GAS TURBINES FAULT IDENTIFICATION BY FUSING VIBRATION TRENDING AND GAS PATH ANALYSIS

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- The problem of engine fault diagnosis
- Description of the diagnostic fusion procedure
  - o Process level fusion
  - o PDF integration
    1. Performance data
    2. Vibration data
  - o Fusion mechanism
- Method Implementation and Results
  - o Data description
  - o "First Pass" analyses
  - o PDF integration
  - o Fusion results
  - o "Second Pass" analysis
- Summary - Conclusions

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The problem of fault diagnosis (GPA-performance)

***u*: variables defining operating point.**

***f*: set of *health parameters*, representing health condition of the engine.**

***Y*: set of measured variables (speeds, pressures, temperatures etc).**

$$Y = F(u, f)$$

- **The diagnostic procedure obtains solution for the inverse problem.**
- **Usually system of equations underdetermined.**
    1. **Two different "Passes" are performed for more refined solution.**
    2. **Various selection approaches for reducing number of *health parameters*.**

The problem of fault diagnosis (Vibration)

- **Vibration measurements are monitored through stations of an engine.**

- **Alleged thresholds separate "healthy" from "faulty" engine operation.**
  1. **Violation of thresholds may indicate "faulty" operation.**
  2. **A continuous probabilistic approach assess engine health condition in a flexible manner.**

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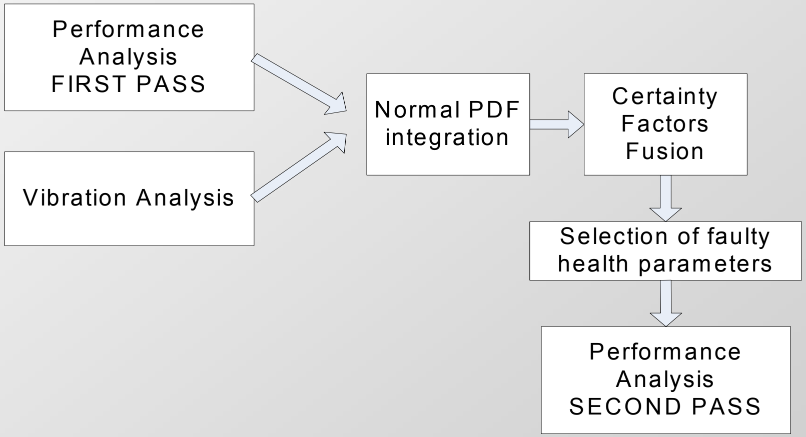
Process level fusion

- The proposed fusion technique is based on process level fusion notion.
- Different nature data are utilized, both performance and vibration.
- Vibration data are utilized in order to down select ***health parameters***.
- The processing of the data is interweaved.
- To accomplish that, a transformation to a common form must be performed.
- This common form is chosen to be a probabilistic form.
- The fusion procedure adopts the ***Certainty Factors (CF)*** theory.



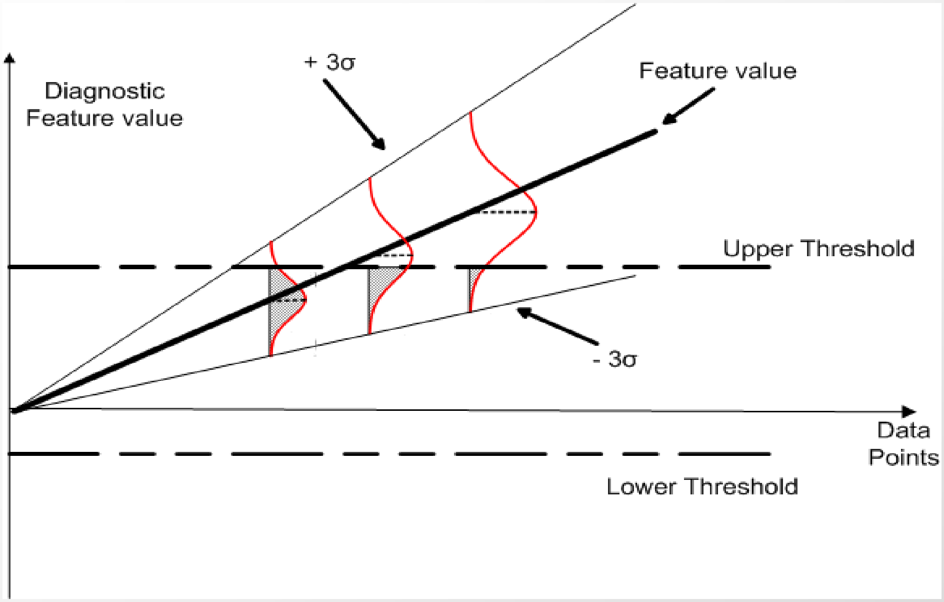
Schematic of the proposed fusion procedure

PDF-integration

- The transformation to the common probabilistic form is performed through the PDF-integration technique
- This technique permits a flexible assessment of engine health condition considering the thresholds of “healthy” and “faulty” operation, as mentioned earlier.
- Series of Diagnostic Features are utilized.
- Diagnostic Features are considered the estimations of health parameters and the vibration data.
- A Gaussian normal PDF distribution may be assumed without loss of generality

PDF-integration

- The considered thresholds are the limits of the integration.



Schematic of probability extraction.

