Propulsion Diagnostic Method Evaluation Strategy (ProDiMES): Public Benchmarking Results

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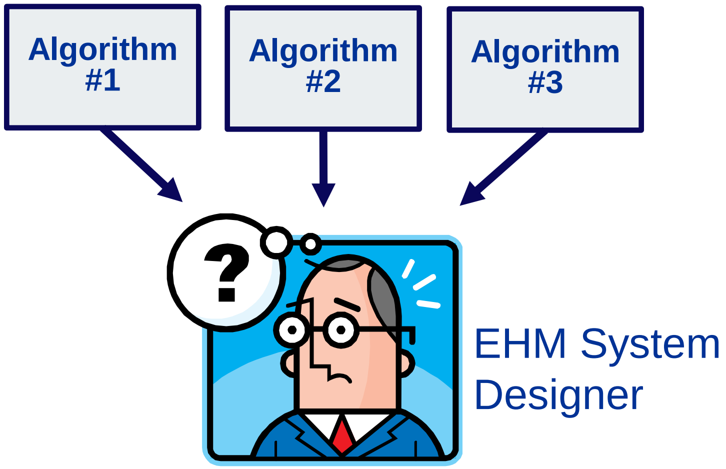
Outline

- Background and <u>Pro</u>pulsion <u>Di</u>agnostic <u>M</u>ethod <u>E</u>valuation <u>S</u>trategy (ProDiMES) Overview
- Review of gas path diagnostic methods applied to ProDiMES
- Blind-test-case results
- Lessons learned and recommendations for improvement
- Summary

Background: Public Benchmarking of Engine Health Management Methods

- NASA Glenn sponsored a survey of advancements in aircraft Engine Health Management (EHM) technologies with Scientific Monitoring, Inc.
- Survey results showed that often …
  - Terminologies are different
  - Algorithms are different
  - Applications are different
  - Presentations are different
- → No basis of comparison

