Predictive Health Monitoring for Aircraft Systems using Decision Trees and Genetic Evolution

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Committee
Professor David Baglee
Mª del Carmen Valero
Professor Giulio D’Emilia
Agenda

Background
Goals & Objectives
Methodology
Results
Conclusion
Agenda

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Background – PAHMIR

• **Preventive Aircraft Health Monitoring and Integrated Reconfiguration**

• Cooperative project between
  Airbus Germany (Project Lead)
  Hamburg University of Applied Sciences

• Funded by city of Hamburg

• Duration: 3 years (2008 – 2011)
Background – PhD

- Started 2008 at HAW Hamburg and Linköping University
  Prof. Dieter Scholz & Prof. Petter Krus

- Fulltime work at 2011 as software developer

- Licentiat 2016 in Linköping

- Switching to Luleå Technical University 2016
  Prof. Dieter Scholz & Prof. Diego Galar
Background - Motivation

Without PAHMIR

- In flight
- At Gate
- Next Flight
- Hangar

- Report
- Diagnose
- Plan
- Fix

- Unscheduled Maintenance
- Scheduled Maintenance

Delay
Background - Motivation

With PAHMIR

- In flight
- At Gate
- Next Flight
- Hangar

Unscheduled Maintenance

Scheduled Maintenance

Delay

Report
Forecast
Report
Diagnose
Plan
Fix

Fix
Background - Topic Relevance

- Lufthansa Technik: Condition Analysis
- Boeing: AnalytX
- Airbus: Skywise
  - More than 20 airlines
  - Big data
  - Preventive maintenance
  - Sensor data is transferred in real time
  - Offline monitoring

https://www.flightglobal.com/mro/airbus-sees-big-data-delivering-zero-aog-goal-within-10-years/126446.article

AOG = Aircraft on Ground
(2017)
Background - Aircraft Maintenance

- Preventive Maintenance
  - Regular check intervals
  - Defined maintenance actions
    - A-Check (2 months, overnight)
    - B-Check (3-4 months, only two Boeing aircraft)
    - C-Check (18 months, 2 weeks)
    - IL-Check (4 years)
    - D-Check (6-10 years, 4-6 weeks)
Background - Aircraft Software Development

- DAL (Design Assurance Level)
  - Higher DAL = greater design restrictions (language, syntax, memory …)
  - DAL defines amount of required testing
    - Statement coverage
    - Branch coverage
    - MCDC (Multi Condition Decision Coverage)
- DAL A - Catastrophic
- DAL B - Hazardous
- DAL C - Major
- DAL D - Minor
- DAL E - No effect
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Goals

• Reduce Unscheduled Maintenance
  • Replace components before failure

• Reduce maintenance costs
  • Less unscheduled maintenance

• Use intelligent components
  • Integrated sensors
Objectives and Constrains

- Use existing data and sensors, if possible
- Onboard and offboard data management
- Adaptability
  - Should work with any input data
  - Should not be fixed to one aircraft (type)
- Compliant to aircraft software development
- Compliant to aircraft maintenance procedures
  - Not interfere with existing procedures
- Focus on air conditioning system
  - Active parts (fans)
  - Passive parts (ducts, valves)
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Methodology

- Engineering project
  - Airbus technology development process
  - Technology Readiness Level Review Gates 1-6
- Selected Approach (Inductive Research Approach):
  - Iterative Development
  - Rapid Prototyping
- Advantages:
  - Early discovery of errors and problems
  - Validation and verification for each development stage
  - Functional prototype during each iteration
Methodology – Validation

- Artificial/Synthetic data
- Testrig with original aircraft parts
- Aircraft data
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Published Papers

Paper 1: Effects of Condition-Based Maintenance on Costs caused by Unscheduled Maintenance of Aircraft

Paper 2: Decision Trees and the Effects of Feature Extraction Parameters for Robust Sensor Network Design

Paper 3: Automated Parameter Optimization for Feature Extraction for Condition Monitoring

Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

Paper 5: Decision Trees and Genetic Algorithms for Condition Monitoring Forecasting of Aircraft Air Conditioning

Paper 6: Genetic Algorithms and Decision Trees for Condition Monitoring and Prognosis of A320 Aircraft Air Conditioning
Paper 1: Effects of Condition-Based Maintenance on Costs caused by Unscheduled Maintenance of Aircraft

Journal of Quality in Maintenance Engineering (2016)