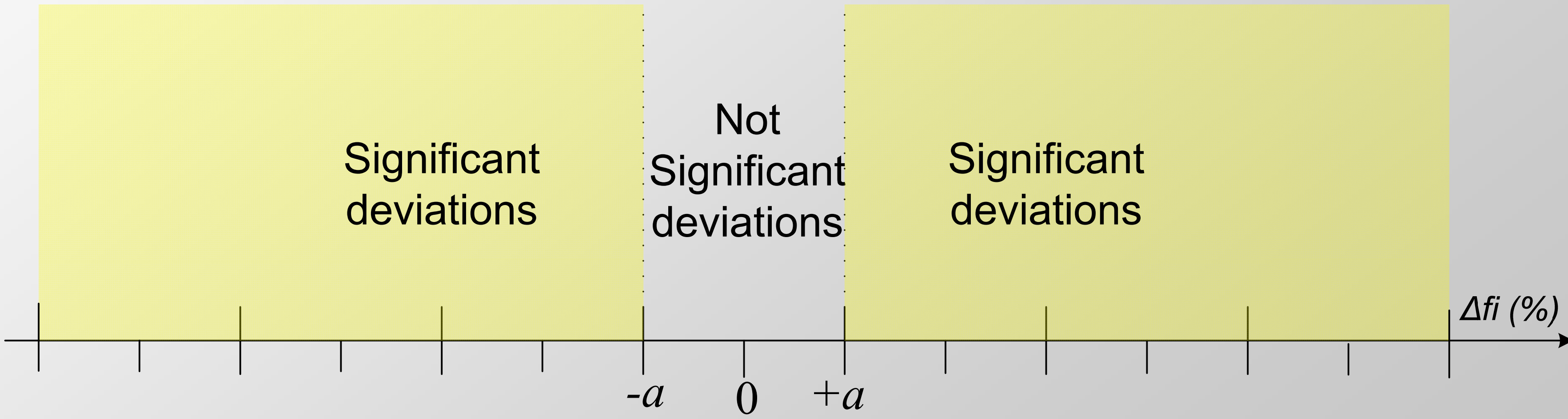
$$P(ValDf \in \text{"}non - faulty\text{"}) = \int_{Lower\ Threshhold}^{Upper\ Threshhold} normpdf(ValDf)\, dValDf$$

$$P(ValDf \in \text{"}faulty\text{"}) = 1 - P(ValDf \in \text{"}non - faulty\text{"})$$

PDF integration (Performance Data)

- **Series of estimations (trends) for all *health parameters*.**
- **Estimations in terms of deltas (Percentage Deviations – Δf).**
- **Definition of threshold α, indicative of fault.**
- **Standard deviation is derived from the available trends:**

$$\sigma_{\Delta f_i} = \sqrt{\frac{\sum_{j=1}^{M}\left(\Delta f_i^{\,j} - \Delta f_{i,LS}^{\,j}\right)^2}{M}}$$



PDF integration (Vibration Data)

- **Series of vibration trends for all *vibration measurements*.**
- **Lower threshold is always considered 0.**
- **Upper threshold is user defined based on the engine component it corresponds to.**
- **Standard deviation is taken equal to 2% (or 3%) of each measured data point.**

Fusion mechanism

- The fusion mechanism adopts the ***Certainty Factors (CF)*** theory.
- ***Certainty Factors (CF)*** theory are an ad hoc probabilistic reasoning method for dealing with uncertainty and constitute a popular alternative to traditional Bayesian reasoning.
- Certainty factors attempt to measure the confidence posed upon a certain hypothesis (or conclusion) by an expert given the presence of some evidence.
- Their values range in the interval [-1,+1] where -1 represents total disbelief and +1 represents total belief.
- Knowledge base consists of a set of rules of the form:

$$\textbf{IF} \text{ <Evidence> } CF_E \ \textbf{THEN} \text{ <Conclusion> } CF_R$$

where CF_E is the certainty factor of the premise of the rule and CF_R is the certainty factor of the entire rule. The latter represents the confidence posed in the rule's reliability when the evidence is known with complete certainty.

Fusion mechanism

- The overall certainty factor CF_{Con} of the conclusion of the rule is given by:

$$CF_{Con} = CF_E \times CF_R$$

- In case of more than one evidence in a rule, the combined premise is derived as:

$$CF_{E_1\,AND\,E_2\,AND\ldots E_N} = MIN\left(CF_{E_1}, CF_{E_2}, \ldots, CF_{E_N}\right)$$
$$CF_{E_1\,OR\,E_2\,OR\ldots E_N} = MAX\left(CF_{E_1}, CF_{E_2}, \ldots, CF_{E_N}\right)$$

- When two (or more rules) support the same conclusion a final certainty factor for that conclusion can be derived, according to the following relation:

$$CF_{FINAL} = \begin{cases} CF_{Con_1} + CF_{Con_2} \times (1 - CF_{Con_1}),\ when\ \ CF_{Con_1} > 0\ and\ CF_{Con_2} > 0 \\ CF_{Con_1} + CF_{Con_2} \times (1 + CF_{Con_1}),\ when\ \ CF_{Con_1} < 0\ and\ CF_{Con_2} < 0 \\ \dfrac{CF_{Con_1} + CF_{Con_2}}{1 - \min\left(\left|CF_{Con_1}\right|, \left|CF_{Con_2}\right|\right)},\ otherwise \end{cases}$$

Fusion mechanism

- Considering the developed fusion technique, the following remarks apply:

  i) The conclusions of the developed rules indicate the faulty engine components,e.g. LPC, so the final $\mathrm{CF_{Con}}$ values represent the final belief of either one of them being in "faulty" state.

  ii) The total number of **IF-THEN** rules, that constitute the knowledge bas, are equal to the maximum between the number of health parameters and vibration measurements.

  iii) A health parameter and a vibration measurement that correspond to the same engine component are tied together to a combined premise utilizing the AND operator.

  iv) The values of the certainty factors for the evidence are derived directly as the probability values for "faulty" state from PDF-integration technique. Thus, these values are in the interval [0,+1] and the value 0 represents now total disbelief.

  v) The values CF_R of the certainty factors for the rules are set equal to unity, so each CF_{Con} from a rule is equal to CF_E.

