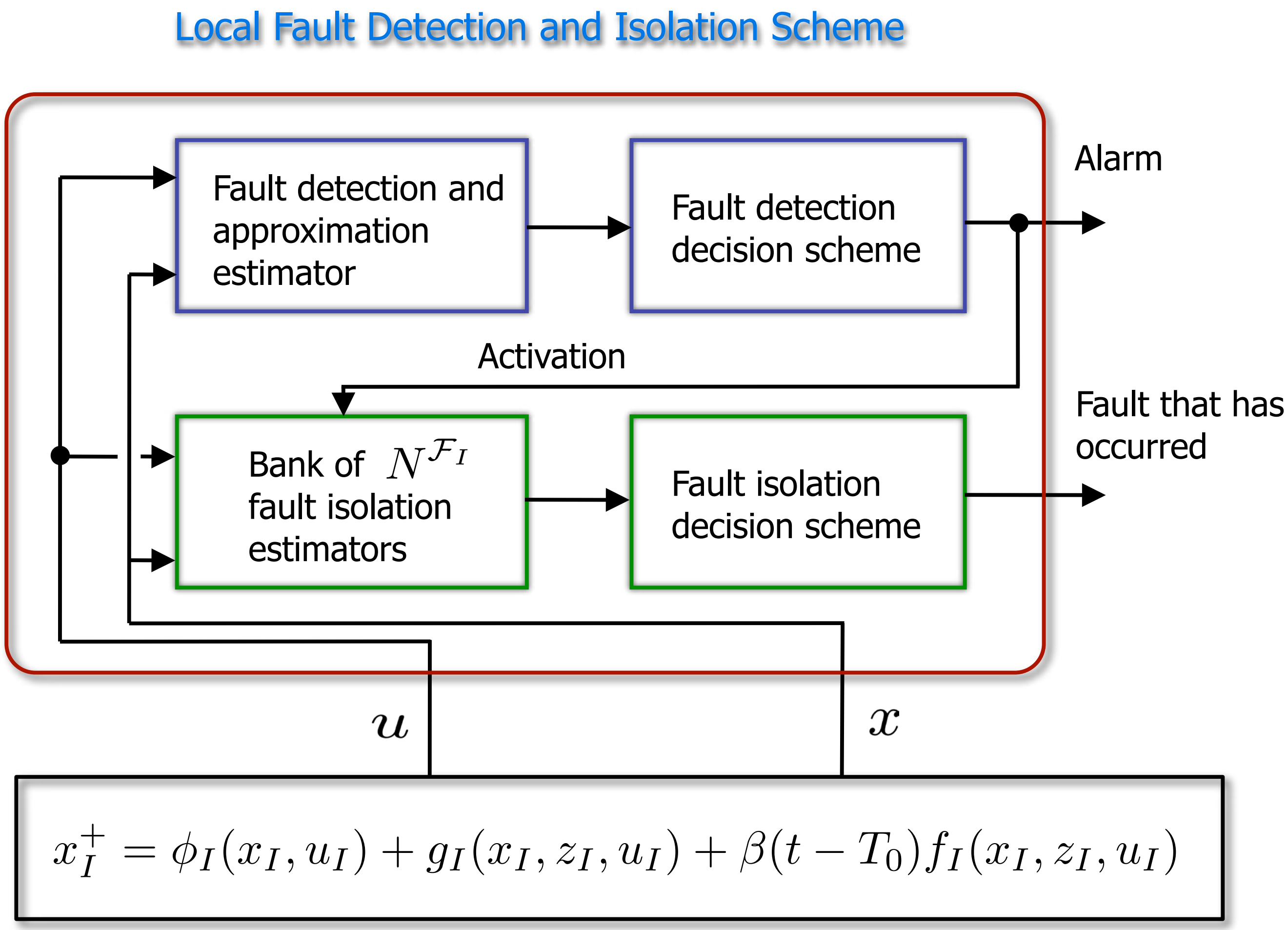
Distributed FDI Architecture



Distributed FDI Architecture



Local FDI architecture



Fault detection and approximation estimator

consensus on
shared variables

$$\hat{x}_I^{+(s_I)} = \lambda(\hat{x}_I^{(s_I)} - y_I^{(s_I)}) + \lambda \sum_{J \in \mathcal{O}_s} W_s^{(I,J)} \left[\hat{x}_J^{\prime(s_J)} - \hat{x}_I^{(s_I)}\right]$$

$$+ \sum_{J \in \mathcal{O}_s} W_s^{(I,J)} \left[\phi_J^{(s_J)}(y_J, u_J) + \hat{g}_J^{(s_J)}(y_J, v_J^{\prime}, u_J, \hat{\vartheta}_J)\right]^{\prime}$$

consensus on
shared variables

on-line parametrized
adaptive approximation
model

delays/packets drop-out
in information
exchanged between
neighbouring diagnosers

Learning algorithm

$$\hat{\vartheta}_I^+ = \mathcal{P}_{\hat{\Theta}_I}\left[\hat{\vartheta}_I + \gamma_I H_I^\top [\epsilon_I^+ - \lambda \epsilon_I\right]$$

where:

