Soft Computing for Fault Diagnosis

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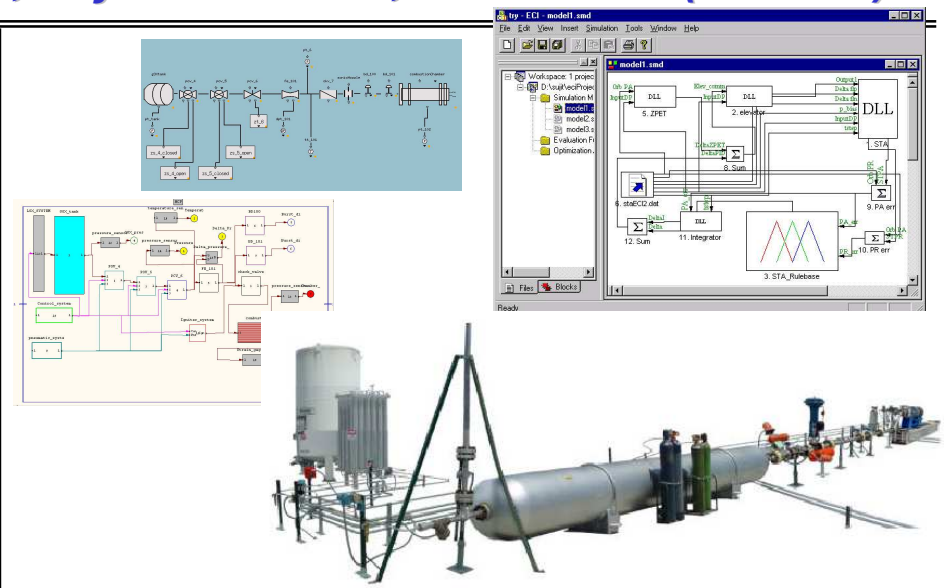
Goal: Fault monitoring and diagnosis in intelligent control requiring complex inferences in continuous states without complete analytical models.

Objectives: Leverage existing knowledge about the devices (i.e., model based approaches) while also learning from experience (data clustering based) to further refine this knowledge in detecting and isolating failures. Leverage existing reinforcement learning techniques for the adaptation, generalizing beyond the specific instances that are observed in the in training set. This is particularly challenging when dealing with real-valued variables whose values change over time.



NASA Relevance:

- Enable fault monitoring and diagnosis in systems such as the Boeing aircraft engine, the Hybrid Combustion Facility (HCF) and SOFIA at Ames, and the International Space Station.

Accomplishments to date:

- Have applied our algorithms to fault diagnosis of a Boeing 400 aircraft engine. The system continuously monitors a large set of variables and diagnoses the major fault categories
- Applied on a test data of 30 firings of the HCF, 5 major fault categories have been identified

Schedule:

- FY01: Develop a data clustering algorithm for fault detection and apply it to a Boeing aircraft 400 series engine
- FY02: Apply a combined model based and data clustering based approach on the Ames Hybrid Combustion Facility. Contrast the results with L2, RODON, and TEAMS
- FY03: Formalize the theory of combined model based and data clustering based approaches for fault monitoring and diagnosis

Perception Based Fault Diagnosis

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Perception Based Reasoning (L.A. Zadeh)

- Perceptions of distance, size, weight, color, force, truth, likelihood, etc.
- Brain's power: Manipulating perceptions
- Perceptions vs. Measurements
  - Measurements are crisp
  - Perceptions are approximate

Computational Theory of Perceptions (L.A. Zadeh)

- A methodology for Computing with words
- Human Concepts have granular structures
- A granule is a clump of physical or mental objects (points) drawn together by indistinguishability, similarity, proximity or functionality
- A granule defined by a generalized constraint: X isr R

Information Granulation (L.A. Zadeh)

- Involves a partitioning of whole into parts
- Human way of employing data compression for reasoning
- For making rational decisions in an environment of imprecision, uncertainty and partial truth

Types of Perceptions

- X is A Possibilistic, partial knowledge
- X isp P Probabilistic, partial certainty
- X isr R Generalized, hybrid

