From Centralized to Distributed Fault Detection: an Adaptive Approximation Approach

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Introduction and Motivations

- Huge recent interest in research and applications into reliable methods for diagnosing faults in complex distributed systems
- Fault diagnosis is important to provide controlled processes with high levels of safety, performance and reliability
- Faults in process equipment and instrumentation or within the process itself can result in 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 so that corrective actions can be taken (e.g., manual or automatic reconfiguration).

A Motivating Specific Example

Process Control in the Steel Industry

Several dangerous manual operations

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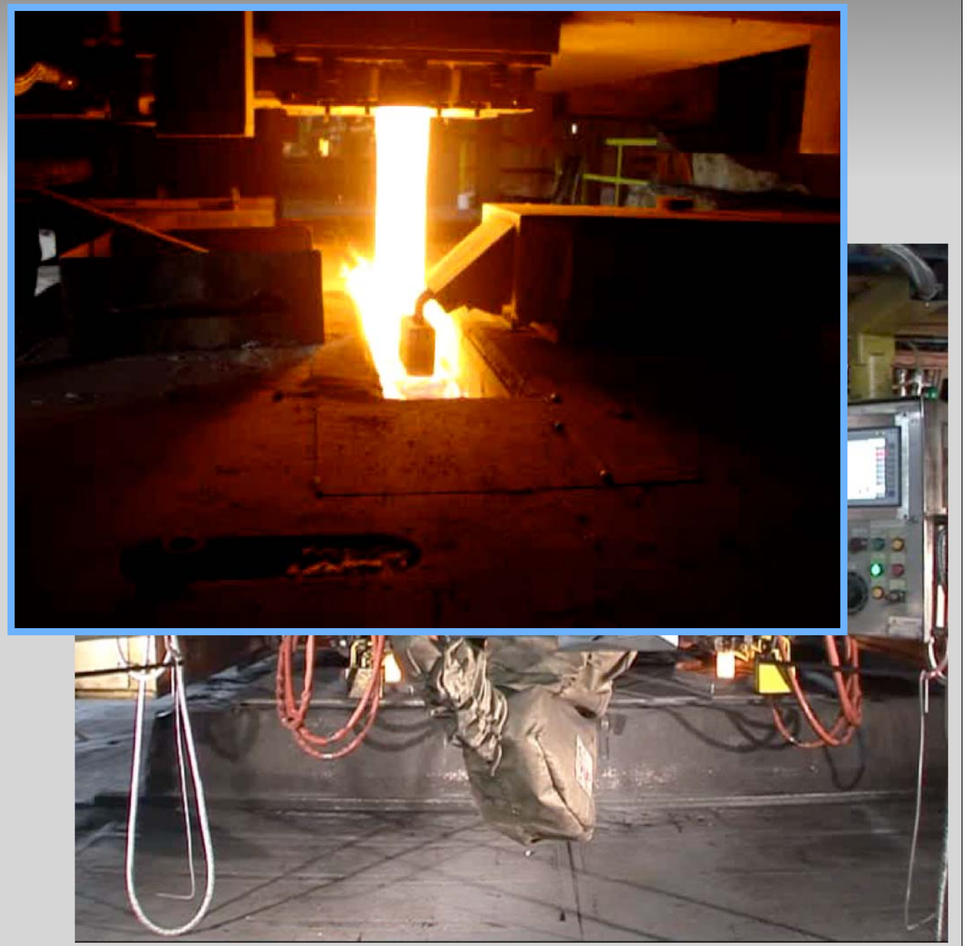
Need for advanced automation systems with high degree of autonomy, availability and dependability



A Motivating Specific Example

Process Control in the Steel Industry

Plant-wide control systems with several levels of hierarchy

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Complex distributed systems with stringent quality and performance requirements

