Advanced Research
Intelligent
Embedded
Systems

Cognitive Fault Detection and Diagnosis in Sensor-based Embedded Systems

Intelligence for Embedded Systems

Ph. D. and Master Course

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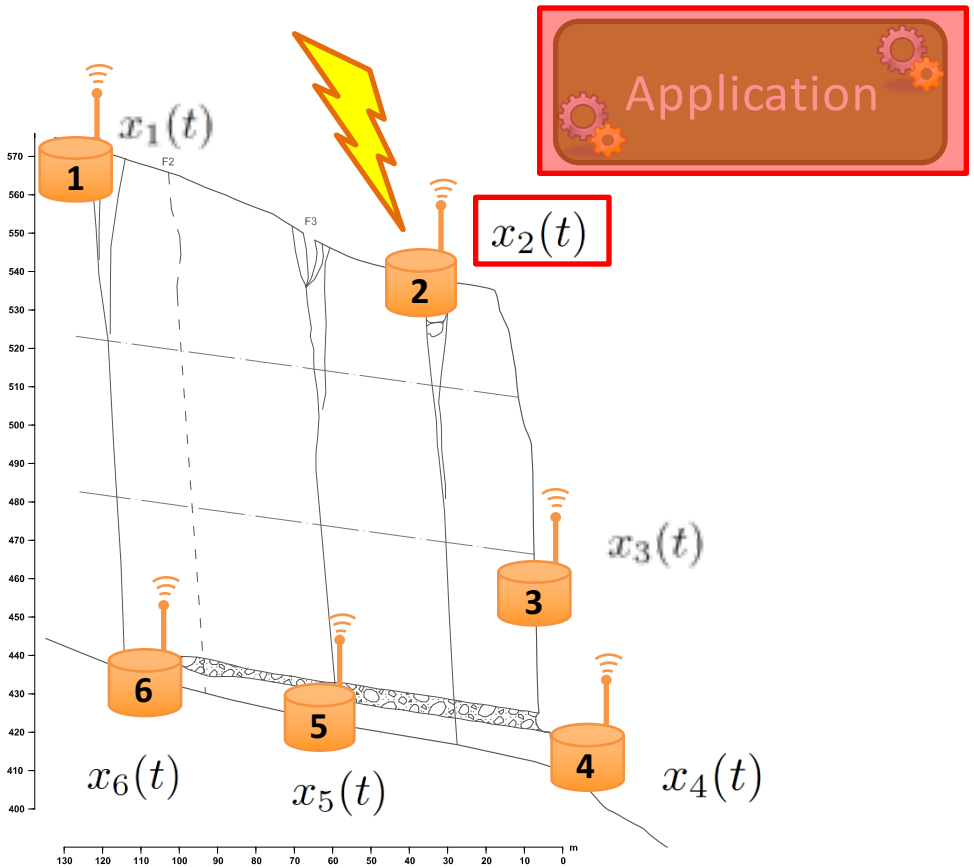
Sensor-based Networked Embedded Systems



Inspect natural environments, CISs or cyber-physical systems by providing:

$$\boldsymbol{X}(t) = \begin{bmatrix} x_1(t) \\ \vdots \\ x_n(t) \end{bmatrix} \in \mathbb{R}^n$$

$\boldsymbol{X}(t)$ are analysed for the purposes of the considered application to make decisions/activate reactions

Sensor networks suffer from faults, ageing effects or thermal drifts in the embedded electronics or the sensors

Fault Detection and Diagnosis Systems

Specific tasks:

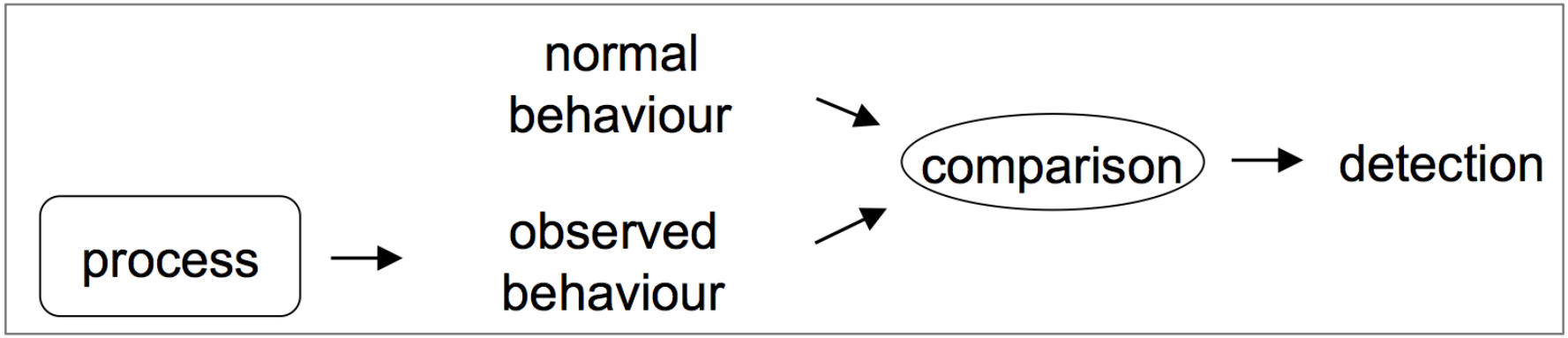
- Detection: perceive as soon as possible if a change has occurred
- Isolation: locate the sensor (or unit) where the fault has occurred
- Identification: gather information about the nature of the fault (e.g., magnitude, type)

In addition:

We want to understand if the change is due to a change in the environment or a fault in the sensors of the embedded system

Traditional Fault Detection mechanisms

- Operating principle: **on-line comparison** of the actual system observed behaviour against the known "normal operation behaviour".

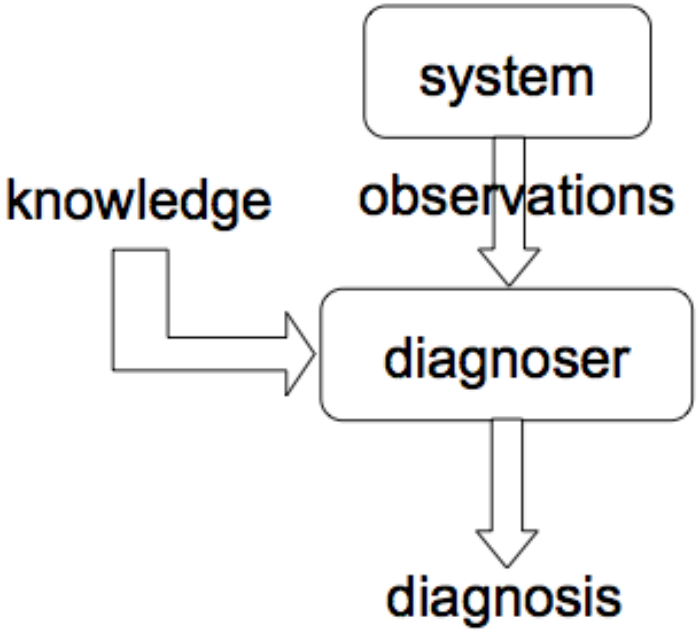


- **Knowledge about the "normal operation behaviour"**:
  - Empirical knowledge
  - Extracted from from data
  - Physical modelling

Traditional Fault Diagnosis Mechanisms

- Fault diagnosis (identification and isolation) relies on comparing the observed behaviour of the monitored system with the a-priori knowledge about it.

