What can systems theory offer DX?

Gautam Biswas &

Mike Chantler

What are we going to talk about?

Mike

- The FDI community
- Dynamic models
- FDI diagnostic techniques
- Statistical approaches
- Summary

Gautam

- Systems theory approaches: state of the art
- Look beyond systems approaches
- What does AI/DX have to offer?
- How do we integrate these approaches?
- Conclusions

The FDI community

- Control Engineering
  - design of feedback control systems
  - control of steady state & dynamic behaviour
  - better control: use models
    - model-based adaptive control
    - state observer based systems
    - but
      - linear models
      - small deviations only
  - Employ continuous mathematics
    - Calculus

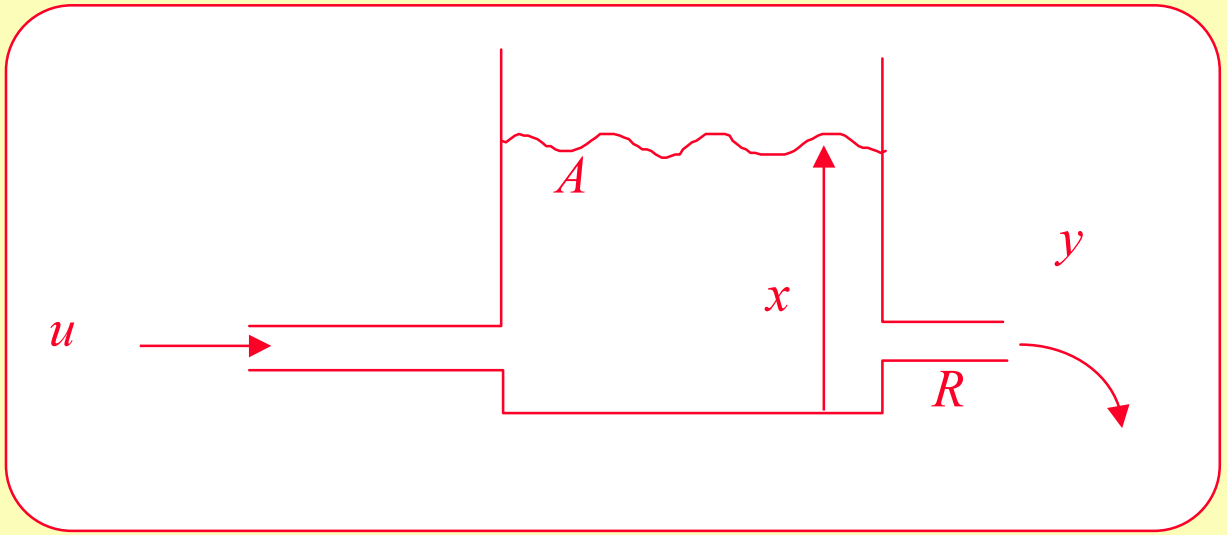
- Process Engineering
  - Fault detection
    - complex plant
    - steady-state operation
    - difficult to model
    - many sensors
    - noise, sensor drift
    - small deviations
      - detection of incipient faults
      - preventative maintenance
  - Employ statistical techniques

FDI tools and approaches

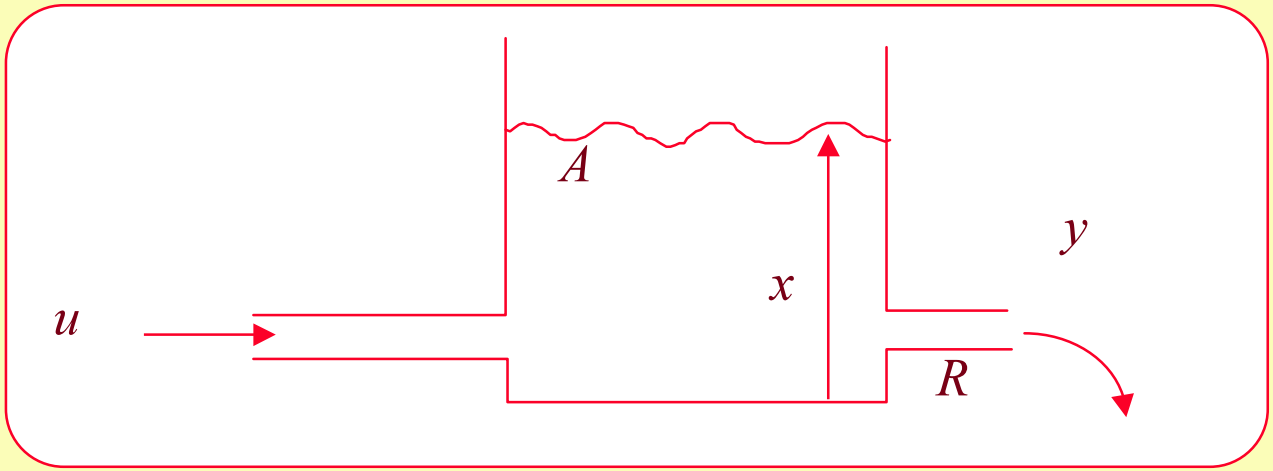
- **dynamic behaviour and dynamic models**
- **motivations**
- **tools**
  - state observers
  - parameter estimation
  - simulation
- **Diagnostic approaches**
- **Application characteristics/goals**

System Dynamics

- Energy transfer
- System state
- o/p dependent on state



Dynamic *models* of systems



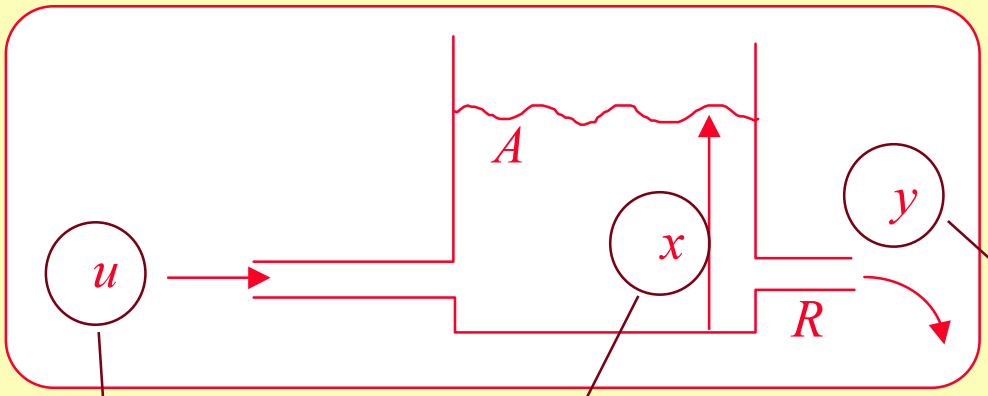
$$\frac{dx}{dt} = \dot{x} = u - y$$
$$y = kx$$

Continuous model
= differential & instantaneous eqns

$$\dot{x} = u - kx$$
$$y = kx$$

State space model

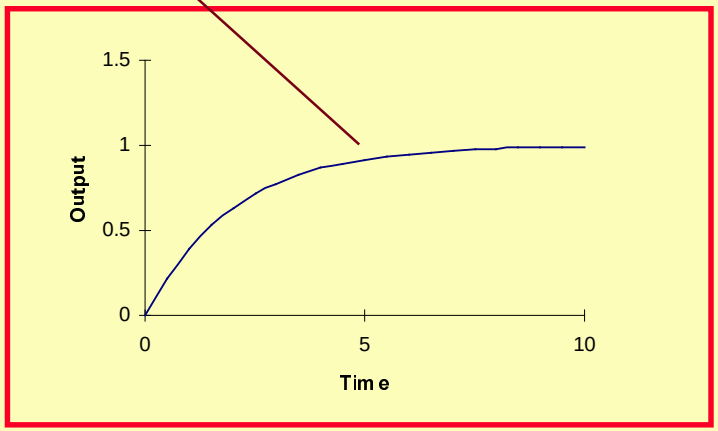
Analysis/simulation of dynamic behaviour



input + system state + model

$$\frac{dx}{dt} = \dot{x} = u - y$$

$$y = kx$$

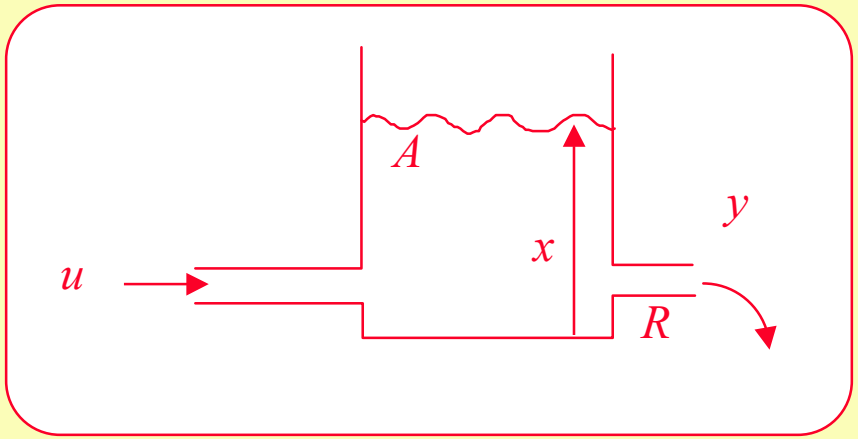


Motivation for using dynamic models

- Some faults can only be detected during transients
- Can provide early warning of steady state problems
- Provides extra information for diagnosis
- Diagnostic system can be used during transients (i.e. don't have to wait for steady state)

