PROGNOSTIC ENHANCEMENTS TO DIAGNOSTIC SYSTEMS

USN OSD SBIR PHASE II N65540-01-C-0015

Dr. Ash Thakker, Global Technology

Dr. George Vachtsevanos, Georgia Tech

Phase II Interim Project Review Meeting
March 07, 2002

Phase II Interim Project Review Meeting Agenda

MARCH 7, 2002

1:00-1:05PM USN NSWC
- Introduction/Update

Mr. Tom Galie

1:05-1:20 PM Global Technology Connection, Inc. (GTC)
- Project Scope, Goals and Schedule
- Milestones/Deliverables

Dr. Ash Thakker.

1:20-2:50PM Georgia Tech- Department of Electrical Engineering
- Current Status and Major Accomplishments
- Demonstration of on line real time Alpha testing and simulation of Prognostic Model

Dr. George Vachtsevanos

2:50-3:15PM
- Planned technical papers/conferences
- Future Work- Beta Testing of Prognostic Model
  - ICAS/HVAC software module interface and integration

Dr. George Vachtsevanos

3:15-3:30PM
- Technology Readiness Level(TRL)
- Feedback

All

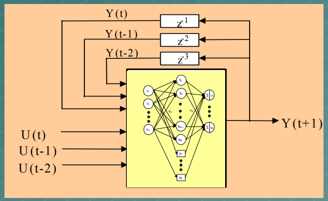
3:30PM Adjourn

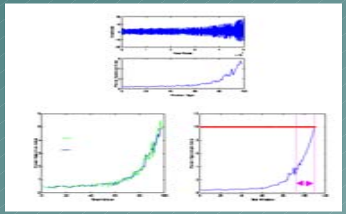
PROGNOSTIC ENHANCEMENTS TO DIAGNOSTIC SYSTEMS

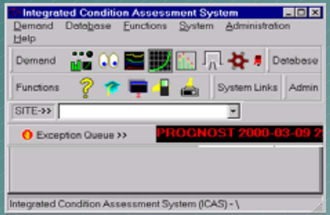
ISSUE: Maintenance of legacy shipboard equipment has become a significant problem

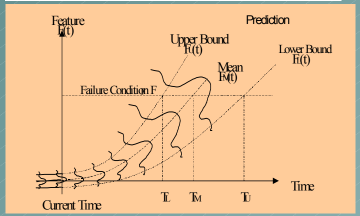
GOAL: Condition-based maintenance of critical shipboard equipment through advanced diagnostics and prognostics

ENABLING TECHNOLOGIES:









- Prognostic algorithms based on dynamic wavelet neural networks
- An open systems interface platform to integrate effectively prognostic algorithms into available diagnostic systems (ICAS)
- User-friendly human systems interfaces
- Intelligent tools for uncertainty management
- A systematic performance assessment methodology

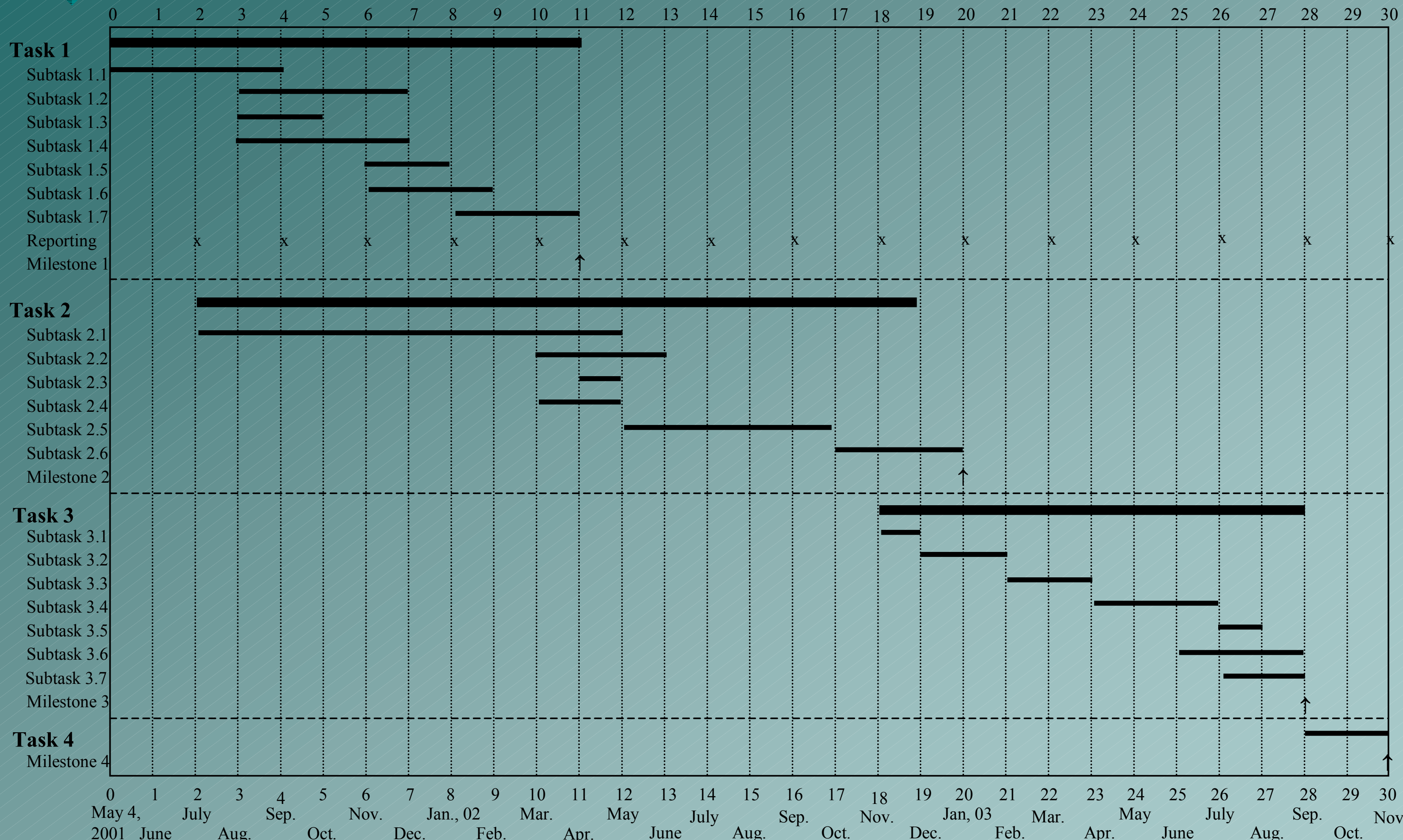
POC CODE & NAME (OPNAV, Technology, Acquisition, and Contractors):

OPNAV SPONSOR: NSWC
TECHNOLOGY SPONSOR: Thom Galie, Program Manager
ACQUISITION SPONSOR: PEO Aircraft Carriers
CONTRACTOR(S): Global Technology Connection, Inc.

Phase II Technical Objectives

1. Complete development of the Prognostic Enhancements to Diagnostic Systems approach initiated in Phase 1. Specifically, complete and optimize code of the selected algorithmic methodology.
2. Verify and validate the prognostic enhancements through computer simulations using experimental data for typical chiller failure conditions.
3. Provide a seamless and full integration of prognostic enhancements with ICAS.
4. Develop, test and evaluate a stand-alone sensor processing, diagnostic and prognostic system.
5. Document the software environment created for the "Roadmap to Prognostic Enhancements to Diagnostic Systems."
6. Transition the "Roadmap to Prognostic Enhancements to Diagnostic Systems Affordability" Software environment to Navy and DoD applications; specifically, implement prognostic algorithms though ICAS on a shipboard AC Plant.
7. Conduct alpha and beta testing to assess and refine the performance of the prognostic algorithms.
8. Prepare a productization and commercialization agenda to be pursued during a Phase III effort.
9. Conduct an aggressive technology transfer program to bring the results of this effort to the military and the industrial communities.

Schedule and Major Milestones



Task 1. Laboratory Scale ICAS/Prognostic Prototype

Subtask 1.1: Define chiller test-bed; design testing program; monitoring requirements; failure mode analysis.

Subtask 1.2: The ICAS platform; transfer ICAS shell to GT laboratory; install and run ICAS routines.

Subtask 1.3: Set up database for testing/evaluation.

Subtask 1.4: Code conversion of DWNN/CPNN prognostic routines.

Subtask 1.5: Run and validate prognostic routines with off-line chiller data.

Subtask 1.6: Integrate/interface algorithms into ICAS environment.

Subtask 1.7: Run and demonstrate in the simulation integrated ICAS/prognostic architecture.

Milestone 1: Demonstration and documentation of integrated ICAS/prognostic routines.

Task 2. Beta Testing of PEDS Architecture at Navy Chiller

Subtask 2.1: Familiarity with chiller system / ICAS interface.

Subtask 2.2: Instrumentation requirements / sensors & data acquisition.

Subtask 2.3: Design of testing program.

Subtask 2.4: Modifications to software for real-time chiller application.

Subtask 2.5: Testing and data analysis.

Subtask 2.6: Assessment of test results and refinements.

Milestone 2: Demonstration of PEDS performance on land based navy chiller.

Task 3. Field Testing and Evaluation of PEDS

Subtask 3.1: Select shipboard chiller and ICAS interface.

Subtask 3.2: Optimize code for PEDS and configure PEDS.

Subtask 3.3: Install on shipboard chiller.

Subtask 3.4: Conduct field testing.

Subtask 3.5: PEDS performance assessment.

Subtask 3.6: Assess applicability of PEDS to other smart carrier systems.

Subtask 3.7: Write final phase II report / documentation.

Milestone 3: Field demonstration of PEDS performance.

Task 4. Productization and Commercialization Activities

Milestone 4: Production model developed; third party for commercialization identified.

Phase II Deliverables

CDRL A001 Bi-Monthly	Jan 15, Mar 15, May 15
CDRL A002 Interim Rept	May 2002 - 330 DAC
CDRL A003 Preliminary Rept	Feb 2003 - 60 DPCC
CDRL A004 Final Rept.	May 2003 -15 DARC
CDRL A005 Patent Application for Invention	June 2003
CDRL A006 Demonstration Project Plan	June 2001
CDRL A006 System/Subsystem Specs	Jul. 2001
CDRL A007 Software Requirements Spec.	Sep 2001
CDRL A008 Software Development Plan (SDP)	Jun. 2001
CDRL A008 Software Design Document (SDD)	July 2001, Apr. 2003
CDRL A009 System/Subsystem Design Description (SSDD) – Hardware Design Doc.	Jul. 2001, Apr. 2003
CDRL A010 Development Design Drawings & Associated Lists – Prem. Design Disclosure	Oct. 2001/15 DARC
CDRL A011 Development Design Drawings & Associated Lists – Final Design Disclosure	CC/30 DARC
CDRL A012 Test Plan – Demonstration Test Plan & Procedures	30 DPTT/15 DARC
CDRL A013 Test/Inspection Report	60 DATC/30 DARC
CDRL A016 Conference Agenda – Meeting Agenda	7 days before mtg
CDRL A018 Presentation Material	10 days after CB

Presentation Outline

- Current Status & Major Accomplishments
- The Real-time Simulation Environment
- The York Failure Data
- The PEDs Architecture
- Database Management
- Data Mining/Feature Extraction
- Diagnostic/Prognostic Algorithms

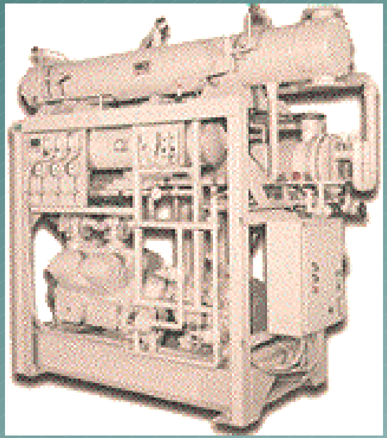
  *Demonstration of On-line, Real-time Simulation
- Future Work

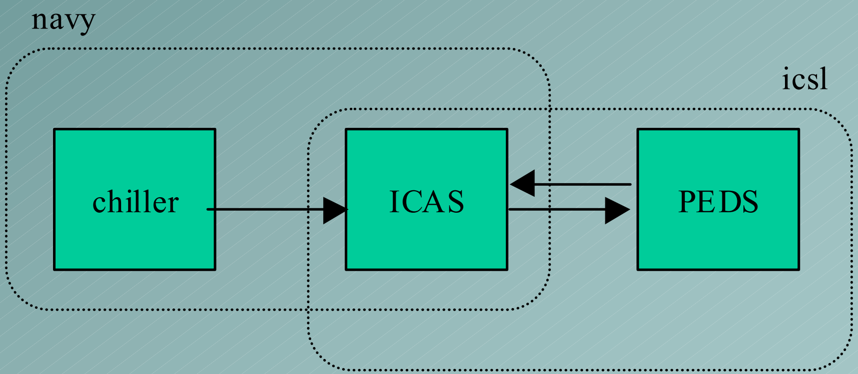
Core CBM Issue : understanding the "physics" of complex dynamical systems

- Failure Mechanisms
- Failure Mode and Effects Criticality Analysis (FMECA)
- Selecting and Extracting Precursors / Features for Fault Diagnosis and Prognosis
- Raw data => Information => Knowledge
- The Hybrid Hardware / Software Interface

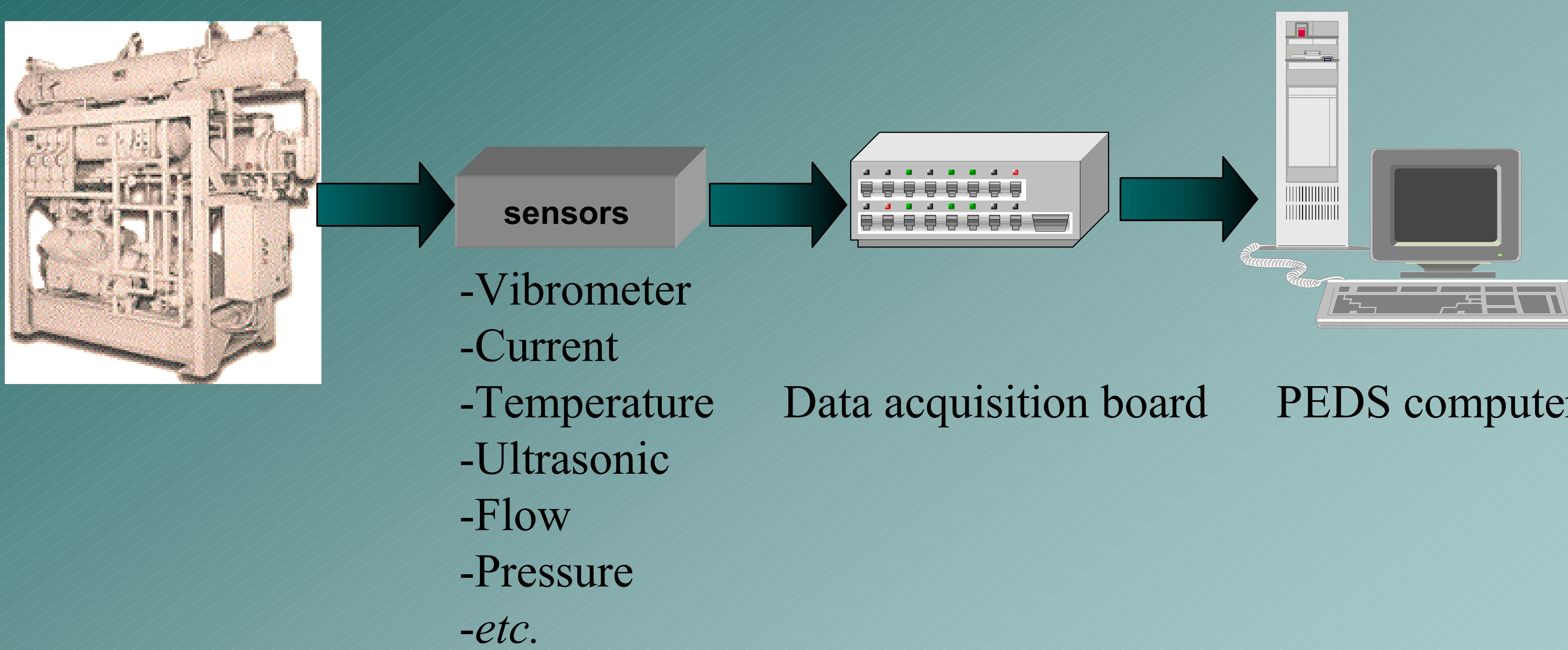
Introduction

- PEDS - prognostic enhancements to diagnostic systems
- Phase I: laboratory research (1999 - 2000)
- Phase II: integration and application (2000 - 2003)
- Phase III: commercialization (2004)





Hardware System Architecture



System Architecture (Multi-Modes)

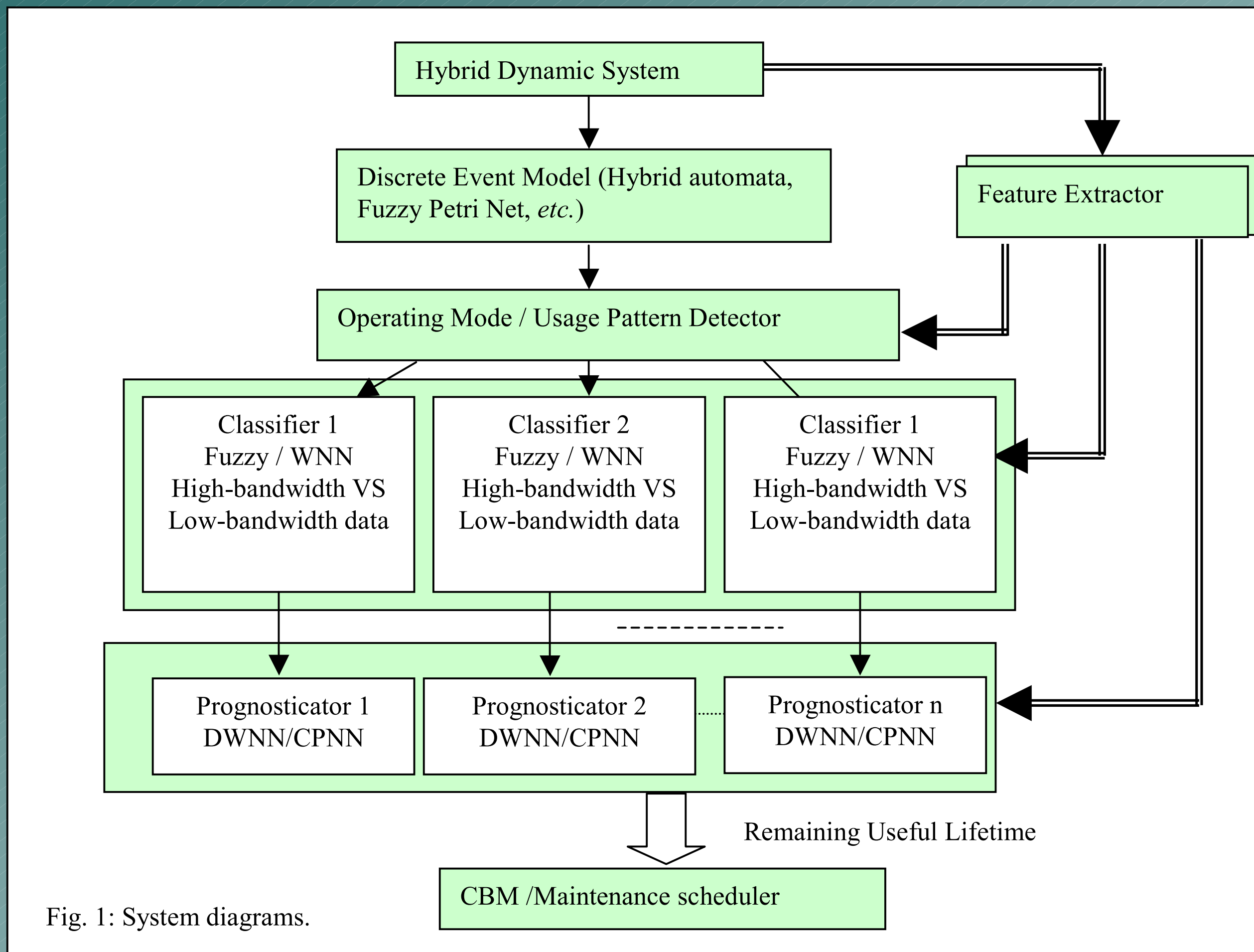
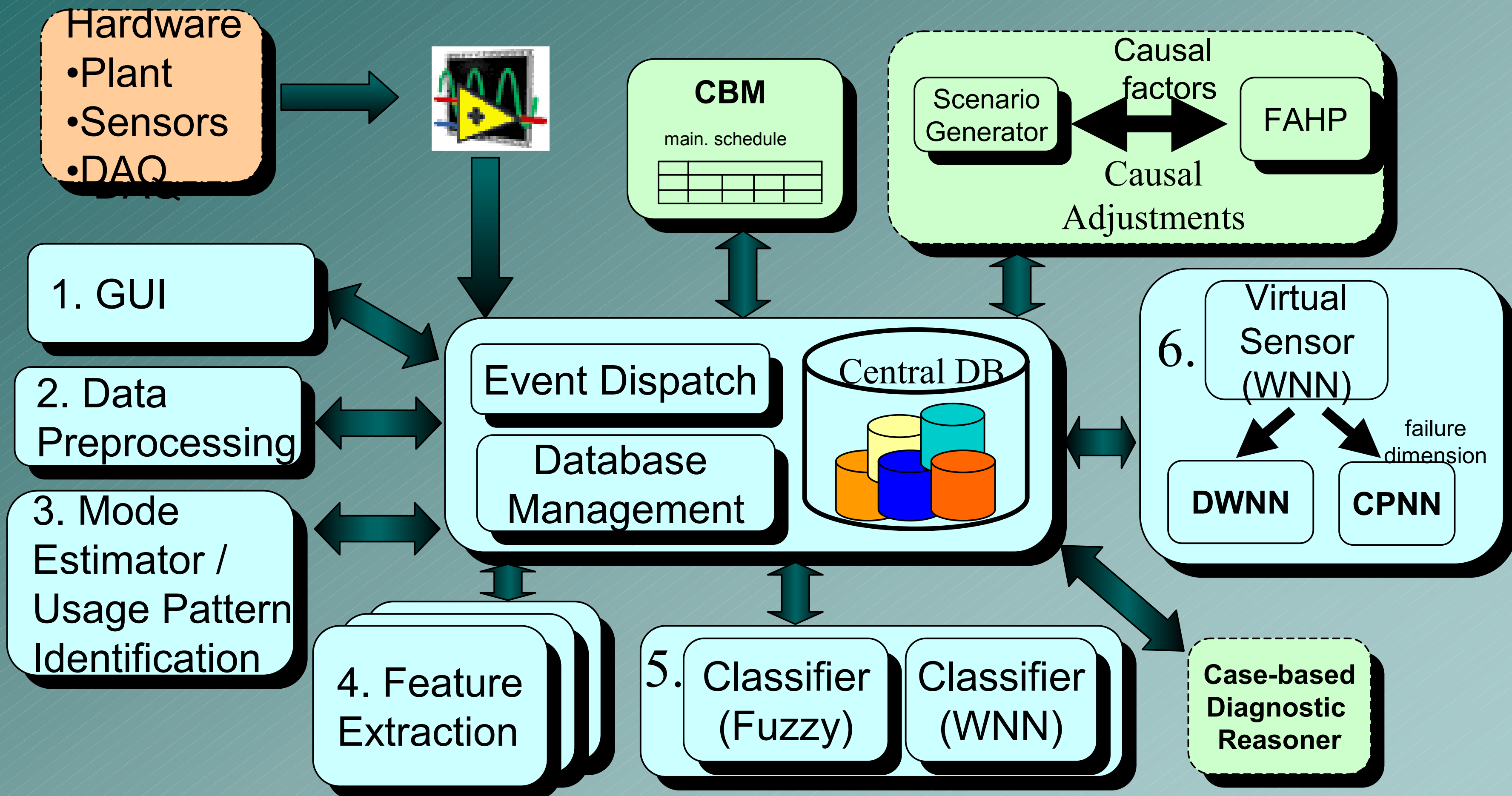
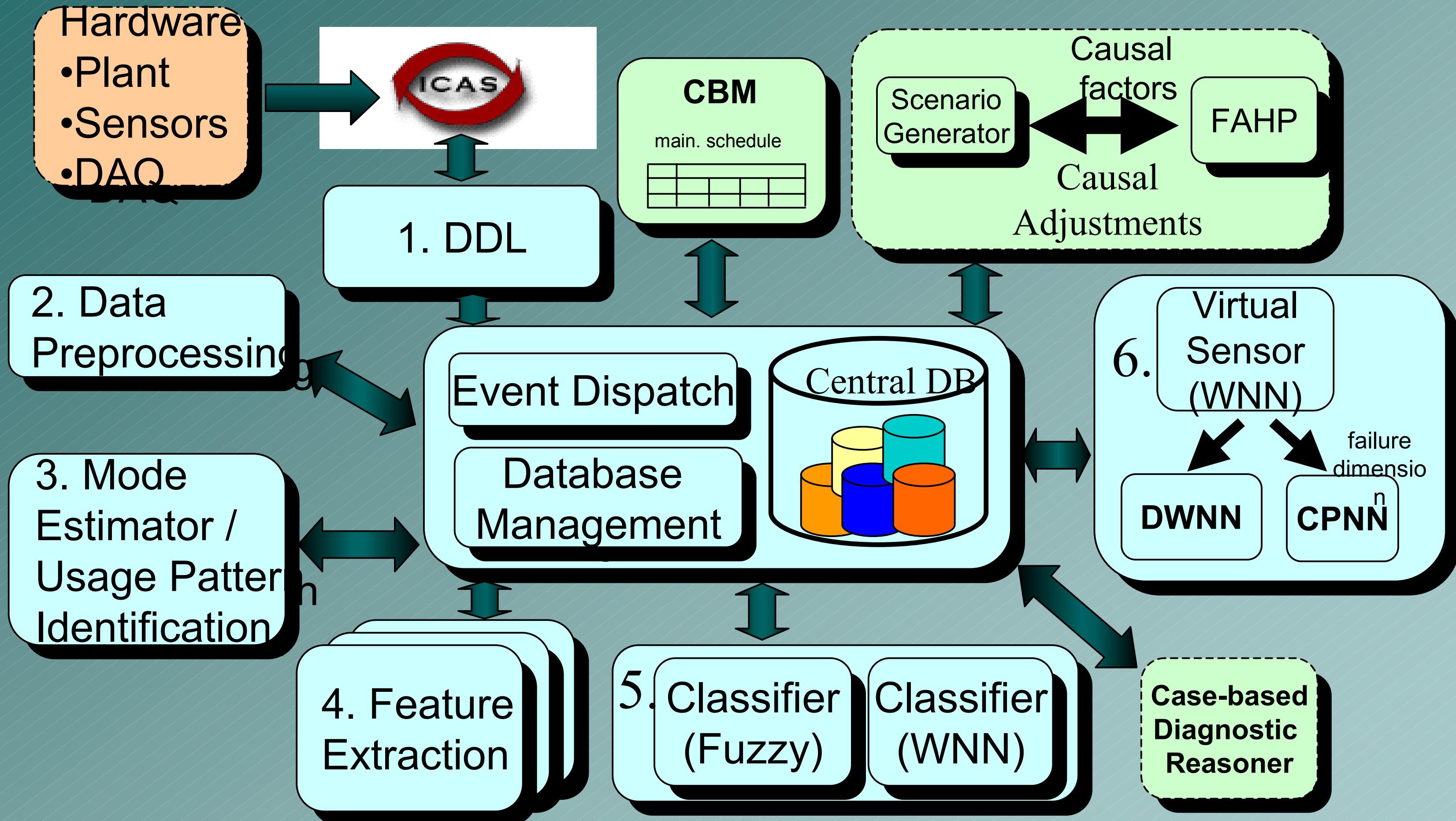


Fig. 1: System diagrams.

