NSF I/UCRC since 2000

Center for Intelligent Maintenance Systems

Infotronics and Prognostics Technologies for Self-Maintenance Systems

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www.imscenter.net

University of Cincinnati

Michigan Engineering

Missouri S&T

Outline

- Unmet Needs
- Advances on Prognostics and Examples
- Design of Self-Maintenance Systems
- Future Trends and Conclusions

IMS Vision and Mission Statement

Center for Intelligent Maintenance Systems

To enable products and systems to achieve and sustain near-zero breakdown performance, and ultimately transform machine condition data to useful information for improved productivity and asset utilization.

The IMS Consortium

Center for Intelligent Maintenance Systems

AMD Smarter Choice
CISCO
TOYOTA
Parker
SIEMENS
ADVANTECH
API
P&G
PMC
OMRON
TechSolve
Syncrude
UNIVERSITY OF Cincinnati
GE Aircraft Engines
DAIMLERCHRYSLER
Inteligistics
Center for Intelligent Maintenance Systems
FESTO
TOSHIBA
BOSCH
100 Years in USA 1906|2006
AVETEC
MISSOURI S&T
THE UNIVERSITY OF MICHIGAN 1817
KISTLER
measure. analyze. innovate.
GM
Ford
Honeywell
Chevron
BorgWarner
HARLEY-DAVIDSON MOTOR COMPANY
CATERPILLAR
21CSI
21ST CENTURY SYSTEMS, INC.
BOEING
NATIONAL INSTRUMENTS
EDAptive COMPUTING, INC.
Industrial Technology Research Institute
Center for Environmental, Safety and Health Technology Development
SPIRIT AEROSYSTEMS
NISSAN

UNIVERSITY OF Cincinnati
MichiganEngineering
MISSOURI S&T

Common Unmet Needs in Future Maintenance and Service

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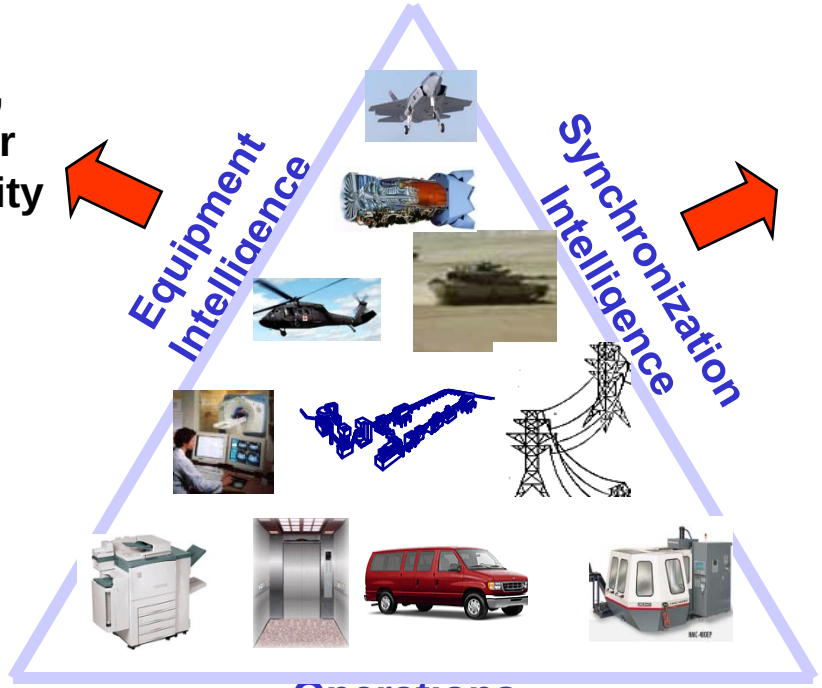
Intelligent Monitoring, Predict and Prevent for Guaranteed Sustainability
Self-Assessment

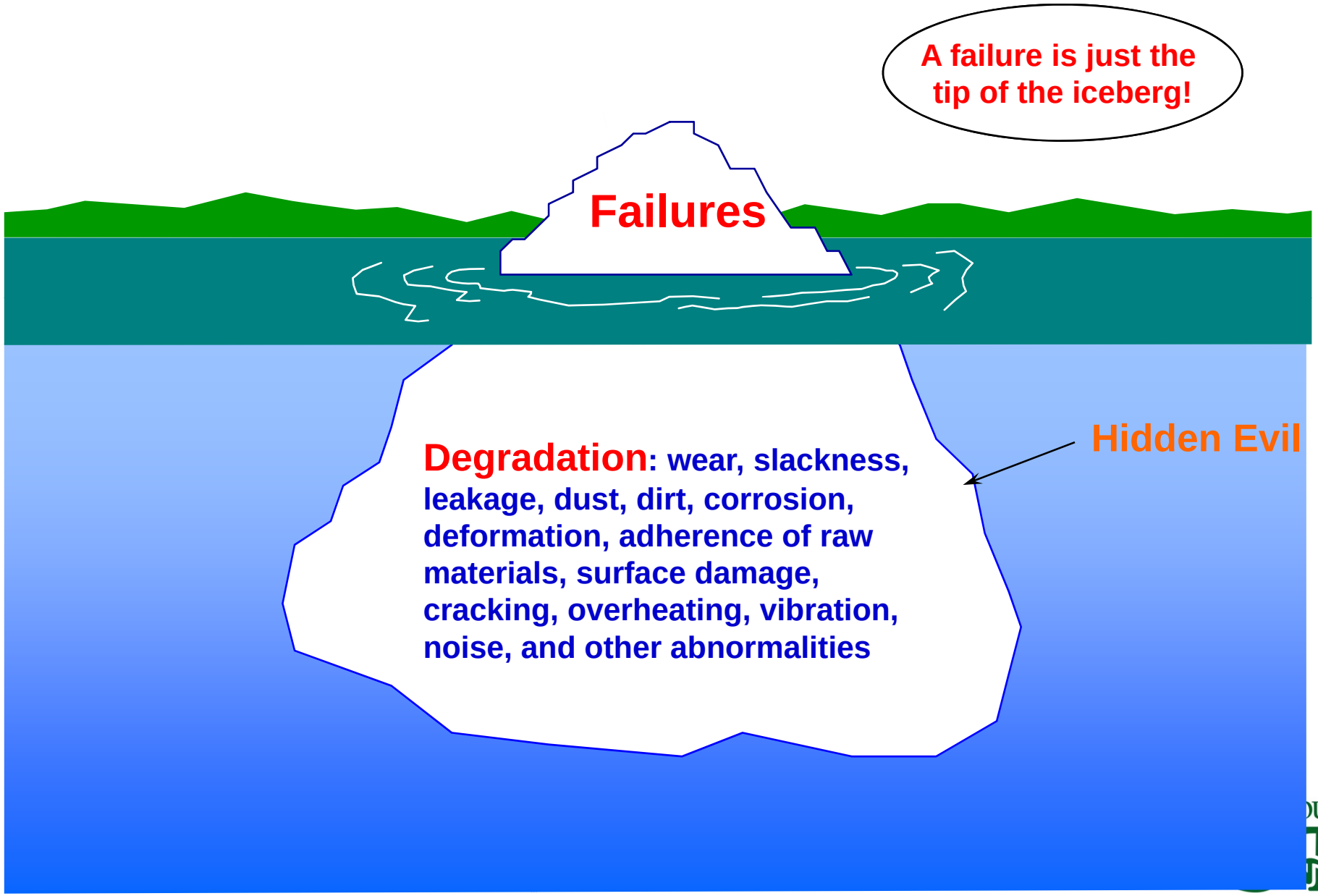


Autonomous Information Flow from Field (user) To Service/Business Systems
Only Handle Information Once (OHIO)

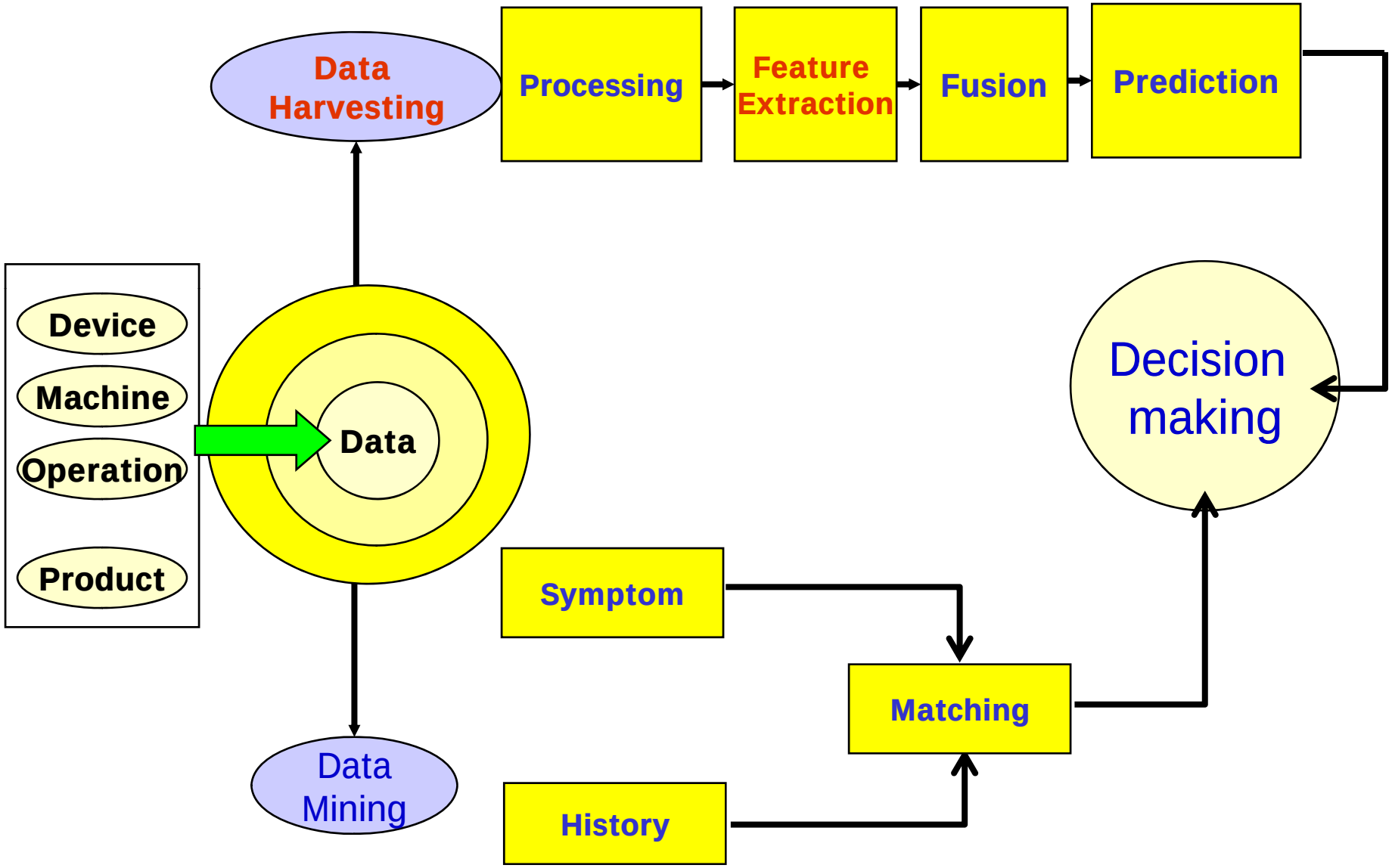
Predict, Prioritize, Optimize, and Plan Maintenance Scheduling For Near-Zero Downtime and
All-Time Readiness

University of Cincinnati · Michigan Engineering · Missouri S&T

Underlying Issue 1: Degradation vs. Failure

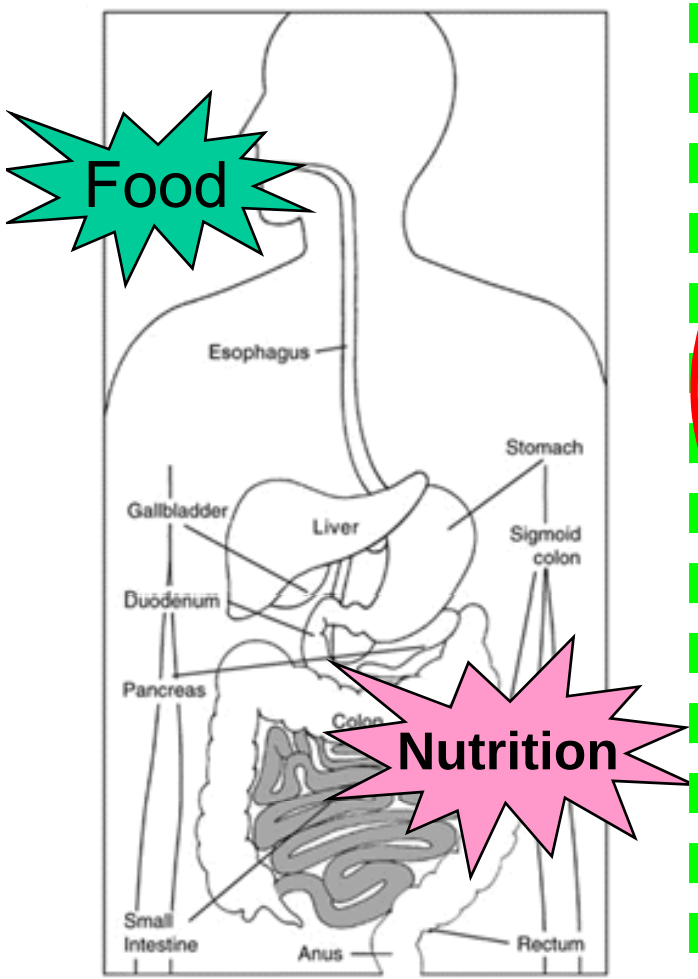


Underlying Issue 2:
Issues on Data, Information, and Decision



Smart Prognostics - *An Analogy*

Center for Intelligent Maintenance Systems
ims



Autonomic Information Logistics

- **Data**
- **Digitization**
- **Digestion**
- **Delivery**
- **Decision**

Infotronics ?