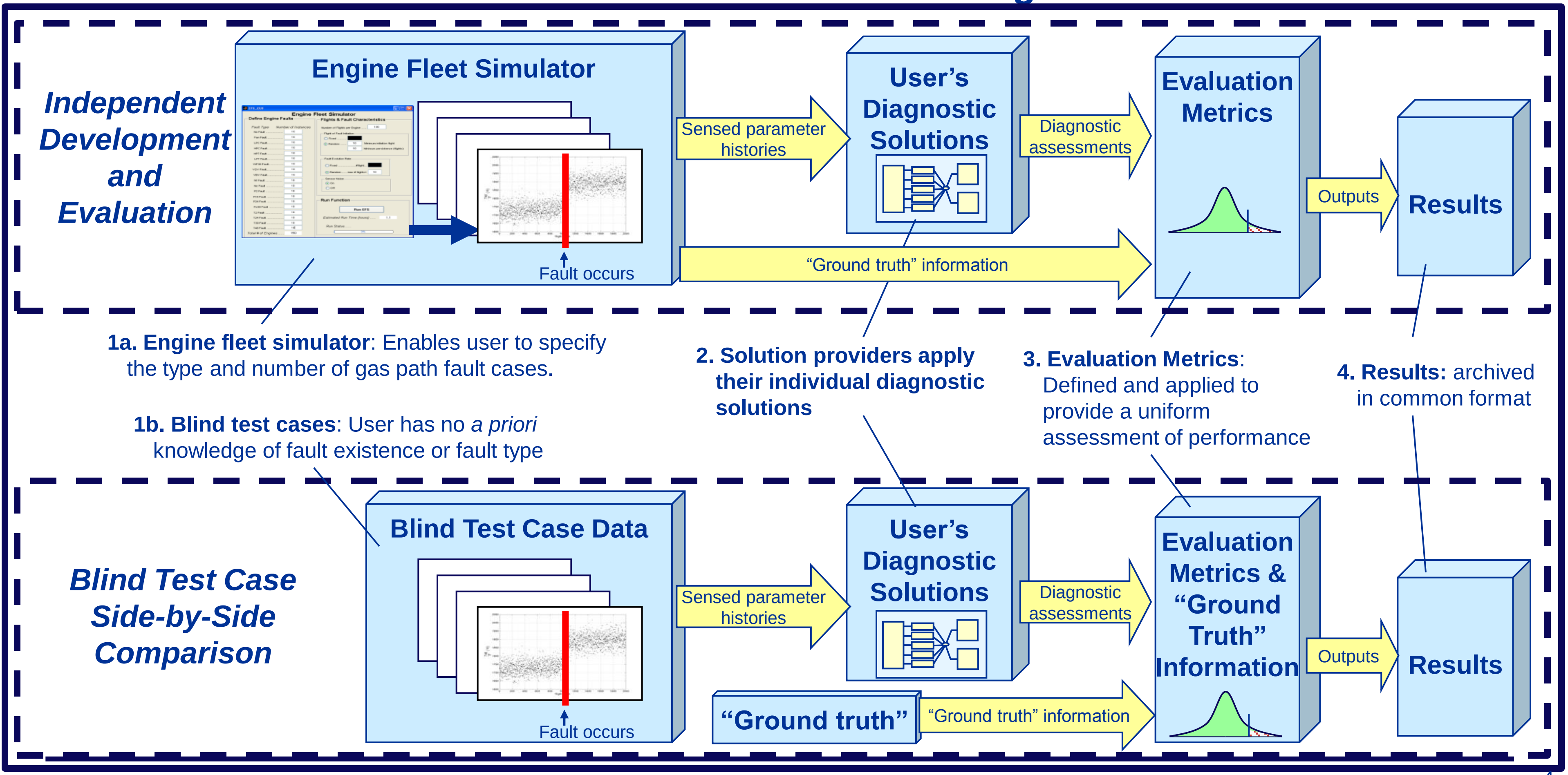


- Recommendation: Define and put forth standardized EHM benchmark problems to compare the merits of different EHM approaches
- Propulsion Diagnostic Method Evaluation Strategy (ProDiMES)
  - An aircraft engine gas path diagnostic benchmarking problem created to facilitate the initial development and comparison of candidate diagnostic methodologies
  - Constructed with support from industry and other government organizations

Propulsion Diagnostic Method Evaluation Strategy (ProDiMES) Overview

- Simulated problem coded in MATLAB
- Available through the NASA Glenn Software Catalog

ProDiMES Public Benchmarking Process



ProDiMES: Gas Path Fault Types and Sensed Parameters

ProDiMES Simulates 18 fault types

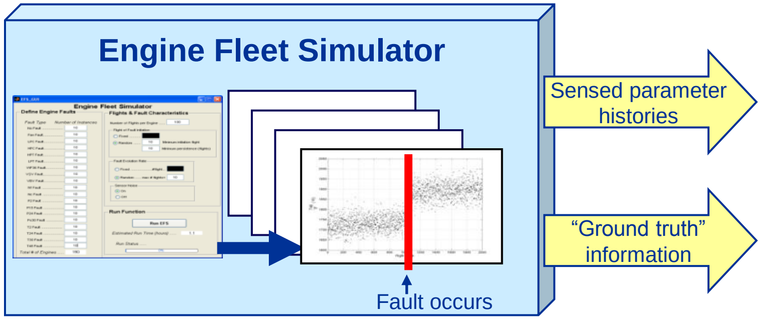
- Turbomachinery, actuator, and sensor faults
- Faults vary in magnitude
- Faults vary in evolution rate (abrupt or rapid)

Fault ID	Fault Type
0	No fault
1	Fan
2	LPC
3	HPC
4	HPT
5	LPT
6	VSV
7	VBV
8	Nf
9	Nc
10	P24
11	Ps30
12	T24
13	T30
14	T48
15	WF36
16	P2
17	T2
18	Pamb

ProDiMES Sensed Parameters

- 8 engine gas path measurements including fuel flow
- 3 environmental parameters (P2, T2, Pamb)
- Collected each flight at takeoff and cruise

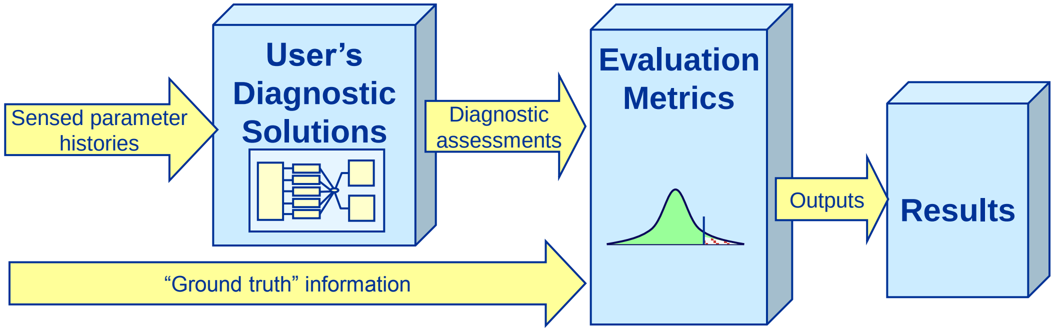
index	symbol	description	units
1	Nf	physical fan speed	rpm
2	Nc	physical core speed	rpm
3	P24	total pressure at LPC outlet	psia
4	Ps30	Static pressure at HPC outlet	psia
5	T24	total temperature at LPC outlet	ºR
6	T30	total temperature at HPC outlet	ºR
7	T48	total temperature at HPT outlet	ºR
8	Wf	fuel flow	pps
9	P2	total pressure at fan inlet	psia
10	T2	total temperature at fan inlet	ºR
11	Pamb	ambient pressure	psia