$\mathcal{P}_{\hat{\Theta}_I}$ projection operator on compact set $\hat{\Theta}_I$

$\epsilon_I = y_I - \hat{x}_I^{s_I}$ (from $\hat{x}_I^{+(s_I)} = \cdots$)

γ_I learning rate matrix

$H_I^\top = \partial \hat{g}_I / \partial \hat{\vartheta}_I$

Fault detection

A local detection threshold $\bar{\epsilon}_i^0(t)$ can be designed depending on a number of important quantities like, for example, bounds on local modelling uncertainties, etc.

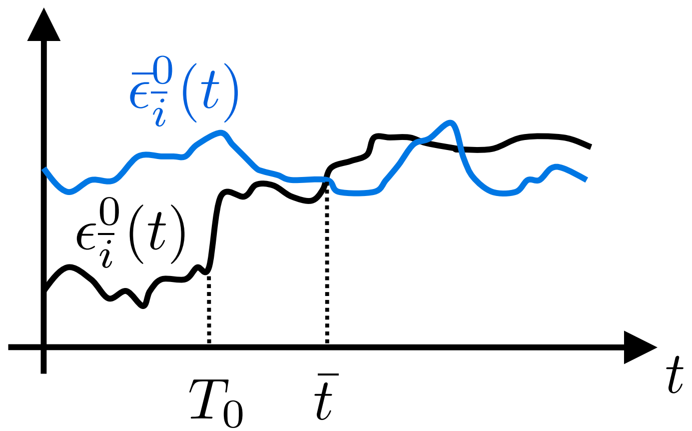
Fault detected if:

$$\exists\, \bar{i} \in \{1, \ldots, n\}$$

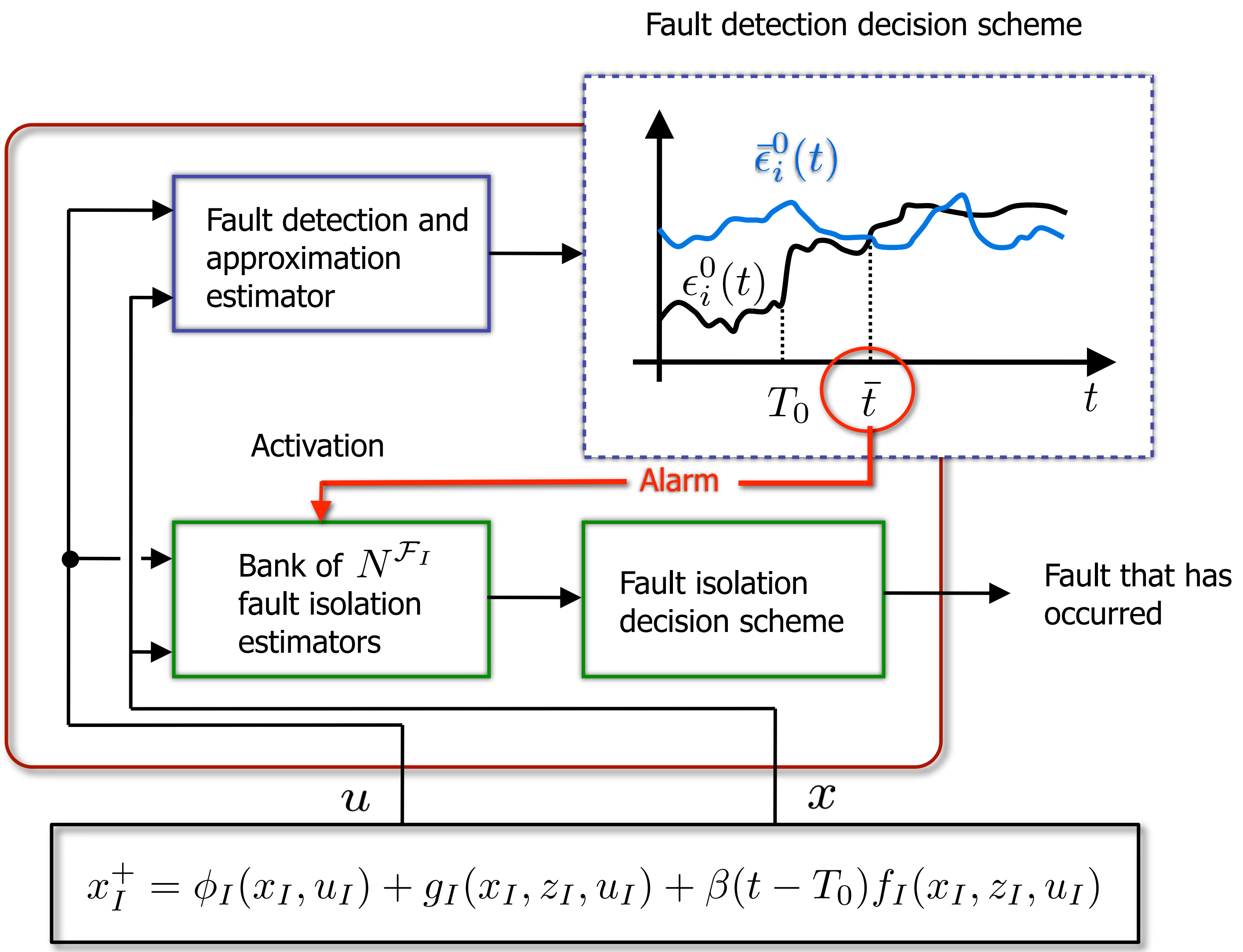
and

$$\exists\, \bar{t}$$

such that $\left|\epsilon_{\bar{i}}^0(\bar{t})\right| > \bar{\epsilon}_{\bar{i}}^0(\bar{t})$



Local detection of a fault activates the isolation phase



Local fault isolation

Fault s isolated if:

$$\forall r \in \{1,\ldots,n\} \setminus \{s\}$$

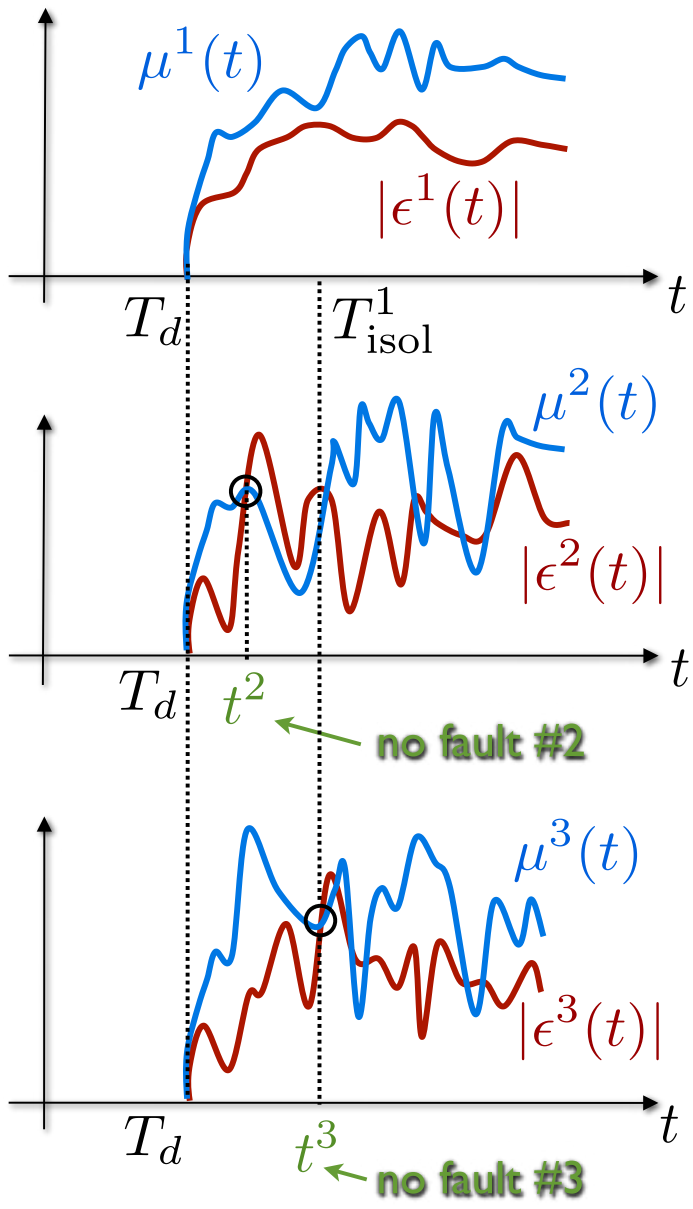
$$\exists \bar{i} \in \{1,\ldots,n\}$$

and

$$\exists\, t^r \geq T_d$$

such that $|\epsilon^r_{\bar{i}}(t^r)| > \mu^r_{\bar{i}}(t^r)$

Three-faults scalar example



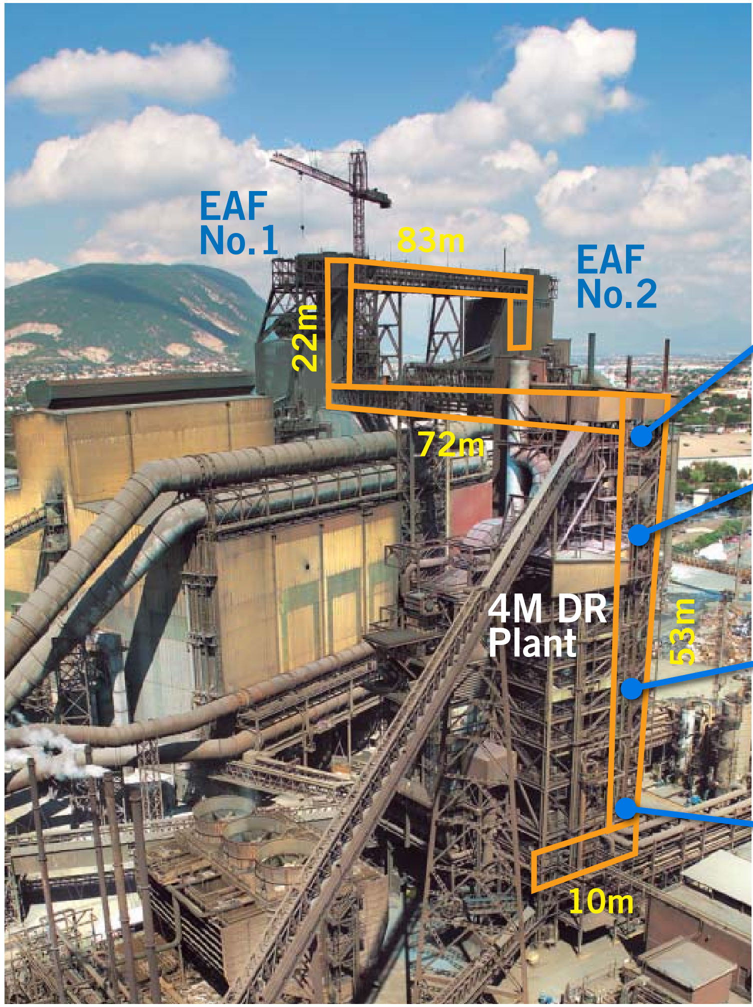
Direct Reduction Steel Plant

- Chemical plant for turning iron ore into ~94% pure iron
- Technology born in the '70s
- World production rose from 0.7 to 64 Mt/year (currently 6% of total iron production - steadily increasing)
- More economical and environment friendly than blast furnaces (40-60% less CO_2)

Direct Reduction Steel Plant

- Typical production: 200 t/hour, worth about 100.000 Euro/hour
- Energy consumption: 600 MW, mainly from natural gas
- Time needed for a stop&start: 3 days
- Economical loss caused by a forced maintenance stop due to a fault: about 6 MEuro