A Motivating Specific Example

Process Control in the Steel Industry

Faults and malfunctions are rather frequent

↓

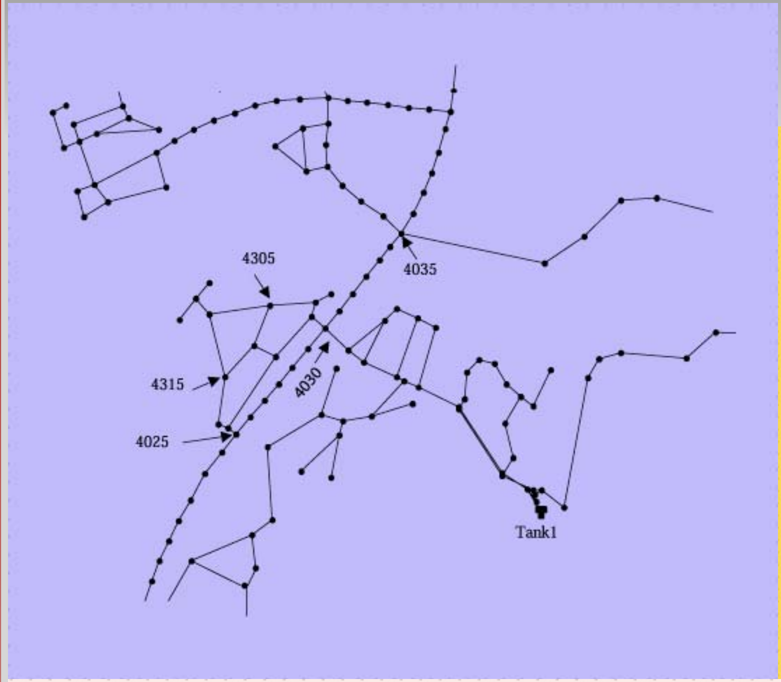
Need for advanced methodologies to timely detect and identify faults during system's operation

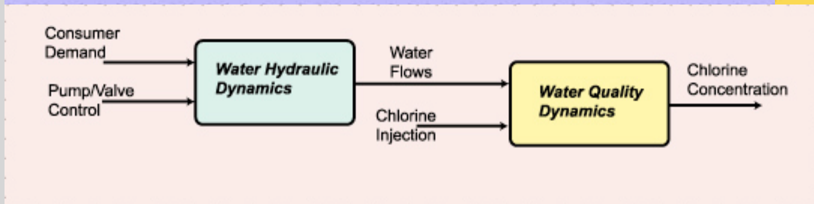
Main Objective

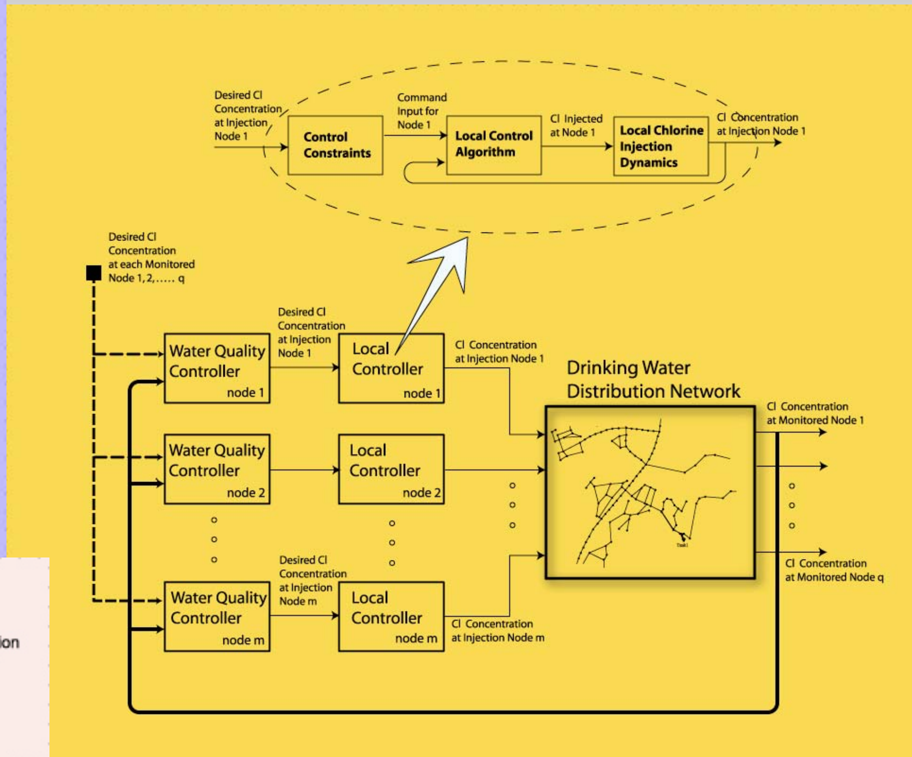
Extend the centralized "learning-based" methodology to the case of distributed systems

