Time, Knowledge, and Decisions: When, How, and What

Soft Computing Applications to Prognostics and Health Management (PHM)

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Outline

• Background: Computational Intelligence (CI)
• Application Focus: Servicing High-cost Equipment
• CI in Services: The Knowledge x Time Framework
• Knowledge Gradient: Tactical PHM Functions
• Time Gradient: Case Studies
• Fusion Issues
• Conclusions and Future Work
Outline

• Background: Computational Intelligence
  – Why?
  – What is it?

• Application Focus: Servicing High-cost Equipment
• CI in Services: The Knowledge x Time Framework
• Knowledge Gradient: Tactical PHM Functions
• Time Gradient: Case Studies
• Fusion Issues
• Conclusions and Future Work
Real World Applications

• Typical Requirements of Real World Applications
  – Integration of Domain knowledge and field data,
  – Imperfect Dynamic Information:
    • Uncertainty and Incompleteness,
    • Environmental, Operational, and Cognitive changes

• Computational Intelligence Models based on:
  – Problem domain knowledge of the process (or product) and
    • Combining first principles and empirical knowledge.
  – Field data that characterize the system’s behavior.
    • Often incomplete and sometimes erroneous.
    • A collection of I/O measurements, representing instances of the
      system's behavior

Computational Intelligence (or Soft Computing) is a flexible
framework with a broad spectrum of design choices to integrate
knowledge and data into approximate models.
Computational Intelligence (CI)

**Definition** *(From the IEEE Computational Intelligence Society)*

“Theory, design, application, and development of biologically and linguistically motivated computational paradigms emphasizing:

- Neural networks,
- Connectionist systems,
- Genetic algorithms,
- Evolutionary programming,
- Fuzzy systems, and
- Hybrid intelligent systems in which these paradigms are contained.”

Source: [http://ieee-cis.org/scope/](http://ieee-cis.org/scope/)

Biologically/Linguistically inspired paradigms usually generate approximate models that exploit the tolerance for imprecision, uncertainty, and partial truth to achieve **tractability, robustness, low solution-cost, and better rapport with reality**
Soft Computing (SC)

Soft Computing =
  Computational Intelligence
    (Fuzzy, Neural, Evolutionary models)
  + Probabilistics
    (Bayesian Models)
  + Statistics
    (Induction Trees, SVM, Random Forest, etc.)
  + Dynamic Models
    (Chaos)
Soft Computing

“In contrast to traditional hard computing, soft computing exploits the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, low solution-cost, and better rapport with reality” (Zadeh 1991)
SC: Probabilistic Systems

Probabilistic Models
- Bayesian Belief Nets
- Dempster-Shafer

Approximate Reasoning

Multivalued & Fuzzy Logics

Functional Approximation/Randomized Search
- Neural Networks
- Evolutionary Algorithms

Example: BBN used for Generators Fault Diagnosis

- P(low P | Blade f)
- Blade fault
- Shaft fault
- Pressure low
- Vibration high

P(Blade f)
SC: Hybrid Probabilistic Systems

- Approximate Reasoning
- Functional Approximation/Randomized Search
- Probabilistic Models
- Multivalued & Fuzzy Logics
- Neural Networks
- Evolutionary Algorithms

- Bayesian Belief Nets
- Dempster-Shafer

- Probability of Fuzzy Events
- Belief of Fuzzy Events
- Fuzzy Influence Diagrams
- Evolved BBN

HYBRID PROBABILISTIC SYSTEMS
SC: FL Systems

Approximate Reasoning

Probabilistic Models
Multivalued & Fuzzy Logics

Functional Approximation/Randomized Search

Neural Networks
Evolutionary Algorithms

Fuzzy Systems
Fuzzy Logic Controllers

Multivalued Algebras

Fuzzy Logic Controllers

State Variables
Output Variable

Interpolation
Defuzzification

Example: Fuzzy Logic Controller
SC: Hybrid FL Systems

Approximate Reasoning

- Probabilistic Models
- Multivalued & Fuzzy Logics

Functional Approximation/Randomized Search

- Neural Networks
- Evolutionary Algorithms

- Fuzzy Systems
- Fuzzy Logic Controllers
- Multivalued Algebras

HYBRID FL SYSTEMS

- NN modified by FS (Fuzzy Neural Systems)
- FLC Tuned by NN (Neural Fuzzy Systems)
- FLC Generated and Tuned by EA

- Meta Level
- Object Level
SC: NN Systems

Approximate Reasoning

Probabilistic Models
Multivalued & Fuzzy Logics

Functional Approximation/Randomized Search

Neural Networks
Evolutionary Algorithms

Feedforward NN
RBF
Single/Multiple Layer Perceptron

Recurrent NN
Hopfield
SOM
ART

Example of Feedforward NN
SC: Hybrid NN Systems

Approximate Reasoning
- Probabilistic Models
- Multivalued & Fuzzy Logics

Functional Approximation/Randomized Search
- Neural Networks
- Evolutionary Algorithms
- Neural Networks (Feedforward, Recurrent)
- Neural Networks (Single/Multiple Layer Perceptron, Hopfield)

Hybrid NN Systems
- RBF
- FLC
- NN
- Optimiz. Problem
- NN topology &/or weights generated by EAs
- NN parameters (learning rate, momentum)

Evolutionary Algorithms
- SOM
- ART

Optimiz. Problem
- EA
- NN
- Optimizat. Problem
SC: EA Systems

Approximate Reasoning

Probabilistic Models

Multivalued & Fuzzy Logics

Functional Approximation/Randomized Search

Neural Networks

Evolutionary Algorithms

Evolution Strategies

Evolutionary Programs

Genetic Algorithms

Genetic Progr.

Example of Binary-Encoded GA

10010110 01100010 10100100 10011001 01111101

. . . . . . . . . . . .

Current generation

Elitism

Selection Crossover Mutation

10010110 01100010 10100100 10011101 01111001

. . . . . . . . . . . .

Next generation

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SC: Hybrid EA Systems

Approximate Reasoning
- Probabilistic Models
- Multivalued & Fuzzy Logics

Functional Approximation/Randomized Search
- Neural Networks
- Evolutionary Algorithms

Hybrid EA Systems
- EA parameters \((N, P_{cr}, P_{mu})\) controlled by FLC
- EA-based search inter-twined with hill-climbing
- EA parameters (Pop size, select.) controlled by EA

Evolution Strategies
- Evolutionary Programs
- Genetic Algorithms
- Genetic Progr.
Outline

- Background: Computational Intelligence (CI)
- **Application Focus: Servicing High-cost Equipment**
  - Business model: Contractual Service Agreements (CSA) & Condition Based Maintenance (CBM)
  - Enabling Technology: Prognostics & Health Mgmt. (PHM)
- CI in Services: The Knowledge x Time Framework
- Knowledge Gradient: Tactical PHM Functions
- Time Gradient: Case Studies
- Fusion Issues
- Conclusions and Future Work
Motivation: Business Model

- **Contractual Service Agreements (CSA)**
  - OEM is responsible for sustained asset performance; e.g. “Power-by-the-hour”
  - Customer pays fixed maintenance price
  - OEM’s Risk: Cost variability

GE Transformation to Lifetime Support: Customer Service Agreements (CSA)

![Graph showing GE's Transformation to Lifetime Support](image-url)
Motivation (cont.)