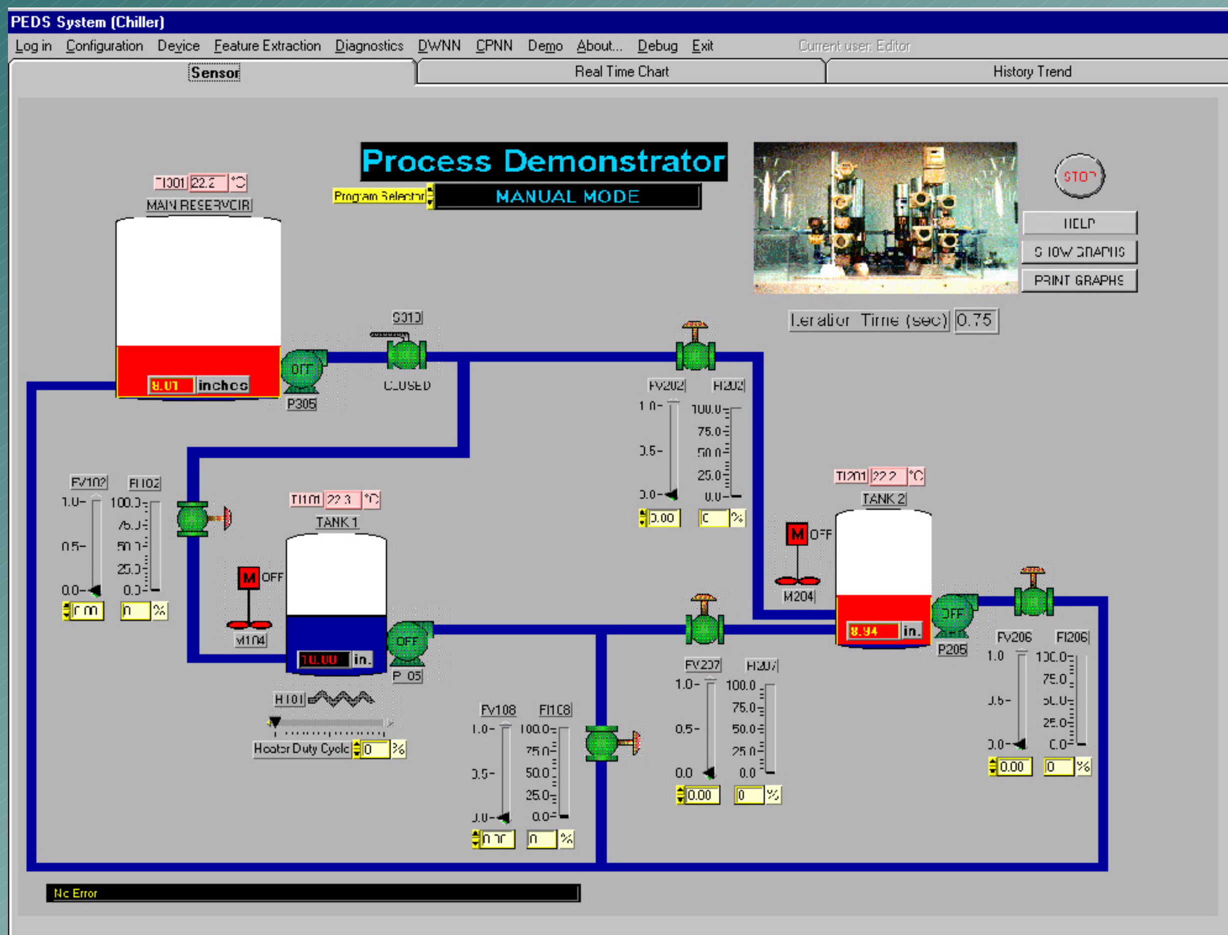
PEDS Software System Architecture (Stand-alone)



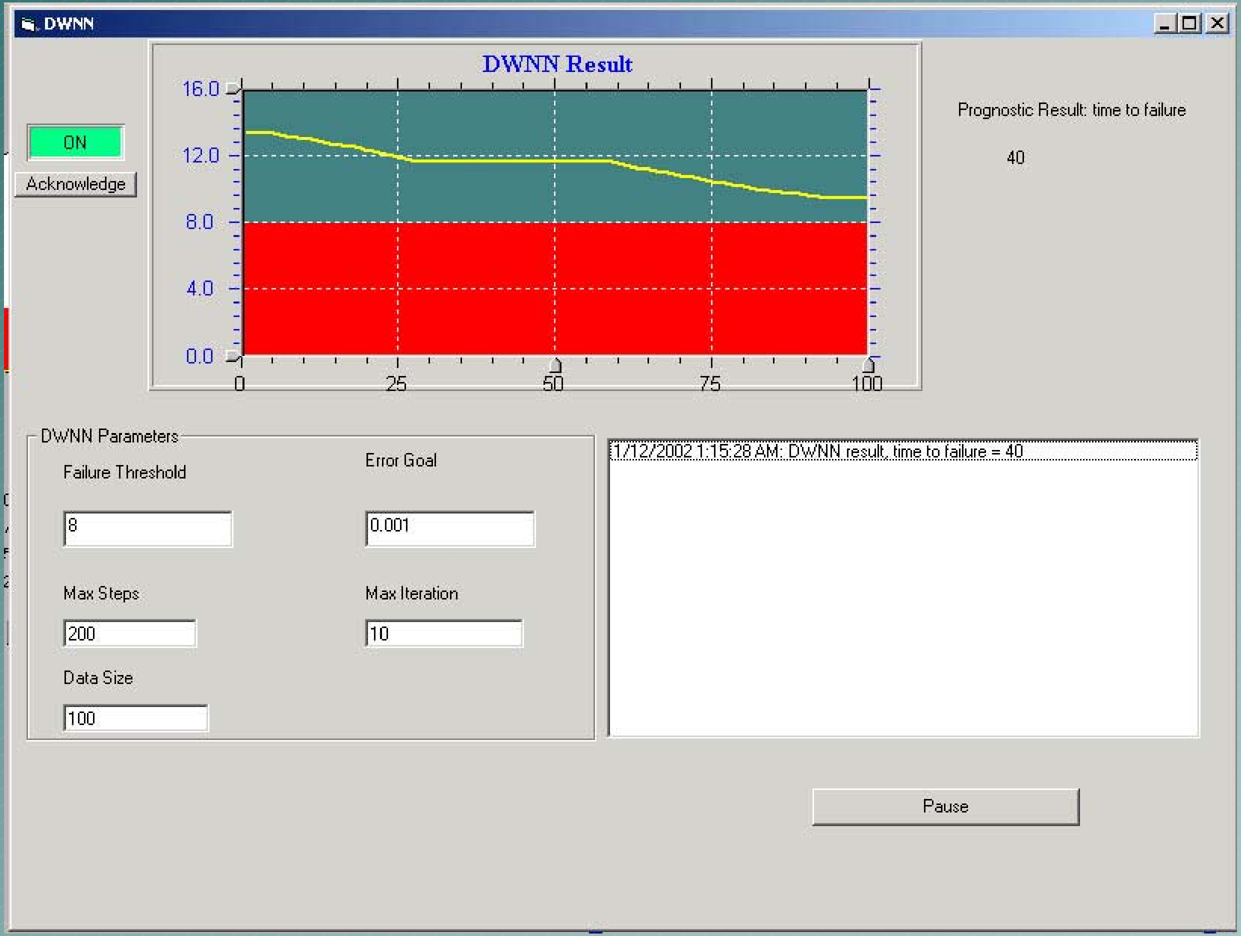
PEDS Software System Architecture (with ICAS)



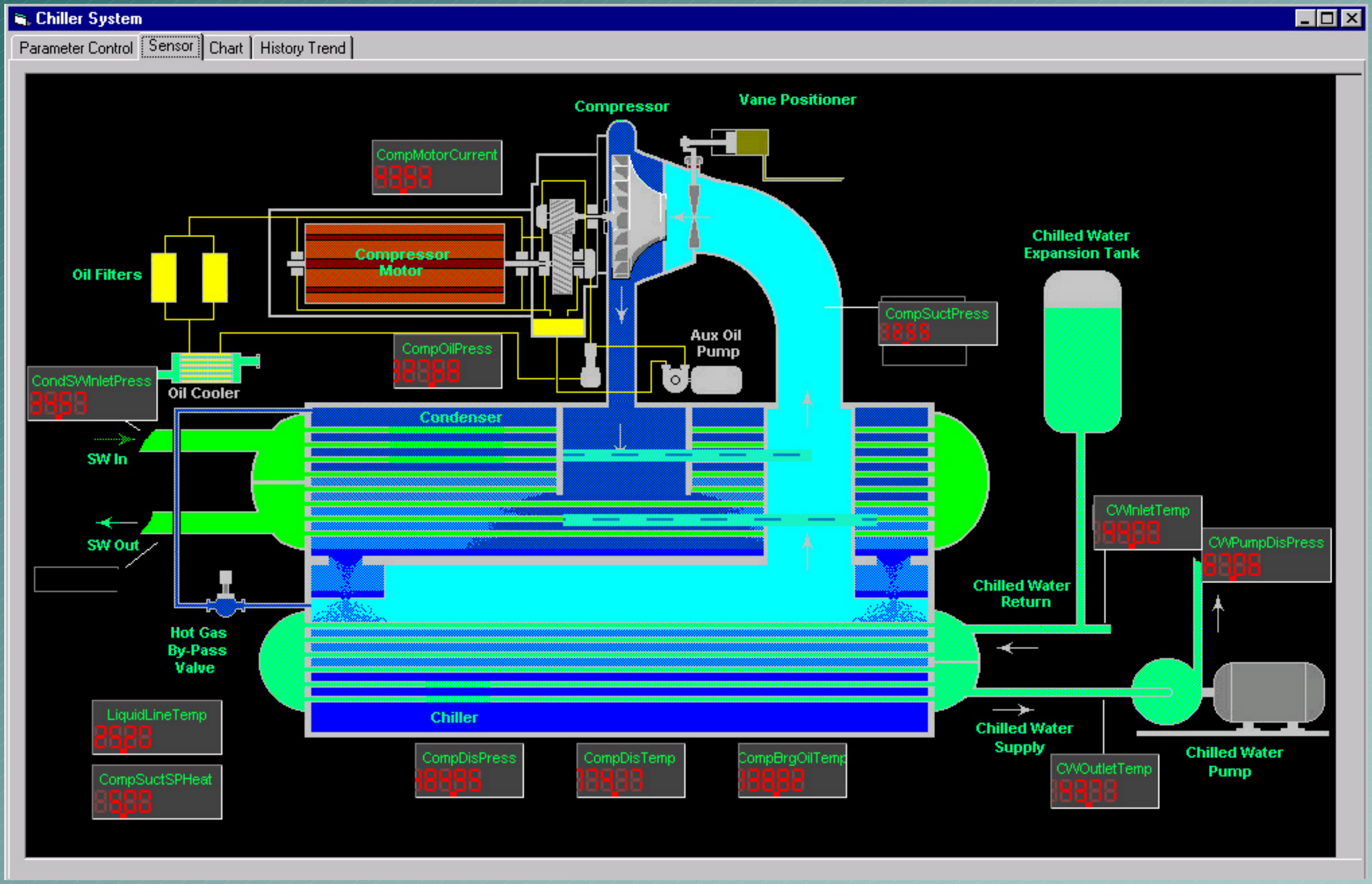
An Example (Process Demonstrator)



An Example (Process Demonstrator)



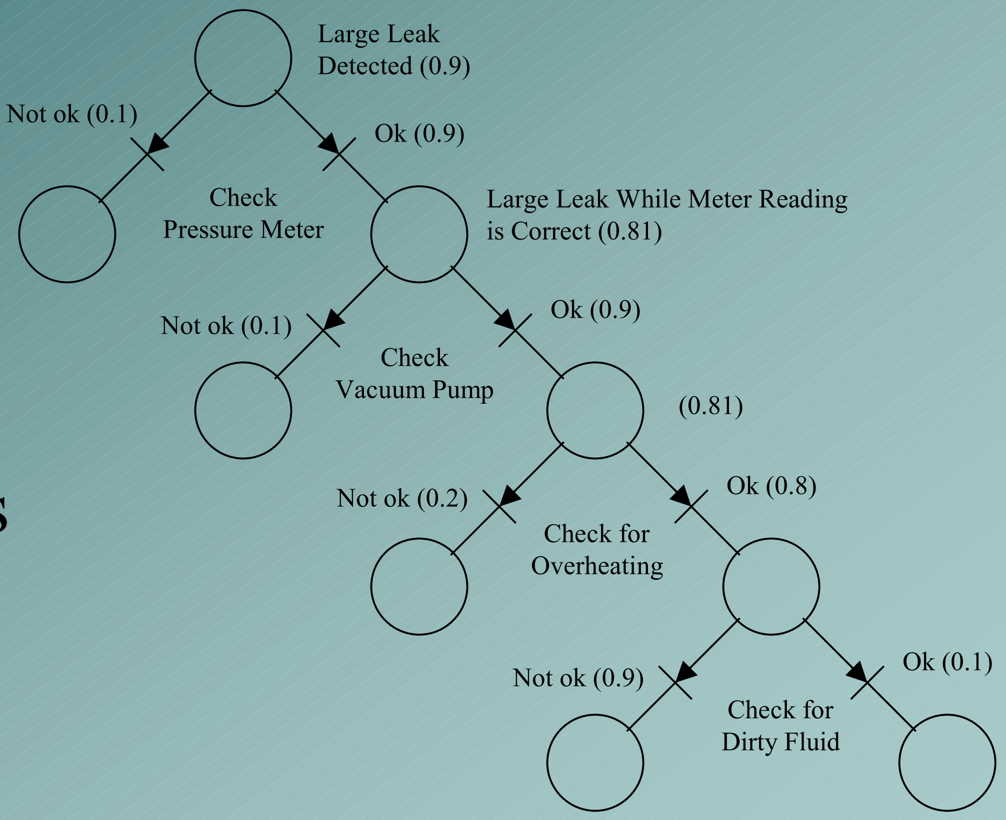
An Example (Chiller)

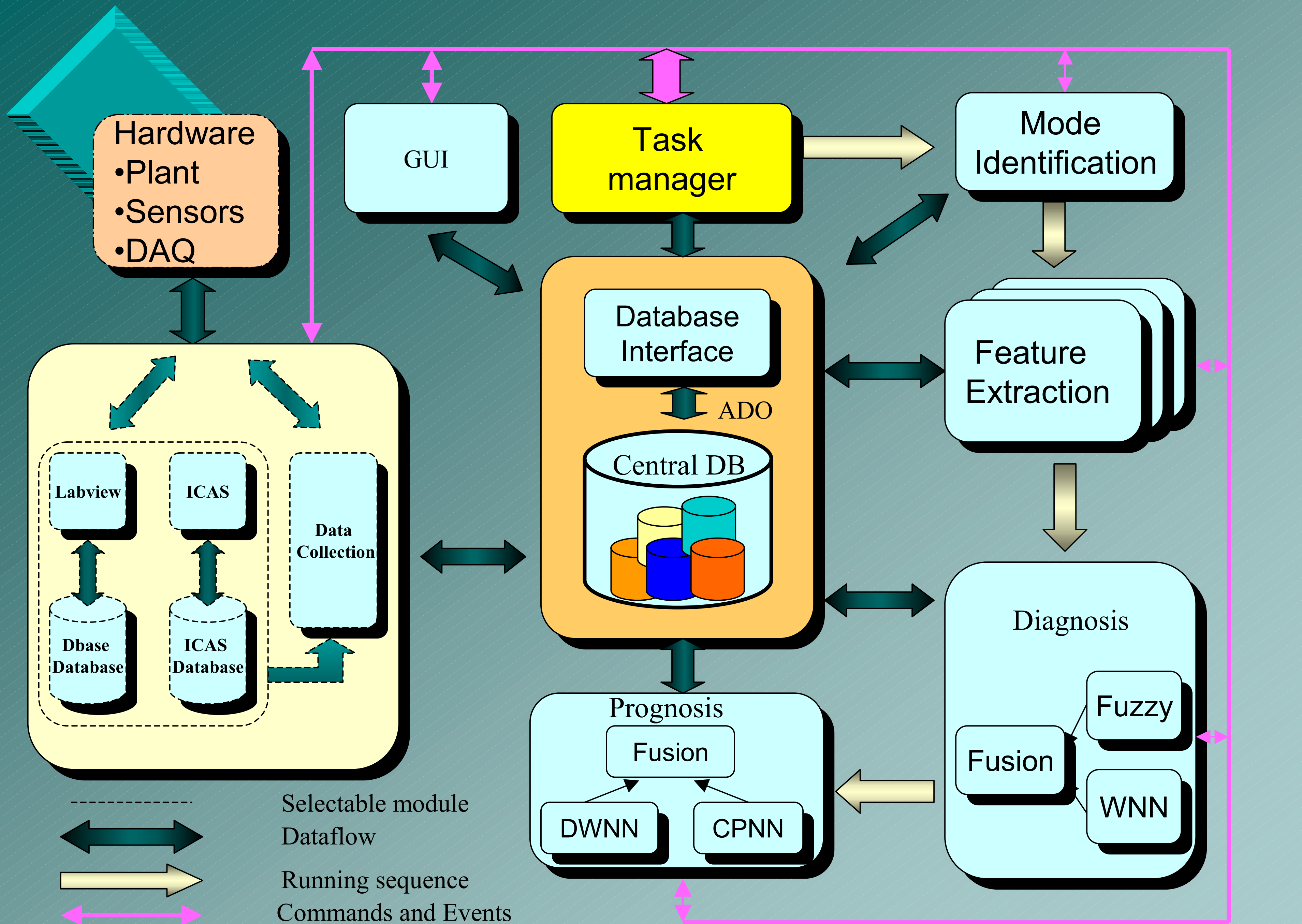


Failure Mode and Effects Criticality Analysis

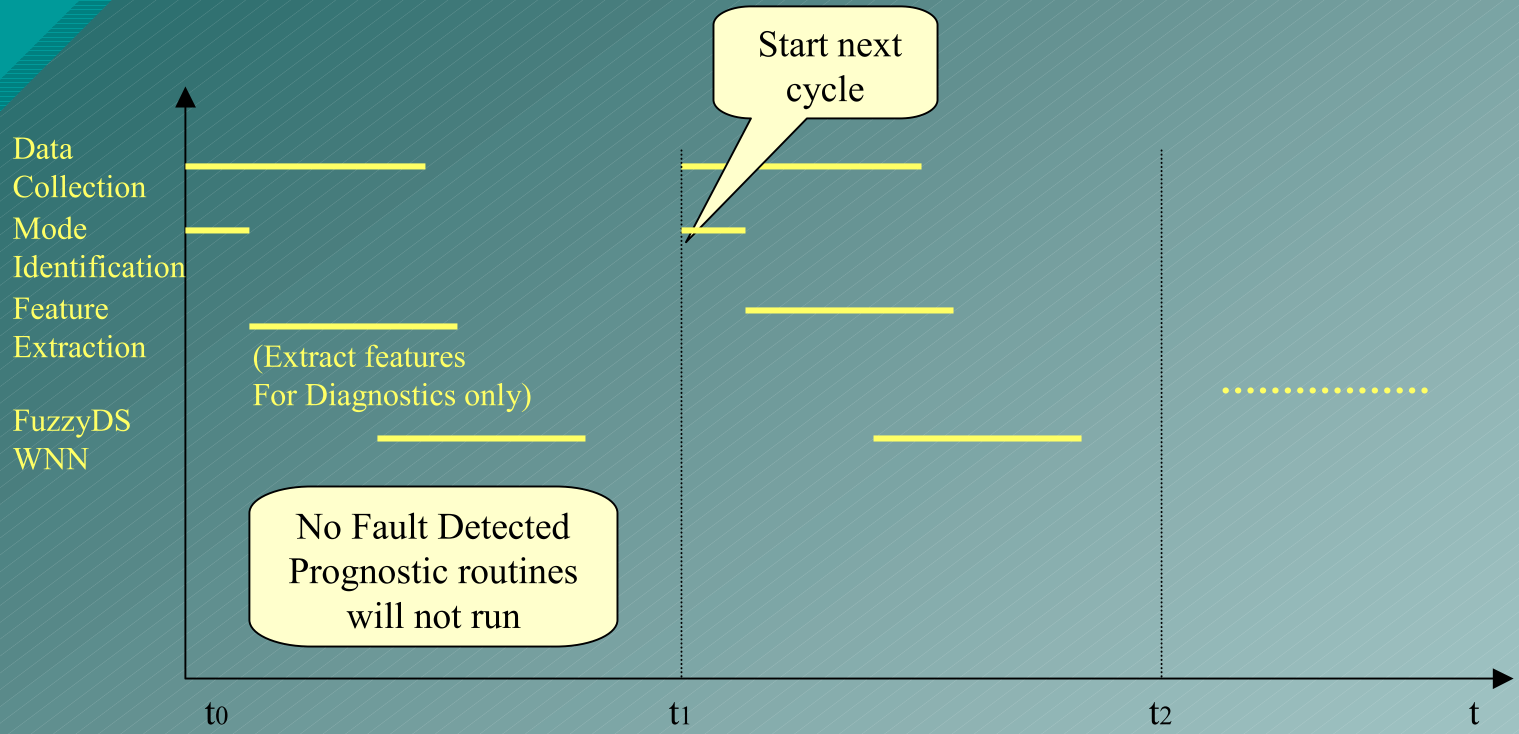
- Failure Mode and Effects Criticality Analysis

  New systematic approach based on fuzzy Petri networks and efficient search techniques to define failure effect – root cause relationships



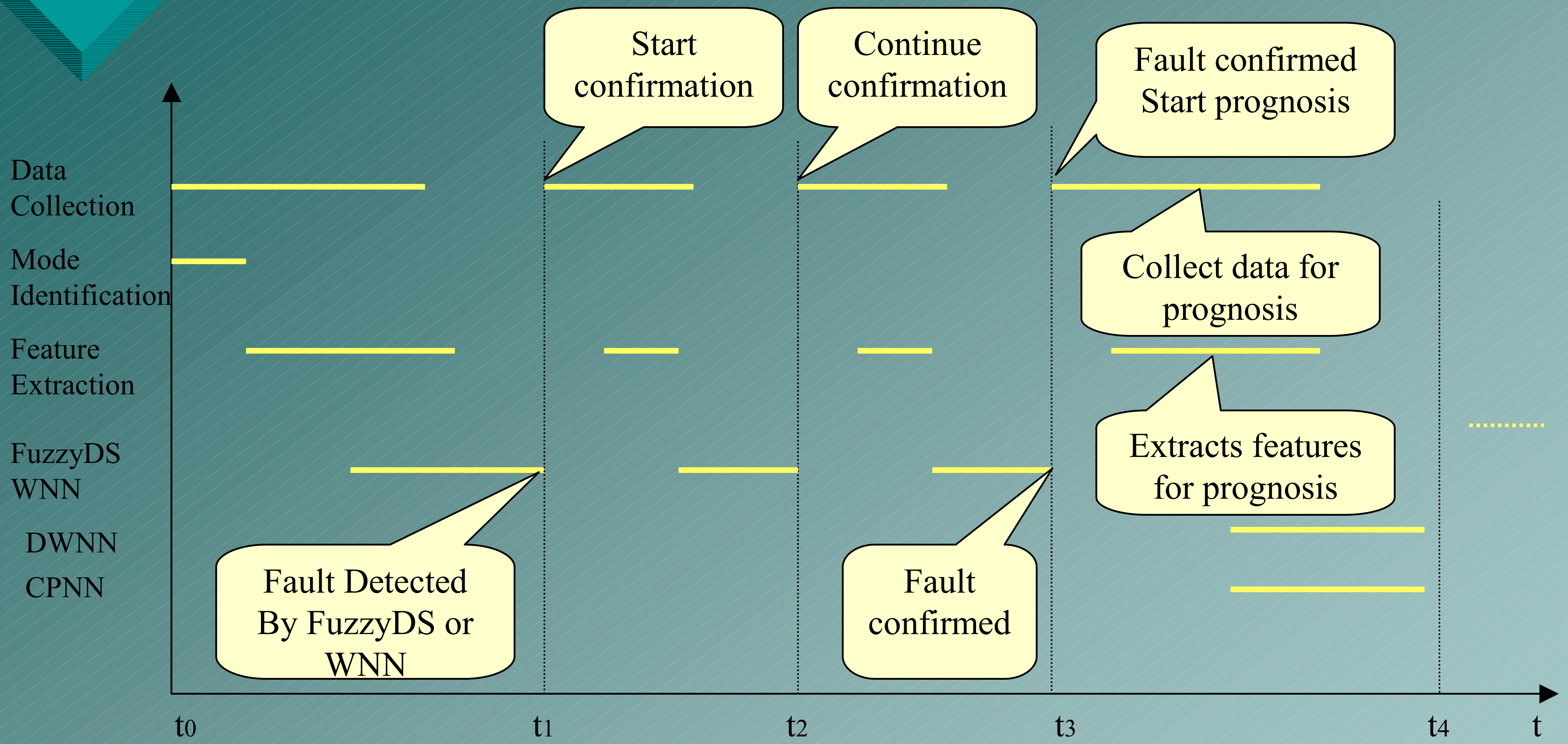

Hardware
•Plant
•Sensors
•DAQ
GUI
Task manager
Mode Identification
Database Interface
ADO
Central DB
Feature Extraction
Labview
ICAS
Data Collection
Dbase Database
ICAS Database
Diagnosis
Fuzzy
Fusion
WNN
Prognosis
Fusion
DWNN
CPNN
Selectable module
Dataflow
Running sequence
Commands and Events

Timing sequence(1)-No fault Detected

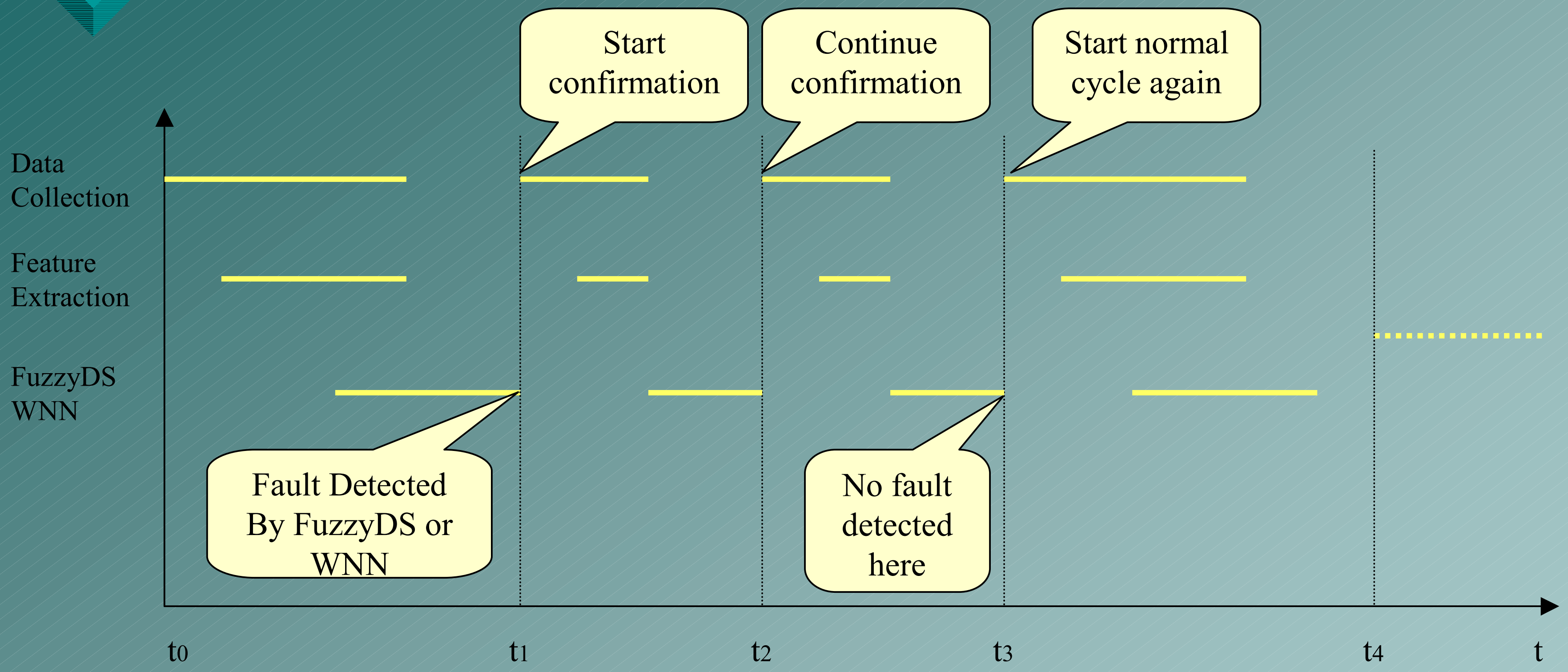


1. The timing sequence is managed by the **Task Manager**
2. Algorithm modules are started by **FEATURE READY** events
3. Each diagnostic module decides upon the presence or absence of a fault
4. The diagnostic modules report their conclusion to the database.
5. Each diagnostic module runs its routine and responds back to the task manager.
6. **Task manager** receives the events and decides which module or algorithm should be started.
7. The diagnostic decision (or No fault) is displayed on the GUI;GUI receives result from database.
8. All prognostic routines are initiated when a fault has been detected.