ProDiMES: Diagnostic Solutions and Metrics

- Diagnostic solutions: designed to process sensed parameter histories and produce a diagnostic assessment for each engine, each flight

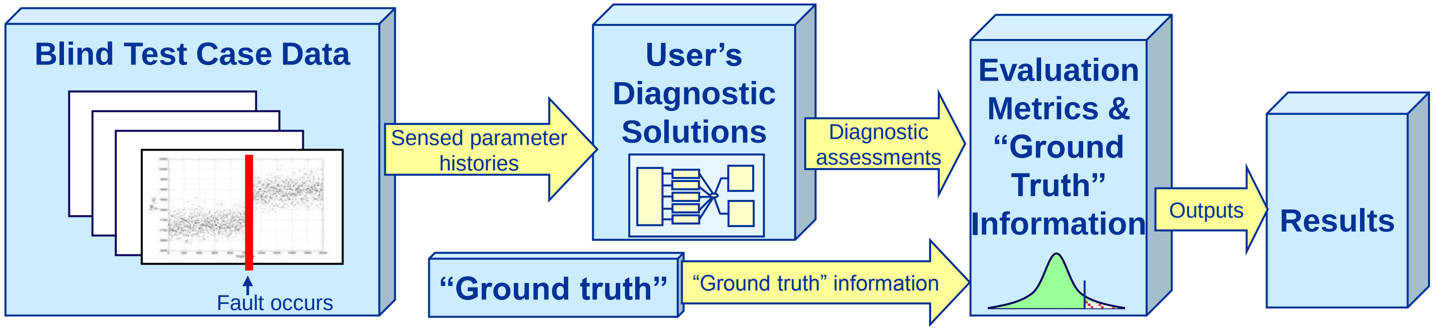
- Metrics: A provided Matlab metrics evaluation routine compares diagnostic assessments against ground-truth fault information and automatically calculates and archives results. Metrics include:
  - Fault detection performance
    - True positives
    - True negatives
    - False negatives (missed detections)
    - False positives (false alarms)
  - Fault classification performance
    - Correct classification rate
    - Mis-classification rate
    - Kappa Coefficient
  - Diagnostic latency
    - # of flights required to diagnose a fault



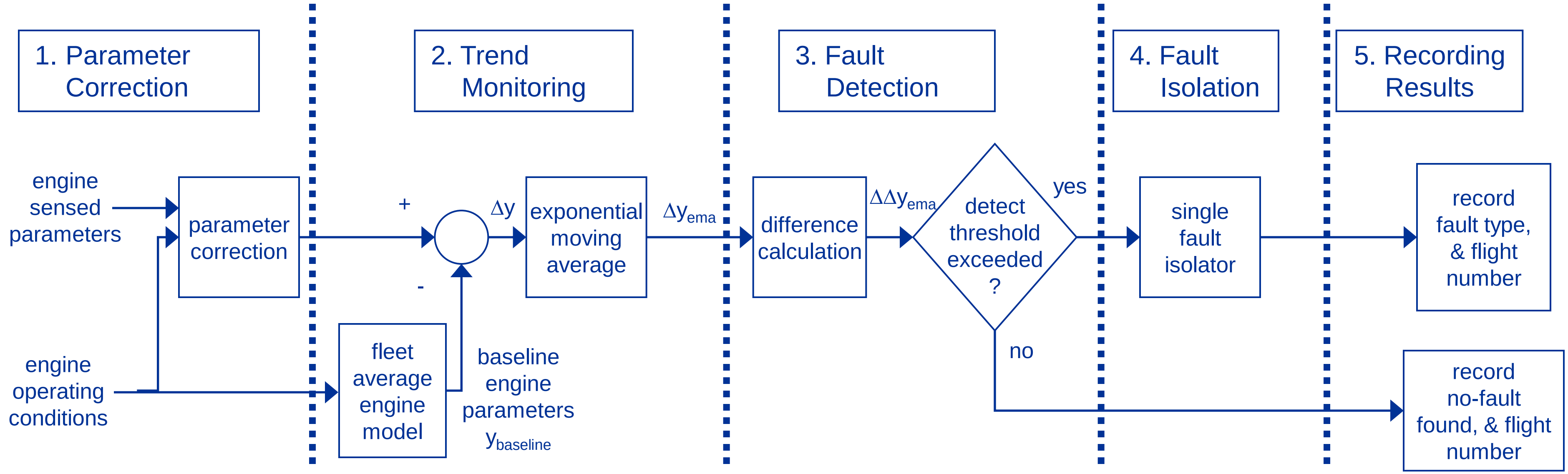
- Emphasis placed on early correct diagnosis of faults
  - Fault detection and classification metrics only evaluated within finite "diagnostic window" of time (diagnostic window = 10 flights for abrupt faults and 15 flights for rapid faults)

