NON-LINEAR ENGINE COMPONENT FAULT DIAGNOSIS FROM A LIMITED NUMBER OF MEASUREMENTS USING A COMBINATORIAL APPROACH

N. Aretakis
Research associate

K. Mathioudakis
Associate Professor

A. Stamatis
Research associate

Laboratory of Thermal Turbomachines
National Technical University of Athens

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- § Definition of the diagnostic problem
- § The principle of the method
  - §Types of faulty situations
  - §The basis of the method: Adaptive Modeling Technique
  - §Engine layout
  - §Diagnostic approach
- § Application Test Cases
- § Summary - Conclusions

Definition Of The Diagnostic Problem

Objective:

Identify component faults, when few measured quantities are available (fewer measurements than unknown “health indices”)

Solution Approach Examined:

Combinatorial approach based on isolating the actual fault identity from all possible solutions (Heuristic data evaluation).

The Diagnostic Problem Examined

Types of Faulty Situations:

I. **Engine Deterioration:** all individual engine components degrades with time

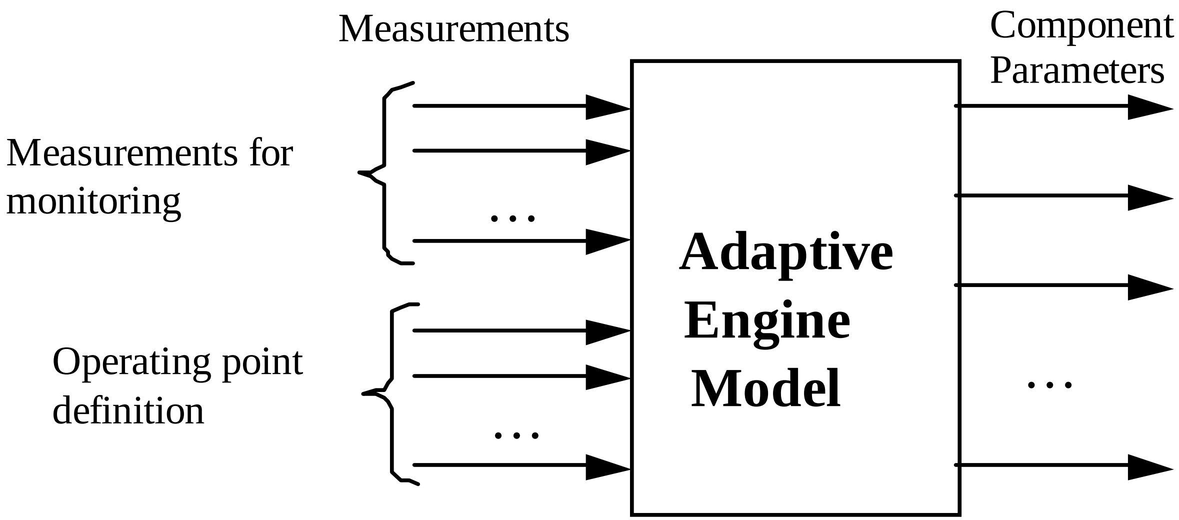
II. **Engine Component Faults:** changes in one or more components leading to degradation of their performance

III. **Individual Engine Identification:** determination of the performance of all individual components of a particular engine

The present method is dealing with Problem II

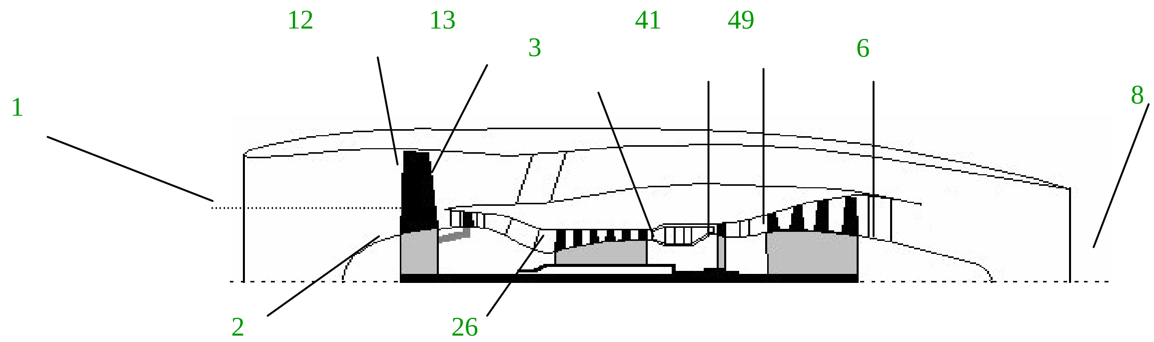
The Basis of the Method

Adaptive Modeling technique



The Principle Of The Method

The method will be presented through its implementation on a modern type jet engine: **A partially mixed, high by-pass ratio turbofan**



Layout of a turbofan engine and

station numbering for positions of interest.