What is, and what is not a `dynamic` model

- **Dynamic models**
  - Memory!
  - Remembers state of energy storage devices
  - Memory = input history

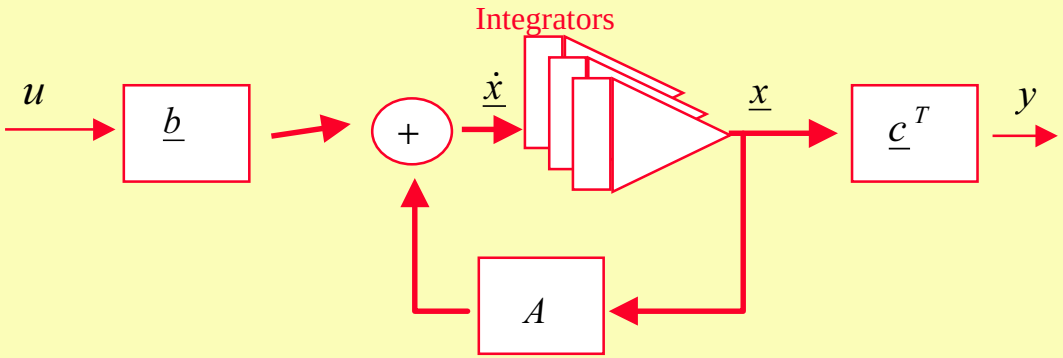


- **Time-varying models**
  - Parameters = function(time)
- **Models with time varying inputs**
  - Variables = function(time)

Standard theory

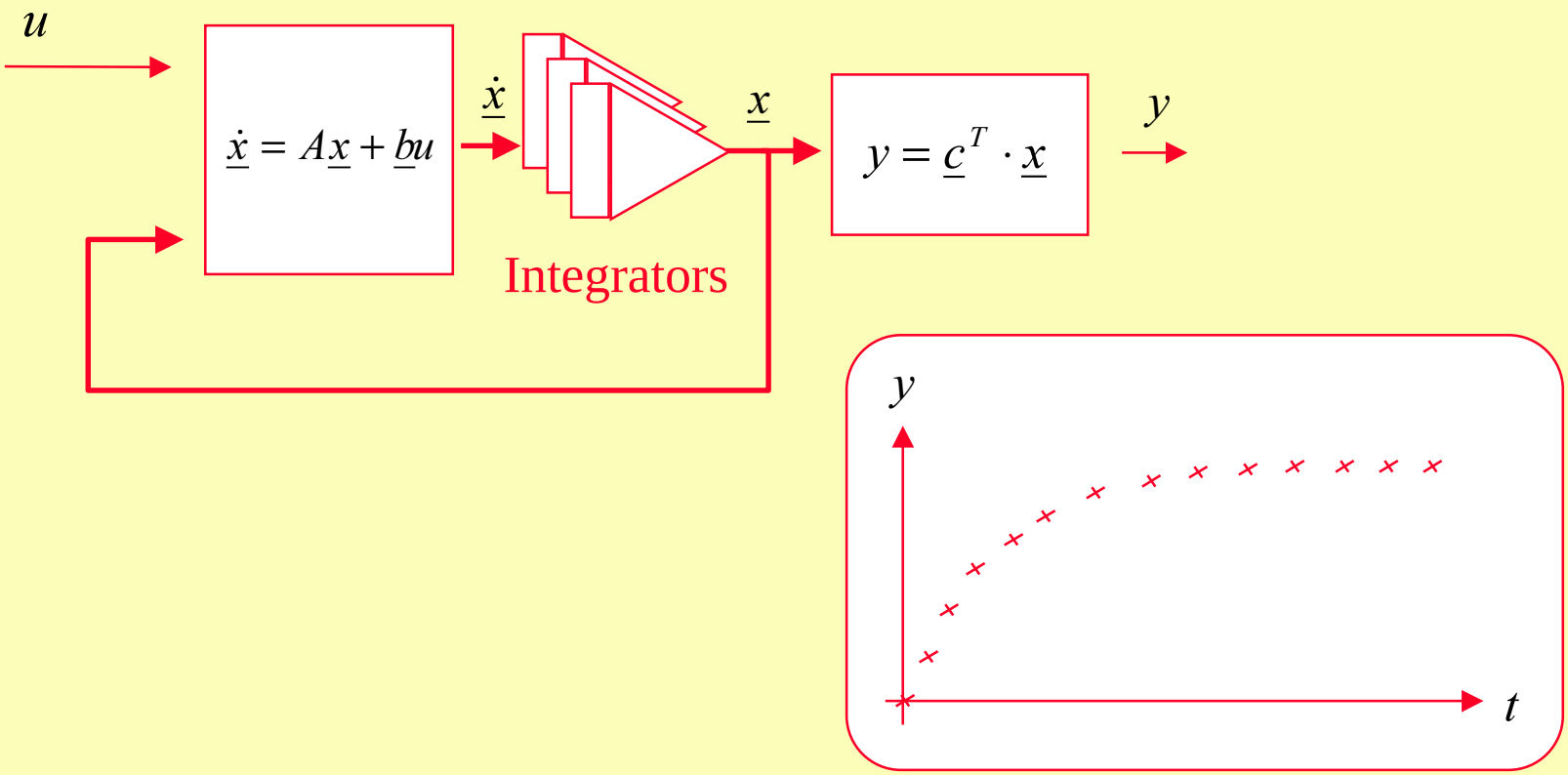
- **Model = conjuction of instantaneous & differential equations**
- **Control theory well developed** (for Linear Time-Invariant systems)
- **State-space model = set of first order differential equations.**

$$\dot{\underline{x}} = A\underline{x} + \underline{b}u$$
$$y = \underline{c}^T \cdot \underline{x}$$
$$\underline{x} = [x_1, x_2, \ldots . x_n]^T$$



- **Notes**
  - ***A* is a matrix of parameters, *b* and *c* are vectors of parameters**
  - **Single-input/single-output form shown - may be multiple-input/multiple-output**
  - **Models may be 'abstract' (parameters may not refer to physical quantities)**