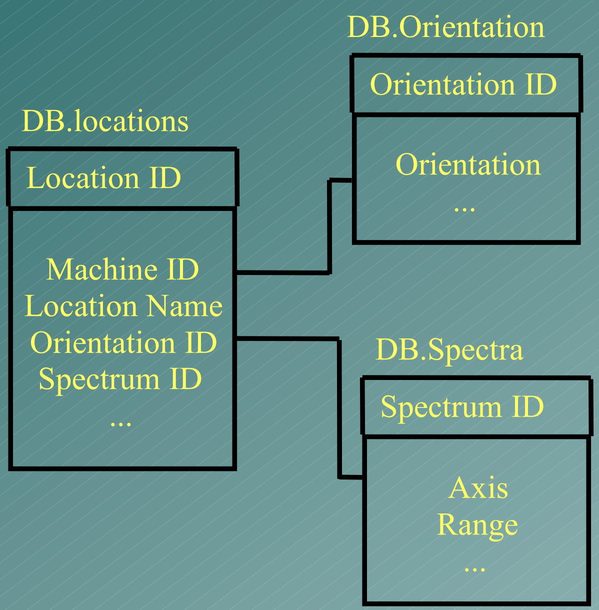
Timing sequence(2)—Fault Confirmed



Timing sequence(3)—Fault not confirmed

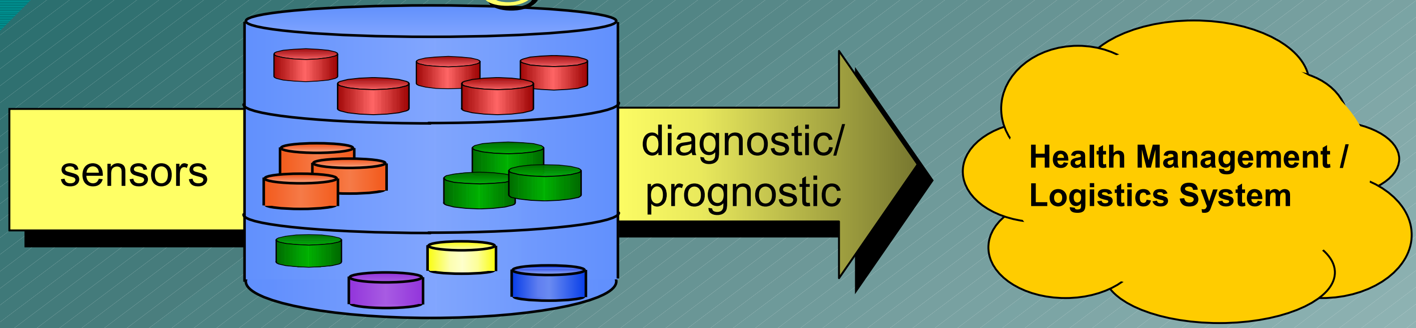


Database Management



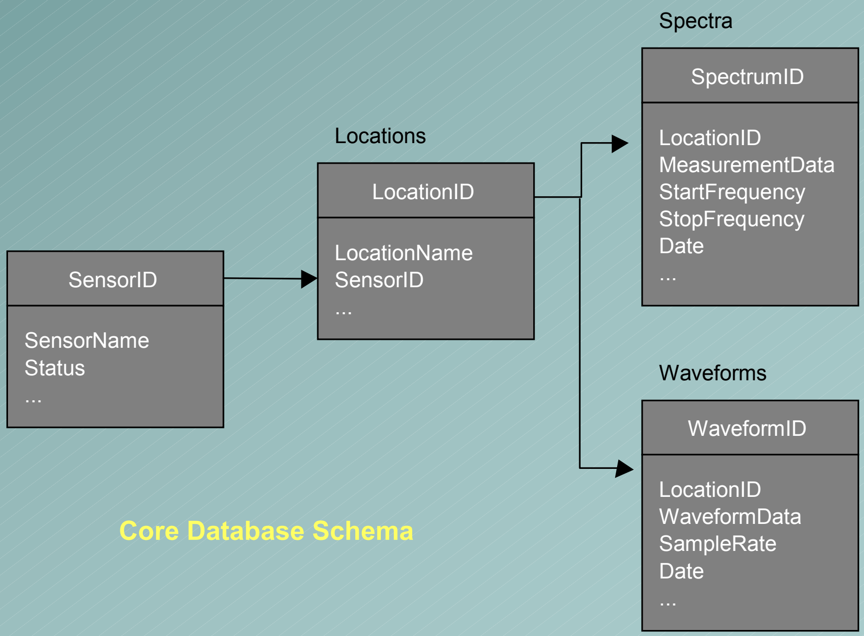
- Relational Database Management System for data representation and conversion for use with diagnostic and prognostic technologies
- Data preprocessing (filtering, compression, etc.) and data validation techniques
- Use declarative query language, SQL

Data Management



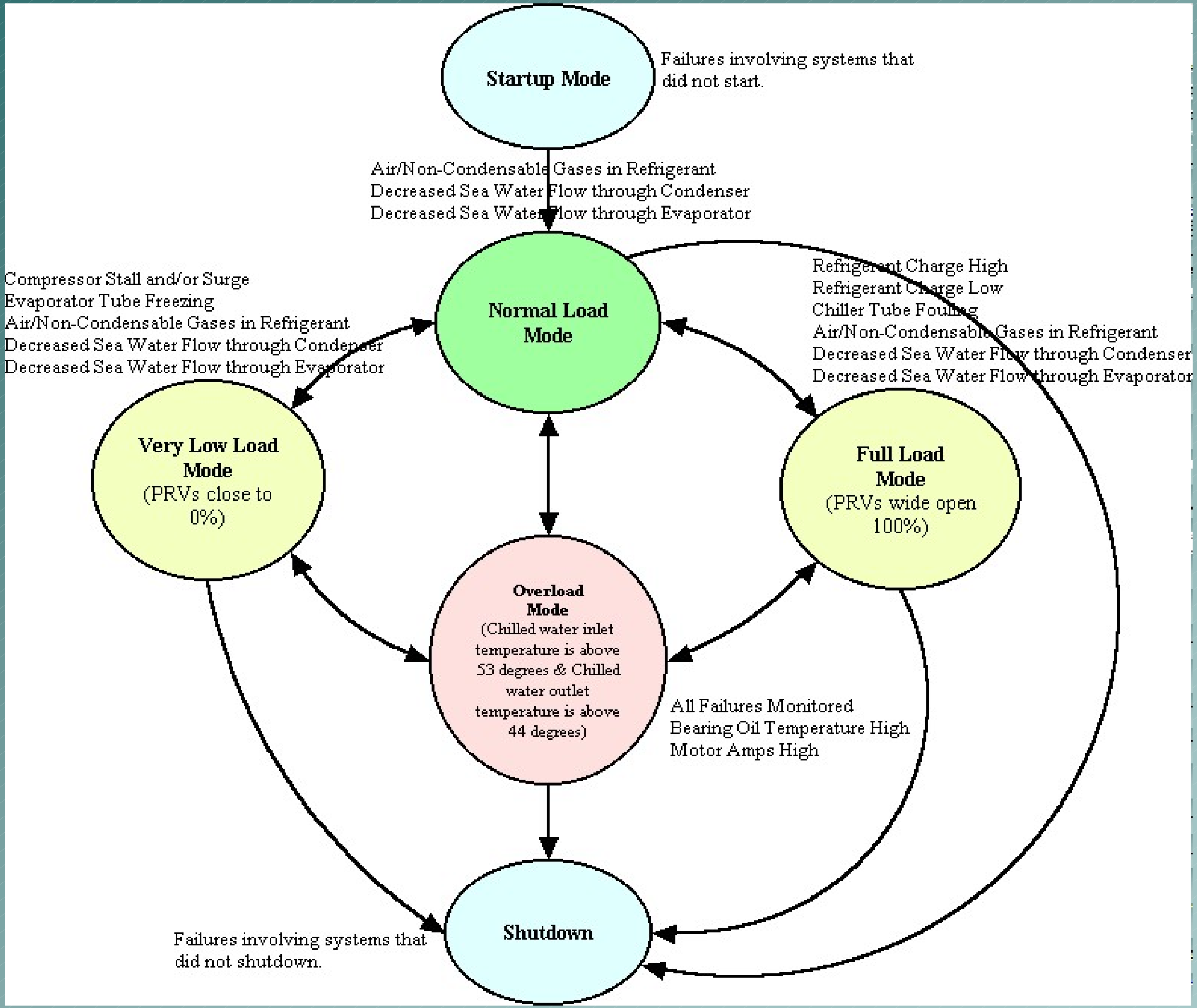
Data Server

- Provides client-server relational database to diagnostic/prognostic modules
- Provides storage for setup information, collected data and analysis results
- Optimizes data availability and reliability
- Defines data collection schedules
- Manages scheduled components, sensor calibrations and input multiplexing
- Increases operational uptime
- Decreases maintenance cost



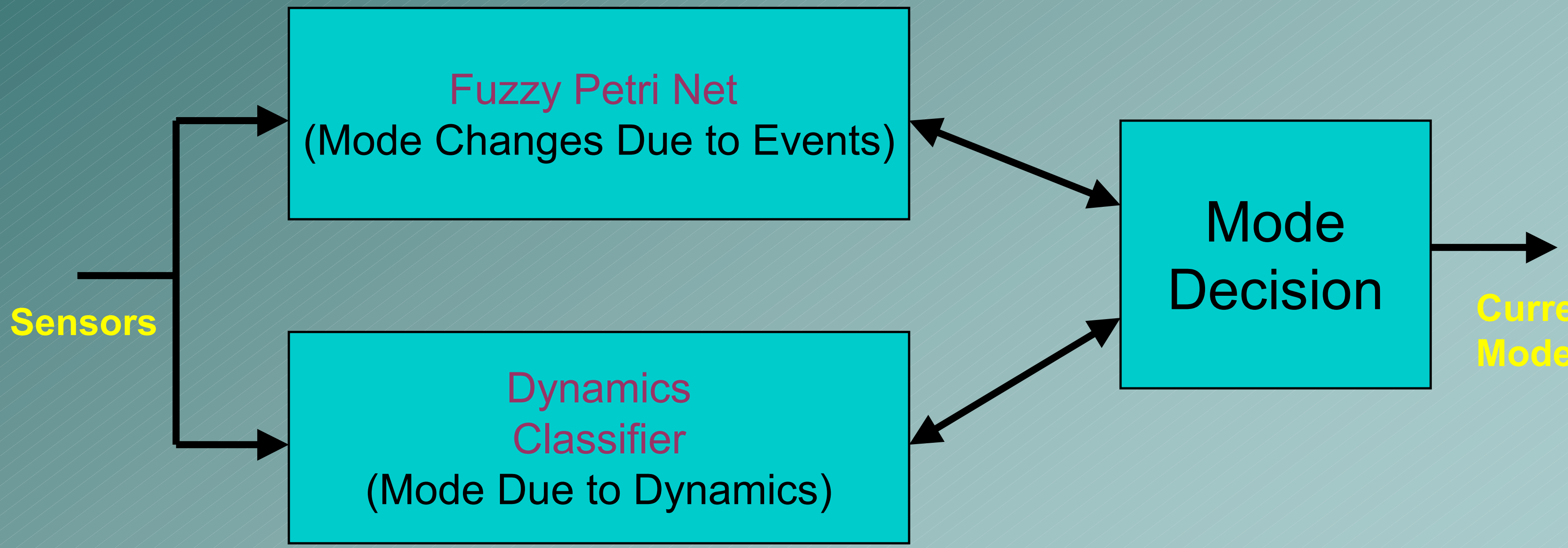
Core Database Schema

Mode Diagram
Example Testbed: AC-Plant

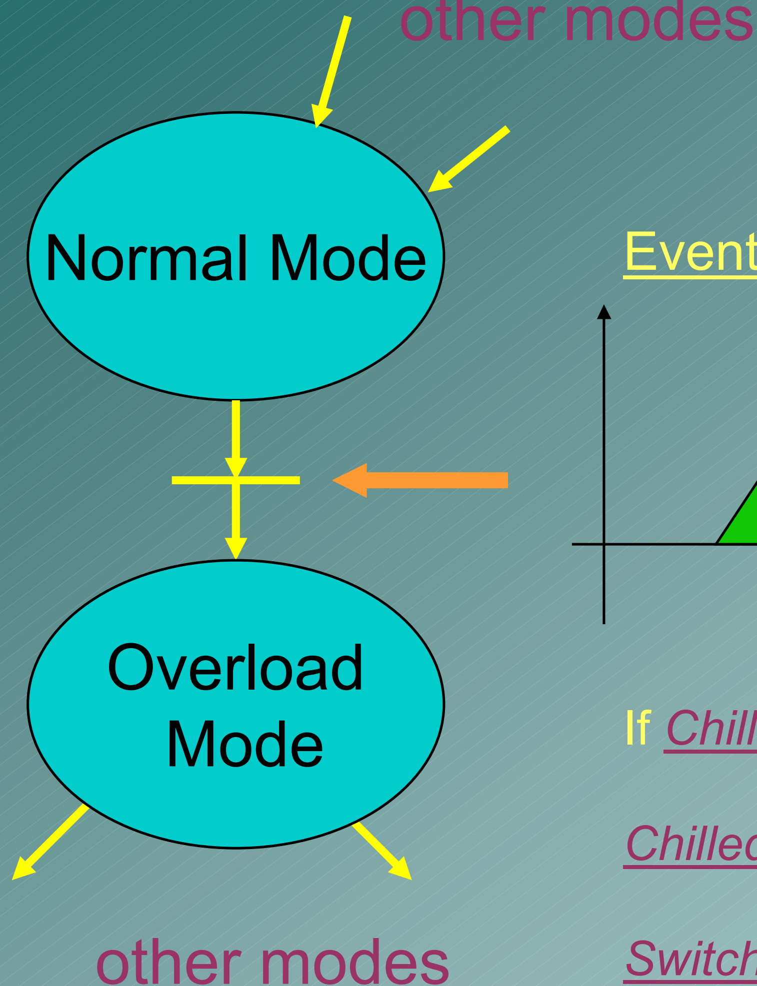


Mode Identification

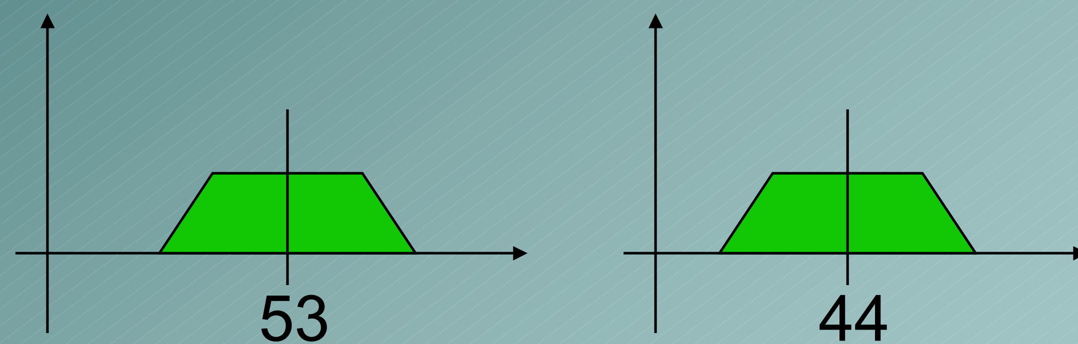
- Modes are characterized by the dynamics, set-points, and controller.
- Modes switch due to events.



Fuzzy Petri Net



Events Characterized by Membership Functions



If *Chilled Water Inlet Temperature is above 53 degrees*

and

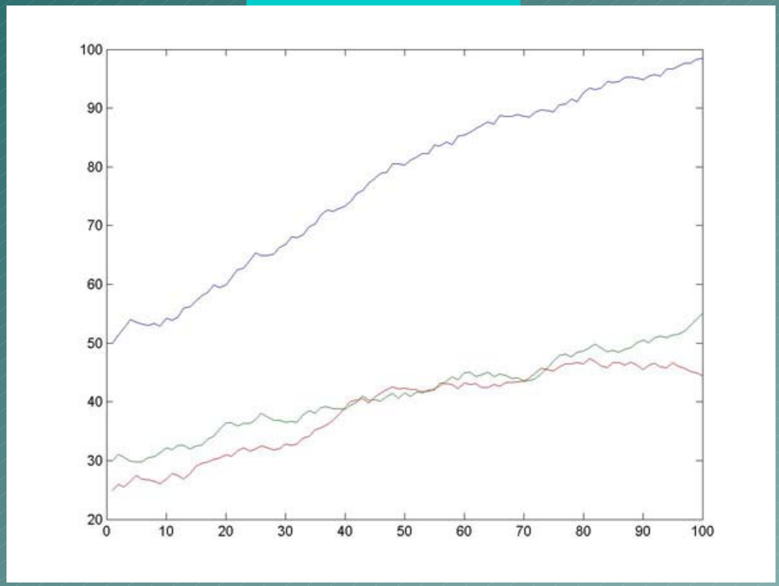
Chilled Water Outlet Temperature is above 44 degrees

then

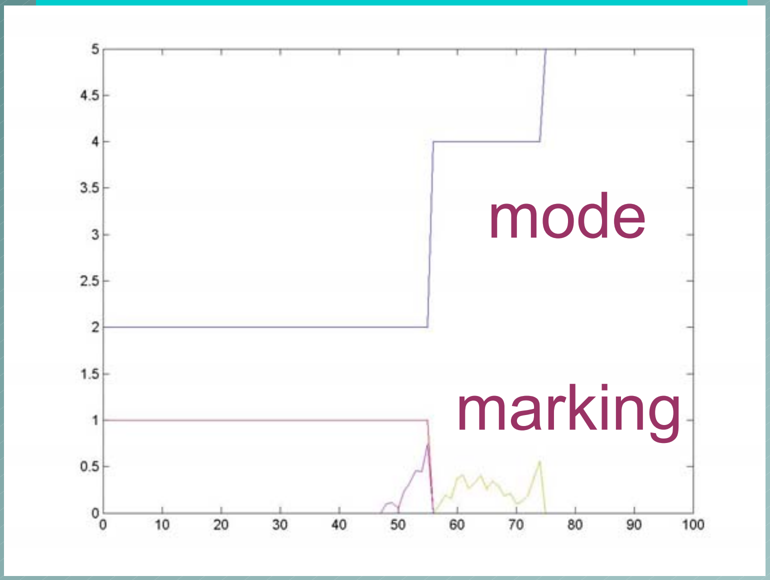
Switch to Overload Mode

Fuzzy Petri Net Simulation

Sensors



Fuzzy Petri net marking



SENSORS

Pre-rotation vane position
Chilled water inlet temperature
Chilled water outlet temperature

MODE CHANGES

Normal Load Mode

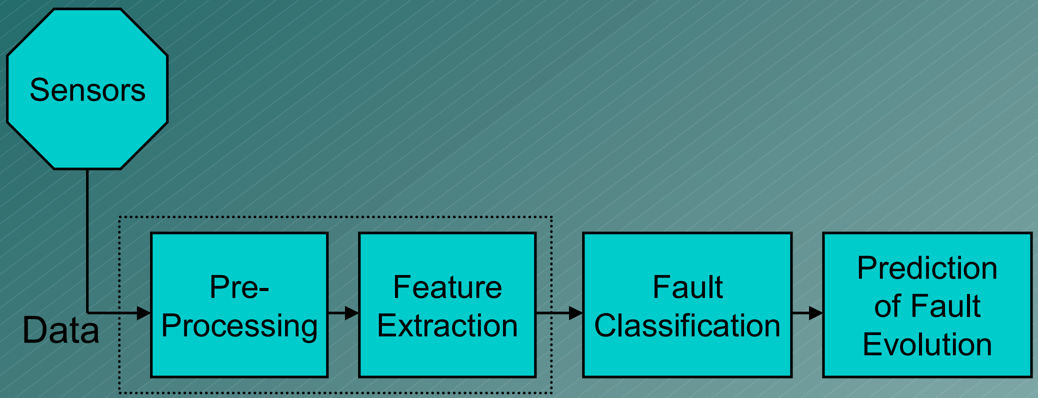
↓

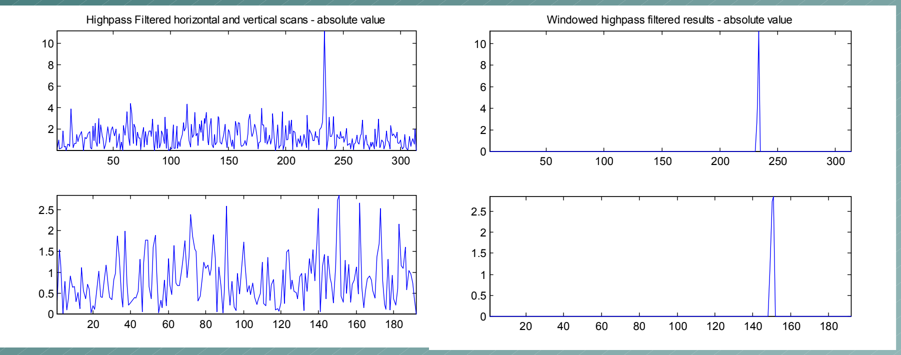
Full Load Mode

↓

Overload Mode

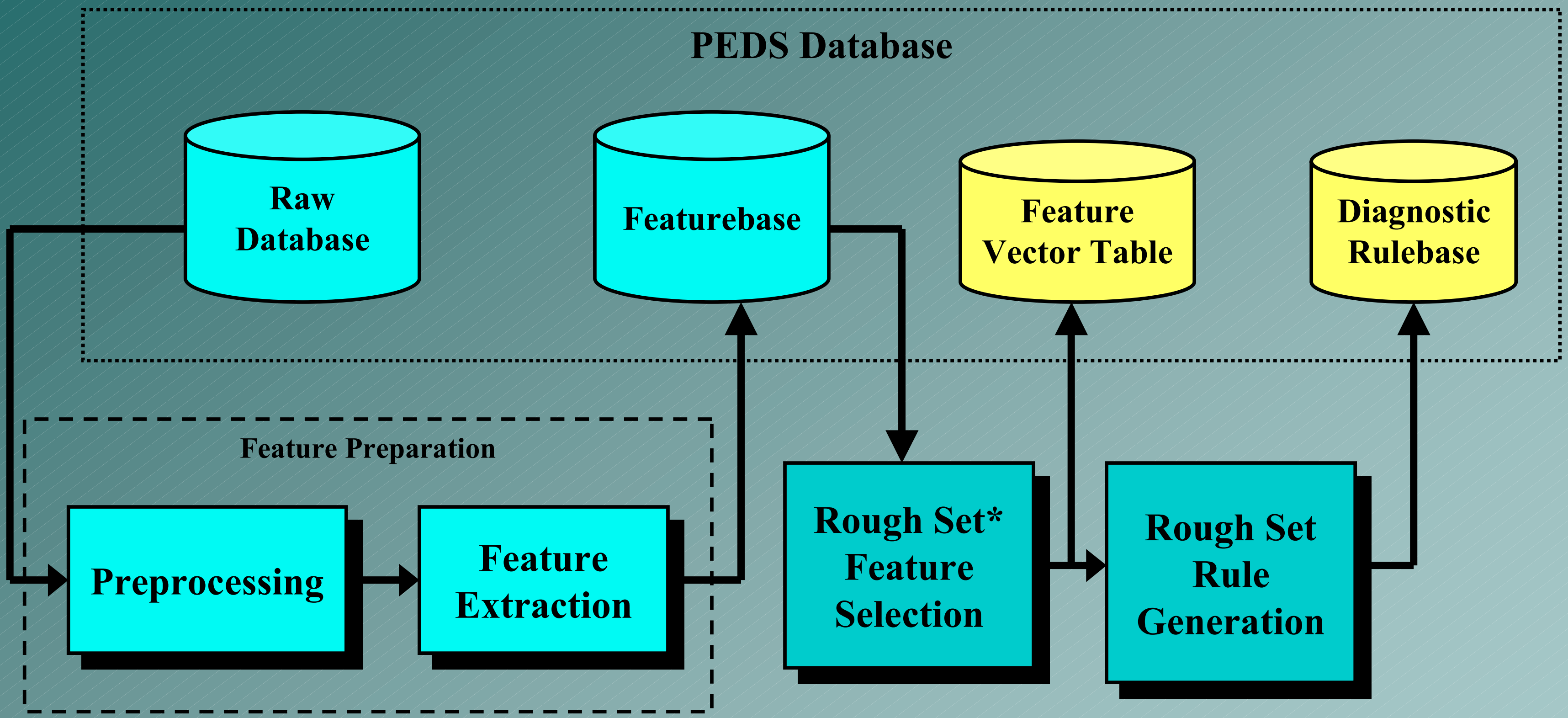
Feature Selection and Extraction





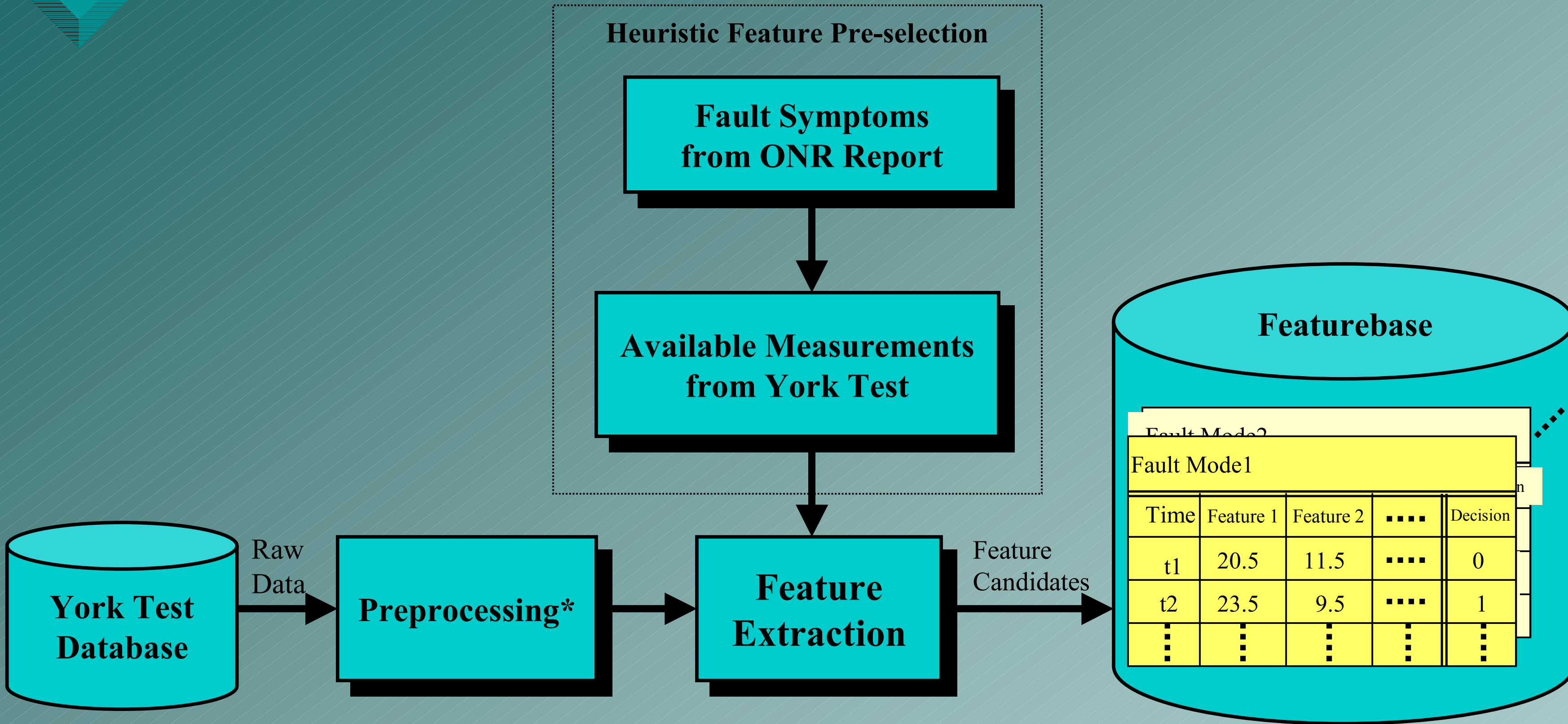
- Motivation: Data driven diagnostic/prognostic algorithms require for fault detection and classification a feature vector whose elements comprise the "best" fault signature indicators
- Intelligent distinguishability and identifiability metrics must be defined for selecting the best features
- Time and frequency domain analysis techniques must be employed to extract the selected features

Overall Procedures for Feature Selection and Diagnostic Rule Generation



* Rough set theory is a popular data mining methodology, which provides mathematical methods to remove redundancies and to discover hidden relationships in a database.

Feature Preparation



* Preprocessing includes removing unreasonable objects from the database and assigning the operational status.

Significance of York Test Fault Modes

Component	Fault Mode	Significance	ONR Report	ICAS (CG-47 AC Plant)	HVAC ISEA	York Test (Test ID)
Compressor	Compressor stall and/or surge	7.5	Y	Y	Y	N (7)
	Shaft seal leakage	5	N	N	Y	N
	Oil level high/low	5	N	Y	Y	N
	High oil temperature (related to Aux. oil pump failure or oil cooler failure)	-	-	Y	-	N (14)
Condenser	Condenser tube fouling	6.5	Y	Y	Y	N
	Condenser water control valve (CWCV) failure	5	N	N	Y	N
	Tube leak	5	N	N	Y	Y (13)
	Decreased sea water flow	5	Y	N	N	Y (9)
Evaporator	Target flow meter failure	5	N	N	Y	N
	Decreased chilled water flow	5	Y	N	N	Y (10)
	Evaporator tube freezing	6	Y	N	Y	N
Refrigerant Pipes	Air/non condensable gases in refrigerant	7	Y	Y	Y	N
	Contaminated refrigerant	6.5	Y	N	Y	Y (12)
	Refrigerant charge low	7	Y	Y	Y	Y (8-a,b,c)
	Refrigerant charge high	7.5	Y	Y	Y	N (8-d)
Controls	PRV/VGD linkage/drive mechanism problem	4.5	Y	N	Y	Y (11)
	Control component failure	6	N	Y	Y	N
Motor	Bearing failure	5	N	Y	Y	N
	Winding failure	5	N	N	Y	N

Y: Fault mode appears on the list of the column reference, N: Fault mode is not on the list of the column reference, Test ID: For test ID, see the York test-plan document, “REVISED CBM AS TESTED.doc”, Significance: See the last page.

According to the York test document, 9 fault modes are planned to be tested. However, data provided to Georgia Tech. includes only 6 fault types (some of them include few symptoms.) The data for “Tube leak” and “High oil temperature” is very limited. Test data doesn’t include measurements related to compressor such as comp. bearing oil temp.