✓ *Remarks:*
  - ✓ *Real-time operation.*
  - ✓ *Knowledge for normal and faulty operations is needed (knowledge about normal operation is enough for FD)*
  - ✓ *All faults have to affect the observed variables (detectable faults) in a different way (isolable faults).*



From Traditional Fault Detection and Diagnosis to Cognitive Approaches

Fault Detection and Diagnosis Systems

These systems consider techniques from several fields (e.g., automatic control, machine learning)

Traditional systems generally require:

- information about the process
- information about the faults
- information about uncertainties

Cognitive Fault Detection and Diagnosis Systems

Overcome traditional assumptions

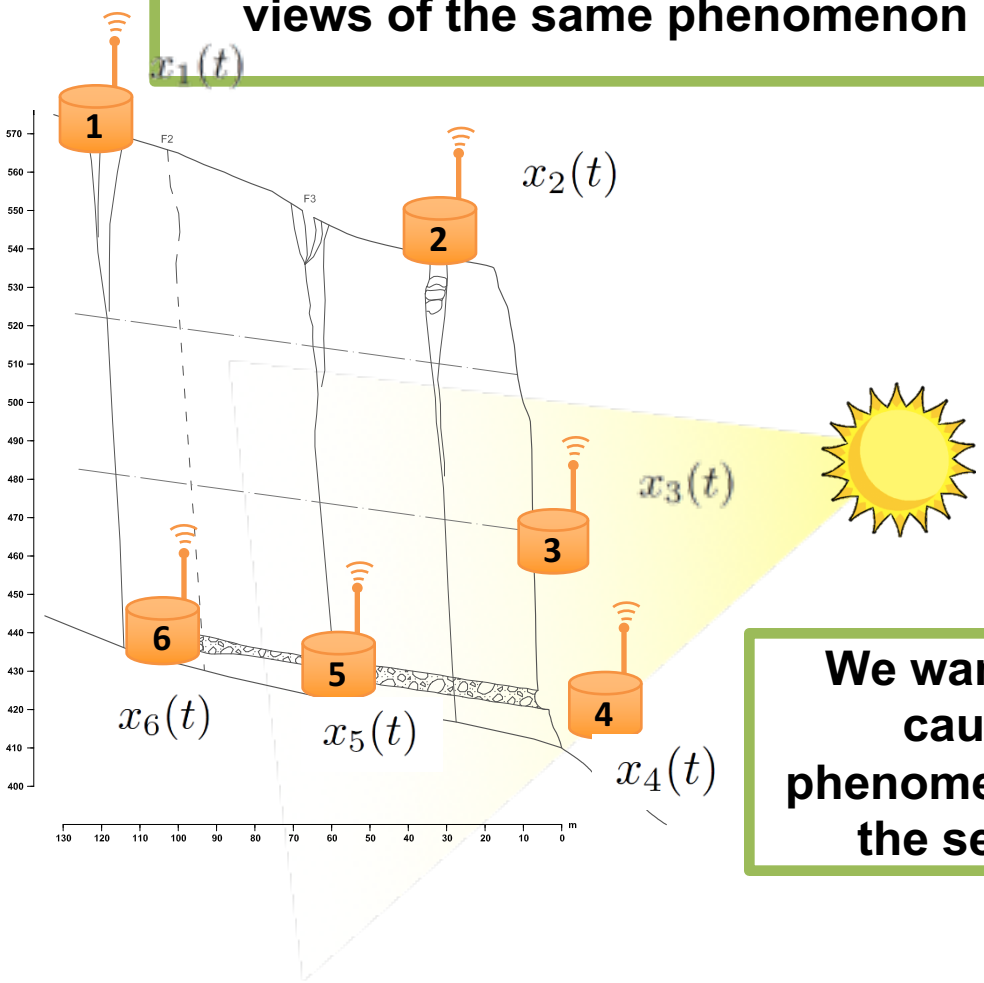
Able to **automatically characterize the nominal state and the faults**, by analyzing the spatial and temporal redundancies existing among provided data

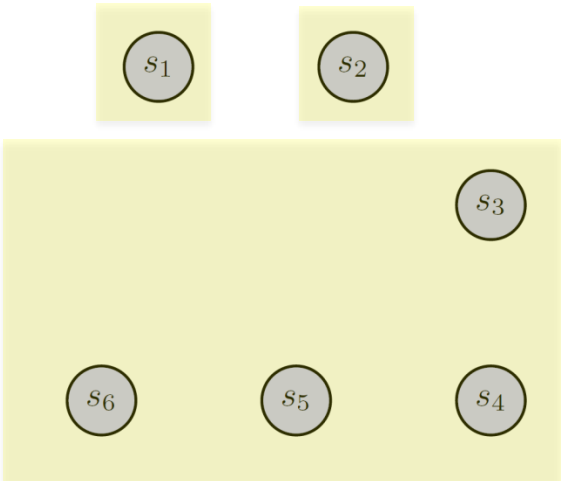
Active field since existing CFDDS are:

- application specific
- limited to a single aspect of fault detection and diagnosis

Cognitive Approaches: Modeling the Temporal and Spatial Dependency Existing Among Data

Different sensors have different views of the same phenomenon

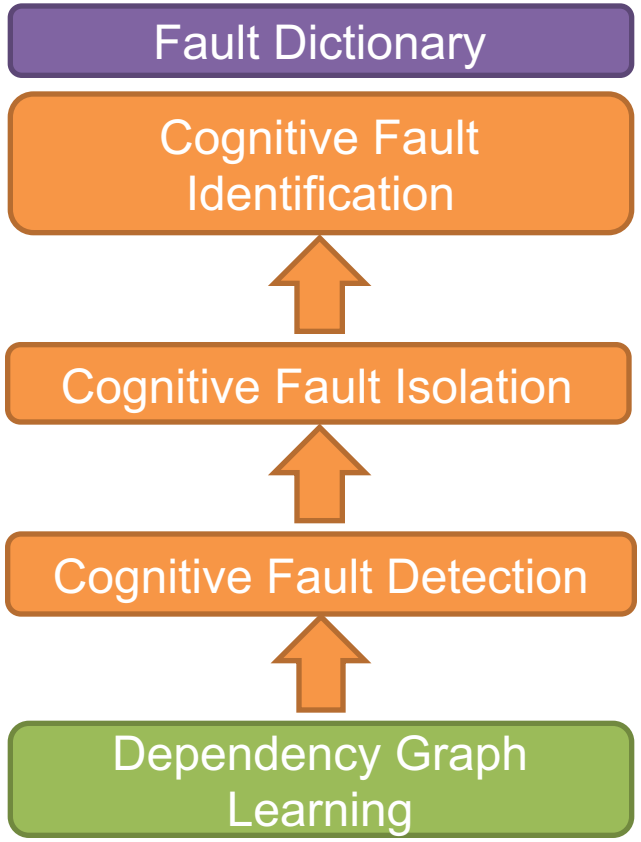


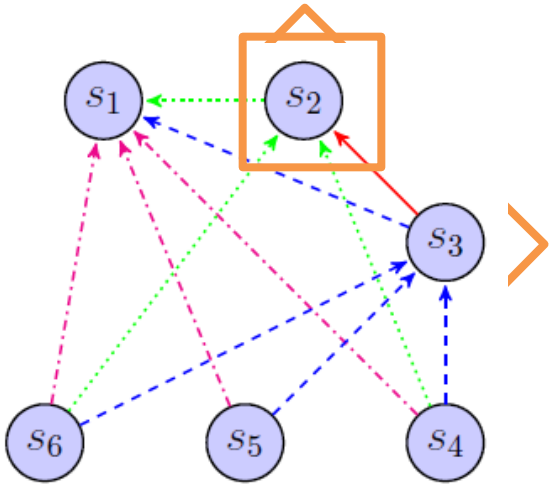


We want to exploit the causality of the phenomenon reflected by the sensor network