Simulation



Simulation = discrete approximation of a continuous process

FDI approaches: model-based techniques

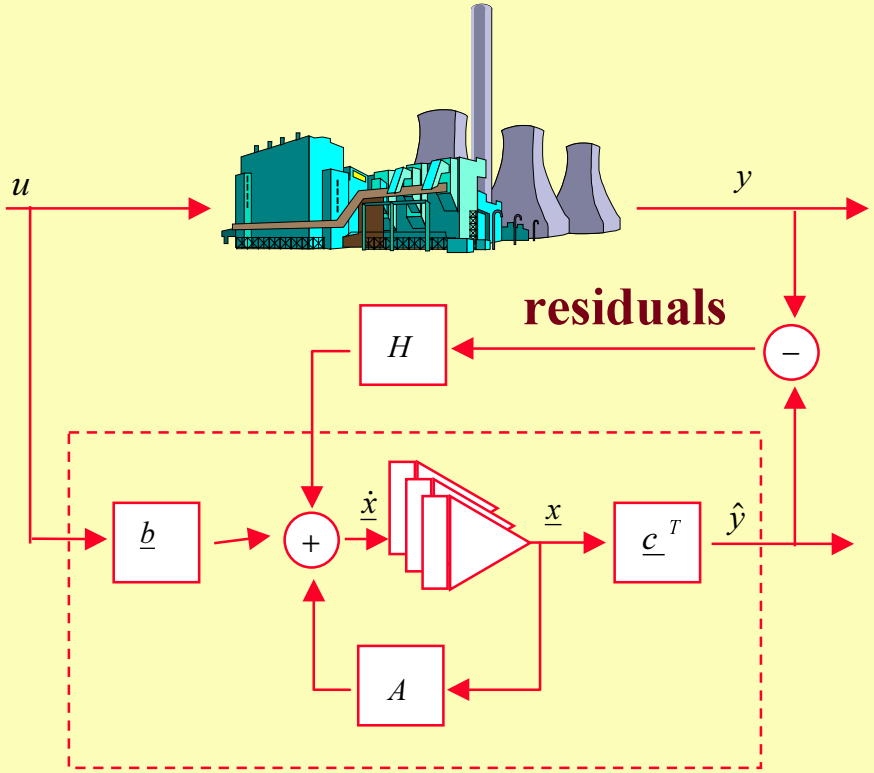
- **State observer [Patton, Frank]**
- **Parity based methods [Gertler, Staroswiecki]**
- **Parameter estimation [Isermann]**

- **But why can't you just use the differential equations?**
  - you can if you can measure the state variables directly
  - otherwise modelling inaccuracies, simulation errors, and noise mean that any prediction of the state variables is very inaccurate

- **Three standard approaches**
  - State observer
  - Parity space approaches
  - Parameter estimation

State observers

- **Origin**
  - Originally developed for control purposes
  - Used to estimate (*observe*) the state of the system
  - Estimate of system state then used to generate control actions
- **Operation**
  - Use inputs and guesstimate of system state to generate estimate of the output
  - Compare estimated and measured output(s) to generate discrepancies (residuals)
  - Use residuals to adjust system state
  - Repeat above continuously
- **Use for fault detection**
  - Look for non-zero residuals
- **Use for fault isolation**
  - Use banks of observers



Parity space approaches

- **Basic approach**
  - Manipulate state space equations to eliminate state variables
  - Formulate resulting equations in terms of a set of residuals that will all be zero if the plant behaves as the model predicts
  - Note there is some freedom in the way in which these residuals may be formed: hence design them so that different sets of residuals respond to different faults (’structured’ residuals)

Parity space approaches (2)

- **Mathematics:** $y = \underline{c}^T \cdot \underline{x}$
  - Differentiate 2nd state space eqn: $\dot{\underline{x}} = A\underline{x} + \underline{b}u$
  - Substitute 1st state space eqn:
  - Repeat a number of times
  - Collect and express (in matrix form)
  - Result:

$$\begin{bmatrix} y \\ \dot{y} \\ \ddot{y} \\ . \\ . \end{bmatrix} = \begin{bmatrix} \underline{c}^T \\ \underline{c}^T A \\ \underline{c}^T A^2 \\ . \\ . \end{bmatrix} \underline{x} + \begin{bmatrix} 0 & 0 & 0 & . & . \\ \underline{c}^T \underline{b} & 0 & 0 & . & . \\ \underline{c}^T A\underline{b} & \underline{c}^T \underline{b} & 0 & . & . \\ . & . & . & . & . \\ . & . & . & . & . \end{bmatrix} \begin{bmatrix} u \\ \dot{u} \\ \ddot{u} \\ . \\ . \end{bmatrix}$$

  - In a more compact form:

$$Y(t) = T\underline{x}(t) + QU(t)$$

Parity space approaches (3)

- **Mathematics (continued)**
  - **Now choose a new matrix (W) such that:**

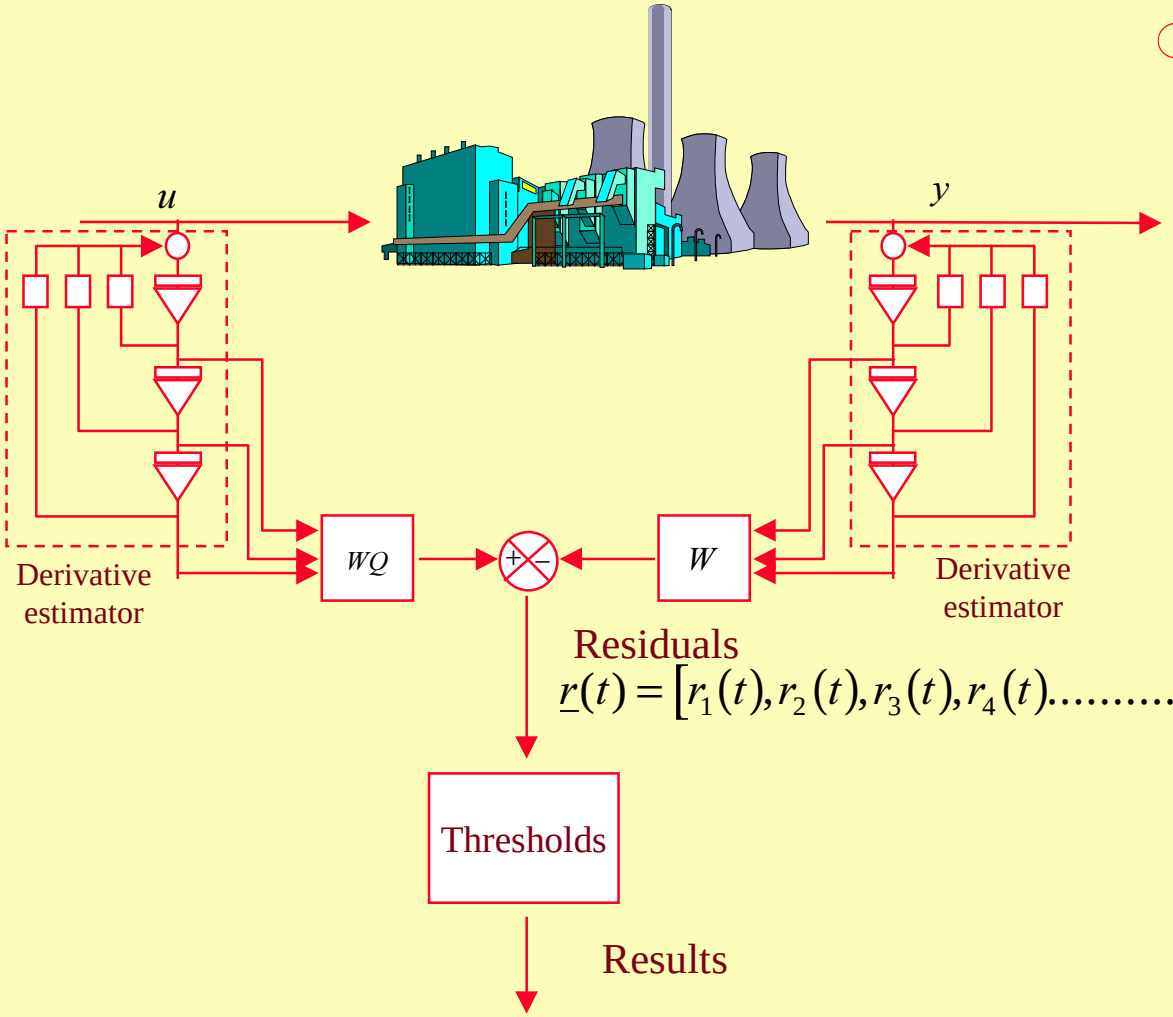
$$WT = \underline{0}$$

  - Now obtain parity relations which are independent of the state variables:

$$\underline{r}(t) = WY(t) - WQU(t)$$

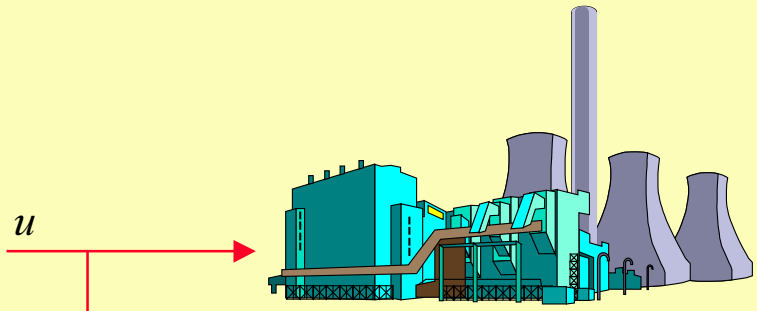
  - Notes:
    - Residuals are a linear combination of the inputs, the outputs, and their derivatives.
    - There is some freedom in choosing W so choose elements to enable residuals to isolate faults
    - Estimate derivatives and higher rates of change using suitable filters.