A new unit of computation

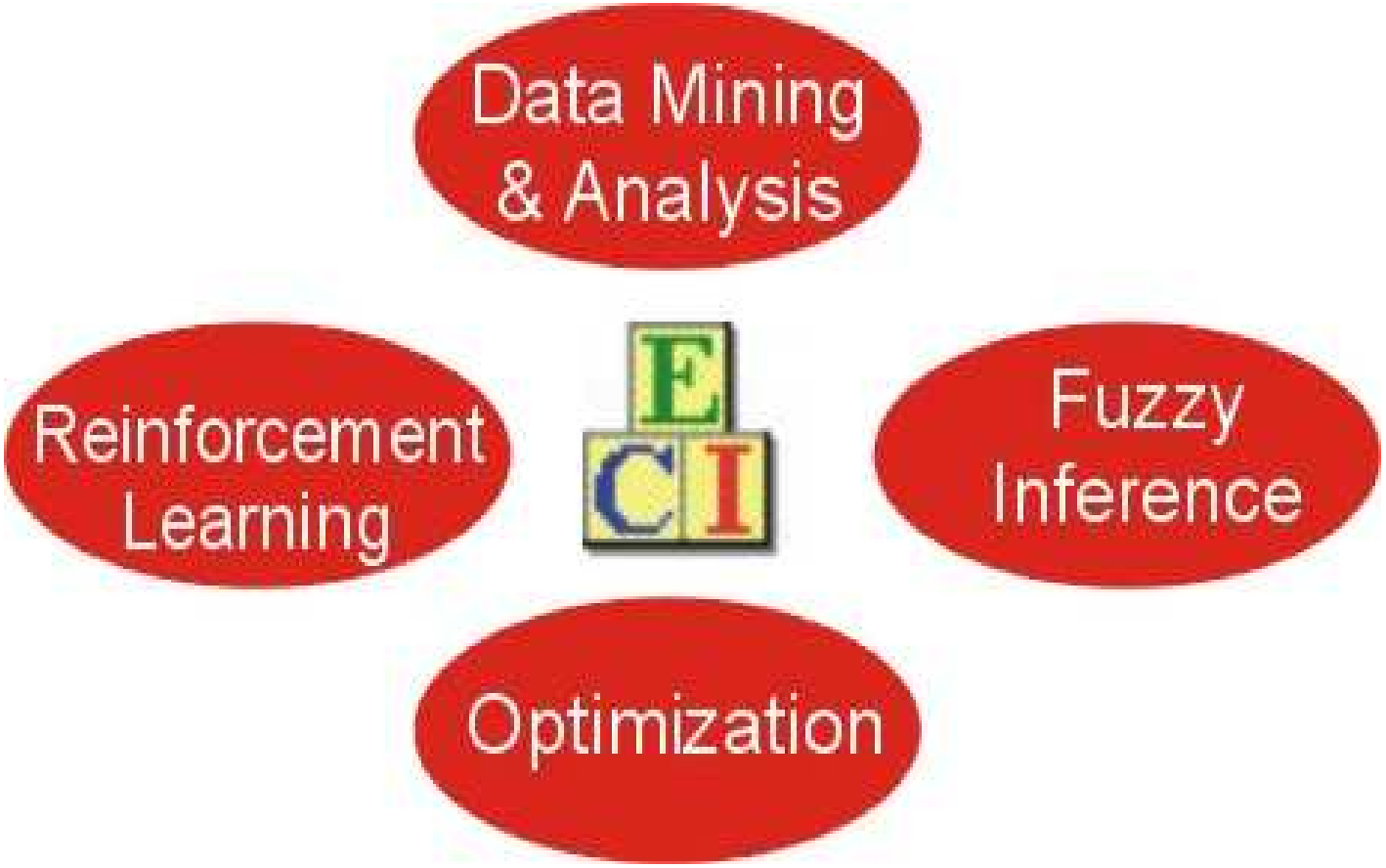
- In traditional computing, the state of the environment is represented by hyper cubes. In perception-based reasoning, the state of the environment is represented by granules.

- Granular Computing provides a powerful generalization of traditional computing.

Human Brain and Perception

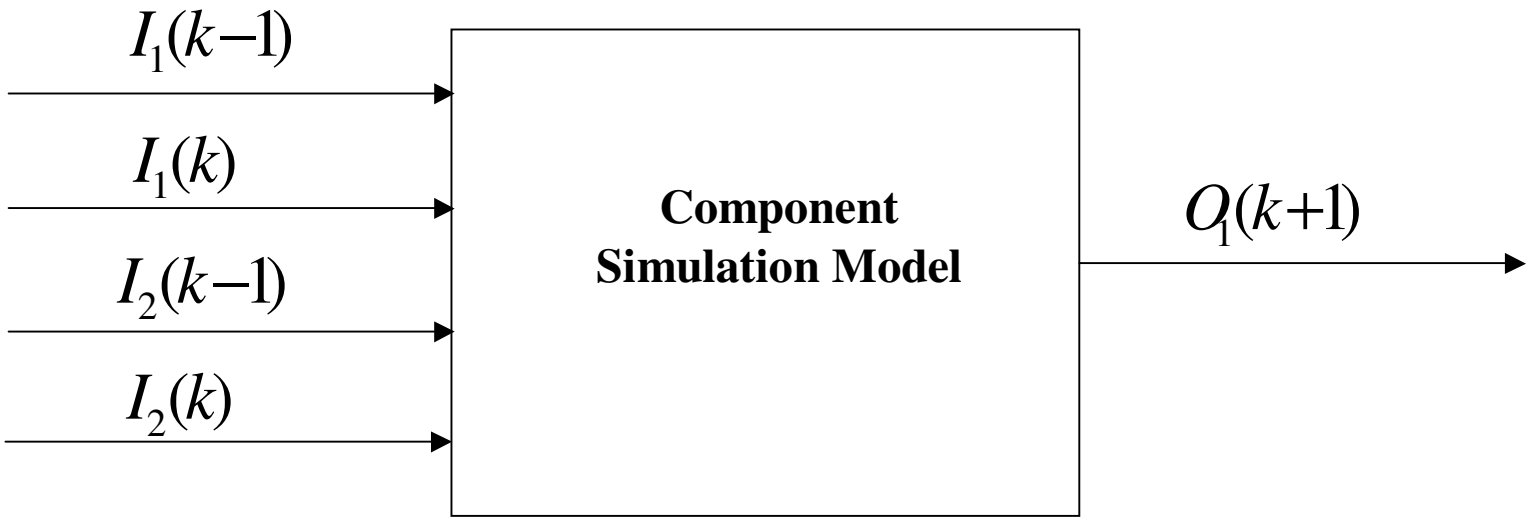
- Perceptual Science Group at MIT
  - Human Visual Perception, machine vision, image processing
- Perception and Neurodynamics lab, OSU
  - This lab conducts research on understanding neurocomputational mechanisms underlying perceptual processes and on building effective algorithms for solving real-world problems related to machine perception