Fusion mechanism

- Considering the developed fusion technique, the following remarks apply:

vi) In case there are more than one health parameters (or vibration measurements) that correspond to an engine component, then one rule is constructed for each one, which is again tied to a combined premise.

e.g. *if there are two health parameters, say f_k and f_l, and one vibration measurement, say Vib_m, that correspond to the LPC component, then two rules will be constructed, which are the following:*

IF f_k $P(f_k \in \text{"}faulty\text{"})$ **AND** Vib_m $P(Vib_m \in \text{"}faulty\text{"})$ **THEN** LPC CF_{R1}

IF f_l $P(f_l \in \text{"}faulty\text{"})$ **AND** Vib_m $P(Vib_m \in \text{"}faulty\text{"})$ **THEN** LPC CF_{R2}

vii) To proceed with "Second Pass" the following selection criterion is applied:

The selected health parameters for estimation in "second pass" are those, whose corresponding engine component has a final $CF_{Con} > 0.5$

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Data Description

- Performance data sets of snapshots - Engine operation at high power level.
- Each snapshot consists of eight performance measurements.
- Estimated *health parameters* equal to number with performance measurements.

No.	Measurements
1	High pressure shaft speed (N2)
2	Air flow rate (W1)
3	Inner fan outlet pressure (P25)
4	Inner fan outlet temperature (T25)
5	HPC exhaust pressure (CDP)
6	HPC exhaust temperature (CDT)
7	Fuel flow rate (Wf)
8	Turbine exhaust static pressure (TEPS)

Available Performance Measurements

No.	Measurements
1	Fan Flow Capacity ($\Delta f1$)
2	Inner Fan Efficiency ($\Delta f2$)
3	Outer Fan Efficiency ($\Delta f3$)
4	HPC Flow Capacity ($\Delta f4$)
5	HPC Efficiency ($\Delta f5$)
6	HPT Efficiency ($\Delta f7$)
7	LPT Efficiency ($\Delta f9$)
8	Nozzle Flow Capacity ($\Delta f11$)

Estimated *Health Parameters*

Data Description

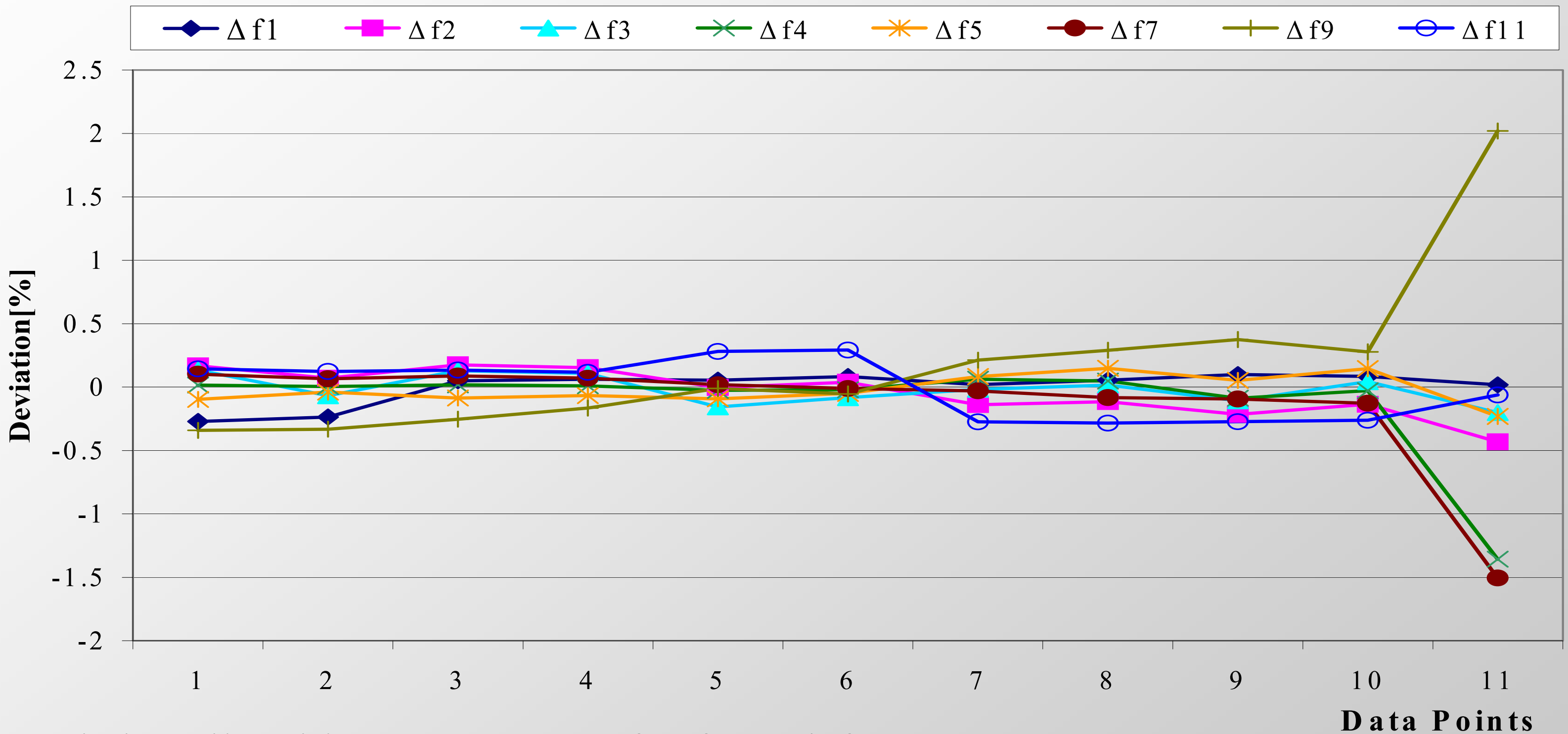
- Vibration data sets of equal number of snapshots as in performance data.
- Engine operation at high power level as in performance data.
- Each snapshot consists of four vibration measurements.