Infotronics **intertwine advanced pervasive and autonomic computing, embedded intelligence, and tether-free communications technologies to enable products and systems to achieve autonomous functional (*self-maintenance, self-service, self-reconfiguration, and self-healing*) objectives.**

Outline

- Unmet Needs
- **Advances on Prognostics and Examples**
- Design of Self-Maintenance Systems
- Future Trends and Conclusions

System Instrumentation Approach

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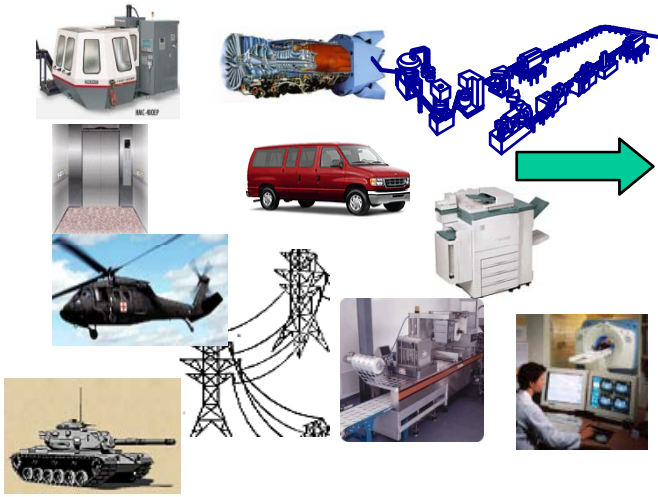
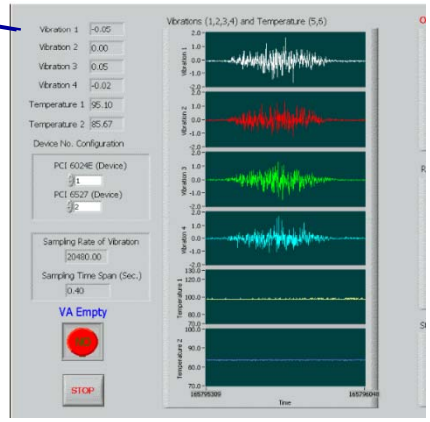
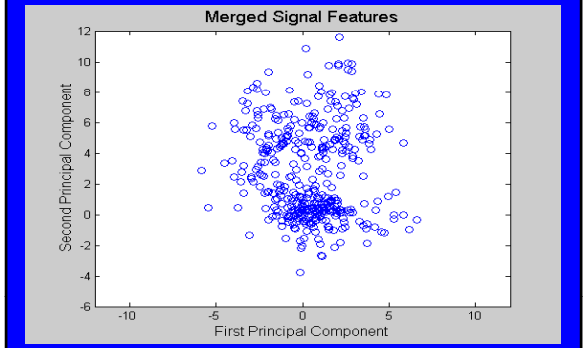
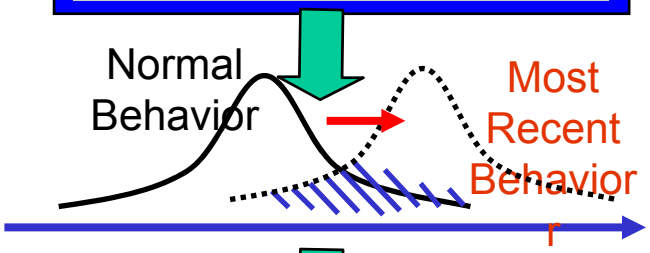


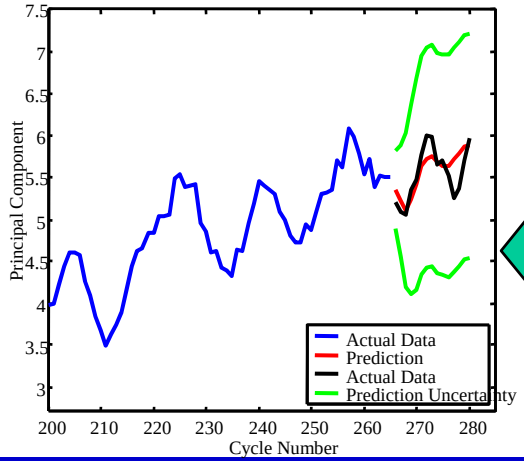


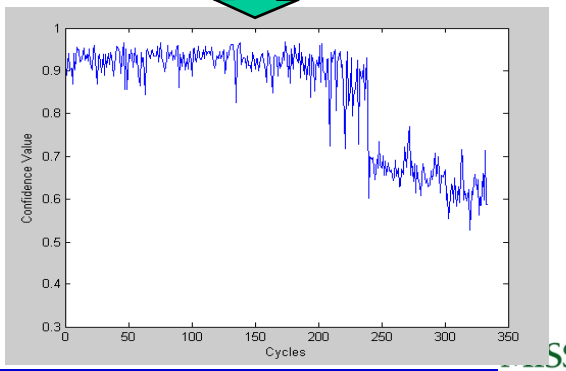
Principal Components Performance Feature





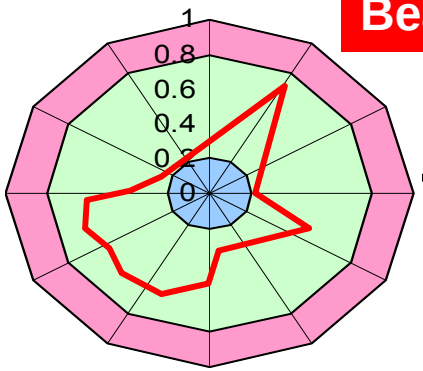
Prediction of Machine Performance Life



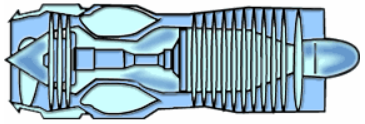


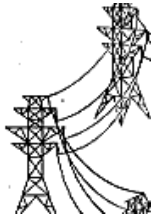
Health Feature Radar Chart

Bearing



Watchdog Agent™ Toolbox of Algorithms





Signal Processing and Feature Extraction Tools

- Time-frequency / Time-frequency moments
- Wavelets / Wavelet packet energies
- Wavelets tree decomposition / Wavelet moments
- Fourier transform / Frequency bands
- Autoregressive (AR) modeling / AR model roots
- Expert extracted features

Performance Assessment Tools

- Logistic regression
- Statistical pattern recognition
- Feature Map pattern matching
- Neural network pattern matching
- Hidden Markov Model (HMM) based performance assessment
- Particle Filter based performance assessment

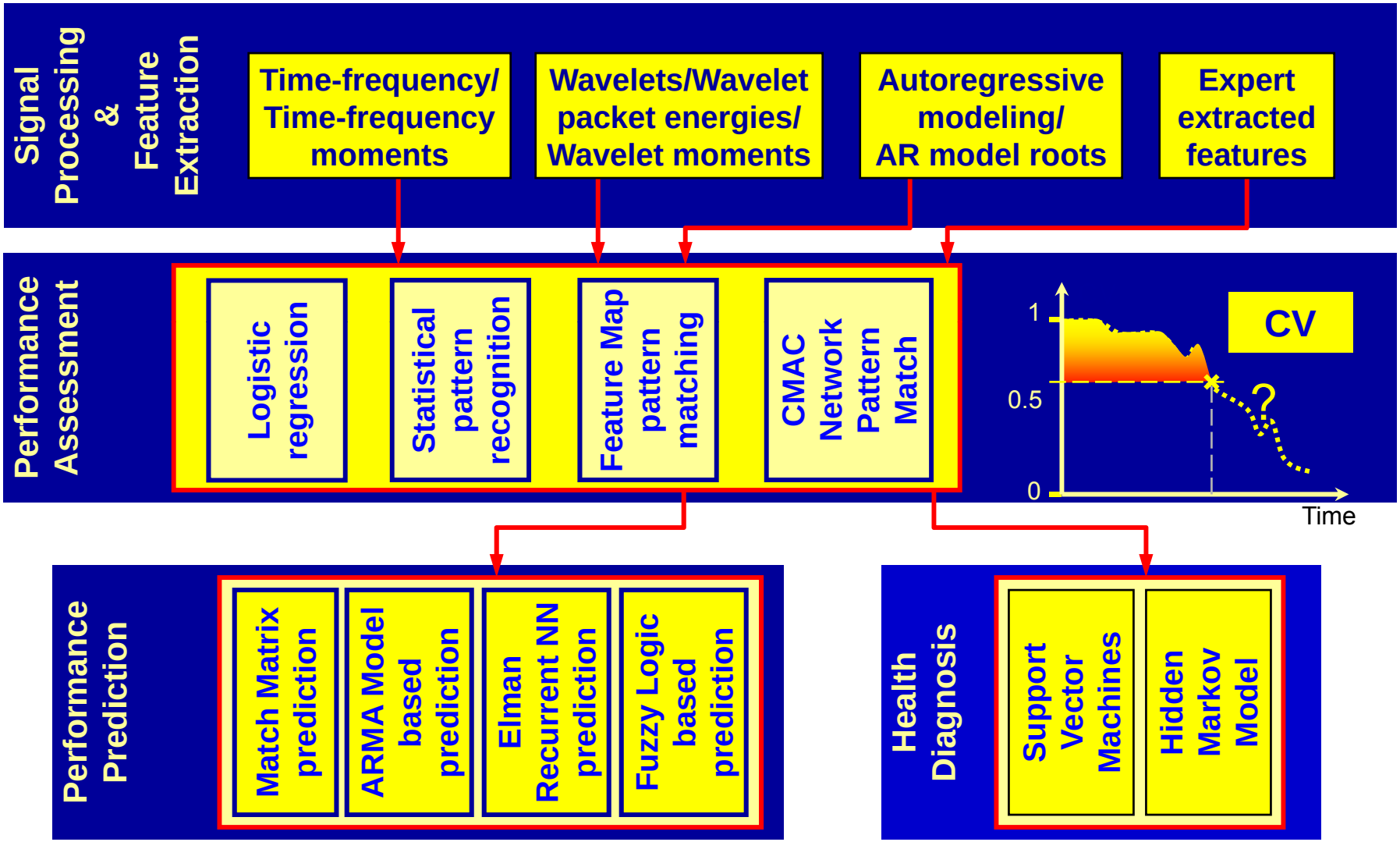
Performance Prediction Tools

- Match Matrix prediction
- Autoregressive Moving Average (ARMA) prediction
- Elman recurrent neural network prediction
- Fuzzy Logic based prediction

Health Diagnosis Tools

- Hidden Markov Model (HMM) based diagnostic tool
- Support Vector Machine (SVM) based diagnostic tool