• Conditioned-based Maintenance (CBM) is critical for CSA.
• CBM enables the repair/replacement of key components as a function of their condition (Remaining Useful Life or RUL) rather than calendar life.
• This capability is enabled by Prognostics (P) and optimized by Health Management (HM).
• PHM is the application focus for this presentation.
PHM: Functional Architecture

Data Pre-Processing
- Platform
  - Raw Sensor Data

Anomaly Detection
- Warnings & Alerts
  - Coarse Granularity Id

Diagnostics
- Subsystem Failure Modes
  - Subsystem Health Assessment (η, Deterior. Index)

Prognostics
- Remaining Useful Life (RUL)

In-flight Fault Accommodation
- Corrective Action Identification
  - Part Level Health RUL Assessment

HM
- On-board Tactical Control

Logistics Decision Engine
- Available Reconfigurations
  - Mission Objectives & Requirements
  - Parts Availability
  - Available Assets
  - Other

Maintenance Actions
- Readiness Improvement Assessment

Optimal Actions, Plans
- Operational Impact Assessment

Part Replenishment Actions
- Inventory Re-Assessment

Part Level Health RUL Assessment

1st Level Interpretation

2nd Level Interpretation

3rd Level Interpretation

Off-board Strategic Planning

PHM Requires a Holistic Approach

IT Infrastructure
PHM Experience at GE

1st Level Interpretation
- Raw Sensor Data
- Cardiac CT image artifact reduction for multi-slice CT systems
- Event detection in reciprocating compressors
- Anomaly detection in aircraft flights

2nd Level Interpretation
- Data Pre-Processing
- Data Acquisition/Proc.
- 2nd Level Interpretation
- Diagnostics
- Automated interpretation of MRI calibration system test (SPT)
- Remote Locomotive diagnostics and repair recommendation (EOA)

3rd Level Interpretation
- Anomaly Detection
- Prognostics
- RUL estimation for engine core comp. & Ball Bearings
- Prediction of Time-to-break for paper web

In-flight Fault Accommodation
- Logistics Decision Engine
- Available Reconfig’s
- Mission Objectives & Requirements
- Parts Availability
- Available Assets
- Other

On-board Tactical Control

Off-board Strategic Planning
- Optimization of Coal-fired boilers (HR/NOx tradeoffs)

Cardiac CT image artifact reduction for multi-slice CT systems
- Event detection in reciprocating compressors
- Anomaly detection in aircraft flights
- Automated interpretation of MRI calibration system test (SPT)
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Outline

• Background: Computational Intelligence (CI)
• Application Focus: Servicing High-cost Equipment

• CI in Services: The Knowledge x Time Framework
  – A Framework based on
    • **Time** – *When?* How soon do we need to decide/act?
    • **Knowledge** - *How?* Which type of domain knowledge can we use?
    • **Decision** – *What?* Which type of decision do we need?

• Knowledge Gradient: Tactical PHM Functions
• Time Gradient: Case Studies
• Fusion Issues
• Conclusions and Future Work
Time Horizon (*When*) and Decision (*What*)

- **Transactional Decision**
  - Asynchronous
  - ns-ms
  - ms
  - sec
  - min
  - hour
  - day
  - week
  - month
  - quarter/year
  - variable frequency

- **Life Cycle**
  - One Shot
  - Tactical
  - Operational
  - Strategic
Time Horizon (*When*) and Decision (*What*)
Time Horizon (When) and Decision (What)
Time Horizon (When) and Decision (What)

- **One Shot**
  - Asynchronous
  - ns-ms

- **Tactical**
  - ms
  - sec

- **Operational**
  - min
  - hour
  - day

- **Strategic**
  - week
  - month
  - quarter/year
  - variable frequency

- **Life Cycle**
  - Long Term Planning, Policy Evaluation
  - Multi-Objective Optimization, MCDM
  - Asset Allocation, Optimization, DM
  - Weekly Schedule & Plan
  - Daily Schedule & Plan
  - Process Control (Chemical), Prognostics
  - Process Control (Human or Automatic)
  - Supervisory Control, State Assessment
  - Anomaly Detection/Id.
  - Real-time Detection (Electromechanical)
  - Real-time Detection (Electronics)
  - Transactional Decision

*Imagination at Work*

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Time Horizon (When) and Decision (What)

- **One Shot**
  - Asynchronous
  - ns-ms
- **Tactical**
  - ms
  - sec
  - min
  - hour
- **Operational**
  - day
  - week
  - month
- **Strategic**
  - quarter
  - year
  - variable frequency
- **Life Cycle**
  - Long Term Planning
  - Multi-Objective Optimization
  - MCDM
  - Model Update & Model Maintenance

- Transactional Decision
- Real-time detection (Electronics)
- Real-time control (Electro-Mechanical)
- Anomaly detection/Ident.
- Supervisory control (Fault Accom.)
- Anomaly detection/Ident; State Assessment
- Process control (Human or Automatic)
- Diagnostics; Prognostics
- Daily Schedule & Plan
- Asset Allocation; Optimization; DM
- Weekly Schedule & Plan
- Multi-Objective Optimization; MCDM
- Process Control (Chemical)
- Decision Support Syst.
- Diagnostics; Prognostics
- Process Control (Chemical)
- Multi-Objective Optimization; MCDM
- Process control (Human or Automatic)
- Decision Support Syst.
- Diagnostics; Prognostics
- Process Control (Chemical)
- Multi-Objective Optimization; MCDM
- Process control (Human or Automatic)
- Decision Support Syst.
**Time Horizon (When) and Decision (What)**

- **One Shot**
  - Asynchronous
  - Single Decisions
  - Time horizon: variable frequency

- **Tactical**
  - Time horizon: minute

- **Operational**
  - Time horizon: hour

- **Strategic**
  - Time horizon: day to year

- **Life Cycle**
  - Model Update & Model Maintenance
  - Multi-Objective Optimization & MCDM

- **Object Level**
  - Process Control (Human or Automatic)
  - Process Control (Chemical)
  - Decision Support System

- **Meta Level**
  - Policy Evaluation
  - Multi-Objective Optimization
  - MCDM

- **Multiple, Repeated Decisions**
  - Real-time control (Electronics)
  - Anomaly Detection/Id
  - Supervisory control; State Assessment
  - Diagnostics; Prognostics

