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

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Committee
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- Professor Giulio D'Emilia

Mike Gerdes
PhD Presentation, Dec 2019

Agenda

Background
Goals & Objectives
Methodology
Results
Conclusion

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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)

AIRBUS

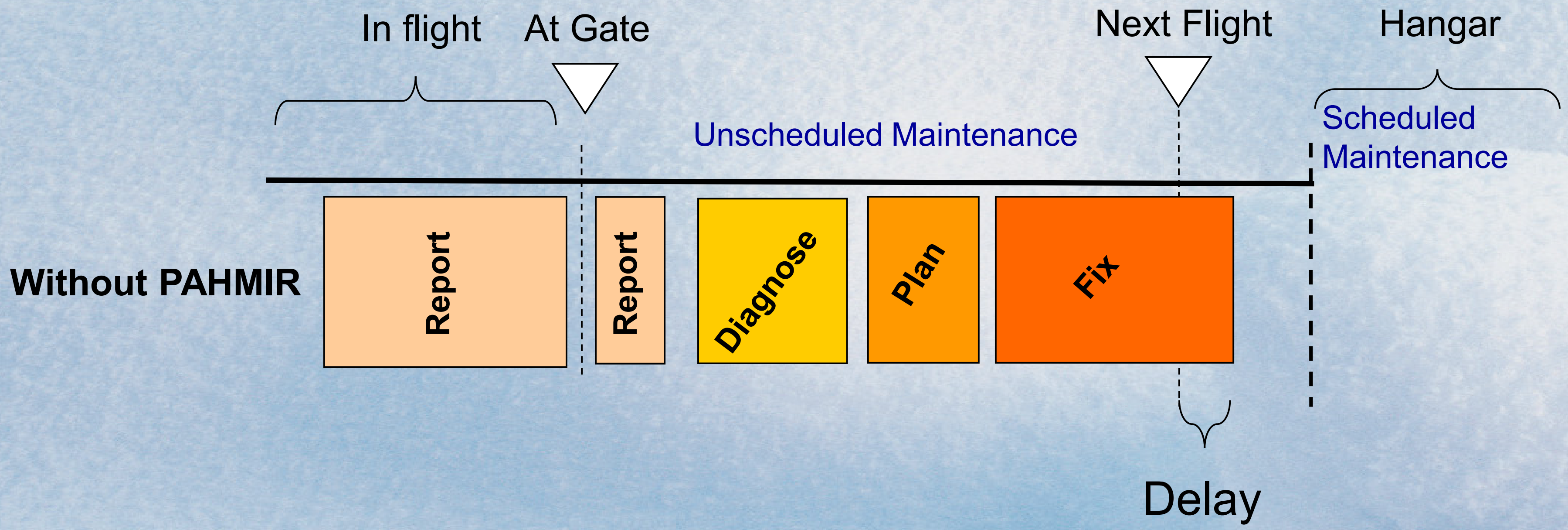
Hochschule für Angewandte Wissenschaften Hamburg
Hamburg University of Applied Sciences

Freie und Hansestadt Hamburg
Behörde für Wirtschaft und Arbeit

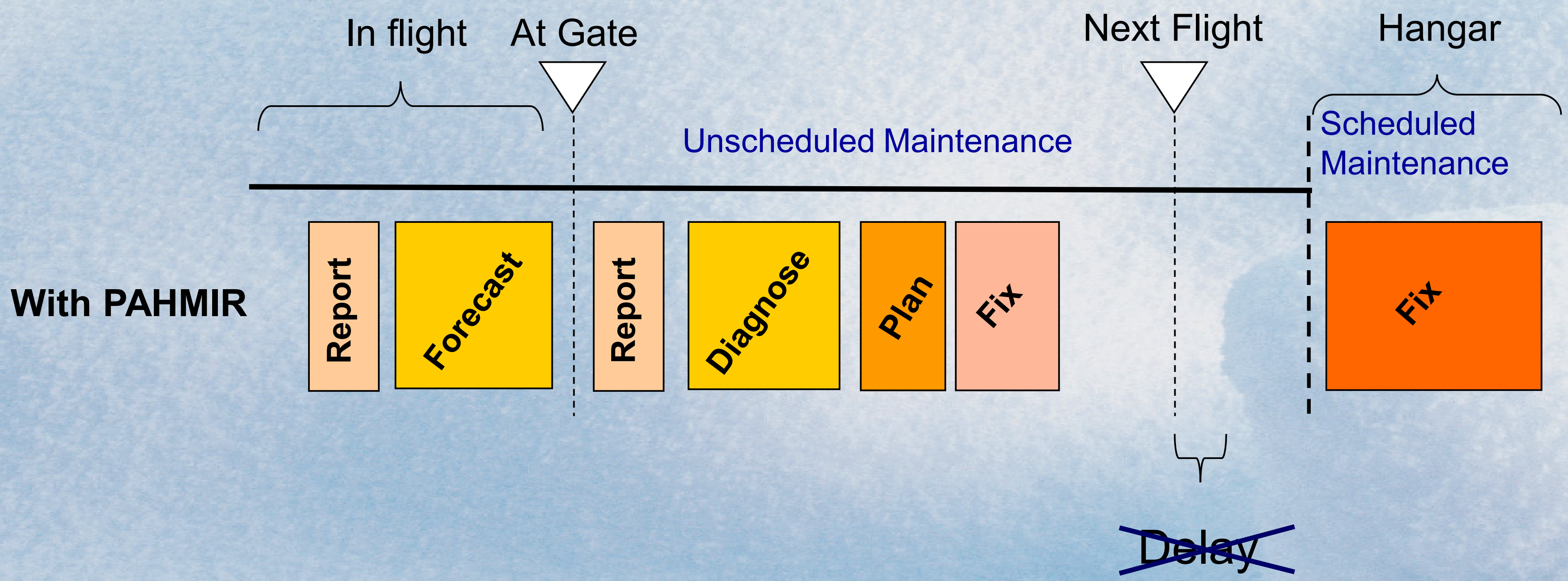
Background – PhD

- 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



Background - Motivation



Background - Topic Relevance

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


FlightGlobal
Pioneering Aviation Insight
NEWS & INSIGHT | HOW WE HELP | PRODUCTS & SERV

NEWS > MANUFACTURER & MRO > MRO > AIRBUS SEES BIG DATA DELIVERING 'ZERO-AOG' GOAL WITHIN 10 YEARS

Airbus sees big data delivering 'zero-AOG' goal within 10 years

12 DECEMBER, 2017 | SOURCE: FLIGHT DASHBOARD | BY: MAX KINGSLEY-JONES | LONDON

AOG = Aircraft on Ground
(2017)

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

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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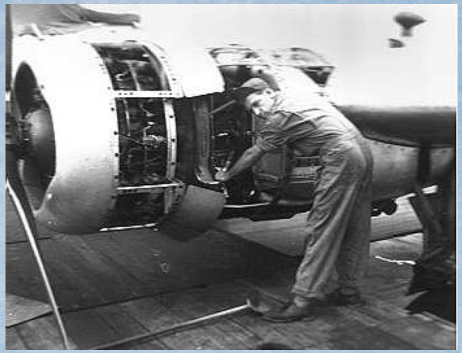
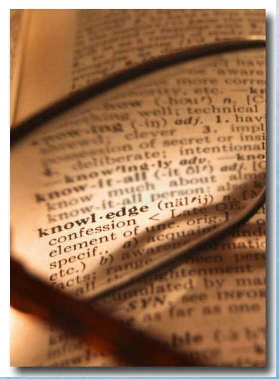
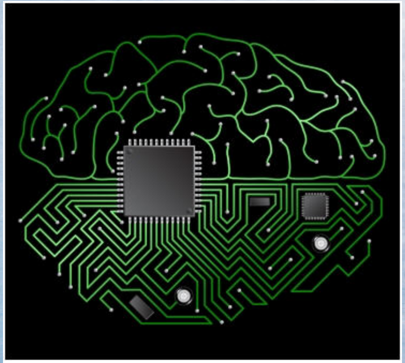
Goals

- Reduce Unscheduled Maintenance
  - Replace components before failure
- Reduce maintenance costs
  - Less unscheduled maintenance
- Use intelligent components
  - Integrated sensors