Example 1: Water Distribution Networks

Objective: control the spatio-temporal distribution of drinking water disinfectant throughout the network by the injection of appropriate amount of disinfectant at appropriately chosen actuator locations





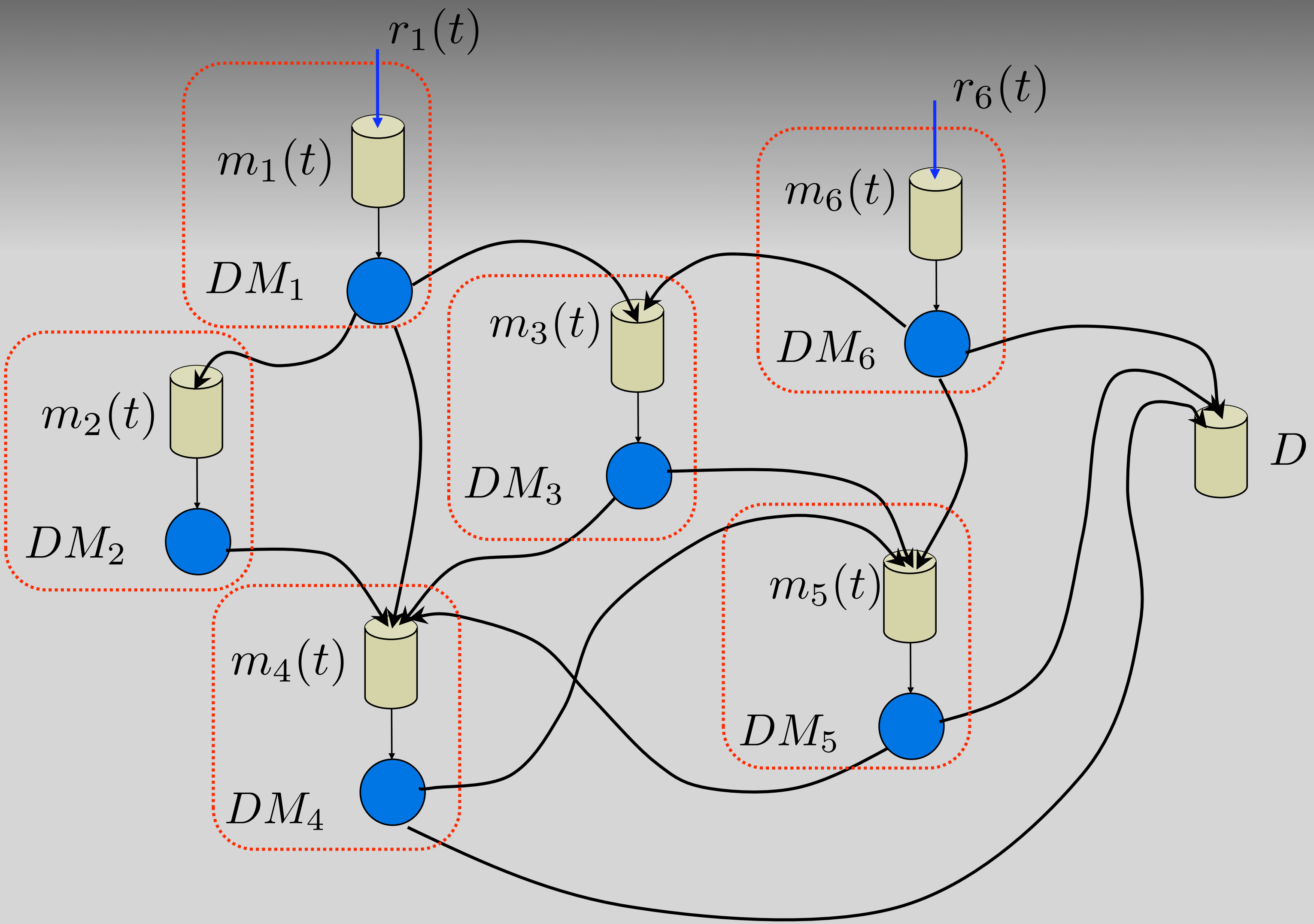


Example 2: Robot Soccer

Objective: By the year 2050, develop a team of fully autonomous humanoid robots that can win against the human world soccer champions.

Robot soccer incorporates various technologies including: design principles of autonomous agents, multi-agent cooperation, strategy acquisition, real-time reasoning, robotics, and sensor-fusion.