Parity based methods (4)



- **Notes**
  - Fault indicated by non-zero residuals
  - But what's "zero"
  - Need thresholds but these are difficult to set
  - Often thresholds are a function of the inputs
  - As with other techniques this approach is designed for linear time-invariant systems

Parameter estimation



Estimation method
(e.g. least squares)

Model structure

$$\dot{\underline{x}} = A\underline{x} + \underline{b}u$$
$$y = \underline{c}^T \cdot \underline{x}$$

Estimates of parameters

Normal values of parameters

Compare

Mapping

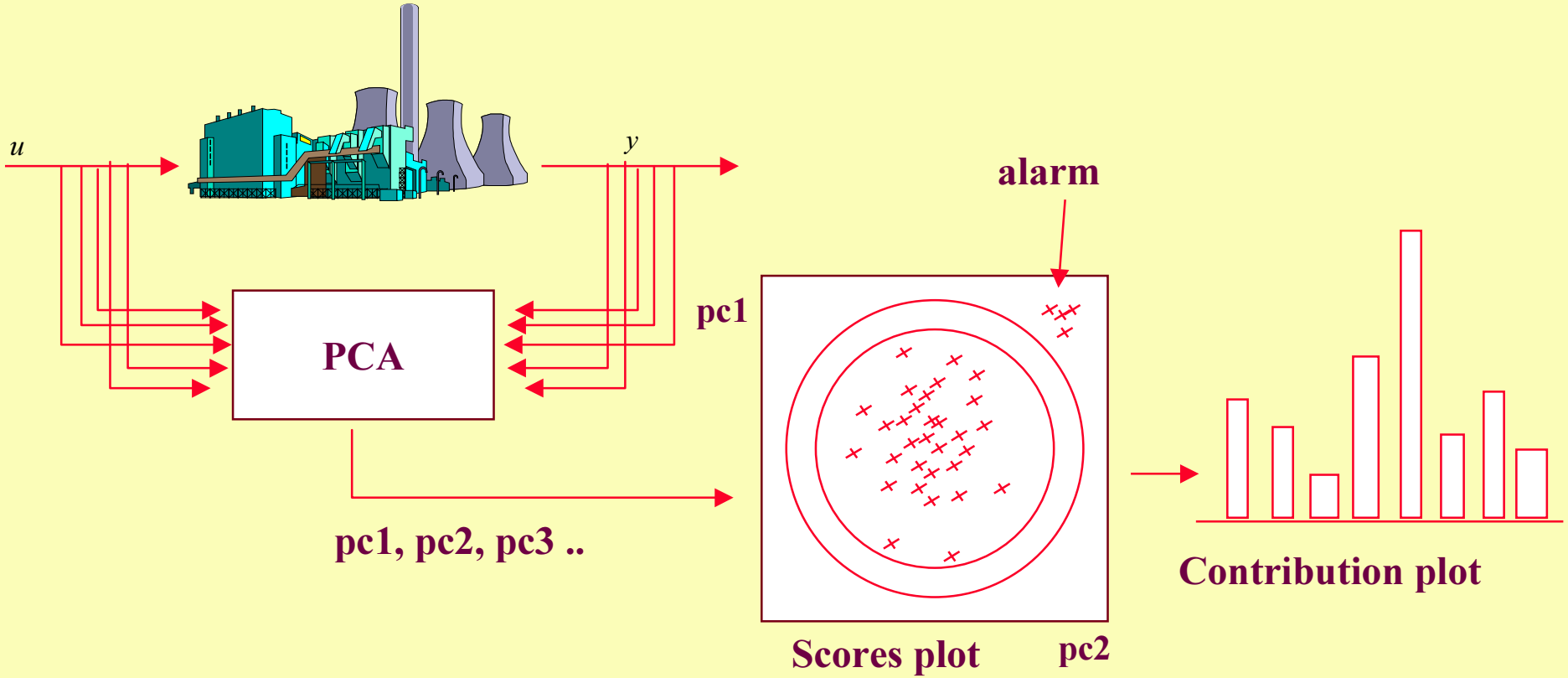
Isolation

FDI model-based approaches: summary

- **Limited measurements (inputs & outputs)**
  - System state observable but not measurable
- **Emphasis on fault detection**
  - Detection of incipient faults
  - Robust to modelling errors and noise
  - Types of fault known a priori
  - Linear models - small deviations
- **Isolation/identification**
  - Physical/mathematical parameter mapping problem
  - Techniques tend to isolate/identify a limited number of plausible faults

FDI approaches: statistical

- PCA (Principal Components Analysis)
- Multivariate statistics (Hotteling's *T* test)
- Not model based, often applied to steady state



FDI aims, application characteristics

- **Problems with many real processes: many measurements not available, measurements are noisy.**
- **Faults of interest to industry are SMALL deviations that occur GRADUALLY over time (these are the difficult ones!)**
- **Hence reliable fault detection is a significant problem.**
- **FDI community concentrates on methods that**
  - are robust to noise/modelling errors,
  - detect relatively small deviations, and
  - where, in general, only the inputs and outputs of the system are measured.

References

- **State space methods**
  B. Friedland, Control System Design: An Introduction to State-space Methods, Mcgraw-Hill, 1986.
- **State observer based methods**
  R. Patton, P. Frank & R. Clark (Eds), “Fault Diagnosis in Dynamic Systems”, pp 48-98, 1989.
- **Parity based methods**
  J. Gertler & D. Singer, "A new structural framework for parity equation-based failure detection and isolation", Automatica, V26, No.2, pp381-188, 1990.
- **Parameter estimation**
  R. Isermann, Fault diagnosis of machines via parameter estimation and knowledge processing, Automatica, 29, pp 815-835, 1993.
- **Statistical approaches**
  J. Morris & E Martin, Process performance monitoring and fault detection through multivariate statistical process control", IFAC symposium "*Fault detection, supervision and safety for technical processes",*
  Hull, Aug 26-28, 1997, pp1-14.

Traditional Systems Theory

POSITIVES

- **Model System Dynamics**
  - State Space Differential Equation Models
- **Deal With Incipient Faults**
  - Small Deviations That Occur Gradually over Time
  - Residue Generation and Sensitivity Analysis
- **Spectrum of Faults: Explicitly Modeled**
  - Actuator
  - Process
  - Sensor

Traditional Systems Theory

POSITIVES (Contd……)

- **Focus on Robustness**
  - Incomplete & Inaccurate Models of Process
  - Sensor Noise
  - Dynamics Account for Unknown System Input

  notes:

  Modified State Space Model

  $\underline{x}=A.\underline{x}+B.\underline{u}+E.\underline{d}+J.\underline{f}$

  $\underline{y}=C.\underline{x}$

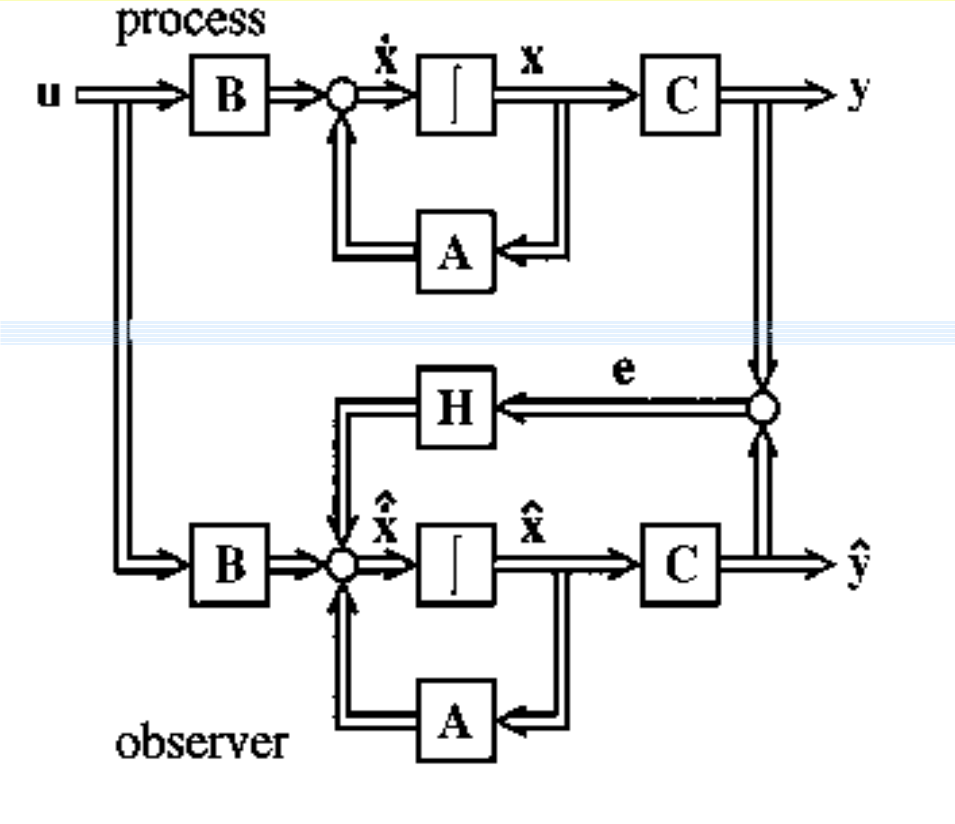
  $\underline{x}$:state vector, $\underline{u}$:input vector, $\underline{d}$: unknown input,