Typical Monitoring Sets

Measurements

	Measurements for Monitoring	Symbol
1	LP Shaft Rpm	XNLP
2	HP Shaft Rpm	XNHP
3	Fan Outer Pressure	P_{13}
4	HP Compressor Outlet Pressure	P_3
5	HP Compressor Outlet Temperature	T_3
6	LP Turbine Outlet Temperature	T_6
7	Fan Outer Temperature	T_{13}
	Operation Point Definition	
1	Ambient Pressure	Pamb
2	Total Inlet Pressure	P_1
3	Total Inlet Temperature	T_1
4	Fuel Flow Rate	WFE

Component Condition Parameters

Component	Health Parameter	Symbol	No
Outer Fan	Flow Factor	SW12	1
	Efficiency Factor	SE12	2
Fan Inner	Flow Factor	SW2	3
	Efficiency Factor	SE2	4
HPC	Flow Factor	SW26	5
	Efficiency Factor	SE26	6
HPT	Flow Factor	SW41	7
	Efficiency Factor	SE41	8
LPT	Flow Factor	SW49	9
	Efficiency Factor	SE49	10
Nozzle	Exhaust Area	A8	11

$$SW_i = \frac{W_i \cdot \sqrt{T_i}}{P_i} \Bigg/ \left(\frac{W_i \cdot \sqrt{T_i}}{P_i} \right)_{ref} \qquad SE_i = \frac{h_i}{h_{i\,ref}}$$

The Principle Of The Method

Measurement Set
7 Measurements → **Adaptive Model Diagnosis** → **Component Condition Parameters (7 Parameters out of 11)**

Given Set ↑

↓ **Unique Solution for each Observable Set**

Define the set of possible situations

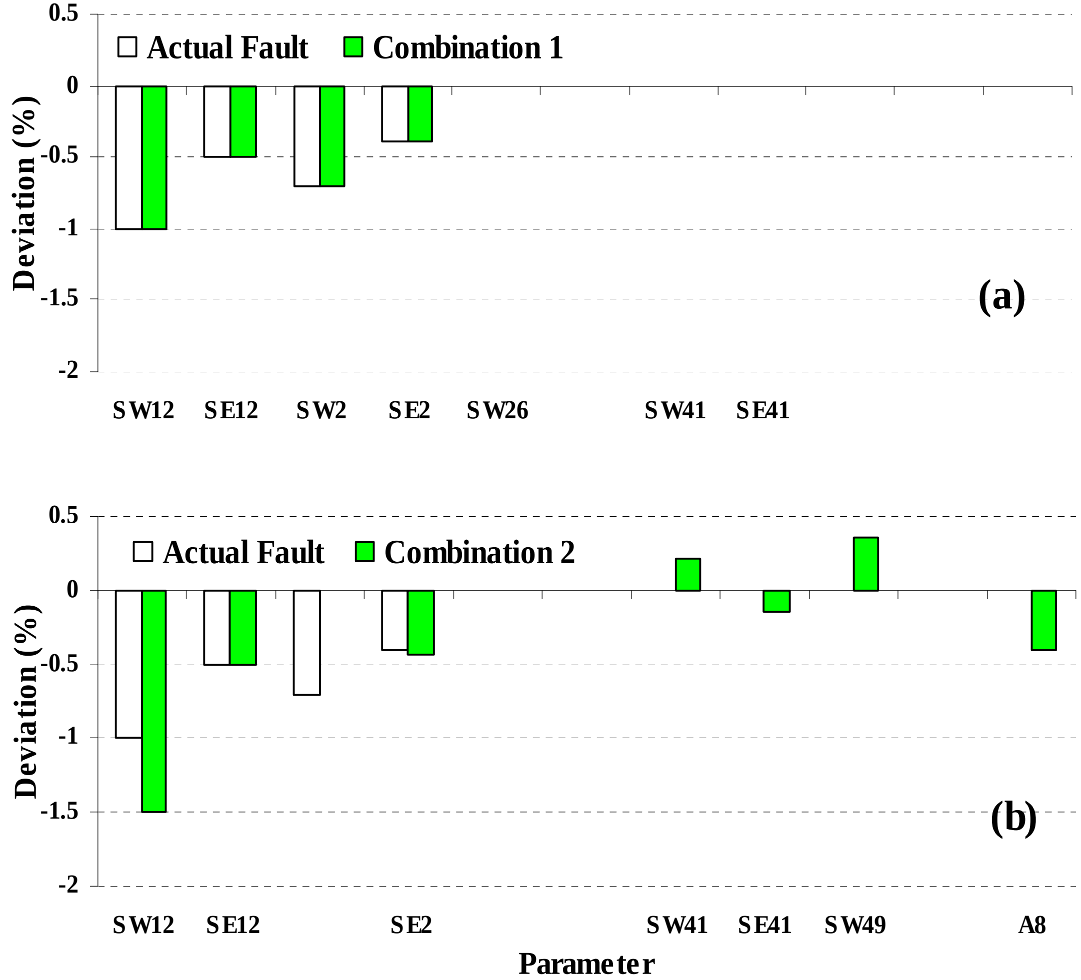
- Apply procedure for all different parameter combinations.

(Present Example: All possible combinations $\binom{11}{7} = 330$)

- Derive Fault Signatures for each parameter combination.

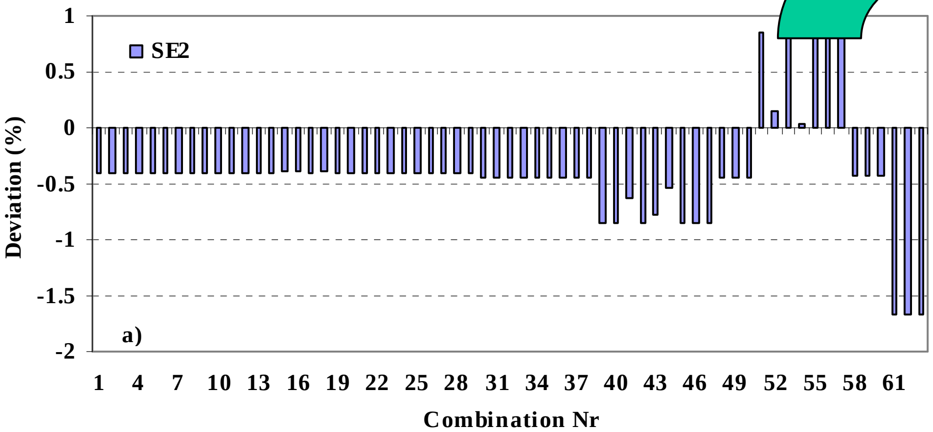
- Combinations may or may not contain the examined fault.