ProDiMES: Blind Test Case Data

- Includes data from approximately 10,000 engines
- A target false positive detection rate (false alarm rate) of once per 1,000 flights is specified
- Blind test case diagnostic assessments are submitted to NASA for evaluation
- Participants receive their own blind test case metric results, plus the anonymous results of other participants



Review of gas path diagnostic methods applied to ProDiMES



Example Gas Path Diagnostic Process

All four gas path diagnostic methods applied to ProDiMES followed similar functional steps consisting of trend monitoring, fault detection, and fault isolation. However, the underlying approaches applied to implement those steps varied.

Summary of Gas Path Diagnostic Methods Applied to ProDiMES

1) Weighted least squares single fault isolation (NASA)
   - Model-based fault isolation approach
2) Probabilistic neural network single fault isolation (NASA)
   - Data-driven fault isolation approach
   - Applies same fault detection logic as diagnostic method #1
3) Performance analysis tool (University of Liège)
   - Applies model-based sparse estimation fault isolation approach
   - Ad hoc logic included to improve detectability of some fault types
4) Generalized observer/estimator for single fault isolation (Wright State University)
   - Nonlinear model-based diagnostic approach
   - Ad hoc logic included to improve detectability of some fault types

Reference: Simon, D.L., Borguet, S., Léonard, O., Zhang, X., (2013), "Aircraft Engine Gas Path Diagnostic Methods: Public Benchmarking Results," ASME-GT2013-95077, 2014 ASME Turbo Expo Conference, San Antonio, TX, June 3-7.

Blind-Test-Case Metric Results: Detection Performance

False Positive Rate (FPR)

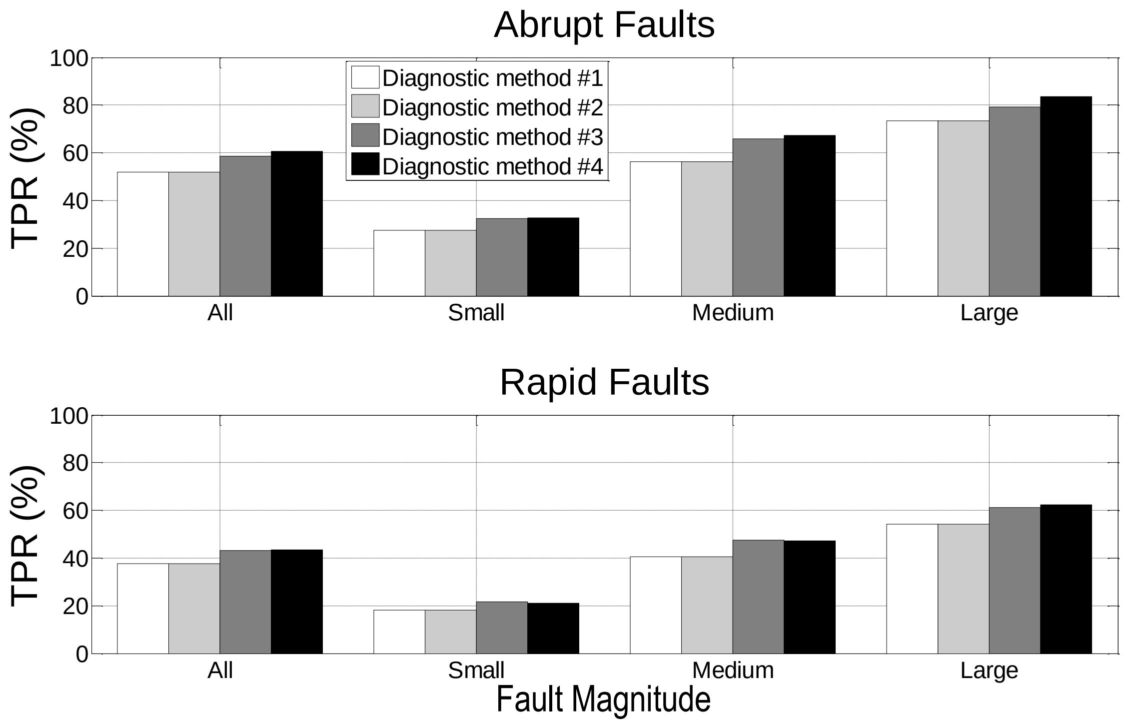
Diagnostic method	FPR	(average # flights per false alarm)
1 & 2	0.09203%	1087
3	0.09240%	1082
4	0.09352%	1069