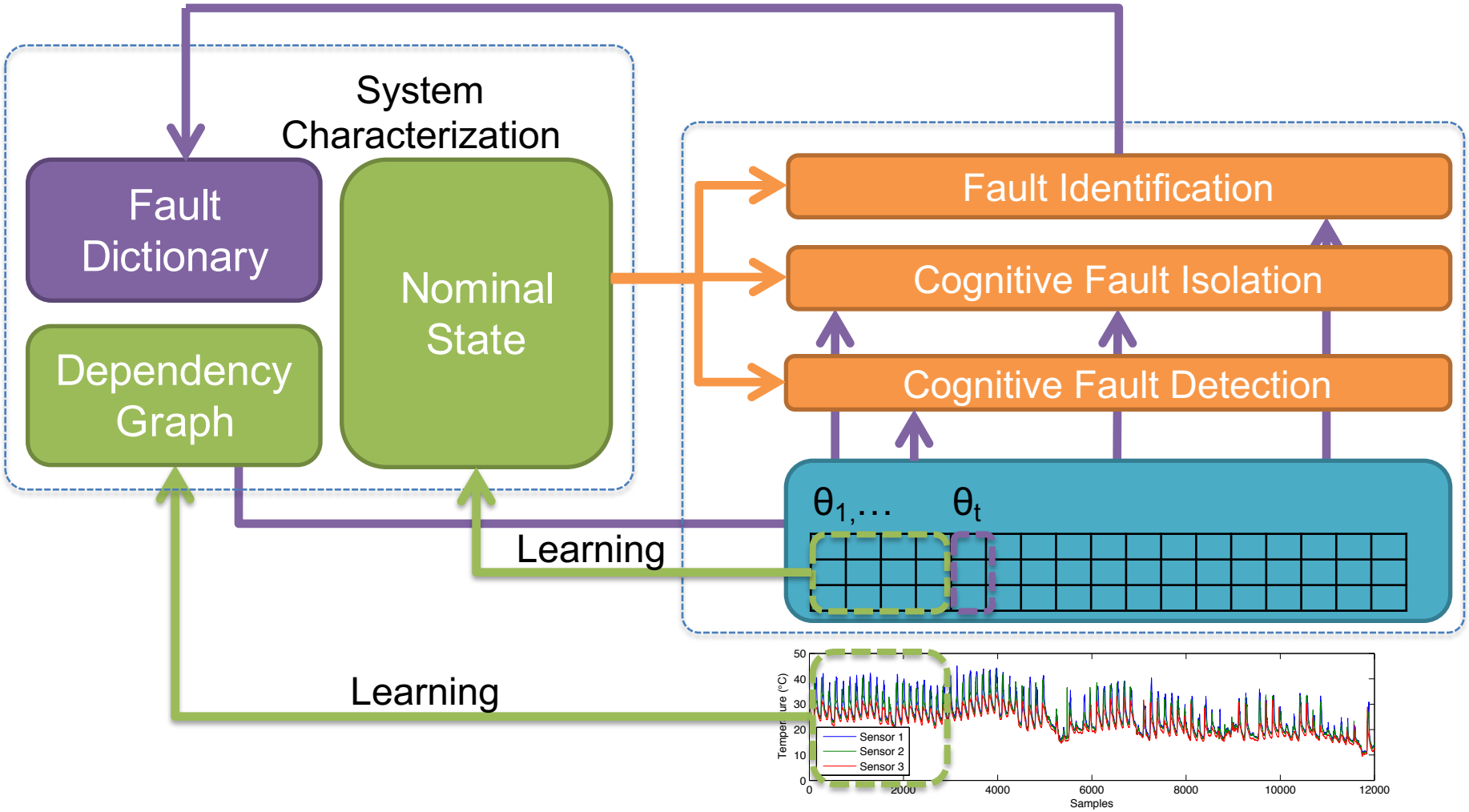
Unit
3,4,5,6
2
1

Cognitive Fault Diagnosis in Sensor Networks

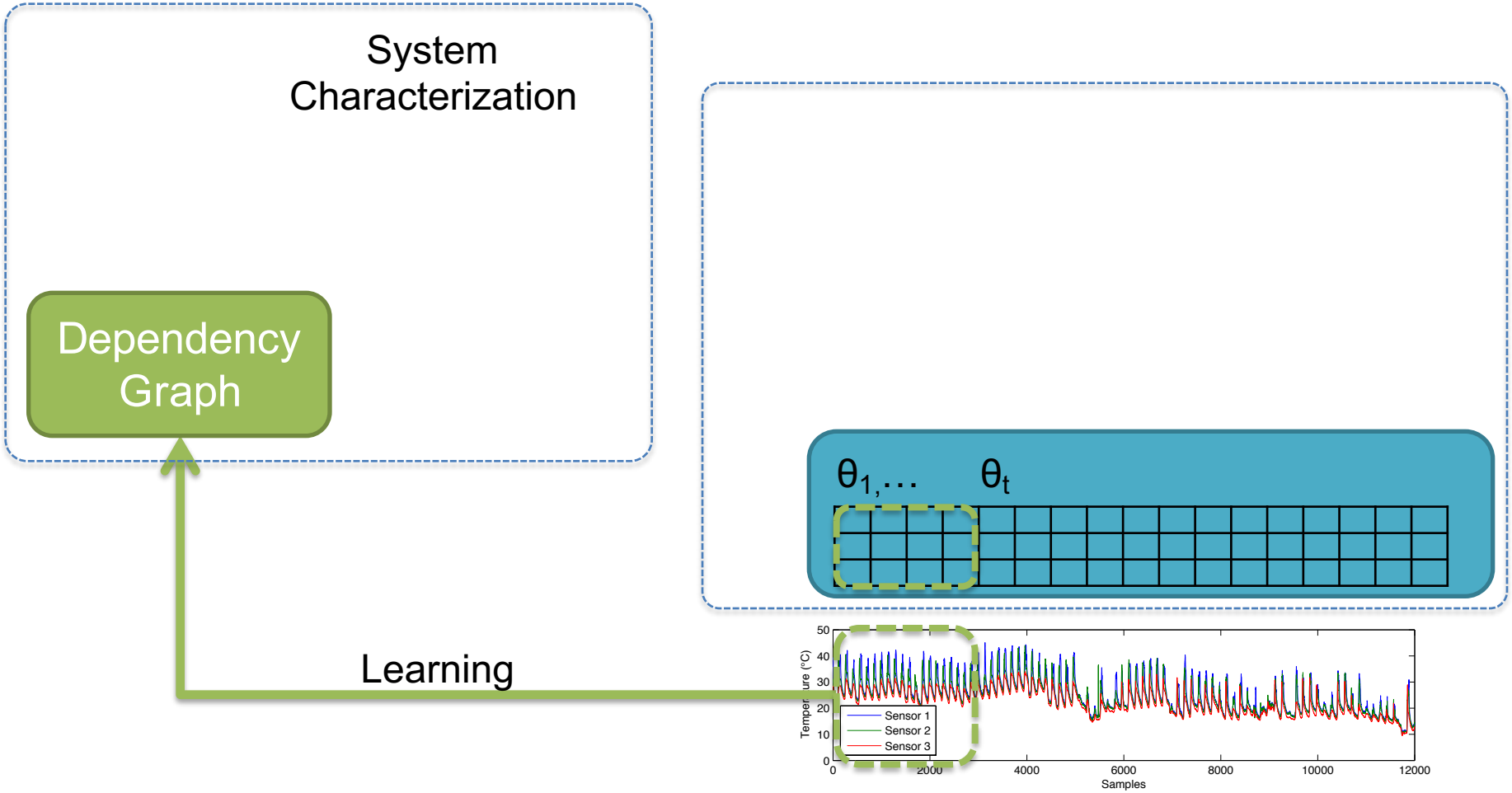




A General Architecture for CFDDS

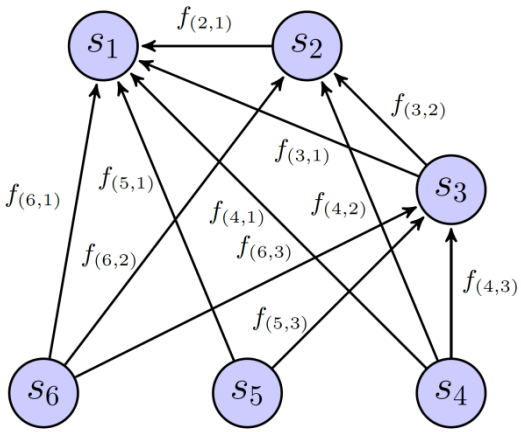


1) Dependency Graph Learning Phase



Dependency Graph Learning

Algorithm based on a theoretically-grounded statistical test to evaluate the dependency between data streams