Direct Reduction Steel Plant



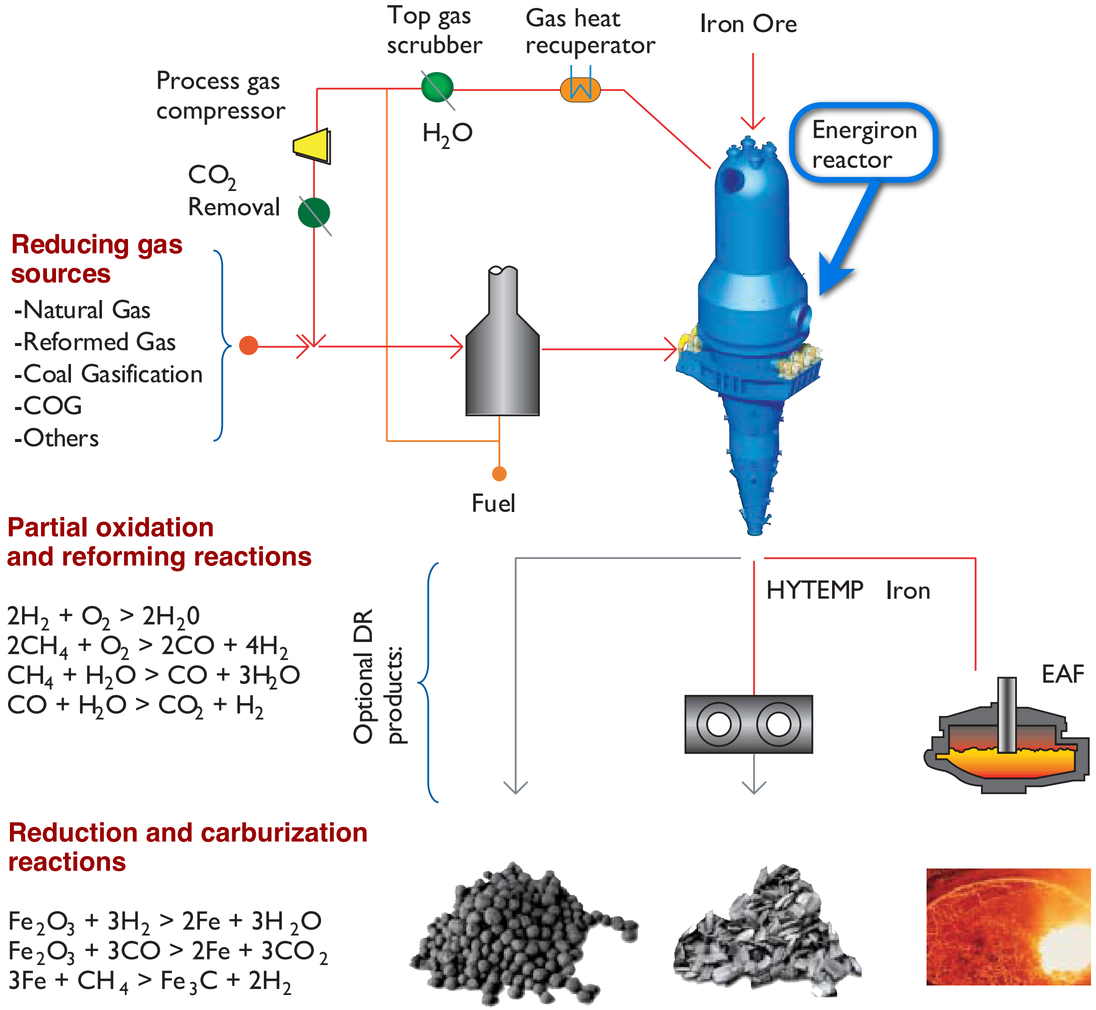
diameter = 10 m

height = 53 m

Courtesy: *Tenova-HYL*

Simplified layout

- Main component: reduction shaft reactor (height ~ 40 m, diameter ~ 10 m)
- Internal pressure ~ 6 bar, internal temperature ~ 1050 C
- Distributed-parameters, highly nonlinear "multi-physics" system
- pellet flow + gas flow + heat transfer + chemical reactions