True Positive Rate (TPR)

Diagnostic method	TPR
1 & 2	44.7%
3	50.9%
4	51.9%

Average Detection Latency

Diagnostic method	Latency (average # flights)
1 & 2	4.86
3	4.02
4	4.24



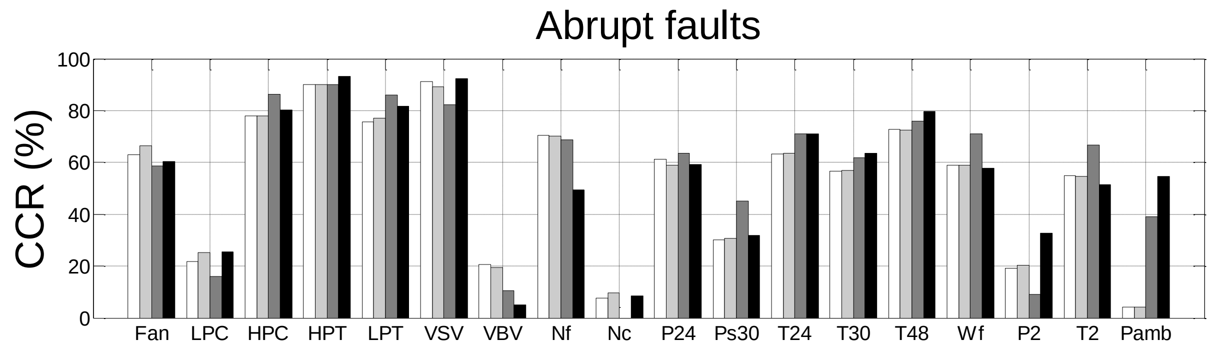
True Positive Rate (TPR)

- All methods satisfy the false positive rate requirement of < 1 false alarm per 1000 flights
- True positive rate (TPR) diagnostic latency results show (as expected)
  - Abrupt faults are easier to detect than rapid faults
  - Larger faults are easier to detect than small faults
- Diagnostic methods #3 and #4 provide better fault detection than method #1 & 2

Blind-Test-Case Metric Results: Classification Performance

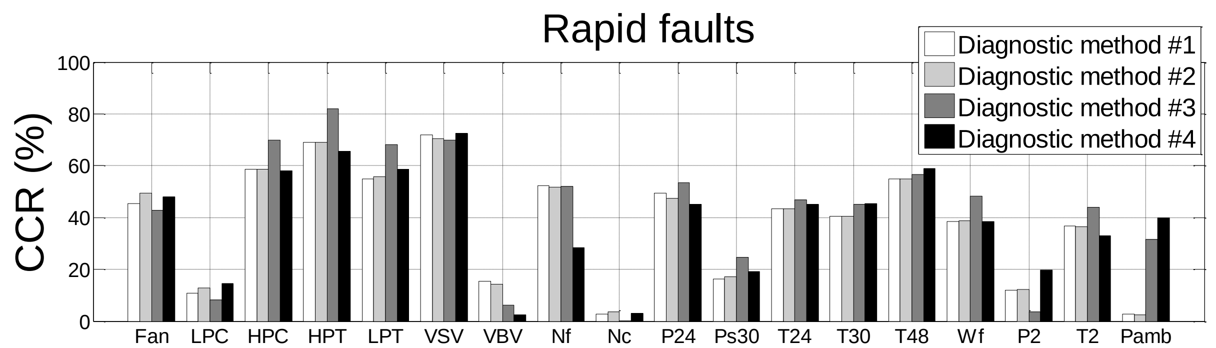
Kappa Coefficient

Diagnostic method	Kappa coefficient
1	0.588
2	0.590
3	0.627
4	0.617



Correct Classification Rate (CCR) and Misclassification Rate (MCR)

Diagnostic method	CCR	MCR
1	43.4%	1.35%
2	43.7%	1.04%
3	46.7%	4.15%
4	45.2%	6.78%