No.	Description	Symbol
1	Contribution of 1st engine order of low pressure shaft on the front of the engine	VFRONTL1
2	Contribution of 1st engine order of high pressure shaft on the front of the engine	VFRONTH1
3	Contribution of 1st engine order of low pressure shaft on the rear of the engine	VREARL1
4	Contribution of 1st engine order of high pressure shaft on the rear of the engine	VREARH1

Available Vibration Measurements

"First Pass" Analyses (Performance data)

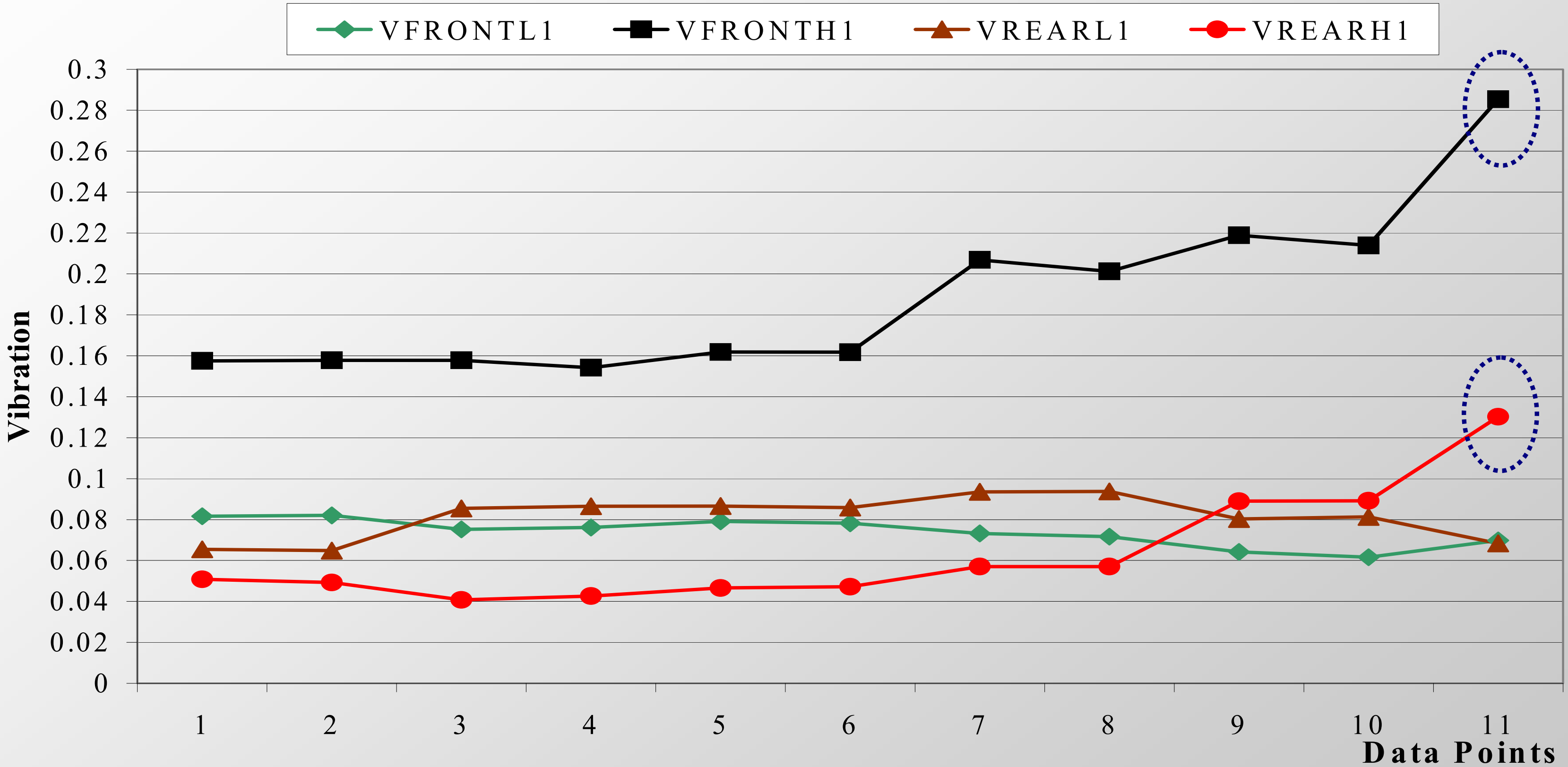
- Well conditioned system of equations for diagnosis.



- Fault localized in parameters *f4*, *f7* and *f9*.
- A non realistic change of a health parameter has been identified.

"First Pass" Analyses (Vibration data)

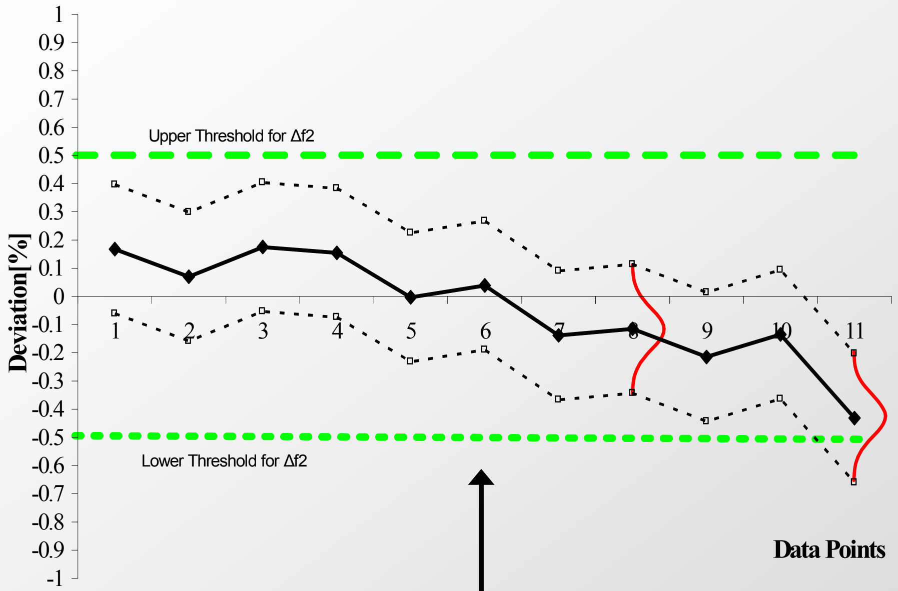
- Abrupt increase for VFRONTH1 and VREARH1 at the last data point.