Example 3: Dynamic Routing in Traffic Networks



Basic Definitions

Fault → Undesired change in the system that tends to degrade overall system 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 of the fault

Fault Diagnosis System: procedure used to detect and isolate faults and assess their significance/severity

Problem Formulation

Main Approaches

Model-based →

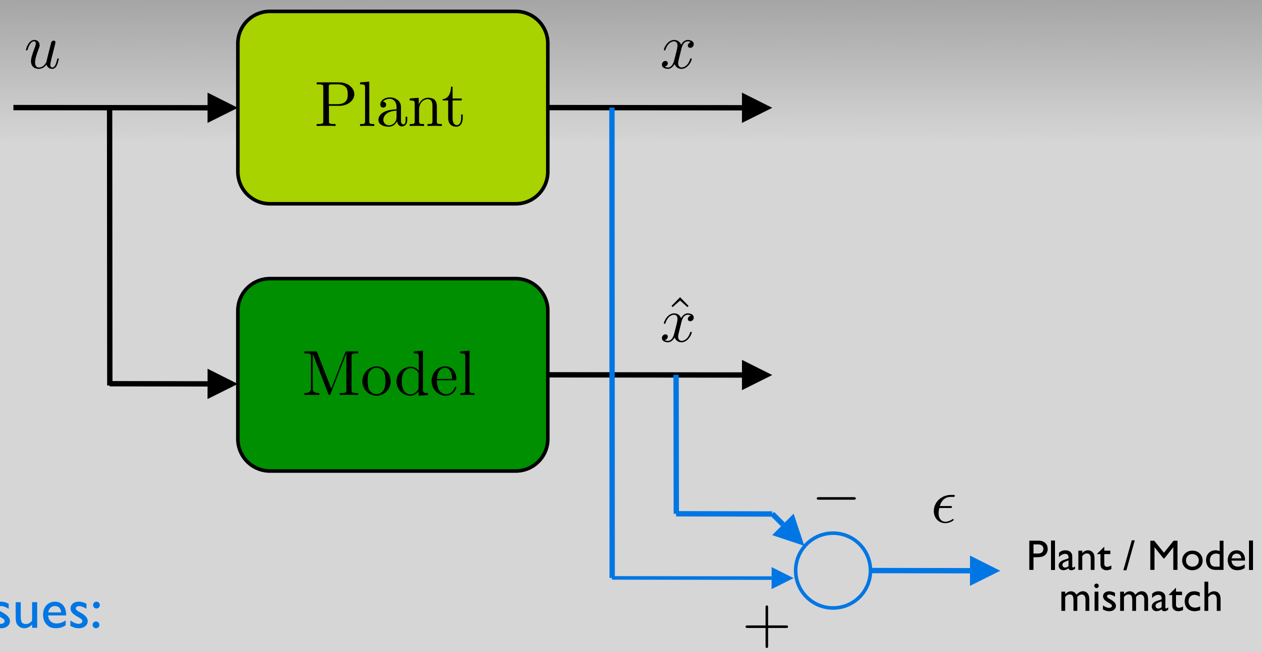
- Analytical redundancy (need for mathematical models)
- State estimation / parameter identification
- Model-uncertainty to be addressed