Selected Fault Modes for York Test (1/2)

Fault Mode	Description	Symptoms	Related Sensors
Decreased sea water flow	Degraded performance means that the pump fails to deliver a nominal amount of water or a decrease in pump discharge head with time, which is generally resulted from pump impeller clearance problem, impeller damage, or pump casing gasket problem.	Decreased pump flow, Decreased pump discharge head press, Increased condenser sea water inlet temperature, Increased condenser sea water discharge temperature, Increased sea water ΔT across condenser, High compressor discharge pressure, Increased condenser pressure, Normal or slightly decreased evaporation pressure, increased compressor motor amps, May result in decrease in chilled water ΔT - but only for severe cases, Change in vibration signature	SW flow, SW pump head pressure, SW pump or motor speed indication , SW pump vibration acceleration, SW valve position indicator Cond inlet temp, cond outlet temp, cond dis temp, cond press Comp dis temp, comp motor current Eva press, eva inlet temp, eva dis tempe PRV Position
Decreased chilled water flow	Degraded performance means that the pump fails to deliver a nominal amount of water or a decrease in pump discharge head with time, which generally is resulted from pump impeller clearance problem, impeller damage, or pump casing gasket problem.	Decreased pump flow, Decreased pump discharge head press, Nominal expansion tank level and pressure, Low compressor suction pressure, Decrease in evaporator pressure, Increase in chilled water ΔT across evaporator, Change in vibration signature	CW flow, CW pump head press, CW pump or motor speed indication, CW pump vibration acceleration Evaporator pressure, evaporator inlet temp, eva dis temp, eva circuit flow meter Comp suct press, comp motor current sensor PRV Position
Contaminated refrigerant (Air/Non-condensable gases in the refrigerant)	Air and non-condensables in the refrigerant usually collects in the condenser, blanketing condenser surfaces causing decreased plant efficiency and can lead to acid formation in the refrigerant which is destructive to internal system parts.	Increased compressor discharge pressure, Increased compressor discharge temperature, Normal inlet sea water pressure and flow Or Increasing compressor discharge sub-cooling	Comp dis press, comp dis temp Cond SW inlet press, SW inlet temp PRV Position Motor current sensing transformer

Selected Fault Modes for York Test (2/2)

Fault Mode	Description	Symptoms	Related Sensors
Refrigerant charge low	Refrigerant gases can escape easily due to their small molecular size. The refrigerant is stored in the evaporator and under full load conditions should barely cover the tops of the cooler tubes. When refrigerant levels are low, the tubes are not completely covered and less refrigerant is boiled off to the compressor. The overall effect is decreased efficiency which may result in loss of cooling.	Refrigerant level below cooler tubes, Slowly increasing full load ΔT across chill water, Increasing temperature between chilled water out and evaporator refrigerant, Slowly increasing compressor discharge subcooling, Low compressor suction pressure, Low compressor discharge pressure, High compressor discharge temperature, Low compressor motor amps	Ref level gage Comp suction pres, comp discharge press, comp dis temp, comp motor current CW outlet temp, CW inlet temp Eva liquid temp, eva press, eva outlet temp PRV Position
PRV/VGD linkage/drive mechanism problem	The Pre-Rotation Vanes serve as load control that modulate the chiller load capacity. The control signals for the PRV's actuator are the chilled water outlet temperature and the compressor motor current.	PRV's that fail to close: Low chilled water outlet temperature, High compressor motor current PRV's that fail to open: High chilled water outlet temperature, Low compressor motor current	CW outlet temp PRVane Position Comp motor current sensing transformer Actuator electronic control signal
High oil temperature	Oil temperature is above the normal operating temperature, which might be caused by improper operation of lube oil cooling system components, misalignment of chill water solenoid valve, heat exchangers, and oil cooler. Ensure sump oil heaters and associated lights are de-energized.	High oil temp.	Comp sump oil temp. Comp bearing oil temp.
Tube leakage	Low expansion tank level and pressure combined with a repeated need for refilling and repressurizing the tank are indications of excessive leakage in the chilled water system.	Low expansion tank level Low expansion tank pressure	Expansion tank level Expansion tank pressure

Available sensors from York Test

No.	Sensor	Units	York Test	ICAS (CG-47 Class AC Plant)
1	EvapGPM	GPM	Available	Not Available
2	CondGPM	GPM	Available	Not Available
3	EvapOn	Deg F	Available	Available (CW inlet temp)
4	EvapOff	Deg F	Available	Available (CW outlet temp)
5	CondOn	Deg F	Available	Available (SW inlet temp)
6	CondOff	Deg F	Available	Available (SW outlet temp)
7	SuctTemp	Deg F	Available	Available (Comp suction temp)
8	DischTemp	Deg F	Available	Available (Comp discharge temp)
9	CondLiqOutTemp	Deg F	Available	Available (Cond. liq. temp)
10	SubcLiqOutTemp	Deg F	Available	Not Available
11	EvapTemp	Deg F	Available	Not Available
12	EvapPress	PSIA	Available	Not Available
13	CondPress	PSIA	Available	Not Available
14	OilPress	PSIA	Available	Available (Comp oil press)
15	PRVPos	%	Available	Available
16	RefrigLBS	LBS	Available	Not Available
17	FullLoad	%	Available	Not Available
18	MotorRPM	RPM	Available	Not Available
19	EvapPDPress	PSID	Available	Not Available
20	CondPDPress	PSID	Available	Not Available

Feature Vectors from York Test

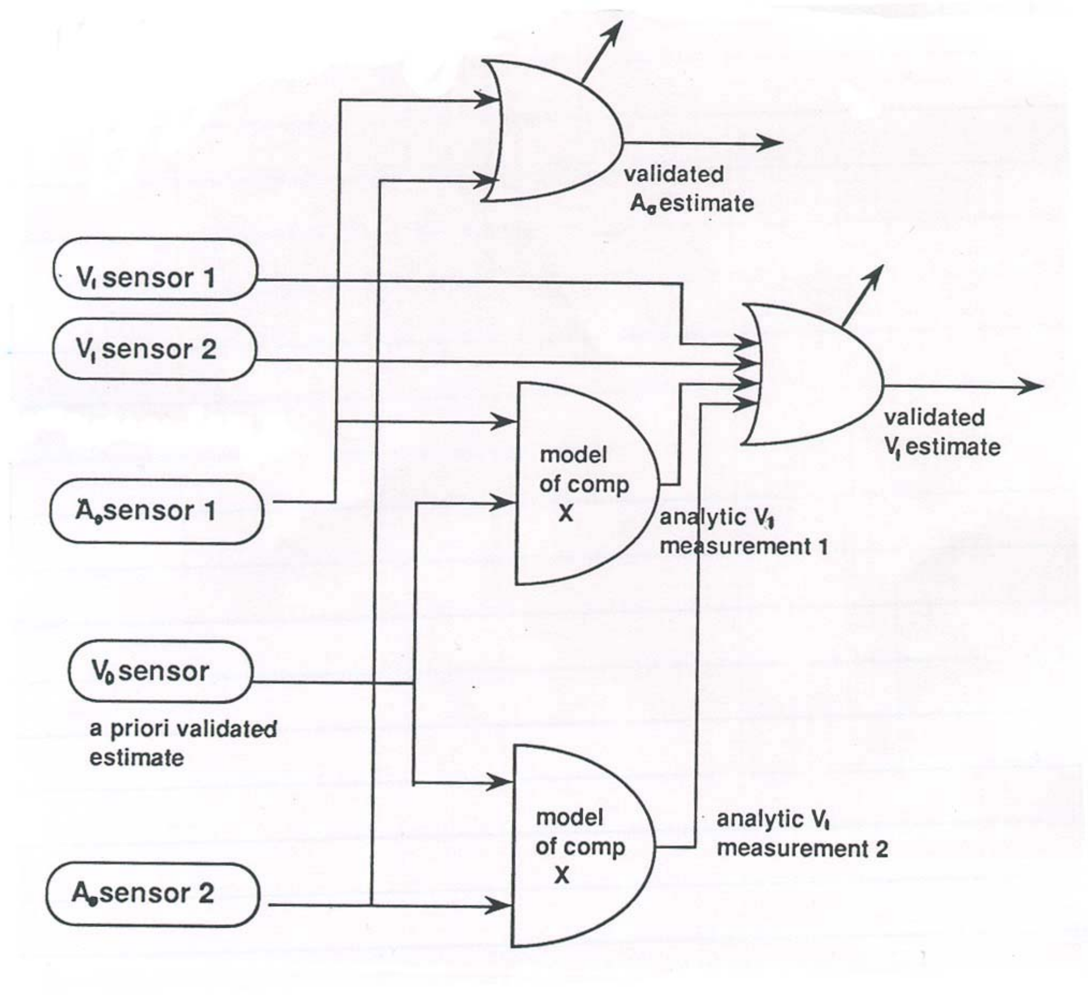
	Measurements / Fault Mode	EvapGPM	CondGPM	EvapOn	EvapOff	CondOn	CondOff	SuctTemp	DischTemp	CondLiqOutTemp	SubcOutLiqTemp	EvapTemp	EvapPress	CondPress	OilPress	PRVPos	RefrigLBS	FullLoad	EvapPDPress	CondPDPress	ΔT bet. Cond. On and Off	Oil Temp	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	**Decreased sea water flow**		V																	V			
2	**Decreased chilled water flow**	V																					
3	**Contaminated refrigerant**														V				V				
4	**Refrigerant charge low**																V						
4	**Refrigerant charge high**																V						
5	**PRV/VGD linkage/drive mechanism problem**				V							V			V	V							
6	**High (bearing) oil temperature**																						
7	**Tube leakage**																						

Required features for each fault mode are marked.

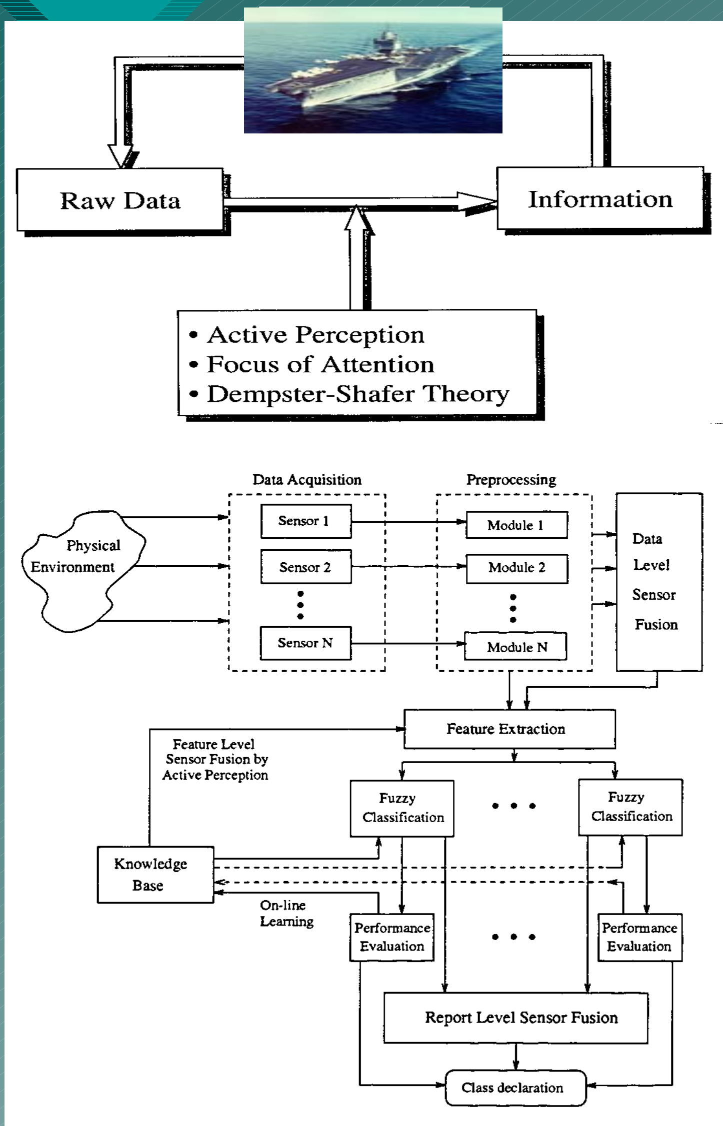
Partial Database of York Sensor Data

DataID	Run Number	Test ID	Test Condition	Surge Results	Important Measurements			
					Load [%]	Cond. Water On [degF]	Evap Water Off [degF]	Refrig LBS
1	999.00				100	85.03	44.08	1176
2	999.00				100	84.92	44.09	1176
3	2.00				11	84.99	43.93	1176
4	2.00				100	84.89	44.04	1176
5	2.10				100	84.88	44.05	1176
6	2.00	6a	Baseline capacity/performance/operational test and mapping		100	84.91	44.09	1176
7	2.10	6a	Baseline capacity/performance/operational test and mapping		100	84.88	44.12	1176
8	2.20	6a	Baseline capacity/performance/operational test and mapping		100	84.88	44.14	1176
9	3.00	6b	Baseline capacity/performance/operational test and mapping		75	84.96	44.11	1176
10	3.10	6b	Baseline capacity/performance/operational test and mapping		75	84.96	44.15	1176
11	3.20	6b	Baseline capacity/performance/operational test and mapping		75	84.93	44.19	1176
12	4.00	6b	Baseline capacity/performance/operational test and mapping		50	84.99	43.96	1176
13	4.10	6b	Baseline capacity/performance/operational test and mapping		50	84.97	43.98	1176
14	4.20	6b	Baseline capacity/performance/operational test and mapping		50	84.97	44	1176
15	5.00	6b	Baseline capacity/performance/operational test and mapping		25	84.89	44.04	1176
16	5.10	6b	Baseline capacity/performance/operational test and mapping		25	84.88	44.02	1176
17	5.20	6b	Baseline capacity/performance/operational test and mapping		25	84.88	44.03	1176
18	6.00	6c	Baseline capacity/performance/operational test and mapping		25	74.92	44.22	1176
19	6.10	6c	Baseline capacity/performance/operational test and mapping		25	74.86	44.26	1176
20	6.20	6c	Baseline capacity/performance/operational test and mapping		25	74.88	44.27	1176
21	7.00	6c	Baseline capacity/performance/operational test and mapping		50	74.92	44.21	1176
22	7.10	6c	Baseline capacity/performance/operational test and mapping		50	74.92	44.25	1176
23	7.20	6c	Baseline capacity/performance/operational test and mapping		50	74.93	44.29	1176
24	8.00	6c	Baseline capacity/performance/operational test and mapping		75	75.21	44.25	1176
25	8.10	6c	Baseline capacity/performance/operational test and mapping		75	75.25	44.29	1176
26	8.20	6c	Baseline capacity/performance/operational test and mapping		75	75.24	44.33	1176
27	9.00	6c	Baseline capacity/performance/operational test and mapping		100	75.11	44.12	1176

The Signal Validation Flow Diagram



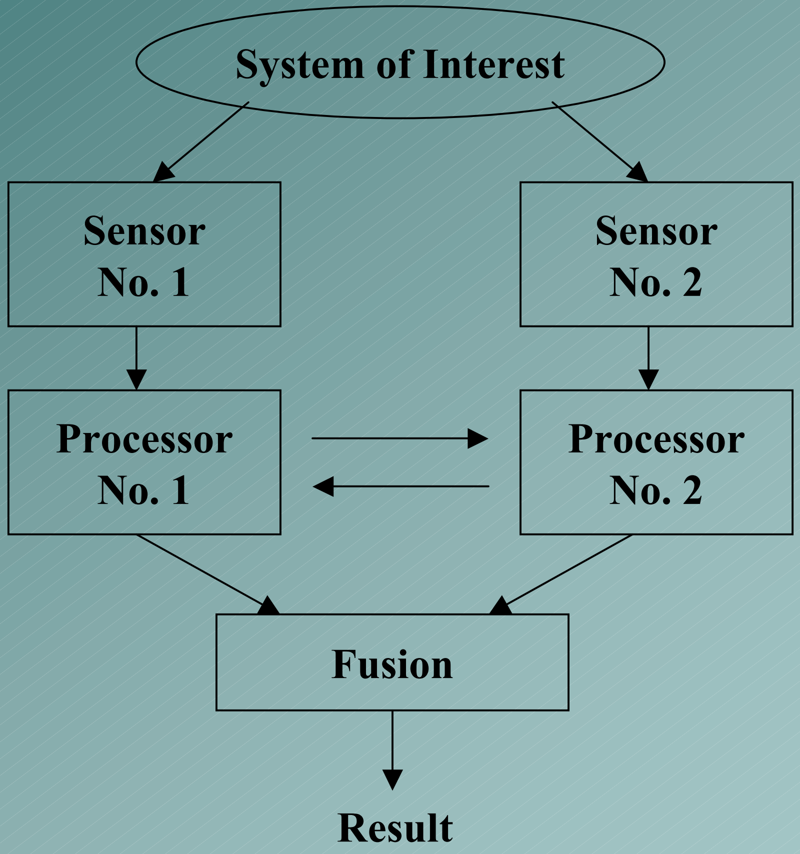
Sensor Fusion (or Integration)



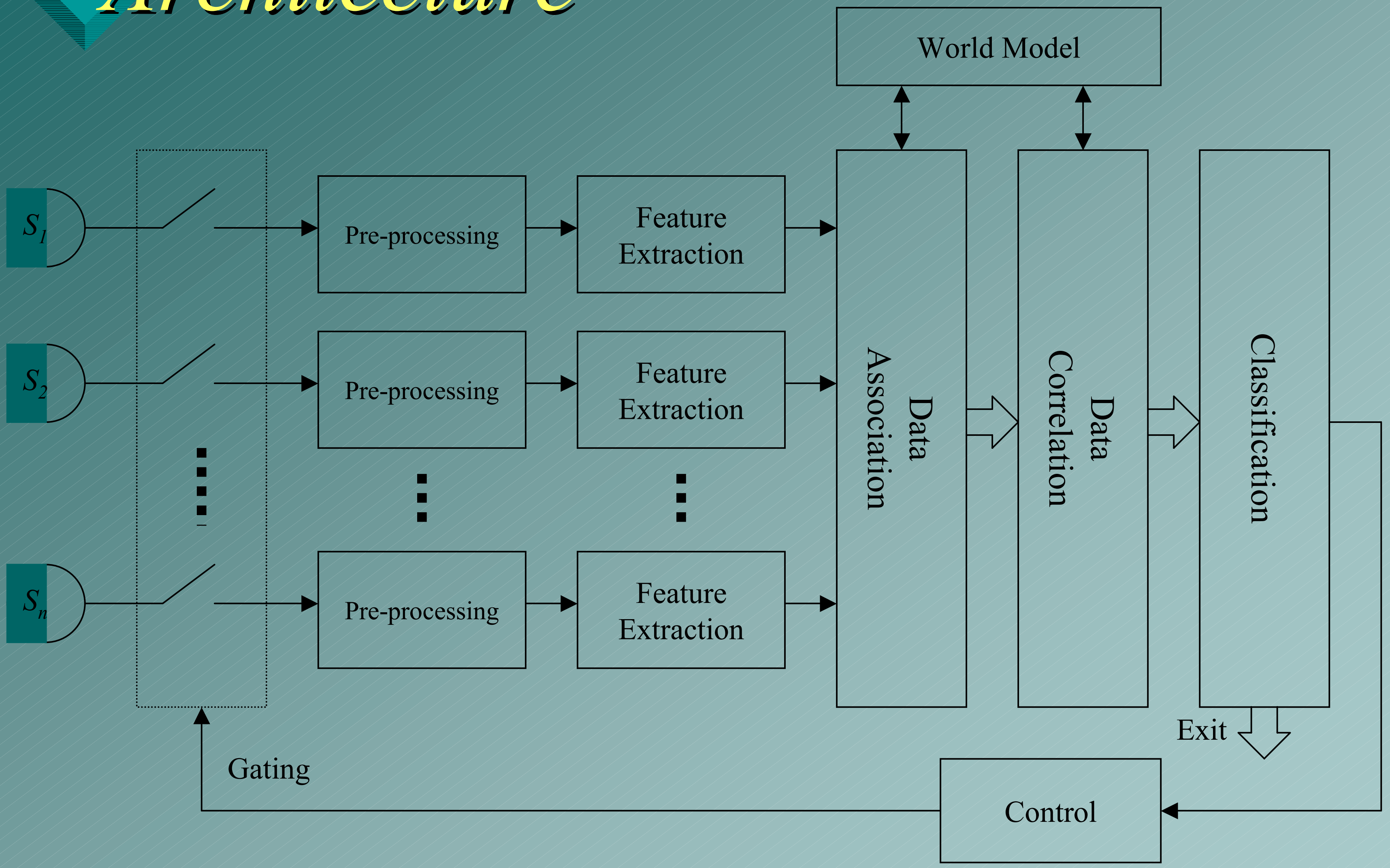
- Objective: Optimize performance of information gathering process
- Intelligent sensor and knowledge fusion algorithms based on focus of attention via active perception and Dempster-Shafer theory
- Sensor integration at various levels of abstraction - the data, feature, sensor and report levels
- Distinguishability and effectiveness measures defined to guide the sensor integration task
- Off-line and on-line learning techniques for effective data combination

Sensor Fusion (cont'd)

- The flow of information in sensor fusion



The Multi-sensor Data Fusion Architecture

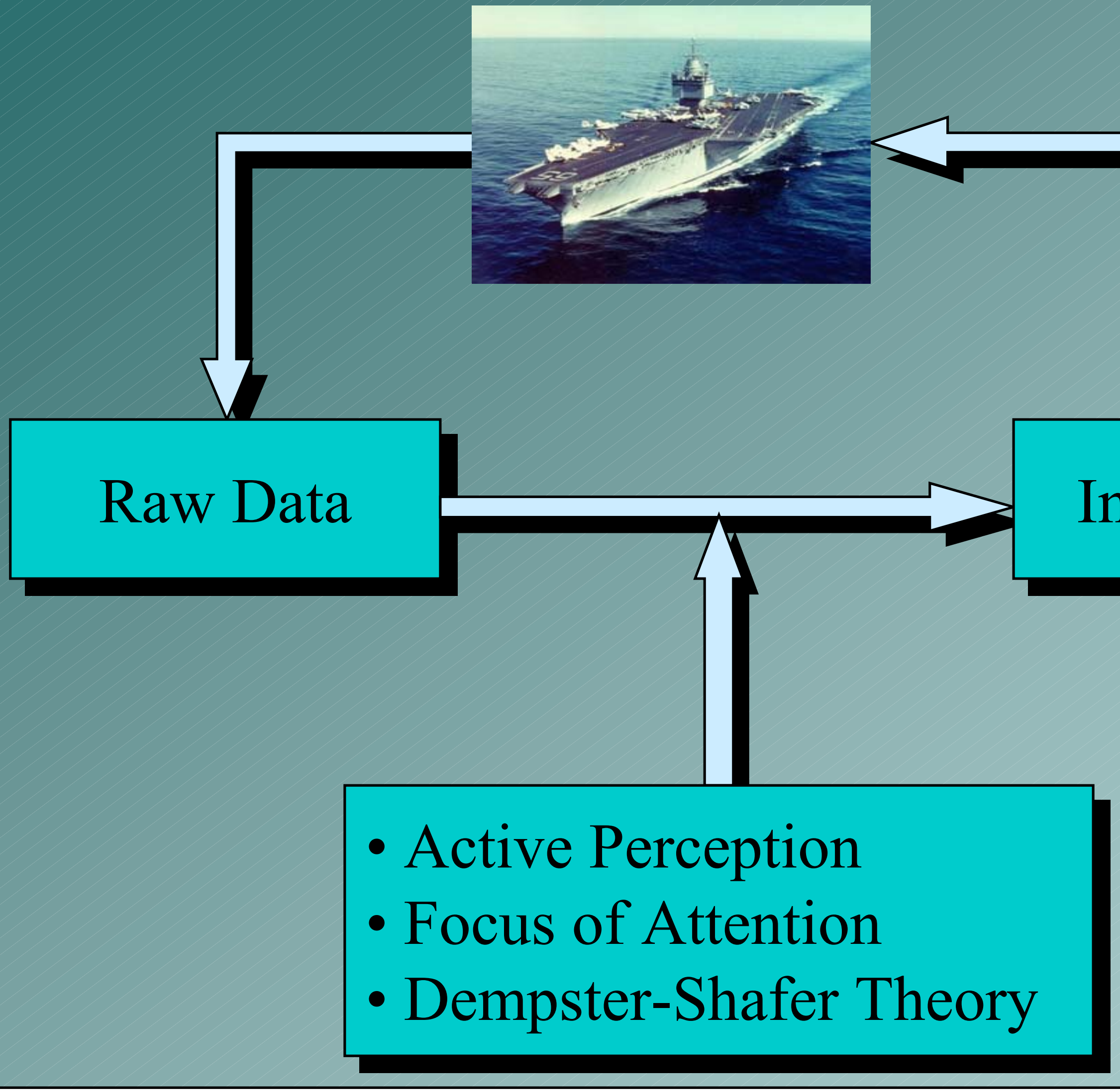


On the Concept of "Fusion"

- Sensor Fusion
  - Data Fusion
  - Feature Fusion
  - Sensor Fusion
  - Report Fusion

- Knowledge Fusion

Feature Level Sensor Integration



An Intelligent Approach To Sensor Fusion

- Pre-Processing
  - De-noising, enhancement, segmentation, etc.
- Degree of Certainty
  - Dempster-Shafer theory
- Active Perception
  - Distinguishability measure
  - Effectiveness measure
  - Off-line learning
  - On-line learning
- Classification

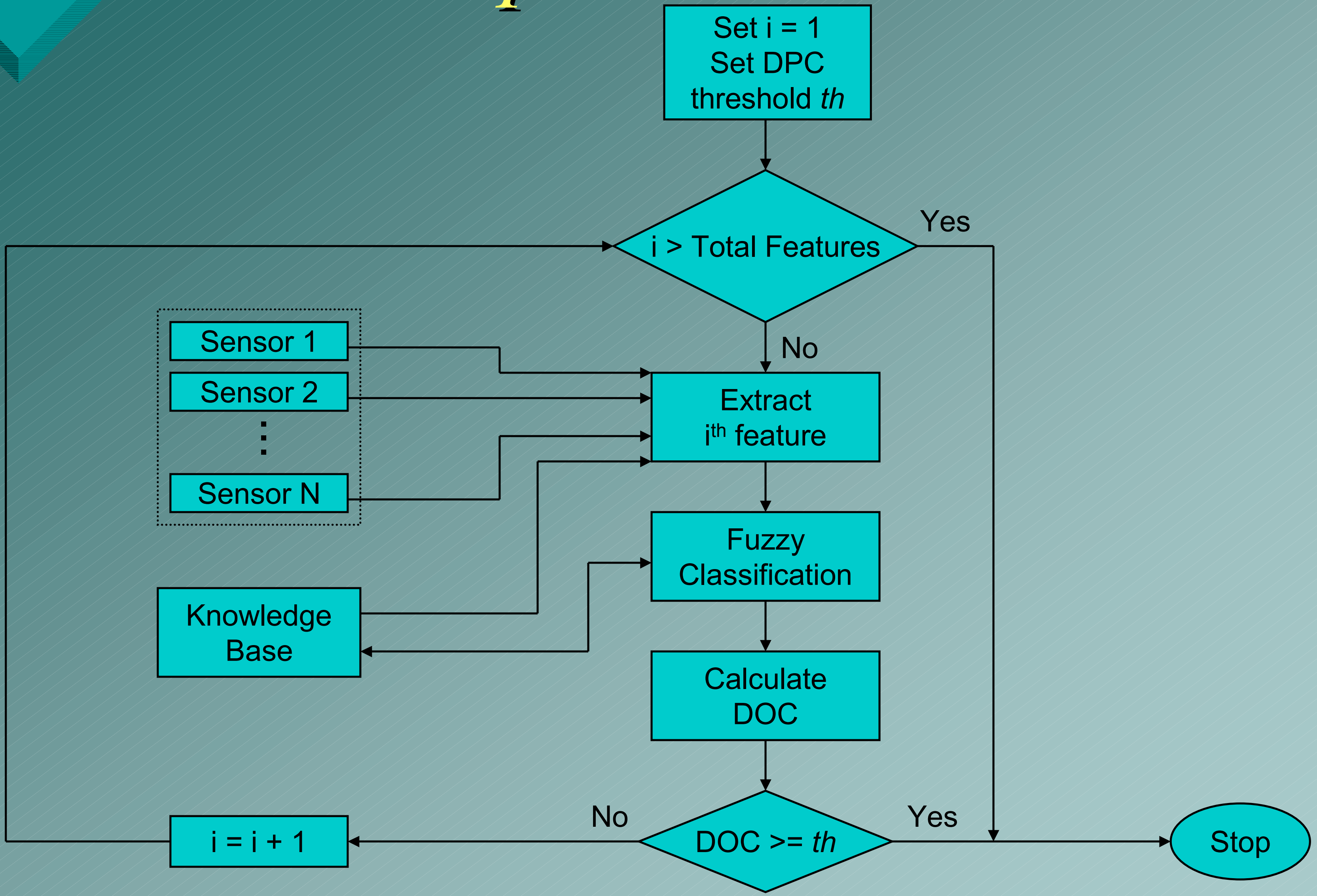
Sensor Fusion

- Sensor fusion related research can be grouped into two categories
  - What-to-fuse
  - How-to-fuse
- What-to-fuse approaches are application specific
- Fusion methodologies used from how-to-fuse viewpoint are
  - Weighted averaging
  - Bayesian reasoning
  - Dempster-Shafer theory
  - Possibility reasoning
- No widely accepted generic approach
- No consideration for processing time

On Active Perception

- Control of sensors during data acquisition to maximize the performance of the information gathering process
- In machine perception, active perception is viewed as active (moving) sensors overcoming constraints imposed by the environment
- Active perception is applied to passive sensors by controlling the manner in which information is used
- The sensor integration paradigm employs multiple and complementary sensors capable of multiple observations providing different viewpoints of the physical environment

