SETTING UP OF A PROBABILISTIC NEURAL NETWORK FOR SENSOR FAULT DETECTION INCLUDING OPERATION WITH COMPONENT FAULTS

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Setting Up Of A Probabilistic Neural Network For Sensor Fault Detection Including Operation With Component Faults

- Definition of the diagnostic problem
- Probabilistic Neural Network Architecture
- PNN diagnostic ability
  - Effect of noise level and operating conditions
  - Minimum detectable sensor biases
  - Multiple sensor faults
  - Sensor fault detection in a faulty engine
  - Sensor fault detection in a deteriorating engine
- Summary - Conclusions

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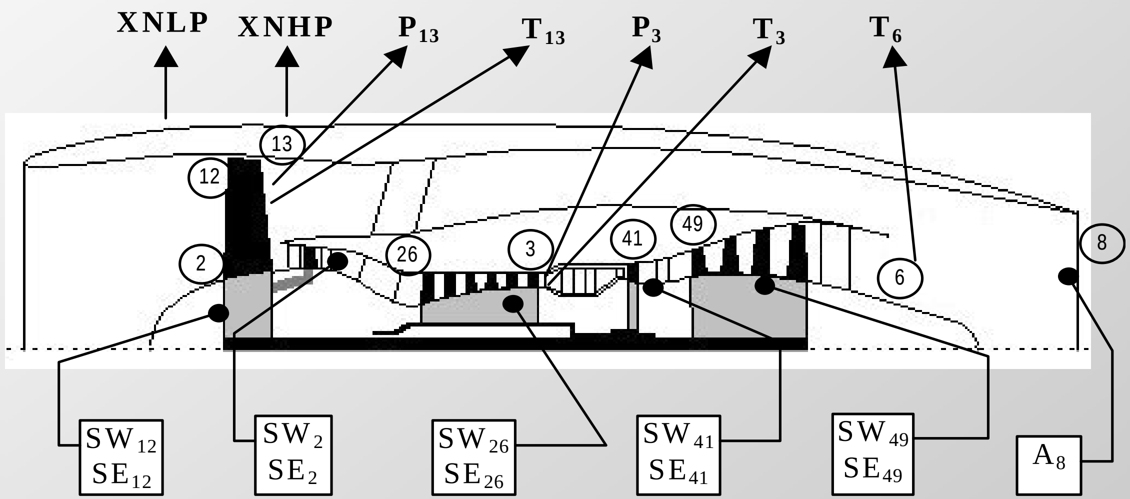
Definition of the Diagnostic Problem