Steps in using Algorithms in Toolbox



Tools for Autonomic Computing

Center for Intelligent Maintenance Systems

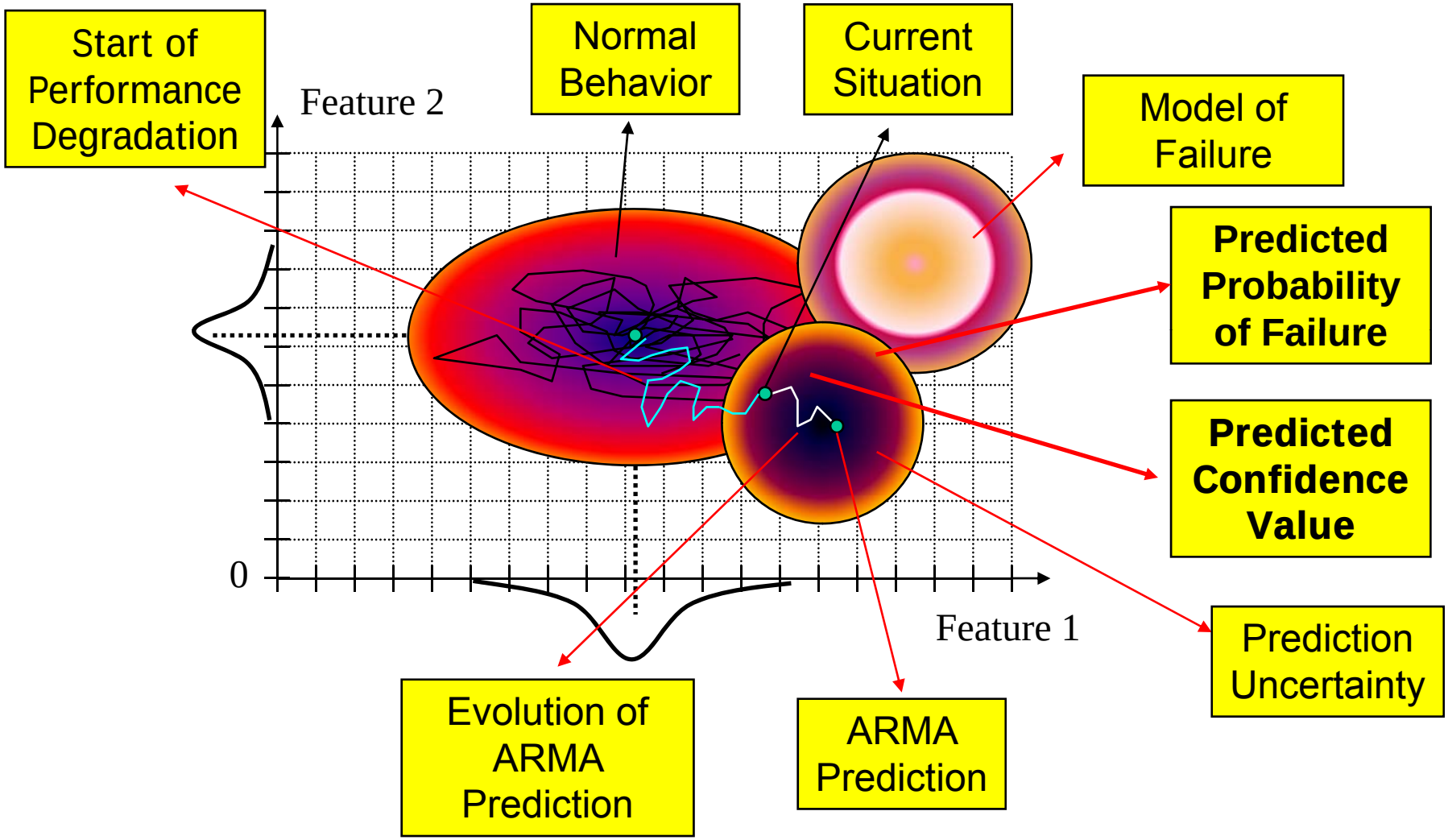
Watchdog Toolbox Selection

Y's (WHATs)		X's (HOWs)			
Customer Requirements and Application Conditions	Importance	Watchdog Tools	Weight	Function	Suggestion Tools
Non-stationary Signals	5	Time-frequency Signal Analysis	0.155	Feature Extraction	Wavelet Packet Decomposition
Stationary signals	1	Wavelet Packet Decomposition	0.161		
High Frequency Signal	5	Autoregressive Modeling	0.098		
Low Frequency Signal	1	Fourier Transform	0.131		
Highy Dynamic Systems	1	Logistic Regression	0.092	Performance Assessment	Statistical Pattern Recognition
Sufficient System Knowledge	1	Feature Map	0.074		
Insufficient System Knowledge	5	Statistical Pattern Recognition	0.119		
Interchangeability	1	Hidden Markov Model (HMM)	0.086		
Human Involvement	5	Particle Filters Performance Assessment	0.086		
Low Cost Implementation	1	Support Vector Machine (SVM)	0.092	Diagnostics	Adaptive Resonance Theory II (ART2)
Possibility of Cost-Effective Embeddding	1	Hidden Markov Model (HMM)	0.080		
		Bayesian Belief Network	0.059		
		Adaptive Resonance Theory II (ART2)	0.113		
		Autoregressive Moving Average (ARMA)	0.125	Prognostics	Autoregressive Moving Average (ARMA)
		Compound Match Matrix / ARMA Prediction	0.089		
		Fuzzy Logic Prediction	0.125		
		Elman Neural Network Prediction	0.122		
		Support Vector Machine (SVM)	0.092		GO BACK

User input

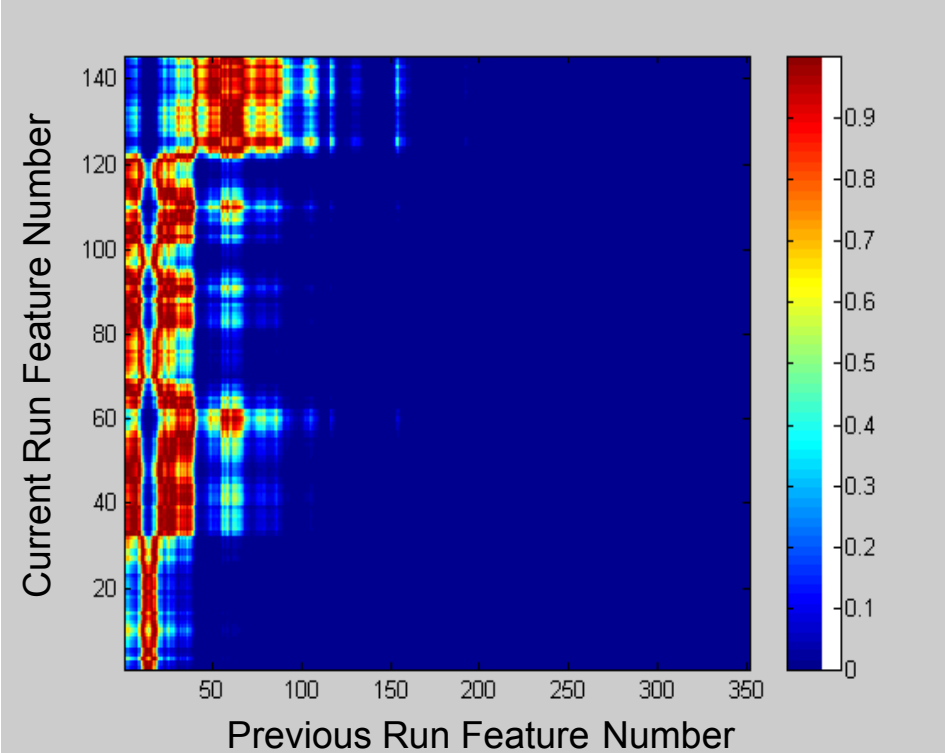
Rate the customer requirements and applications on a scale of 1 - 5. 5 being the most important, 1 the least

Prognostics and Forecasting Methods



Match Matrix Prediction

- What?
  - ARMA prediction based on best match of feature (vector) sequence comparison of different operations
- When?
  - Non-stationary, dynamic signals
  - Long term prediction
  - High dimension of data
- Possible application:
  - Networked products and systems
  - Aircraft or vehicle fleet monitoring
  - Large amounts of historical data