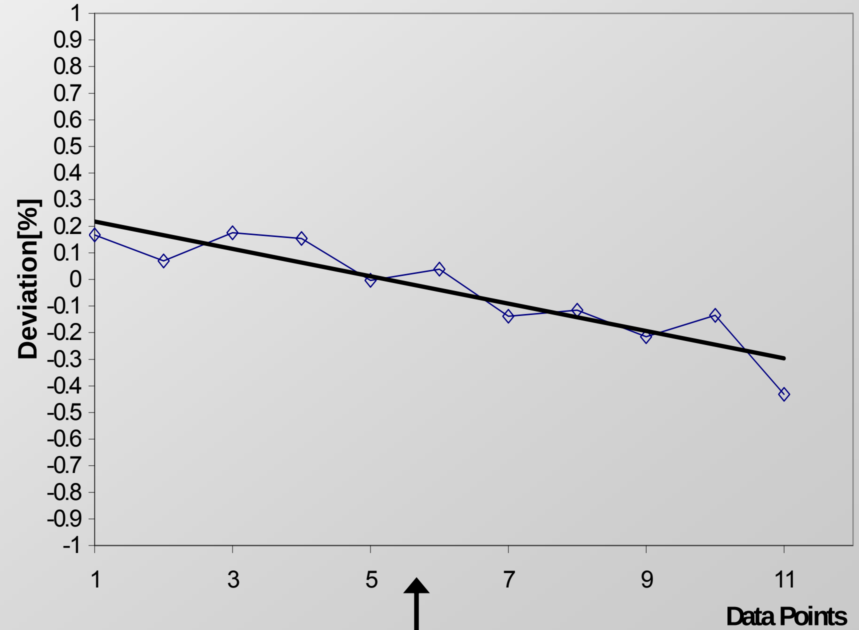


- Each data point tested against adopted thresholds for "healthy" operation.

PDF-integration (Performance data)

- Defined threshold of "healthy" operation is [-*α*,+*α*] = [-0.5%, +0.5%].



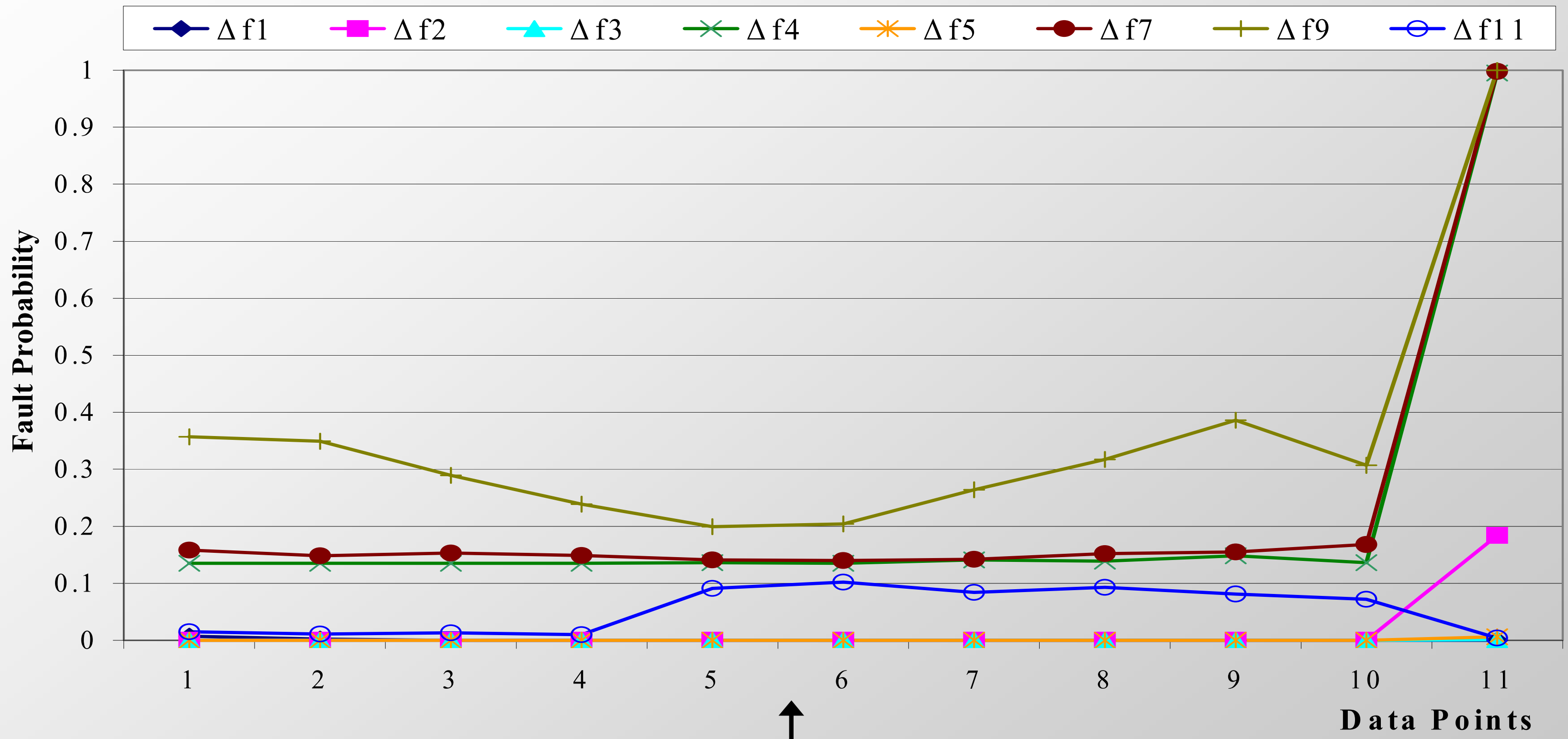


Example representation for PDF-integration at data points 8 and 11 of health parameter Δf2.

