Practical Machine Learning and Artificial Intelligence

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Reliability and Maintainability Center

Dynamic Factory / Teaching Labs

• Practical / Affordable / Implementable Solutions
• Professional Development Training / RMIC®
• Research / Innovation / Proof-of-Concept
• Prepare Industry and COE students for Industry 4.0

“Where Industry and Academia Meet”
Dynamic Factory / Teaching Labs

- Asset Integration
- Workplace Organization
- Design for Maintainability
- Precision Maintenance (with Reliability Solutions)
- Human Factors / Error Reduction
- Visual Controls
- Wireless Sensors / Connectivity
- R&M Best Practice Applications / Concepts
- Predictive Technologies
Dynamic Factory / Teaching Labs

Getting ready for Industry 4.0 and Beyond
ML Implementation Challenges (typical examples)

- Understanding the outcome decisions
- Trusting the decisions
- Attaining quality training data
- Putting it to practice in a timely manner
- Lack of knowledgeable resources

You want an ML tool that is practical, affordable and easily implementable
Source: Gartner – Emerging Technology Roadmaps

<table>
<thead>
<tr>
<th>Workplace Analytics</th>
<th>Large Enterprises</th>
<th>Midsize Enterprises</th>
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<tr>
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<td>2020-2022</td>
<td>2021-2023</td>
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<td>low risk, high value</td>
<td>high risk, high value</td>
<td>med risk, high value</td>
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Now is the time
Implementation is sociotechnical

Zone of Uncertainty

How much, How fast?
Industry 4.0/5.0
Rajiv - How it should work
Intelligent APM founded in RCM

- **Function degradation, not failure focus**
- **P-F is never for an asset but each specific failure mode detection**
- **Different failure modes have different severity (FMEA)**
- **Asset Health is subjective – risk is an objective, science-based principle**
- **P-F slope for random failures can never be computed**

Machine Learning (ML) with rules used to enhance detectability of failure onset and degradation

**Risk = Severity x Occurrence x Detectability**
(of a set of failure modes)
Intelligent APM Implementation

Risk = Severity x Occurrence x Detectability

Detection Agent - 1 (Severity 9)

Agent 1 or 2, or n active = Time in Abnormal Operation (TAO)

Detection Agent - n (Severity 3)

Agent 1 Active X Severity + Agent 2 Active x Severity...+Agent n active x severity = Risk Score

Frequency of Agent activity (Occurrence rate)

Predict \( \frac{dTAO}{dT} \) Rate of degradation

Acceptable degradation

Alarm/Action

Urgent Maintenance

Imminent Failure

Warning/Alert

Rate of change of Risk

Acceptable Risk

Planned Maintenance
Intelligent APM Implementation
Using RCM Implementation Flow

1. Maintenance history and downtime analysis may be used as a substitute or compliment to FMEAs in an intelligent EAM module
2. Rules agents along with operational event frames can be sufficient for some fault types, ML models may not be needed
3. Net P-F is calculated from slope of TAO and drives maintenance actions
The Intelligent EAM layer informs long-term maintenance analytics and decisions

Intelligent APM
- Detection Agents
- Risk & TAO Predictions
- Action Log Created
- Notifications Generated

Intelligent EAM
- Maintenance Planning
- MRO Spares Analysis
- Failure Codes
- Maintenance History
- Long-term Risk Analysis
- Work Order Management
- Work Order Queue
- Work/Spend Analysis
- Lifecycle Analysis

Note: Some functions may exist in CMMS

Detection

Planned Maintenance

(Early Onset of Failure)

Urgent Maintenance

(Imminent Failure)

Urgent Action taken

Maintenance shop & operations
Victor - How it did work - success
Artificial Intelligence Test – IFF/RMC

Victor Foster and Chris Lemmon
CASE STUDY #1 - GEARBOX OIL LEVEL

Old Gearbox strategy was run to failure

1. High cost of repair
2. Cost of equipment downtime

New Gearbox strategy trip on high temp

1. Capital $9,000 each to install IR sensor
2. Does not require change out or downtime

100% Rotating Planetary Gearbox

NEW! - AI SOLUTION

1. AI trained to identify anomalous behavior of asset
GEARBOX OIL LEVEL – ANOMALY DETECTION

DATA Integration + Preparation

Baseline = Good Operation

Get Insights

Select Algorithms + Features

Test = Real or Simulated Failures

Deploy!

Train Models

Validate

Test + Iterate

Deploy!

Baseline = Good Operation

Training Data

Testing Data

Performance Metrics

User Feedback

Timelines

User Training
Model Building
1 hour
10 min

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Oil level was found to be low and refilled.

Alarmed around 12 hrs before shutdown.

Zero alarm after oil refill.

Software alarm in Orange “GO VOLS”.

Motor Load.
results Case Study 1- Gearbox

• Al strategy determined that temp was not predictor to failure!

• Benefits to Al
  1. Test theory before capital spend! Identify what are the best correlating attributes of failure mode.
  2. Fast response
     1. Case study 1 took 10 min to test theory
  3. Continues monitoring with multi veritable conditioning
     1. Excludes planned downtimes or known process issue

The capital I spend would have paid for years of software!!!!!!
Case Study 2- Fan resonant frequency

**CHALLENGES**

- Resonant frequencies of fans are manually determined and subject to change upon maintenance/repair.
- Resonance is **ALWAYS changing**

**SOLUTION**

- Automatically and continuously analyze vibration and speed of fan to determine resonant frequencies
- Alert operator when frequency bands change to let them update PLC to speed through
Resonant Band recommendations

• AI models can periodically analyze historical fan vibration and speed data and determine the resonant frequencies
• Models can then continue to monitor these frequencies to determine when they change after a repair or maintenance
• Changes can be alerted to operators in real-time
Questions