Correct Classification Rate

- Diagnostic method #3 provides the best Kappa coefficient and correct classification rate (CCR), followed by methods #4, #2, and #1
- Diagnostic methods #1 and #2 provide the best (lowest) misclassification rate (MCR) results
- Results show that certain faults are easier to classify (i.e., HPC, HPT, LPT, VSV), while others are more challenging (i.e., VBV, Nc, P2, Pamb)

Blind-Test-Case Metric Results: Overall Metric Rankings

Diagnostic Method Ranking for Each Metric

Diagnostic method	FPR rank	TPR rank	Detection latency rank	Kappa coefficient rank	CCR rank	MCR rank
1	3rd	3rd	3rd	4th	4th	2nd
2	3rd	3rd	3rd	3rd	3rd	1st
3	2nd	2nd	1st	1st	1st	3rd
4	1st	1st	2nd	2nd	2nd	4th

- Diagnostic method #4 provides the best detection performance
- Diagnostic method #3 provides the best classification performance
- Diagnostic method #2 provides the best (lowest) mis-classification rates

- Question: What diagnostic performance is obtained by pairing the best performing fault detection strategies with each fault classification method?

Blind-Test-Case Metric Results: New Detection-Classification Pairings

New Detection-Classification Pairing Results

Detection approach	Classification approach	FPR	(average # flights per false alarm)	TPR	CCR	MCR	Kappa Coefficient
1&2	1	0.09203%	1087	44.7%	43.4%	1.35%	0.588
	2	0.09203%	1087	44.7%	43.7%	1.04%	0.590
	3	0.09203%	1087	44.7%	40.8%	3.87%	0.570
3	1	0.09240%	1082	50.9%	47.8%	3.14%	0.634
	2	0.09240%	1082	50.9%	47.7%	3.20%	0.633
	3	0.09240%	1082	50.9%	46.7%	4.15%	0.627
4	1	0.09352%	1069	51.9%	48.6%	3.35%	0.641
	2	0.09352%	1069	51.9%	49.0%	2.99%	0.643
	3	0.09352%	1069	51.9%	45.0%	6.90%	0.616
	4	0.09352%	1069	51.9%	45.2%	6.78%	0.617

Legend: Blue font = original detection/classification pairing
Red font = new detection/classification pairing

- Classification methods #1 and #2 are found to give slightly better CCR, MCR and Kappa coefficient results.
- Demonstrates the importance of applying a common detection approach when comparing classification strategies.

Lessons Learned and Recommendations for Improvement

- Lessons Learned
  - An inherent coupling exists between fault detection and fault classification performance—establishing a common detection approach allows different classification approaches to be more readily compared
  - Adding additional diagnostic logic was found to help improve the diagnosis of fault types with low signal-to-noise ratios
  - Analytical (model-based) and empirical (data-driven) classification approaches were found to provide similar diagnostic performance when applied to ProDiMES

- Recommendations for Improvement
  - Add more realism to the problem (e.g., data dropouts, measurement covariance and flight-to-flight variation based on actual data)
  - Include intermittent fault types and overhaul/maintenance actions
  - Offer ProDiMES as a conference challenge problem to help further the development and evaluation of diagnostic methods

Summary

- The Propulsion Diagnostic Method Evaluation Strategy (ProDiMES) provides a means to conduct an initial comparison of candidate gas path diagnostic methods
- The tool was found to provide a suitably challenging problem
- Common problem, terminology and metrics were acknowledged as beneficial
- Several potential enhancements identified for inclusion in a possible future release of the software