  $\underline{f}$:event vector (process or actuator faults)

Residue generation and observer schemes designed to separate unknown input effects from processor and actuator faults

Traditional Systems Theory
Observer Schemes

- compensate for effects of different initial conditions
- decouple fault effects from unknown input



Traditional Systems Theory

POSITIVES (Contd……)

- **Detectability & Diagnosability**
  - Sensor Placement such that important faults can be detected one on one
  - Functional redundancy approaches to confirm faults
- **Better Suited to Deal with Real Observations**
  - Quantitative Models
  - State Estimation in the Presence of Noise (Kalman Filters)

Traditional Systems Theory

NEGATIVES

- **Estimation Methods Assume Linear Models**
  - what about non-linear systems?
- **Quantitative Methods**
  - accuracy and precision of simulation methods ?
- **Focus on Fault Detection**
  - not fault isolation
- **Deal With Incipient Faults**

but what about:

- abrupt faults
- intermittent faults

Traditional DX/AI Approaches

SHORTCOMINGS

- **Models for Dynamic Analysis**
  - underconstrained
    (hypothesized fault sets very large and result in computational intractability)
  - Do not model systems dynamics well
    (cannot analyze fault transients)
  - Problems with Feedback Loops
    (produce ambiguities in the analysis)
- **Analysis Procedures**
  - Assume deviations are easy to compute
    - cannot make such assumptions for real measurements in the presence of noise
  - Independent multiple fault analysis as opposed to cascaded faults
  - Cannot differentiate between sensor, actuator, and process faults

Beyond Traditional Systems Theory

- **Modeling Approaches**
  - Structural, Topological Models
  - Build systems models by composition (reusable generic components)
- **Fault Isolation Schemes**
  - Functional redundancy applied to causal models
  - Qualitative constraint propagation
- **Extend Spectrum of Faults**
  - Abrupt Faults

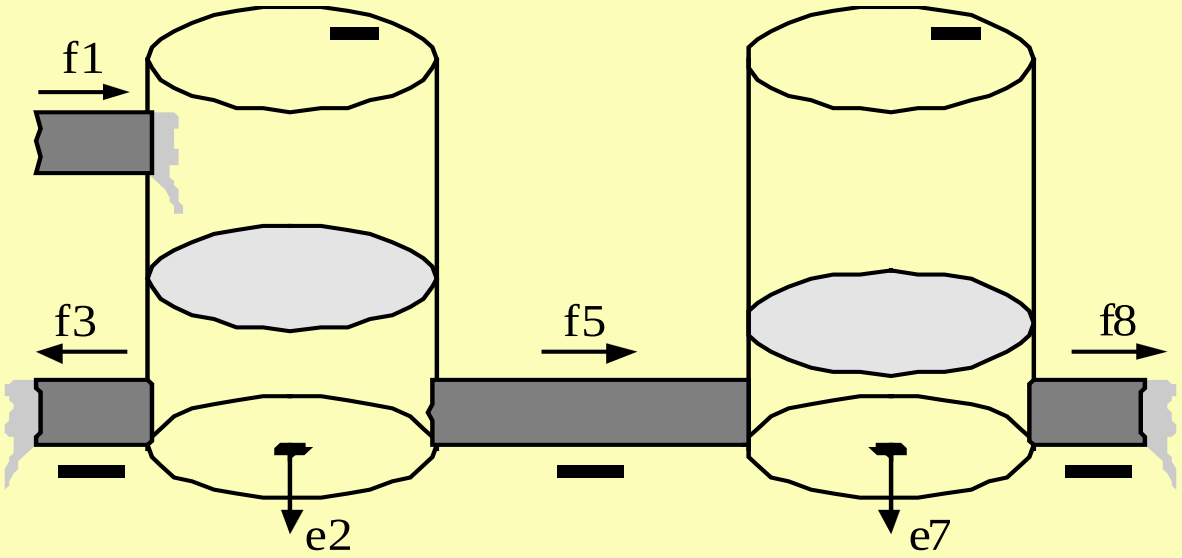
Modeling for Diagnosis

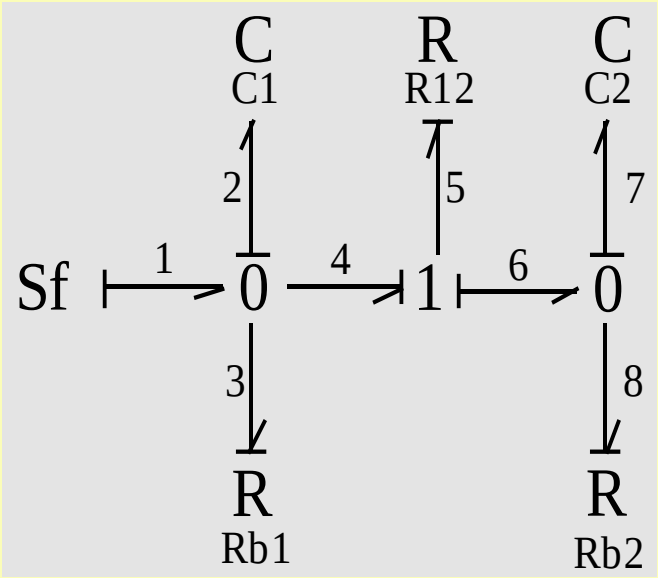
(Monitoring, Fault Detection and Fault Isolation)

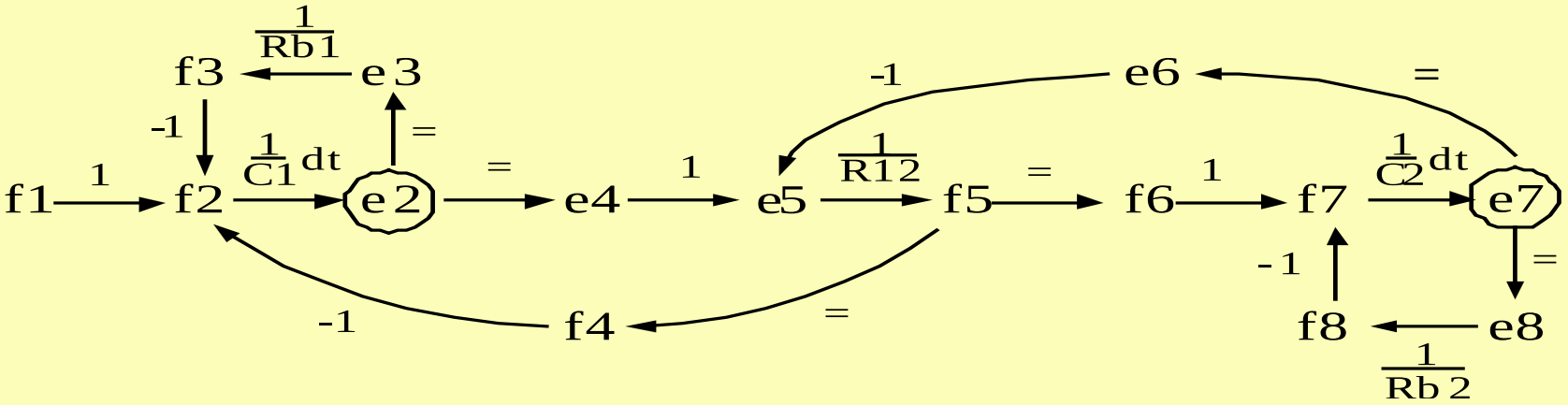
- **Dynamic, topological models that capture physical constraints: energy,and power**
- **Compositional Modeling**
  - Example: Modeling language: Bond graphs
- **Need to describe both normal and faulty system behavior**
- **Causal, temporal behavior for fault analysis and monitoring**
- **Handle both qualitative and quantitative information**
- **Allow analysis controllability, observability, and diagnosability**