- **Multi-Objective Optimization**
  - Multi-Objective Optimization & MCDM

- **Long Term Planning**
  - Long Term Planning & Policy Evaluation

- **Model Update & Maintenance**
  - Model Update & Maintenance

- **Life Cycle**
  - Lifecycle Decisions

- **Time**
  - Time Horizon (When)
  - Decision (What)
Domain Knowledge (How): An Analogy

Linguistic Knowledge

PHM Domain Knowledge

Platform Agnostic

Platform Dependent
Domain Knowledge *(How)*: An Analogy

**Lexicon** is the list of words that can be used to form sentences in a language.

→ *Use only “legal”, pre-defined error messages and treat them as words*
Domain Knowledge (How): An Analogy

Morphology studies word structure

→ Leverage taxonomic information (message specificity) or other relations among words (e.g., event messages)
Domain Knowledge (How): An Analogy

Marked-Up Lexicon is the list of words that can be used to form sentences in a language plus associated annotation (labels)

→ Distinguish between “good” and “bad” pre-defined error messages and treat them as labelled words

Marked-Up Lexicon is the list of words that can be used to form sentences in a language plus associated annotation (labels)
Domain Knowledge (How): An Analogy

Syntax defines the correct composition of language constituents (regardless of meaning)

→ Leverage word order (messages time-order) and word composition into sentences (signatures), etc.
Semantics decomposes the meaning of text into the meaning of its components and their relationship

→ Leverage the meaning of messages, composed them with those of parametric data, extract their meaning (features), etc.
Pragmatics uses external knowledge (environment, context) to refine meaning

→ Use contextual knowledge (operational regimes, environmental conditions, health deterioration) to determine the (degree of) appropriateness of alternative models and select the best (mixture).
A Framework for SC Applications in PHM

Number of Models

- Single Model
- Multiple (Fused) Model

Domain Knowledge
- Pragmatics
- Semantics

Time Horizon
- Asynch.
- sec
- min
- hour
- day
- week
- month
- quarter
- year
- variable freq.

Number of Models
- One Shot
- Tactical
- Operational
- Strategic
- Meta

Domain Knowledge

Multiple (Fused) Model

Single Model

Asynchr.

ns
ms
sec
min
hour
day
week
month
quarter
year
variable freq.

Number of Models

- Single Model
- Multiple (Fused) Model

Domain Knowledge

Pragmatics
- Transactional Decision
- Anomaly Detection/Id Fault Accomp.
- Diagnostics Prognostics

Semantics
- Syntax
- Marked-up Lexicon
- Morphology
- Lexicon

Anomaly Detection

Anomaly Detection & Identification

Diagnostics

Scheduling
- Contingency Planning
- Policy Evaluation
- Multi-Objective Opt.
- MCDM

Model Update & Maintenance

Scheduling

Asset Allocation
- Optimizations

Planning
- Long-Term Planning

Asset Allocation

Anomaly Detection & Id

Identification

Fault Accom.

Diagnostics

Prognostics

Update & Maintenance

Domain Knowledge

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## A Framework for SC Applications (the plane)

<table>
<thead>
<tr>
<th>Typical Technologies</th>
<th>Time Horizon Domain Knowledge</th>
<th>One Shoot</th>
<th>Tactical</th>
<th>Operational</th>
<th>Strategic</th>
<th>Meta</th>
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</thead>
<tbody>
<tr>
<td>Kolmogorov Complexity, SOM, One-Class SVM, NN, Parametric Statistics, Unsupervised ML techniques</td>
<td>Lexicon</td>
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<td>Anomaly Detection</td>
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<tr>
<td>Kolmogorov Complexity, SOM, One-Class SVM, NN, Parametric Statistics, Unsupervised ML techniques</td>
<td>Morphology</td>
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<td>Anomaly Identification</td>
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<tr>
<td>Supervised ML techniques (NN, CART, RF, ...)</td>
<td>Marked-up Lexicon</td>
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<tr>
<td>Automated Signature Extraction (via Kernel Extraction), Grammatical Inference, ...</td>
<td>Syntax</td>
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<td></td>
<td>Anomaly Id. Diagnostics</td>
<td>Scheduling</td>
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<tr>
<td>Feature Subset selection, Clustering, 1st Principles-based simulations, Fuzzy Models, Temporal Reasoners. Planners, ...</td>
<td>Semantics</td>
<td>Transactional Decision</td>
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<td>Anomaly Id. Diagnostics Prognostics Control</td>
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</tr>
<tr>
<td>Model Selection, Model Mixing, Fuzzy Models, Single- or Multi- Objective Optimizers, Stochastic Simulators, Preference Tradeoffs. Interactive Visualization Tools, etc.</td>
<td>Pragmatics</td>
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<td></td>
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<td></td>
<td>Scheduling Planning Readiness Assessment Asset Allocation Optimization DM</td>
<td>Long-Term Planning Contingency Planning Asset Management MOO, Tradeoffs, MCMD</td>
<td></td>
<td>Model Update &amp; Maintenance</td>
</tr>
</tbody>
</table>

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## Outline

- Background: Computational Intelligence (CI)
- Application Focus: Servicing High-cost Equipment
- CI in Services: The Knowledge x Time Framework

### Knowledge Gradient: Tactical PHM Functions

- **Lexicon** → Anomaly Detection
- **Morphological** → Anomaly Identification
- **Syntax** → Diagnostics
- **Semantics** → Prognostics
- **Pragmatics** → Hierarchical Control

### Time Gradient: Case Studies
- Fusion Issues
- Conclusions and Future Work
Leveraging Domain Knowledge in Tactical Applications
Leveraging Domain Knowledge in Tactical Applications

<table>
<thead>
<tr>
<th>Time Horizon</th>
<th>Domain Knowledge</th>
<th>Tactical</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lexicon</td>
<td>Anomaly Detection</td>
<td>Anomaly Detection</td>
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<tr>
<td>Morphology</td>
<td>Anomaly Detection</td>
<td>Anomaly Detection</td>
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<tr>
<td>Marked-up Lexicon</td>
<td>Anomaly Identification</td>
<td>Anomaly Identification</td>
</tr>
<tr>
<td>Syntax</td>
<td>Anomaly Id. Diagnostics</td>
<td>Anomaly Id. Diagnostics</td>
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<tr>
<td>Semantics</td>
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<td>Pragmatics</td>
<td>Anomaly Id. Diagnostics Prognostics Control</td>
<td>Anomaly Id. Diagnostics Prognostics Control</td>
</tr>
</tbody>
</table>

**Use legal, pre-defined error messages and treat them as words**

**Leverage taxonomic information (message specificity) or other relations among words (e.g., event messages)**

**Leverage annotations (labels) marking up specific words (error messages) as corresponding to normal or faulty conditions**

**Leverage word order (messages time-order), word composition into sentences (signatures), etc.**

**Leverage the meanings of messages, extract their meanings (features), understand their relationships, composed them with the meaning of parametric data, etc.**

**Use contextual knowledge (operational regimes, environmental conditions, health deterioration) to determine the (degree of) suitability of alternative models and select the best (mixture). This is the strongest leverage to design for and manage complexity.**
Lexical Knowledge for Anomaly Detection

Given a fleet of assets (aircraft engines, CT scanners, locomotives, etc), provide early warning of anomalies based on symbolic data (e.g. error messages).
Anomaly Detection Algorithms

1. Use operational data recorded from multiple flight instances to construct an anomaly map & detect potentially anomalous flights.