Considers the **Multivariate Conditioned Granger Causality**

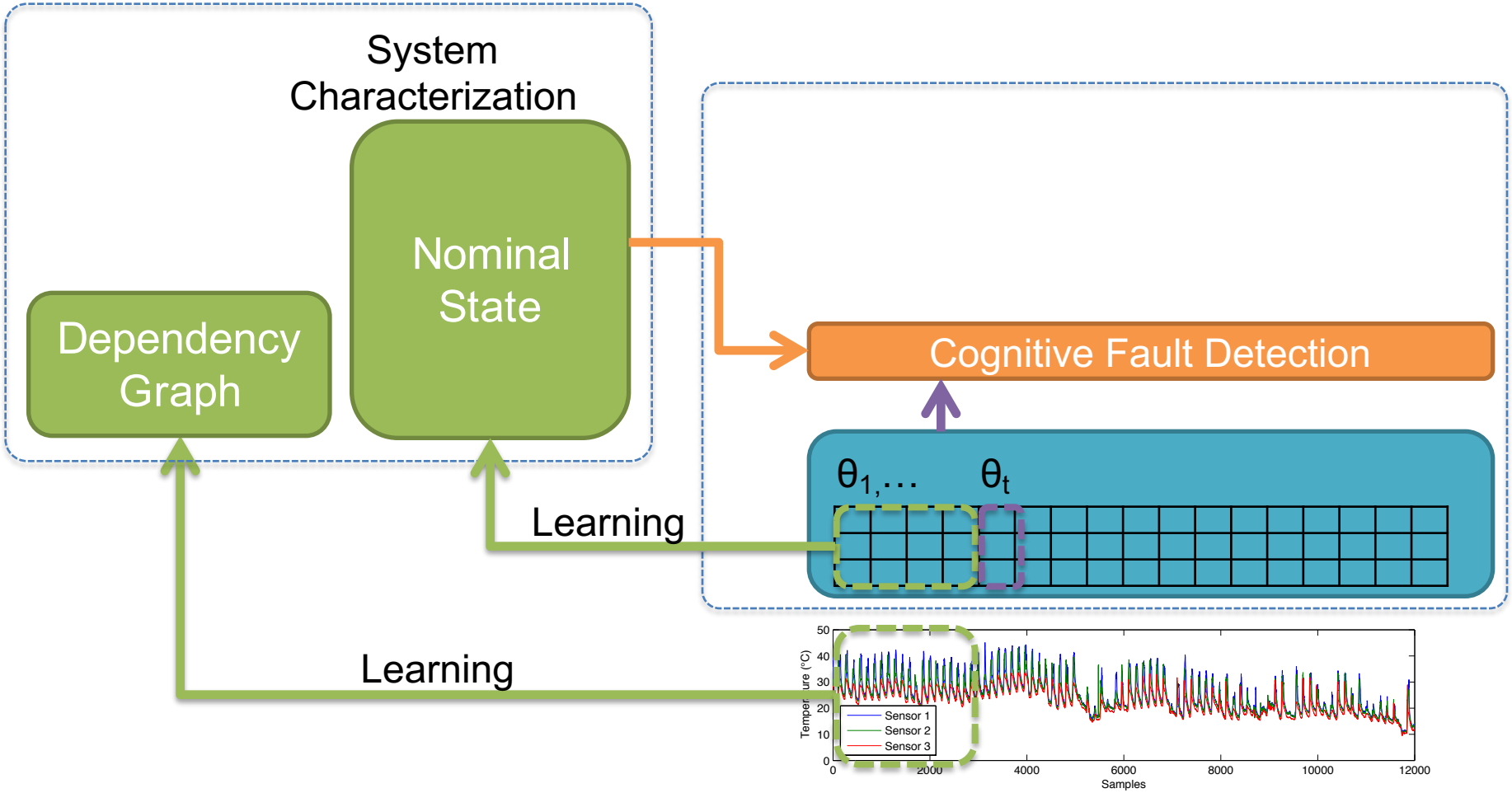
Algorithm 2 Granger-Based Dependency Graph Learning Algorithm

Input: faulty-free dataset $Z_{M,M}$, confidence level α_g
Output: dependency graph $\mathcal{G}$
Set an empty dependency graph $\mathcal{G} = (V, E)$, with $V = \{s_1, \dots s_n\}$ and $E = \emptyset$
for $j \in \{1, \dots, n\}$ **do**
  Estimate coefficients $\hat{a}_{ijk}$ of VAR model $\mathcal{M}_f^{(j)}$ from data $Z_{M,M}$;
  for $i \in \{1, \dots, n\}$ **do**
    if $i \neq j$ **then**
      Estimate coefficients $\hat{a}'_{ijk}$ of VAR model $\mathcal{M}_r^{(ij)}$ from data $Z_{M,M}$;
      Compute F_{ij};
      if $F_{ij} \geq F_{\frac{\alpha_g}{n(n-1)}}(p_f - p_r, M - p_f - 1)$ **then**
        $E \leftarrow E \cup \{e_{ij}\}$;
      end if
    end if
  end for
end for
return $\mathcal{G}$;

$$\mathcal{M}_f^{(i)} : \; x_i(t) = \sum_{k=1}^{\tau} \sum_{h=1}^{n} a_{ihk} x_h(t-k),$$

$$\mathcal{M}_r^{(ij)} : \; x_i(t) = \sum_{k=1}^{\tau} \sum_{h=1, h \neq j}^{n} a'_{ihk} x_h(t-k),$$

2) Cognitive Fault Detection Phase



Cognitive Fault Detection Phase

Traditional solutions

Fault Detection

- Data driven approaches
- Signal-based techniques
- Model-based methods
- **Cognitive change detection methods**

} Require a priori information on the system or on the faults

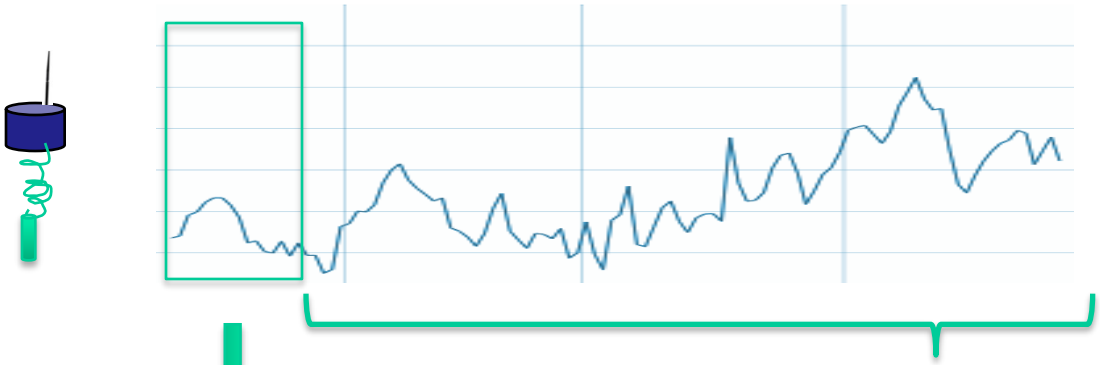
Cognitive solutions

Cognitive Fault Detection

- ICI-based CDT
- HMM-CDT
- Ensemble of HMM-CDT

ICI-based Change Detection Test

Sensing Unit



Estimate the model parameters $\hat{\theta}$

Operational phase (i.e., $y(t), y(t-1), \ldots$)

$\hat{y}(t, \hat{\theta})$

$e(t) = y(t) - \hat{y}(t, \hat{\theta})$

<u>Fault detection action</u>: a change detection test on $e(t)$

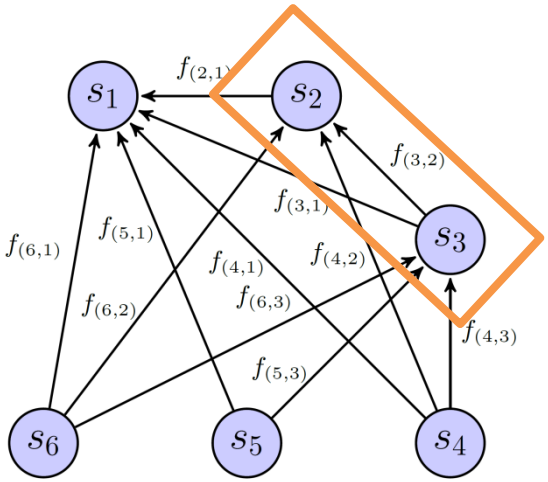
The *ICI-based CDT* assesses the stationary of $e(t)$ over time

Fault Detection and Diagnosis in Parameter Space

Each edge in the dependency graph models a functional constraint between a couple of sensors

$$f_{(i,j)}\left(t, \boxed{\theta}, x_j(t-1), \ldots, x_j(t-\tau_j), x_i(t), \ldots, x_i(t-\tau_i+1)\right)$$