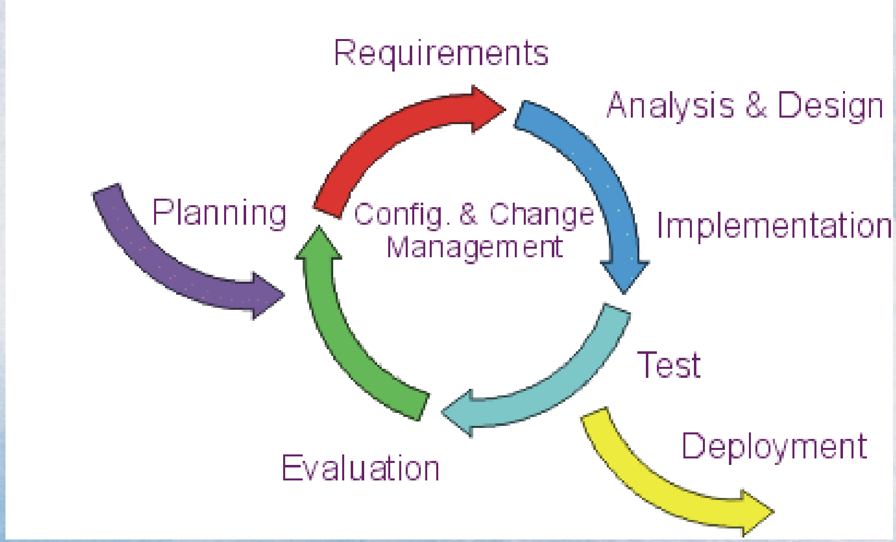
Objectives and Constrains

- 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)
- Complient to aircraft software development
- Complient to aircraft maintenance procedures
  - Not interfere with existing procedures
- Focus on air conditioning system
  - Active parts (fans)
  - Passive parts (ducts, valves)

Agenda

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 develoment 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)

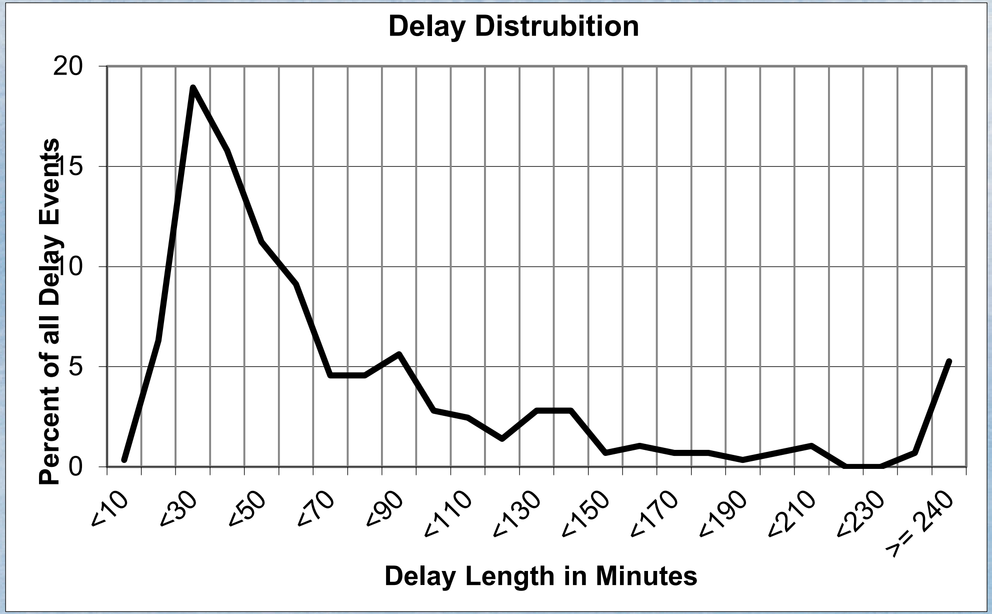
- Cost effects of predictive maintenance
  - Cost of 1 minute of delay is about 81 € (2015) (The Cost of Delay to Air Transport in Europe – Eurocontrol)
  - Cancellation is much much higher
- Analyse delays of aircraft air conditioning

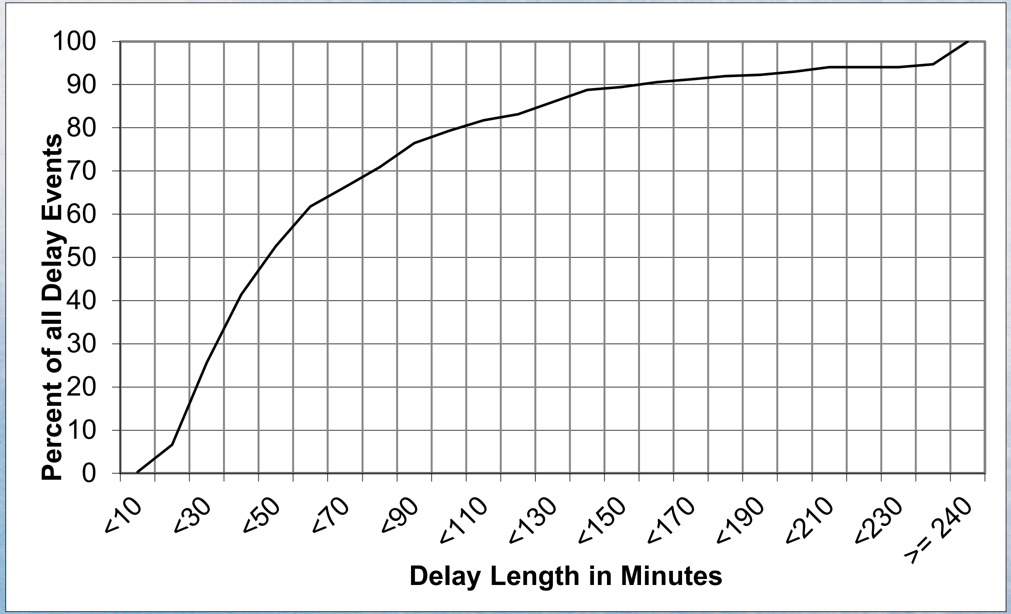
Paper 1: Effects of Condition-Based Maintenance on Costs caused by Unscheduled Maintenance of Aircraft

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

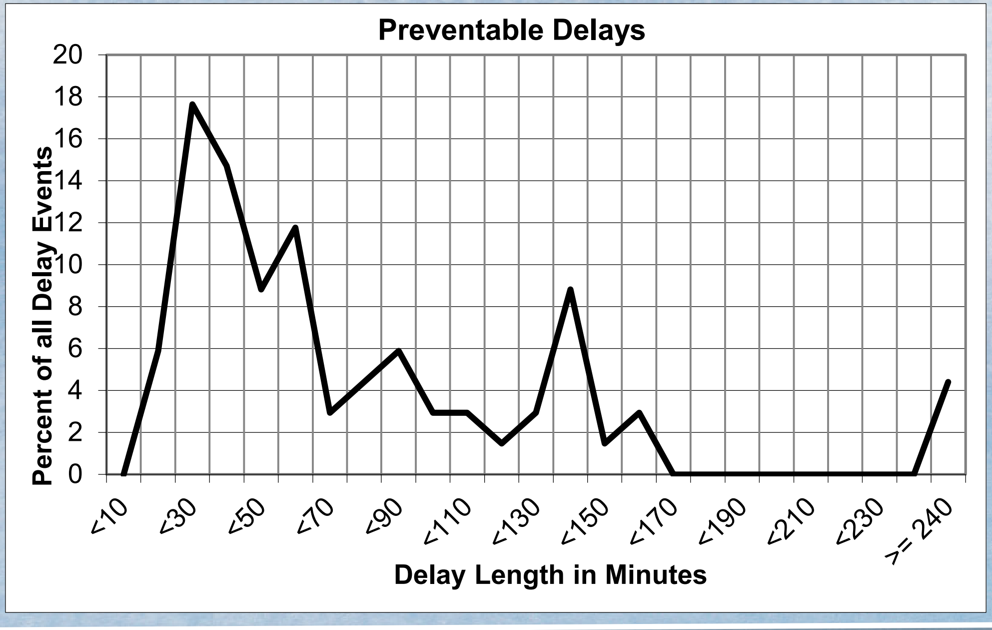
Paper 1: Effects of Condition-Based Maintenance on Costs caused by Unscheduled Maintenance of Aircraft

