Intelligent Health Monitoring of Critical Infrastructure Systems

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- Power systems
- Water systems
- Telecommunication networks
- Transportation systems

→ Interdependent systems that work together to provide the essential services of a modern society

- **Critical Infrastructure Systems (CIS) are crucial for everyday life and well-being**
  - Citizens expect/rely that CIS will **always** be available (24/7).
  - Citizens expect that they will be managed **efficiently** (low cost).
- **Critical infrastructure systems do fail**
  - Natural disasters (earthquakes, flooding)
  - Accidental failures (equipment failures, human error, software bugs)
  - Malicious attacks (directly, remotely)
- **When critical infrastructures fail the consequences are tremendous**
  - Societal consequences
  - Health hazards
  - Economic effects

- **The problem of managing Critical Infrastructure Systems is expected to get more difficult**
  - CIS were not designed to be so large – they evolved due to growing demand
  - Deregulation has resulted in more heterogeneous and distributed infrastructures, which make them more vulnerable to failures and attacks
  - Renewables and environmental issues present new challenges
  - There are more and more interdependencies between CIS
  - Fewer people understand how these networks work and the interactions between all the components
  - There are no reliable models that can predict their behavior under all the various scenarios
  - Mega-cities: 30 by 2020, 60 by 2050

- Safety critical systems
- Complex, Large-scale
- Data-rich environments
- Spatially distributed
- Dynamic, time-varying, uncertain
- Similarities the underlying dynamics
- Similarities in the impact of failures

Common Objectives

- Need to develop information processing methodologies to extract meaning and knowledge out of the data
- Need to utilize data knowledge to design software, hardware and embedded systems that operate autonomously in some intelligent manner
- Ultimately: real-time decisions in the management of large-scale, complex and safety-critical systems
- Interactions between critical infrastructures
- Smarter Infrastructure Networks

Key Issues

- System Identification, Prediction/Forecasting
- Optimization, Scheduling
- Feedback Control, Coordination/Cooperation
- Fault Monitoring
- Fault Isolation, Fault Accommodation