2. Use properties of anomaly map to detect the onset of operational faults early.

3. Use early detection of developing faults to drive safety, maintenance preparedness, other metrics.
Anomaly Detection

• Individual anomaly detection techniques
  • limitations on accuracy and robustness
  • Each classifier will have False Positives and False Negatives

• Combining diverse detectors overcomes individual limitations
  • Each classifier should have DIFFERENT False Positives and False Negatives

• Three approaches:
  - Information theory -> Clear identification of anomalies
  - Artificial Intelligence -> Define a precursor zone
  - Statistics -> Most robust classifier
Anomaly Detection for Aircrafts

A/C

~ 1000 downloads
~ 3000 flights
6 anomalies
2,994 Healthy flights

Fault Code | Corrective Action | Aircraft Number | Date of Squawk | Date of Completion
--- | --- | --- | --- | ---
211XXXXX | R2 Cabin pressure controller | 5550 | 1-Jul-04 | 3-Jul-04
29XXXXXX | Replaced O-ring on booster pack hyd filter bowl. | 5536 | 28-Jul-03 | 28-Jul-03
3010XXXX | Installed Diode on TB105CT | 5536 | 11-Jul-03 | 22-Jul-03
3010XXXX | Installed Diode on TB105CT | 5536 | 11-Jul-03 | 22-Jul-03
3010XXXX | Repositioned Elements | 5501 | 2-Apr-02 | 13-Apr-02
3010XXXX | R2 Timer unit | 5501 | 16-Apr-02 | 18-Apr-02

AC# | From | To | # of Downloads
--- | --- | --- | ---
5408 | 11/21/04 1:26 PM | 4/18/05 4:48 PM | 89
5414 | 2/10/05 6:00 PM | 3/16/05 9:07 PM | 30
5416 | 12/4/04 3:21 PM | 3/22/05 1:12 AM | 68
5444 | 12/20/04 10:04 AM | 2/5/05 12:14 PM | 40
5458 | 12/20/04 8:38 AM | 2/10/05 8:38 AM | 42
5459 | 12/29/04 3:50 PM | 4/8/05 2:38 PM | 32
5460 | 1/18/05 3:36 AM | 4/11/05 1:55 PM | 82
5461 | 1/20/05 9:21 AM | 3/2/05 5:45 AM | 43
5463 | 2/9/05 5:02 AM | 4/6/05 10:04 AM | 25
5479 | 2/3/05 1:12 PM | 3/11/05 6:14 AM | 32
5480 | 12/12/04 6:57 AM | 4/6/05 9:36 AM | 73
5481 | 2/22/05 2:24 AM | 4/4/05 5:16 PM | 47
5482 | 2/8/05 5:16 PM | 3/3/05 1:55 PM | 13
5484 | 11/25/04 11:02 AM | 3/31/05 6:28 PM | 67
5485 | 2/15/05 12:43 PM | 4/19/05 7:40 PM | 55
5496 | 2/2/05 5:31 AM | 4/7/05 12:00 AM | 83
5500 | 11/23/04 4:04 PM | 4/9/05 12:28 PM | 39

HISTOGRAM OF FC

imagination at work
Anomaly Detection Algorithms Data Preprocessing: Encoding non-parametric data

FADEC Messages from flight \( x \)

Frequency Extraction (Histogram)

String Conversion

This string represents flight \( x \)

Fault Codes Histogram

<table>
<thead>
<tr>
<th>Fault Code</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>FC 1</td>
<td>0.07</td>
</tr>
<tr>
<td>FC 2</td>
<td>0.04</td>
</tr>
<tr>
<td>FC 3</td>
<td>0.11</td>
</tr>
<tr>
<td>FC 4</td>
<td>0.19</td>
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<tr>
<td>FC 5</td>
<td>0.30</td>
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<tr>
<td>FC 6</td>
<td>0.11</td>
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<tr>
<td>FC 7</td>
<td>0.15</td>
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<tr>
<td>FC 8</td>
<td>0.00</td>
</tr>
<tr>
<td>FC 9</td>
<td>0.04</td>
</tr>
</tbody>
</table>

The string conversion process involves extracting data from FADEC messages, converting them into a frequency histogram, and then representing the frequency distribution of fault codes.
Anomaly Detection Algorithms Using Information Theory

Detector based on Kolmogorov Complexity
- 2D Display obtained by projecting 84-dimensional object while minimize distorsion

Clear Identification of anomalies

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Anomaly Detection Algorithms Using Self-Organizing Maps (AI)

1. Train SOM on normal data to obtain normal operating envelope
2. Declare a case novel if its projection to the map falls outside the envelope

Identification of "Precursor Zone"
Anomaly Detection Algorithms
Using Random Forest (Statistics) [Breiman & Cutler]

- FADEC Messages
  - Frequency extraction
  - String Encoding
    - Random Forest Computation
    - Multi Dimensional Scaling (MDS) projection
  - Minimal Spanning Tree (MST)
  - Distance threshold to segment MST

DATA: 2449 possible fault codes
131 active over 84 flights
RF: 30 forests with new synthetic data
500 trees per forest
OOB error rate (7%)

Random Forest

MDS projection

MST
Anomaly Detection Algorithms Using Random Forest (Statistics) [Breiman & Cutler]

- Minimal Spanning Tree (MST)
- Distance threshold to segment MST
- Random Forest Computation
- Multi Dimensional Scaling (MDS) projection

DATA: 2449 possible fault codes
131 active over 84 flights
RF: 30 forests with new synthetic data
500 trees per forest
OOB error rate (7%)
Fusion of Anomaly Detection Algorithms (cont.)