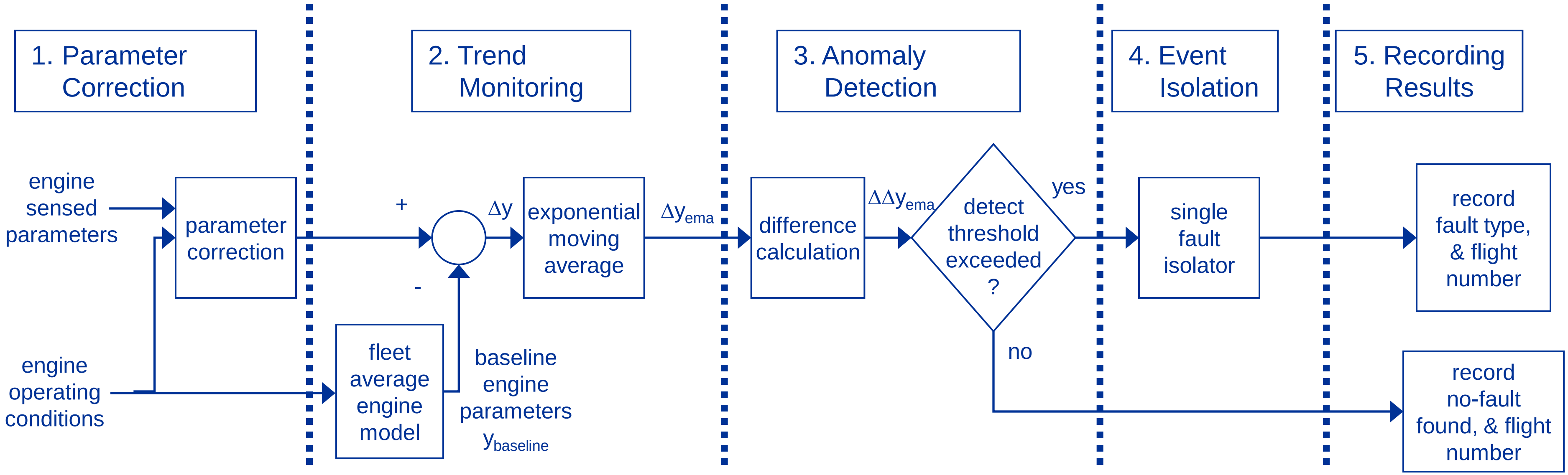
References

- Simon, D.L, Bird, J., Davison, C., Volponi, A., Iverson, R.E., (2008), “Benchmarking Gas Path Diagnostic Methods: A Public Approach,” NASA/TM-2008-215271, ASME GT2008-51360, ASME Turbo Expo 2008, Berlin, Germany.
- Simon, D.L., (2010), “Propulsion Diagnostic Method Evaluation Strategy (ProDiMES) User’s Guide,” NASA/TM-2010-215840.
- Simon, D.L., Borguet, S., Léonard, O., Zhang, X., (2013), “Aircraft Engine Gas Path Diagnostic Methods: Public Benchmarking Results,” ASME-GT2013-95077, 2014 ASME Turbo Expo Conference, San Antonio, TX, June 3-7.

ProDiMES can be requested through the NASA Glenn Software Catalog: https://sr.grc.nasa.gov/public/project/28/

Backup Slides

Diagnostic Methods #1 and #2



Diagnostic Process Applied for Diagnostic Methods #1 and #2

- Method #1 single fault isolator: Weighted least squares
  - Each potential fault type is individually considered, and the fault type that best matches the observed fault signature in a weighted least squares sense is classified as the fault type.

- Method #2 single fault isolator: Probabilistic neural network
  - Applies a radial basis neural network trained off-line using the MATLAB *newpnn* function. Returns the fault type of highest probability given the observed fault signature as an input.

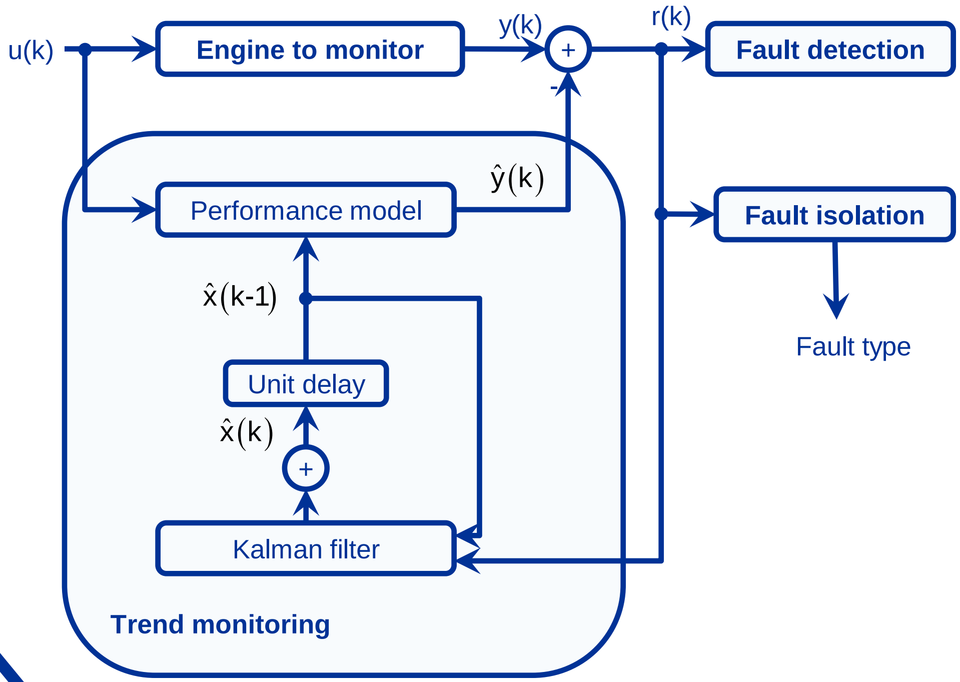
Diagnostic Methods #3: Performance Analysis Tool

- Trend monitoring: Estimates and trends progressive engine deterioration applying a constant gain extended Kalman filter.