Networked Intelligent Agent Systems

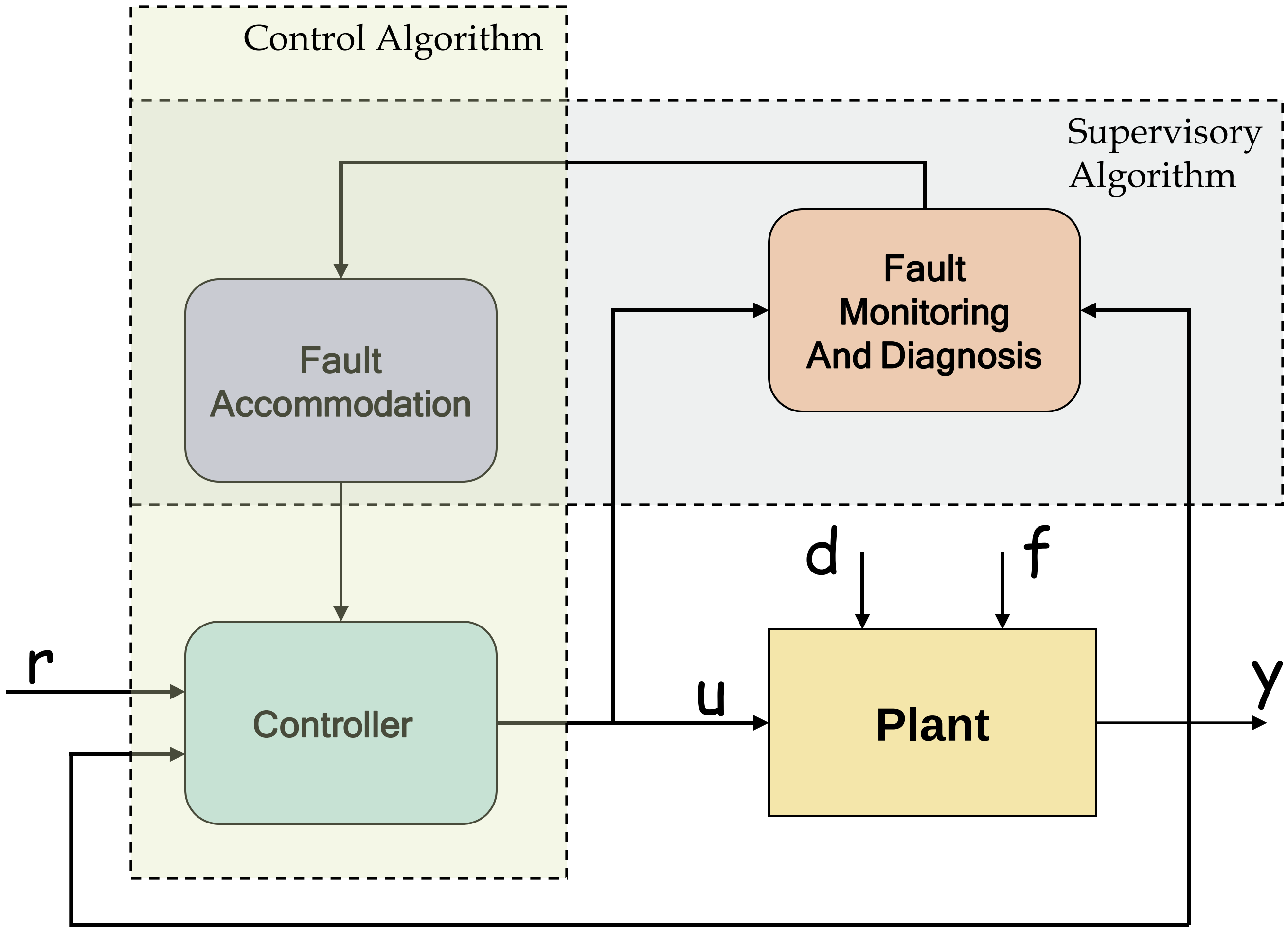
- **Intelligent Agents**
  - Sensing capabilities
  - Actuator capabilities
  - Computing and data processing capabilities
  - Communication capabilities
- **Monitoring and control of CIS using networked intelligent agent systems**
- **Self-adapt and self-improve**
- **Fault accommodation and self-healing**
- **Cooperation between intelligent agents**