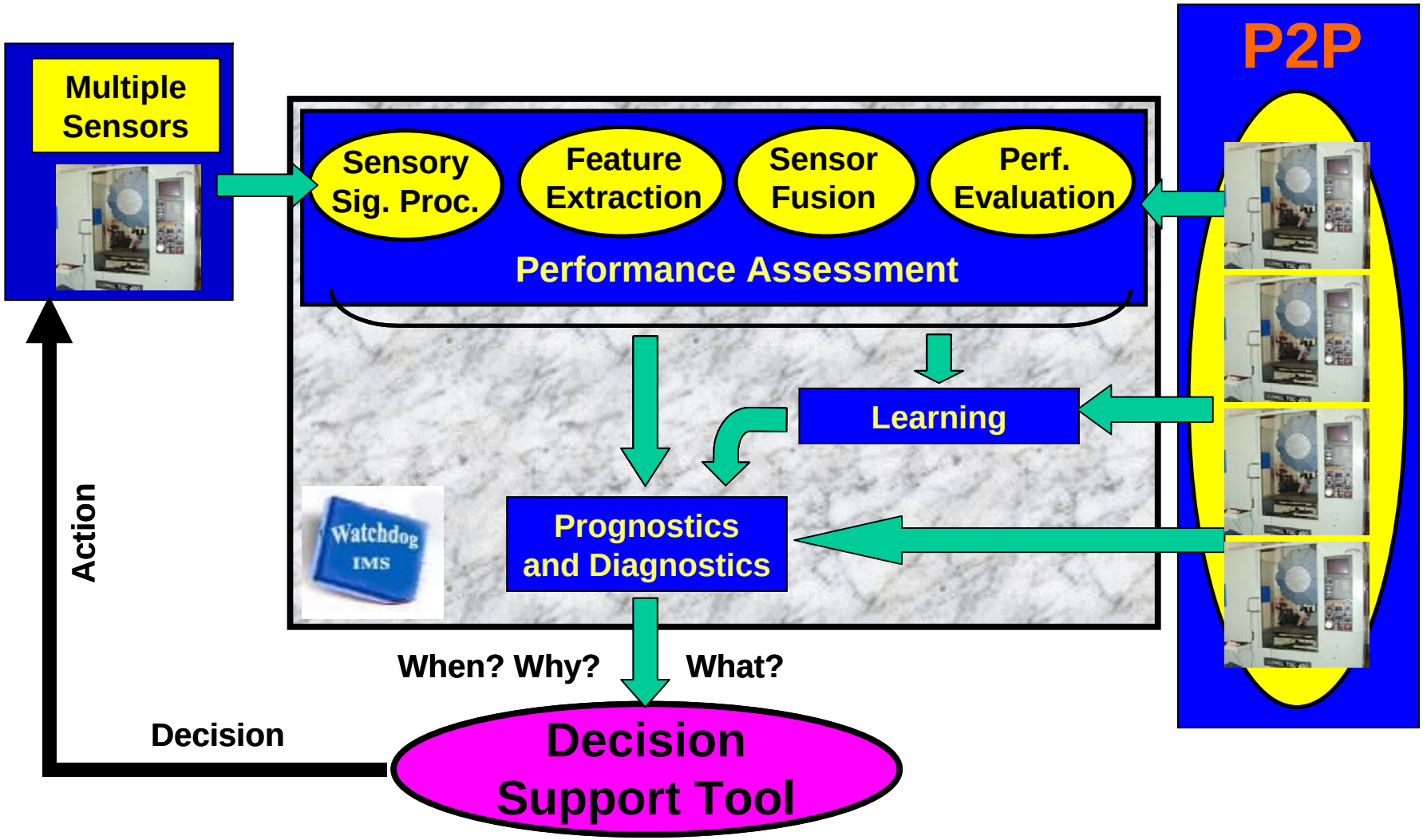


Matching index evaluation

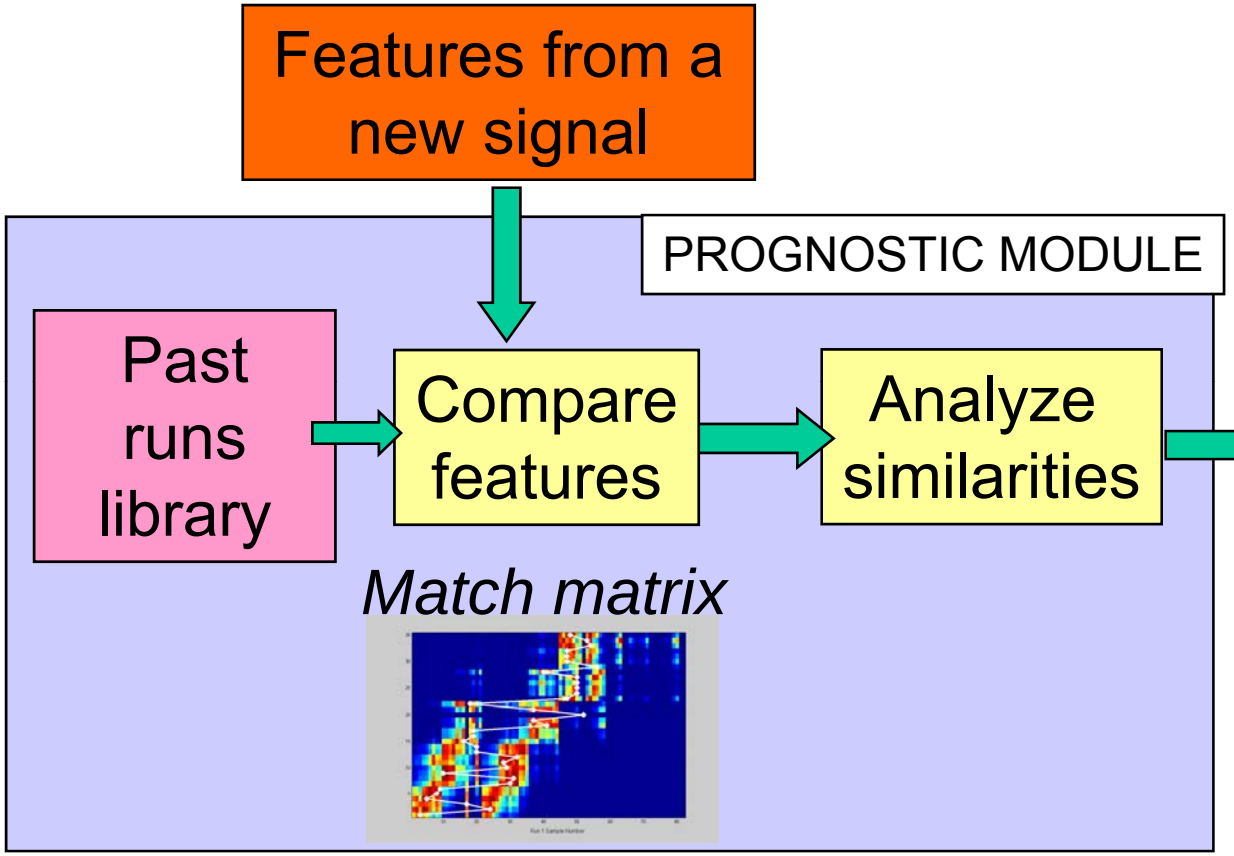
$$M_{i,j} = \exp\left(-\sum_{k=1}^{n} \frac{\left(f_k^i - f_k^j\right)^2}{2\sigma_k^2}\right), \quad \sigma_k^2 = \mathrm{var}(f_k)$$

$$\vec{f}^{\,i} = [f_1^i, f_2^i, \cdots f_n^i]^T, \vec{f}^{\,j} = [f_1^j, f_2^j, \cdots f_n^j]^T$$

Peer-to-Peer (P2P) Comparison Tool

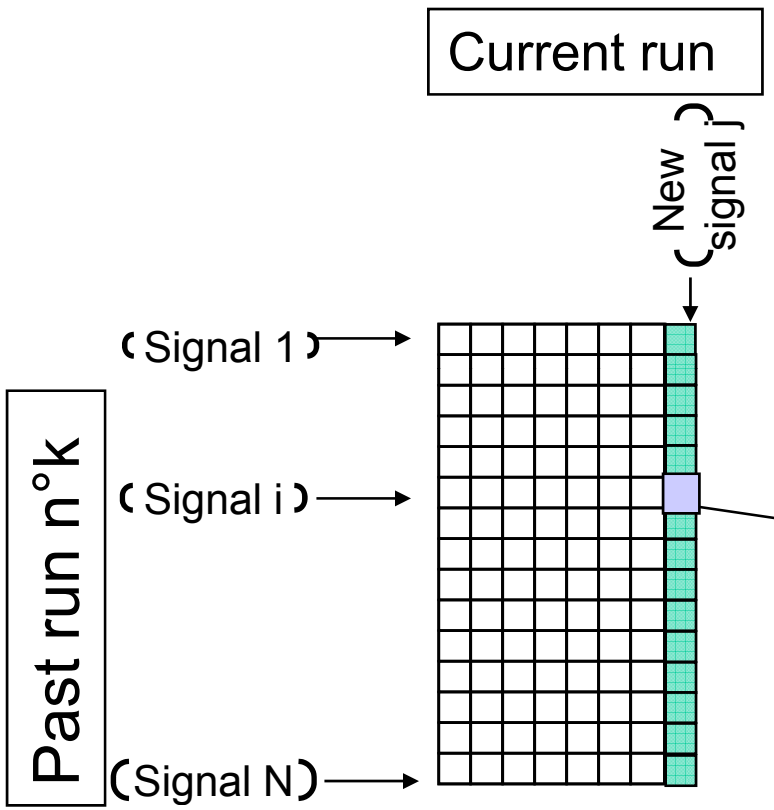


Match Matrix Method



- WHEN : Predict degradation and evaluate a probability distribution of future degraded states
- WHY : Identify similar degradation processes
- WHAT : Point out the pieces than need to be maintained or replaced

Match Matrix Creation



MATCH MATRIX

- the index i time
- {signal i} is the vector $\begin{Bmatrix} f(1,i) \\ \dots \\ f(m,i) \\ \dots \\ f(n,i) \end{Bmatrix}$

- f(m,i) is feature m of signal i

$$M_{i,j} = \exp\left(-\sum_{k=1}^{n} \frac{\left(f_k^i - f_k^j\right)^2}{2\sigma_k^2} \right)$$

$$M_{i,j} \in [0,1]$$

σ_k is the variance of feature k learned during the learning period of past run

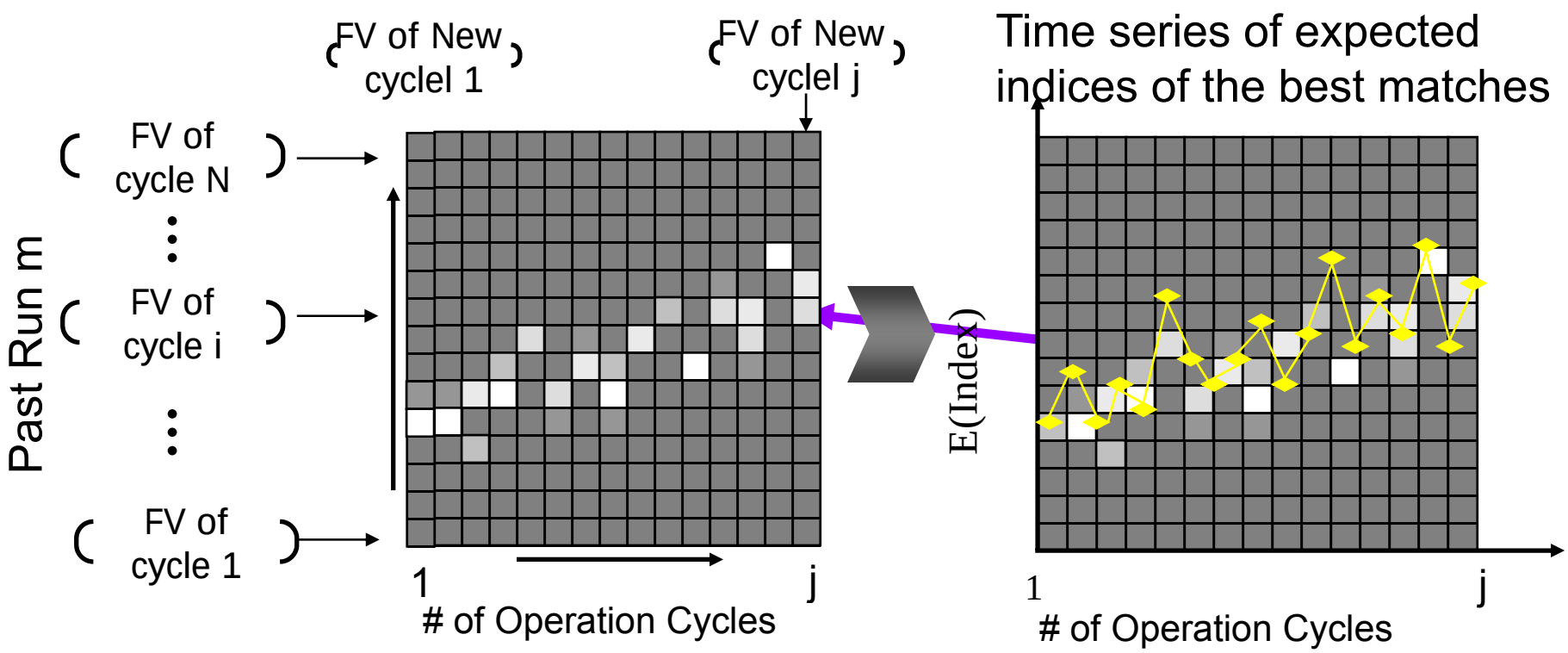
Prediction Based on Compound Model

- Similarity measure:

$$M = \exp\left(-\sum_{k=1}^{n}\frac{\left(f_k^1 - f_k^2\right)^2}{2\sigma_k^2}\right), \sigma_k^2 = \mathrm{var}(f_k)$$

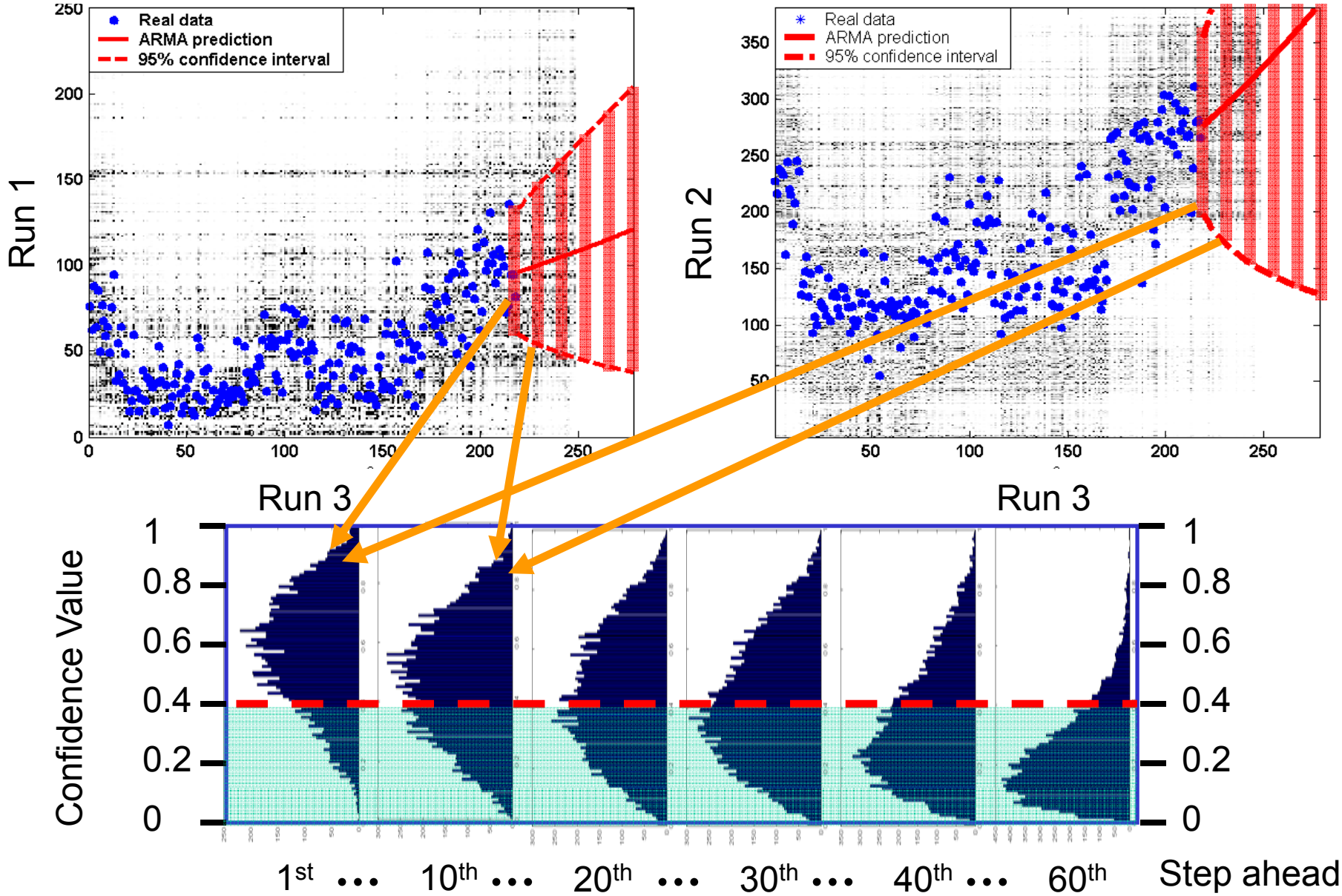
$$\vec{f}^{\,1} = [f_1^1, f_2^1, \cdots f_n^1]^T, \vec{f}^{\,2} = [f_1^2, f_2^2, \cdots f_n^2]^T$$