Linear fitted curve for trend of health parameter Δf2.

PDF-integration (Performance data)

- Health Parameters *f4, f7* and *f9* are selected for being in a "faulty" state.



Probabilities for "faulty" state of all health parameters after PDF-integration.

PDF-integration (Vibration data)

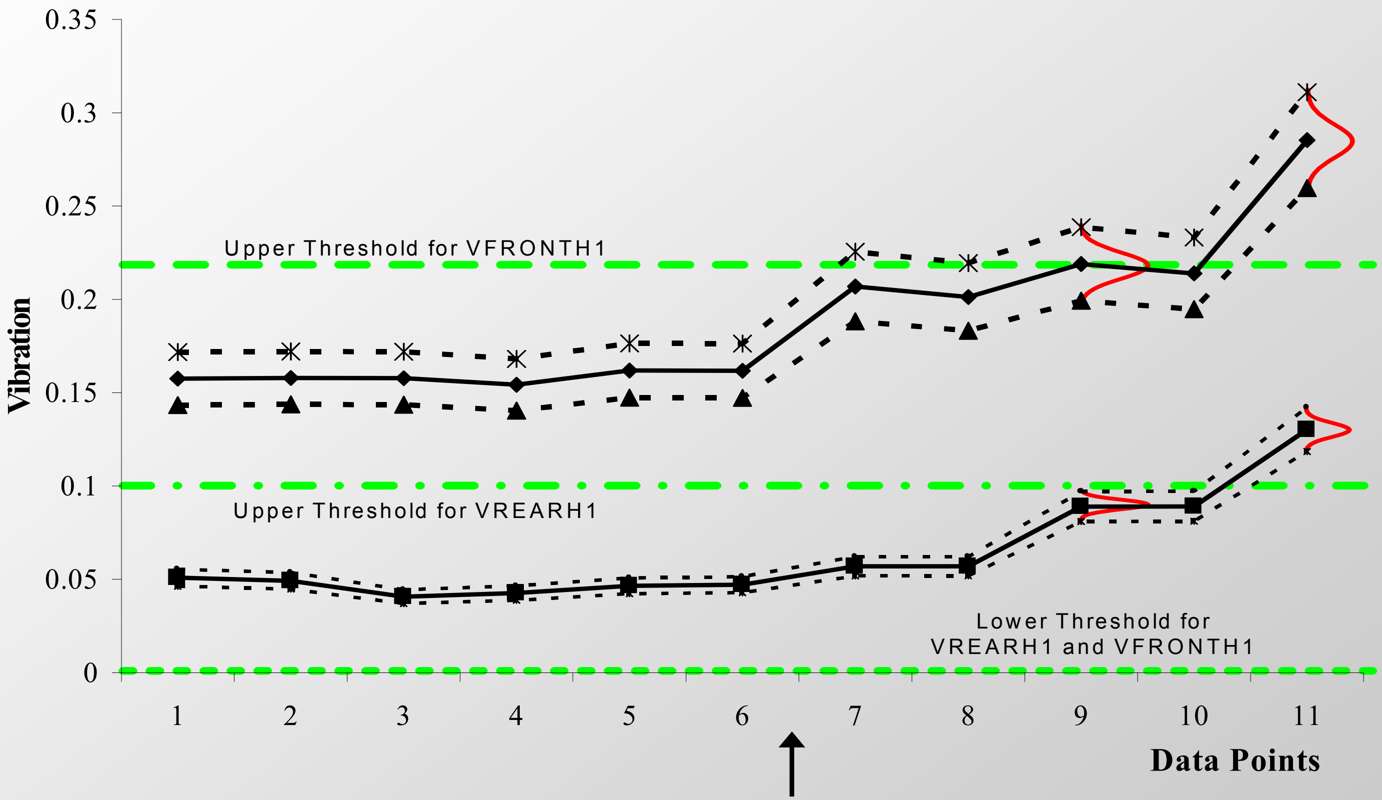
- Defined thresholds of "healthy" operation vary for vibration measurements.

No.	VFRONTL1	VREARL1	VREARH1	VFRONTH1
1	0-0.08	0-0.08	0-0.08	0-0.2
2	0-0.08	0-0.08	0-0.08	0-0.22
3	0-0.08	0-0.08	0-0.08	0-0.24
4	0-0.08	0-0.08	0-0.08	0-0.26
5	0-0.08	0-0.08	0-0.08	0-0.28
6	0-0.09	0-0.09	0-0.09	0-0.2
7	0-0.09	0-0.09	0-0.09	0-0.22
8	0-0.09	0-0.09	0-0.09	0-0.24
9	0-0.09	0-0.09	0-0.09	0-0.26
10	0-0.09	0-0.09	0-0.09	0-0.28
11	0-0.1	0-0.1	0-0.1	0-0.2
12	0-0.1	0-0.1	0-0.1	0-0.22
13	0-0.1	0-0.1	0-0.1	0-0.24
14	0-0.1	0-0.1	0-0.1	0-0.26
15	0-0.1	0-0.1	0-0.1	0-0.28
16	0-0.11	0-0.11	0-0.11	0-0.2
17	0-0.11	0-0.11	0-0.11	0-0.22
18	0-0.11	0-0.11	0-0.11	0-0.24
19	0-0.11	0-0.11	0-0.11	0-0.26
20	0-0.11	0-0.11	0-0.11	0-0.28
21	0-0.12	0-0.12	0-0.12	0-0.2
22	0-0.12	0-0.12	0-0.12	0-0.22
23	0-0.12	0-0.12	0-0.12	0-0.24
24	0-0.12	0-0.12	0-0.12	0-0.26
25	0-0.12	0-0.12	0-0.12	0-0.28

Considered integration combinations for available vibration measurements.