• Cost effects of predictive maintenance
  • Cost of 1 minute of delay is about 81 € (2015) (The Cost of Delay to Air Transport in Europe – Eurocontrol)
  • Cancellation is much much higher
• Analyse delays of aircraft air conditioning
Paper 1: Effects of Condition-Based Maintenance on Costs caused by Unscheduled Maintenance of Aircraft

Method:

- Airbus In-Service data
  - Air Conditioning (ATA21) of A340-600 fleet
- Analysis
  - How long are delays?
  - Which are easy preventable?
  - Which are difficult to prevent?
  - Which delays are not preventable?
- Calculate costs savings based on preventable delays
Paper 1: Effects of Condition-Based Maintenance on Costs caused by Unscheduled Maintenance of Aircraft

![Delay Distribution](image1)

![Delay Distribution](image2)
Paper 1: Effects of Condition-Based Maintenance on Costs caused by Unscheduled Maintenance of Aircraft

- 20% of delays can be prevented with existing sensors
- 80% of delays can be prevented with additional sensors
Paper 2: Decision Trees and the Effects of Feature Extraction Parameters for Robust Sensor Network Design

Eksploatacja i Niezawodnosc – Maintenance and Reliability (2017)

- Evaluate decision trees for classification
  - Easy to understand
  - Easy to modify
  - Established

- Evaluate influence of features
Paper 2: Decision Trees and the Effects of Feature Extraction Parameters for Robust Sensor Network Design

Method:
- PC fan data
  - With workday noise
  - One sample every 10 minutes
  - Different added weight
- Aircraft sensor data
- Parametric feature extraction
  - Mean/Max/Average
  - Time and Frequency domain
- Decision trees (C4.5)
Paper 2: Decision Trees and the Effects of Feature Extraction Parameters for Robust Sensor Network Design

Results:

- Feature extraction
  - Difficult to find the best parameter set
  - Classification accuracy is strongly influenced by quality of features

- Sensor Optimization
  - Decision trees help to find significant sensors
Paper 3: Automated Parameter Optimization for Feature Extraction for Condition Monitoring

14th IMEKO TC10 Workshop on Technical Diagnostics (2016)

- Improve accuracy of classification
  - Finding best feature extraction parameters
- Automated feature extraction
- Evaluate alternatives to decision trees
Paper 3: Automated Parameter Optimization for Feature Extraction for Condition Monitoring

- Different search algorithms
  - Genetic evolution
  - Greedy search
  - Simulated annealing

- Different classifiers
  - Decision trees
  - Support vector machines
  - Bayesian network
Paper 3: Automated Parameter Optimization for Feature Extraction for Condition Monitoring
Paper 3: Automated Parameter Optimization for Feature Extraction for Condition Monitoring

- Airbus Test Rig
- Sound and vibration data of High Pressure fan
- Two inlet and one outlet valve for clogging simulation
- 600 samples collected
  - 25 combinations (0°/0°/0°, 0°/0°/45°, 0°/45°/90°)
  - 24 samples per valve combination
Paper 3: Automated Parameter Optimization for Feature Extraction for Condition Monitoring

<table>
<thead>
<tr>
<th>Pattern Recognition Algorithm</th>
<th>Correctly Classified Samples</th>
<th>Training Time without optimization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision Trees</td>
<td>91.7 %</td>
<td>71 seconds</td>
</tr>
<tr>
<td>SVM</td>
<td>98.9 %</td>
<td>1860 seconds</td>
</tr>
<tr>
<td>Bayesian Network</td>
<td>98.9 %</td>
<td>193 seconds</td>
</tr>
</tbody>
</table>
Paper 3: Automated Parameter Optimization for Feature Extraction for Condition Monitoring

<table>
<thead>
<tr>
<th>Pattern Recognition Algorithm</th>
<th>Correctly Classified Samples</th>
<th>Training Time with optimization and 20 generations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision Trees</td>
<td>94.4 %</td>
<td>1381 seconds</td>
</tr>
<tr>
<td>SVM</td>
<td>99.4 %</td>
<td>12312 seconds</td>
</tr>
<tr>
<td>Bayesian Network</td>
<td>99.4 %</td>
<td>2791 seconds</td>
</tr>
</tbody>
</table>
Paper 3: Automated Parameter Optimization for Feature Extraction for Condition Monitoring

- Greedy search:
  - Fastest
  - Unlikely to find best set

- Simulated Annealing
  - Slowest
  - No better results than Greedy Search

- Genetic Evolution
  - Speed in the middle
  - Best results
Additional Validation Results (not published)