- Creation of match matrix:



FV: Feature vector

Probability of Failure/ Unacceptable Behavior



Prediction Tools Comparison

	Advantage	Disadvantage
ARMA	• Capable of capturing linear, stationary processes • Good short term prediction • Fast Calculation	• Not able to capture non - stationary, dynamic process • Only use a limited historic data
Match Matrix	• Utilizes large amount of historic data • Has good long term prediction accuracy	• Degradation process must be represented by “run” • Needs long reference runs to get accurate prediction
NN	• Utilizes large amount of historic data • Provides good long term predict • Capable of capturing non-linear, dynamic processes	• Long training time (for large number of input neurons) • No standard algorithm to find the structure

Commercial Hardware -1

ADVANTECH

UNO-2160 Watchdog Agent® System

Robust Embedded OS

- Windows CE.NET
- Windows XP embedded

High Performance and Rugged

- Fanless Celeron 400MHz CPU
- 256/512MB SDRAM
- 9-30VDC power input
- -10 to 50C operating temp
- Hardware Watchdog Timer

Non-volatile Storage Media

- CompactFlash
- 2.5" HDD
- Battery Backed RAM

Built-in Comm. Interfaces

- 2x Ethernet ports
- 4x Serial ports
- 2x USB ports
- 1x Printer port

Expansion Capability

- 1x PC Card slot (PCMCIA)
- 2x PC/104 slots

Commercial Hardware -2

NATIONAL INSTRUMENTS

CompactRIO reconfigurable embedded system

I/O

- *Analog Input/Output, Digital Input/Output*
- *(Low / high speed, simultaneous / multiplexed)*

Real-time controller

- *200 MHz Pentium Class*
- *64 MB or 512 MB Flash*

Reconfigurable Chassis

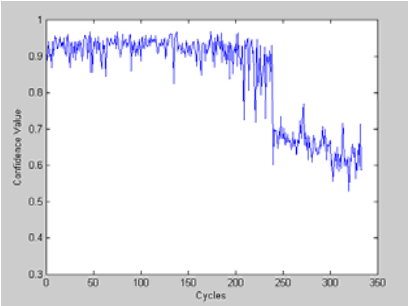
- *4-slot or 8-slot 1 M Gate or 3M Gate FPGA*

Connectivity

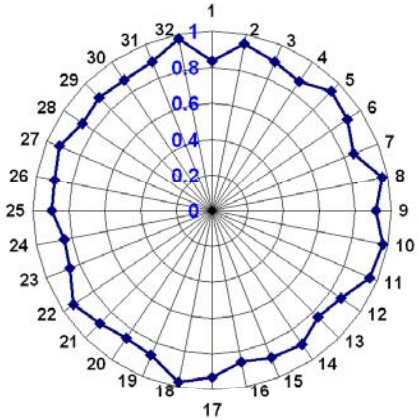
- *Standard connector depends on the module*
- *Options: Strain Relief Connector Block, Custom Cable, etc.*

Information Delivery

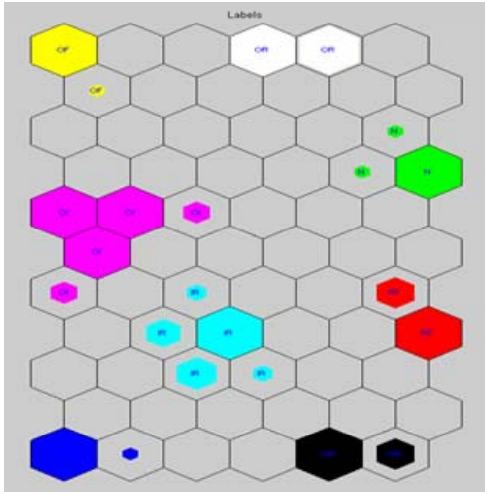
Results of Smart PrognosticsTools for Asset Health Information



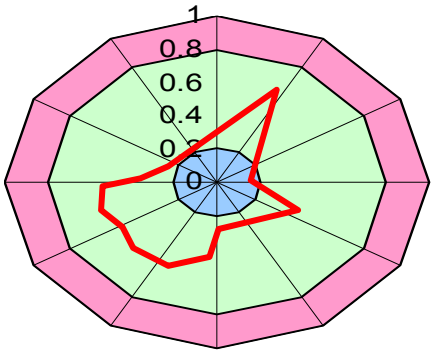
Confidence Value for performance degradation assessment (0-1)



Health Radar Chart for multiple components degradation monitoring



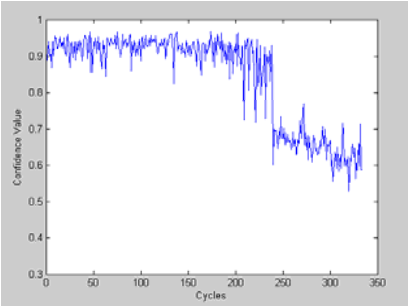
Health Map for potential issues and pattern classification



Risk Radar Chart to Prioritize Maintenance Decision

Information Delivery

Results of Smart PrognosticsTools for Asset Health Information



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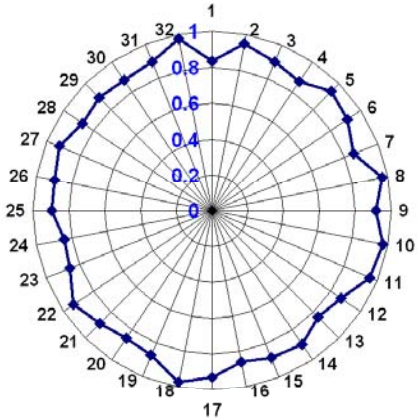

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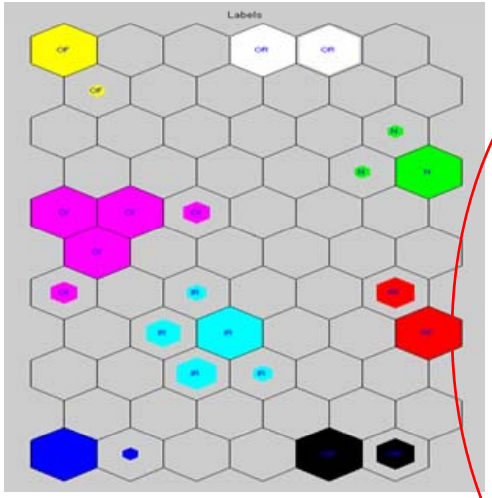

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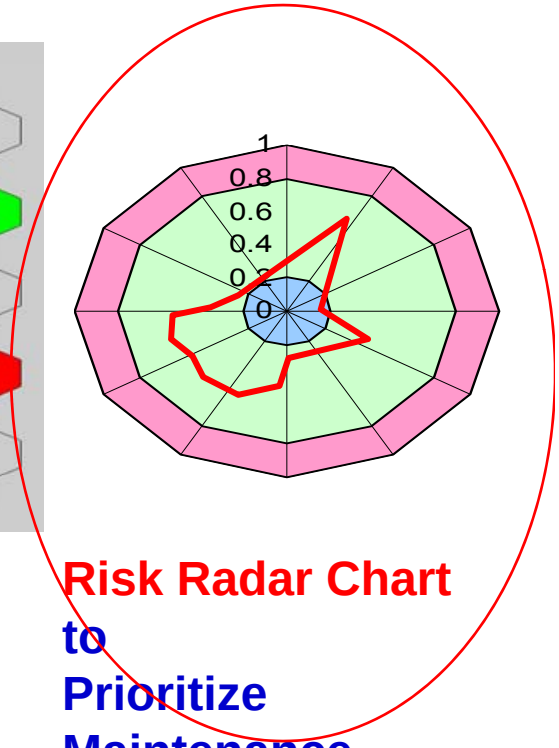


Risk Radar Chart to Prioritize Maintenance Decision

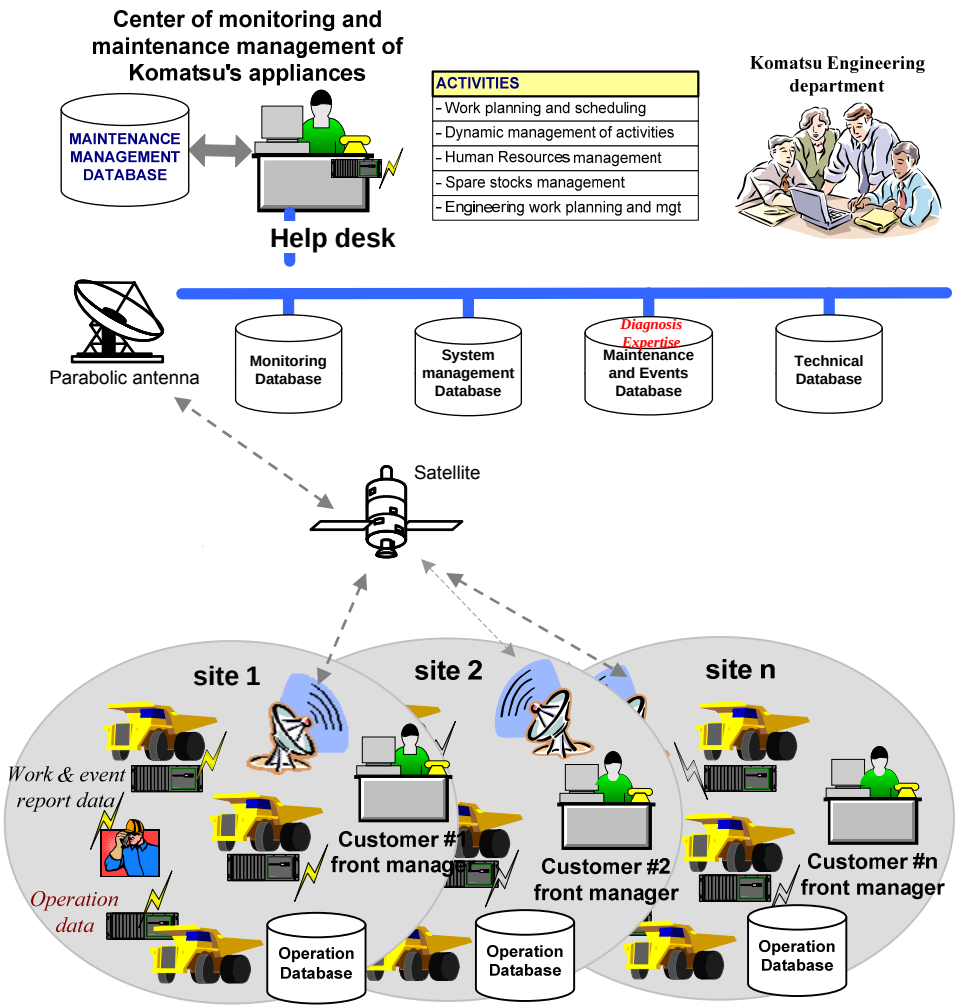
Komatsu

Smart Field Services for

Earth Moving Equipment

Business Background

- Komatsu Ltd. has developed the necessary infrastructure for collecting data from individual construction machines from their place of operation, via the user
- Need to transform data into information and decisions