An expert system shell for fault diagnosis



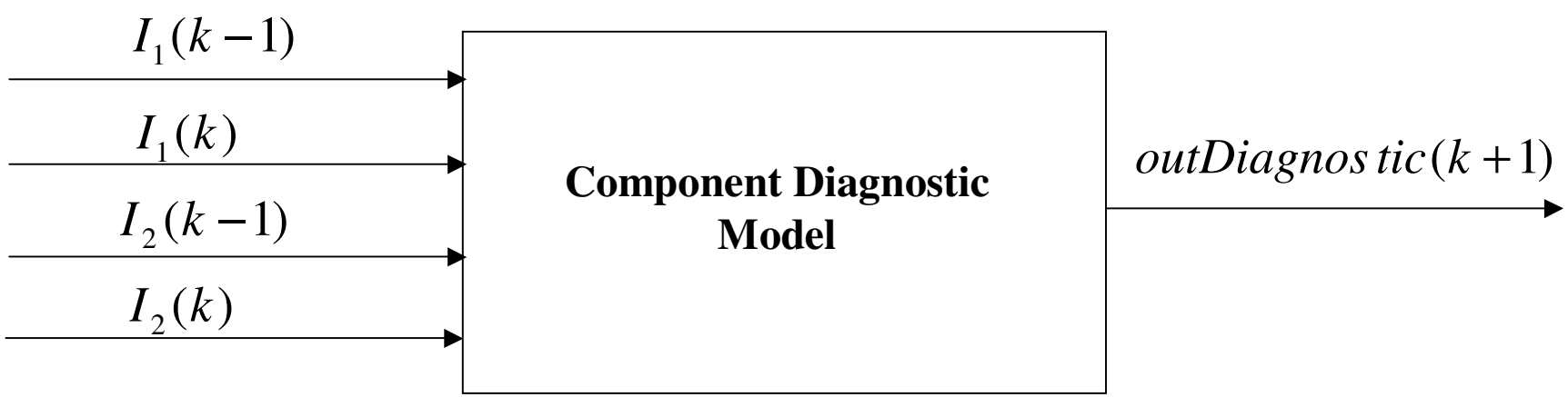
Step 1

- A component



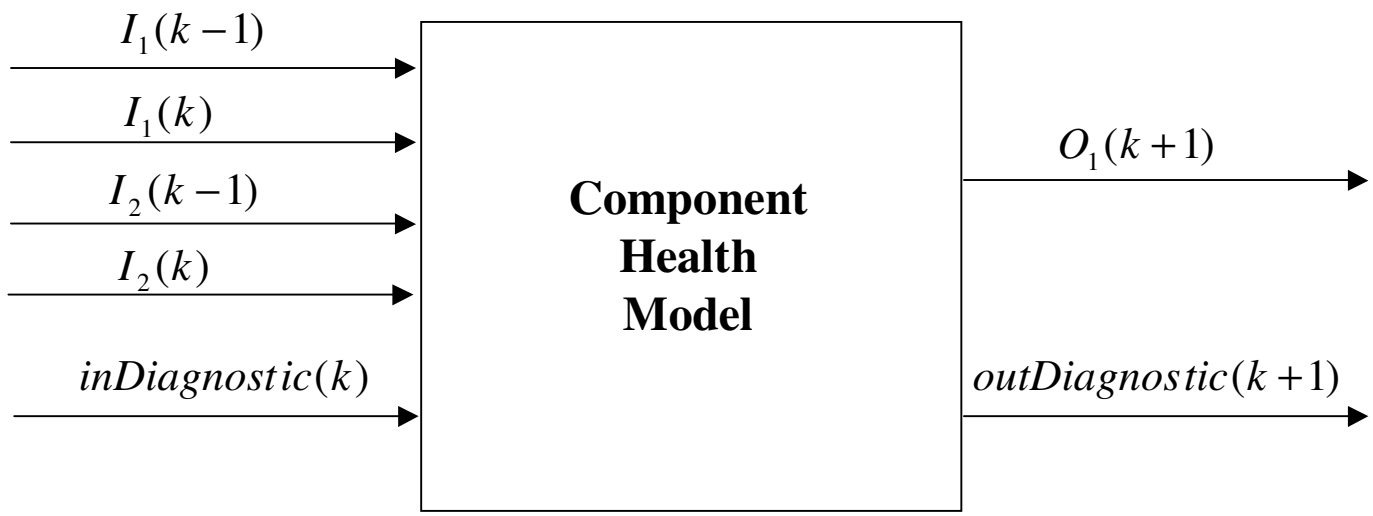
Step 2

- Diagnostic model

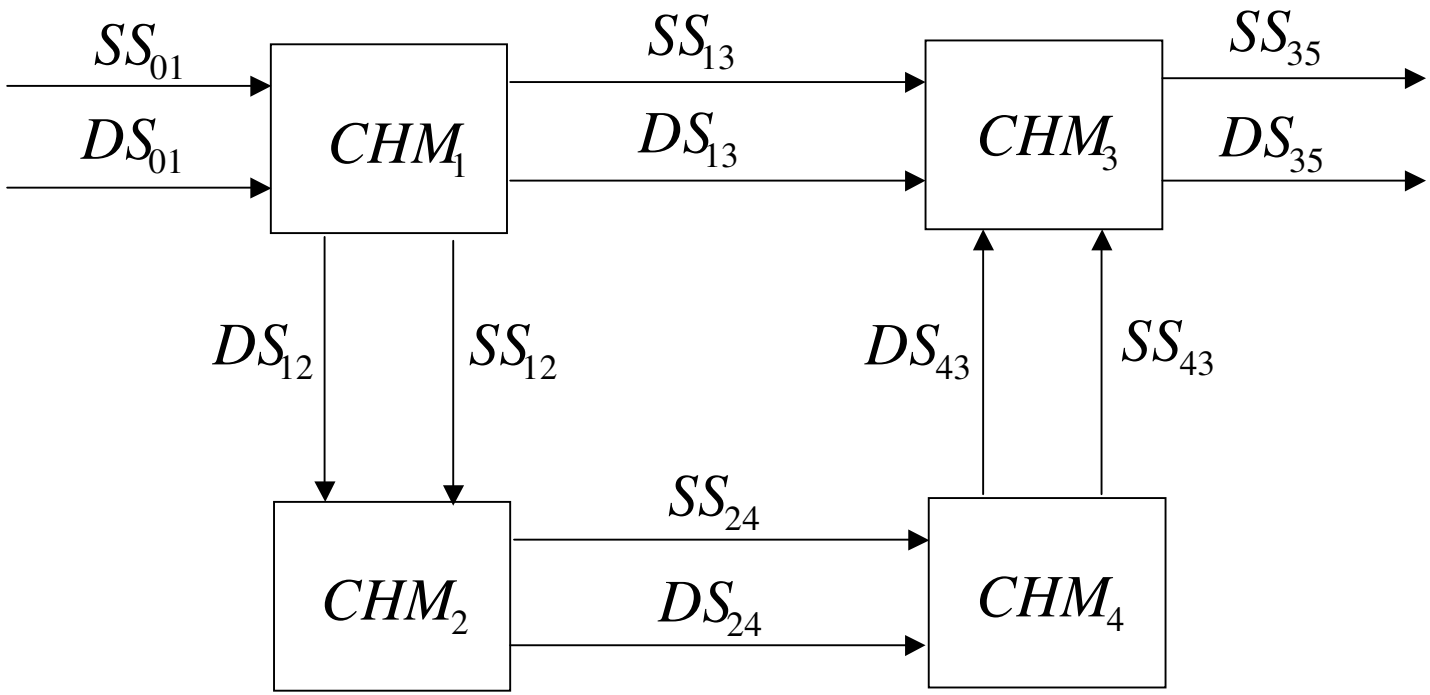


Step 3

- Component health model

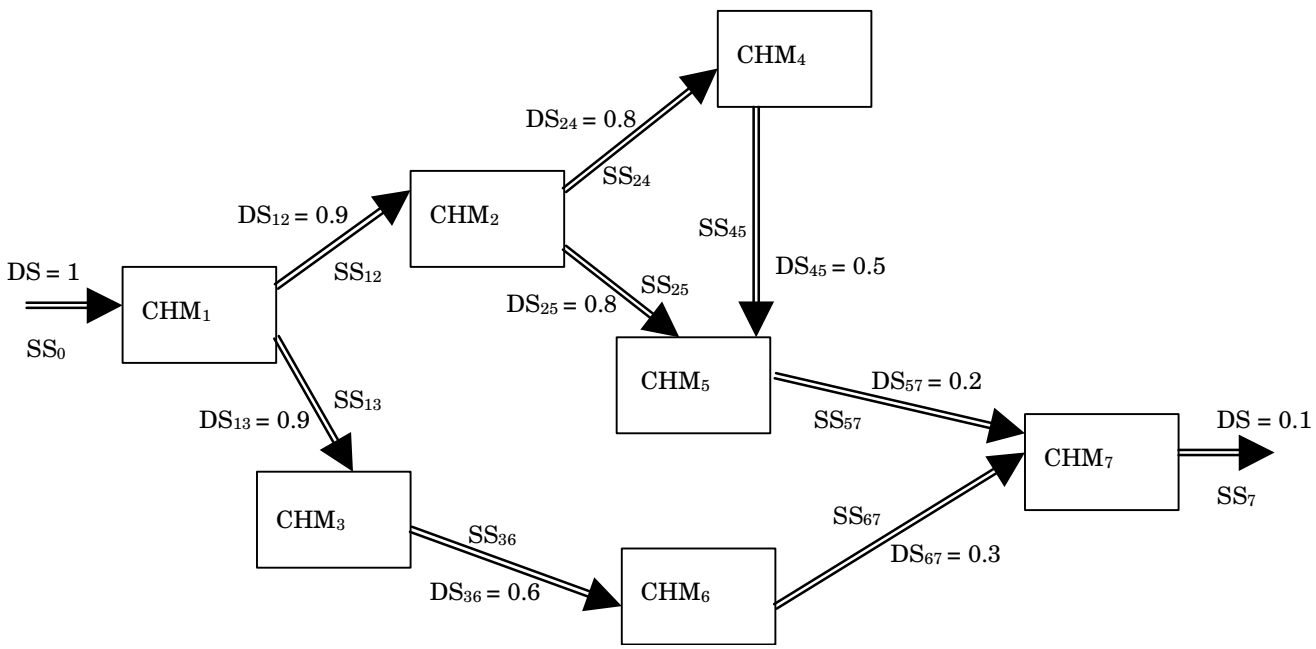


Step 4



System Health Model

Step 4


CHM4
DS24 = 0.8
SS24
DS12 = 0.9
CHM2
SS45