Each functional relationship is approximated with a Linear Time Invariant (LTI) model and analyze the statistical behaviour of the LTI estimated parameter $\boxed{\hat{\theta}}$

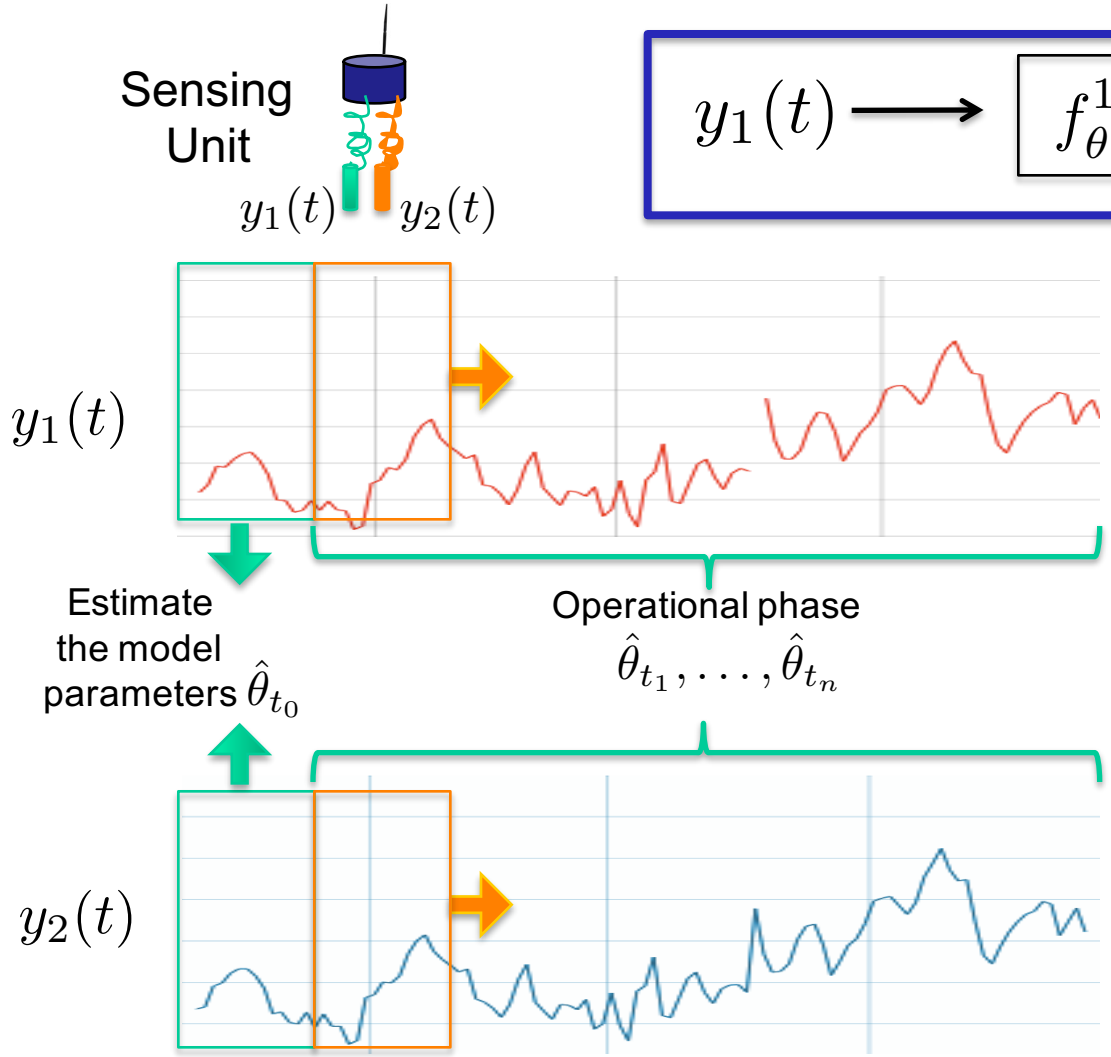


Under weak assumptions over the functional relationship and the estimation process (Ljung):

$$\lim_{N\to\infty} \sqrt{N}\Sigma_N^{-\frac{1}{2}}(\hat{\theta}-\theta^o) \sim \mathcal{N}(0, I_p)$$

Theoretical justification to consider a Gaussian topology of the parameter space

HMM-based Change Detection Test



$$y_1(t) \longrightarrow \boxed{f_\theta^{1,2}} \longrightarrow y_2(t)$$

<u>Fault detection action</u>: model the statistical behavior the $\hat{\theta}_{t_i}$ s by means of HMM

If the likelihood of the HMM decreases below a threshold, a change in the relationship is detected