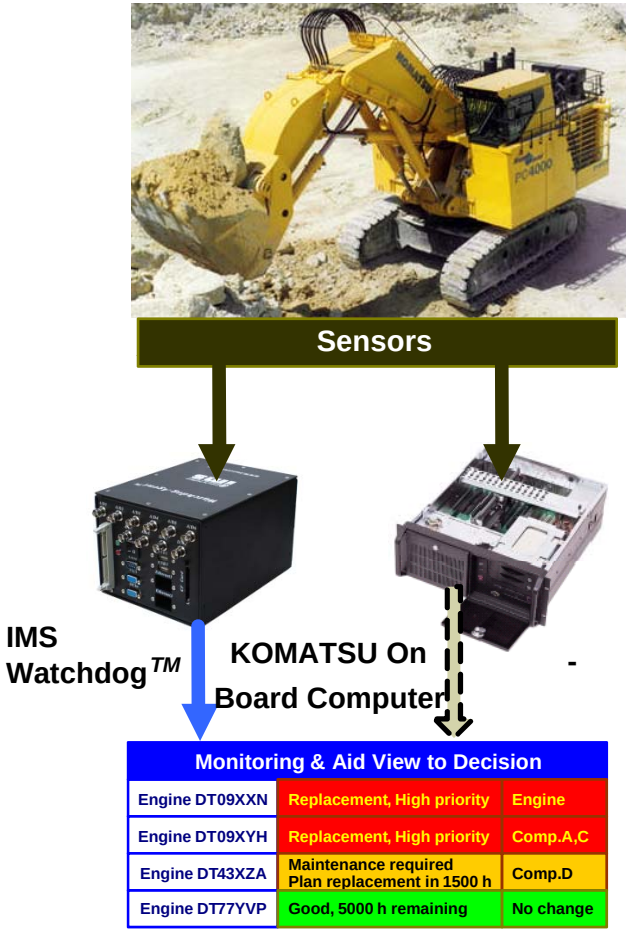


Focus on Smart Asset Business

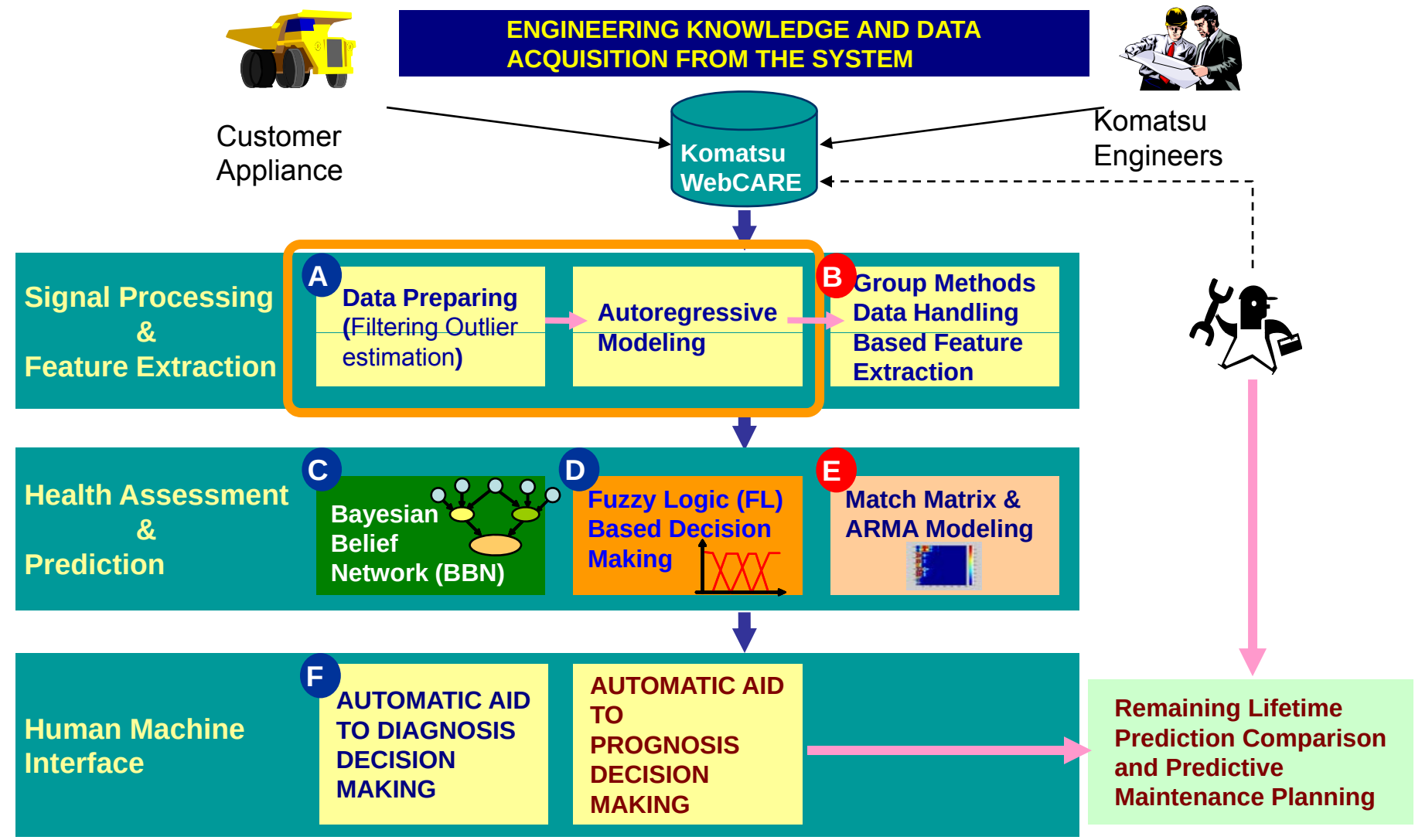
- **Failure prediction & diagnosis failures**
  - **to reduce down time, maintenance & support costs**
    - **by detecting incipient degradations of all components**
    - **by identifying and isolating failure critical components**
- **Degradation monitoring of engine and transmission systems**
  - **to estimate lifetime with higher accuracy**
  - **to prevent or delay failures**
  - **to expand components overall life**
    - **using appropriate and key data**
    - **using features for key performance index**

Komatsu IT-Embedded Approach

- to increase quality of data in Komatsu database
- to enable more advanced predictive maintenance decision making base on analytical reliability models
- to achieve intelligent maintenance excellence
- and to implement knowledge based decision making approach



Smart Software Tools



Decision Support Tools for Smart Service Recommendation

Failure Mode Effects & Risk Assessment Tools

FL or Reliability based Prognostics

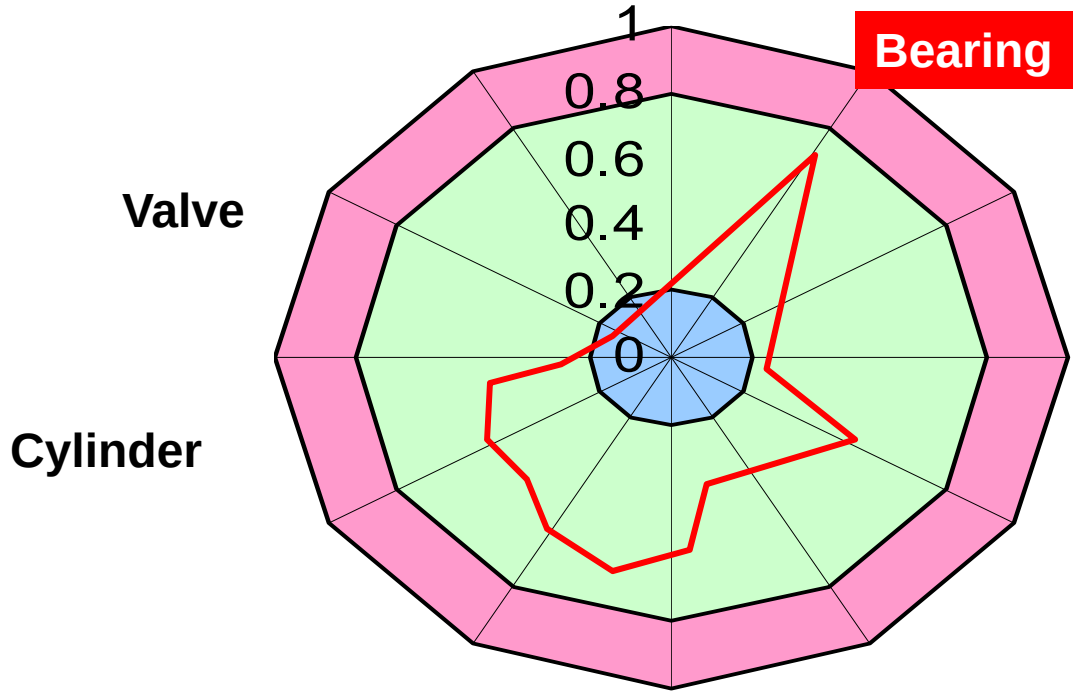
System ref.	Engine ref.	Failure Mode	Causes	Effect on the system	Component	D	P	C	S	Prognostic
Machines										
Machine A	Engine AX	FM 1 FM 2	Wear Cracking Cable disc. Sensor fails Injector	Fall of the cabin	Cylinder Inlet Valve R Inlet Valve L Injector ...	4	0.6	2	H	Change engine
Machine B	Transmit. BY	Derailment of the cabin	Wear Cracking Sensor fails	Fall of the cabin	Shaft Gears Bearing		0.9	1	M	Change Bearing

D: Detectability
P: Probability
C: Cost
S: Severity

BBN output

Decision Aid

Autonomic Service Logistics



Logistic Information

- Engine/Asset Location
- Components Availability
- Review Previous Maintenance Actions
- Recommend and Assign Right Technician
- Estimate Maintenance cost

Outline

- Unmet Needs
- Advances on Prognostics and Examples
- **Design of Self-Maintenance Systems**
- Future Trends and Conclusions

Autonomic Systems

- Autonomic nervous system model
- Involves four qualities (Self-CHOP)
  - Self-configure
  - Self-heal
  - Self-optimize
  - Self-protect
- Practical Uses
  - Applications
  - Data stores
  - Networks
- Value

Ref: IBM

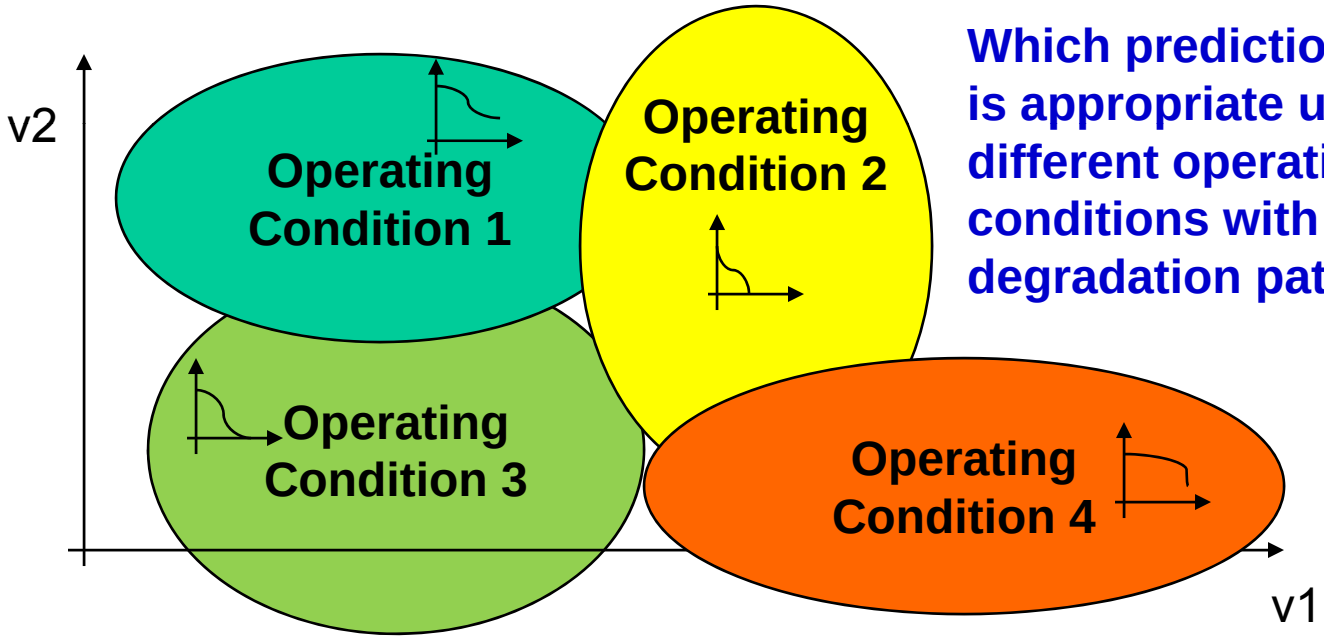
Self-Maintenance and Self-Healing Systems

- Ability to recognize current, predict future or react to past deviance from nominal conditions
- Complex rules design
  - Room for improvement
  - Self-awareness (conditions)
- Self-learning