Active Perception in Sensor Fusion



Knowledge Fusion

- The highest tier of the data/sensor fusion architecture
- Relies on expert technologies to aggregate diagnostic / prognostic reports, resolve conflicts and integrate maintenance decisions into an Object Oriented System Model (OOSM)
- Provides interfacing to other facilities (internet, computers, etc.) and the operator / user

Knowledge Fusion: System Requirements

- The knowledge fusion components must be able to accommodate inputs which are:
  - Incomplete
  - Time-disordered
  - Fragmentary
- and which have:
  - Gaps
  - Inconsistencies
  - Contradictions

Knowledge Fusion: System Requirements (cont'd)

- The knowledge fusion components will have to be able to:
  - Collate
  - Compare
  - Integrate
  - Interpret the data

Knowledge Fusion: System Requirements (cont'd)

- In order to do this, it must provide:
  - inference control-multiple experts may be working concurrently
  - multi level data management (this may be the domain of the object-oriented system model)-data, reports, conclusions, hypotheses all need to be represented and coordinated
  - spatial and temporal reasoning-sequencing and proximity will form the basis of some of the knowledge fusion (again, this will rely on the OOSM)

Knowledge Fusion: Expert Technologies

- Dempster-Shafer Probability Theory
- State-based Feature Recognition (state machines)
- Rule-Based Expert Systems
- Neural Networks
- Fuzzy Logic
- Petri Nets

Knowledge Fusion: Situation Awareness Example (ONR CBM Study)

- *Start-up initiated*
- DLI Message: Motor Bearing Problem
- KF: Ignore DLI Message temporarily (not pertinent during start-up)
- KF: Allocate bandwidth to monitor motor bearing after start-up
- KF: Add "monitor motor bearing" task to agenda after start-up

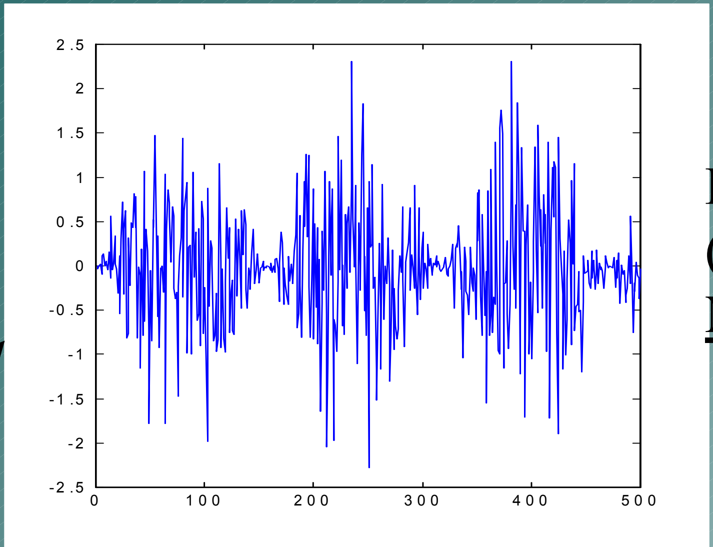
Knowledge Fusion: Control Sequence Example

- *Start-up initiated*
- Safeties checked
- Chilled water pump started
- WAIT: 5 seconds
- KF: Monitors sequence and timing
- Condenser water pump started
- WAIT: 1 minute to 5 minutes
- Controller verifies water flow
- Tower fans started
- Oil pump started
- WAIT: 15 seconds

Knowledge Fusion: Multi-Source Example

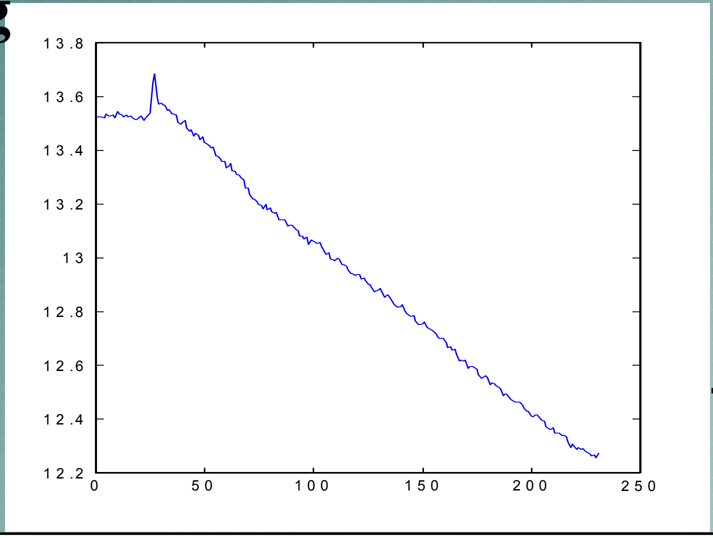
- Input: Sensors detected delta-t heat exchanger report no temperature change
- KF: Sensor reports ignored, state is start-up
- *Start-up complete*
- Input: Sensors detecting delta-t across heat exchanger report no temperature change
- KF: Sensor reports indicate decreased flow through heat exchanger

The Diagnostic Module



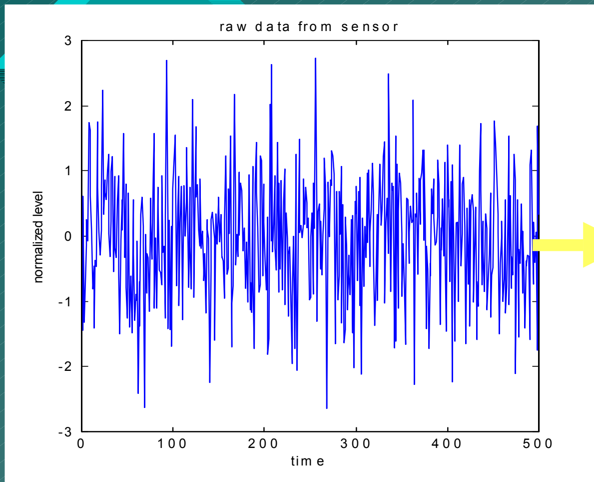
High-frequency failure modes (engine stall, etc.): **<u>The Wavelet Neural Net Approach</u>**

A Two-Prong Approach

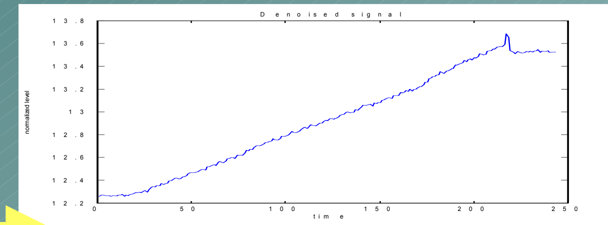


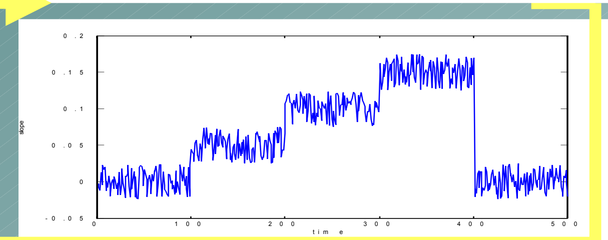
Low-frequency events (Temperature, RPM sensor, etc.): **<u>The Fuzzy Logic Approach</u>**

Sensor Data



Features





Preprocessing and Feature Extraction

Failure Templates

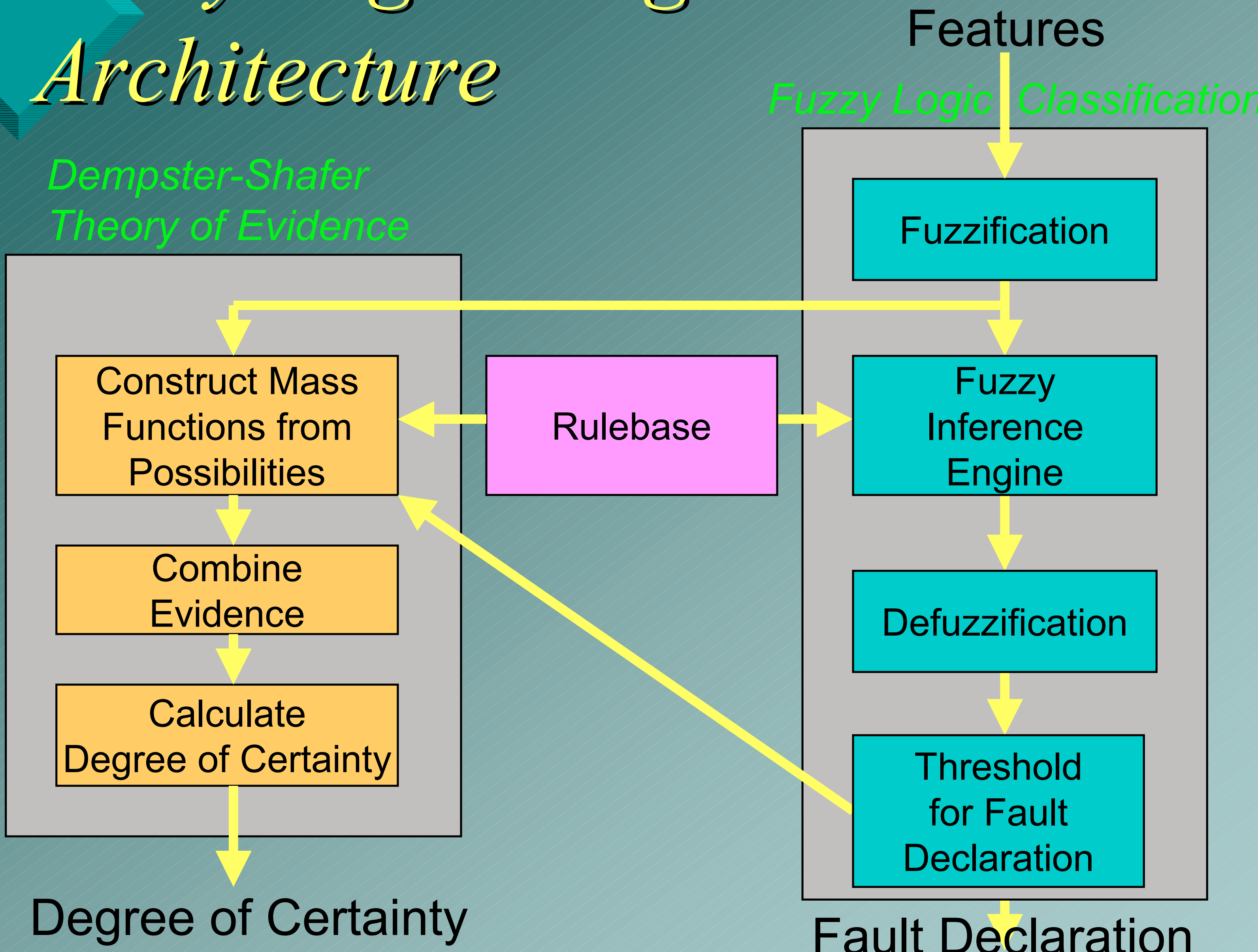
Fuzzify Features

Inference Engine

Fuzzy Rule Base
(1) If symptom A is high & symptom B is low
then failure mode is F1
(2) ...

(Defuzzify) Failure Mode

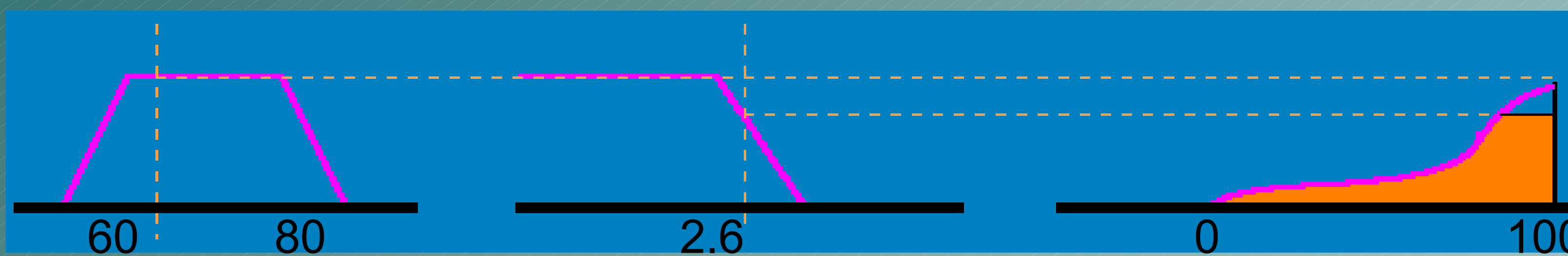
Fuzzy Logic Diagnostic Architecture



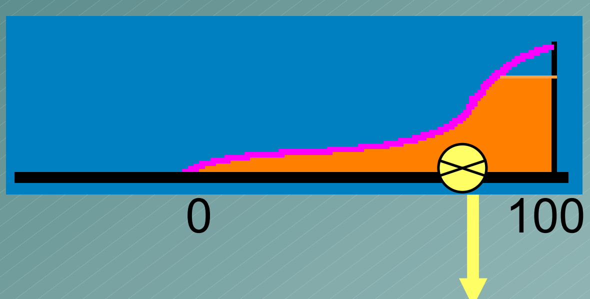
Fuzzy Logic Diagnostics: One Rule Example

Fuzzification/Inference Engine

If Current Mode is Normal or Full Load or Low Load and OilPress is Normal and EvapPDPress is Low then Refrigerant Contaminated High

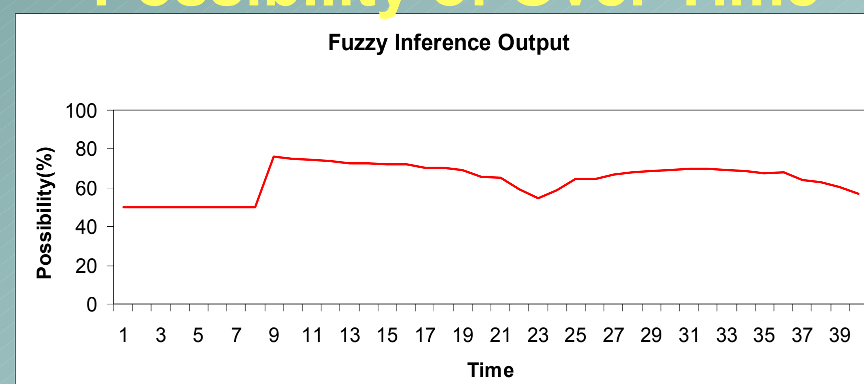


Defuzzification Max/Centroid Method



Possibility 85

Possibility of Over Time



Dempster-Shafer Theory of Evidence: A two expert example

Mass Functions derived from OILPRESS feature possibilities

MASS FUNCTIONS (OILPRESS EXPERT)

m_1({Refrigerant Contaminated}) = 0.5
m_1({Refrigerant Not Contaminated}) = 0.2
m_1({Refrigerant Contaminated, Refrigerant Not Contaminated}) = 0.3

Mass Functions derived from EVAPPDPRESS feature possibilities

MASS FUNCTIONS (EVAPPDPRESS EXPERT)

m_2({Refrigerant Contaminated}) = 0.2
m_2({Refrigerant Not Contaminated}) = 0.1
m_2({Refrigerant Contaminated, Refrigerant Not Contaminated})=0.7

Dempster's Rule of Combination

$$m_{12}(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - K}$$

Combined Evidence

MASS FUNCTIONS (OILPRESS AND EVAPPDPRESS)

m_{12}({Refrigerant Contaminated}) = 0.551
m_{12}({Refrigerant Not Contaminated}) = 0.292
m_{12}({Refrigerant Contaminated, Refrigerant Not Contaminated}) = 0.157

Belief and Ignorance Representation

$$Belief_{m_{12}}(A) = \sum_{B \subseteq A} m(B)$$

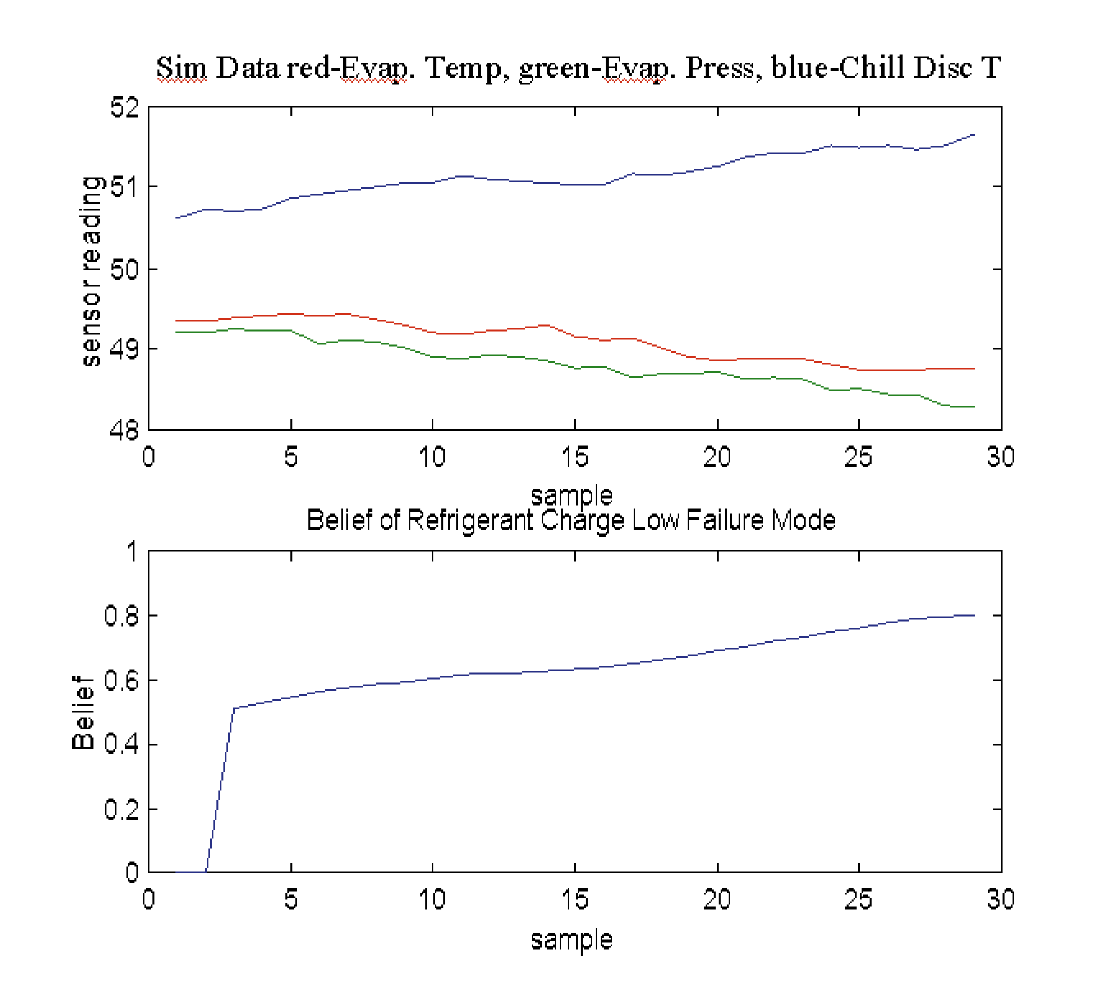
BELIEF FUNCTIONS (OILPRESS AND EVAPPDPRESS)

Belief({Refrigerant Contaminated}) = 0.551+0.157 = 0.708
Belief({Refrigerant Not Contaminated}) = 0.292 + 0.157 = 0.449
Ignorance({Refrigerant Contaminated}) = 1 - 0.708 + 0.449 = 0.741
Degree of Certainty({Refrigerant Contaminated}) = 0.551-0.449 = 0.102

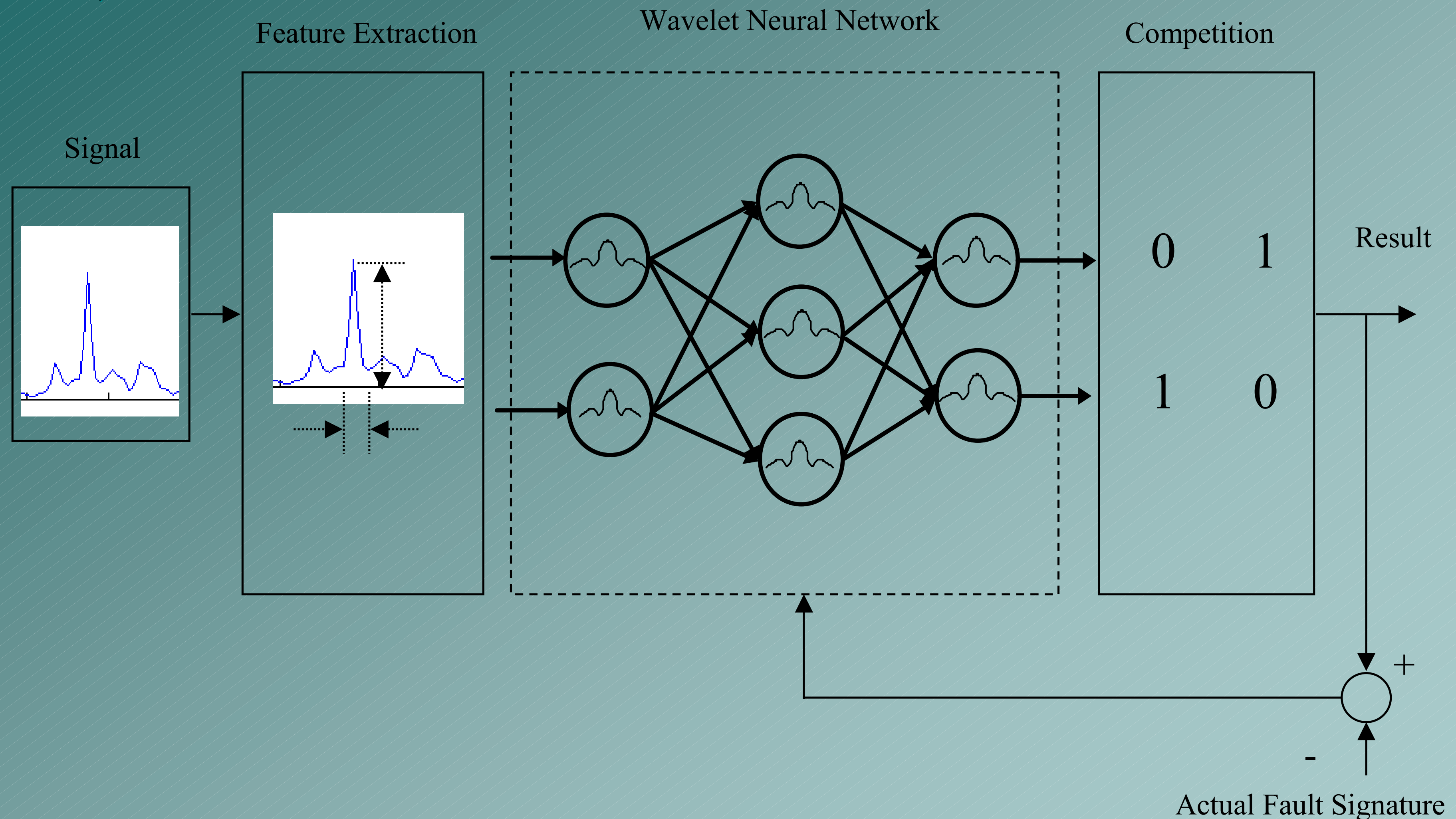
Degree of Certainty of Refrigerant Contamination

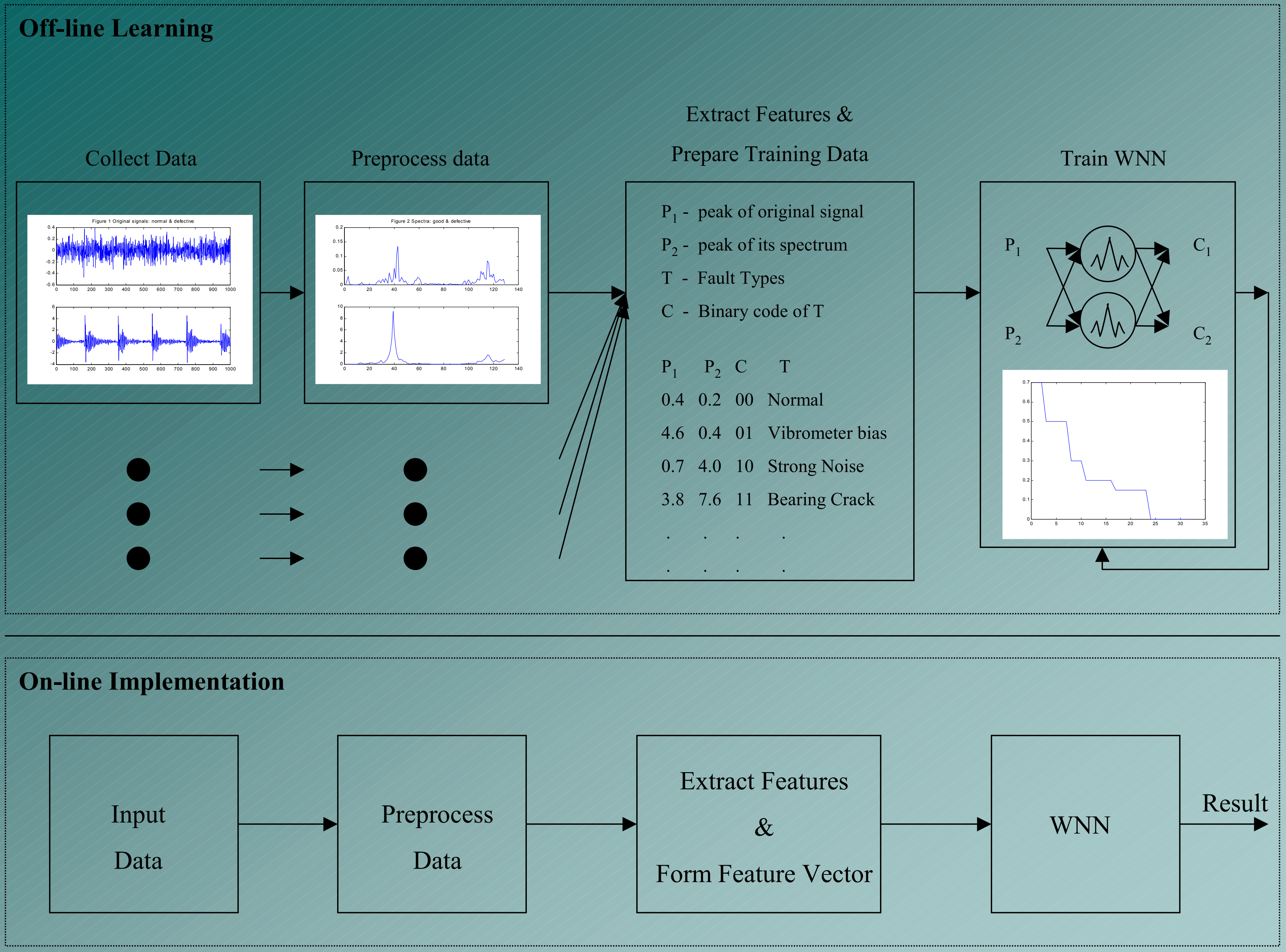
0.102

Dempster-Shafer Theory of Evidence Simulation

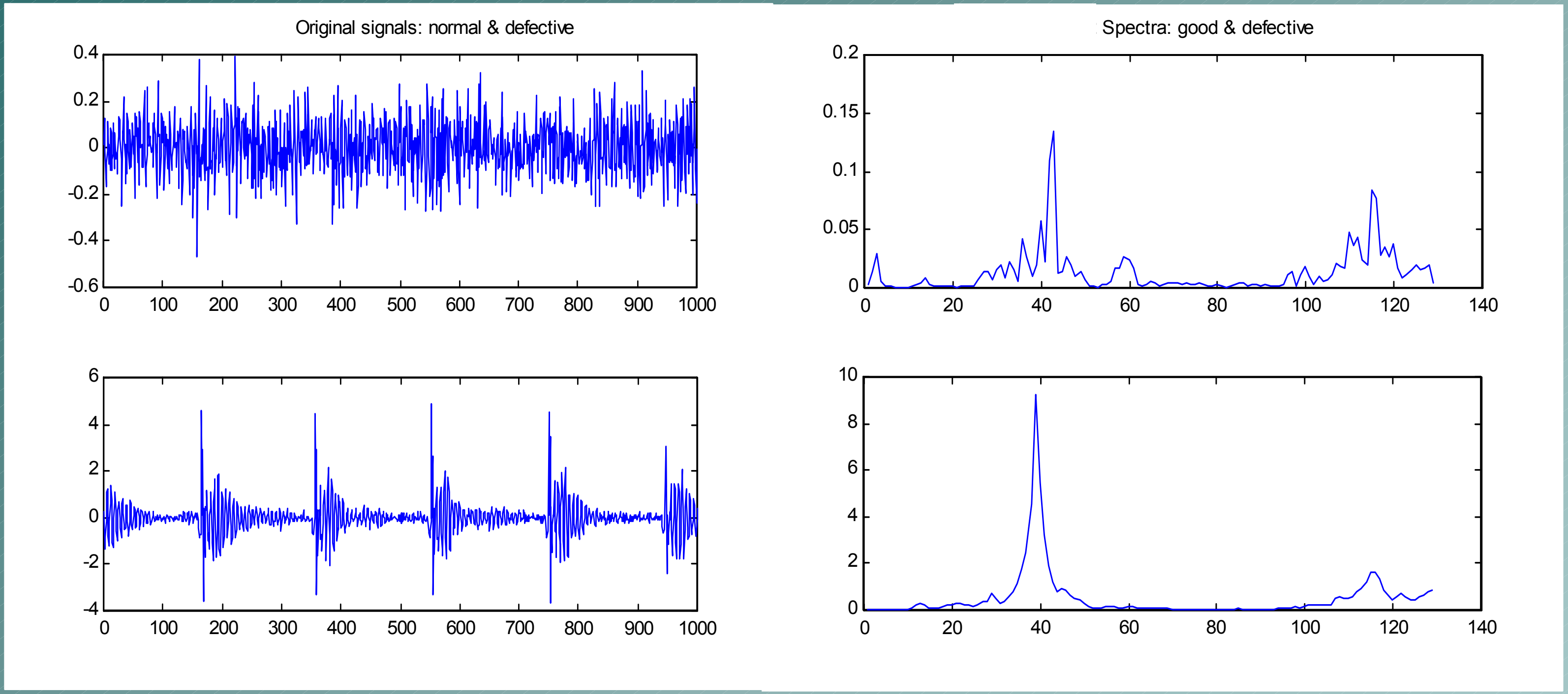


Wavelet Neural Network Based Fault Classification





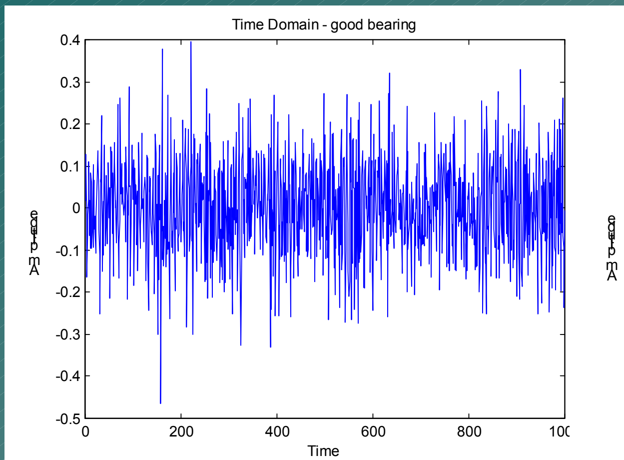
Off-line Learning
Collect Data
Figure 1 Original signals: normal & defective
Preprocess data
Figure 2 Spectra: good & defective
Extract Features &
Prepare Training Data
P_1 - peak of original signal
P_2 - peak of its spectrum
T - Fault Types
C - Binary code of T
P_1 P_2 C T
0.4 0.2 00 Normal
4.6 0.4 01 Vibrometer bias
0.7 4.0 10 Strong Noise
3.8 7.6 11 Bearing Crack
Train WNN
P_1
P_2
C_1
C_2
On-line Implementation
Input Data
Preprocess Data
Extract Features & Form Feature Vector
WNN
Result