Cognitive Fault Detection: Ensemble Approach to HMM-based Analysis

Nominal State

Ensemble of HMMs trained over the parameter vectors

$$\Theta_L = (\hat{\theta}_1, \ldots, \hat{\theta}_L)$$

Fault Detection

Evaluate the discrepancy of

$$\Theta_{t,k} = (\hat{\theta}_{t-k+1}, \ldots, \hat{\theta}_t)$$

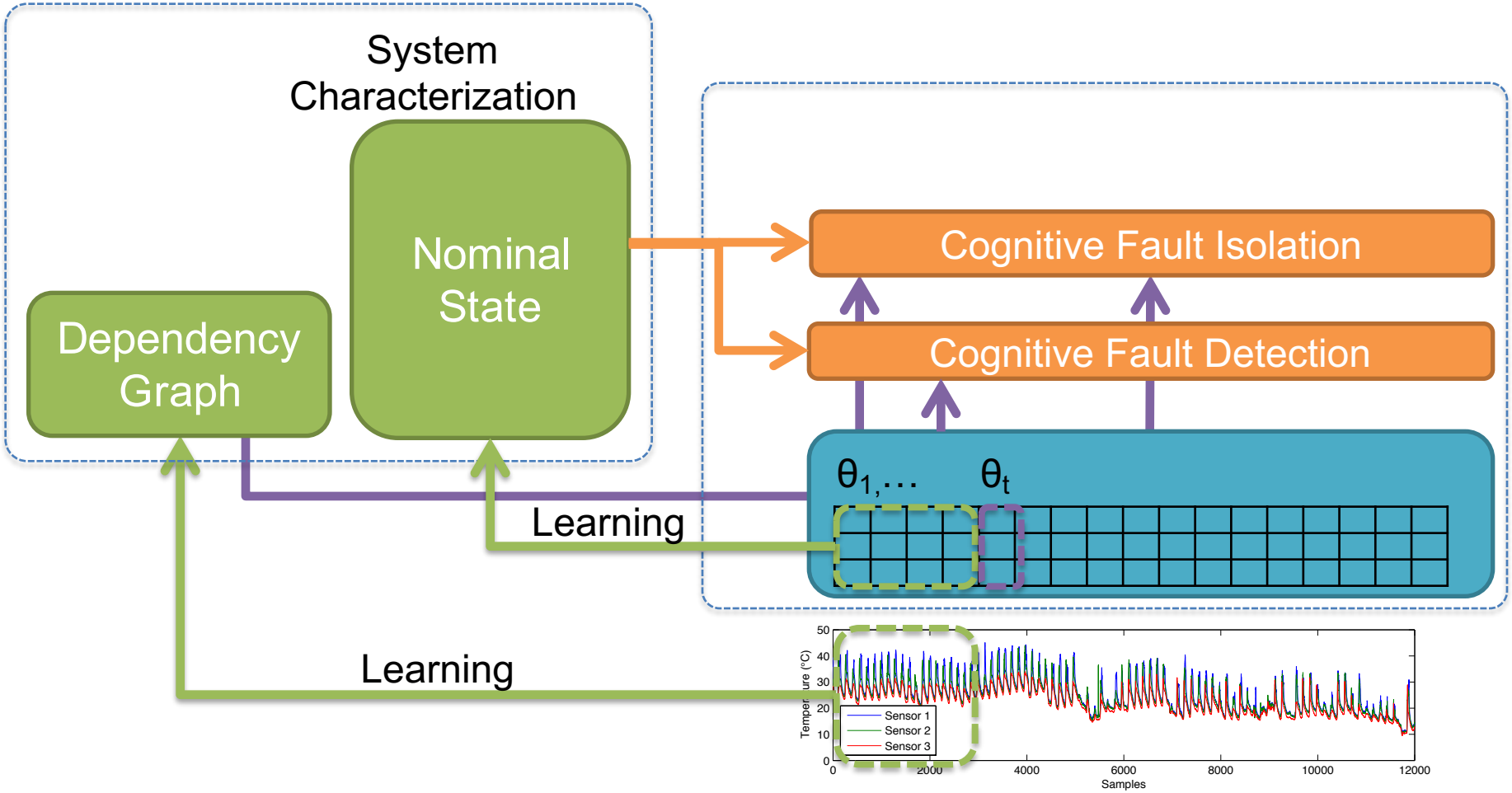
by computing the HMMs loglikelihoods

Algorithm 3 EHMM-CDT algorithm

Data: [illegible] method $\mathcal{A}$, C_D;
Result [illegible]
Estimat [illegible]
for $i \in$ [illegible]
  Estimate HMM $\mathcal{H}_i$ using $\Theta'_{L,M}$ by considering a random initialization point;
end for
Built the ensemble $\mathcal{E} = \{\mathcal{H}_1, \ldots, \mathcal{H}_e\}$;
Estimate the sequence $\Theta'_{M,M+O}$ from $Z^{(ij)}_{O,M+O}$;
for $h \in \{M+k, \ldots, O\}$ **do**
  for $i \in \{1, \ldots, e\}$ **do**
    Compute $l(\mathcal{H}_i, \Theta'_{k,h})$;
  end for
  Compute $\mathcal{A}(h) = \mathcal{A}(l(\mathcal{H}_1, \Theta'_{k,h}), \ldots, l(\mathcal{H}_e, \Theta'_{k,h}))$;
end for
Compute $\mathcal{T}$;
while a new couple $[x_i(t), x_j(t)]$ is available at time t **do**
  Estimate $\hat{\theta}_t$ by using $Z^{(ij)}_{N,t}$;
  Built the sequence $\Theta'_{k,t}$;
  for $i \in \{1, \ldots, e\}$ **do**
    Compute $l(\mathcal{H}_i, \Theta'_{k,t})$;
  end for
  Compute $\mathcal{A}(t) = \mathcal{A}(l(\mathcal{H}_1, \Theta'_{k,t}), \ldots, l(\mathcal{H}_e, \Theta'_{k,t}))$
  if $\mathcal{A}(t) \leq \mathcal{T}$ **then**
    return $T \leftarrow t$;
  end if
end while
return $T \leftarrow \emptyset$;

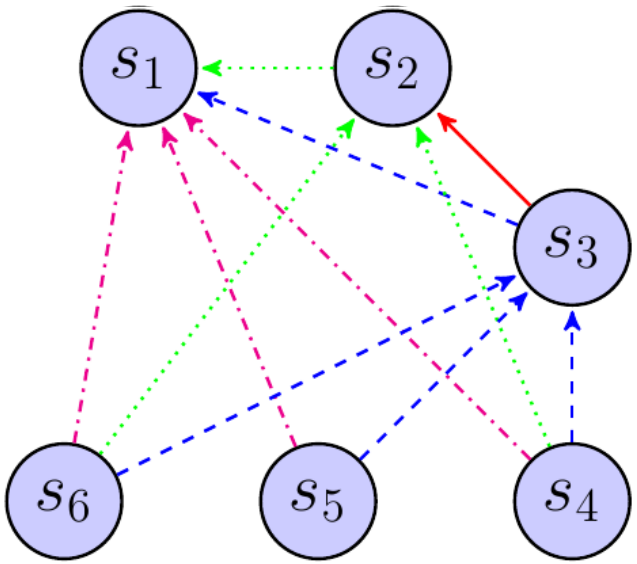
Gaussian emission probabilities for HMM

3) Cognitive Fault Isolation Phase



Cognitive Fault Isolation

Given a detection on $f_{(3,2)}$



Logic partition of the dependency graph

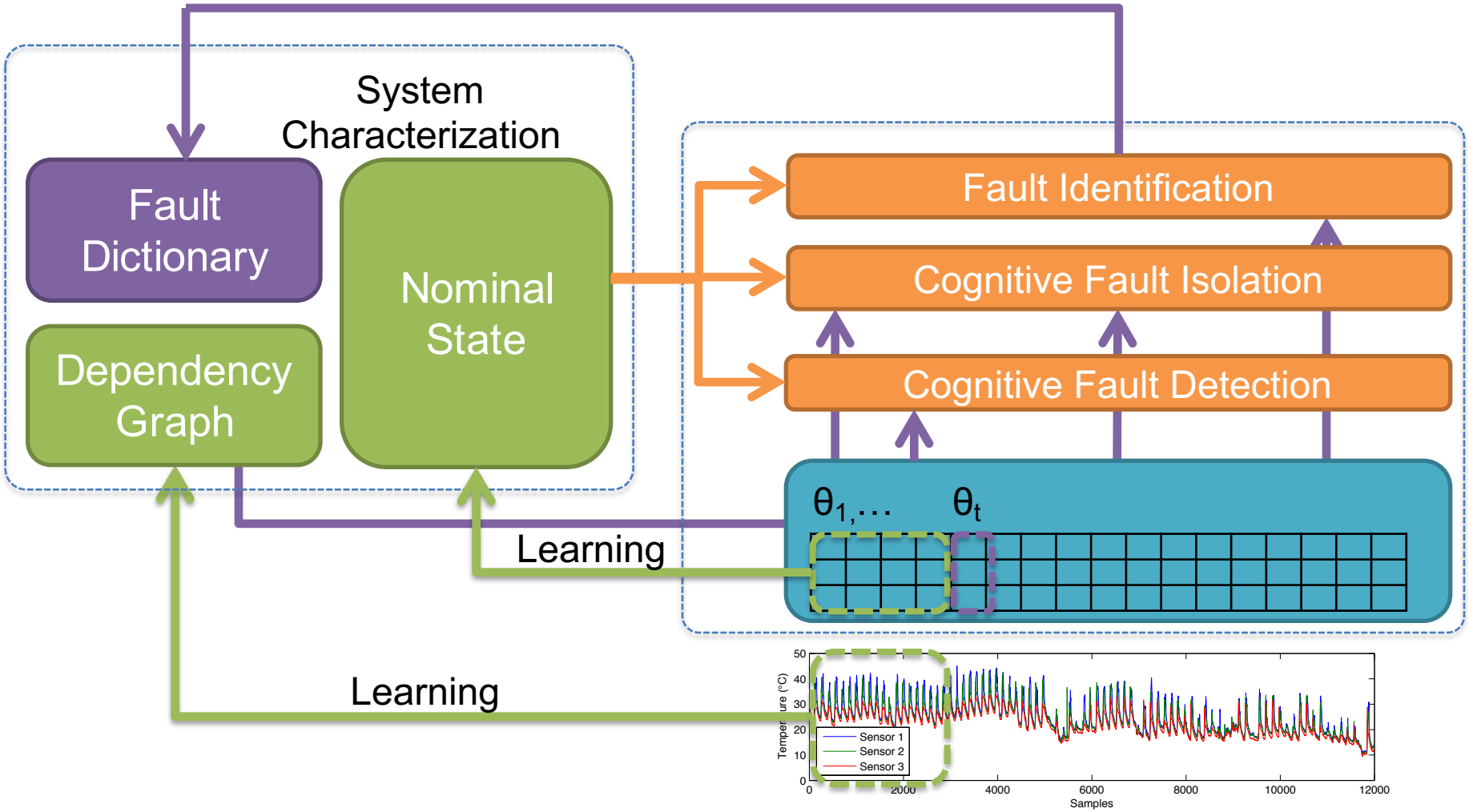
We consider the HMM loglikelihoods on different group of relationships