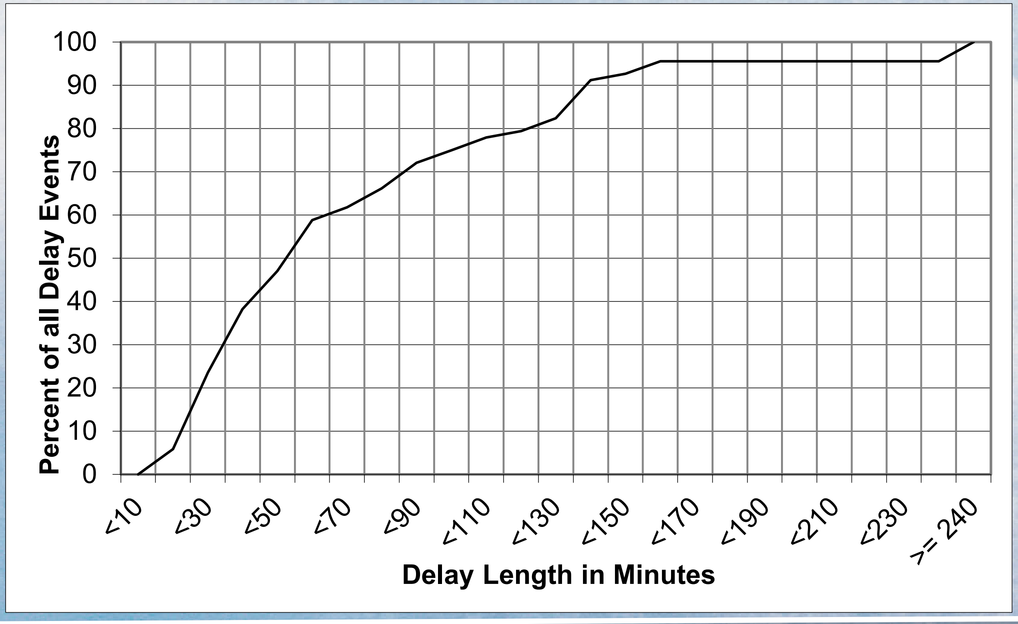




Paper 1: Effects of Condition-Based Maintenance on Costs caused by Unscheduled Maintenance of Aircraft

- 20% of delays can be prevented with existing sensors
- 80% of delays can be prevented with additional sensors



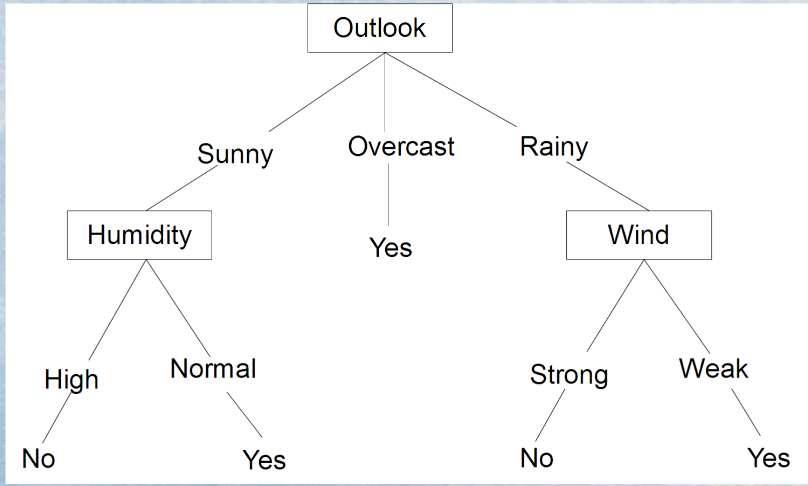


Paper 2: Decision Trees and the Effects of Feature Extraction Parameters for Robust Sensor Network Design

Eksploatacja i Niezawodnosc – Maintenance and Reliability (2017)

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

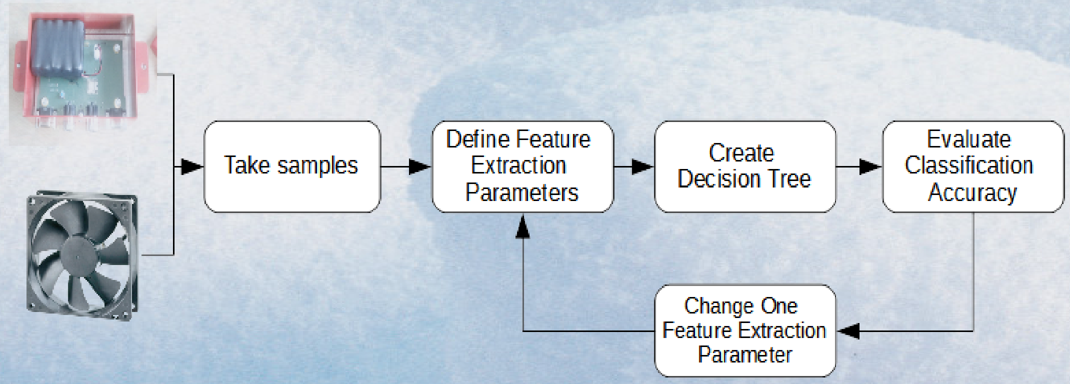
- Evaluate influence of features



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 weigth
- 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)

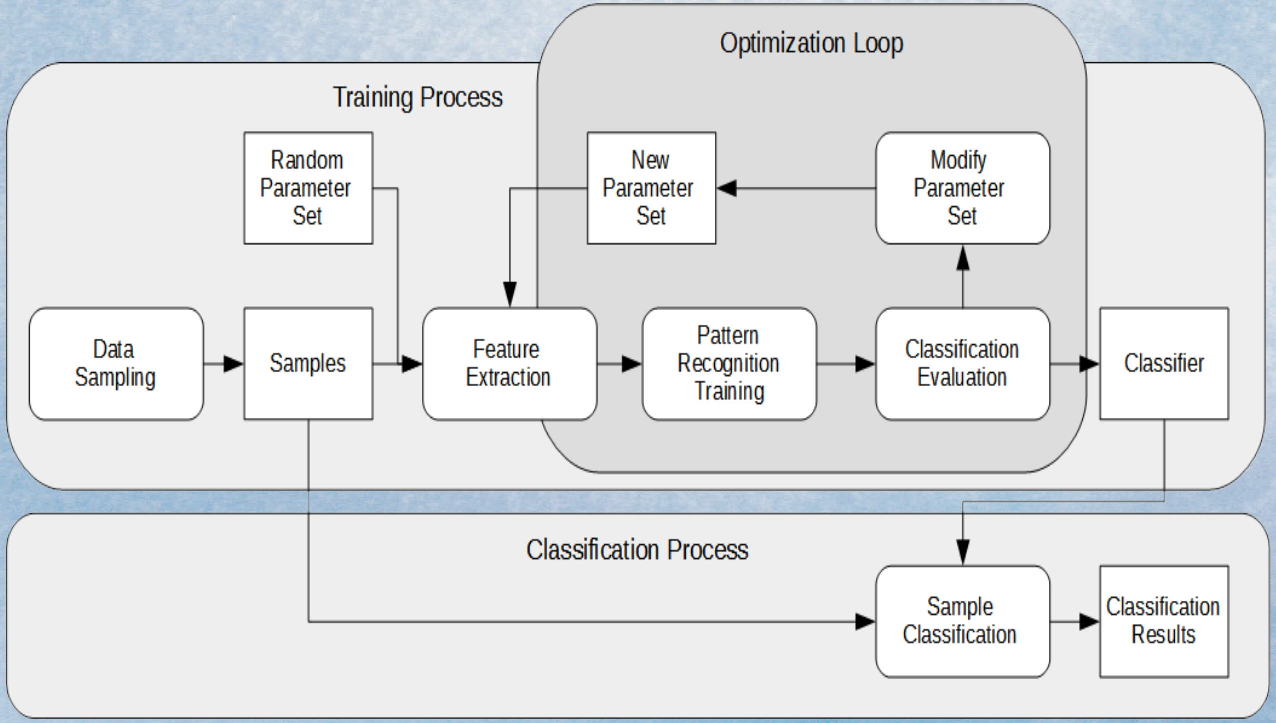
- Improve accuracy of classification
  - Finding best feature extraction parameters
- Automated feature extraction
- Evaluate alternatives to decision trees

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

Pattern Recognition Algorithm	Correctly Classified Samples	Training Time without optimization
Decision Trees	91.7 %	71 seconds
SVM	98.9 %	1860 seconds
Bayesian Network	98.9 %	193 seconds

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

Pattern Recognition Algorithm	Correctly Classified Samples	Training Time with optimization and 20 generations
Decision Trees	94.4 %	1381 seconds
SVM	99.4 %	12312 seconds
Bayesian Network	99.4 %	2791 seconds