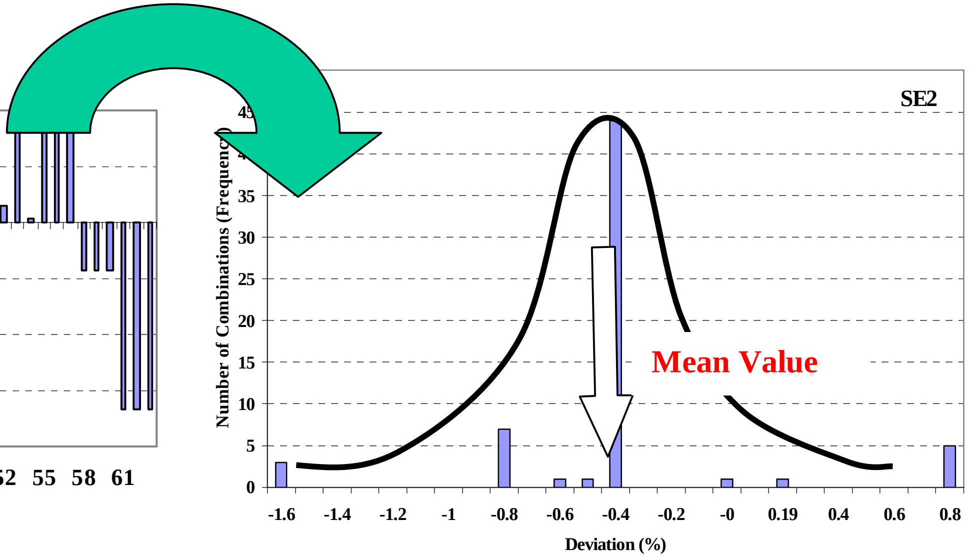
Example Situations



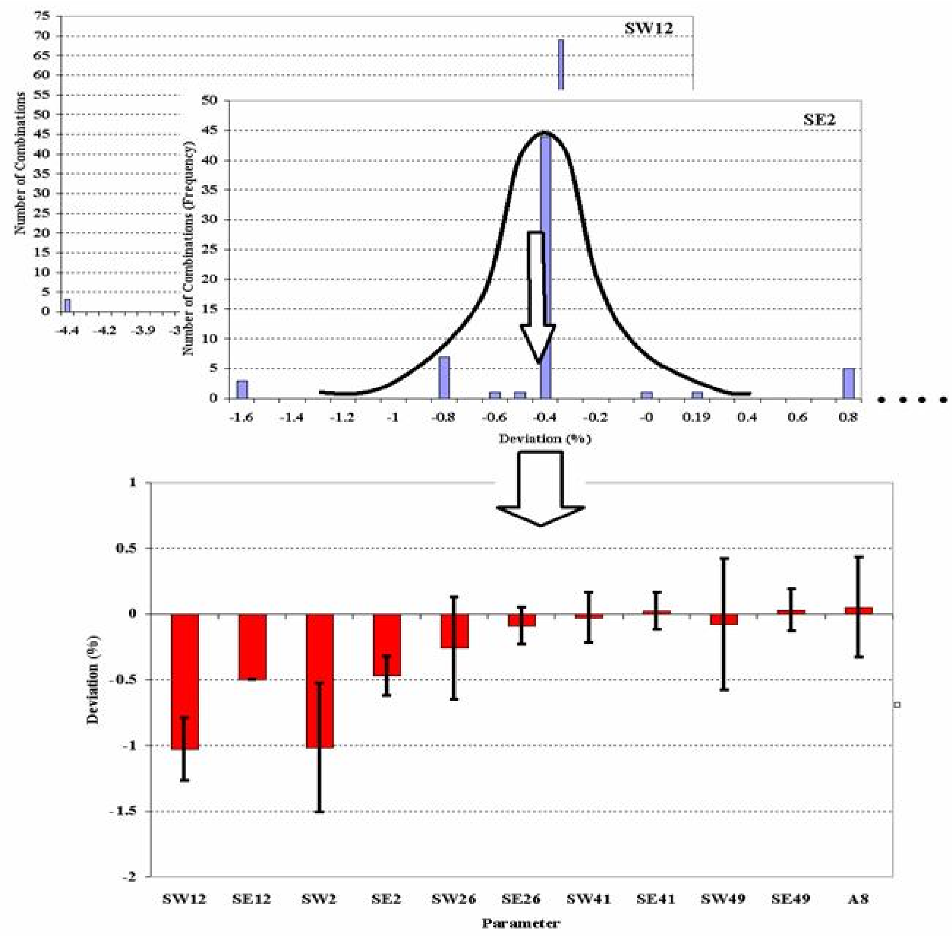
Statistical analysis of all possible solutions

F Obtain parameter distribution from calculated values for different combinations (for every single parameter).