PDF-integration (Vibration data)

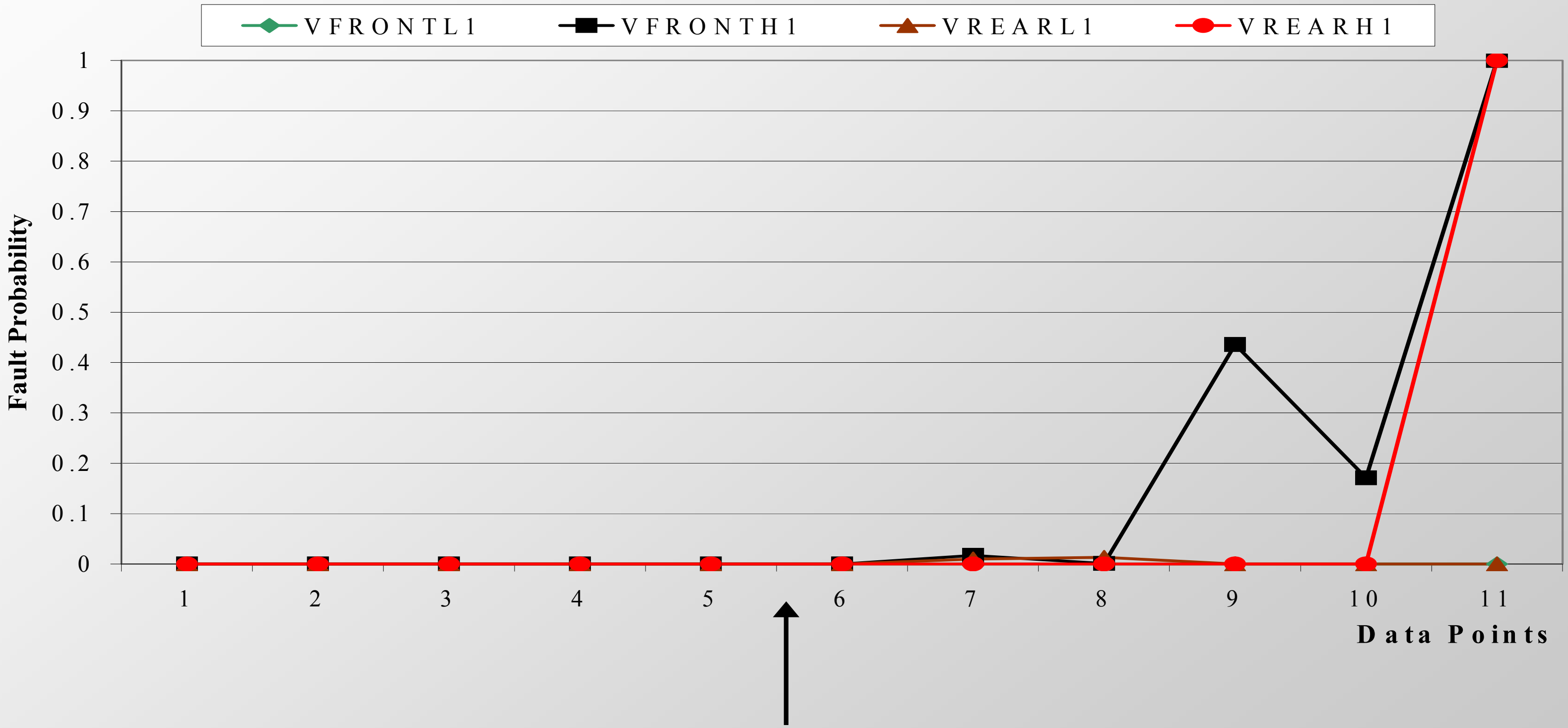
- Standard deviation (σ) has been taken equal to 3σ = 9% of the measured values.



PDF-integration at data points 9 and 11 of VFRONTH1 and VREARH1
(integration combination 12)

PDF-integration (Vibration data)