Determine if the readings from a number of instruments are correct or not



High-by-Pass ratio, partially mixed, turbofan engine used as a test case

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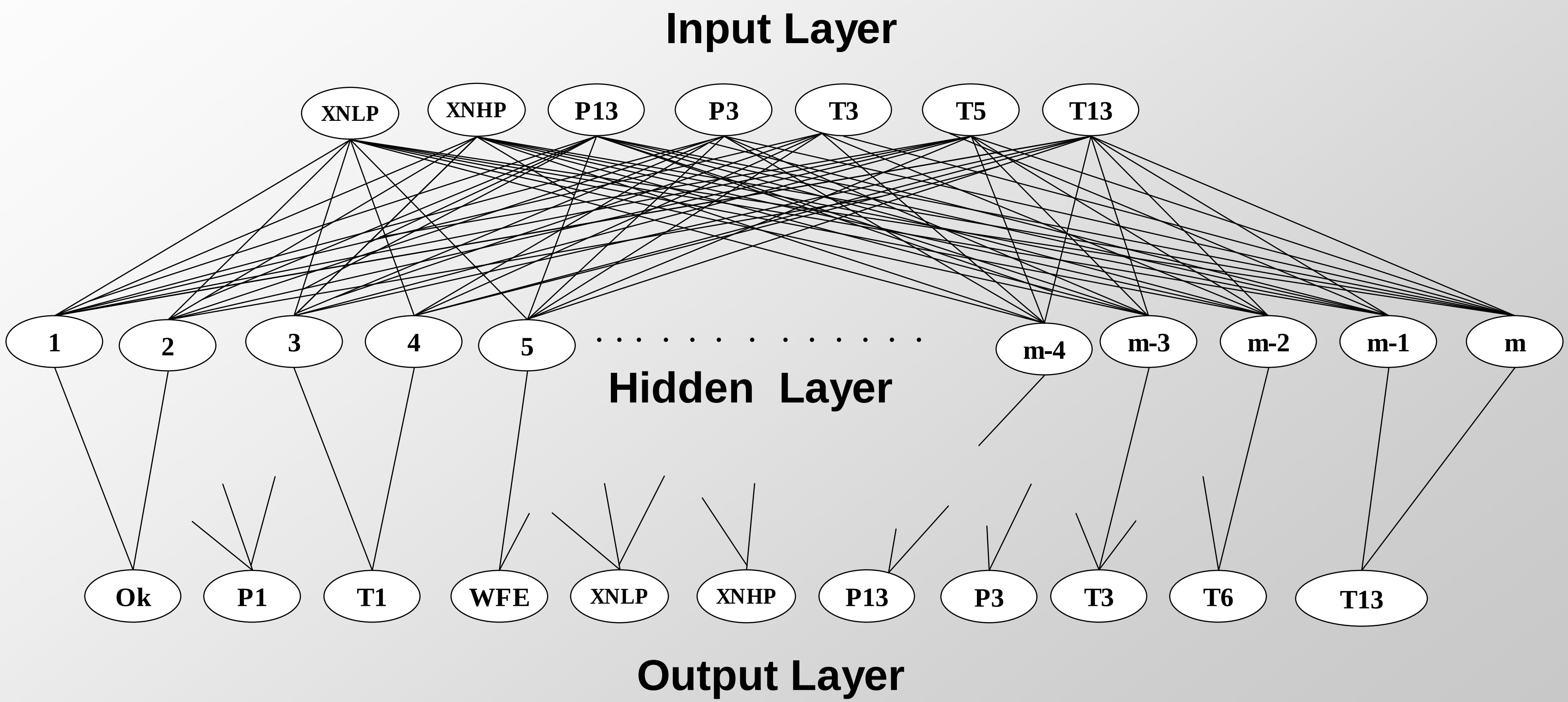
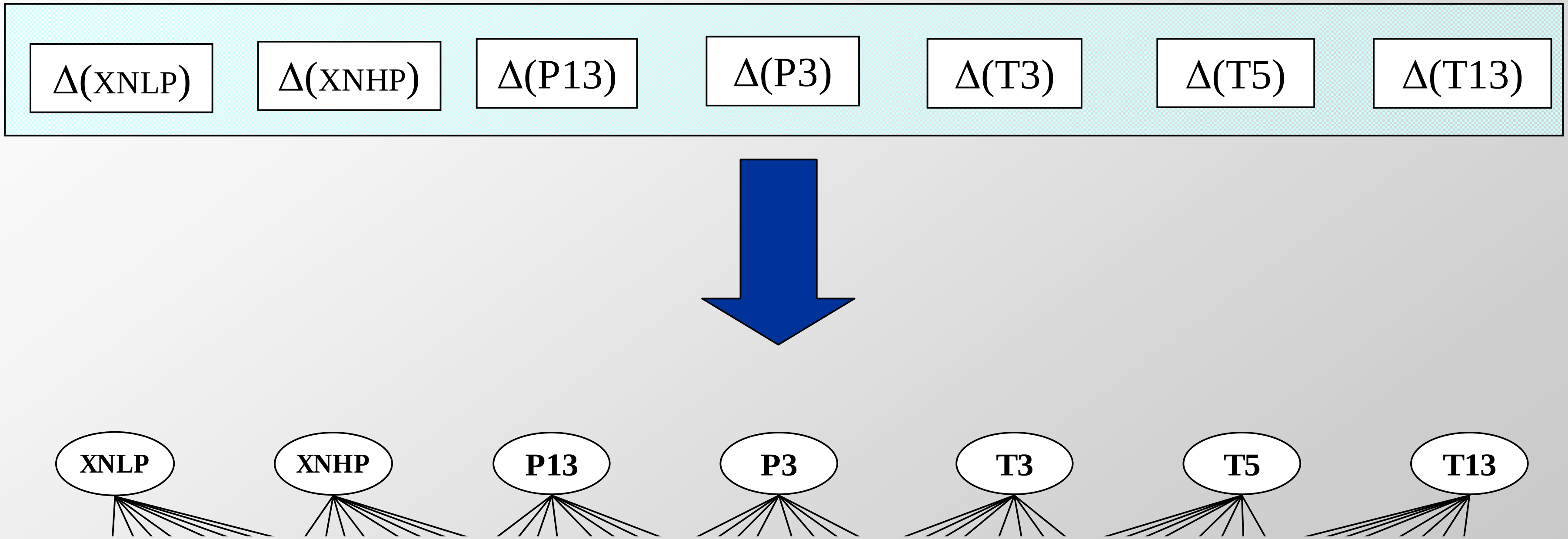
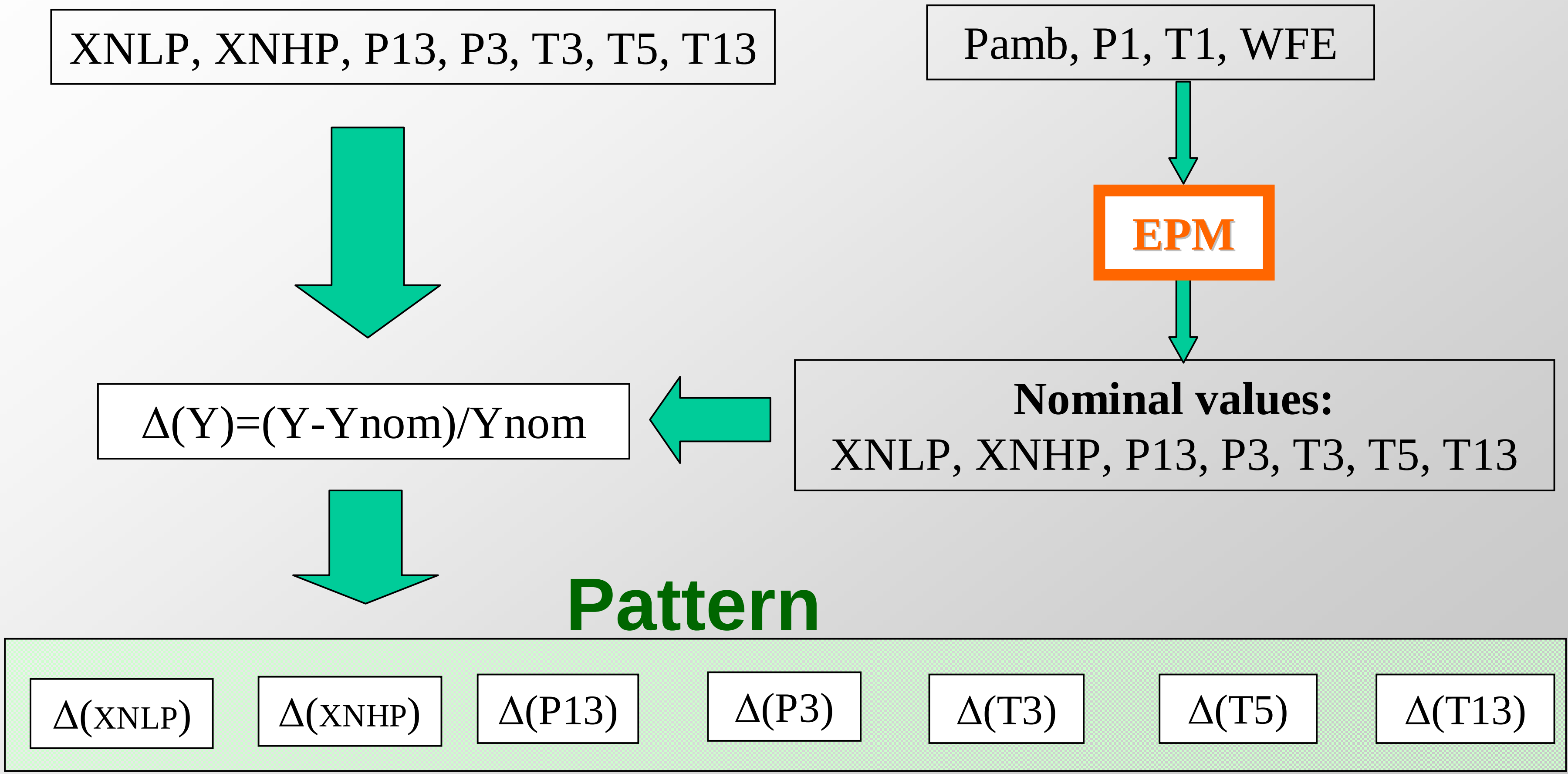
Structure of the Probabilistic Neural Network