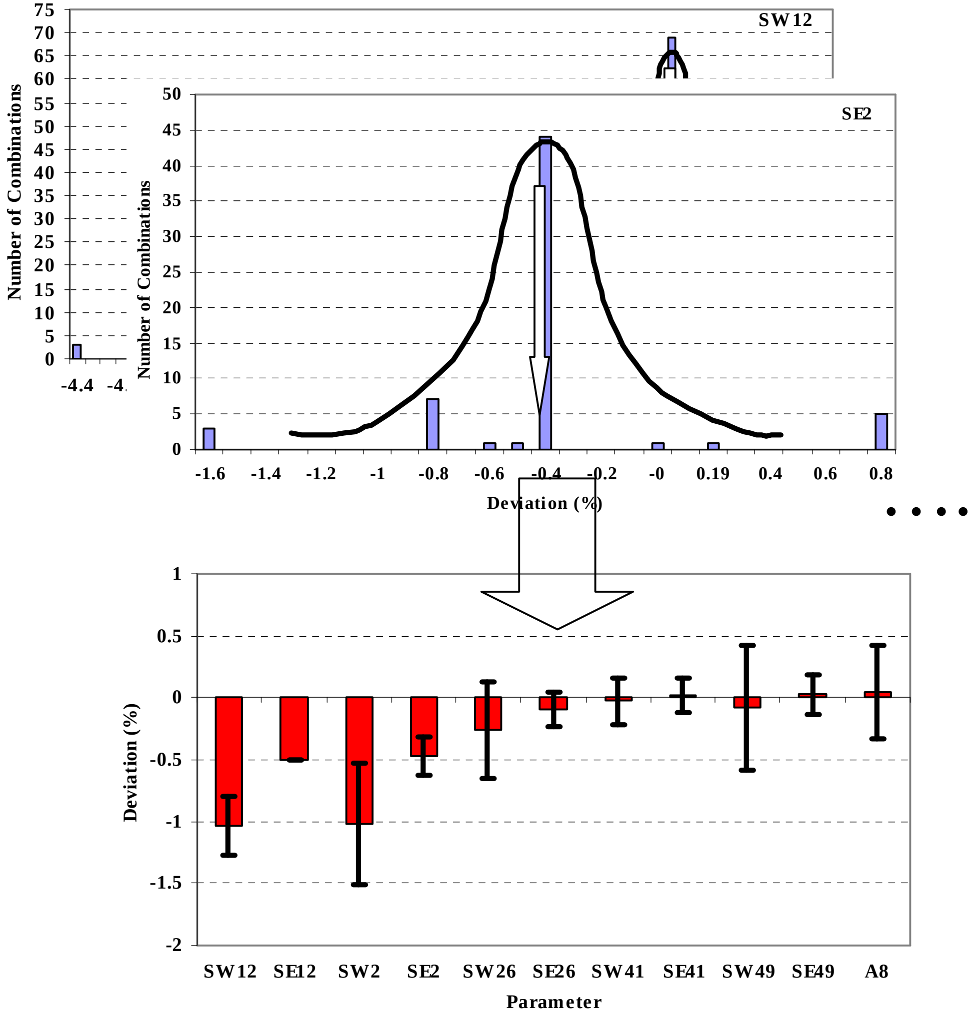


Produce most probable fault signature



- Evaluate mean value and standard deviation for each individual parameter.
- Combine them to produce the fault signature

Produce most probable fault signature



- Evaluate mean value and standard deviation for each individual parameter.
- Combine them to produce the fault signature

Criteria for Faulty Component Isolation (1st Pass)

- A Diagnostic index is derived for each component parameter

$$DI_{x_i} = \frac{\left|\bar{x}_i\right|}{s_{\bar{x}_i}}$$

- The Diagnostic index is derived for each component.

$$Diag_i = \sqrt{DI_{1i}^{\;2} + DI_{2i}^{\;2}}$$

- A faulty component is identified as the one that corresponds to the diagnostic index of maximum value

Improvement of Estimation of Deviations

2nd Pass:

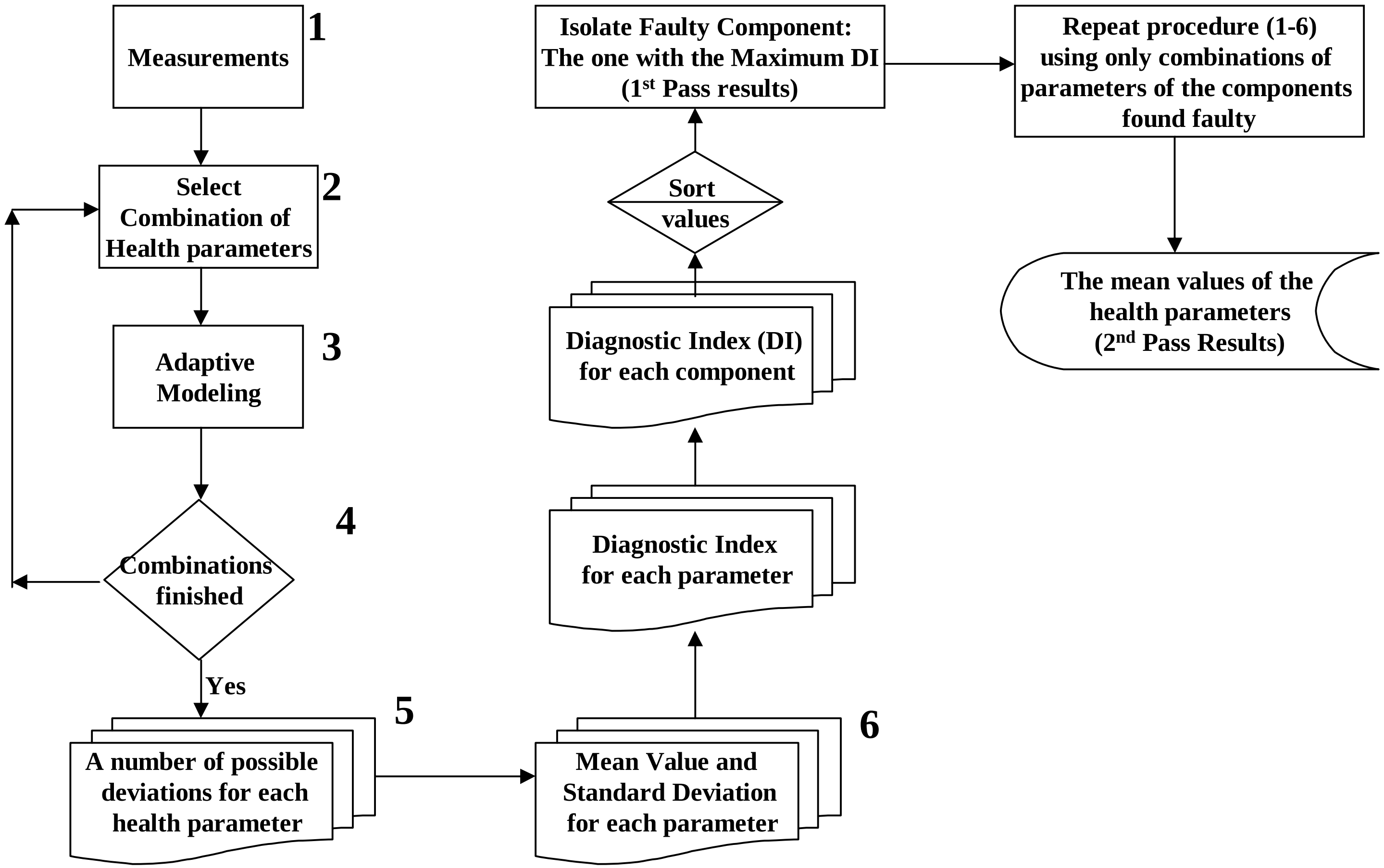
- **The procedure is repeated, using only combinations containing the health parameters of the components found faulty from 1st pass.**

Best fit approach:

- **The magnitude of deviations of the parameters of the component found faulty are derived , minimizing a function of the following form.**

$$OF = \sum_{i=1}^{M} \left[\frac{1}{\sigma_{Y_i}} \frac{Y_i^{model} - Y_i^{measured}}{Y_i^{measured}} \right]^2$$

Block Diagram Of The Method



Application Test Cases

Percent Deviations of health indices Values for simulating faults

	Outer Fan		Fan Inner		HPC		HPT		LPT		Nozzle
Fault ID	**SW12**	**SE12**	**SW2**	**SE2**	**SW26**	**SE26**	**SW41**	**SE41**	**SW49**	**SE49**	**A8**
A	-1	-0.5	-0.7	-0.4							
B		-1									
C					-1	-0.7					
D						-1					
E					-1						
F							1				
G							-1	-1			
H								-1			
I										-1	
J									-1	-0.4	
K									-1		
L									1	-0.6	
M											1
N											-1
O											2

Application Test Cases

Data sets :

- **Two types of data sets were used:**
  - **(a) Noise free data in order to examine how the method performs when an exact solution exist**
  - **(b) Data to which noise was added for a more realistic application**

Sensor	Pamb	P1	T1	WFE	XNLP	XNHP	P_{13}	P_3	T_3	T_6	T_{13}
3 sigma	100 Pa	100 Pa	2 K	2 gr/s	6 rpm	12 rpm	300 Pa	5 KPa	2 K	2 K	2 K

- **A sequence of different flight conditions (50 sets) simulating real operation was created using the engine model for each examined fault.**

Application Test Cases

Overall Identification Results:

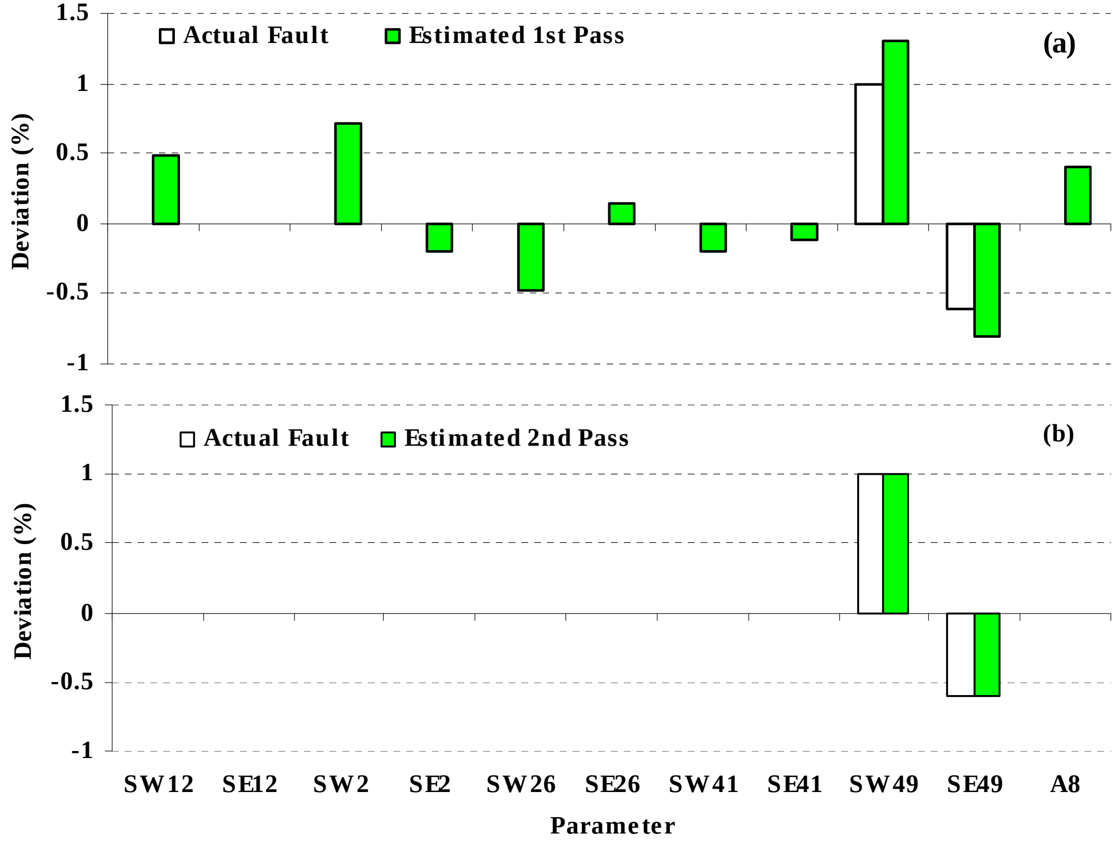
Fault	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
Noise Free Data	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
Noisy Data	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1

1: correct detection **0: incorrect detection**

- The proposed method allows the identification of a significant percentage of the examined faults
- Faults C (HPC fault) and J (LPT fault) seems to be non-identifiable (observability problem)
- The correct detection of fault C and the failure for fault K for noisy data sets is due to information counterfeiting because of the presence of noise

Application Test Cases

Comparison between 1st Pass and 2nd Pass (Fault L, Noise Free Data)