- Record sound and vibration
  - Fan
  - Filter

- Two valves
  - 1 inlet
  - 1 outlet

- Clog filter with dust
  - 25 gram steps
Additional Validation Results (not published)

- Detection of clogging possible (sound and vibration)
- High detection rate >90%
- Forests increase accuracy

<table>
<thead>
<tr>
<th>Dust</th>
<th>Classification results using 1 decision tree (samples per class)</th>
<th>Classification results using 3 decision trees (samples per class)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25 gram</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>50 gram</td>
<td>15</td>
<td>15</td>
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<tr>
<td>75 gram</td>
<td>15</td>
<td>15</td>
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<tr>
<td>100 gram</td>
<td>13</td>
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<td>125 gram</td>
<td>13</td>
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<td>150 gram</td>
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<tr>
<td>175 gram</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>200 gram</td>
<td>19</td>
<td>15</td>
</tr>
</tbody>
</table>
Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

International Journal of System Assurance Engineering and Management (2016)

- Improve decision tree results
  - How reliable a classification is

- Identify other likely conditions
  - Similarity of input to different classes
  - How close to “class border“
  - For failure diagnosis
Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

- Fuzzy decision tree classifications
- Weighting each tree node decision
  - Different weighting functions
  - Decision value is based on distance from node value
- One result value for each class
  - Result value for each class is max leaf value
- Decision Tree Forest
  - Each tree with a different feature set
Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

100 Hz = 7; 233 Hz = 40; 1023 Hz = 50

Input

- 0/0
  - 100 Hz >= 10
    - 1/1
      - 1023 Hz >= 23
        - No
          - Class 1
        - Yes
          - 233 Hz >= 45
            - No
              - Class 2
            - Yes
              - 0.85/1

- 100 Hz = 7; 233 Hz = 40; 1023 Hz = 50
  - 0/0
    - 100 Hz >= 10
      - 1/1
        - 1023 Hz >= 23
          - No
            - Class 1
          - Yes
            - 233 Hz >= 45
              - 1.41/2
                - No
                  - Class 1
                - Yes
                  - 2/2

Mike Gerdes
PhD Presentation, Dec 2019
Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

100 Hz >= 10

100 Hz = 7; 233 Hz = 40; 1023 Hz = 50

1023 Hz >= 23

1023 Hz = 7; 233 Hz = 40; 1023 Hz = 50

233 Hz >= 45

233 Hz = 40; 1023 Hz = 50

Class 1

Class 2

Class 3

Class 4

Class 1

Class 2

Class 3

Class 4

1.41/2

2/2

1.85/2

1.80/2

0.71

1

0.93

0.90
Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

- Airbus test rig
  - HP Fan and filter
  - One inlet (valve 1) and one outlet valve (valve 2)

- Clogging simulation by using valves
Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

- Similarity measurement
  - Base class „15/0“

<table>
<thead>
<tr>
<th>Valve2/Valve1</th>
<th>0</th>
<th>15</th>
<th>30</th>
<th>45</th>
<th>60</th>
<th>75</th>
<th>90</th>
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</thead>
<tbody>
<tr>
<td>0</td>
<td>0.5714</td>
<td>1</td>
<td>0.9213</td>
<td>0.5</td>
<td>0.65</td>
<td>0.7583</td>
<td>0.655</td>
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<tr>
<td>15</td>
<td>0.672</td>
<td>0.8357</td>
<td>0.6929</td>
<td>0.6667</td>
<td>0.6512</td>
<td>0.7278</td>
<td>0.4944</td>
</tr>
<tr>
<td>30</td>
<td>0.75</td>
<td>0.5</td>
<td>0.5</td>
<td>0.6</td>
<td>0.4444</td>
<td>0.5714</td>
<td>0.4286</td>
</tr>
<tr>
<td>45</td>
<td>0.65</td>
<td>0.75</td>
<td>0.5712</td>
<td>0.5667</td>
<td>0.25</td>
<td>0.5</td>
<td>0.25</td>
</tr>
</tbody>
</table>
Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

• Forest increases accuracy by 5%
  • From 94% to 99%
  • Improvement from paper 3
Paper 5: Decision Trees and Genetic Algorithms for Condition Monitoring
Forecasting of Aircraft Air Conditioning

Expert Systems With Applications (2013)

- Prediction of a health time series
  - Use time series features
  - Based on fuzzy decision tree classification
Paper 5: Decision Trees and Genetic Algorithms for Condition Monitoring Forecasting of Aircraft Air Conditioning

- Iterative prediction
  - Predict a single data point
  - Add data point to current history