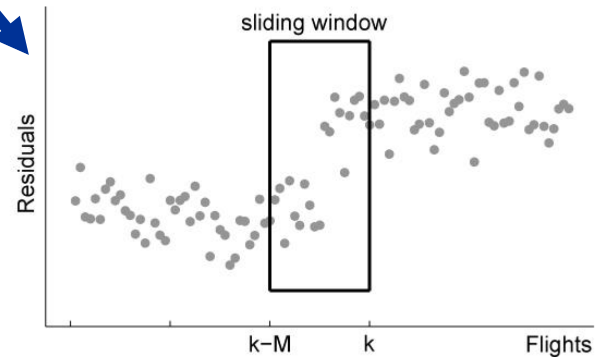
- Fault detection: Applies a likelihood ratio test to determine if a statistically significant change in residuals has occurred within the recent past sliding window of data. If so, a fault detection occurs.

- Fault isolation: Performed applying a sparse estimation approach which promotes larger variation in fewer elements of the estimated health parameter vector. The entity with the largest estimated magnitude is isolated as the fault type.

- Note: ad hoc detection logic was added to improve the detectability of the P2 and Pamb sensor faults



Performance Analysis Tool Architecture



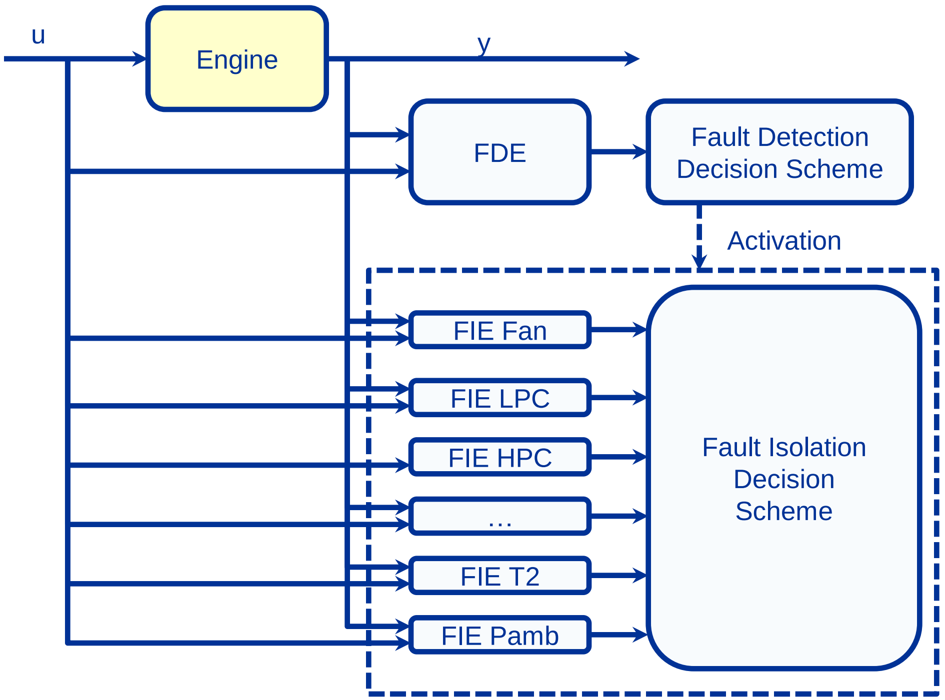
Sliding window applied for fault detection

Diagnostic Methods #4: Generalized observer/estimator for single fault isolation

- <u>Fault detection</u>: Applies a model-based Fault Detection Estimator (FDE), which calculates residuals between sensed and expected engine outputs. Each residual is individually compared against defined thresholds for fault detection purposes.

- <u>Fault isolation</u>: Applies a model-based bank of Fault Isolation Estimators (FIE's), each designed for an individual fault type. Upon fault detection, the FIE that produces the smallest residuals against engine sensed outputs is classified as the fault type.

- Note: ad hoc (specialized) FIE's for P2, T2, and Pamb sensor faults are included to accentuate the diagnosis of these fault types.



Generalized observer/estimator for single fault isolation architecture