DS = 1
SS12
DS45 = 0.5
SS25
CHM1
DS25 = 0.8
SS0
CHM5
DS57 = 0.2
SS13
DS13 = 0.9
SS57
DS = 0.1
CHM7
SS7
CHM3
SS67
SS36
DS67 = 0.3
DS36 = 0.6
CHM6

Engine Health Maintenance

- Data was collected from a Boeing 747-400 simulator at NASA Ames.
- Of the ninety variables collected, seven were selected as pertinent for the detection of three particular faults.
- Faults: engine flameout, recoverable stall and low speed rotor failure

Fault Detection Example

If EngineThrust (t) is SMALL1

and EngineThrust (t-1) is MEDIUM1

and EnginePressureRatio(t) is VERY-SMALL2

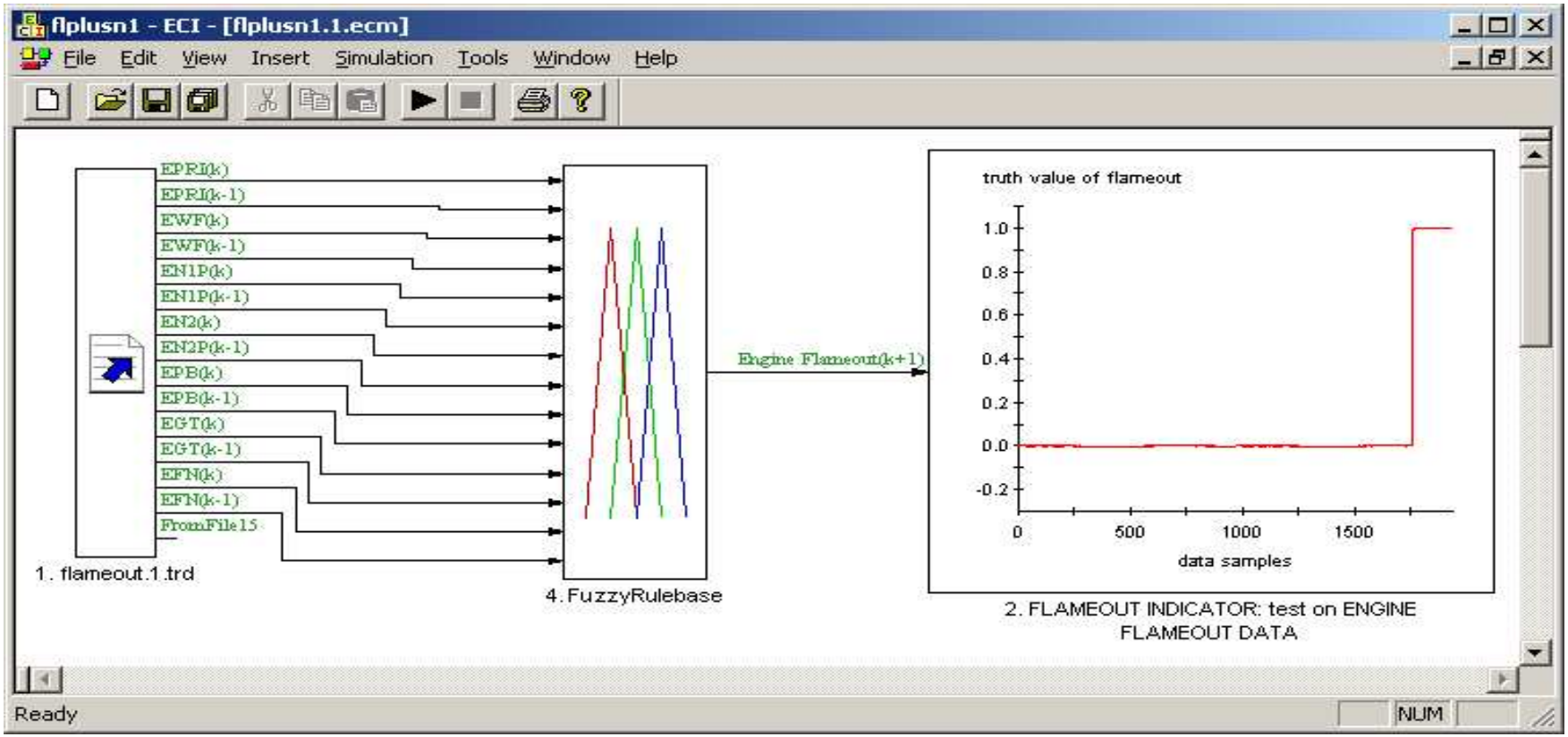
and EnginePressureRatio(t-1) is SMALL2

then EngineFlameout(t+1) is

a + b*EngineThrust(t) +
c*EngineThrust(t-1) +
d*EnginePressureRatio(t) +
e*EnginePressureRatio(t-1)