Reactor: Modelling for FD

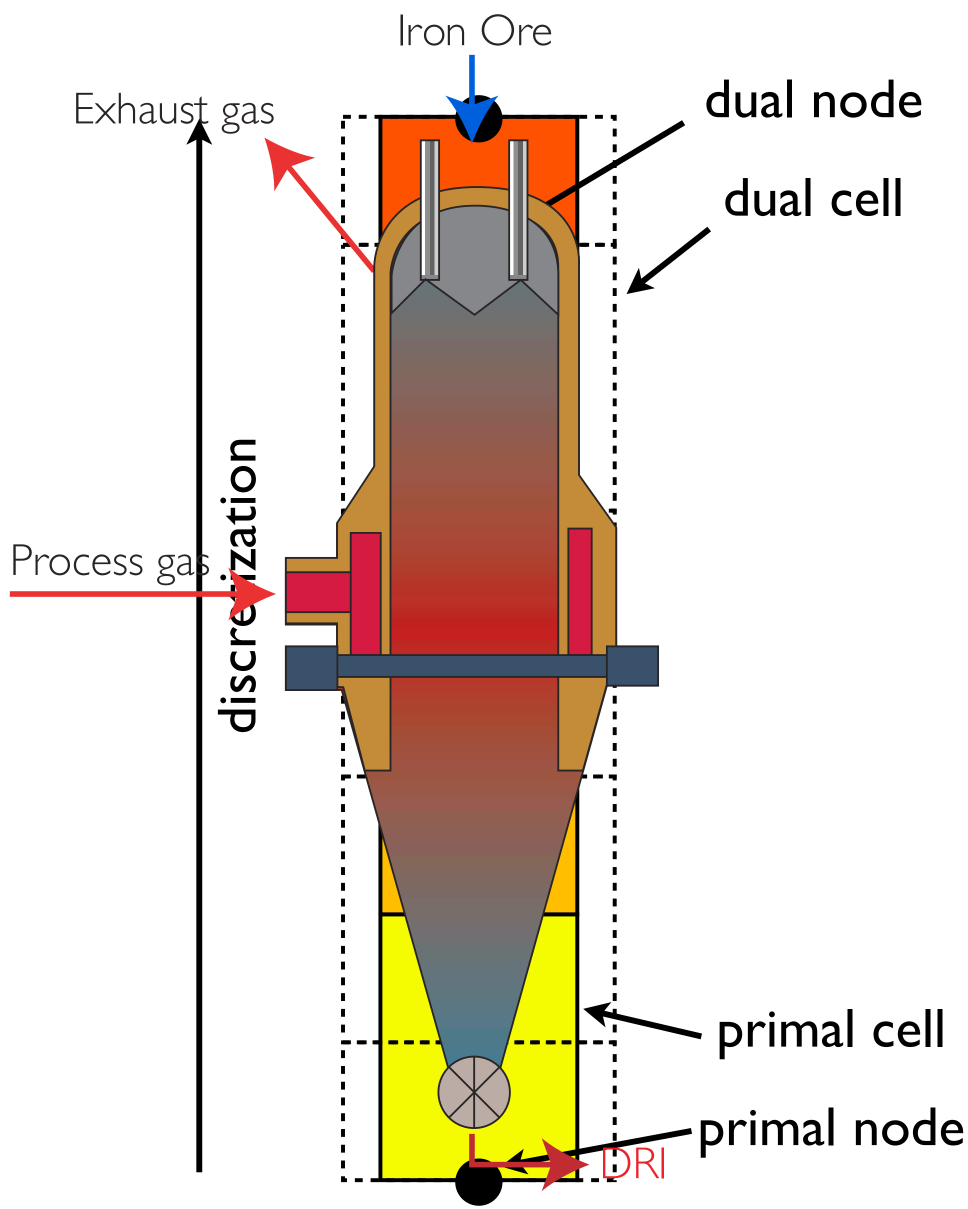
“Unusual” modelling paradigm

Cell method: discrete formulation of Field Laws:

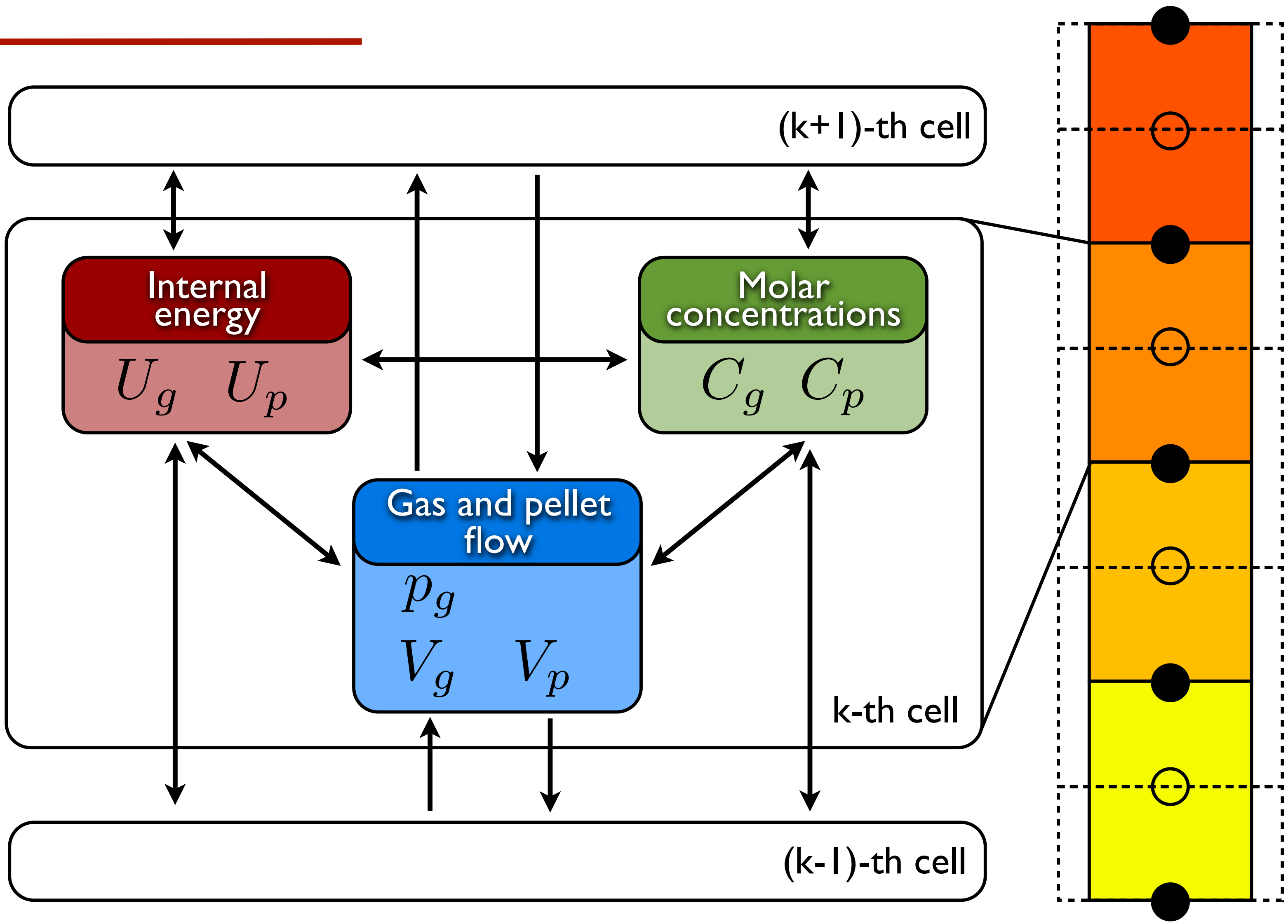
discrete equations defined on two staggered grids:

- first grid: primal cells
- second grid: dual cells

E. Tonti, “A Direct Discrete Formulation of Field Laws: The Cell Method,” *CMES*, vol.2, no.2, pp.237-258, 2001.



Inside a cell



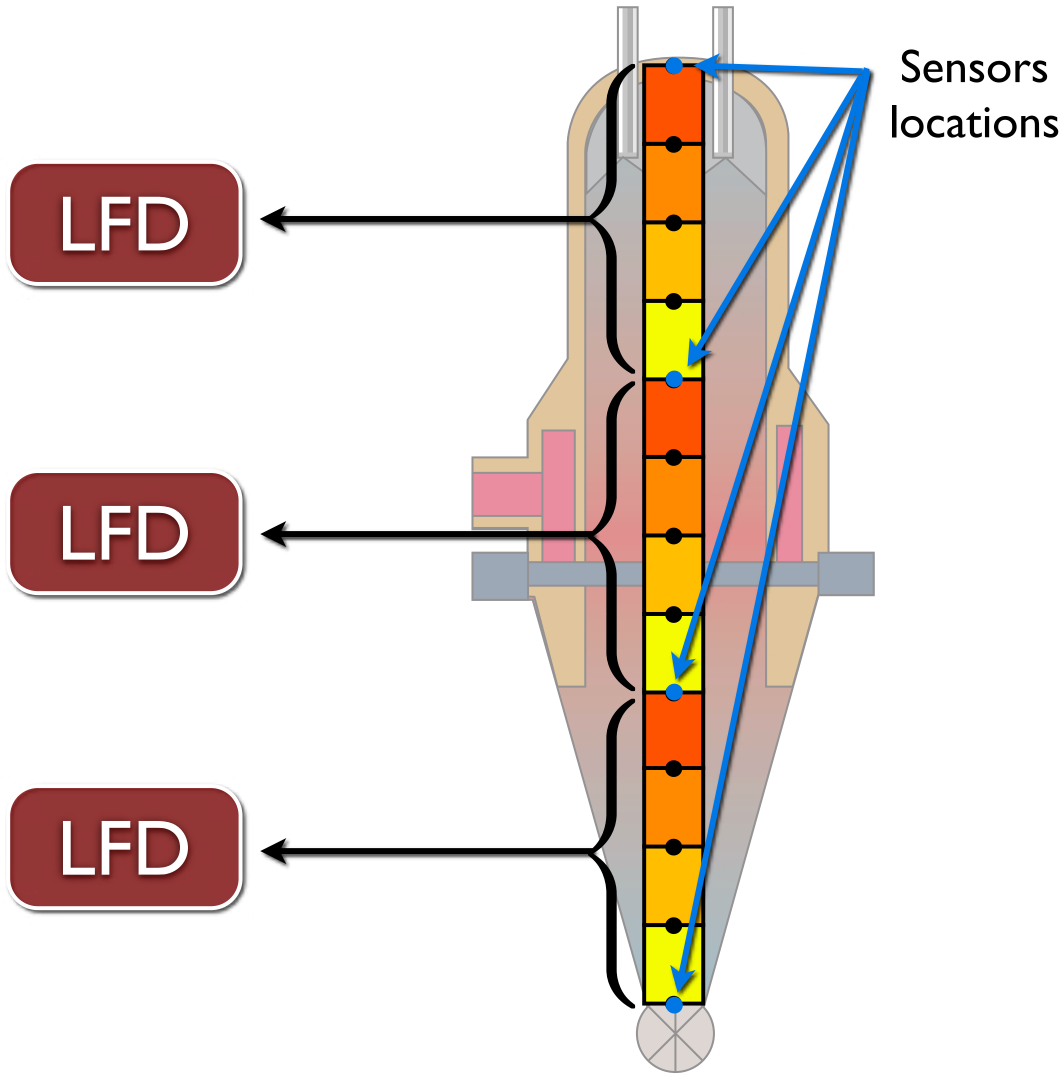
g: "gas"