- Fusion
  - Fusion of detectors outputs
  - Fusion of detectors states (pairwise distance matrices)

Family of Anomaly Detectors (Fault codes): n flights

Distance from origin based on detector

<table>
<thead>
<tr>
<th>D1</th>
<th>D2</th>
<th>D3</th>
<th>D4</th>
<th>D5</th>
<th>D6</th>
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T-norms

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<tr>
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Fusion of detectors states (pairwise distance matrices)

D1 F1 F2 F3 . . . Fn
F1 0.4 0.8 . . . .
F2 0.1 0.3 .
F3 . . .
... .
Fn 0.1 0 . . . 0.2
Fusion of Anomaly Detection Algorithms

Fusion of detectors increases robustness and accuracy
Morphological Knowledge for Anomaly Detection and Identification

**Variable**

Pragmatics

Anomaly Id. Diagnostics

Prognostics

Control

Semantics

Anomaly Id. Diagnostics

Syntax

Marked-up Lexicon

Morphology

**Anomaly Detection**

**Anomaly Id. Diagnostics**

**Prognostics**

**Time Horizon**

Domain Knowledge

Tactical

**Morphology**

**Domain Knowledge**

**Tactical**

**Anomaly Detection**

**Anomaly Id. Diagnostics**

**Prognostics**

**Control**

**Semantics**

**Anomaly Id. Diagnostics**

**Syntax**

**Marked-up Lexicon**

**Morphology**

**Variable**

C₁ = Variable Bleed Valve: VBV

C₂ = High Pressure Turbine: HPT

C₃ = Low Pressure Turbine: LPT

C₄ = Electronic Engine Control: EEC

Cₘ = Variable Stator Vein: VSV

**Featureless Similarity Detector** (based on Kolmogorov Complexity)

- Unsupervised Clustering using $D_B$

**NCD(Flight n+1, Normal_Flight)**

**m** Dissimilarity Vector Component

$\rho(\text{Flight}_j, \text{Flight}_k) = \cos \theta$

$D_B(\text{Flight}_j, \text{Flight}_k) = \sqrt{1 - \rho(\text{Flight}_j, \text{Flight}_k)}$

Spain, June 20, 2007
Marked-Up Lexical Knowledge for Anomaly Detection and Identification

Training Set

NCD(Cᵢᵣun_j, CᵢᵣNormal_Run)

Run 1 Run 2 Run j Run n

m Dissimilarity Vector Components

NCD(Cᵢᵣun_j, CᵢᵣNormal_Run)

NCD(Cᵢᵣun_j, CᵢᵣNormal_Run)

Run 1 Run 2 Run j Run n

m Dissimilarity Vector Components

Normality (N) or Fault Code (Fᵢ)

Labeled State: Normal (N) or Fault Code (Fᵢ)

Using Trained Neural Networks for Anomaly Identification/Diagnostics

NCD(Run n +1, Normal_Run)

Run n +1

m Dissimilarity Vector Components

NCD(Run n +1, Normal_Run)

Run n +1

m Dissimilarity Vector Components

Unlabeled State (Normal or Fᵢ)

Labeled State: Normal (N) or Fault Code (Fᵢ)

Run n +1

m Dissimilarity Vector Components

NCD(Run n +1, Normal_Run)

Run n +1

m Dissimilarity Vector Components

Unlabeled State (Normal or Fᵢ)

Labeled State: Normal (N) or Fault Code (Fᵢ)

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m Dissimilarity Vector Components

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Run n +1

m Dissimilarity Vector Components

Unlabeled State (Normal or Fᵢ)

Labeled State: Normal (N) or Fault Code (Fᵢ)
Syntactic Knowledge for Anomaly Identification

Good failure data from platform

Signature extraction:

- Manual Process:
  Knowledge Engineering: 19/21 = 90%

- Automated learning of error signatures:
  Kernel segmentation on multivariate time series data: 16/21 = 76% (rev 1)
Diagnostics based on Automated Fault Signature extraction & Pattern Recognition

- **Key Goal**
  - Automated extraction and application of fault signatures from time-series data for asset diagnostics

- **Solution**
  - Automated signature extraction and pattern recognition based detection
    - Use knowledge of existing fault condition and failure mode of asset to **extract and learn potential fault signatures** from multiple time-series variables
    - Perform analyses to retain most discriminating set of signatures
    - Apply pattern recognition techniques to locate presence or absence of failure-mode in real-time using library of signatures learned.

- **Benefits**
  - Advanced diagnostic ability
  - Potential prognostic ability

**Automated Fault Signature Extraction** initializes & maintains rule based system without human intervention
Automated Fault Signature Extraction

1) build library of potential fault signatures

2) match signatures to real data

3) evaluate features

4) use discriminant features to classify real data

- use peak match magnitude as feature

<table>
<thead>
<tr>
<th>1     2     3</th>
<th>err %</th>
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</thead>
<tbody>
<tr>
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<td>11.11</td>
</tr>
<tr>
<td>1     3     1</td>
<td>40.00</td>
</tr>
<tr>
<td>0     2     5</td>
<td>28.57</td>
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Semantic Knowledge for Anomaly Detection and Identification

Time Horizon

Domain Knowledge

Tactical

Anomaly Detection

Anomaly Detection

Anomaly Id. Diagnostics

Anomaly Id. Diagnostics

Diagnostics

Pragmatics

Anomaly Id.

Diagnostics

Syntax

Marked-up Lexicon

Anomaly Detection

Anomaly Detection

Morphology

Anomaly Detection

Lexicon

Tactical

Domain Knowledge

Semantics

Feature-based Similarity Detector: designed via Evolutionary Algorithms and fuzzy clustering (Collective Mind)

Utilization/Operations

Maintenance Actions

Parts Orders

Configuration DB’s

Evolutionary Search

(using Wrapper Approach)

Feature Subset

Similarity Criteria

FEATURE-BASED DETECTOR
Semantic Knowledge for Anomaly Detection and Identification

Fuzzy Instance Based Model (Fuzzy IBM)

Weighted Similarity

Local Models & Aggregation

Chromosome

Evolved Peers
Non Peer-Heuristics
Random

Selection Performance

Time Slices
Semantic Knowledge for Anomaly Detection and Identification

Fuzzy Instance Based Model (Fuzzy IBM)

Local Models \(\{x \rightarrow y\}\) & Aggregation

Weighted Similarity

\[
TGBF_i(x_i; a_i, b_i, c_i) = \begin{cases} \frac{1}{1 + \frac{x_i - c_i}{a_i}} & \text{if } GBF > 10^{-3} \\ 0 & \text{otherwise} \end{cases}
\]

Local Models

\[
R_i(O(u_i)) = D_{i,j} \cdot \frac{1}{\alpha + (1 - \alpha)D_{i,j}}
\]

History Exponential Average

\[
\alpha = \frac{1}{\sum \frac{1}{\alpha}}
\]

Chromosome

\[
[w_1, w_2, \ldots, w_n] [(a_1, b_1), (a_2, b_2), \ldots, (a_n, b_n)] [\alpha]
\]
Evolutionary Search for Designing A Fuzzy Instance-Based Model using a Wrapper Approach

EVOLUTIONARY ALGORITHM

Fitness Function: Quantify Quality of Chromosome

\[ f = \frac{TP}{(TP + FP)} \]

**Fuzzy IBM EVALUATION**

Leave-One-Out Testing

- Retrieval. Similarity, Local models: Weights, GFB Parameters, \( \alpha \)
- Quantify Similarity
- Prediction
- Prediction-based Selection of best units

Maintenance & Utilization CB

Instance of FIBM Engine

XML Config File

Probe Case

Select Probe

Remaining Life

Rank by Remaining Life

Rank Within Percentile ?