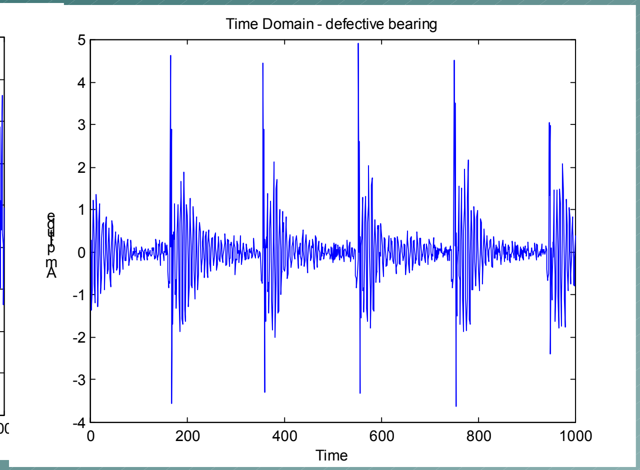


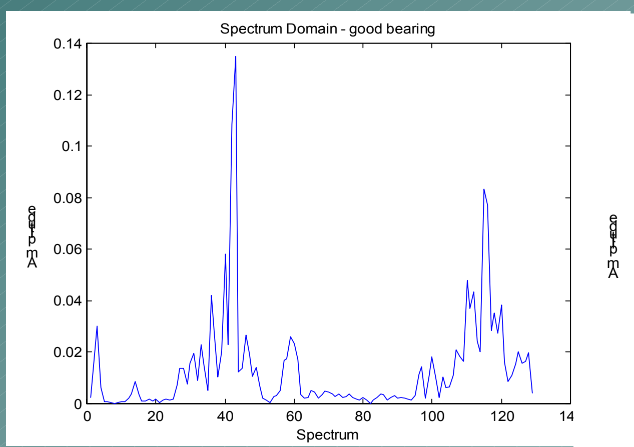
Vibration Signals from a good and a defective bearing

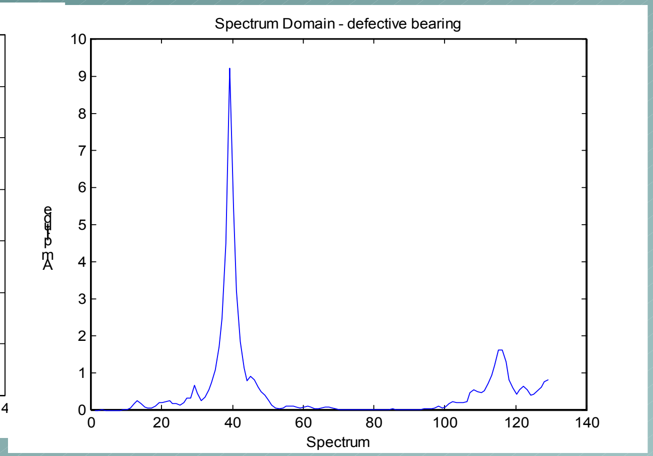
PSDs of the vibration signals

Bearing Fault Diagnosis









For the good bearing,

features = [0.3960 0.1348]

For the defective bearing,

features = [4.9120 9.2182]

[0 1] = WNN([0.3960 0.1348])
===> The bearing is good!

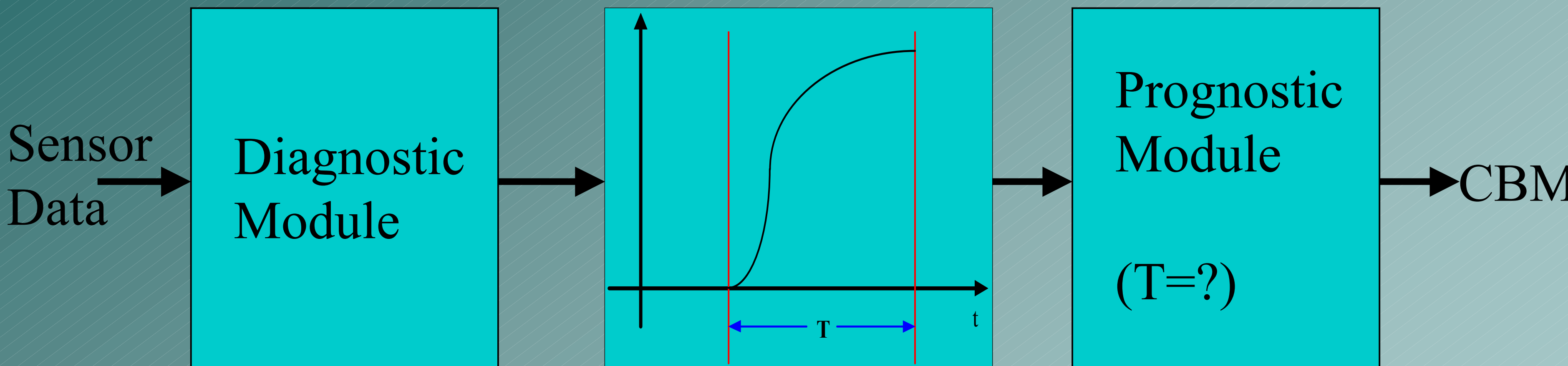
[1 0] = WNN([4.9120 9.2182])
===> The bearing is defective!

Prognostics

- Objective
  - Determine time window over which maintenance must be performed without compromising the system's operational integrity

The Prognostic Module

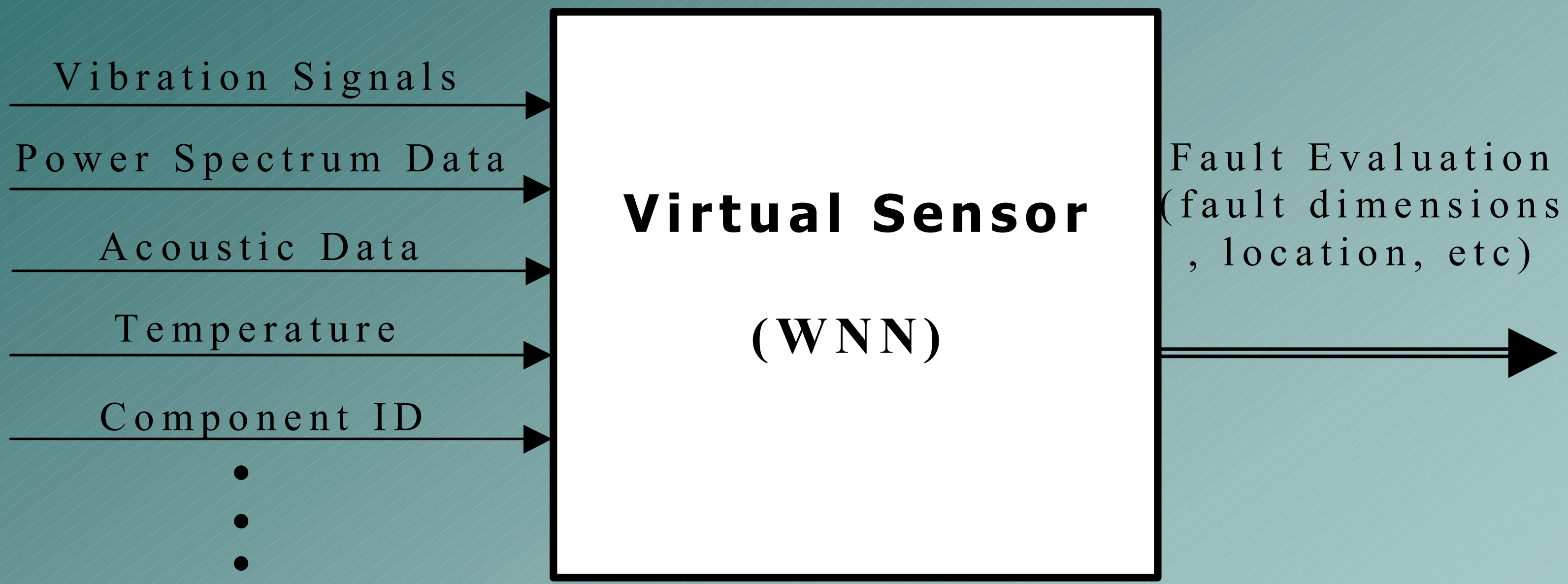
<u>QUESTION</u>: Once an **<u>impending</u>** failure is detected and identified, how can we predict the time window during which maintenance must be performed?



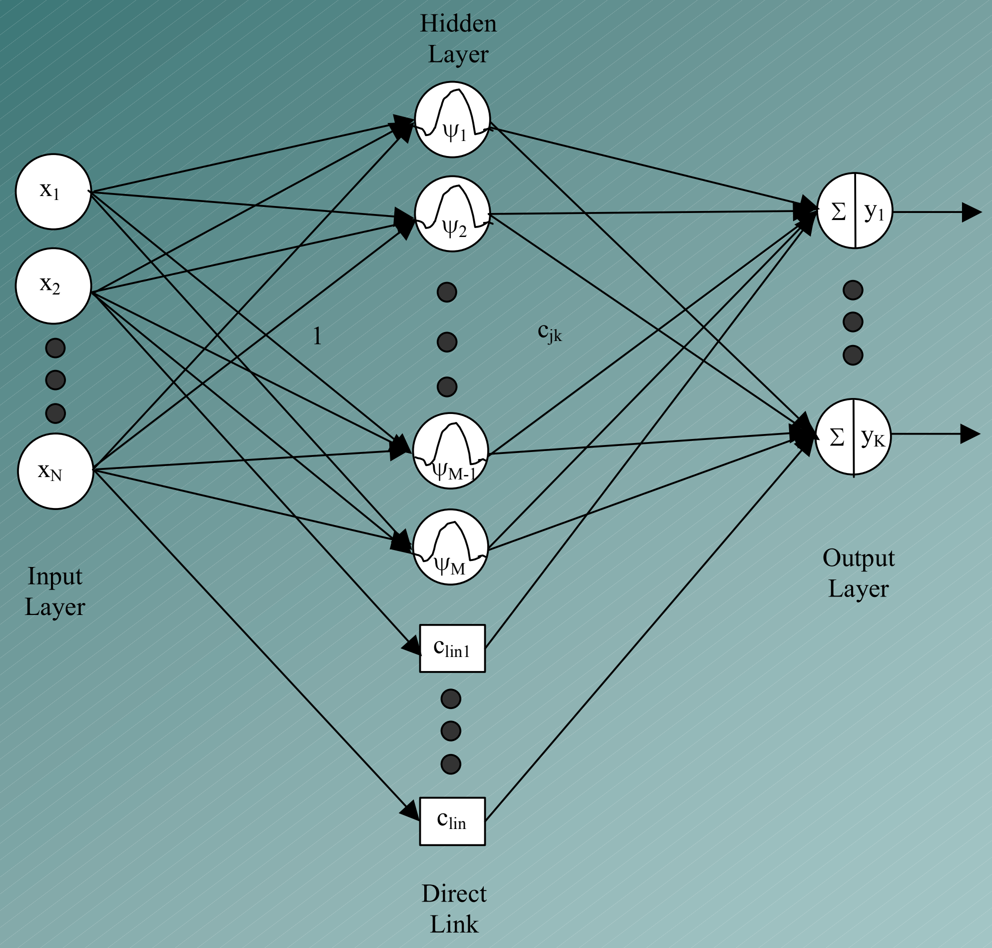
<u>APPROACH</u>:

- Employ a recurrent neuro-fuzzy model to predict time window *T*
- Update prediction continuously as more information becomes available from the diagnostic module

Virtual Sensor

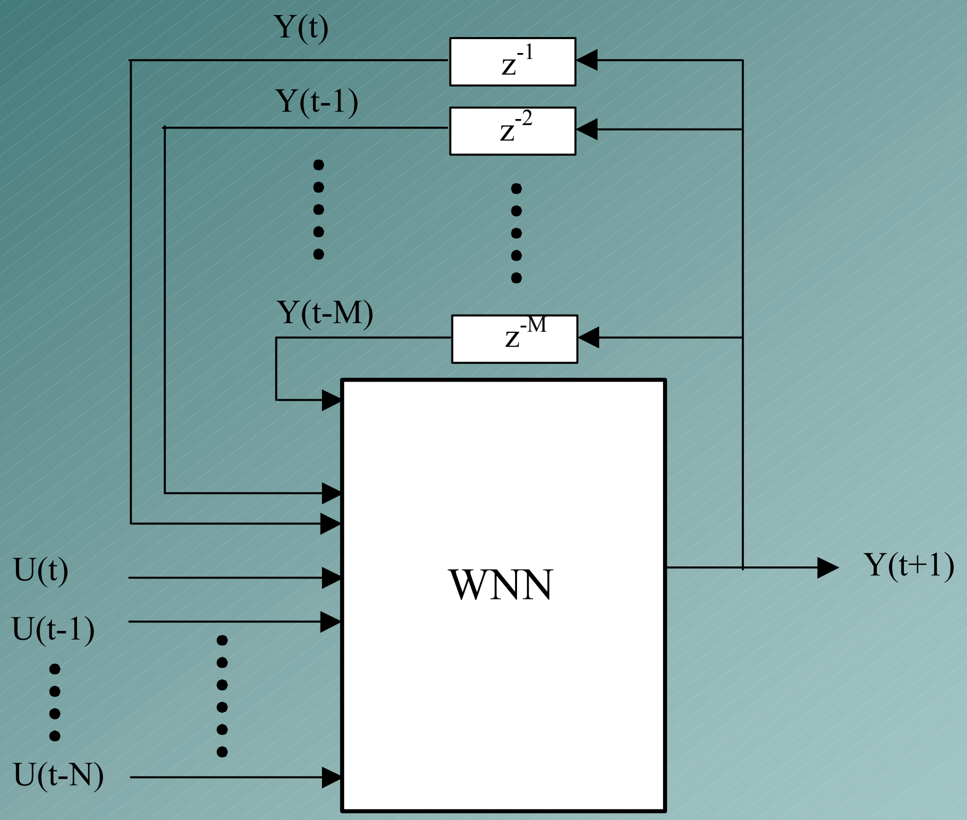


Wavelet Neural Network (WNN)



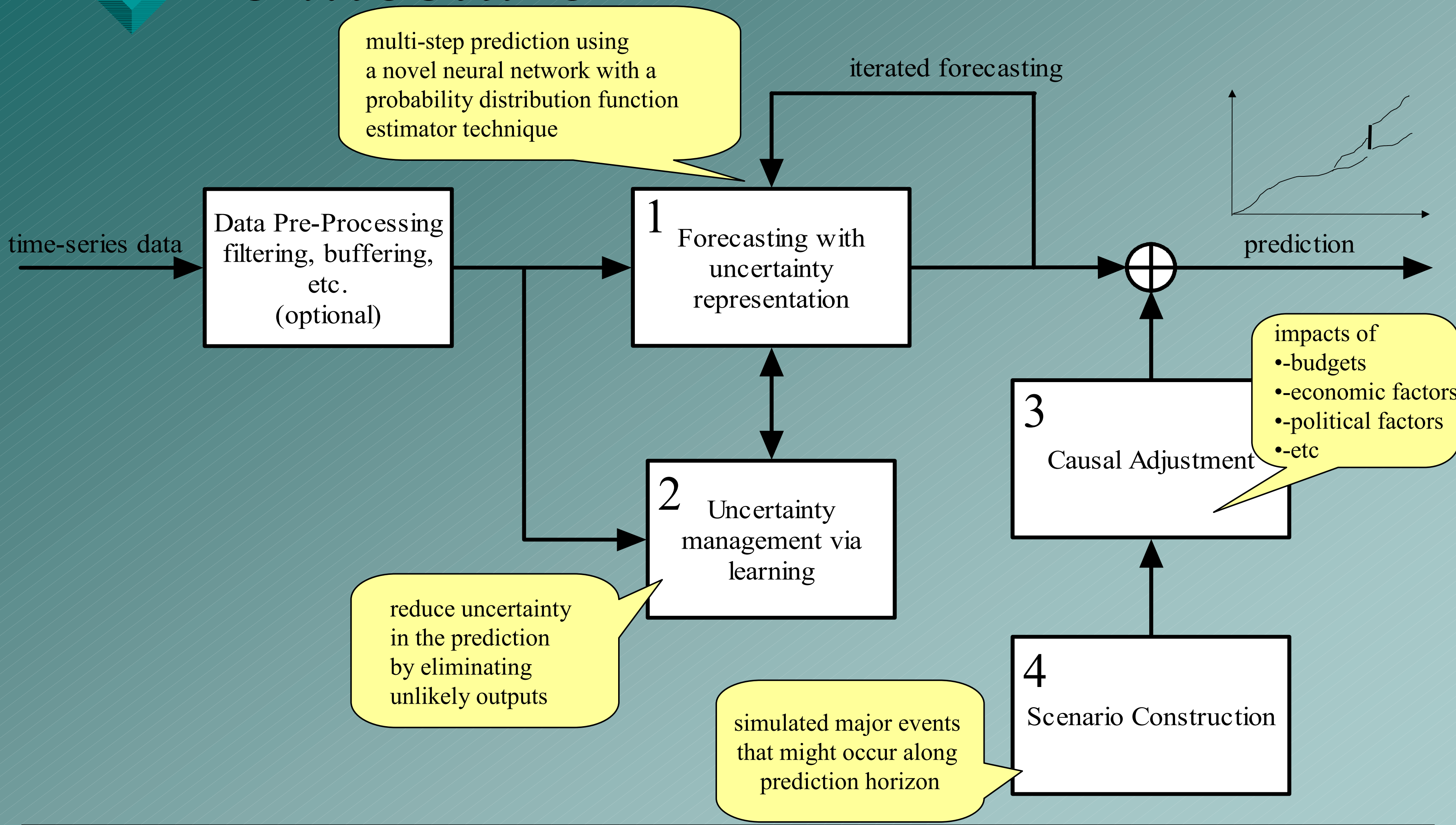
$$y = [\psi_{A_1,b_1}(x)\ \psi_{A_2,b_2}(x)\ \cdots\cdots\ \psi_{A_M,b_M}(x)]C + [x_1]C_{lin}$$

Dynamic Wavelet Neural Network (DWNN)



$$Y(t+1) = WNN(Y(t), \ldots, Y(t-M), U(t), \ldots, U(t-n))$$

Time Series Prediction Architecture

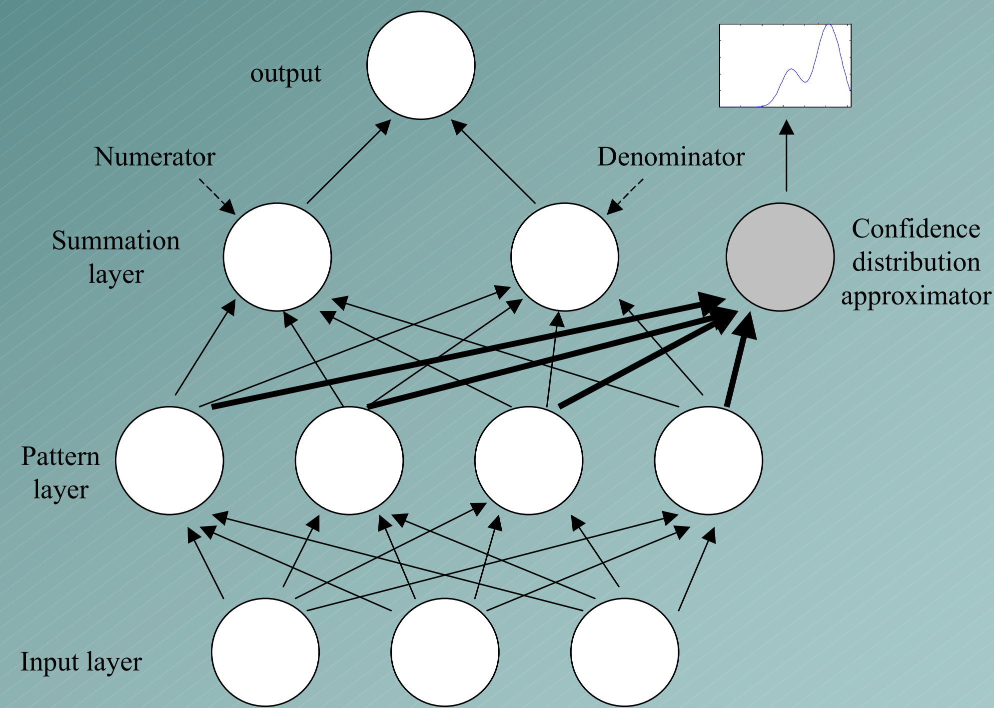


The Confidence Prediction Neural Network (CPNN)

- For CPNN, each node assigns a weight (degree of confidence) for an input **X** and a candidate output $Y_{i.}$
- Final output is the weighted sum of all candidate outputs.
- In addition to the final output, the confidence distribution of that

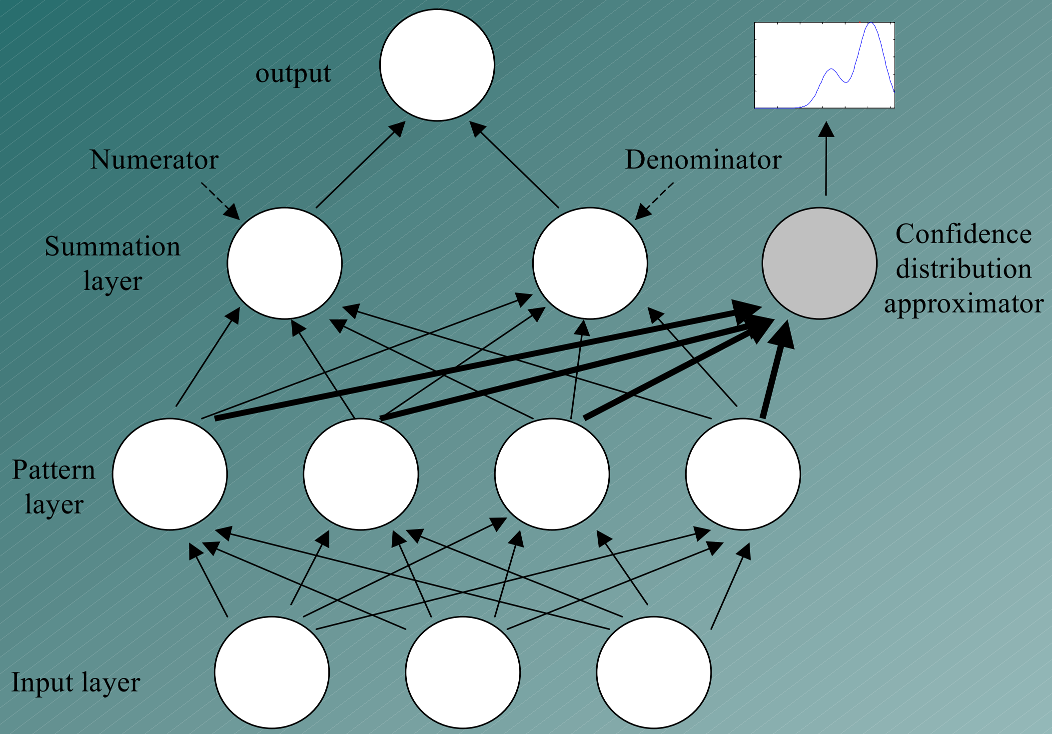
  output can be computed as

$$CD(\boldsymbol{X},Y) = \frac{1}{(2\pi)\sigma_{CD}} \cdot \frac{1}{l}\sum_{i=1}^{l} C(\boldsymbol{X},Y_i)\exp[-\frac{(Y-Y_i)^2}{2\sigma_{CD}^2}]$$



CPNN

Built-in Learning of the CPNN



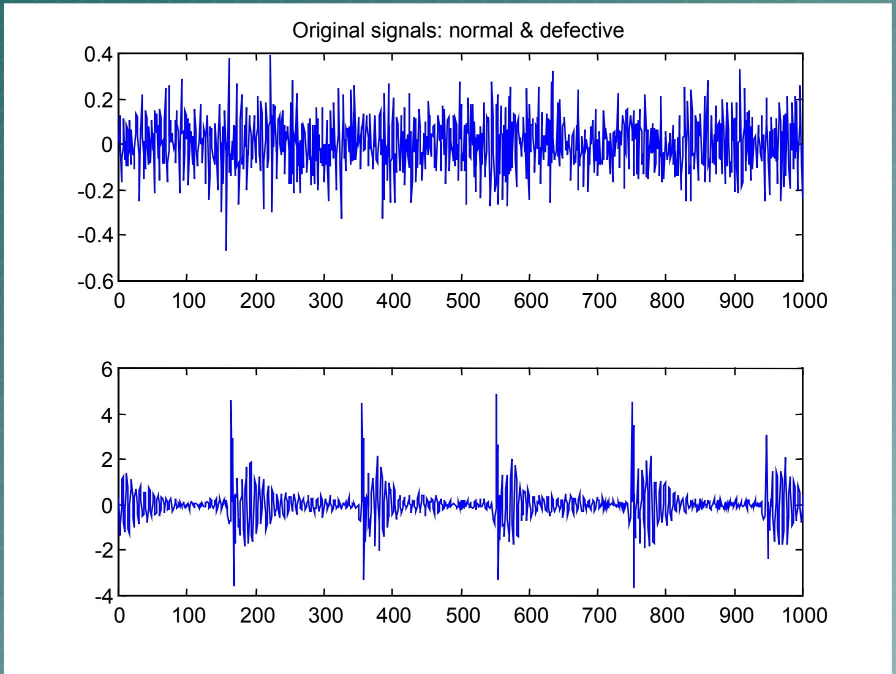
Lazy Learning (built-in)

(David W.Aha, 1997)

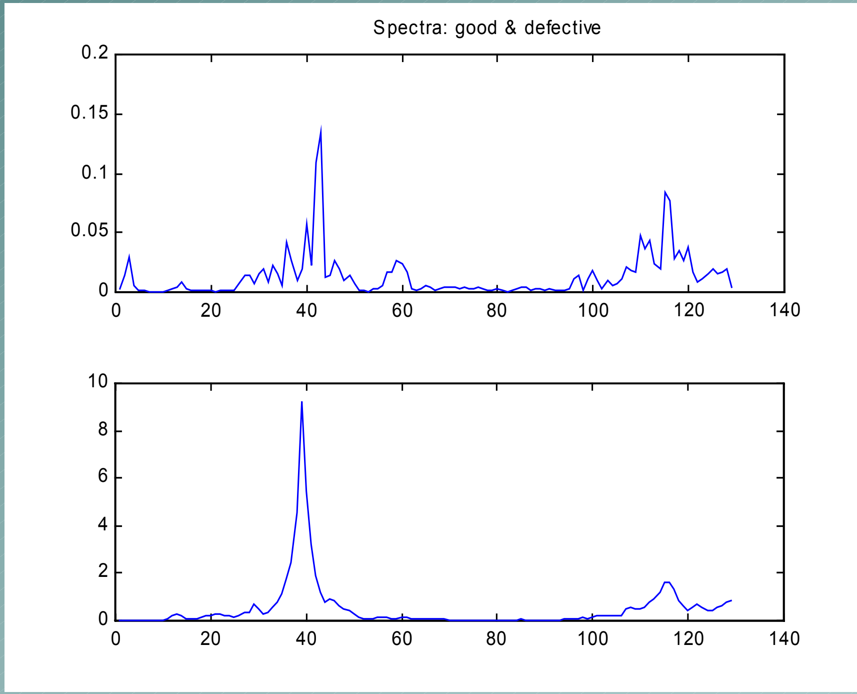
- *defer processing*
- *reply to information requests by combining their stored data*
- *discard the constructed answer and any intermediate results*
- *e.g., case-based, memory-based, exemplar-based, prototype-based learning*
- *AKA, "Just-In-Time" Learning (Cybenko,1996)*