Bond Graph and Temporal Causal Graph

Two-tank System

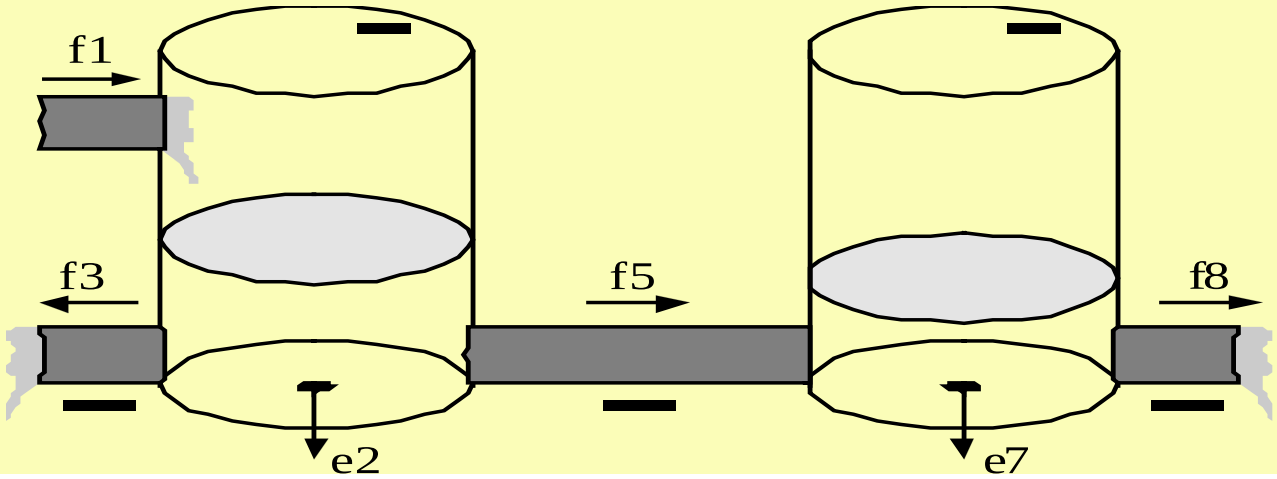


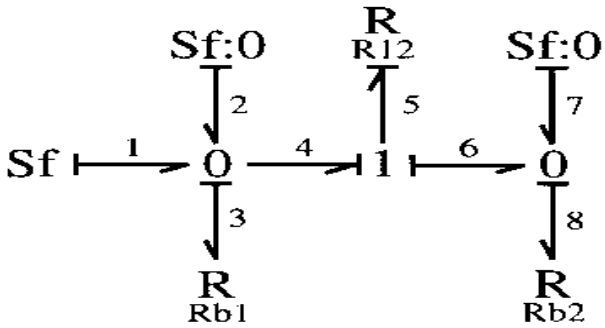


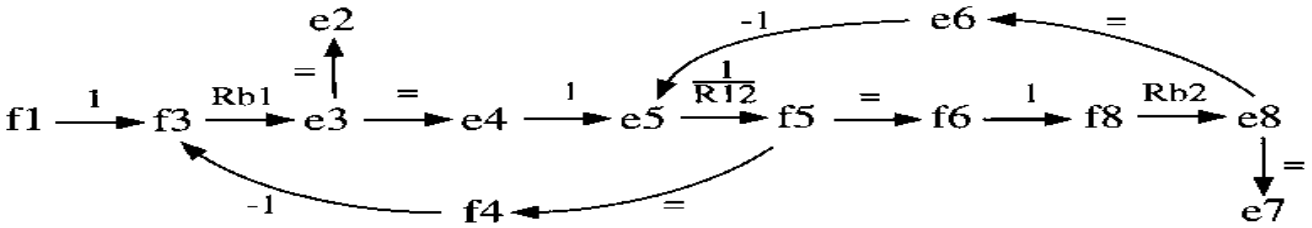


Two Tank System

Steady State Model







Beyond Traditional Systems Theory (contd.…)

- Qualitative schemes -- Avoid Precision/ Instability Problems of Numerical Analysis in Complex System Simulation

- Possibility for Incorporating Different Operating Regions in Tracking System Behavior

  (introduce Hybrid Models)

Integrated Systems Theory and AI Approaches

example: Model-based Fault Diagnosis of Chemical Processes (Kramer, et al.)

- **Modeling of dynamic systems using SDG representation - causal graphs with variables taking on qualitative values**
- **Look for initial response (transient) + steady state response of variable**
- **Systematic schemes for handling feedback loops**
- **Result - focused interpretations of behavior due to disturbances**

Integrated Systems Theory & AI Approaches

example: Abrupt Fault Isolation in Dynamic Continuous Systems (Mosterman & Biswas)

Modeling

- **Parsimonious topological system models**
  - Based on Dynamic Systems theory
  - Bond Graph Approaches
    - lumped parameter assumption
    - system configuration & functionality well-defined
    - continuity of power, conservation of energy.
- **Dynamic System Model**
  - Temporal Causal Graph
  - Transient Analysis of faulty behaviors
  - Qualitative Framework

Integrated Systems Theory & AI Approaches

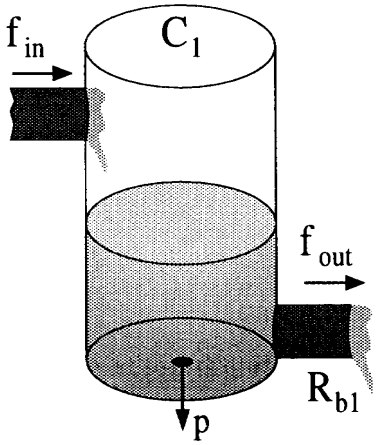
example: Abrupt Fault Isolation in Dynamic Continuous Systems
(Mosterman & Biswas)
Fault Isolation and Monitoring

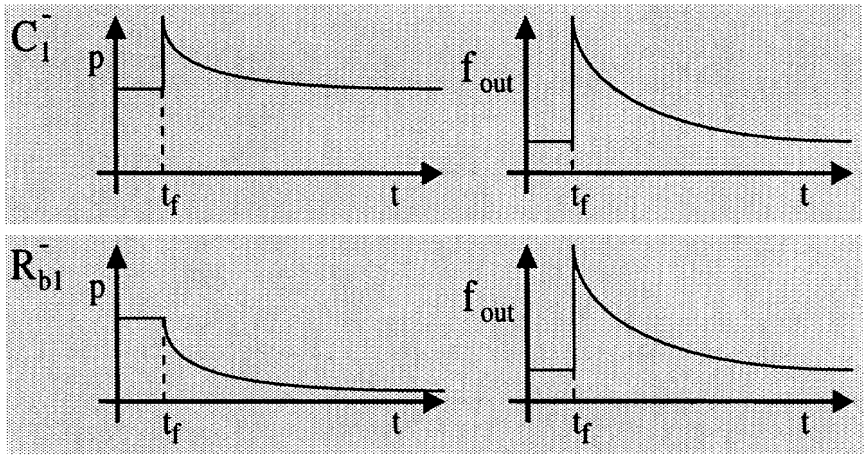
- **Transient Analysis of Faulty Behaviors**
  - based on Temporal Causal Graph
  - transients represented as signatures:
    qualitative higher order time derivatives
- **Tracking of Dynamic Response to Faults**
  - Progressive Monitoring
- **Suspension of Transient Analysis**

Diagnosis Framework: Basics

(Mosterman and Biswas)