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

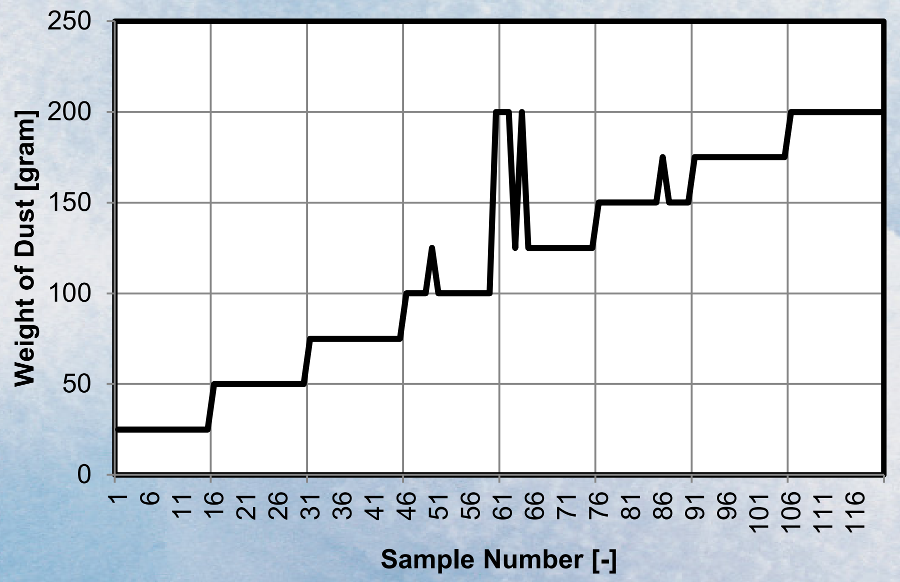
Additional Validation Results (not published)

- 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

Dust	Classification results using 1 decision tree (samples per class)	Classification results using 3 decision trees (samples per class)
25 gram	15	15
50 gram	15	15
75 gram	15	15
100 gram	13	13
125 gram	13	17
150 gram	14	14
175 gram	16	16
200 gram	19	15



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

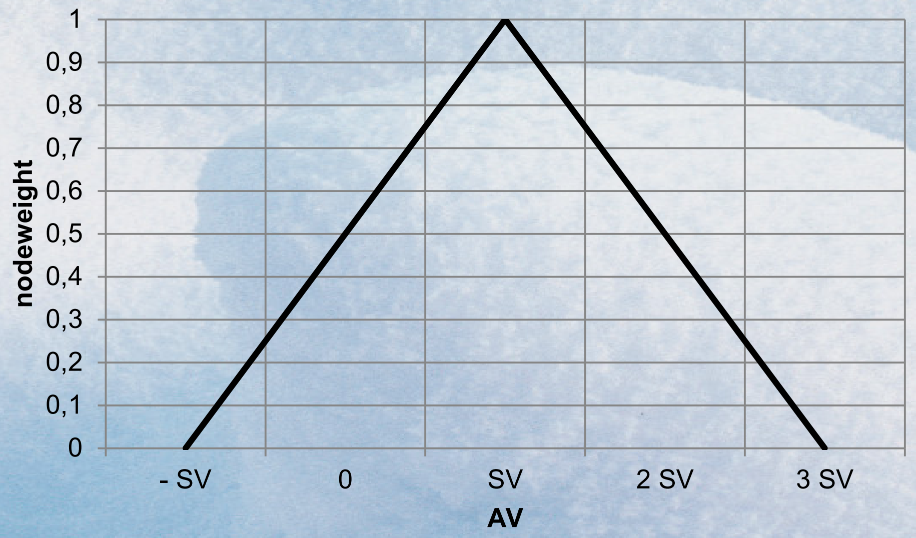
- Identify other likely conditions
  - Similarity of input to different classes
  - How close to „class border“
  - For failure diagnosis

Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

- Fuzzy decision tree classifications
- Weighting each tree node decision
  - Different weigthing 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



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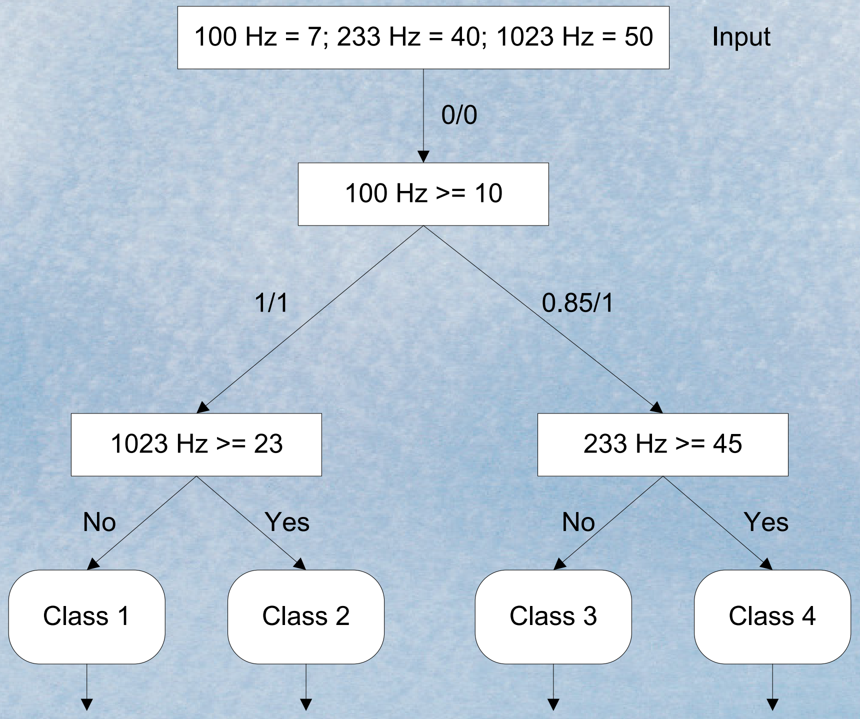