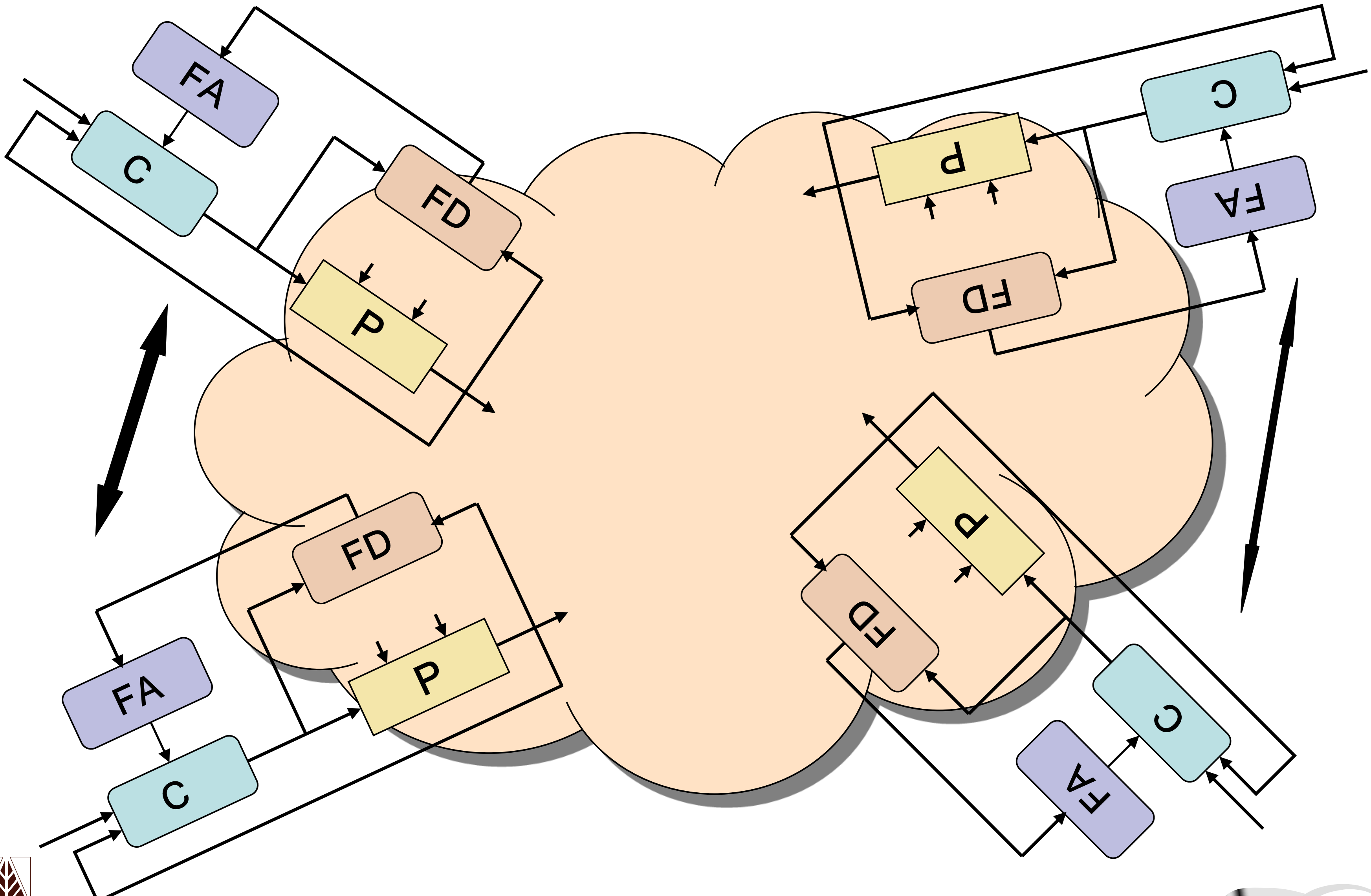
Optimal Placement of Intelligent Agents

- Costly → utilize as many agents as needed
- Sensor/Actuator placement to facilitate:
  - Control Objective
  - Fault Diagnosis Objective
  - Fault Tolerance Objective
  - Security Objective
- Activate as needed?
- Mobile sensor/actuator framework?

→ New system-theoretic approaches are needed for sensor and actuator placement

General Centralized Architecture

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

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

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

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

where for each i = 1, …., 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

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.

Types of FAULT ISOLATION:

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

Class of fault functions f :