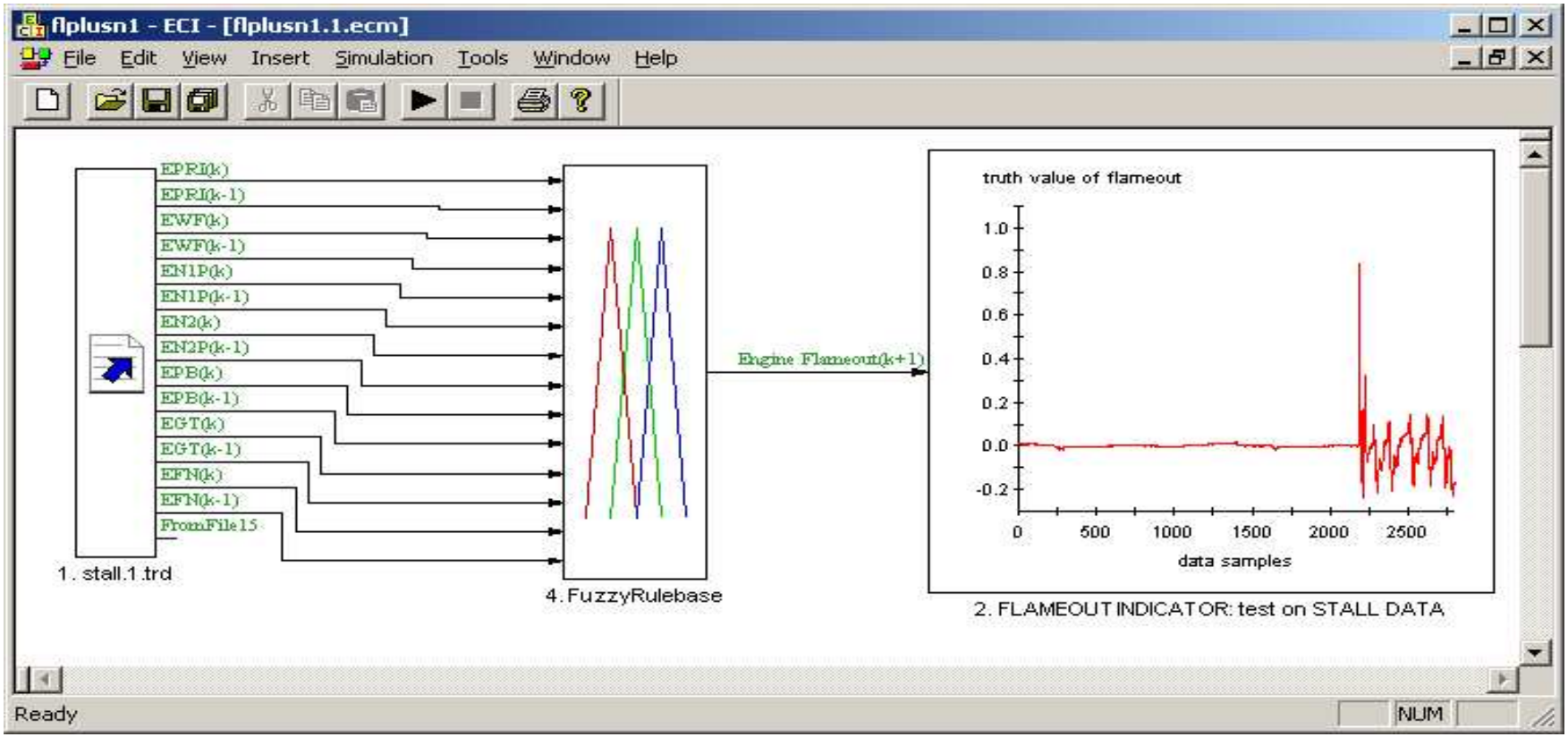
Sample Rule for Aircraft Engine Fault predictor