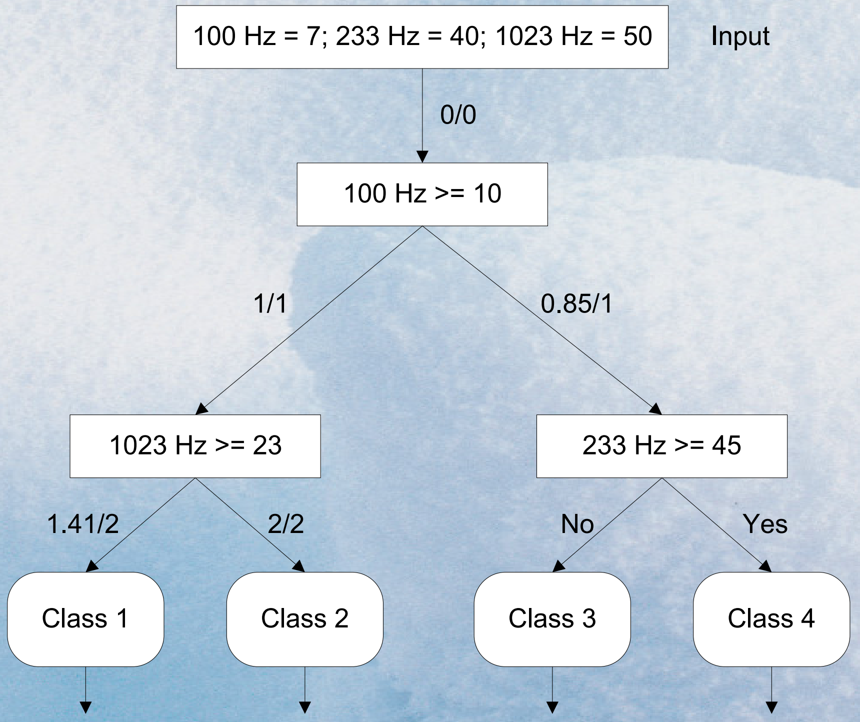

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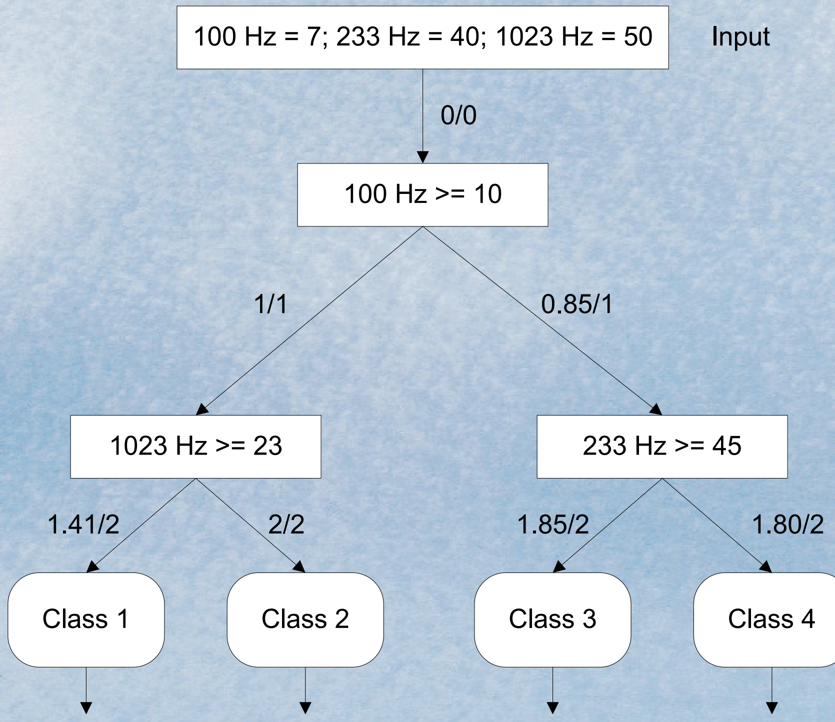
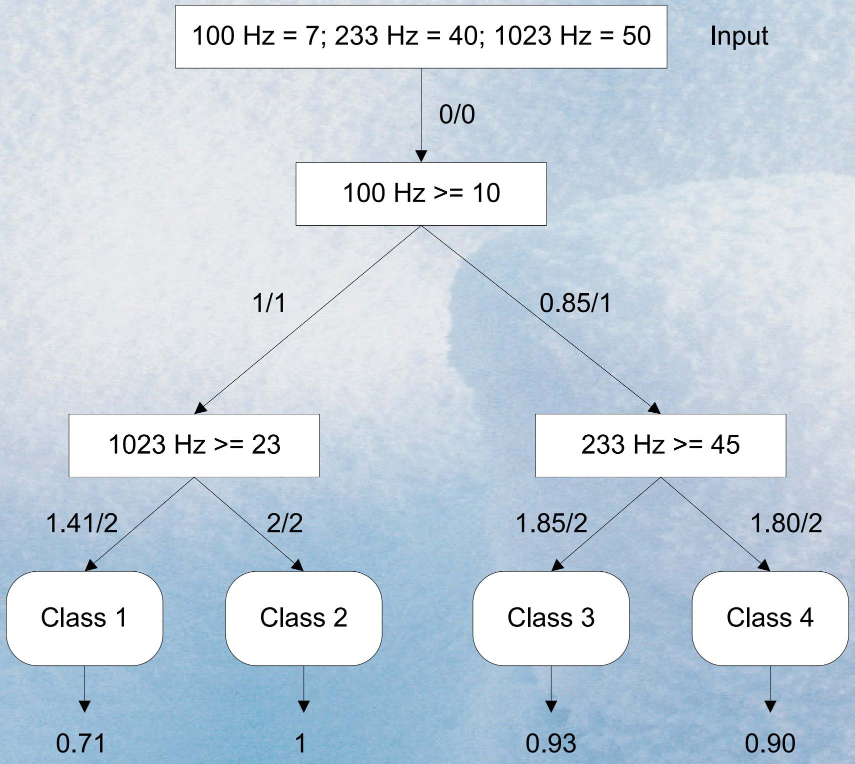




Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

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

- Cloggling simulation by using valves

Paper 4: Fuzzy Condition Monitoring of Recirculation Fans and Filters

- Similarity measurement
  - Base class „15/0“

Valve2/Valve1	0	15	30	45	60	75	90
0	0.5714	1	0.9213	0.5	0.65	0.7583	0.655
15	0.672	0.8357	0.6929	0.6667	0.6512	0.7278	0.4944
30	0.75	0.5	0.5	0.6	0.4444	0.5714	0.4286
45	0.65	0.75	0.5712	0.5667	0.25	0.5	0.25

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

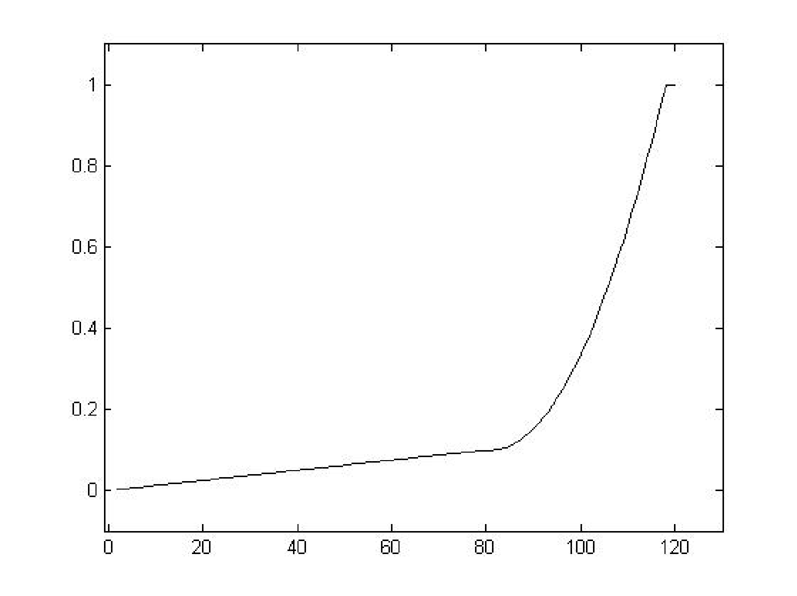
Expert Systems With Applications (2013)

- 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



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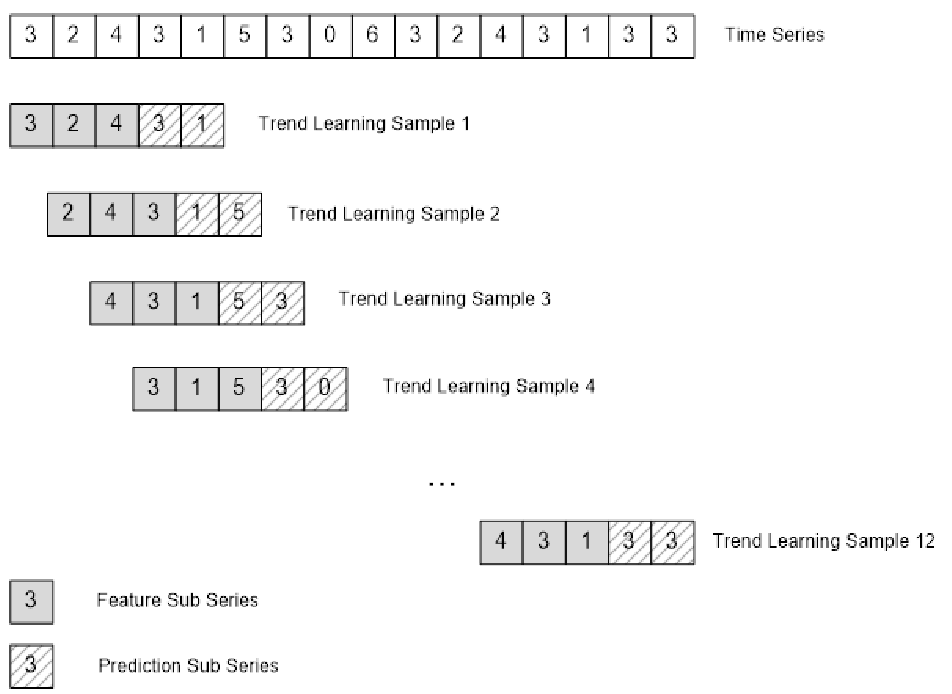