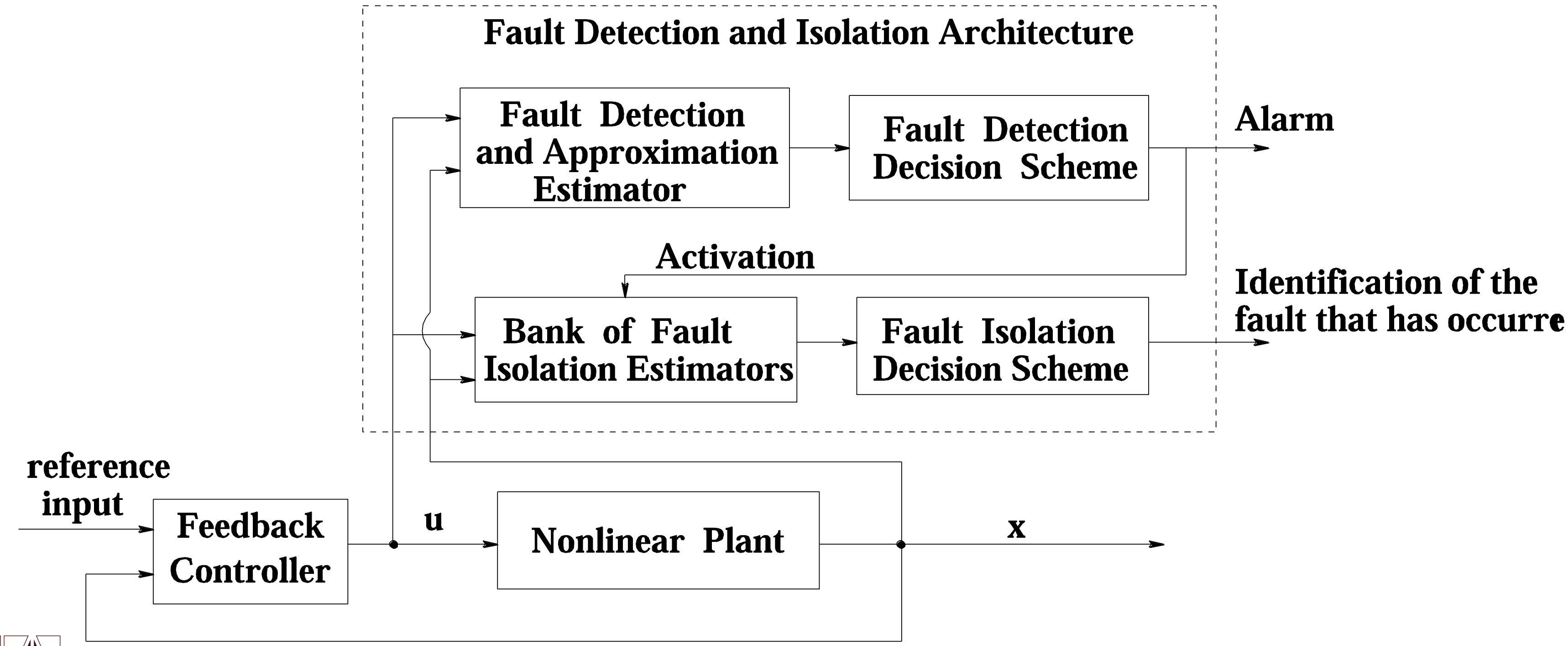
$$f(x,u) \in \mathcal{F} = \left\{ f^1(x,u), \ldots, f^N(x,u) \right\}$$

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

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

- 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 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)

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 the unknown fault function

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

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

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

Dead-zone operator

Learning Algorithm -- Remarks

- **Even in the absence of a fault the modeling error is not necessarily zero, so the threshold is also nonzero**
- **The dead-zone prevents adaptation so that there are no false alarms**
- **The decision for the occurrence of a fault is made when at least one of the thresholds is exceeded**
- **The projection operator is used to guarantee that stability of the learning algorithm in the presence of residual approximations errors**

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

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:

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

- The following is a simplified uniform detection threshold which is robust: $\bar{\epsilon}_i^0 = \bar{\eta}_i/\lambda_i^0$

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.