Model-free →

- Signal-based methods (no need for mathematical models)
- Need for historical data under healthy and faulty modes of behavior

Problem Formulation

Model-based analytical redundancy



Key design issues:

- Effects of modeling uncertainties
- Non-conservative diagnosis thresholds

Problem Formulation

Model

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

where:

- $x \in \Re^n$ state vector
- $u \in \Re^m$ control vector
- $\phi : \Re^n \times \Re^m \mapsto \Re^n$ nominal model dynamics (healthy mode of behavior)
- $\eta : \Re^n \times \Re^m \times \Re^+ \mapsto \Re^n$ modeling uncertainty
- $f : \Re^n \times \Re^m \mapsto \Re^n$ change in the system due to a fault
- $\mathcal{B}(t - T_0)$ matrix function representing the time profiles of the faults

Problem Formulation

Model

Assumption

The system states and controls remain bounded before and after the occurrence of a fault:

there exists some stability region $\mathcal{D} \subset \Re^n \times \Re^m$ such that

$$[x(t), u(t)] \in \mathcal{D}\,,\, \forall\, t \geq 0$$

Problem Formulation

Modeling uncertainty

The modeling error $\eta(\cdot)$ includes external disturbances as well as modeling uncertainties and

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

where for each $i = 1, \ldots, n$ the bounding function $\bar{\eta}_i(x,u,t)$ is

- known
- integrable
- bounded for all $t \geq 0$ and for all (x,u) in some compact region of interest $\bar{\mathcal{D}} \supseteq \mathcal{D}$

Problem Formulation

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.

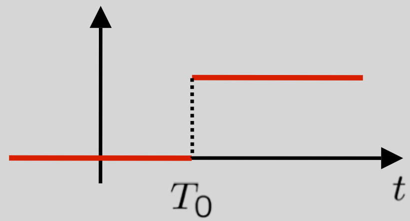
- $f(x, u)$ fault function
- $\mathcal{B}(t - T_0) = \text{diag}\ [\beta_1(t - T_0), \cdots, \beta_n(t - T_0)]$ time profile of a fault which occurs at some unknown time T_0

Problem Formulation

Fault Modeling

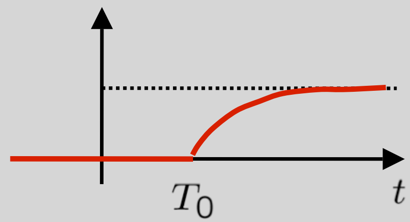
Abrupt

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



Incipient

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



$\alpha_i > 0$ unknown fault evolution rate

Fault Detection and Approximation Estimator

Structure of the Estimator

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

On-line Neural Approximation Model

where:

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

$\hat{f} : \Re^n \times \Re^m \times \Re^p \mapsto \Re^n$ on-line neural approximation model

$\hat{\theta}^0 \in \Re^p$ vector of adjustable weights

$\Lambda^0 = \mathrm{diag}(\lambda_1^0, \cdots, \lambda_n^0)$ where $-\lambda_i^0 < 0$ is the estimator pole

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

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

Healthy situation

Fault Detection and Approximation Estimator

On-line Neural Approximators

$$\hat{f}_i(x, u, \hat{\theta}^0) = \sum_{j=1}^{\nu} c_{ij} \varphi_k(x, u, \sigma_j), \;\; i = 1, \ldots, n$$

where:

$\varphi_j(\cdot, \cdot, \cdot)$ given parametrized basis functions

σ_j given parameter vectors shaping the basis functions $\varphi_j(\cdot, \cdot, \cdot)$

c_{ij} parameters (weights) to be determined:

$$\hat{\theta}^0 = \mathrm{col}\left[c_{ij},\, j = 1, \ldots, \nu; i = 1, \ldots, n\right]$$

in the presence of a fault, $\hat{f}$ provides the adaptive structure for approximating on-line the unknown fault function