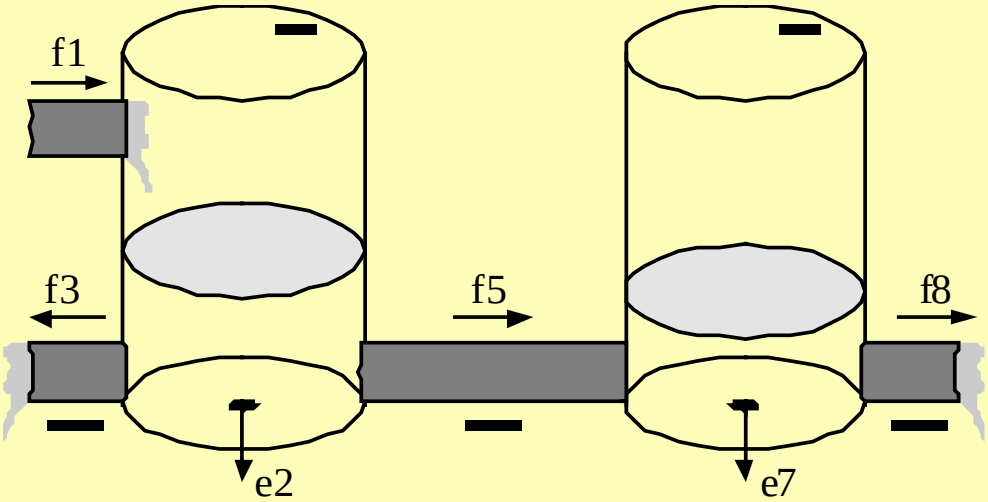
- **Observation: measured variable**
- **Assumption: Measurement sampling rate faster than system time constants in normal and faulty operation.**
- **Faults: model parameters deviated form normal operating values**
- **Discontinuity: abrupt change in signal value much smaller than time scale of observation**

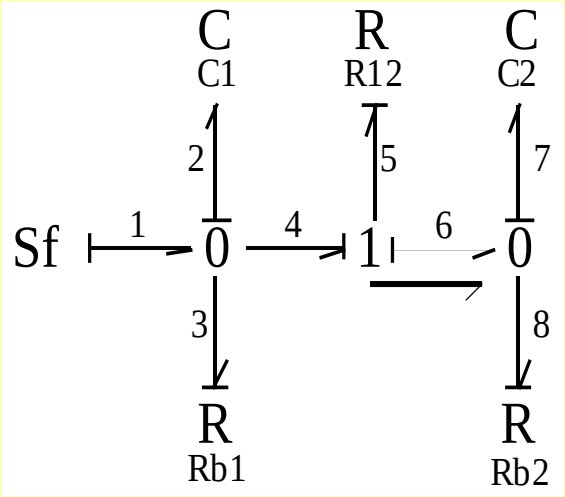


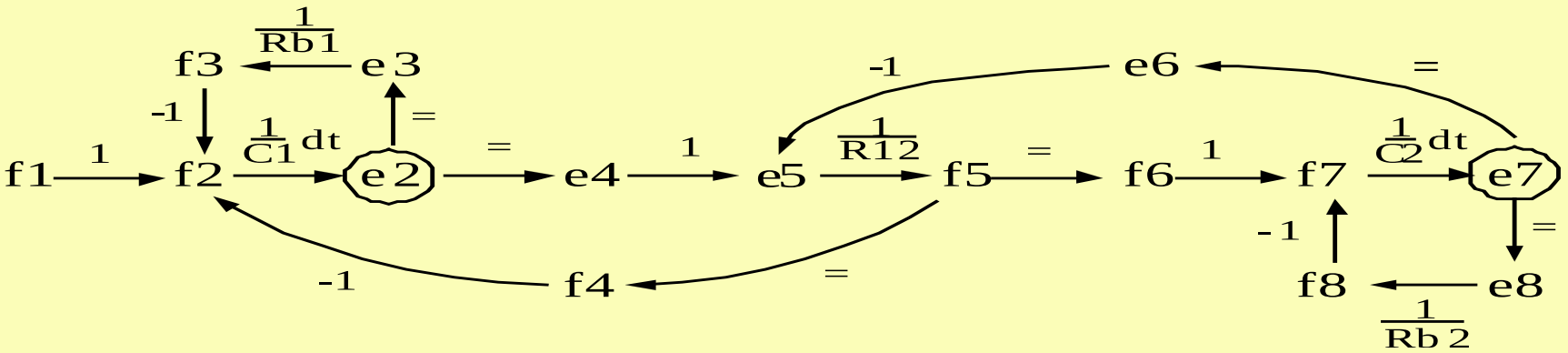


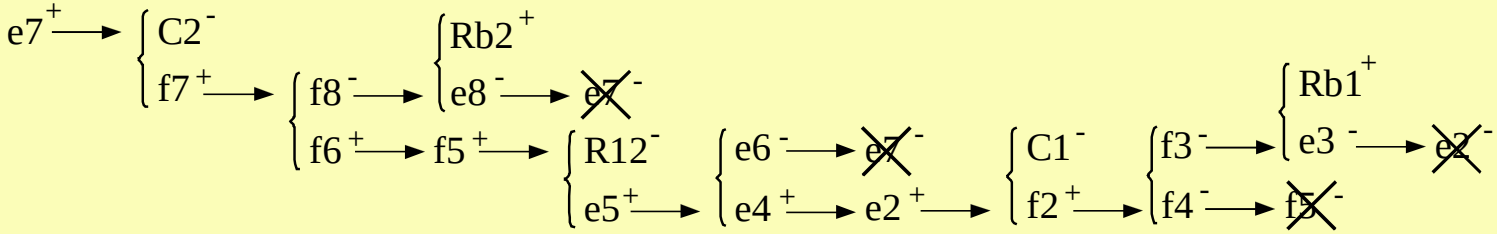
Generate Fault Hypotheses

Backward Propagation (Mosterman and Biswas)







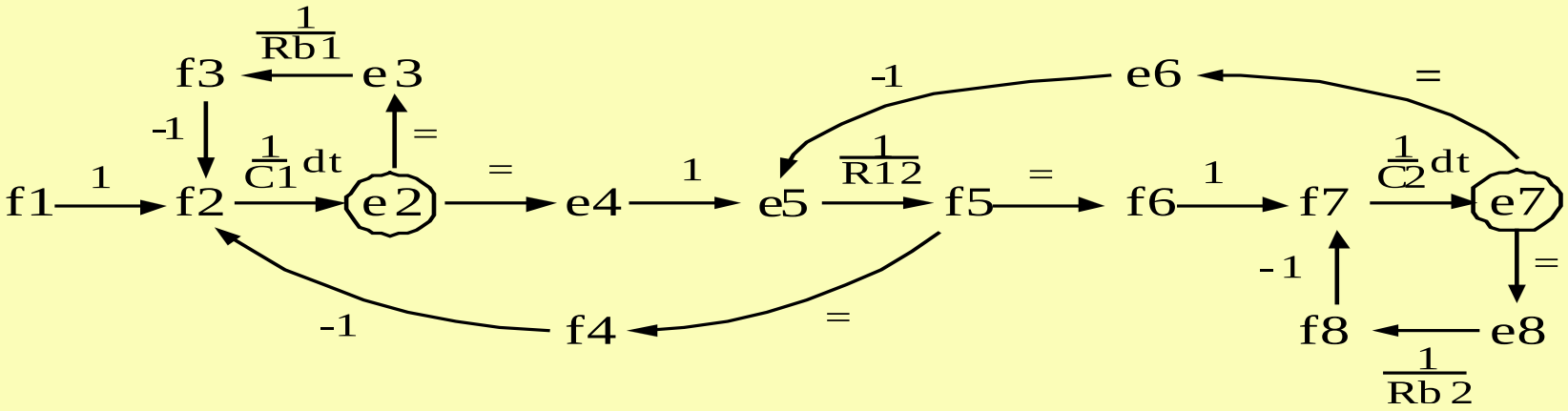


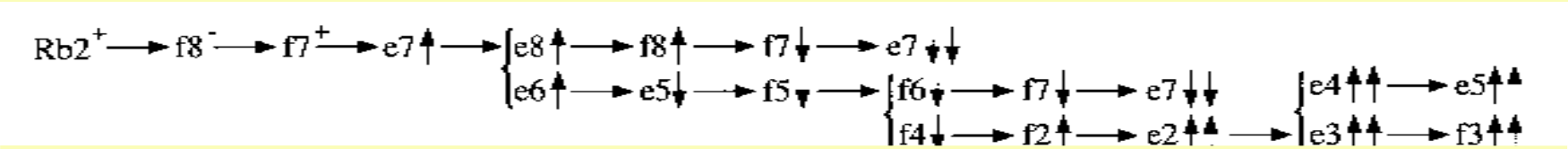
Possible Faults: $C2^-$ $Rb2^+$ $R12^-$ $C1^-$ $Rb1^+$

Signatures for Individual Faults

Forward Propagation (Mosterman and Biswas)

- Signatures **for individual faults**
  Signature: **predicted magnitude, 1st and higher order derivative effects of system variable as qualitative values in response to a fault.**
- **Temporal links imply integrating edges, affects derivative of variable on the effect side**
  Start with 0-order changes
  Every integrating edge increases order by one.