- Training data
  - Parts of the time series
  - Set of extrapolation functions as classes
  - Class equals the best function for prediction
  - Test series contains irregularity
Paper 5: Decision Trees and Genetic Algorithms for Condition Monitoring Forecasting of Aircraft Air Conditioning
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Forecasting of Aircraft Air Conditioning
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Forecasting of Aircraft Air Conditioning

Results with 0% noise

![Graphs showing forecasting results with 0% noise](image-url)
Paper 5: Decision Trees and Genetic Algorithms for Condition Monitoring
Forecasting of Aircraft Air Conditioning

Results with 2% noise
- Only noisy test data
- Training and test data noisy
Paper 5: Decision Trees and Genetic Algorithms for Condition Monitoring
Forecasting of Aircraft Air Conditioning

Results with 5% noise
• Only noisy test data
• Training and test data noisy
Paper 6: Genetic Algorithms and Decision Trees for Condition Monitoring and Prognosis of A320 Aircraft Air Conditioning

Insight - Non-Destructive Testing and Condition Monitoring (2017)

- Real World Validation of Concept
  - A320 aircraft from ETIHAD Airways

- A320 air conditioning sensor data
  - 589 flights over 6 months

- Results were not as expected
  - Concept needed to be reworked
Paper 6: Genetic Algorithms and Decision Trees for Condition Monitoring and Prognosis of A320 Aircraft Air Conditioning

<table>
<thead>
<tr>
<th>Cabin Compartment Temperature Group</th>
<th>Zone Control</th>
<th>Numerical</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cabin Compartment Temperature Group 2</td>
<td>Zone Control</td>
<td>Numerical</td>
</tr>
<tr>
<td>Cabin Compartment Temperature Group 3</td>
<td>Zone Control</td>
<td>Numerical</td>
</tr>
<tr>
<td>Cabin Temperature Regulation Valve Position Group 1</td>
<td>Zone Control</td>
<td>Numerical</td>
</tr>
<tr>
<td>Cabin Temperature Regulation Valve Position Group 2</td>
<td>Zone Control</td>
<td>Numerical</td>
</tr>
<tr>
<td>Cabin Temperature Regulation Valve Position Group 3</td>
<td>Zone Control</td>
<td>Numerical</td>
</tr>
<tr>
<td>Duct Overheat Warning Group 1</td>
<td>Zone Control</td>
<td>Boolean</td>
</tr>
<tr>
<td>Duct Overheat Warning Group 2</td>
<td>Zone Control</td>
<td>Boolean</td>
</tr>
<tr>
<td>Duct Overheat Warning Group 3</td>
<td>Zone Control</td>
<td>Boolean</td>
</tr>
</tbody>
</table>
Paper 6: Genetic Algorithms and Decision Trees for Condition Monitoring and Prognosis of A320 Aircraft Air Conditioning

Iterative approach did not work
- Too much noise
- No clear degradation pattern

New concept
- Keep crisp classification process
- Use class switches for health prediction
- Health "classes" based on flight hours
  - Start of data is 0% degradation
  - End of data is 100% degradation
Paper 6: Genetic Algorithms and Decision Trees for Condition Monitoring and Prognosis of A320 Aircraft Air Conditioning
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Extrapolation of system health
- Linear prediction
- Non-Linear prediction

Prediction limited
- No prediction beginning at time 0
- 400+FH needed to prediction
- Simple and fast
Agenda

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Conclusion - Applications

- Onboard monitoring
  - Reduce unscheduled maintenance

- Offboard fleet monitoring
  - Identification of stressing routes
  - Identification of aircraft with high maintenance requirements
  - Maintenance planning and routing

- Parallel to fixed maintenance intervals
  - Collect data to validate change to fixed intervals
  - Perform maintenance based on actual condition
Conclusion - Challenges

- Needs a lot of data
- Training not online
- Training and sampling takes a lot of time
- Difficult to get samples of all system states
- More advanced method possible (depending on available computation power)
- Getting new sensoring equipment into an aircraft is a lot of work
  - Certification
  - Finding a partner
Conclusion - Future Work

- Integrate DecisionTree updating
- Use advanced feature extraction methods
  - Auto-correlation
  - Wavelets
- More Testing for Health prediction
  - More Data for validation
  - More classes for earlier and more detailed prediction
- Usage of better suited frameworks and languages
Conclusions - Summary

- The developed method allows a prediction of the health status of a complex system
- Many data samples are needed
- Basic and well researched methods were used
- Simulates expert knowledge and aircraft development methodology
- Tested with real and noise aircraft data for an unknown system