p: "pellet"

Distributed FD of the DRI reactor

Key point:

the discrete-cell model "imposes" the decomposition of the large scale system into "strings" of cells between measurement locations

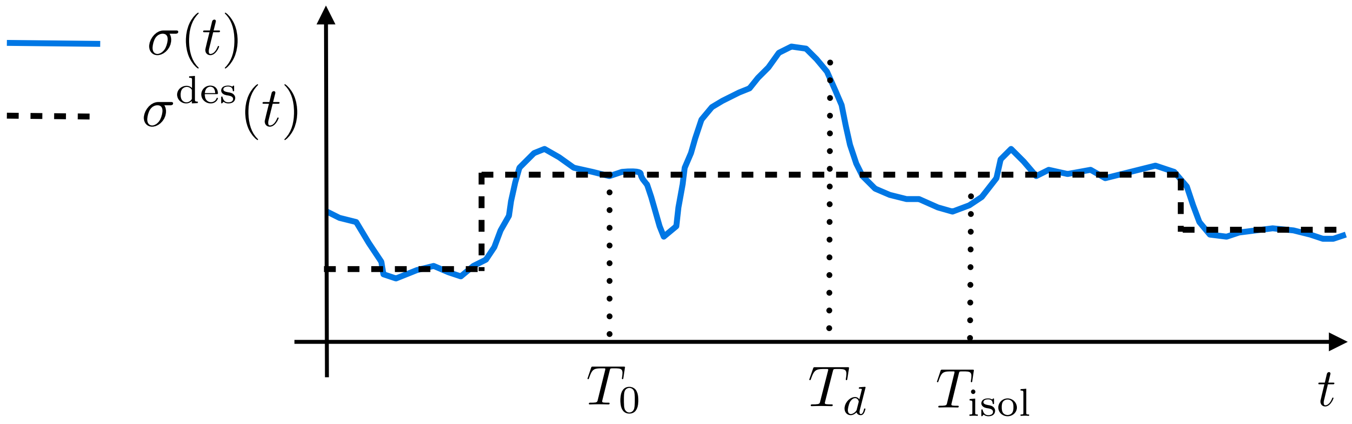


Remarks

What I did not tell you:

- Theoretical results available on **distributed** fault **detectability** and **isolability** [Ferrari et al, *IEEE TAC 2012*, Boem et al., *EJC 2011*]

- **Fault-tolerant control** schemes integrating the FD methodology with reconfigurable controllers are available for local sub-systems



The extension to the distributed fault-tolerant control problem of CPSs is very challenging. Efforts in this direction are under way.

Concluding remarks

- Safety-critical CSPs: need of effective monitoring and diagnosis methodologies and tools
- Several CPSs are very large-scale spatially distributed systems: need of distributed diagnosis tools with scalability characteristics
- Enormous value comes from exploiting the richness of the ever-increasing amount of available data from sensors (wireless or not)
- On-line approximation/learning: a key enabling factor to achieve effective distributed diagnosis and prognosis