The fault time profile is incipient fault are modelled as

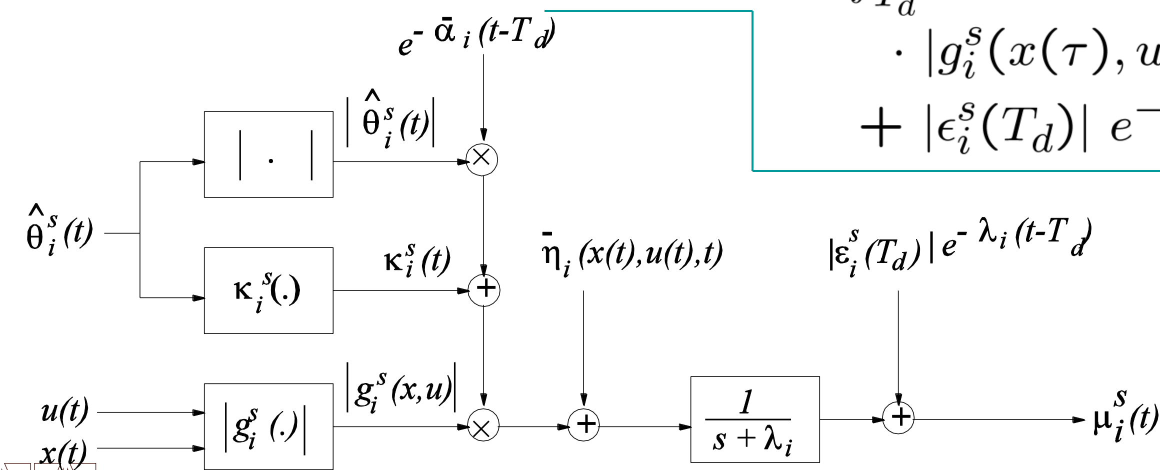
known lower bound for the unknown evolution rate

$$\alpha_i > \bar{\alpha}_i, \quad i = 1, \cdots, n$$

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

Practically implementable adaptive isolation threshold

$$\mu_i^s(t) = \int_{T_d}^{t} e^{-\lambda_i(t-\tau)}\left[\left(\kappa_i^s(\tau) + e^{-\bar{\alpha}_i(\tau-T_d)}|\hat{\theta}_i^s(\tau)|\right) \cdot |g_i^s(x(\tau), u(\tau))| + \bar{\eta}_i\,(x(\tau), u(\tau), \tau)\right]d\tau + |\epsilon_i^s(T_d)|\, e^{-\lambda_i(t-T_d)}.$$