Rb_2^+ 2nd Order signature of e_7: < 0,+,- >

Monitoring Implementation

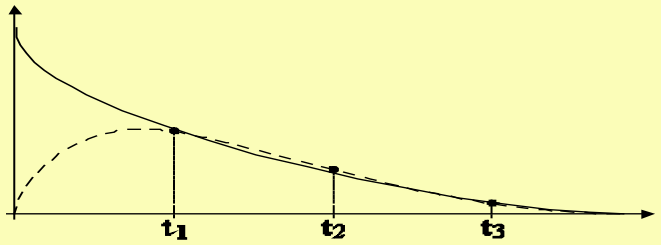
(Mosterman and Biswas)

Comparing Actual Observations to Predicted Signatures

Need to track transients in a qualitative framework

Issues:

- ❒ Time step for recording measurements- sampling rate
- ❒ Discontinuity detection & Sensitivity to Normal Operations



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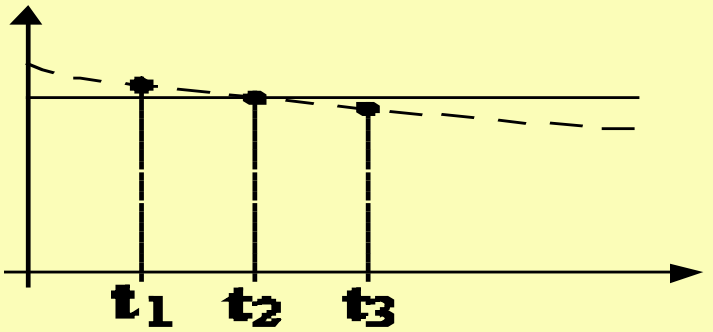
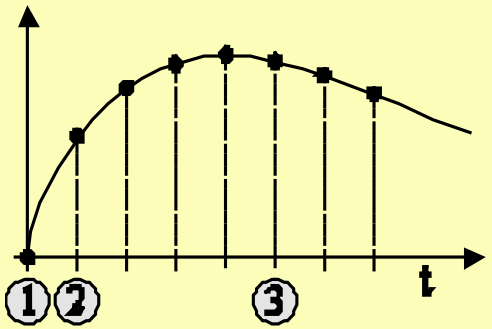


too fine

Monitoring Implementation

(Mosterman and Biswas)

- **Issue: Initial Signatures based on state vector at point in time of failure**
- **But system dynamic, so signatures can change over time**
- **Use Progressive Monitoring**
- **Use higher-order derivatives as a predictor of future behavior**
- **Activated when there is a discrepancy between predicted and observed value.**



dt	0	1	2
①	0	+	-
②	+	+	-
③	+	-	-

Monitoring for Dynamic Systems

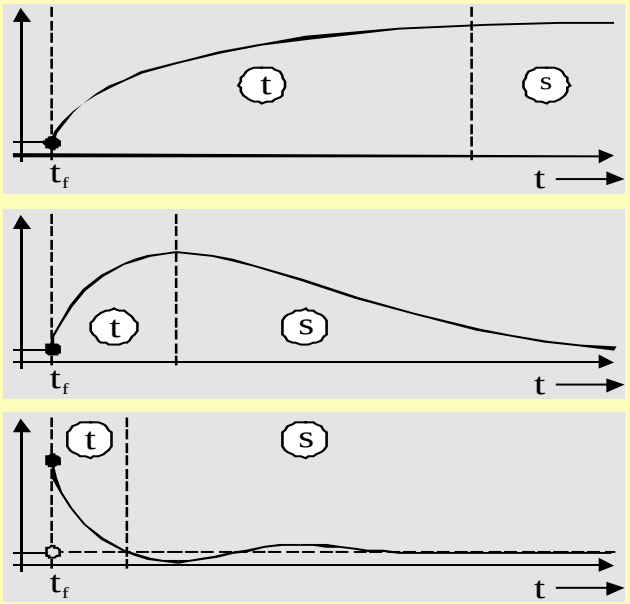
(Mosterman and Biswas)

Temporal Behavior: Signal Transients

(a)

(b)

(c)



When to suspend **transient analysis.**

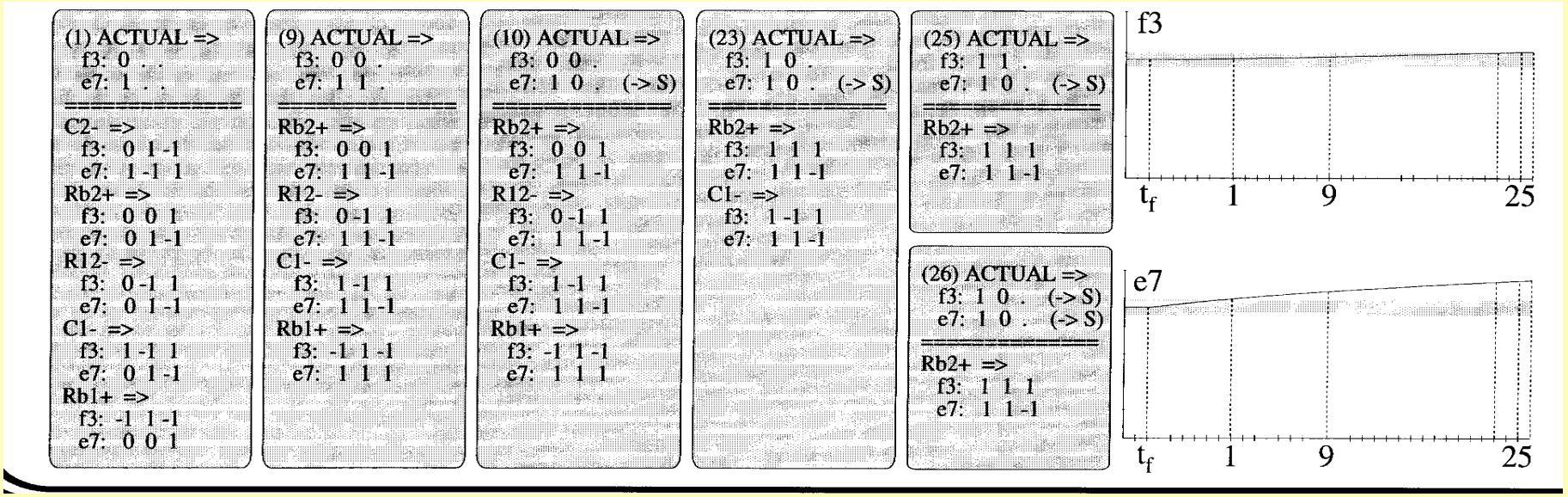
- **(a) Compensatory Response**
- **(b) Inverse Response: slope reverses**
- **(c) Reverse Response: (overshoot) slope and magnitude change sign**

Fault Isolation Using Progressive Monitoring

Simulated Two Tank System

(Mosterman and Biswas)

- Fault: R_{b2}^{+}
- Measured *Variables:* e_7, f_3



What Are the Contributions of DX/AI techniques?

- **Topological Models**
  - Aid Fault Isolation
  - Measurement Selection/ Sensor Placement
- **Qualitative Analysis**
  - Higher Order Systems - simulators are hard to come by
  - Simplifies Transient Analysis
- **Cognitive Aspects**
  - Operator Interface Design

Where Do DX/AI Techniques Need Systems Approaches?

- **More Sophisticated Dynamic Models**
  - Qualitative and quantitative Analysis
- **Robust Monitoring Methodologies**
  - Detect and interpret Transients
  - Noise Tolerant
  - Reliable Deviations
- **When fault isolation depends on**
  - Magnitude of changes (Sensitivity Analysis)
  - Rates of change (Time constants)

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