Fault Detection and Approximation Estimator

Learning Algorithm

- State estimation error $\epsilon^0 = x - \hat{x}^0$
- Updating law:

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

where

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

$\mathcal{P}_{\Theta^0}$ projection operator on the compact set $\Theta^0 \subset \Re^p$

$$Z = \frac{\partial}{\partial\hat{\theta}^0}\hat{f}(x,u,\hat{\theta}^0)$$

Fault Detection and Approximation Estimator

Learning Algorithm

- $D[\cdot]$ dead-zone operator:

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

$\bar{\epsilon}_i^0(t)$ detection threshold function

Fault Detection and Approximation Estimator

Learning Algorithm: Remarks

- Even in the absence of faults:

$$\eta(x,u,t) \neq 0 \Longrightarrow \epsilon^0(t) \neq 0$$

- $D[\cdot]$ prevents adaptation of $\hat{\theta}^0$ when

$$|\epsilon_i^0(t)| \leq \bar{\epsilon}_i^0(t), \quad i = 1, \ldots, n$$

- The projection operator guarantees stability of the learning algorithm in presence of approximation errors

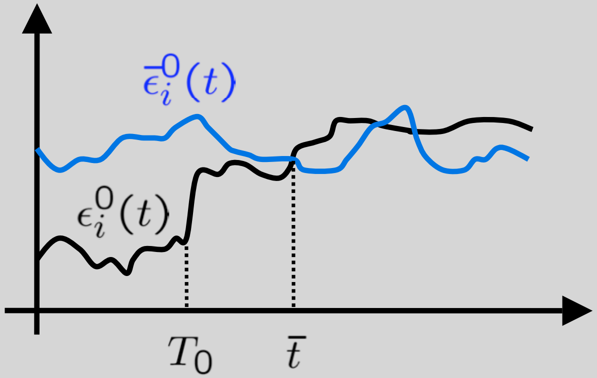
Fault Detection and Approximation Estimator

Fault Detection Decision

A fault is detected if:

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

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



Fault Detection Time:

$$T_d = \inf \bigcup_{i=1}^{n} \left\{ t \geq T_0 : |\epsilon_i^0(t)| > \bar{\epsilon}_i^0(t) \right\}$$

Fault Detection and Approximation Estimator

Fault Detection Threshold

- Absence of faults
- Initial weight vector such that

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

$$|\epsilon_i^0(t)| \le \bar{\epsilon}_i^0(t) = \int_0^t e^{-\lambda_i^0(t-\tau)} \bar{\eta}_i[x(\tau), u(\tau), \tau]\, d\tau$$

Robustness: no false alarms

Fault Detection and Approximation Estimator

Fault Detectability

Theorem 1

For some i there exists an interval $[t_1, t_2],\ t_1 \geq T_0$ such that

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

↳ $|\epsilon_i^0(t_2)| > \bar{\epsilon}_i^0$ fault detected at time $t_2 > T_0$

Towards Distributed Fault Detection

Limitations of Centralized Approach

- The FD problem for a sufficiently large-scale system cannot be solved in practice
- Real-time diagnosis is limited by:
  - Computation power needed for simulating the system model
  - Communication resources needed to convey all the measurements
- Many system that are inherently large-scale and/or spatially distributed may benefit from a DFD architecture

Towards Distributed Fault Detection

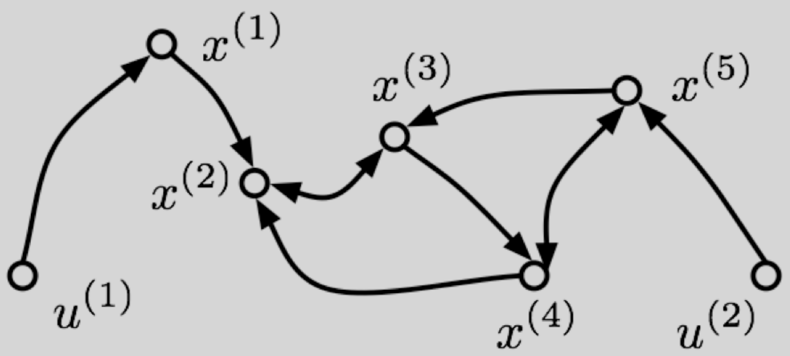
Problem formulation

- Let $\mathcal{S}$ be a large-scale physical system with measurable state $x \in \Re^n$ and input vector $u \in \Re^m$

$$\dot{x} = \phi(x, u)$$

- The structure of $\mathcal{S}$ is described by a digraph $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$ where $\mathcal{N}$ is the set of nodes and