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

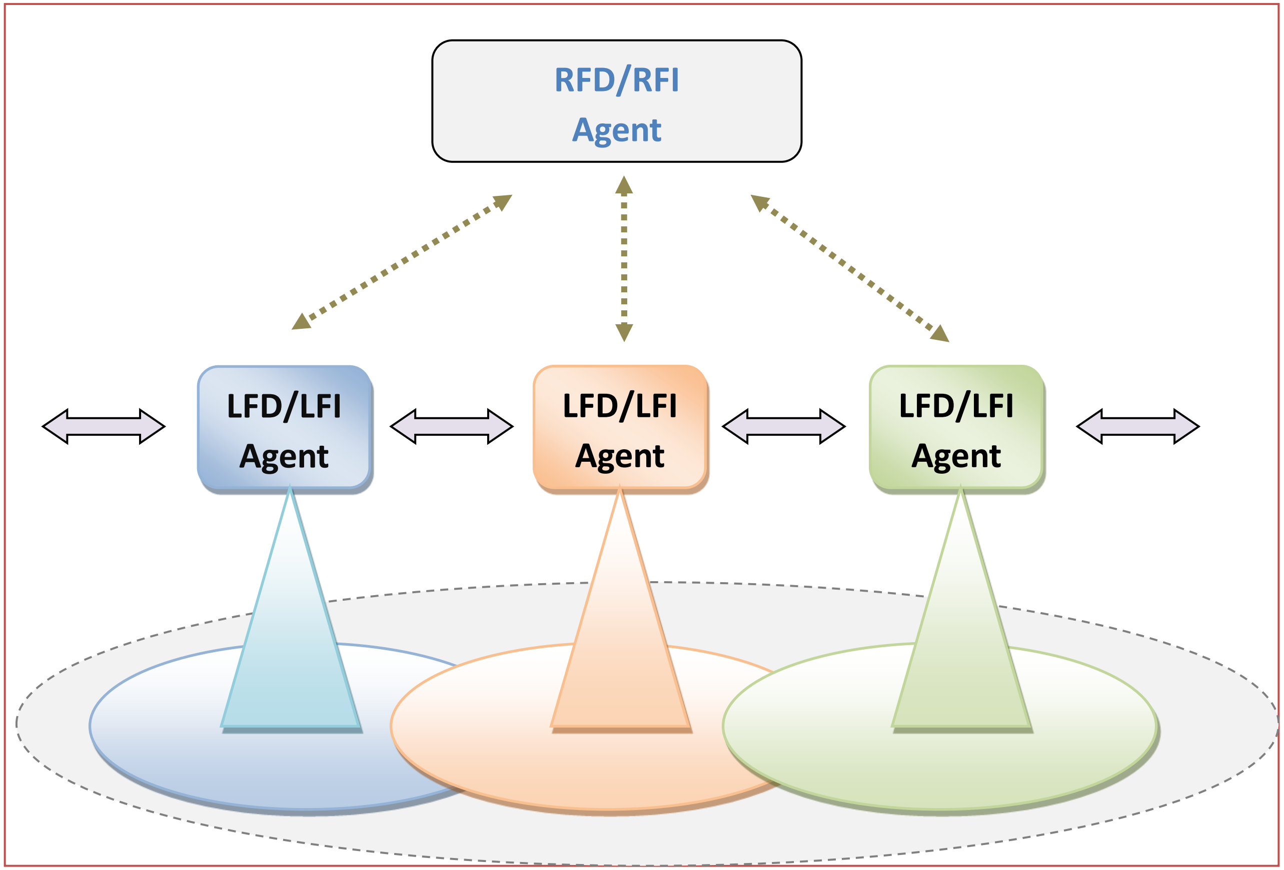
Fault isolability condition

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

Fault Diagnosis and Security

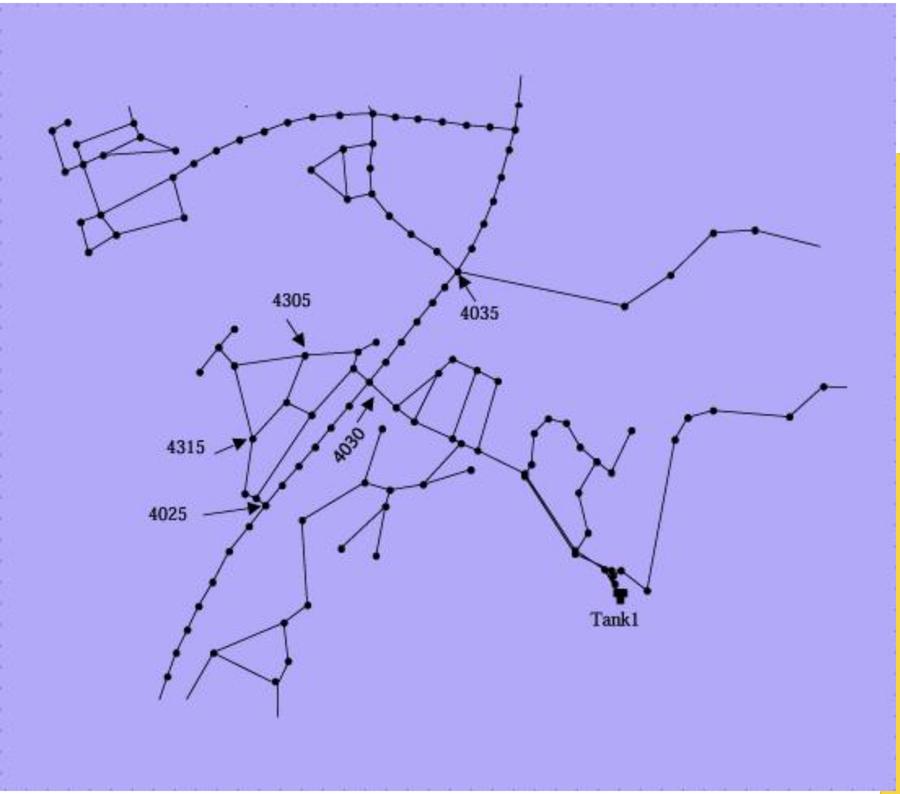
- Targeted faults
- Early detection is crucial
- Sensor placement is a key issue
- Need to consider the impact dynamics