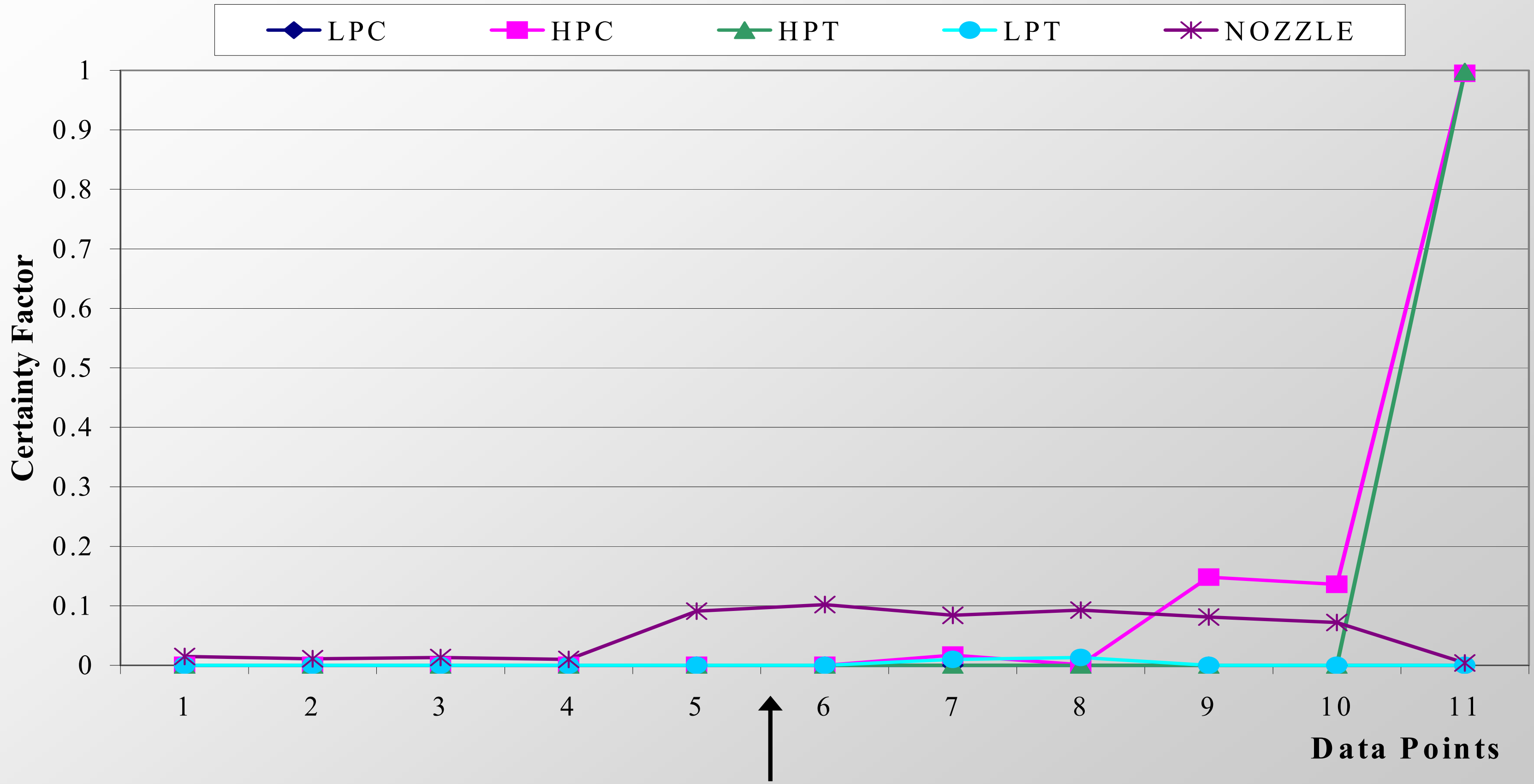
- For all considered integration combinations VFRONTH1 and VREARH1 found to be in a "faulty" state.



Probabilities for "faulty" state of all vibration measurements after PDF-integration (integration combination 12)

Fusion Results

- For all examined cases, the high pressure components were selected as “faulty”.



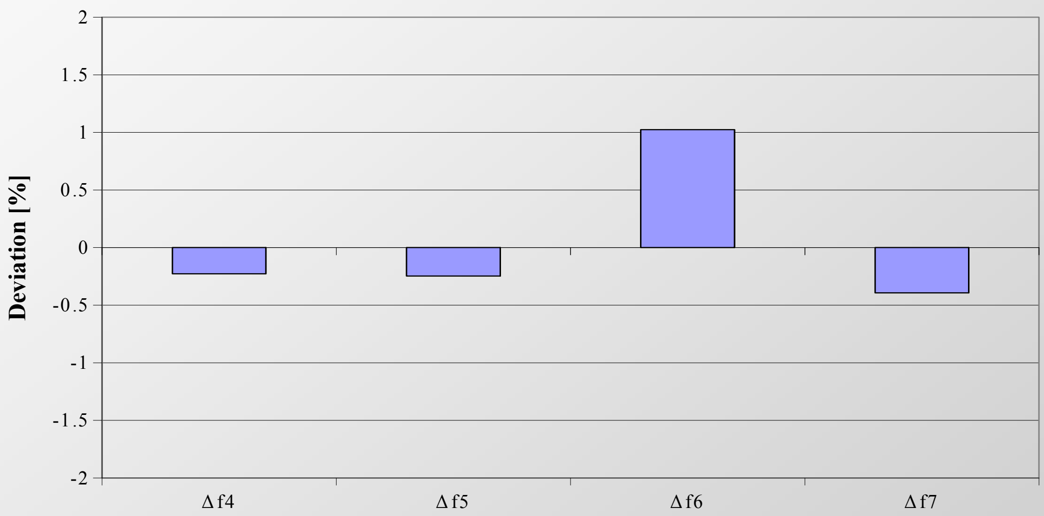
Certainty Factors derived by fusion. HPC and HPT found “faulty”.
(vibration combination 12 + performance)

"Second Pass" Analysis (Performance data)

- Estimation of four *health parameters* of high pressure engine components.

No.	Measurements
1	High pressure shaft speed (N2)
2	HPC exhaust pressure (CDP)
3	HPC exhaust temperature (CDT)
4	Fuel flow rate (Wf)

Adaptation Performance Measurements for "Second Pass"



- *Δf6* is related to HPT parameters.
- Correct identification of HPT fault.

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Summary - Conclusions

- **A fusion method for enhancing the effectiveness of a non-linear GPA technique has been presented. The fusion method combines data of a different nature and refines the final diagnosis by narrowing the possible location of a fault.**
- **The fusion module is based on the certainty factors theory. Prior to that, the PDF integration module translates the available diagnostic assessments to probabilistic forms. The rule base compensates also for cases where bad estimations, such as awkward deviations, may exist.**
- **The proposed fusion scheme can be applied to any set of probabilities produced by other methods (e.g. Bayesian Belief Networks, Probabilistic Neural Networks, Pattern Recognition methods).**
- **The PDF integration procedure, allows the derivation of probabilities that can be fed to other probabilistic-based (or probabilistic-like) fusion methods.**
- **Both PDF integration and fusion technique can be embedded to other diagnostic algorithms, a feature of more general usefulness. The selection criterion to proceed with "second pass" permits single or multi fault scenarios at the same time.**
- **Effectiveness of the method has been demonstrated by application to sets of vibration and performance measurements that contained an engine component fault. It was shown that the proposed method constitutes a reliable tool for the improvement of the final diagnostic decision.**