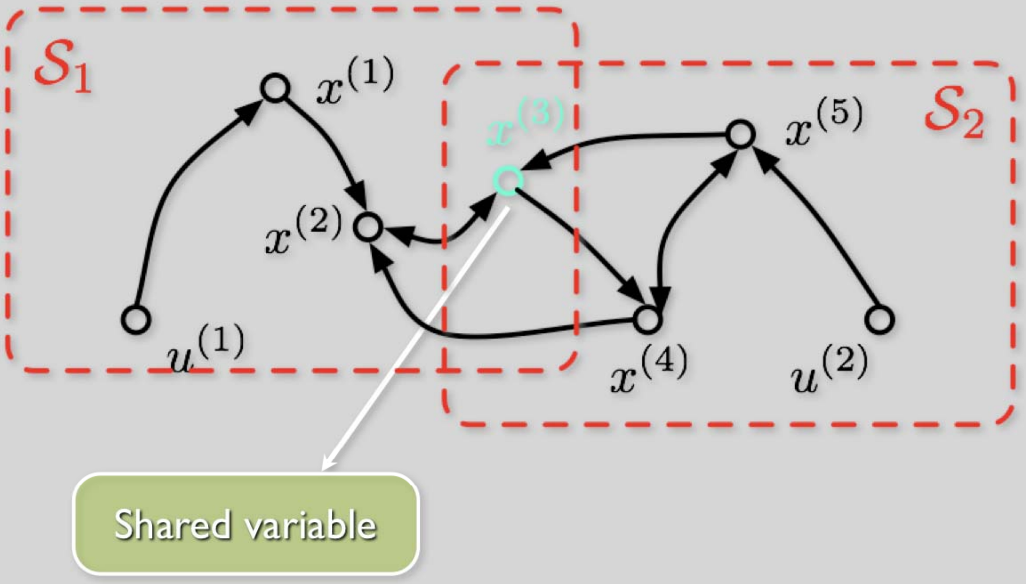
$$\mathcal{E} = \left\{(x^{(i)}, x^{(j)}) \colon x^{(i)} \text{acts on } x^{(j)}\right\} \cup \left\{(u^{(i)}, x^{(k)}) \colon u^{(i)} \text{acts on } x^{(k)}\right\}$$



Towards Distributed Fault Detection

Problem formulation: decomposition

- $\mathcal{S}$ may be decomposed into N subsystems $\mathcal{S}_i$ by introducing extraction index sets $\mathcal{I}_i$ so that
  - $x_i = \mathrm{col}(x^{(k)} : k \in \mathcal{I}_i)$ local state
  - $u_i = \mathrm{col}(u^{(k)} : (u^{(k)}, x^{(j)}) \in \mathcal{E},\ j \in \mathcal{I}_i)$ local input



Towards Distributed Fault Detection

Problem formulation: decomposition

- The dynamics of $\mathcal{S}_i$ is decomposed into a local nominal function and an interconnection function

$$\dot{x}_i = \phi_i(x_i, u_i) + g_i(x_i, \bar{x}_i, u_i)$$

- $\bar{x}_i$ is the vector of interconnection variables by which the neighboring subsystems $\mathcal{S}_j,\ j \in \mathcal{J}_i$ affect $\mathcal{S}_i$
- $\mathcal{J}_i$ is the neighbors index set

$$\mathcal{J}_i = \left\{ j \colon (x^{(l)}, x^{(m)}) \in \mathcal{E},\ l \in \mathcal{I}_j,\ m \in \mathcal{I}_i,\ i \neq j \right\}$$