Example 1



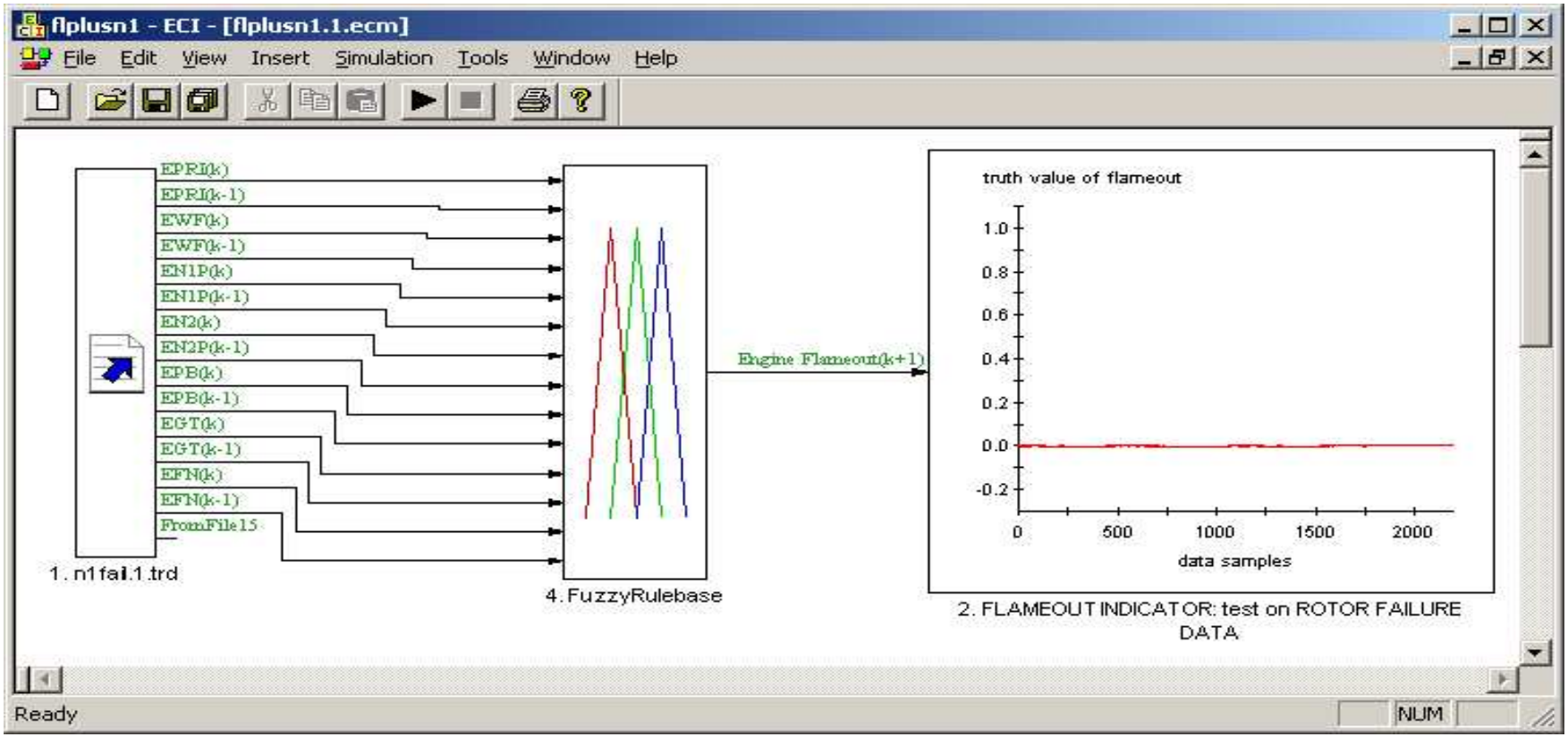
Engine Flameout Indicator: test on Engine Flameout data