Ground Truth

<table>
<thead>
<tr>
<th>Predicted</th>
<th>T</th>
<th>F</th>
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<tbody>
<tr>
<td>T</td>
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<td>FP</td>
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<tr>
<td>F</td>
<td>FN</td>
<td>TN</td>
</tr>
</tbody>
</table>

Fuzzy IBM Decision

**CBR EVALUATION**

Pop.(i+1)

- Mutation
  - Uniform
  - Gaussian
  - Original
- Elitist (best from Pop i)

- P(selection) Fitness Pop.(i)

Chromosome Decoder

- Decoder
- Chromosome
Manage complexity by leveraging contextual knowledge, such as
Operational regimes or modes
- Training, War-time deployment
- Subsonic, Supersonic
- Velocity, Position, Force feedback
- Coarse, Fine Control

Different steady states
Configurations, Load conditions, Op-tempos

Environmental conditions
Health deterioration

to determine the degree of relevance of alternative models
and select the best mixture
Pragmatic Knowledge for Anomaly Detection, Identification, and Control

<table>
<thead>
<tr>
<th>Time Horizon</th>
<th>Tactical</th>
</tr>
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<tbody>
<tr>
<td>Domain Knowledge</td>
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</tr>
<tr>
<td>Pragmatics</td>
<td>Anomaly Id. Diagnostics Prognostics Control</td>
</tr>
</tbody>
</table>

Manage complexity by leveraging contextual knowledge, such as Operational regimes or modes (Coarse, Fine Control) to determine the degree of relevance of alternative models and select the best mixture.

Figure 2: Hierarchical control scheme for series resonant converter.

Piero P. Bonissone © IWANN 2007, S. Sebastian, Spain, June 20, 2007
Pragmatic Knowledge for Anomaly Detection, Identification, and Control

Manage complexity by leveraging contextual knowledge, such as Operational regimes or modes:

- Coarse, Fine Control

Coarse Fuzzy PI

Fine Fuzzy PI

<table>
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<tr>
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<th>PS</th>
<th>PM</th>
<th>ZE</th>
<th>NL</th>
<th>NVL</th>
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Fuzzy Logic Controller (FLC) and Switching Regulator Circuit (SRC)
Pragmatic Knowledge for
Anomaly Detection, Identification, and Control

Manage complexity by leveraging contextual knowledge
Problem decomposition using:
- CART (Classification Analysis and Regression Tree)
- ANFIS (Adaptive Neural Fuzzy Inference System)
- Multiple ANFIS models

CART (Classification Analysis and Regression Tree)
Pragmatic Knowledge for Anomaly Detection, Identification, and Control

ANFIS (Adaptive Neural Fuzzy Inference System)

<table>
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Inputs IF-part Rules + Norm THEN-part Output

Layers: 0 1 2 3 4 5

Context

Local Models

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<tr>
<th>$x_1$</th>
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<tbody>
<tr>
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<td>$B_1$</td>
<td>$f_1(x_1, x_2)$</td>
</tr>
<tr>
<td>$A_2$</td>
<td>$B_1$</td>
<td>$f_2(x_1, x_2)$</td>
</tr>
<tr>
<td>$A_2$</td>
<td>$B_2$</td>
<td>$f_3(x_1, x_2)$</td>
</tr>
<tr>
<td>$A_1$</td>
<td>$B_2$</td>
<td>$f_4(x_1, x_2)$</td>
</tr>
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Pragmatic Knowledge for Anomaly Detection, Identification, and Control

ANFIS (Adaptive Neural Fuzzy Inference System)

Time Horizon
Domain Knowledge
Tactical

Inputs
IF-part
Rules + Norm
THEN-part
Output

Domain Knowledge
Lexicon
Anomaly Detection

Inputs
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Anomaly Id. Diagnostics

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Domain Knowledge
Pragmatics
Anomaly Id. Diagnostics
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Pragmatic Knowledge for Anomaly Detection, Identification, and Control

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**ANFIS Model for Voltage Instability Margin Prediction**

- Current Load
- PQV-surface
- Voltage Instability Margin
- Load trajectory
- Collapse Line

For a given network configuration (number of generators, network topology, number of capacitors)

Manage complexity by leveraging contextual knowledge, such as Different steady states (Configurations, Load conditions) to determine the degree of relevance of alternative models and select the best mixture
## Pragmatic Knowledge for Anomaly Detection, Identification, and Control

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</table>

**Multiple ANFIS Models for Voltage Instability Margin Prediction**

- Different PQV models for different network configurations (# generators, network topology, # capacitors)
- Weighted Combination
- Local Models
Embedding Knowledge in the Design of an Evolutionary Algorithm

- **Solution Representation**
  - Data Structures (Parsimonious; Avoid unfeasible solutions)
  - Encoding (Natural encoding: binary, real, integer)
  - Constraints (Static: embedded in DS; Dynamic: penalty functions)

- **Initial Population**
  - Boundary Conditions (Exercise boundary conditions)
  - Best Guesses (Seed candidate solutions)

- **Variational and Selection Operators**
  - Customized Mutation (self-repair)
  - Customized Crossover
  - Variable Selection Pressure (Increasing from linear to NL)

- **Assignment, Tuning and Control of EA parameters**
  - Prior Design (Usually from literature studies of parameters)
  - Offline Tuning
  - On-Line Control

Meta-Heuristics
## Evolutionary Fuzzy Systems (EFS)

<table>
<thead>
<tr>
<th>EFS Application Type</th>
<th>Domain Knowledge</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation and tuning of fuzzy rule-based systems for classification, control, fusion, etc.</td>
<td>EA: Pragmatics</td>
</tr>
<tr>
<td></td>
<td>FS: Semantics</td>
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<tr>
<td></td>
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</tr>
<tr>
<td>Fuzzy Control of lower-level fuzzy controllers: Fuzzy Supervisory Cntr’l</td>
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<tr>
<td></td>
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</tr>
<tr>
<td>Evolutionary algorithms’ fitness function computed by fuzzy systems</td>
<td>EA: Semantics</td>
</tr>
<tr>
<td></td>
<td>FS: Semantics</td>
</tr>
</tbody>
</table>

- **Off-Line Meta-heuristics**
- **On-Line Meta-heuristics**
- **Both FS and EA at Object-level**
Tuning & Control of Evolutionary Algorithm Parameters