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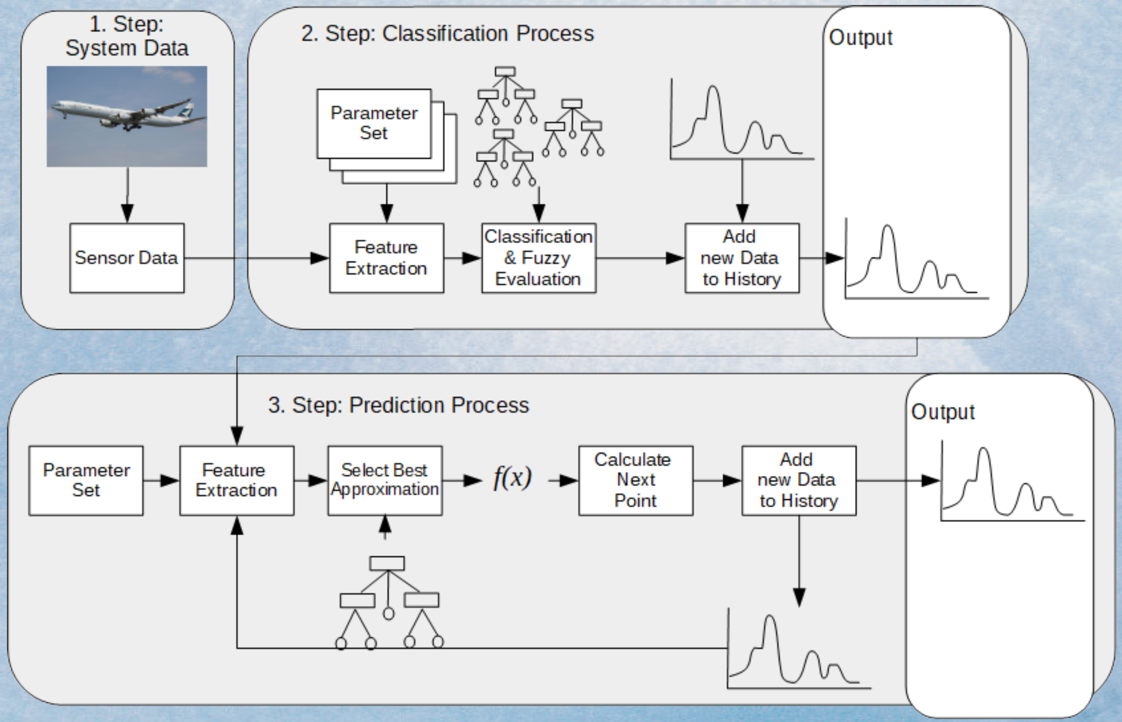

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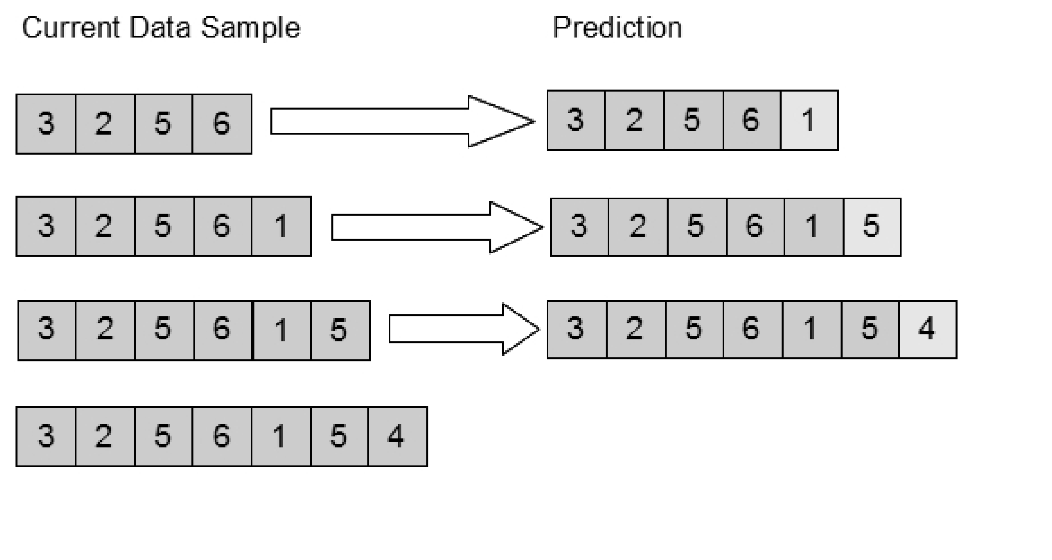
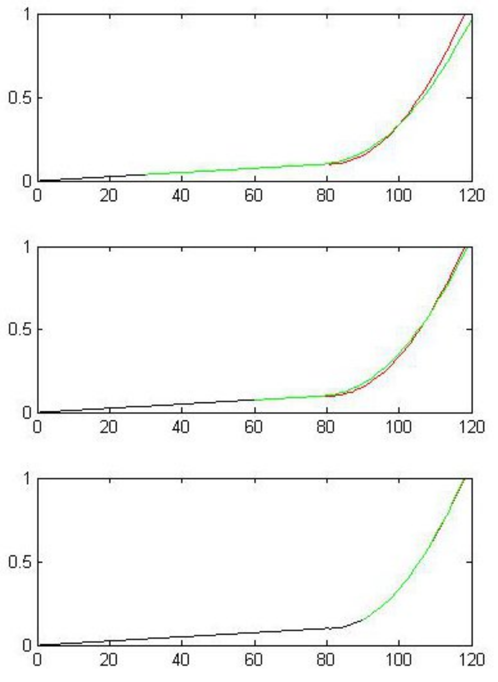


Paper 5: Decision Trees and Genetic Algorithms for Condition Monitoring Forecasting of Aircraft Air Conditioning

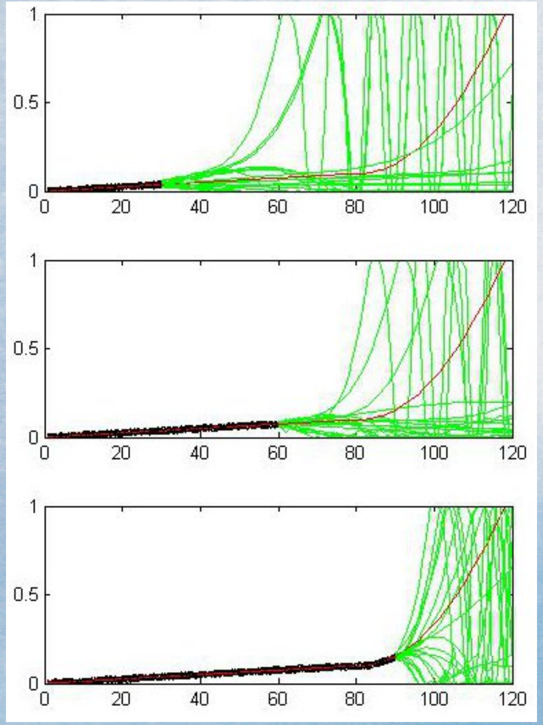
Results with 0% noise

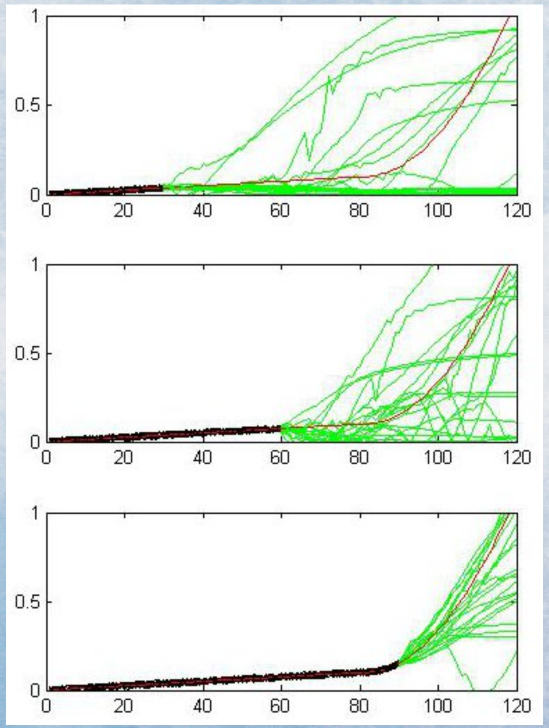


Paper 5: Decision Trees and Genetic Algorithms for Condition Monitoring Forecasting of Aircraft Air Conditioning