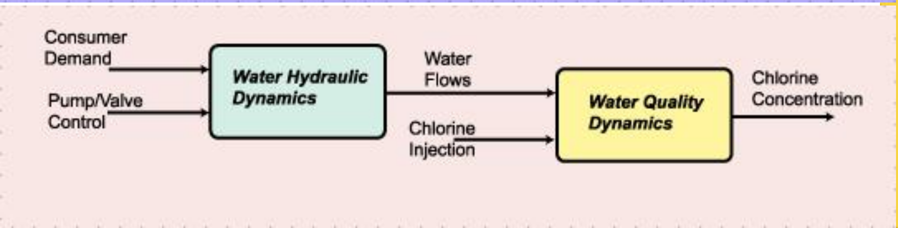
Distributed-Hierarchical Fault Diagnosis

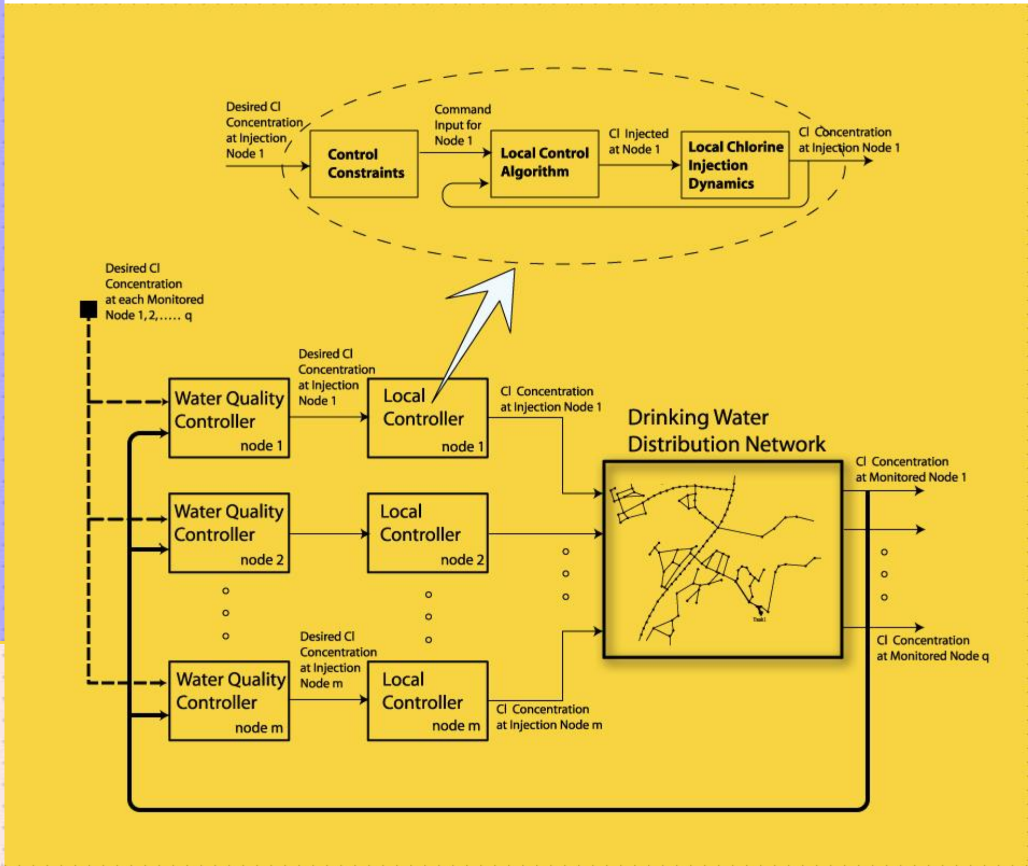


Example: Drinking Water Distribution Networks

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







Key Research Issues

- Development of suitable architectures
  - Distributed
  - Decentralized
  - Hierarchical
- Communication and cooperation between intelligent agents
  - How much communication is needed?
- Development of hardware devices
  - Cost
  - Size
  - Reliability
  - Energy efficiency
- Development of algorithms for real-time information processing
- Intelligent decision support systems