**Prior Design**
(from literature)
- Static Setting
- Static Usage

**Parameter Setting**
(from literature)

**Parameter Values**

**Parameter Tuning**

**Parameter Control**
- Deterministic (Schedule)
- Adaptive (controller)
- Self-Adaptive (Evolved)

**Offline Tuning**
Characteristics:
- Dynamic Setting
- Static Usage

**On-Line Control**
Characteristics:
- Dynamic Setting
- Dynamic Usage
Offline Meta-Heuristics:
EA generates Structure & Parameters

Object-level Problem Solver (PS)

Meta- Level PS

Performance of Object-level PS

Parameters of Object-level PS

Suite of Representative Problems

Off-line Tuning

Run-time Parameters for Object-level PS

Object-level Problem Solver (PS)

Object-level Problem

Run-time Environment
Examples of Offline Meta-Heuristics

Meta-Level PS

Object-Level PS

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>EA</td>
<td>NN</td>
<td>EA</td>
<td>EA</td>
<td>EA</td>
<td>EA</td>
<td>EA</td>
</tr>
<tr>
<td>FLC</td>
<td>FL</td>
<td>Controller</td>
<td>NN</td>
<td>EA</td>
<td>BBN</td>
<td>F-CBR</td>
</tr>
</tbody>
</table>

- Generation and tuning of fuzzy rule-based systems for classification, control, fusion, etc.
- Tuning of Evolutionary Algorithm Parameters
- Generation and tuning of fuzzy instance- or case-based systems for classification, prediction, etc.

EA: Pragmatics
FS: Semantics

Tuning FLC Parameters
Tuning FLC Parameters
Tuning Gain Schedule Parameters
Tuning NN Parameters
Tuning EA Parameters
Evolving Tuning Bayesian Classifiers
Tuning CBR Classifiers
On-Line Meta-Heuristics: KB Controller for Object-Level Problem Solver

State Variables: Performance of Object-level PS

Control Variables: Modified parameters for Object-level PS

Off-line KB definition
Examples of On-Line Meta-Heuristics

<table>
<thead>
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<th>Object- Level PS</th>
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- FS: Pragmatics
- FS: Semantics
- EA: Semantics

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Outline

• Background: Computational Intelligence
• Application Focus: Servicing High-cost Equipment
• CI in Services: The Knowledge × Time Framework
• Knowledge Gradient: Tactical PHM Functions

• Time Gradient: Case Studies
  – Expert On Alert (Condition Based Maintenance)
  – Coal-Fired Boiler Management (Operational Optimization)

• Fusion Issues
• Conclusions and Future Work
Case Study 1: GE Rail - Proactive Maintenance Recommendations

**EOA™ Overview**

**Expert on Alert™ RM&D Service**
- Failure reduction… “Fix right the first time”
- Fewer shoppings… “Fix out of the shop”
- Shop efficiency… “Expert Diagnostics”
- Lower parts cost… “Correct part removal”

**Enabled By…**
- Wireless, real time data management
- Expert diagnostic tools & rules
- Closed loop diagnostic system & process
- Seamless B2B integration with maintenance systems

**Benefits Proven On Over 4,000 Locomotives**

- Wireless, real time data management
- Expert diagnostic tools & rules
- Closed loop diagnostic system & process
- Seamless B2B integration with maintenance systems

**EOA™ Continuous Learning**

- **Key Goal:** Using existing locomotive sensors and wireless communication system, provide railroads with condition-based maintenance and repair service (advanced failure notifications to schedule corrective repair)

**Technology … Fix it Right the 1st Time … Everywhere**

**Solution:** Hybrid rule-based & case based reasoners predicting incipient locomotive failures. The reasoner uses a workflow system to specify best suggested repair procedure and notify the RR

**Benefits:** Decrease number of road failures and increase % utilization. Change unscheduled maintenance events into scheduled ones.
Expert-on-Alert (EOA™): A Commercial Success Story for GE Rail

Complex, Mobile, Repairable System...
• 24 Microprocessor Controllers
• No new sensors (used existing controllers' sensors)
• 200,000 parts
• 100,000+ miles/year
• Extreme operating environment
• 20 years of life
• Continuous Field Modifications (multi/year)
• 3-4 Scheduled Shop-visits/year
• 4-5 Un-Scheduled Shop-visits /year
• 2-3 Overhauls over life
• Distributed Maintenance Environment (different shops, different people)

History of Expert-On-Alert™ (EOA™)
• Launched 1998: 200 locomotives - CBR + BBN
• 1999: 600 locomotives - CBR
• 2000: 1000 - 1500 locomotives - CBR + JDPAD(Rule Based):
• 2001:
• 2002:
• 2003: 4000 locomotives:
• 2004-07: 6000+ locomotives:
  - Process Automation: Tools + 30% Auto RX
  - Improved Rx Precision,
  - Vastly increased parameter availability
  - Improved Rx Precision & larger fleet coverage
Expert-on-Alert (EOATM): A Commercial Success Story for GE Rail

Complex, Mobile, Repairable System...
- 24 Microprocessor Controllers
- No new sensors (used existing controllers' sensors)
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- 2-3 Overhauls over life
- Distributed Maintenance Environment (different shops, different people)

Improving Performance

Failures per Locomotive per Year [FLY]
Cost incurred on track-blockage & labor per FLY: $17K per FLY
Cumulative FLY cost reduction over fleet [1997-2004]: ~ $300MM

Locomotive Availability
Value of 1% increase in availability per locomotive: $3.5K/loco
Cumulative Value of Availability over fleet [1997-2004]: ~ $30MM
A Product Offering

LOCOCOMM® is an integrated onboard computer (CBC) and communications management unit (CMU) that serves as the basis for GE Transportation Systems’ information-based services. The unit is coupled with a multimode communications antenna package that gives customers wireless data transmission capability from locomotives on the move.

LOCOCOMM® can host a variety of GE or third-party applications on its industry-standard ‘WinTel’ platform. GE Transportation Systems’ current locomotive application suite includes: Expert-on-Alert, PinPoint, LocoCAM and Smart Fueling (described below).

Expert-on-Alert™

Expert-on-Alert (EOA)™ is an advanced and continuous-learning remote monitoring & diagnostic (R&M&D) solution designed to reduce the isolation portion (troubleshooting) of every locomotive maintenance dollar. EOA keeps locomotives out of shop and fixes them the first time.

PinPoint™

PinPoint is an integrated locomotive tracking and monitoring application designed to maximize locomotive utilization. Beyond basic GPS information, PinPoint provides embedded geo-fencing capability, locomotive status information, complex dwell measurements and user configurable notifications.

LocoCAM™

LocoCAM is a forward-looking integrated video recorder system designed to aid in accident investigations, guard corporate image and detect fraudulent claims. Moreover, LocoCAM provides real-time health and tampering information to ensure system availability.