Fault in S_2

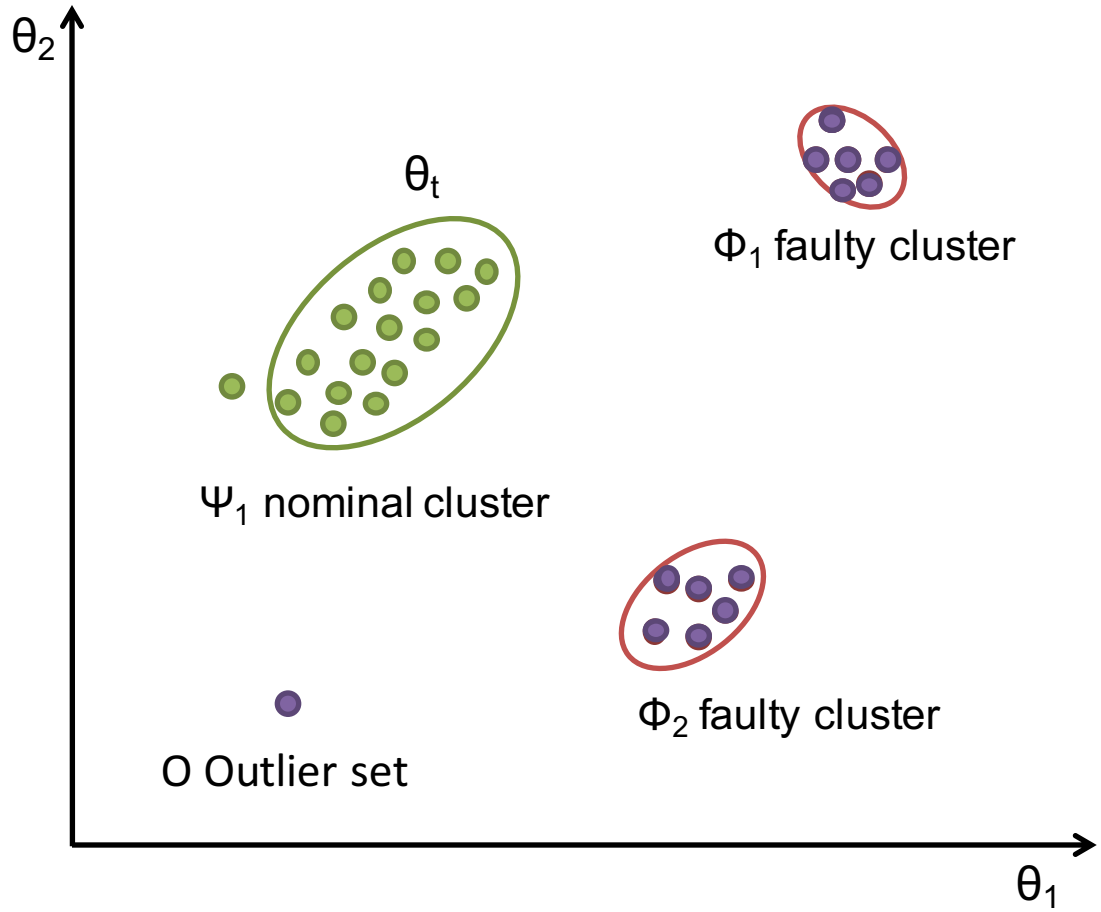
Fault in S_3

Change in the environment

4) Cognitive Fault Identification Phase



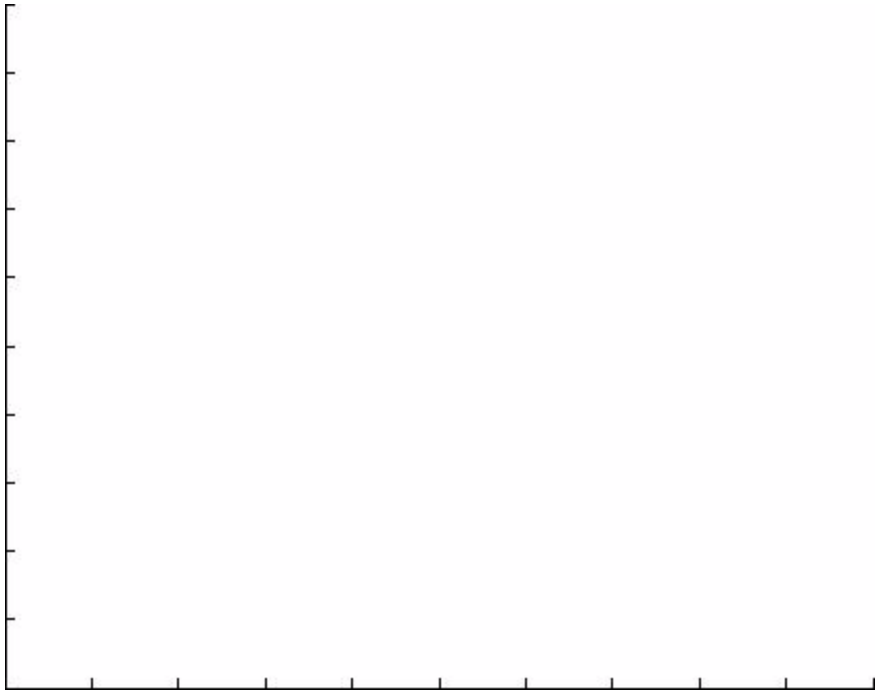
Evolving Clustering in Parameter Space



Algorithm 4 Evolving Clustering-Based Identification Algorithm

Data: Training set $Z^{(ij)}_{M,M}$; α_s, α_m, η_t;
Results: Nominal cluster Ψ, Fault dictionary Φ;
Compute mean $\bar{\theta}_\Psi$ and covariance matrix S_Ψ for the nominal state cluster
Set $n_\Psi = L$ and $t_\Psi = L$;
Set $\Phi = \emptyset$ ($\phi = 0$) and $O = \emptyset$;
while A new $\hat{\theta}_i$ is available **do**
  if the spatial condition holds Ψ **then**
    Associate $\hat{\theta}_i$ to Ψ;
    if $|t_\Psi - i| \leq \eta_t$ **then**
      Update Ψ;
    end if
    $t_{\Psi^*} \leftarrow i$;
  else
    if $\phi > 0$ and the spatial condition holds for at least one $\Phi_j \in \Phi$ **then**
      Select Φ^* minimizing the Mahalanobis distance;
      Associate $\hat{\theta}_i$ to Φ^*;
      if $|t_{\Phi^*} - i| \leq \eta_t$ **then**
        Update Φ^*;
        for $\hat{\theta}_h \in O$ **do**
          if the spatial condition holds for Φ^* **then**
            Remove $\hat{\theta}_h$ from outlier set O
            Associate $\hat{\theta}_h$ to Φ^*
            if $|t^*_\Phi - h| \leq \eta_t$ **then**
              Update Φ^*;
            end if
          end if
        end for
        for $\Phi_j \in \Phi, \Phi \neq \Phi^*$ **do**
          if the merging conditions hold for Φ^*, Φ_j **then**
            Merge Φ^*, Φ_j;
          end if
        end for
      end if
      $t_{\Phi^*} \leftarrow i$
    else
      Insert $\hat{\theta}_i$ in O;
      Create $\bar{O}$ according to cluster creation algorithm
      if $\bar{O} \neq \emptyset$ **then**
        $\phi \leftarrow \phi + 1$
        Create Φ_ϕ using $\hat{\theta}_k \in \bar{O}$
      end if
    end if
  end if
end while

Example of CFDDS Identification phase



Identification Algorithm Key Points

Parameter insertion in clusters

$$m(\theta, \Upsilon_{j^*}) \leq \frac{(\upsilon_{j^*}^2 - 1)p}{\upsilon_{j^*}(\upsilon_{j^*} - p)} F_{p,\upsilon_{j^*}-p,\alpha_s} \quad \Rightarrow \quad \frac{\upsilon}{\upsilon+1} m(\theta, \Upsilon) \sim \frac{(\upsilon-1)p}{(\upsilon-p)} F_{p,\upsilon-p}$$

Cluster merging

$$m(\bar{\theta}_{\Upsilon_j}, \Upsilon_k) \leq \frac{(\upsilon_k+1)(\upsilon_j-1)p}{\upsilon_j(\upsilon_k\upsilon_j - \upsilon_k - p + 1)} F_{p,\upsilon_k\upsilon_j-\upsilon_k-p+1,\frac{\alpha_m}{2}}$$

$$m(\bar{\theta}_{\Upsilon_k}, \Upsilon_j) \leq \frac{(\upsilon_j+1)(\upsilon_k-1)p}{\upsilon_k(\upsilon_j\upsilon_k - \upsilon_j - p + 1)} F_{p,\upsilon_j\upsilon_k-\upsilon_j-p+1,\frac{\alpha_m}{2}} \quad \Rightarrow \quad \frac{\upsilon'\upsilon}{\upsilon'+1} m(\bar{\theta}_\Upsilon, \Upsilon') \sim \frac{\upsilon'(\upsilon-1)p}{(\upsilon'\upsilon - \upsilon' - p + 1)} F_{p,\upsilon'\upsilon-\upsilon'-p+1}$$