Results with 2% noise

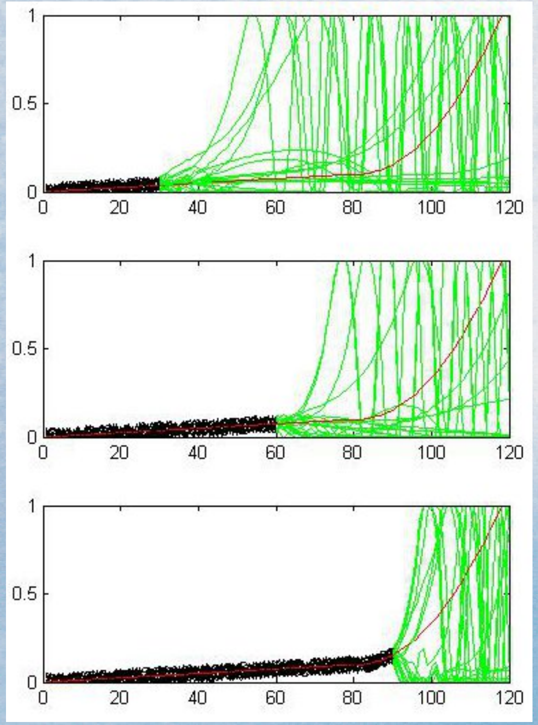
- Only noisy test data
- Training and test data noisy

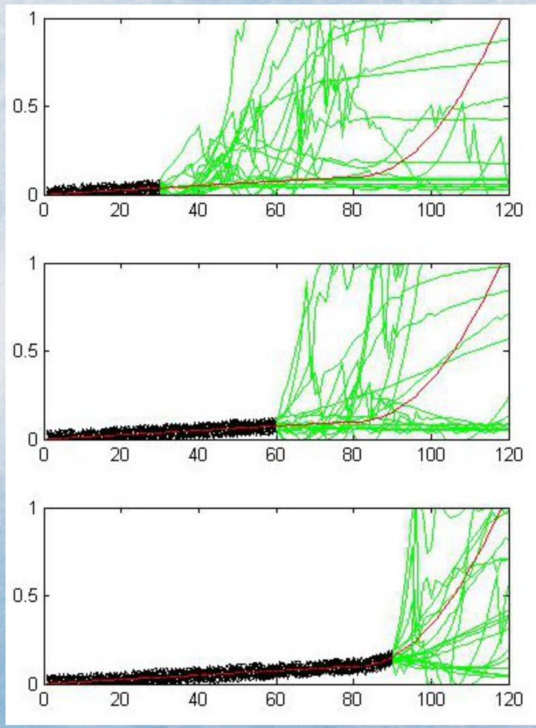




Paper 5: Decision Trees and Genetic Algorithms for Condition Monitoring Forecasting of Aircraft Air Conditioning

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

Cabin Compartment Temperature Group 1	Zone Control	Numerical
Cabin Compartment Temperature Group 2	Zone Control	Numerical
Cabin Compartment Temperature Group 3	Zone Control	Numerical
Cabin Temperature Regulation Valve Position Group 1	Zone Control	Numerical
Cabin Temperature Regulation Valve Position Group 2	Zone Control	Numerical
Cabin Temperature Regulation Valve Position Group 3	Zone Control	Numerical
Duct Overheat Warning Group 1	Zone Control	Boolean
Duct Overheat Warning Group 2	Zone Control	Boolean
Duct Overheat Warning Group 3	Zone Control	Boolean

Paper 6: Genetic Algorithms and Decision Trees for Condition Monitoring and Prognosis of A320 Aircraft Air Conditioning