Intelligent Monitoring, Control and Security of Critical Infrastructure Systems (IntelliCIS)

IC0806 – Project Dates: July 2009 – July 2013

Participation of researchers from 25 countries

Info: http://w3.cost.esf.org/index.php?id=110&action_number=IC0806

Objective: to form a European-wide scientific and technology knowledge platform and instigate interdisciplinary interaction in the development of innovative intelligent monitoring, control and safety methodologies for critical infrastructure systems, such as electric power systems, telecommunication networks, and water systems.

Conclusions

- Intelligent monitoring, control and security of critical infrastructure systems.
- Development of a common system-theoretic framework for fault diagnosis and security of critical infrastructure systems.
- Cross-fertilization of ideas between the various applications and between industry and academia.
- Abrupt and incipient faults; Nonlinear uncertain systems; unstructured fault models.
- Analytical results on detectability, isolability, fault isolation time, closed--loop stability of the fault tolerant control scheme, tracking properties.
- Adaptive neural approximation models used for estimating on-line the fault function.
- Enormous scientific and commercial growth potential with high impact on the well-being and economy of people worldwide.

- M. Polycarpou and A. Helmicki, ``Automated Fault Detection and Accommodation: A Learning System Approach," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 25, no. 11, pp. 1447-1458, November 1995.
- A. Vemuri and M. Polycarpou, ``Robust Nonlinear Fault Diagnosis in Input-Output Systems," *International Journal of Control*, vol. 68, no. 2, pp. 343-360, 1997.
- A. Vemuri and M. Polycarpou, ``Neural Network Based Robust Fault Diagnosis in Robotic Systems," *IEEE Transactions on Neural Networks*, vol. 8, no. 6, pp. 1410-1420, November 1997.
- M. Polycarpou and A. Trunov, ``Learning Approach to Nonlinear Fault Diagnosis: Detectability Analysis," *IEEE Transactions on Automatic Control*, vol. 45, no. 4, pp. 806-812, April 2000.
- M. Polycarpou, ``Fault Accommodation for a Class of Multivariable Nonlinear Dynamical Systems Using a Learning Approach," *IEEE Transactions on Automatic Control*, vol. 46, no. 5, pp. 736-742, May 2001.
- X. Zhang, M. Polycarpou and T. Parisini, ``Robust Fault Isolation of Nonlinear Input-Output Systems," *International Journal of Control*, vol. 74, no. 13, pp. 1295-1310, August 2001.
- X. Zhang, M. Polycarpou and T. Parisini, ``A Robust Detection and Isolation Scheme for Abrupt and Incipient Faults in Nonlinear Systems," *IEEE Transactions on Automatic Control*, vol. 47, no. 4, pp. 576-593, April 2002.
- X. Zhang, T. Parisini and M. Polycarpou, “Adaptive Fault-Tolerant Control of Nonlinear Uncertain Systems: An Information-Based Diagnostic Approach,” *IEEE Transactions on Automatic Control*, vol. 49, no. 8, pp. 1259-1274, August 2004.
- X. Zhang, T. Parisini and M. Polycarpou, “Sensor Bias Fault Isolation in a Class of Nonlinear Systems,” *IEEE Transactions on Automatic Control*, vol. 50, no. 3, pp. 370-376, March 2005.
- X. Zhang, M. Polycarpou and T. Parisini, “Design and Analysis of a Fault Isolation Scheme for a Class of Uncertain Nonlinear Systems,” *IFAC Annual Reviews in Control*, vol. 32, no. 1, pp. 107-121, April 2008.

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Thank you for your attention!

Questions?