Smart Fueling™

Smart Fueling utilizes real-time burn-rate and off-board fuel information, and complex algorithms to reduce costs associated with fueling. The benefits of Smart Fueling include increased train velocity, reduced rolling inventory, the elimination of fuel deports and out-of-fuel events, and automated DTL auditing.

http://www.gettransportation.com
Case Study 2: GE Energy - Multi-Objective Asset Management:
Selecting settings for a coal-fired plant

**Tactical - Operational - Strategic - Meta**

Multi-Objective Decision Making: Control Setting Selection

**Key Goal:** Generate hierarchical control settings for Coal-Fired boiler to reduce emissions (NOx) and decrease fuel cost (Heat Rate), while satisfying all operational constraints (load, CO, SO, etc.)

**Solution:**
- Use **predictive models** (hybrid first-principle and data-driven) to determine (HR, NOx) coordinates of given setting.
- Use of **Evolutionary Multi-Objective Search** to generate Pareto Surface in (HR, NOx)

---

Pareto Front for Heat Rate and NOx

**Pizzazz:**
- Excess O2
- Aux Air Damper
- OFA Damper Position
- MI

**Constraints Satisfaction Evaluation**

**EPA Fines Threshold**

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Technology and Objectives

- Pareto Frontier ➔ best achievable operation
- Goals:
  - Minimize NOx
  - Minimize Heat Rate (∝ fuel usage cost)
  - Operate the boiler at Pareto frontier
- Constraints:
  - Generate Load
  - Meet SO and CO emission constraints

- Neural-network modeling
- Evolutionary multi-objective optimization
- Near term: validation on coal-fired boilers
- Long term: leverage to diverse plant assets
Closed-loop Optimization: Flexible DM

1.2% HR improvement

2.5% HR improvement

18.0% NOx improvement

27.5% NOx improvement
Outline

- Background: Computational Intelligence
- Application Focus: Servicing High-cost Equipment
- CI in Services: The Knowledge x Time Framework
- Knowledge Gradient and PHM Functions
- Time Gradient
- Fusion Issues

Conclusions and Future Work
- Fusion
- Evolving Model Design
- Model lifecycle
Conclusions

- Developed broad set of PHM algorithms for:
  - **Anomaly Detection**
    - Bearing Anomaly Detection
    - C130J
  - **Diagnostics**
    - HiMars
    - C130J
    - Fault Detection (Boeing)
    - Automated Defect Analysis PII
    - Smart Wires
    - Electrostatic Percipitators
  - **Prognostics**
    - Aircraft Engine
    - Ball Bearings
    - Evo Locomotives
    - Paper Machines
  - **On-board Fault Accomodation**
    - Rapid Fault Detection & Operability Restoration
  - **Offboard Decision Support System**
    - Aircraft Engine Maintenance Optimization
    - Logistics Decisions for Aircraft Engines (nominal data)
    - Coal Burning Optimization
Developed broad set of PHM algorithms for:

**Anomaly Detection**
- Bearing Anomaly Detection
- C130J

**Diagnostics**
- Trucks
- Aircrafts
- Fault Detection (Boeing)
- Automated Defect Analysis PII
- Smart Wires
- Electrostatic Percipitators

**Prognostics**
- Aircraft Engine
- Ball Bearings
- Evo Locomotives
- Paper Machines

**On-board Fault Accommodation**
- Rapid Fault Detection & Operability Restoration

**Offboard Decision Support System**
- Aircraft Engine Maintenance Optimization
- Logistics Decisions for Aircraft Engines (nominal data)
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**Conclusions**
## Conclusions

Developed broad set of PHM algorithms for:

**Anomaly Detection**
- Bearing Anomaly Detection
- C130J

**Diagnostics**
- Trucks
- Aircrafts
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**Prognostics**
- Aircraft Engine
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**On-board Fault Accommodation**
- Rapid Fault Detection & Operability Restoration

**Offboard Decision Support System**
- Aircraft Engine Maintenance Optimization
- Logistics Decisions for Aircraft Engines (nominal data)
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### Diagnostics

- Automated interpretation of MRI calibration system test (SPT)
- Remote Locomotive diagnostics & repair recommendation (EOA)
- Automated failure signature extraction
- Diagnostics driven by anomaly detection (work in progress)
- Fusion of parametric and non-parametric fault information
- DSS for pipelines fault identification
- Condition assessment system for detecting and diagnosing ESPs or wires faults/defects

---

2nd Level Interpretation
Conclusions

Developed broad set of PHM algorithms for:

**Anomaly Detection**
- Bearing Anomaly Detection
- C130J

**Diagnostics**
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- Automated Defect Analysis PII
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**Prognostics**
- Aircraft Engine
- Ball Bearings
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- Paper Machines

**On-board Fault Accommodation**
- Rapid Fault Detection & Operability Restoration

**Offboard Decision Support System**
- Aircraft Engine Maintenance Optimization
- Logistics Decisions for Aircraft Engines (nominal data)
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RUL estimation for engine core components.

RUL estimation for ball bearing

Locomotive RUL estimation based on parametric model for health assessment

Prediction of Time-to-break for paper web

3rd Level Interpretation
Conclusions

Developed broad set of PHM algorithms for:

**Anomaly Detection**
- Bearing Anomaly Detection
  - C130J

**Diagnostics**
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**On-board Fault Accommodation**
- Rapid Fault Detection & Operability Restoration

**Offboard Decision Support System**
- Aircraft Engine Maintenance Optimization
- Logistics Decisions for Aircraft Engines (nominal data)
- Coal Burning Optimization

Fault Accommodation

Real-time gain adjustment to restore stall margins in the presence of a fault

On-board Tactical Control
Developed broad set of PHM algorithms for:

**Anomaly Detection**
- Bearing Anomaly Detection
- C130J

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**On-board Fault Accommodation**
- Rapid Fault Detection & Operability Restoration

**Offboard Decision Support System**
- Aircraft Engine Maintenance Optimization
- Logistics Decisions for Aircraft Engines *(nominal data)*
- Coal Burning Optimization

**Maintenance cost Optimization by:**
- Adjusting workscope policy
- Adjusting blade repair, inspection, rebuild, and scrap policies

**Logistics Optimization:**
- Mission Reliability, cost, time to repair

**Optimization of Coal-fired boilers (HR/NOx tradeoffs)**

**Off-board Strategic Planning**
More Conclusions

• By *increasing domain knowledge utilization* we can address more complex PHM issues at the expense of developing platform-agnostic approaches (as in *weak vs strong* AI methods)

• *Operational and strategic* PHM functions require deeper domain knowledge

• By employing *Multiple Model Fusion* [usually in tactical applications] we improve decision accuracy and robustness at the expense of additional model maintenance costs

• *Lifecycle issues* can be addressed by partially automating model design search, driven by updated training sets and local or global search