Example 2

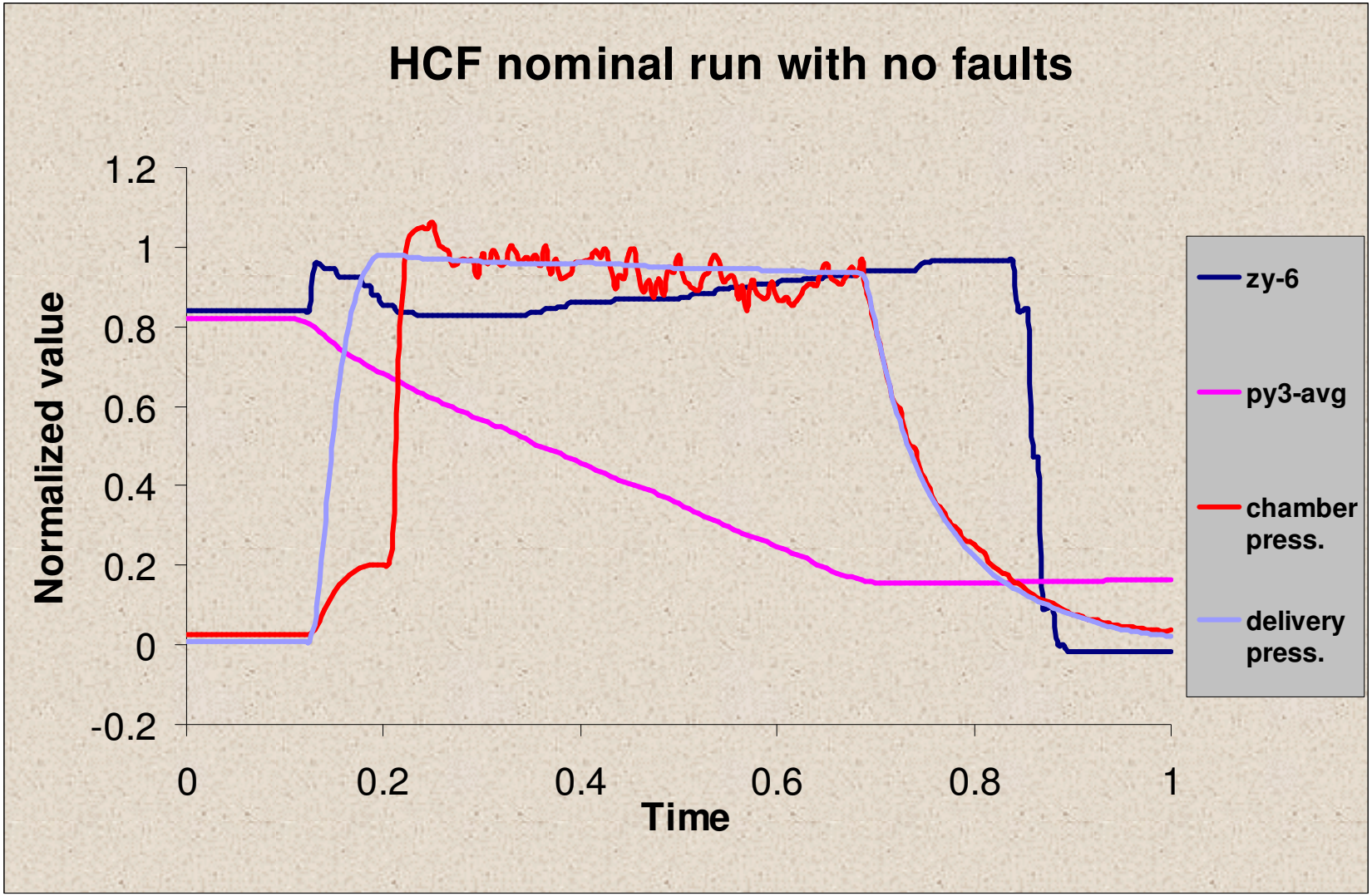


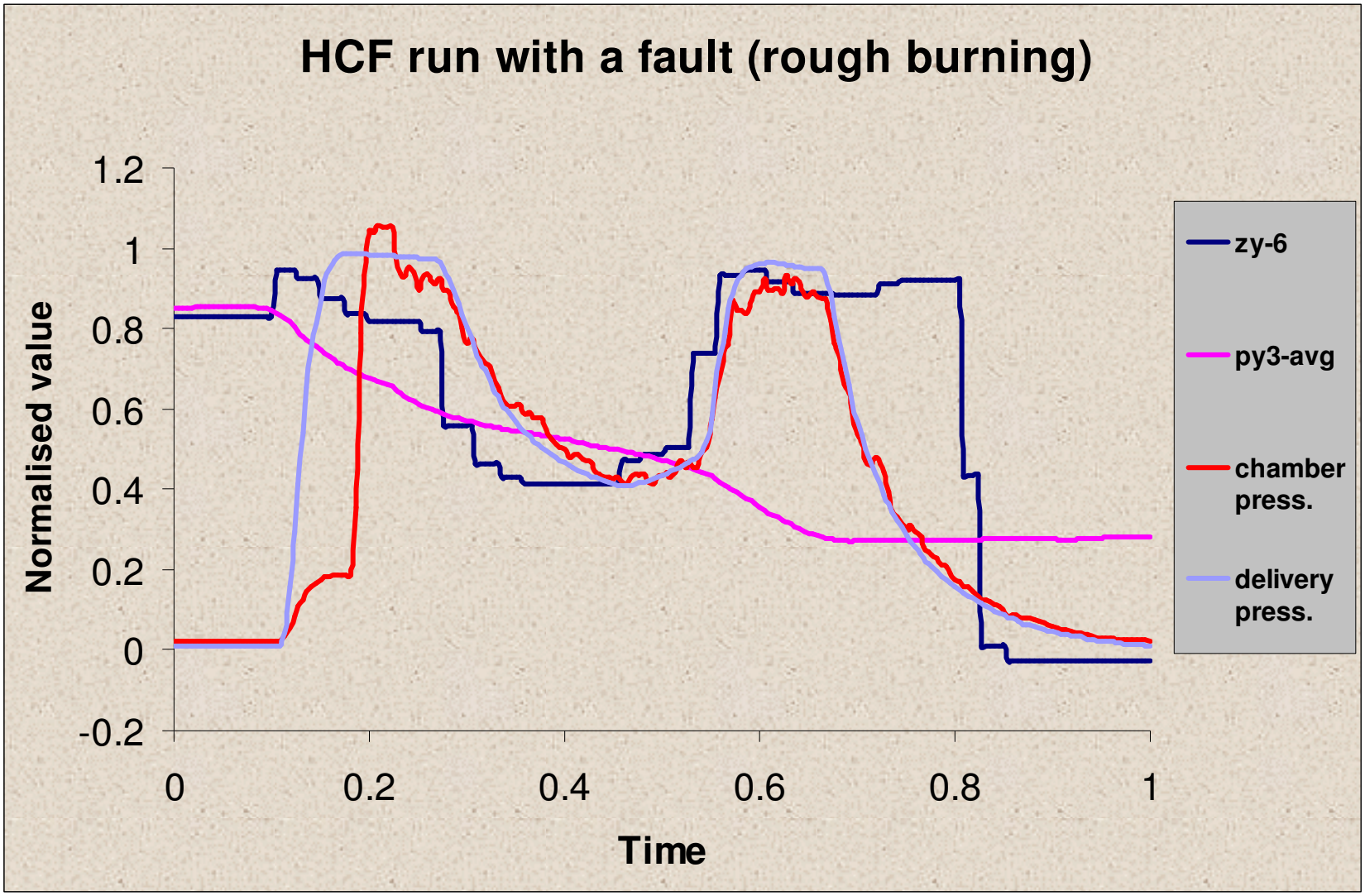
Engine Flameout Indicator: test on Stall data

Example 3



Engine Flameout Indicator: test on Rotor Failure data


HCF nominal run with no faults
Normalized value
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0
0.2
0.4
0.6
0.8
1
Time
zy-6
py3-avg
chamber press.
delivery press.


HCF run with a fault (rough burning)
Normalised value
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0
0.2
0.4
0.6
0.8
1
Time
zy-6
py3-avg
chamber press.
delivery press.