Cluster creation

Joint spatial-temporal norm

$$||\theta||_w^2 = w\frac{\sum_{j=1}^{p}(\theta^j)^2}{2p} + (1-w)\frac{|i|}{i_c}$$

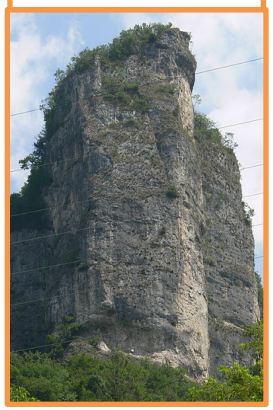
Kolmogorov-Smirnov test

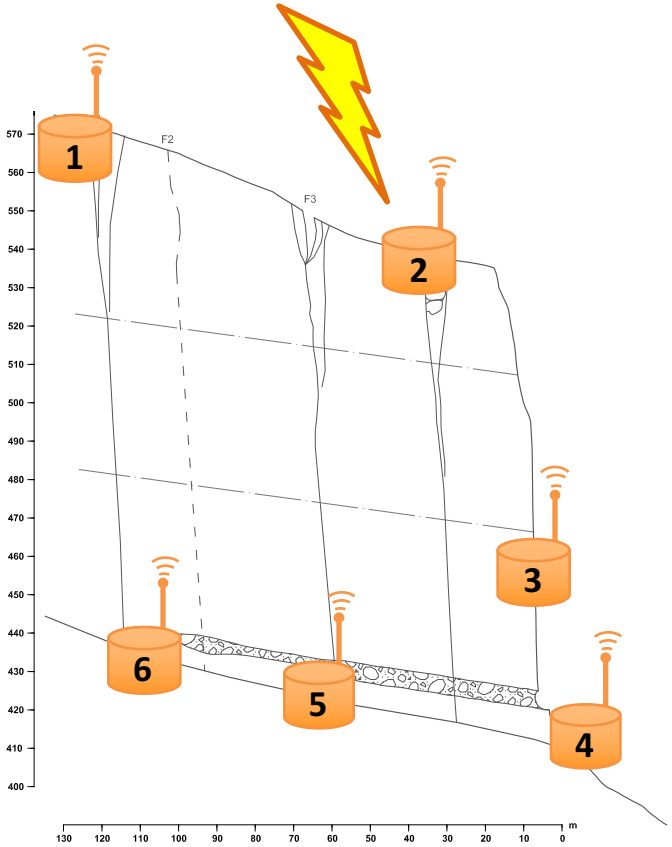
$$H_0 : \hat{F} = F_\Gamma \text{ vs. } H_1 : \hat{F} \neq F_\Gamma$$

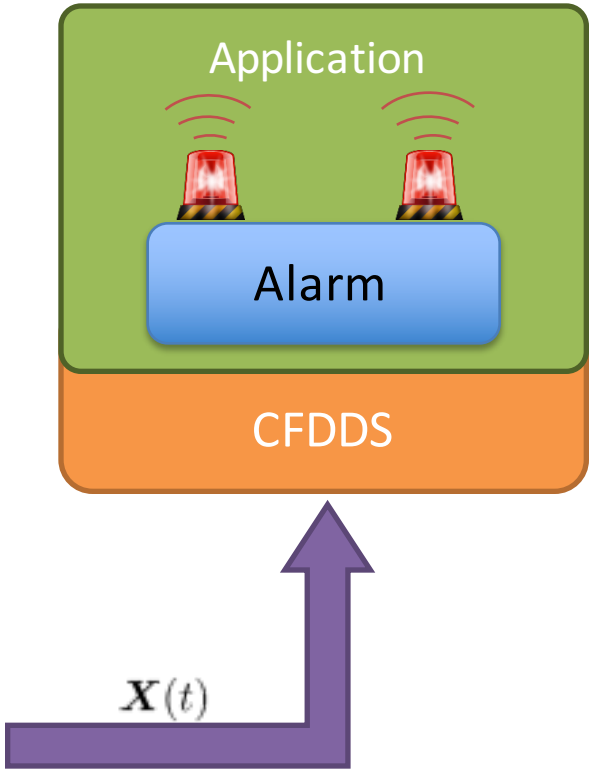
$$D^p = \max_{0\leq\alpha\leq1} |\hat{F}(B_\alpha) - F_\Gamma(B_\alpha)|$$

Applicative Scenario: Environmental Monitoring of Rock Collapse and Landslide

Rialba Towers rock collapse and landslide forecasting system



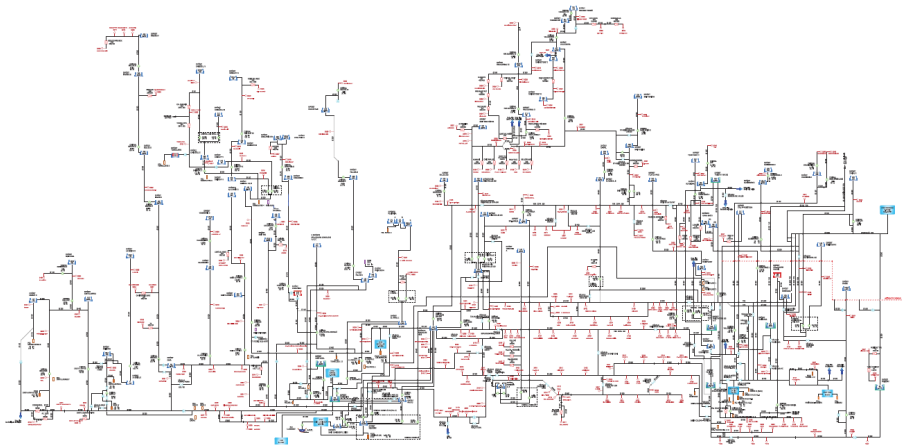


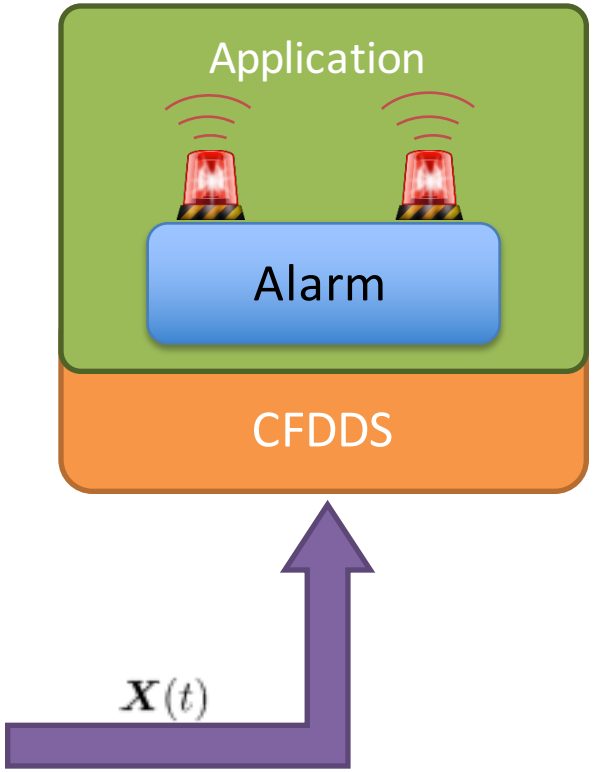


Applicative Scenario: Barcelona WNDS

Complex system even if the physical model of its parts are known

The isolation is fundamental for prompt maintainance of the system





General Comments about Cognitive FDDSs

- FDDSs based on the **cognitive approach** are able to cover all the phases of fault detection and diagnosis in the sensor-based networked embedded scenario

- These systems exploit the temporal and spatial relationship existing among data with the dependency graph, to **characterize the nominal state** of the inspected system and to **learn the fault dictionary** during the operational life of the system, without requiring a priori information