Structure of the Confidence Prediction Neural Network (CPNN)

Example: Prognosis of Rolling-Element Bearing Failure

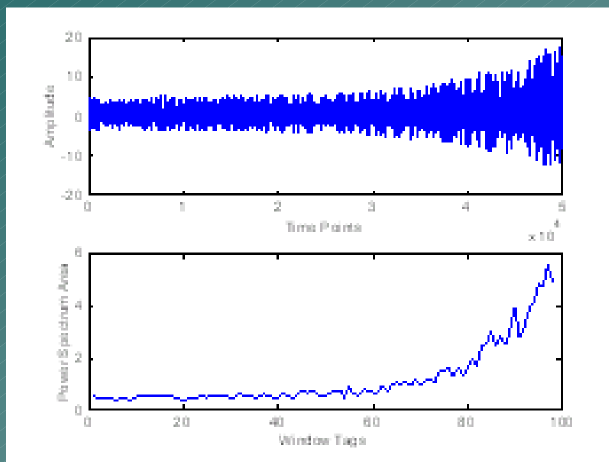


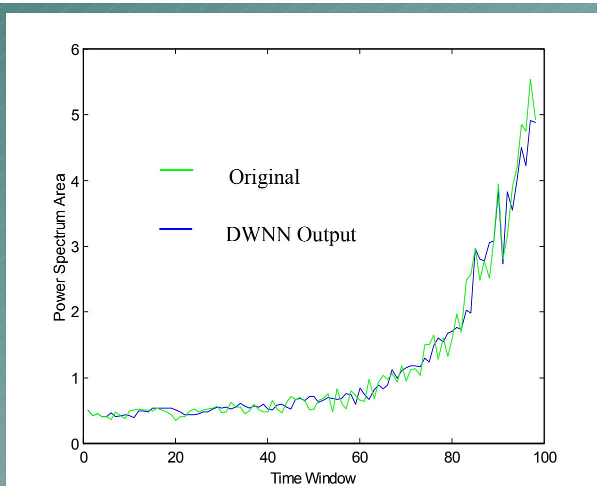
Vibration signals from a good and defective bearing

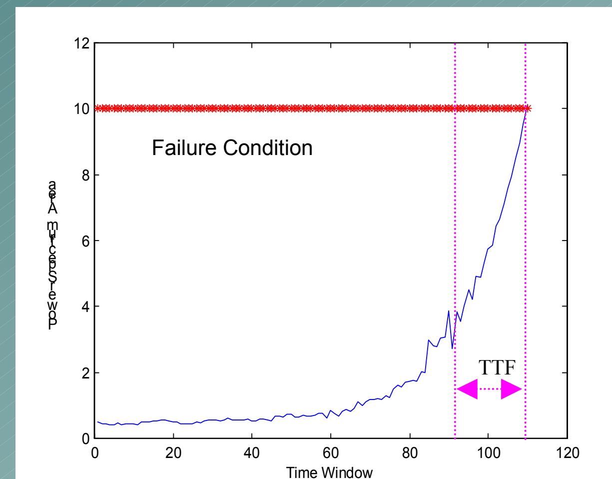


Power Spectral Densities of the vibration signals

Bearing Fault Prognosis

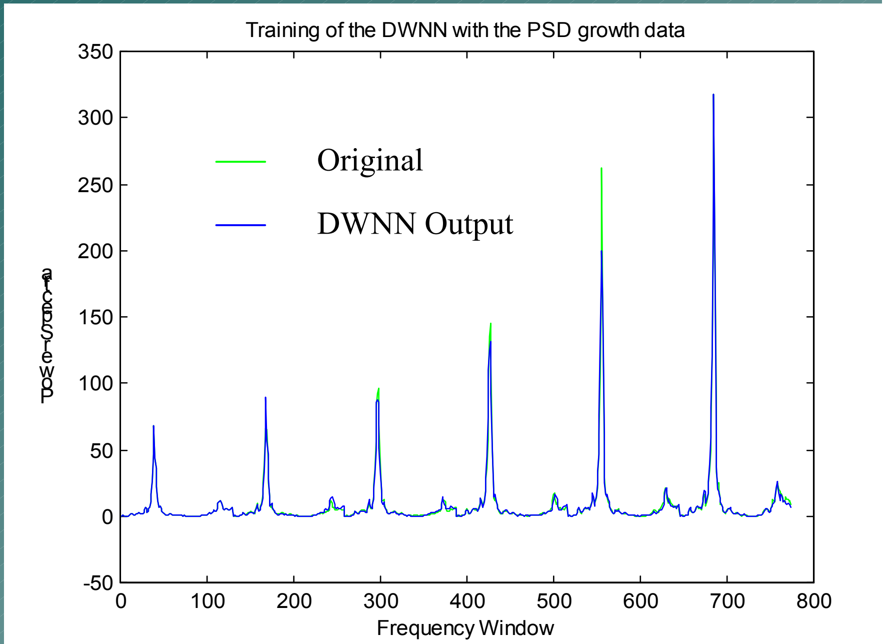


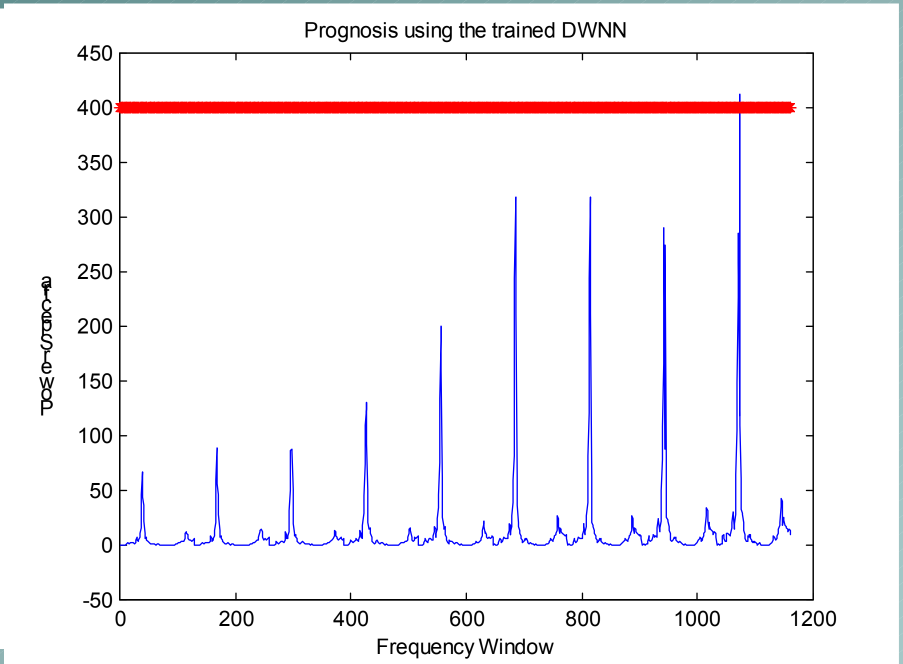




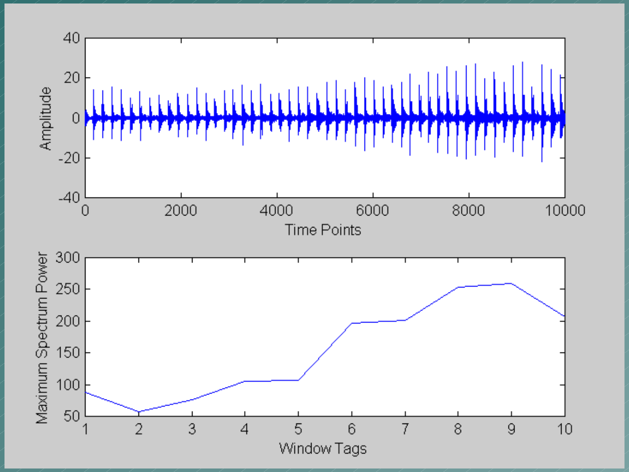
TTF = 19 time units

Prognosis in the frequency domain:

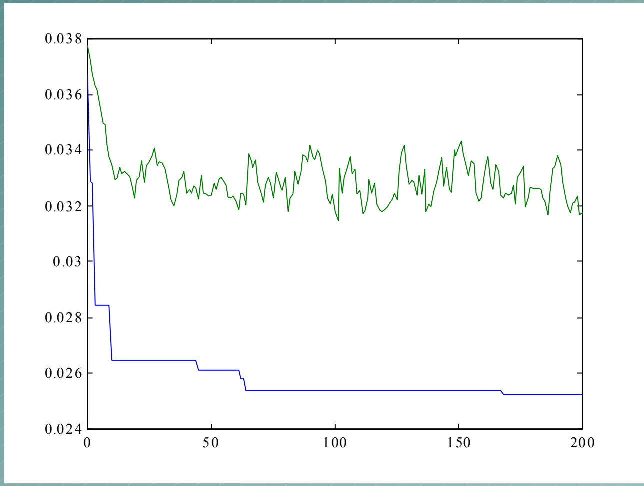




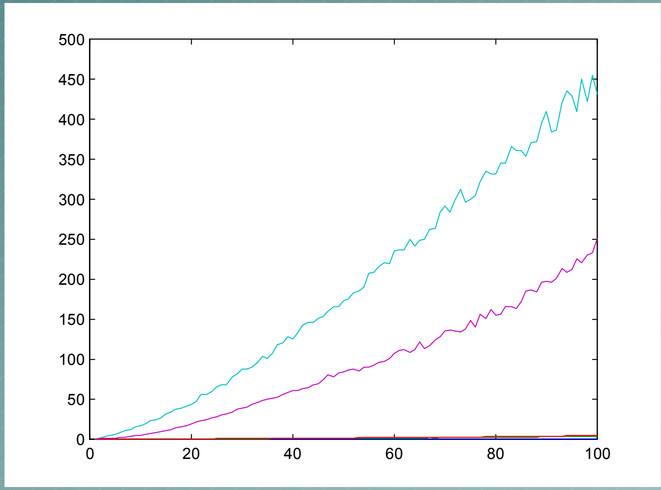
Vibration Data with Growth and Its max PSDs



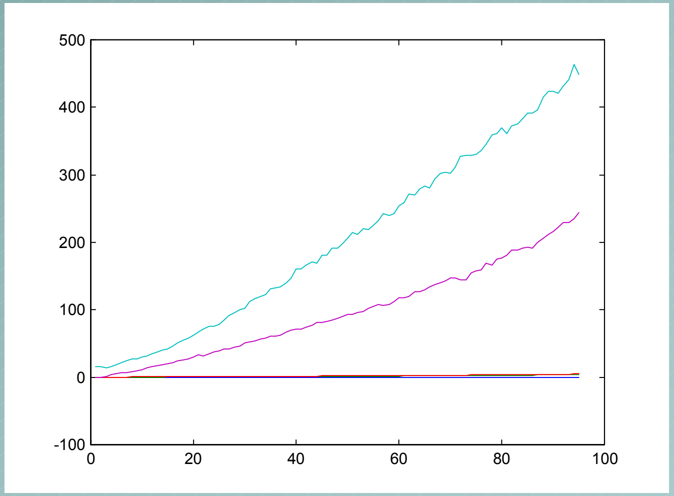
Training of DWNN Using GA



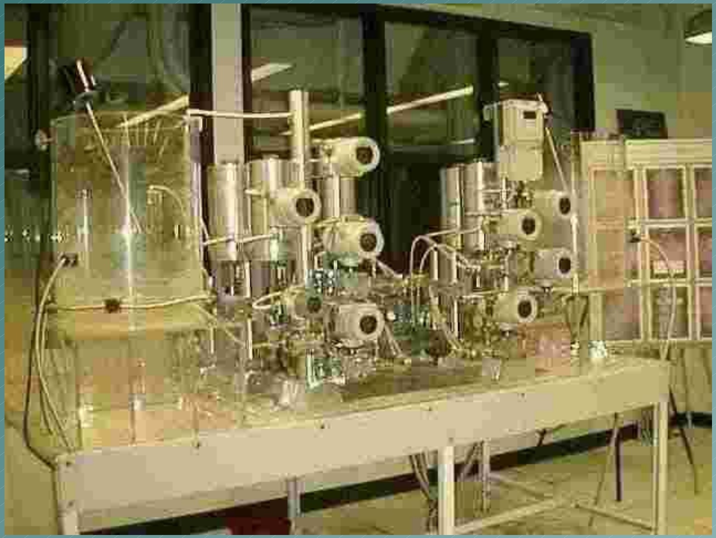
Original MaxPSD profiles for the three axes