Issues on Dynamic Prognostics

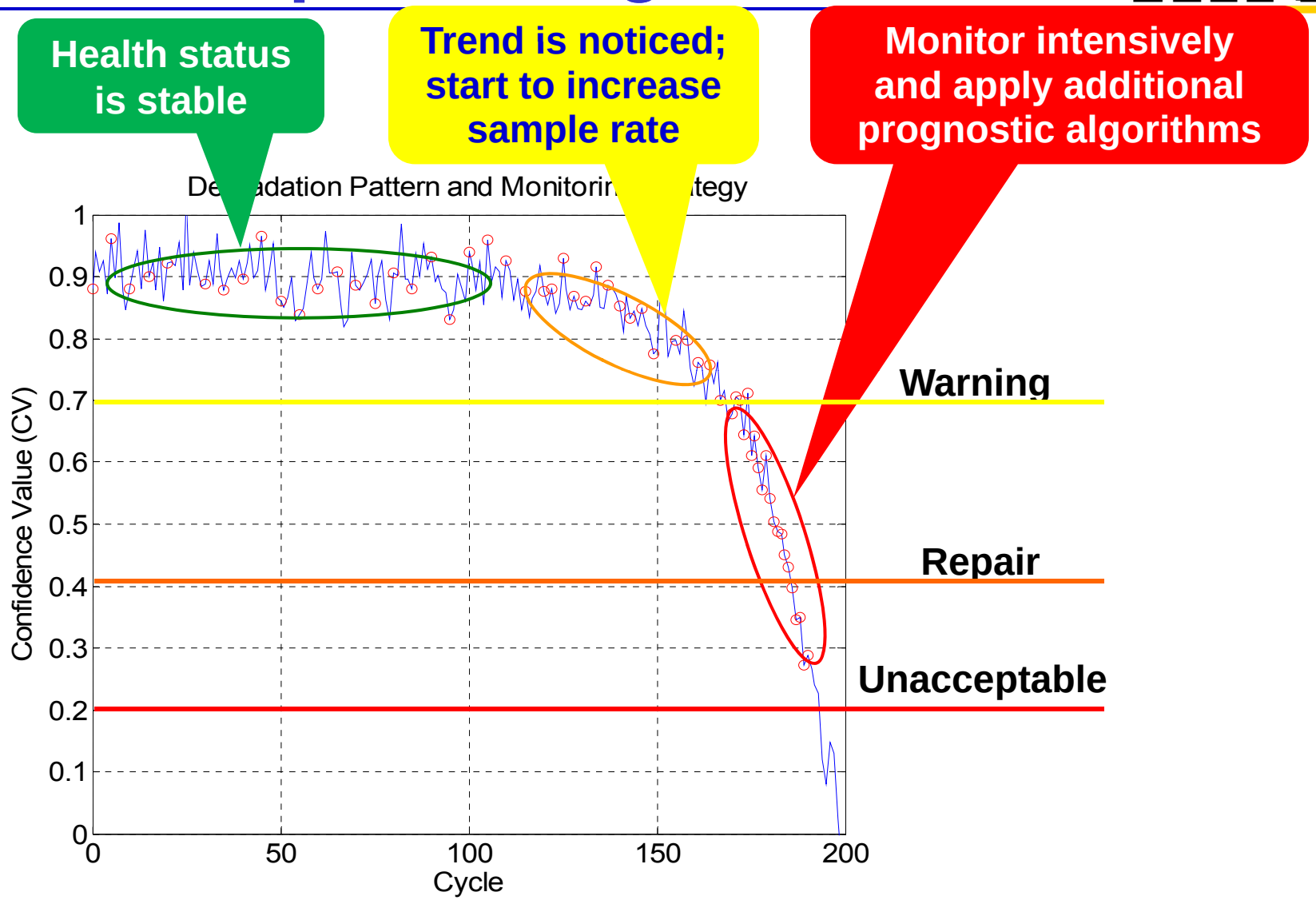
Needs for Robust Prognostics in Dynamic Conditions

Single model can not always meet the accuracy requirements for prediction when the machine operating condition changes (e.g. different degradation stages, etc.).



Which prediction model is appropriate under different operating conditions with dynamic degradation patterns?

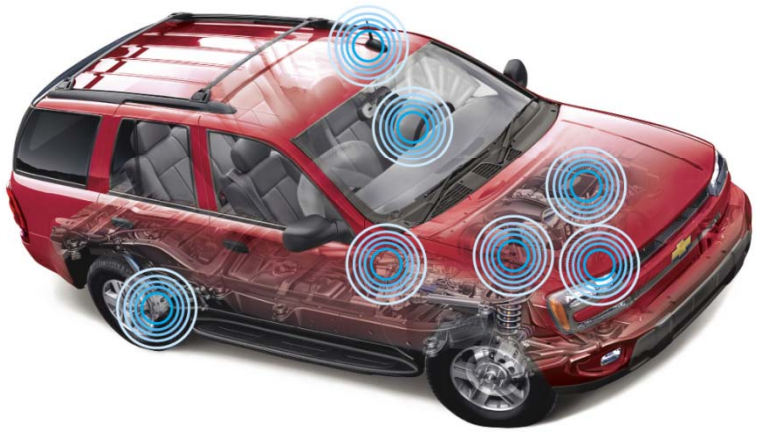
Adaptive Prognostics



Case Study –
GM OnStar—Mobility Service Business

Prognostics Tools for Vehicle Telematics

- Oil pressure and Oil levels
- Fuel level
- Odometer reading
- Vibration and Acoustic data
- Air Pressure in tire and Flat tire
- Condition of air bags
- Box itself
- Different points on engine and transm
- Anti brake system



IMS and EDAptive® VeSPA™

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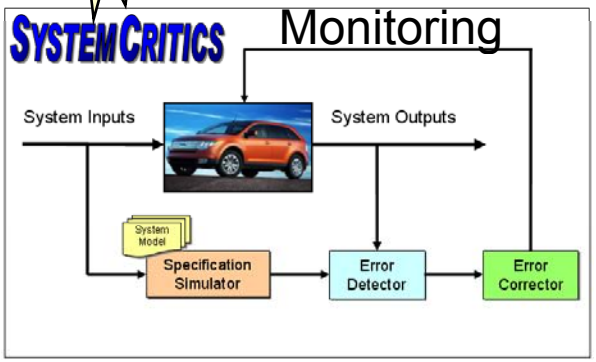
System Critics with Sensor Degradation Detection

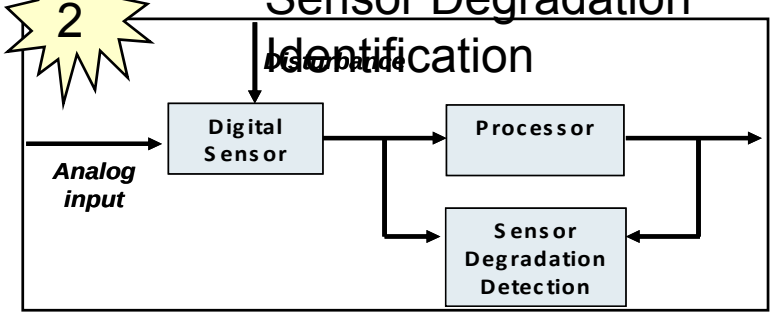
1

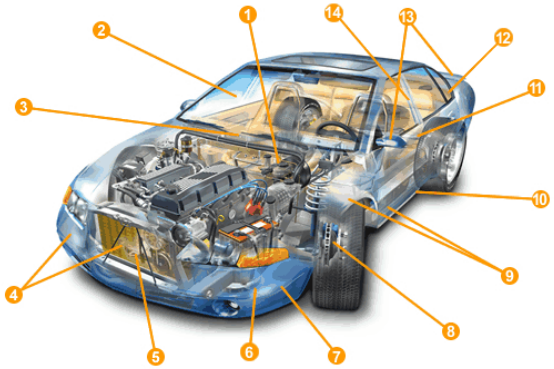
System Monitoring



2

Sensor Degradation Identification





- Cruise Control
- Airbag Deployment
- Tire Pressure
- Traction Control

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Vehicle Sensor Protection Algorithms

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Future Combat Systems (FCS) and Needs

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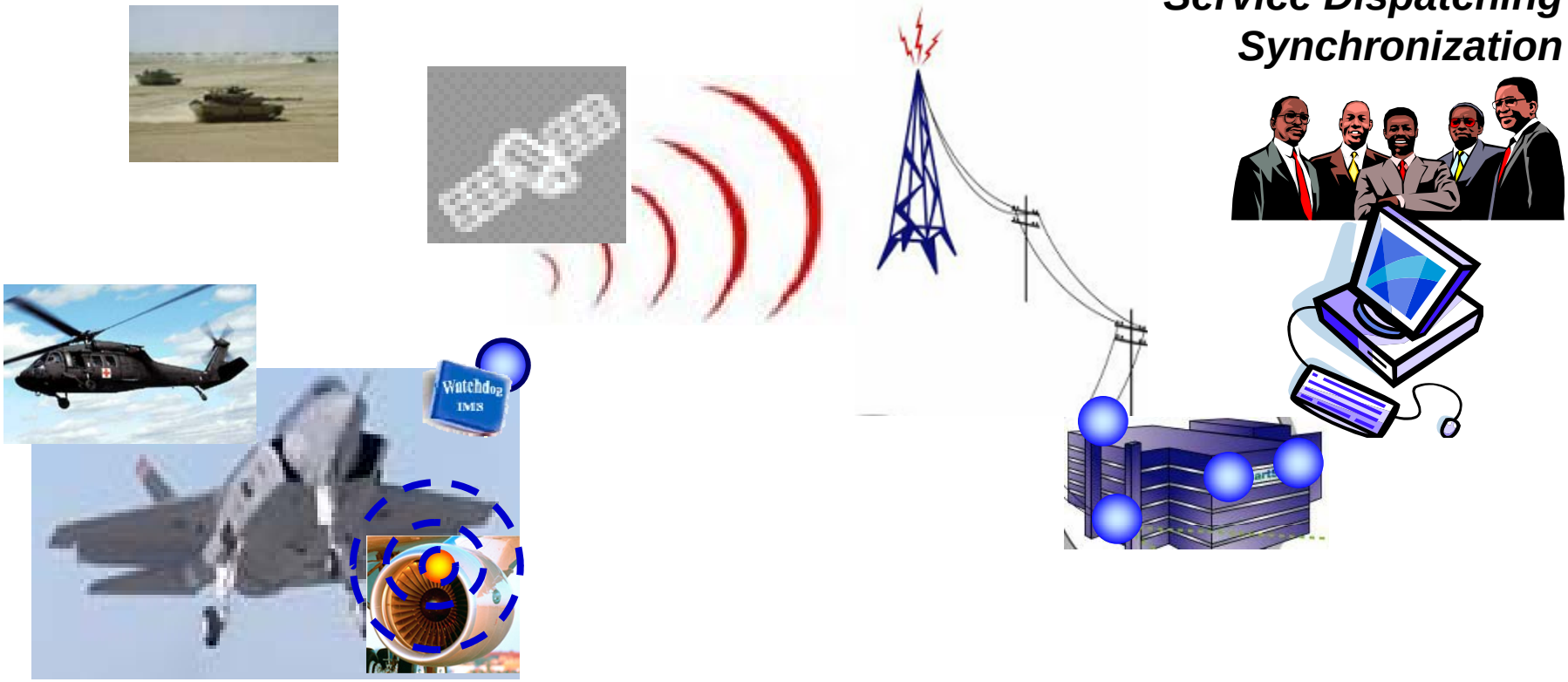
Condition-based Needs

Smart E-Service/E-Maintenance Platform

Alarms
Prognostics
Remote diagnostics
Service Dispatching
Synchronization



Self-Maintenance Systems

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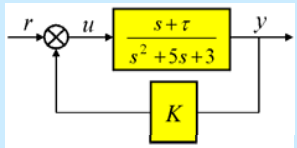
Performance Degradation

Equipment or Process

Sensors



Model

Expert Knowledge

Watchdog Agent™

Degradation Information

Assessment

Prognostics

Diagnostics

When?
Why?
What?