Towards Distributed Fault Detection

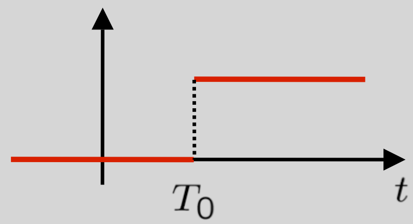
Problem formulation: faults

- The fault is modeled analogously to the centralized case

$$\dot{x}_i = \phi_i(x_i, u_i) + g_i(x_i, \bar{x}_i, u_i) + \mathcal{B}_i(t - T_0) f_i(x_i, \bar{x}_i, u_i)$$

- $\mathcal{B}_i(t - T_0)$ fault time profile
  - Only abrupt faults are considered:

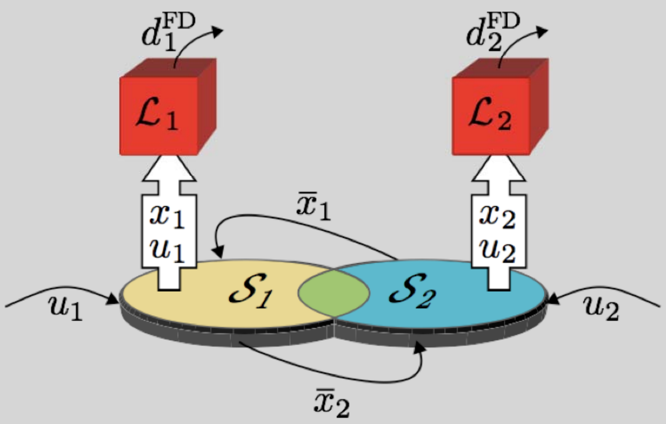
$$\beta_i(t - T_0) = \begin{cases} 0 & \text{if} \quad t < T_0 \\ 1 & \text{if} \quad t \geq T_0 \end{cases}$$



Towards Distributed Fault Detection

DFD Architecture

- Given a decomposition of a system into N subsystems $\mathcal{S}_i$
- A network of N Local Fault Detectors (LFD) provides fault decisions d_i^{FD} regarding the subsystems health
- The LFDS are allowed to take direct measurements of local variables x_i and u_i , and exchange the interconnection variables $\bar{x}_i$ via fault-free links
- LFDs monitoring shared variables may take a common decision by allowing more communication and employing consensus techniques



Towards Distributed Fault Detection

LFD structure

- LFDs involving only non-shared variables take on the same structure as in the centralized case
- LFDs involving shared variables have to cooperate on detection decision via a consensus mechanism towards a common improved decision
- The estimators using consensus on shared variables take on the form

smoothes disagreements

smoothes estimation error

$$\dot{\hat{x}}_i^{(s_i)} = -\lambda \left[\sum_{j \in \mathcal{O}_s} \left(\hat{x}_i^{(s_i)} - \hat{x}_i^{(s_j)} \right) + d_s \left(\hat{x}_i^{(s_i)} - x_i^{(s_i)} \right) \right] + \frac{1}{d_s} \sum_{j \in \mathcal{O}_s} \left[\phi_j^{(s_j)}(x_j, u_j) + \hat{g}_j^{(s_i)}(x_j, \bar{x}_j, u_j, \hat{\theta}_j) \right]$$

average of dynamical models

Towards Distributed Fault Detection

Results and Remarks

- Without consensus LFDs with low mismatch and/or high uncertainties may not reach a detection decision
- The proposed consensus-based estimation scheme could improve LFDs' detection capabilities because of the information provided by other LFDs with higher mismatches and lower uncertainties
- The influence of the interconnections is learned on-line via an adaptive neural approximation scheme
- Analytical, simulation, and experimental results have been obtained on fault detectability for distributed systems

Towards Distributed Fault Detection

Open issues

- Fault identification
- Learning-stopping algorithms
- Unreliable communication channels
- Optimal detectability decompositions of large-scale systems