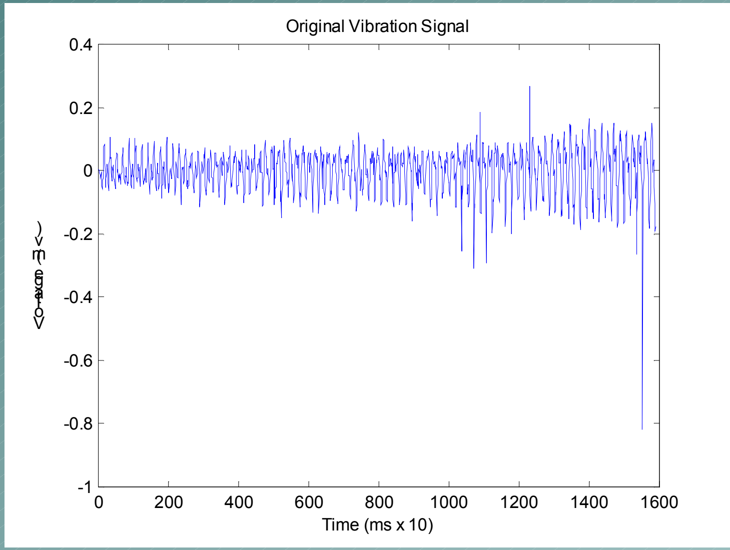


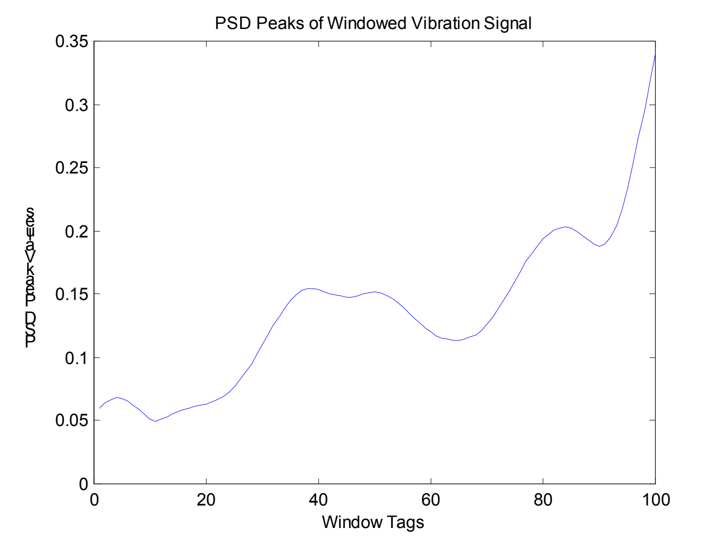
DWNN-Produced MaxPsd profiles



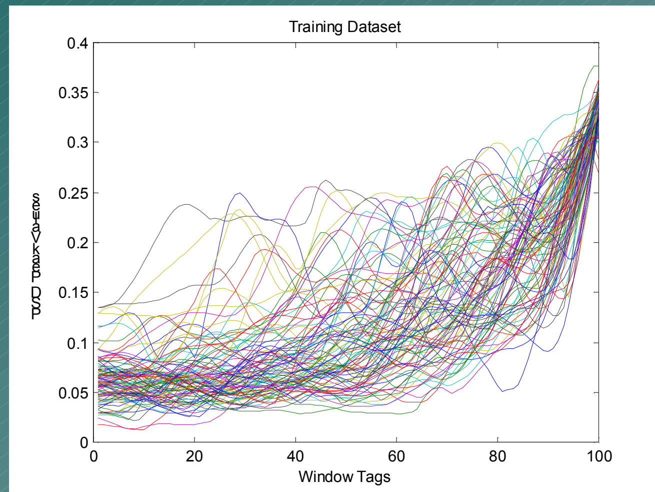
Mounting Bolt Faults

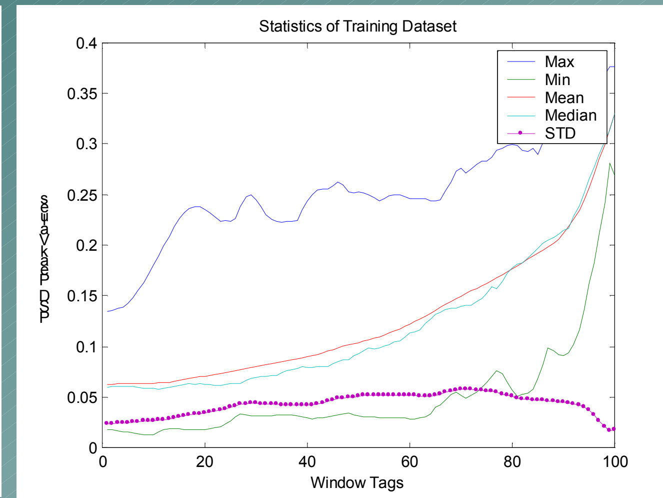




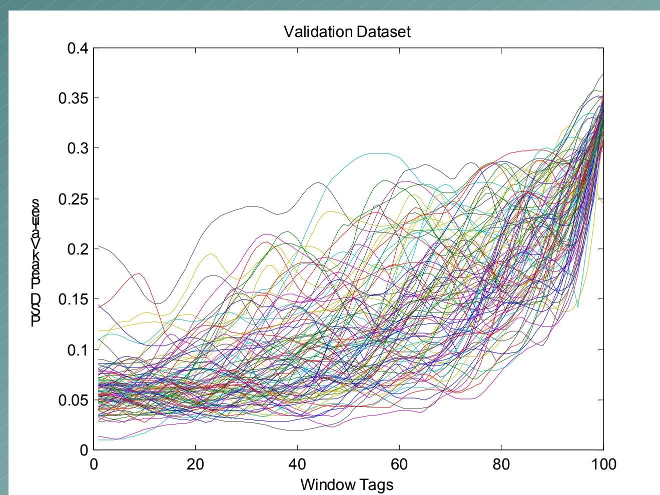


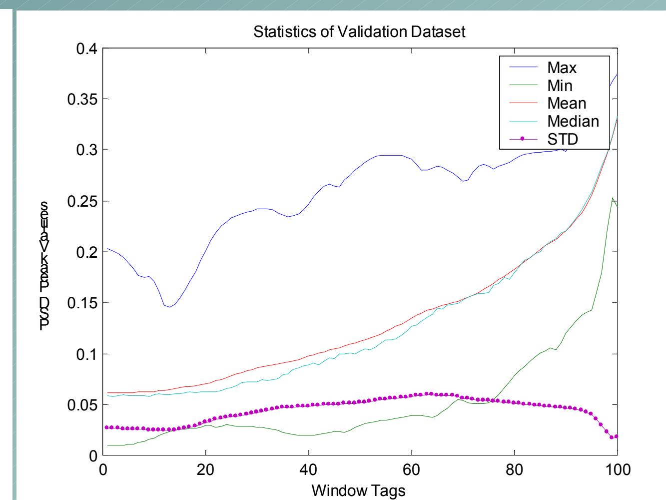
Training Data



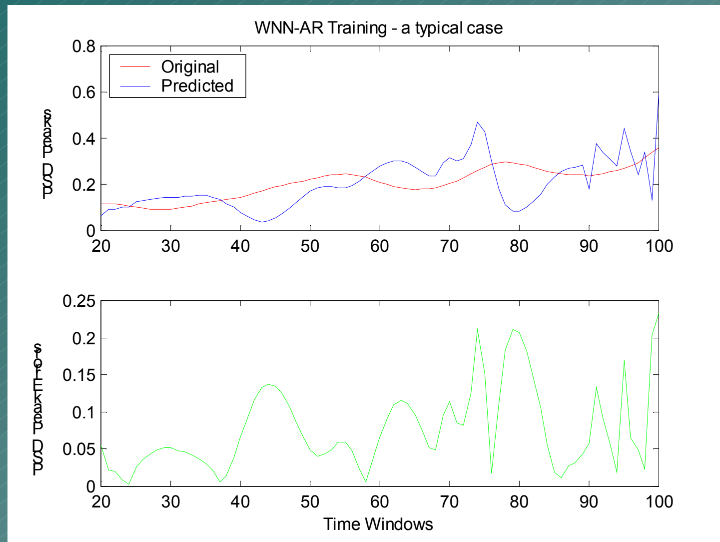


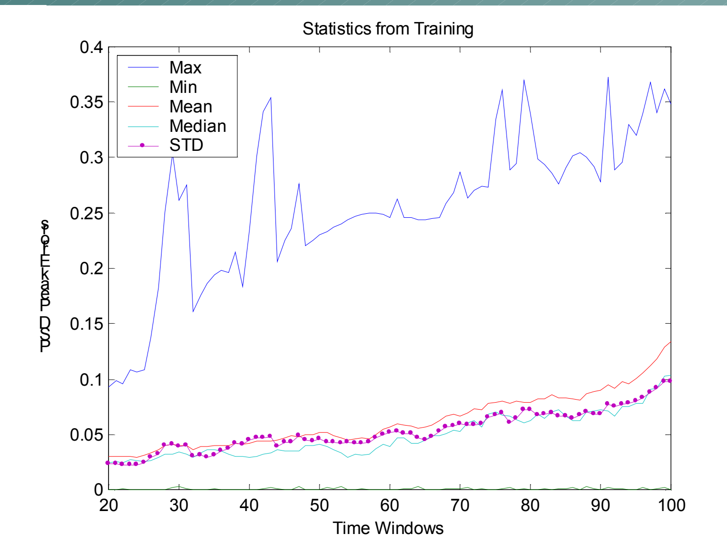
Validation Data



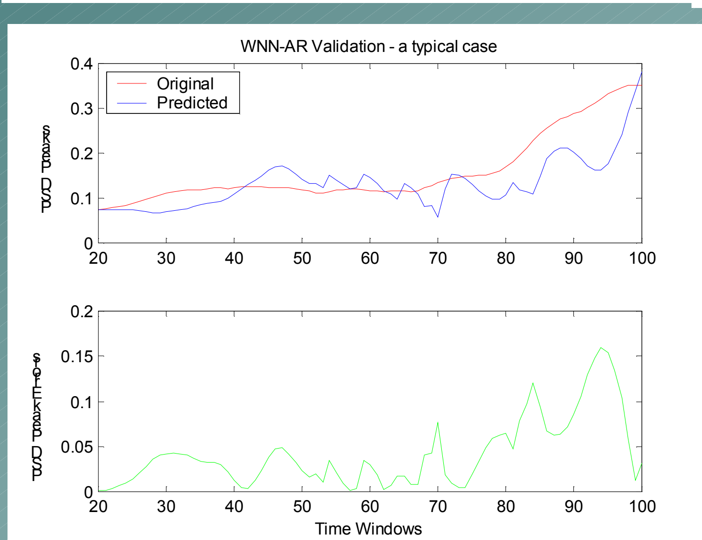


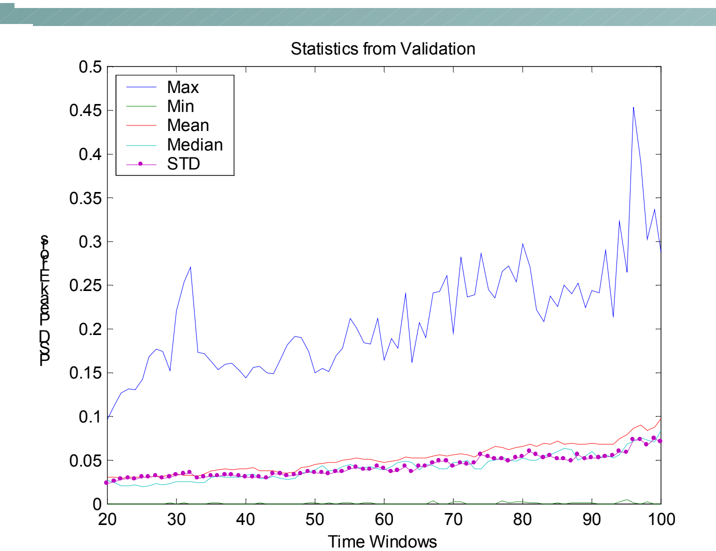
Training



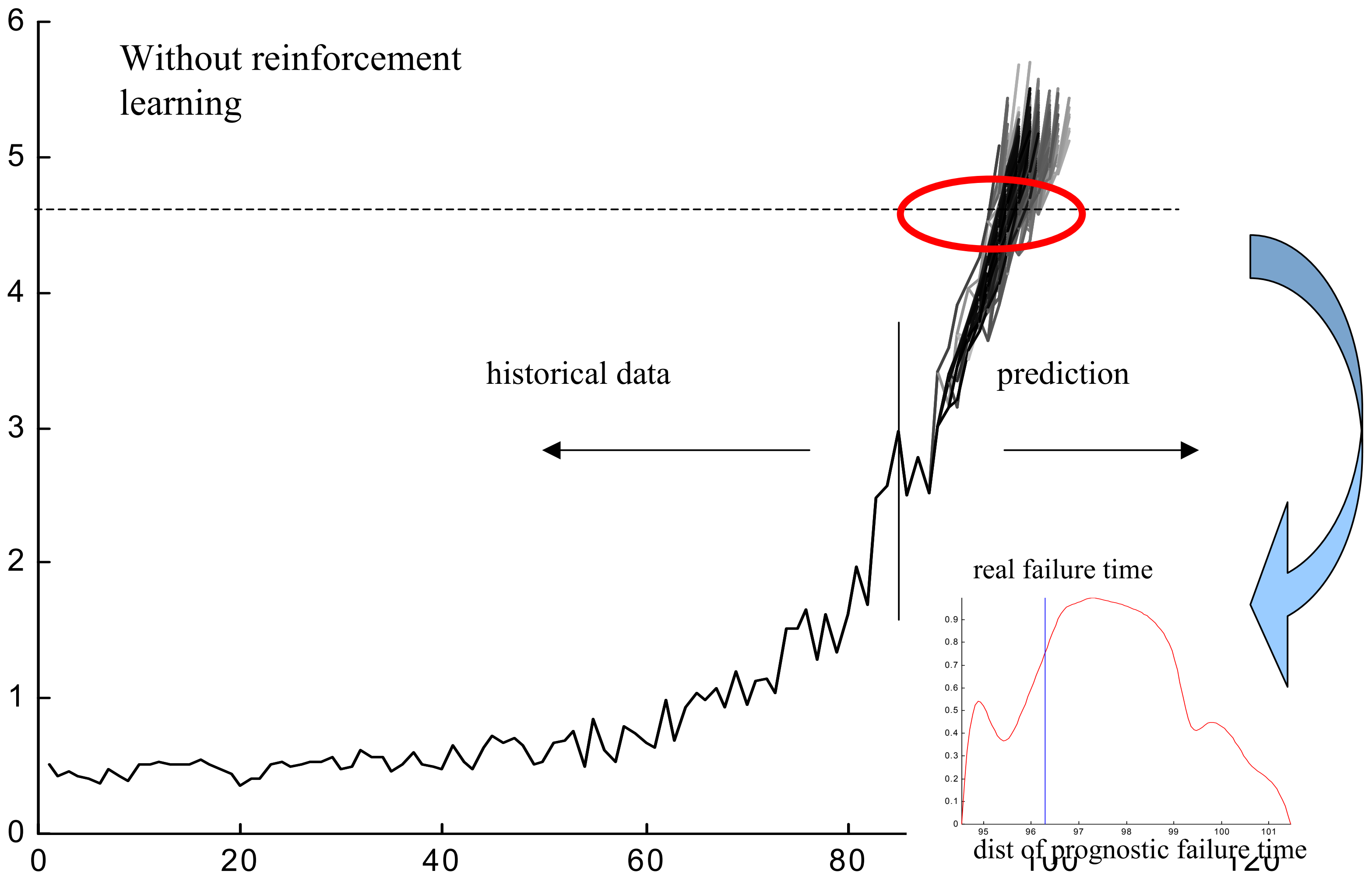


Validation

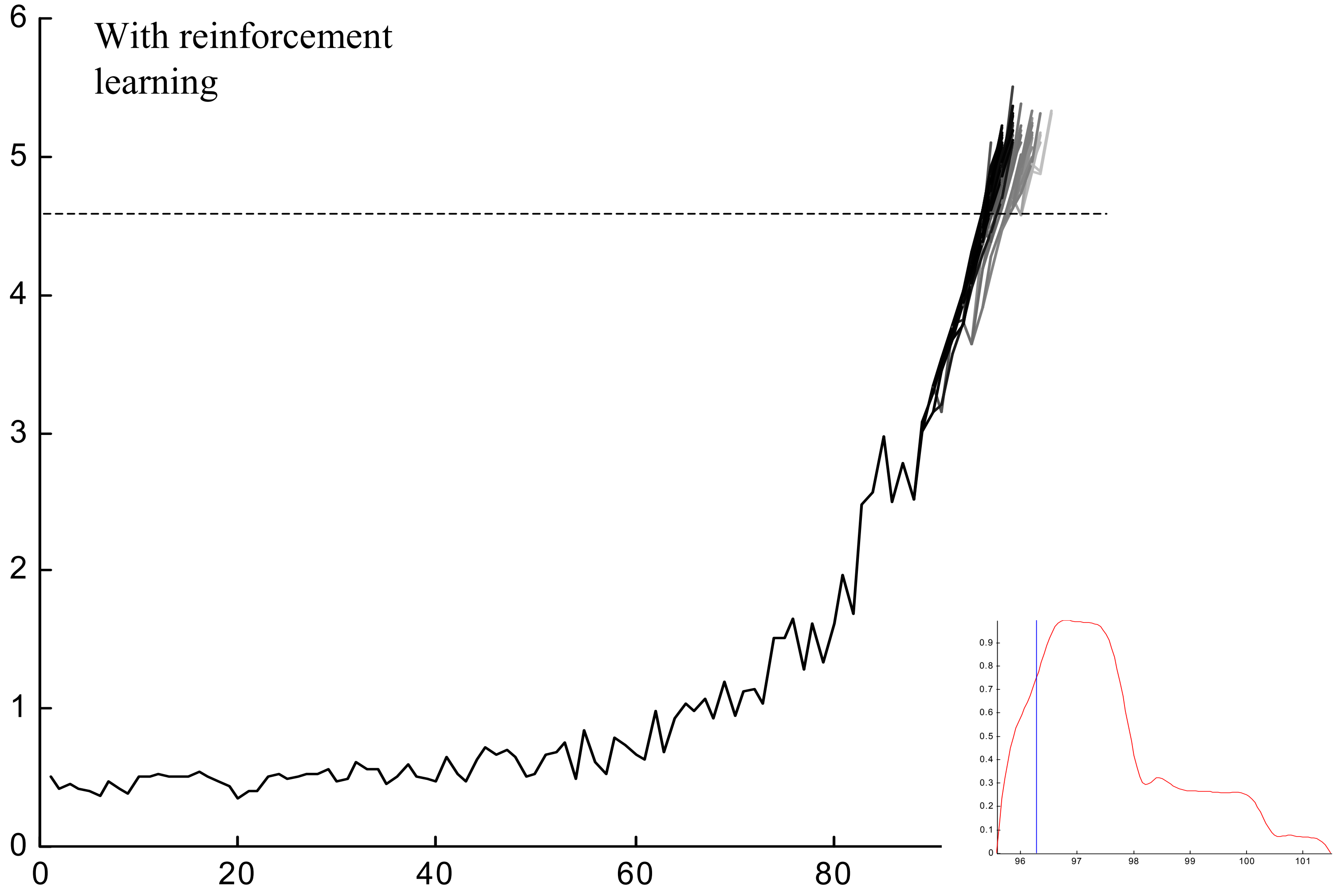




Prognostic Results

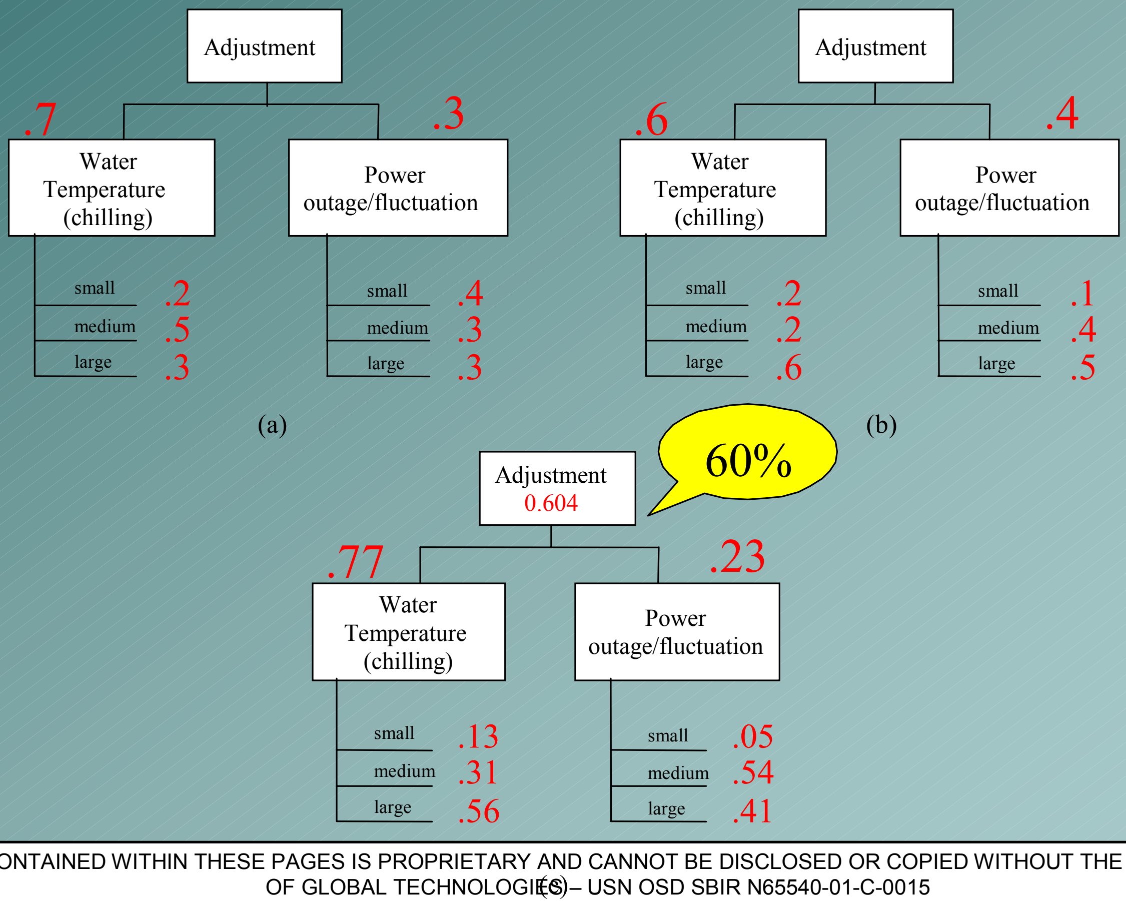


Prognostic Results



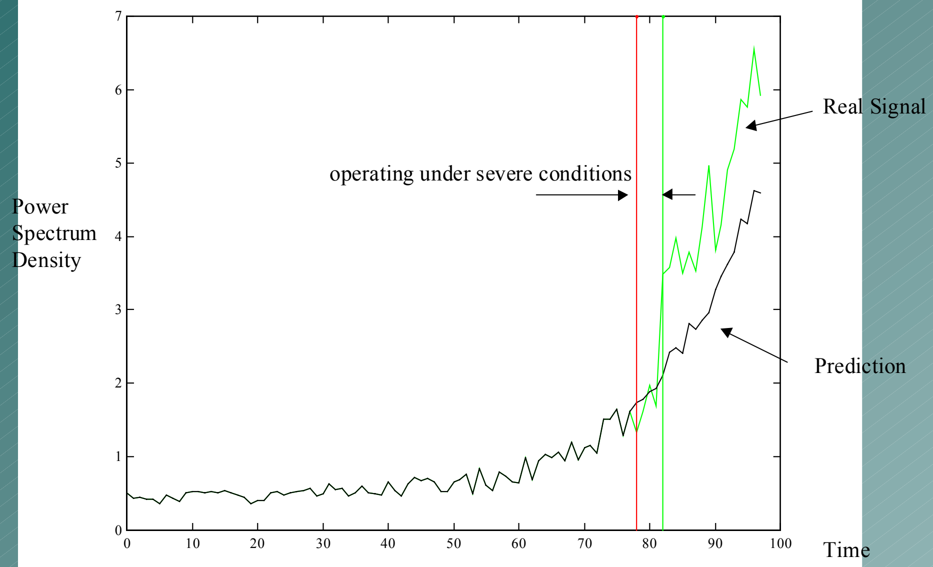
Accounting for Extreme Performance conditions - The Fuzzy Analytic Hierarchy Process

Accumulate experts' opinion to effect causal adjustment

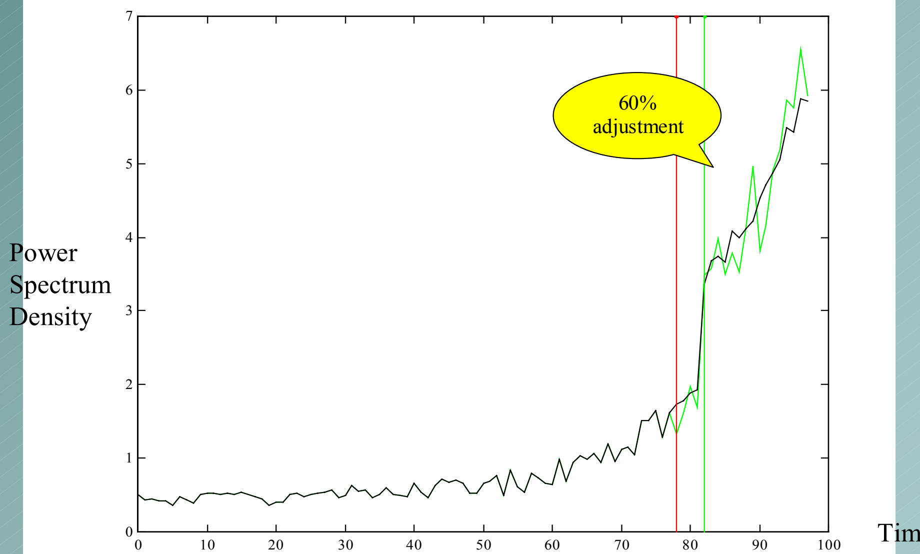


Accounting for Extreme Performance conditions - The Fuzzy Analytic Hierarchy Process (cont'd)

Accumulate experts' opinion to effect causal adjustment



Fault prognosis without casual adjustment



Fault prognosis with casual adjustment

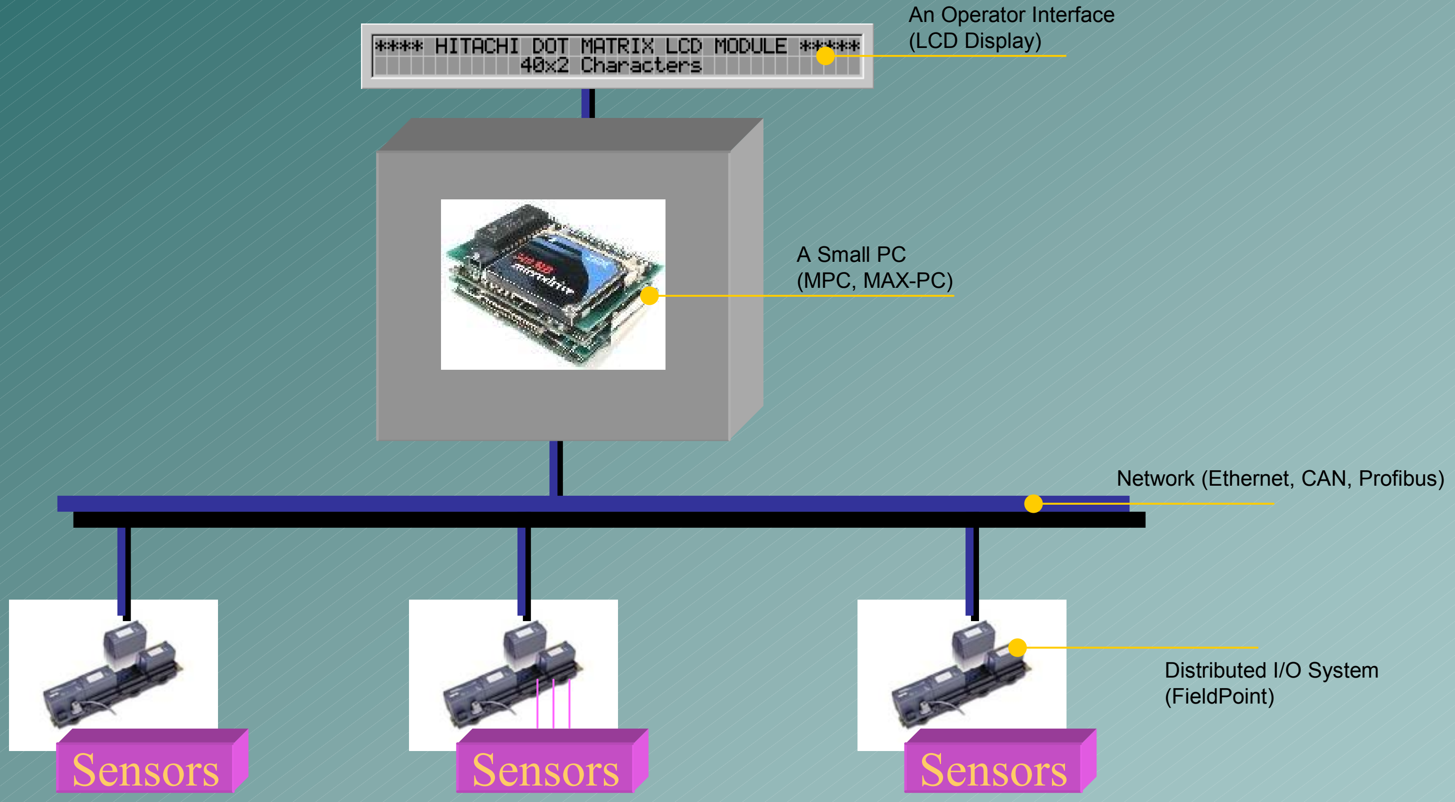
Embedded Distributed Diagnostic Platform (EDDP)

- Intelligent Distributed systems with embedded processing can help implement a reliable control for critical operations.
- Replace long wires of sensor-data with a single low-cost network cable:
  - Save time and money during both installation and maintenance.
  - Reduce noise corruption problems by avoiding the use of long-distance analog signal wiring.
- Use standard operating systems and IDEs to manage project development phase.

EDDP System Components

- Hardware:
  - Modular I/O (e.g. NI's FieldPoint System, or MAX-IO).
  - Embedded PC (e.g. MPC - Matchbox PC of TIQIT or MAX-PC of Strategic-Test).
  - Network (e.g. Ethernet, CAN, PROFIBUS).
  - User Interface (e.g. LCD Panel, VGA-capable head-mounted display).
- Software:
  - Windows CE, Linux, QNX, VxWorks, or OsX operating systems.
  - SCADA / MMI applications.
  - Embedded databases (like Polyhedra).
  - RAD tools (like eMbedded Visual Studio of Microsoft).

A Possible EDDP Configuration



Current R&D Thrusts

- View complex system (gas turbine, etc.) as hybrid system, i.e. consisting of discrete events and continuous dynamics.
- Develop mode detection and identification algorithms.
- Customize diagnostic / prognostic strategies to reflect current operating conditions.
- Develop embedded diagnostic platforms.
- Explore CBM standards - MIMOSA, OSA / CBM.
- Develop an Intelligent Agent (IA) framework for internet-based distributed diagnostics / prognostics.

SENSOR SELECTION AND PLACEMENT

- Objective:

  Determine the optimum type and placement of sensors

- Current Status:

  Ad hoc;heuristic methods;

  Mostly “an art”

- Future Direction:

  Put some “science” into the problem

Approach:

- Use the notion of observability .
- Employ a high-level physical model of process –may not be quantitatively accurate but qualitatively correct.
- Pose the question of which physical variables must be measured at what locations and at what levels of accuracy.
- Consider the issue of analytical measurements to complement physical ones.

Approach(Continued):

- Estimate the important physical states and detect the occurrences of faults at the required speed and accuracy.
- Discretize continuous spatial domains to yield a discrete set of feasible locations for a particular sensor type.
- Search over all feasible combinations of measurement types,accuracies,and locations to optimize the total cost with respect to some performance and resource constraints

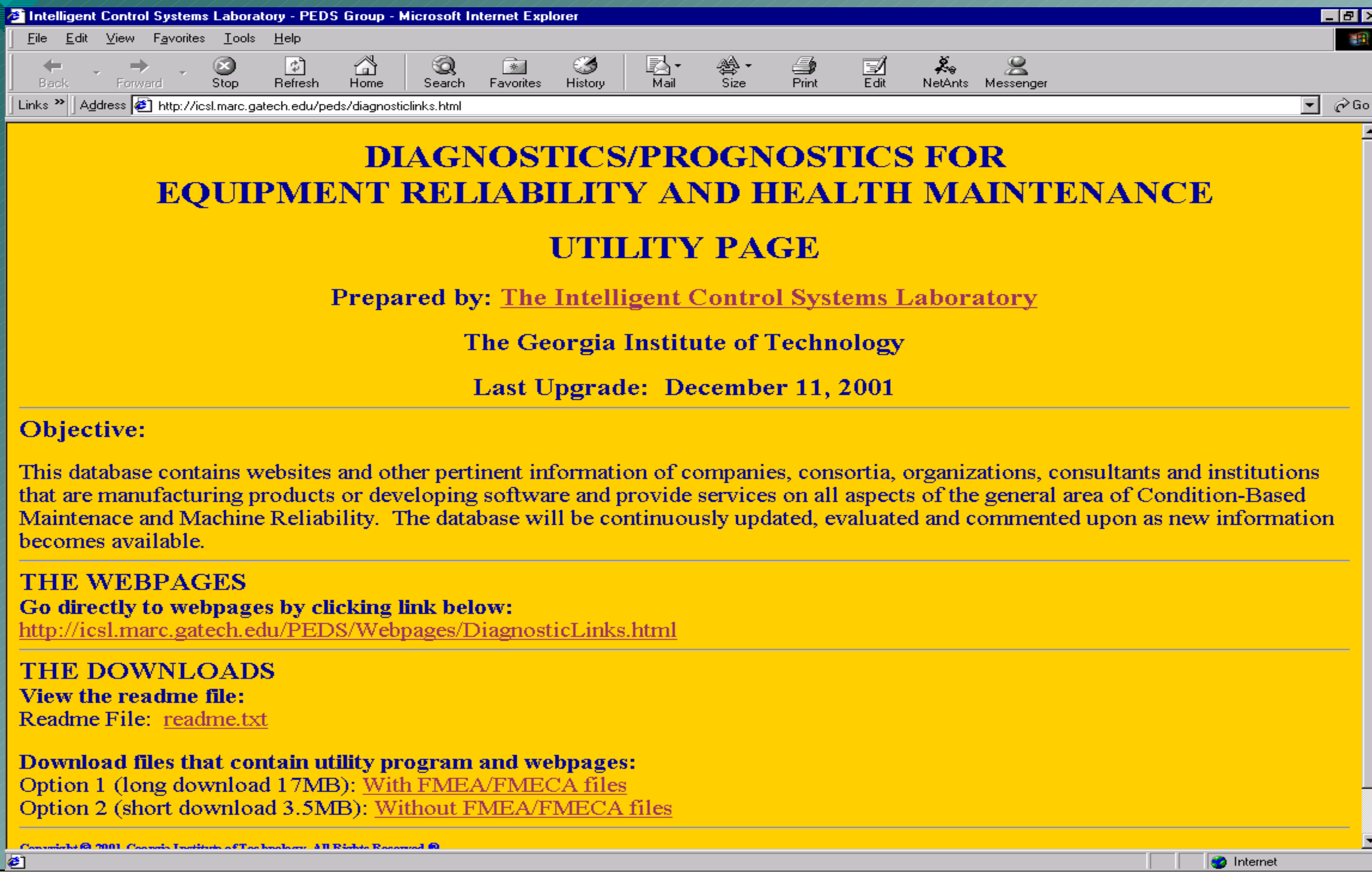
Approach(Continued):

- Develop and implement a case library
- Implement natural language understanding techniques.
- Automate a Dynamic Case-Based Reasoning Algorithm
- Test and Evaluate prototype system.

IMPACT ON STUDENT LEARNING

- Graduated 6 recent Ph.Ds in CBM-related areas
- Six Ph.D students currently in pipeline
- Introduced CBM-related material into Intelligent Control graduate course .
- Students conducting laboratory projects/experiments in diagnostics and related areas.

GT's CBM Web Site



Intelligent Control Systems Laboratory - PEDS Group - Microsoft Internet Explorer

Address: http://icsl.marc.gatech.edu/peds/diagnosticlinks.html

DIAGNOSTICS/PROGNOSTICS FOR EQUIPMENT RELIABILITY AND HEALTH MAINTENANCE

UTILITY PAGE

Prepared by: The Intelligent Control Systems Laboratory

The Georgia Institute of Technology

Last Upgrade: December 11, 2001

Objective:

This database contains websites and other pertinent information of companies, consortia, organizations, consultants and institutions that are manufacturing products or developing software and provide services on all aspects of the general area of Condition-Based Maintenace and Machine Reliability. The database will be continuously updated, evaluated and commented upon as new information becomes available.

THE WEBPAGES

Go directly to webpages by clicking link below:

http://icsl.marc.gatech.edu/PEDS/Webpages/DiagnosticLinks.html

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THE DOWNLOADS

View the readme file:

Readme File: readme.txt

Download files that contain utility program and webpages:

Option 1 (long download 17MB): With FMEA/FMECA files

Option 2 (short download 3.5MB): Without FMEA/FMECA files

FUTURE WORK

On ICAS

<u>Current Status</u>: We are using ICAS as a bridge between the LabView data collection module and the PEDS database.

<u>Future Plans</u>: Would like to utilize as many ICAS functionalities as possible, i.e. data storage and data management, GUI, any appropriate diagnostic routines, interfaces, etc.

Beta Testing

- Ground-based Chiller Availability
- Sensor Requirements
- ICAS
- Data Acquisition System
- Testing Program
  - Failure Modes
  - Seeding of "Soft" Failures
  - Personnel Resources
- Assessment Methodology
- PEDS Improvements/Tuning
- Preparation for Shipboard Field Testing

HVAC CONTROLLERS

The Challenge: Monitoring and diagnostics/prognostics of closed-loop controllers.

Digital Controllers: Difficult or impossible to obtain fault trending information.

A Possible Approach: Monitor/validate sensor and actuator status. View closed-loop controller as an input-output subsystem and monitor how closely the output is tracking the commanded set point.

The HVAC Controller Architecture

A distributed loop controller structure that regulates key process variables – pressure, flow rate, etc.

Leveraging of PEDS Technologies

- AAAV Program/GD
- Army's Advanced Diagnostics Program
- DARPA's Software Enabled Control Program
- Industry Applications

Outreach Activities

Conferences/Workshops

- Special session at MARCON 2002 on "Prognostic Enhancements to Diagnostic Systems: The U.S. Navy Perspective"
- AAAI Symposium on Machine Diagnostics/Prognostics Organizing Committee, March 25-27, 2002, Palo Alto, CA

Conference/Workshop Presentations Journal Publications

- G. Hadden, P. Bergstrom, T. Samad, B. H. Bennett, G. Vachtsevanos, and J. Van Dyke, "System Health Management for Complex Systems," in *Automation, Control and Complexity, An Integrated Approach*, Edited by T. Samad and J. Weyrauch, John Wiley and Sons, Ltd, pp. 191-214, 2000.
- P. Wang and G. Vachtsevanos, "Fault Prognostics Using Dynamic Wavelet Neural Networks", Journal of Artificial Intelligence for Engineering Design, Analysis and Manufacturing, Vol.15, pp. 349-365, 2001.
- G. Vachtsevanos, P. Wang, N. Khiripet, A. Thakker and T. Galie, "An Intelligent Approach to Prognostic Enhancements of Diagnostic Systems", Proceedings of SPIE 15th Annual International Symposium on Aerospace/Defense Sensing, Simulation, and Controls, Orlando, Florida, April 16-20, 2001.
- G. Vachtsevanos and P. Wang, "A Wavelet Neural Network Framework for Diagnostics of Complex Engineered Systems", (invited) Proceedings of 2001 Joint IEEE Conference on Control Applications and the International Symposium on Intelligent Control, Mexico City, Mexico, September 5-7, 2001.

Conference/Workshop Presentations Journal Publications (cont.)

- G. Vachtsevanos, P. Wang, T. Galie and A. Thakker, "Fault Prognosis Using Dynamic Wavelet Neural Networks", Proceedings of AUTOTESTCON 2001 Conference, August 20-23, 2001.
- N. Khiripet and G. Vachtsevanos, "Machine Failure Prognosis Using a Confidence Prediction Neural Network", Proceedings of 8th International Conference on Advances in Communications and Control, Crete, Greece, June 25-29, 2001.
- N. Khiripet, G. Vachtsevanos, A. Thakker and T. Galie, "A New Confidence Prediction Neural Network for Machine Failure Prognosis", Proceedings of Intelligent Ships Symposium IV, Philadelphia, PA, April 2-3, 2001.
- G. Vachtsevanos, P. Wang and N. Khiripet, "Prognostication: Algorithms and Performance Assessment Methodologies", Proceedings of MARCON 2000, Maintenance and Reliability Conference, May 8-10, 2000, Knoxville, Tennessee, pp. 8.01-8.12, 2000.

Conference/Workshop Presentations Journal Publications (cont.)

- G. Vachtsevanos, “Machine Fault Diagnosis and Prognosis – A Novel Approach” ISA Textile Industry Dision Workshop on Measurement and Optimization of Manufacturing Utilities, Greenville, SC, October 20, 1999.
- G. Vachtsevanos, “ Machine Pathology: A Novel Architecture for Fault Diagnosis and Prognosis,” 7th International Conference on Advances in Communications and Control, Athens, Greece, June 28 – July 2, 1999.
- P. Wang, N. Propes, N. Khiripet, Y. Li and G. Vachtsevanos, “An Integrated Approach to Machine Fault Diagnosis”, IEEE Annual Textile Fiber and Film Industry Technical Conference, Atlanta GA, May 4-6, 1999.
- G. Vachtseanos and P. Wang, “An Intelligent Approach to Diagnosis and Prognosis”, The 53rd Meeting of the Society for Machinery Failure Prevention Technology, MFPT Forum, Virginia Beach April 19-22, 1999.

Conference/Workshop Presentations Journal Publications (cont.)

- G. Hadden, G. Vachtsevanos, B. Bennett and J. Van Dyke, "Machinery Diagnostics and Prognostics/Condition Based Maintenance: A Progress Report, Failure Analysis: A Foundation for Diagnostics and Prognostics Development," Proceedings of the 53rd Meeting of the Society for Machinery Failure Prevention Technology, April 1999.
- P. Wang and G. Vachtsevanos, "Fault Prognosis Using Dynamic Wavelet Neural Networks," Proceedings of MARCON 99, Maintenance and Reliability Conference, pp. 23.01 – 23.11, Gatlinburg, TN, May 9–12, 1999.

Short Courses

Intensive four-day short course on “Fault Diagnostics/Prognostics for Equipment Reliability and Health Maintenance” to be presented May 20-23, 2002 at Georgia Tech.

Technology Readiness Level	Description
1. Basic principles observed and reported.	Lowest Level of Technology Readiness. Scientific research begins to be translated into applied research and development. Examples might include paper studies of a technology's basic properties.
2. Technology concept and/or application formulated.	Invention begins. Once basic principles are observed, practical applications can be invented. Applications are speculative and there is no proof or detailed analysis to support the assumptions. Examples are limited to analytic studies.
3. Analytical and experimental critical functions and/or characteristic proof of concept.	Active research and development is initiated. This includes analytical studies and laboratory studies to physically validate analytical predictions of separate elements of the technology. Examples include components that are not yet integrated or representative.
4. Component and/or breadboard validation in laboratory environment.	Basic technological components are integrated to establish that they will work together. This is relatively "low fidelity" compared to the eventual system. Examples include integration of "ad hoc" hardware in the laboratory.
5. Component and/or breadboard validation in relevant environment.	Fidelity of breadboard technology increases significantly. The basic technological components are integrated with reasonably realistic supporting elements so that it can be tested in a simulated environment. Examples include "high fidelity" laboratory integration of components.
6. System/subsystem model or prototype demonstration in a relevant environment.	Representative model or prototype system, which is well beyond that of TRL 5, is tested in a relevant environment. Represents a major step up in technology's demonstrated readiness. Examples include testing a prototype in a high fidelity laboratory environment, or in a simulated operational environment.
7. System prototype demonstration in an operational environment.	Prototype near, or at, planned operational system. Represents a major step up from TRL 6, requiring demonstration of an actual system prototype in an operational environment, such as an aircraft, vehicle, or space. Examples include testing the prototype in a test bed aircraft.
8. Actual system completed and "flight qualified" through test and demonstration.	Technology has been proven to work in its final form and under expected conditions. In almost all cases, TRL represents the end of true system development. Examples include developmental test and evaluation of the system in its intended weapon system to determine if it meets design specifications.
9. Actual system "flight proven" though successful mission operations.	Actual application of the technology in its final form and under mission conditions, such as those encountered in operational test and evaluation. In almost all cases, this is the end of the last "bug fixing" aspects of system development. Examples include using the system under operational mission conditions.