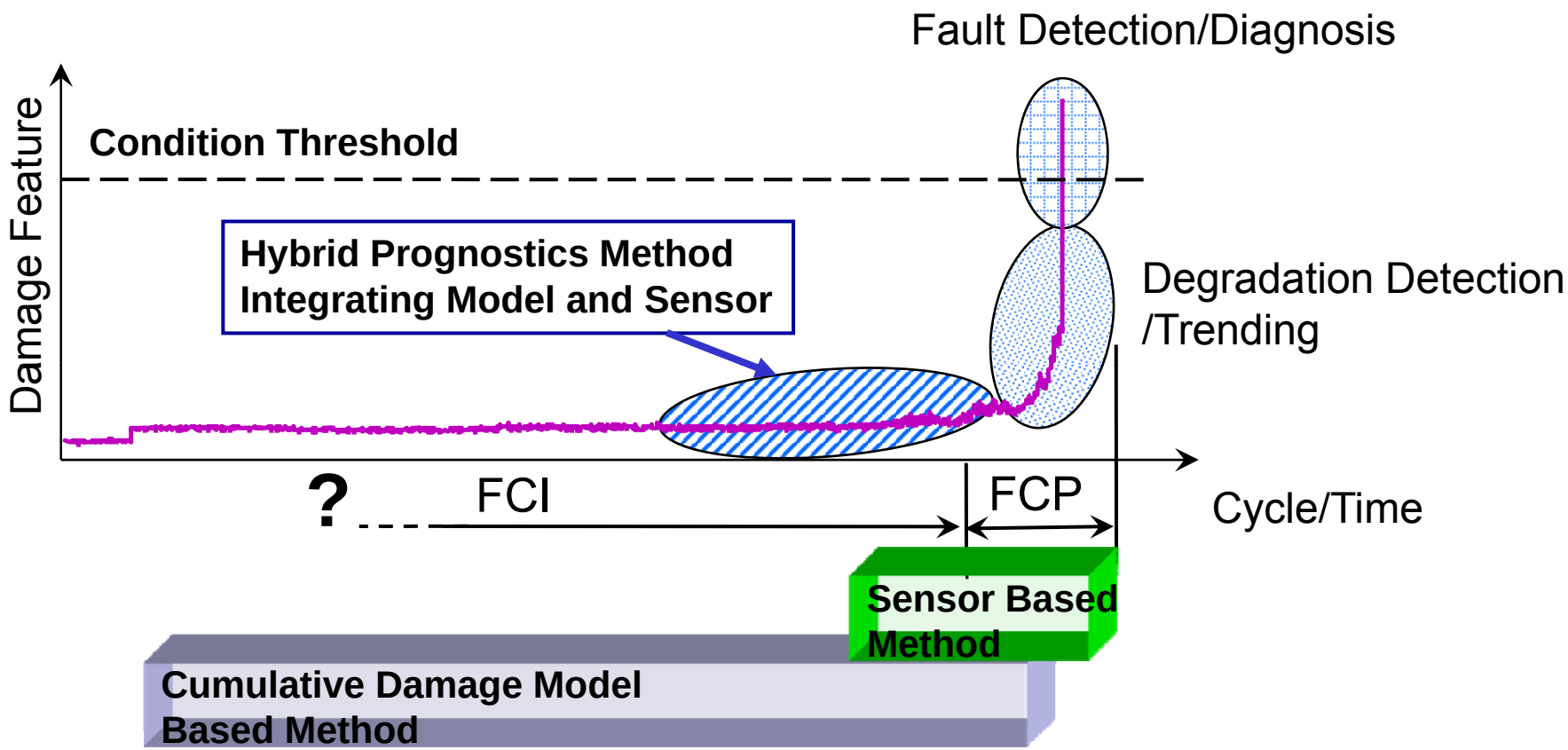
Decision Support Tool

- Near-Zero-Downtime Service
- Autonomous Service Request for Spare Parts
- Asset Optimization

Prognostics of Critical Components of Military Vehicle

- Power train
  - Engine
  - Battery
  - …
- Hydraulic system
  - Cylinder
  - Pump
  - …
- Turret
  - Bearing
  - Gear
  - …
- Traction
  - Track
  - Axis
  - Gear
  - …
- …

Hybrid Prognostic Method



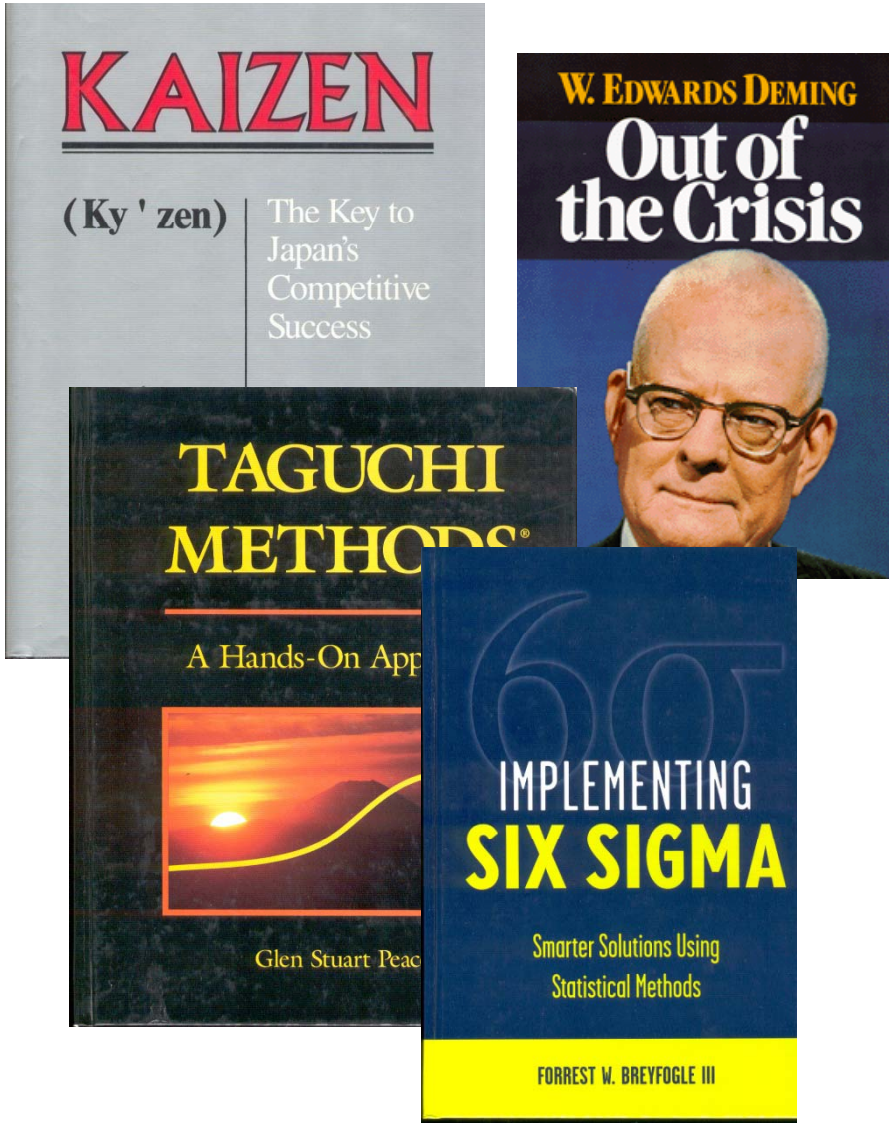
FCI: Fatigue Crack Initiation
FCP: Fatigue Crack Propagation

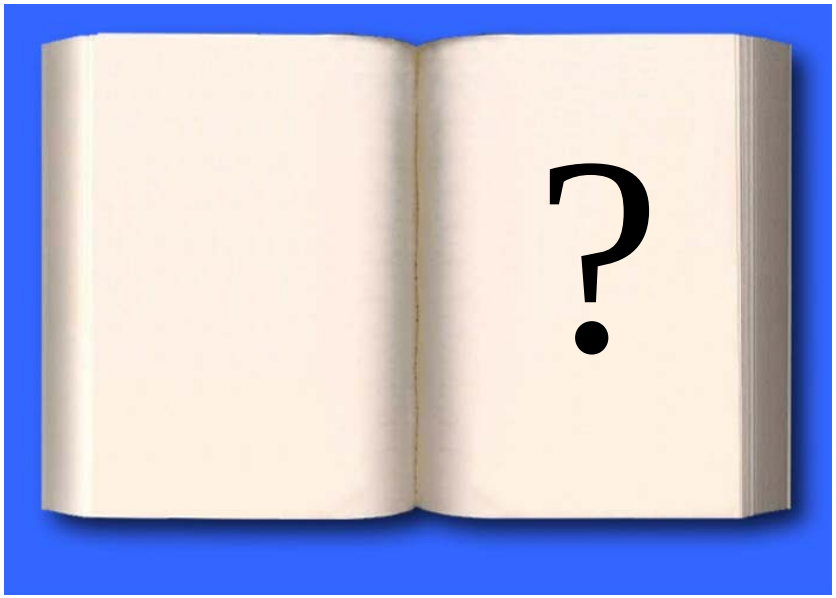
Track the system damage level from the fatigue crack initiation stage

Outline

- Unmet Needs
- Advances on Prognostics and Examples
- Design of Self-Maintenance Systems
- Future Trends and Conclusions

Evolution Continues…





IMS Design for Zero Breakdown (DF0B) vs Design for Six-Sigma (DFSS)

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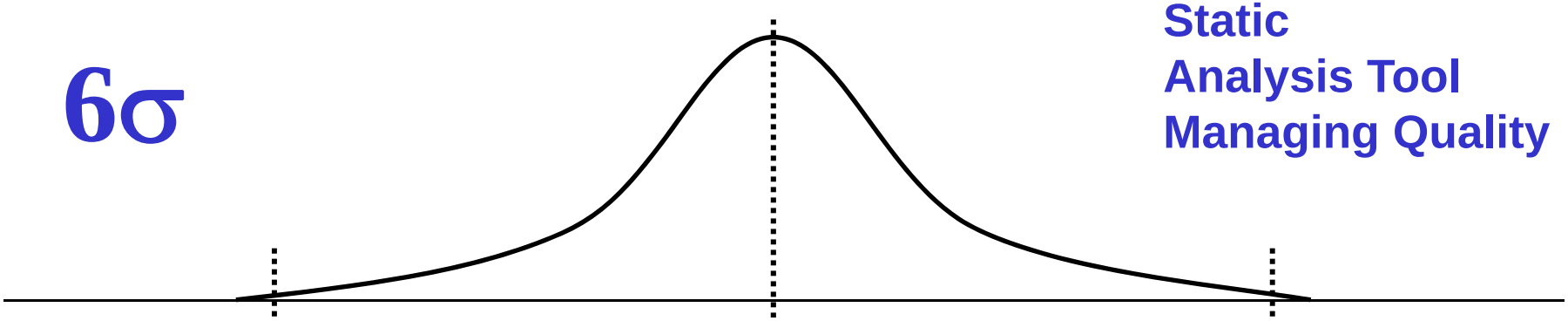
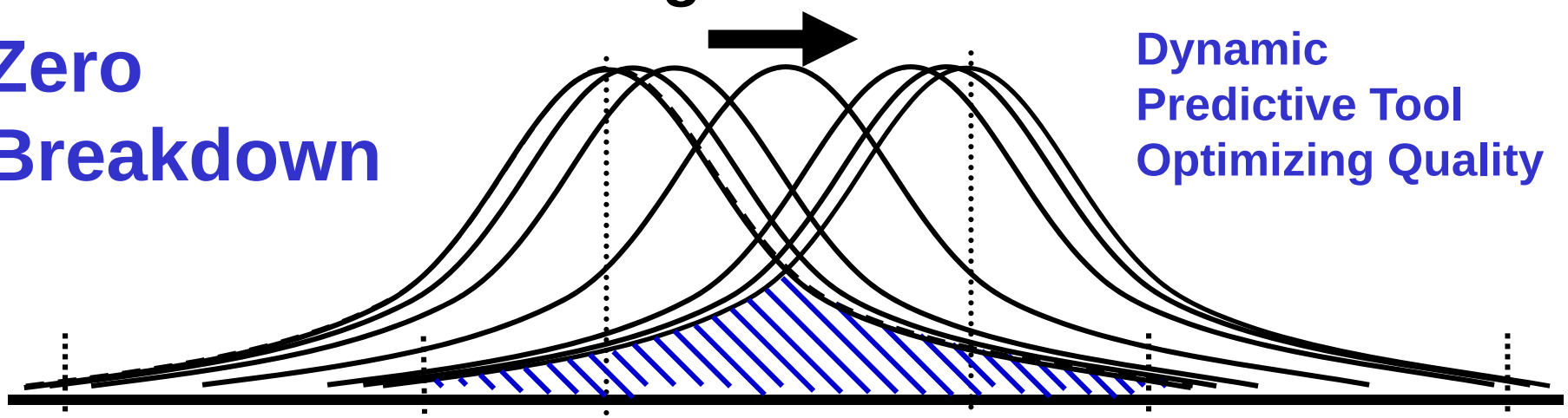
6σ



Static
Analysis Tool
Managing Quality

degradation

Zero Breakdown



Dynamic
Predictive Tool
Optimizing Quality

confidence value

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Thank You !

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