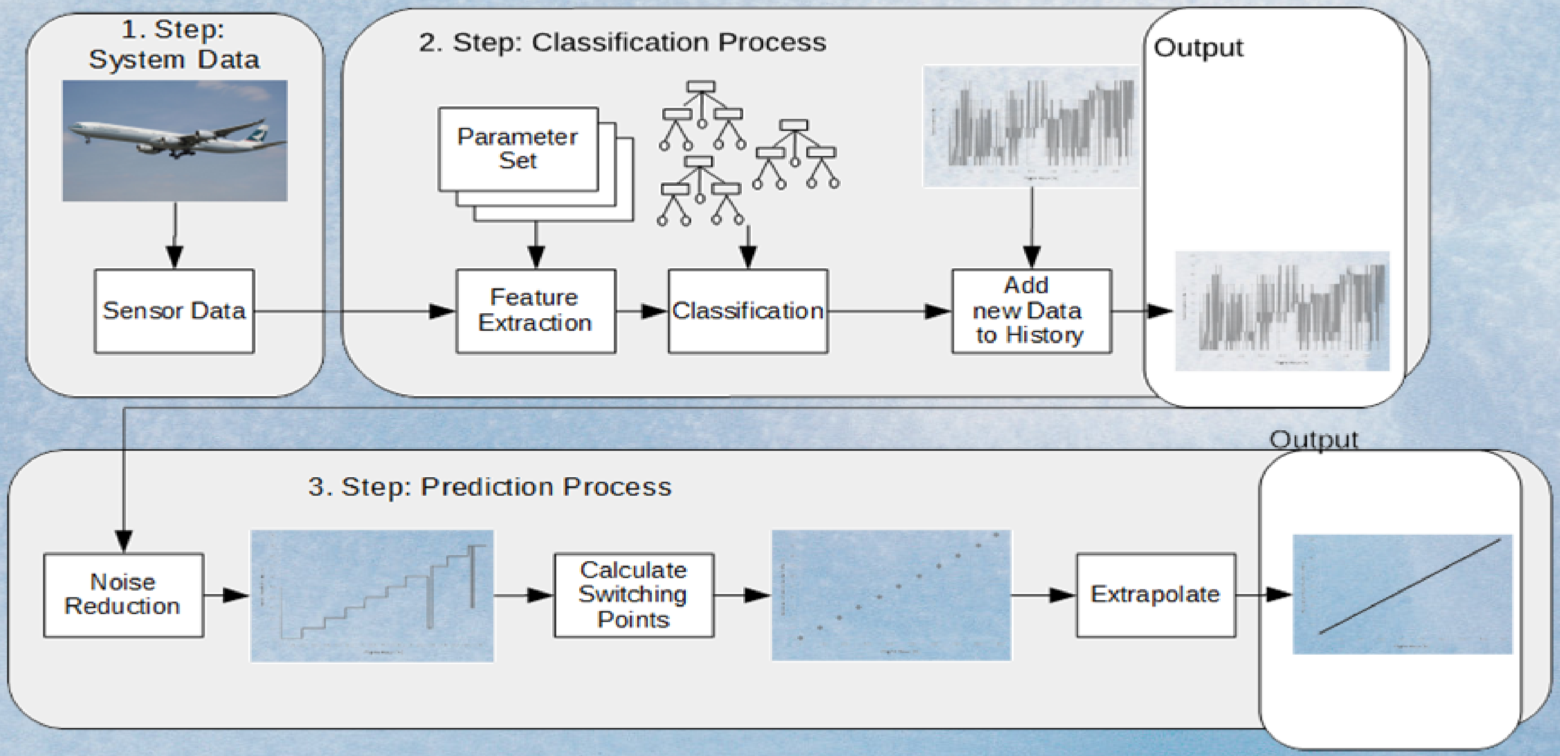
Iterative approach did not work

- Too much noise
- No clear degradation pattern

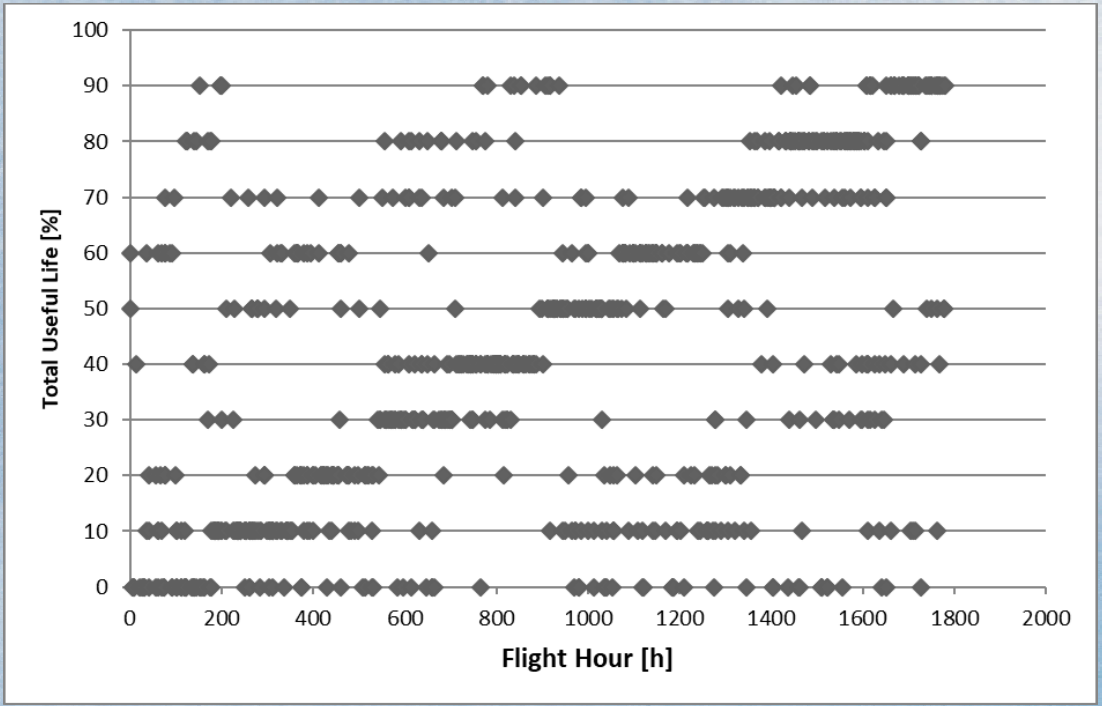
New concept

- Keep crisp classification process
- Use class switches for health prediction
- Health „classes“ based on flight hours
  - Start of data is 0% degration
  - End of data is 100% degration

Paper 6: Genetic Algorithms and Decision Trees for Condition Monitoring and Prognosis of A320 Aircraft Air Conditioning

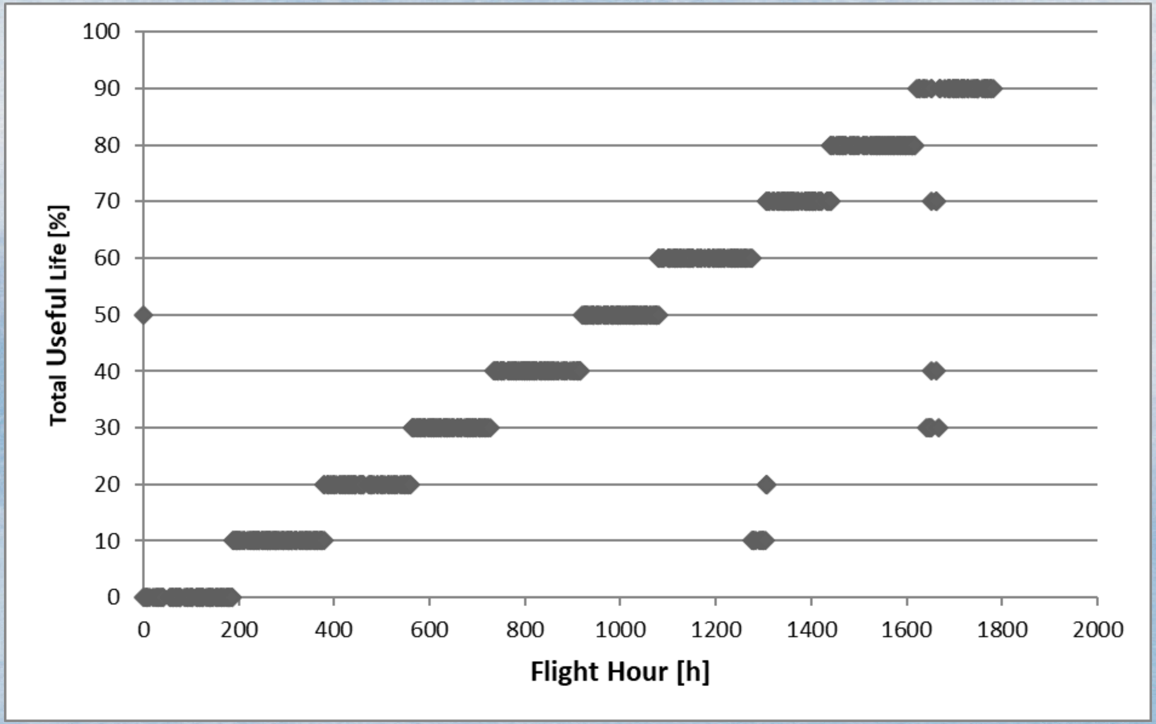


Paper 6: Genetic Algorithms and Decision Trees for Condition Monitoring and Prognosis of A320 Aircraft Air Conditioning



Classification/ Class	0	10	20	30	40	50	60	70	80	90
0	0	36	24	23	10	24	29	16	28	6
10	19	0	40	3	4	45	21	12	1	17
20	16	38	0	4	0	29	68	9	0	0
30	28	0	3	0	37	8	6	12	72	4
40	16	6	0	45	0	9	0	20	38	29
50	21	49	28	0	4	0	36	9	0	32
60	30	48	35	1	0	42	0	7	0	0
70	31	30	11	38	20	21	32	0	29	6
80	29	0	0	67	55	0	0	25	0	13
90	23	20	0	10	46	23	0	6	17	0

Paper 6: Genetic Algorithms and Decision Trees for Condition Monitoring and Prognosis of A320 Aircraft Air Conditioning

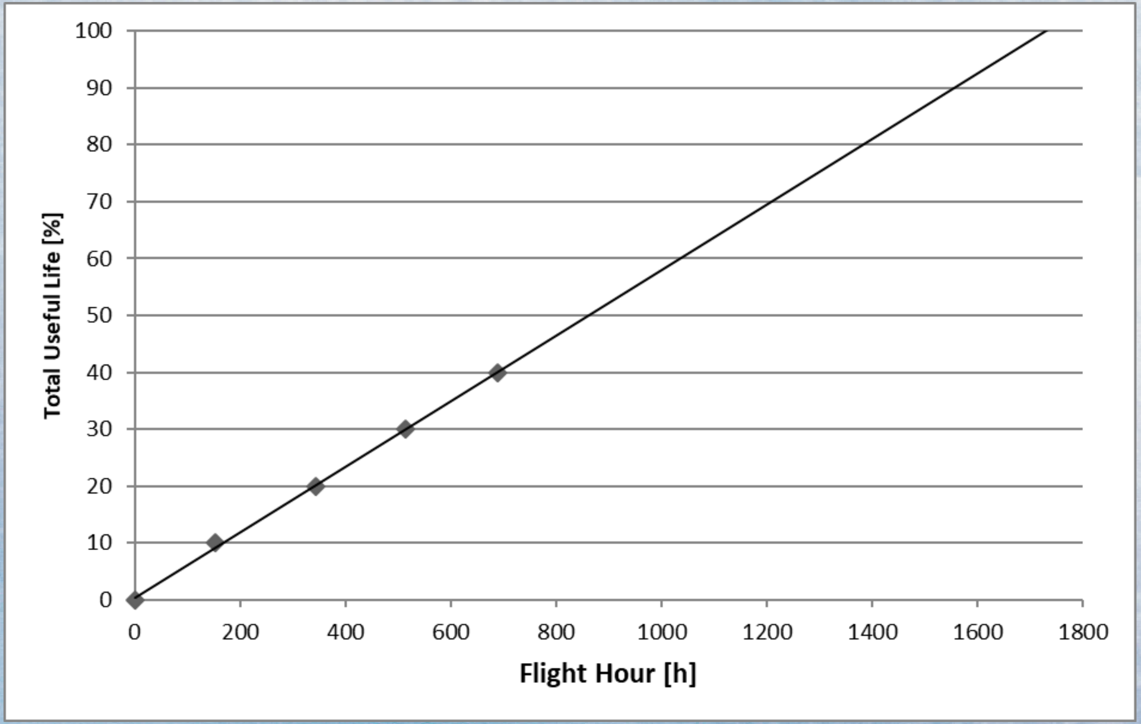


Classification/ Class	0	10	20	30	40	50	60	70	80	90
0	0	21	32	21	7	8	9	6	7	47
10	22	0	32	25	9	23	18	21	10	24
20	23	19	0	36	36	8	17	6	2	25
30	26	49	35	0	54	15	16	0	0	0
40	31	4	29	32	0	36	8	0	0	0
50	16	15	28	41	34	0	20	0	0	0
60	19	22	15	16	5	10	0	10	27	23
70	14	21	15	0	0	0	51	0	25	54
80	2	5	6	0	0	0	68	43	0	73
90	30	28	29	0	0	0	33	48	46	0

Paper 6: Genetic Algorithms and Decision Trees for Condition Monitoring and Prognosis of A320 Aircraft Air Conditioning

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

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 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

Conculsions - 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