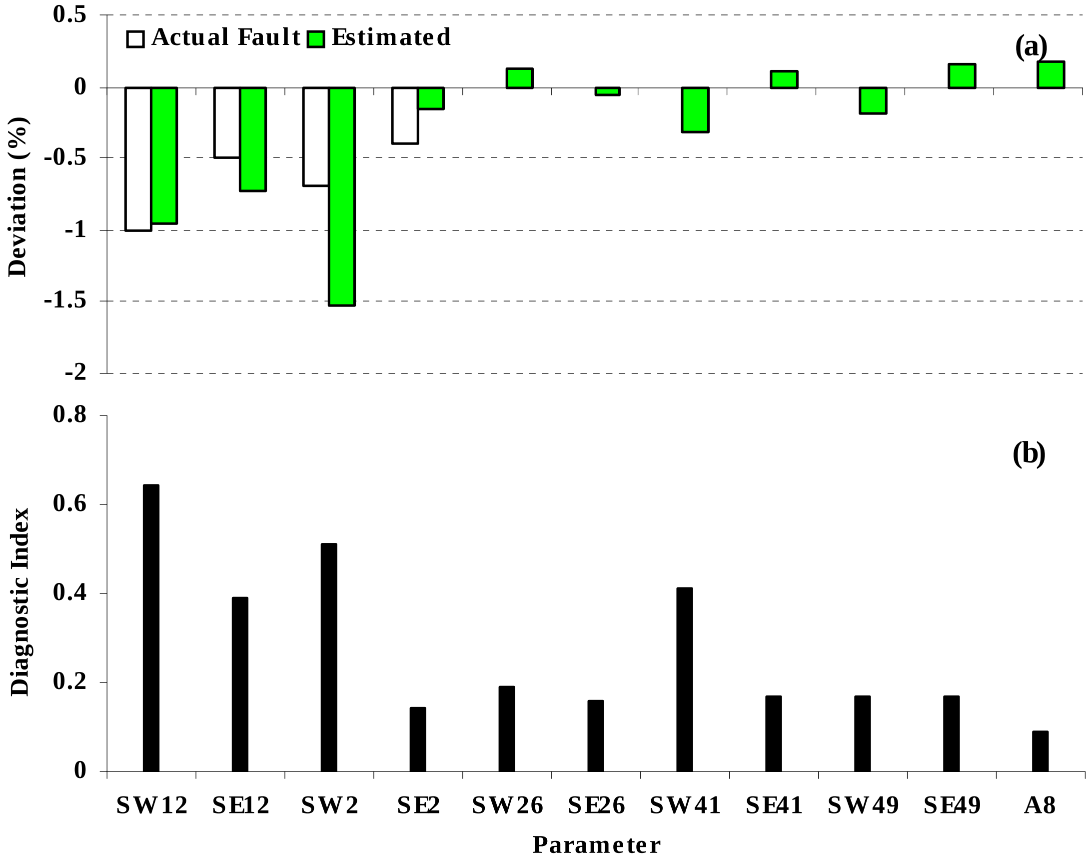


1st Pass

2nd Pass

Application Test Cases

Fault A, Noisy Data, 2nd Pass

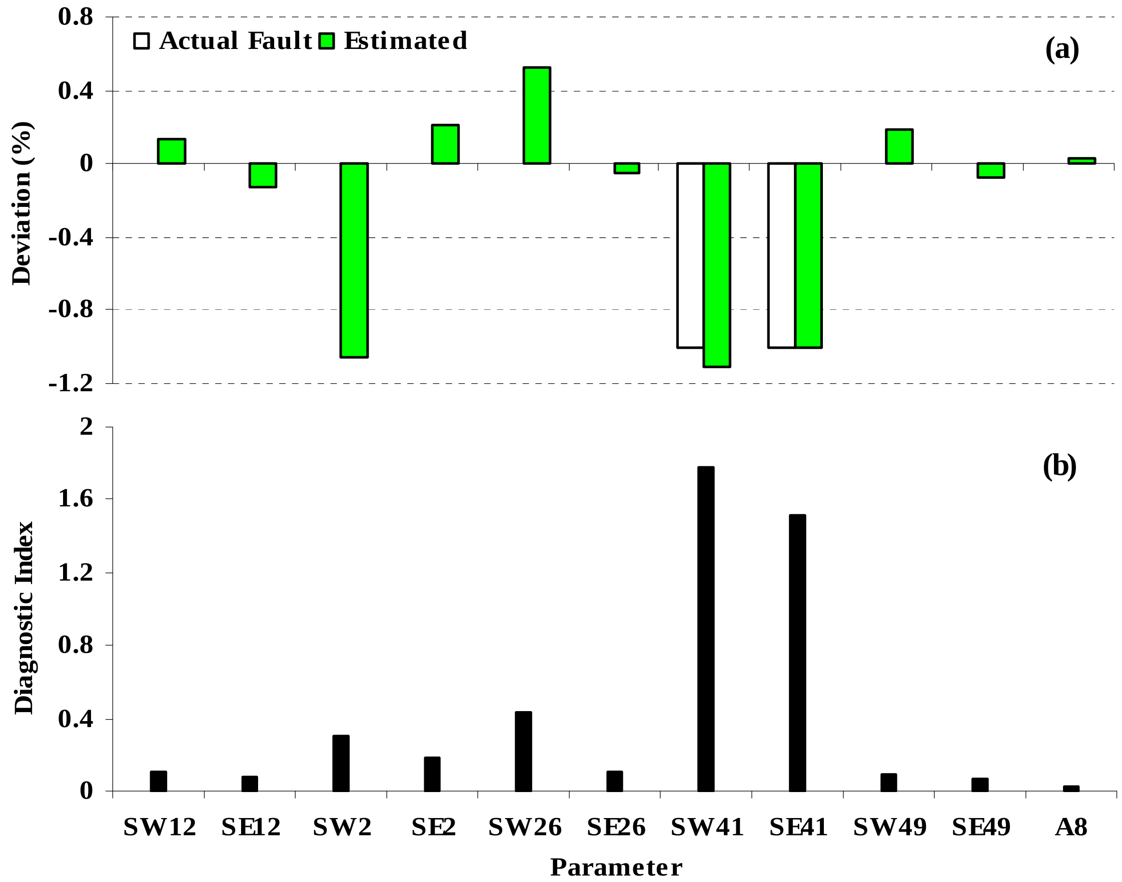


Fault Signature

Diagnostic Index

Application Test Cases

Fault G, Noisy Data, 2nd Pass

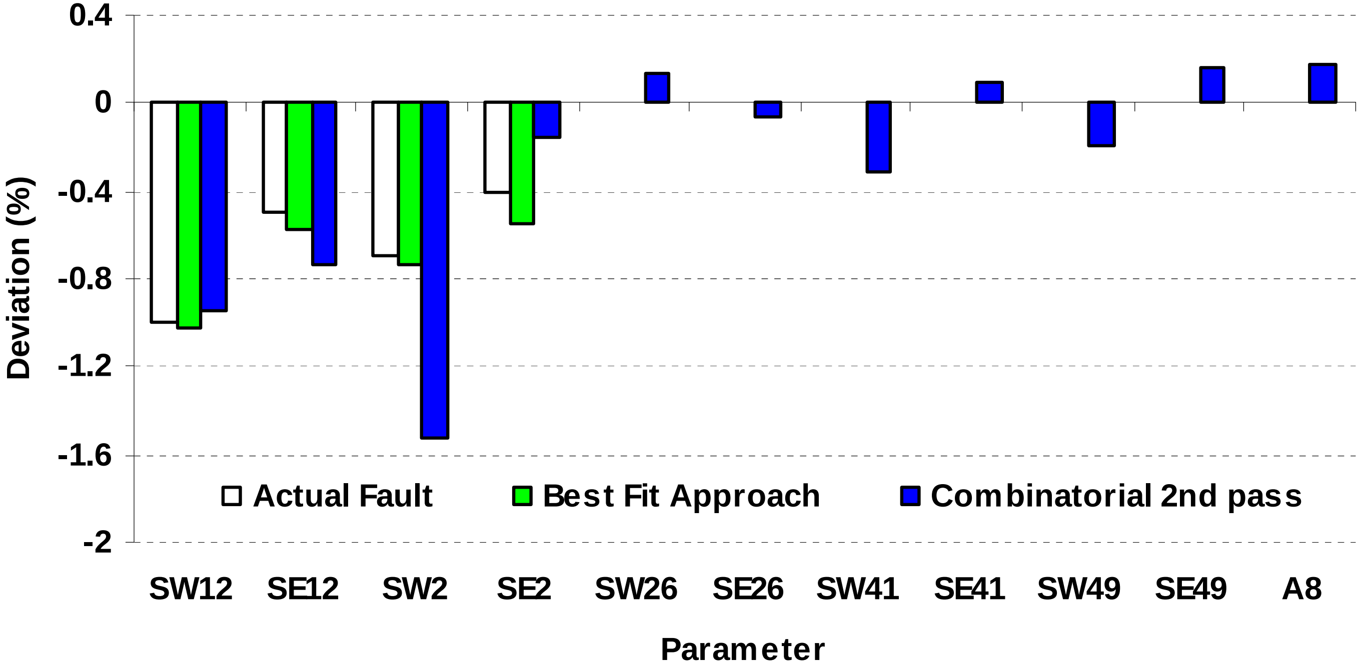


Fault Signature

Diagnostic Index

Application Test Cases

Comparison between 2nd Pass and Best Fit (Fault A, Noisy Data)



Application Test Cases

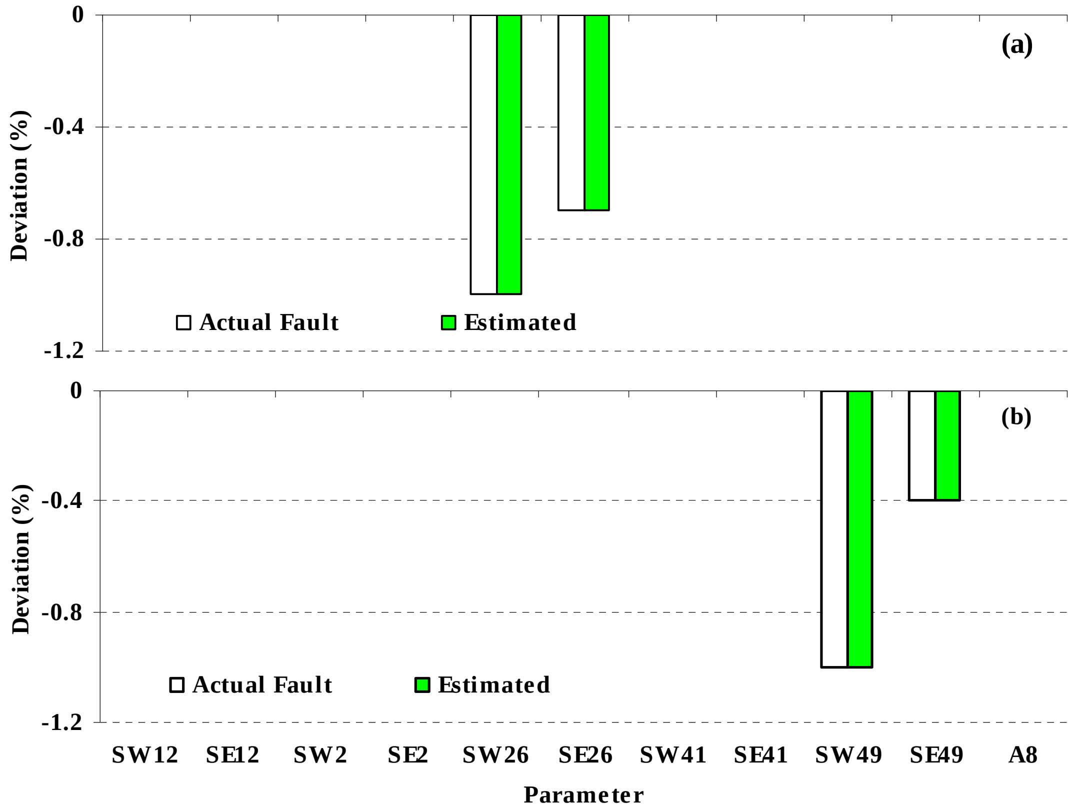
Estimation of Deviations (Best Fit approach)

Fault					
A	Act.	SW12: -1	SE12: -0.5	SW2: -0.7	SE2: -0.4
	Est.	-1	-0.6	-0.7	-0.6
B	Act.	SE12: -1	SW2: 0		
	Est.	-1.3	-0. 1		
D	Act.	SW26: 0	SE26: -1		
	Est.	0.2	-1.1		
E	Act.	SW26: -1	SE26: 0		
	Est.	-1	-0. 1		
F	Act.	SW41: 1	SE41: 0		
	Est.	1	0		
G	Act.	SW41: -1	SE41: -1		
	Est.	-1	-1.1		
H	Act.	SW41: 0	SE41: -1		
	Est.	0	-1.1		

Fault			
I	Act.	SW49: 0	SE49: -1
	Est.	0	-1.1
L	Act.	SW49: 1	SE49:-0.6
	Est.	1	-0.7
M	Act.	A8: 1	
	Est.	1	
N	Act.	A8: -1	
	Est.	-1	
O	Act.	A8: 2	
	Est.	2	

Application Test Cases

Estimated fault signatures for Fault C and J when additional Measurements are used (2nd Pass, Noise Free Data)



Adding pressure at HPC Inlet

Also adding pressure at LPT inlet

Conclusions

- A method for diagnosing faults in the components of a jet engine was presented, suitable for cases that a limited instrumentation set is available.
- The method can both isolate and identify the fault in individual components.
- The method was tested on an extensive set of component faults, with an instrumentation set typical for today's engines.
- It was found that it can detect and identify correctly faults in all components, with some limitation for some HPC and LPT faults.
- It was shown that this weakness is eliminated with the addition of inter-spool measurements, while keeping the measurement set realistic.