Input layer: Deltas of the measurements



Pattern Generation from Measurements



Turbofan Engine Modeling

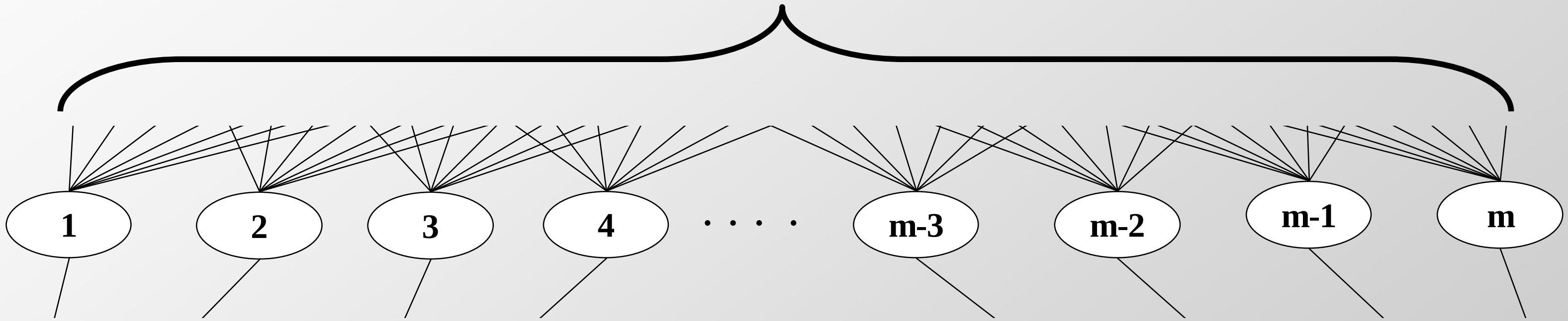
- **Quantities defining the operating Conditions:**
  - **Ambient Pressure**
  - **Fuel consumption**
  - **Engine Inlet Conditions (pressure, temperature)**
- **Fault Parameters:**
  - **Flow factors along the engine**
  - **Efficiency factors along the engine**
  - **Exhaust area**

EPM

- **Measured quantities:**
  - **Shafts' speed (low and high pressure)**
  - **Pressures and temperatures along the engine**

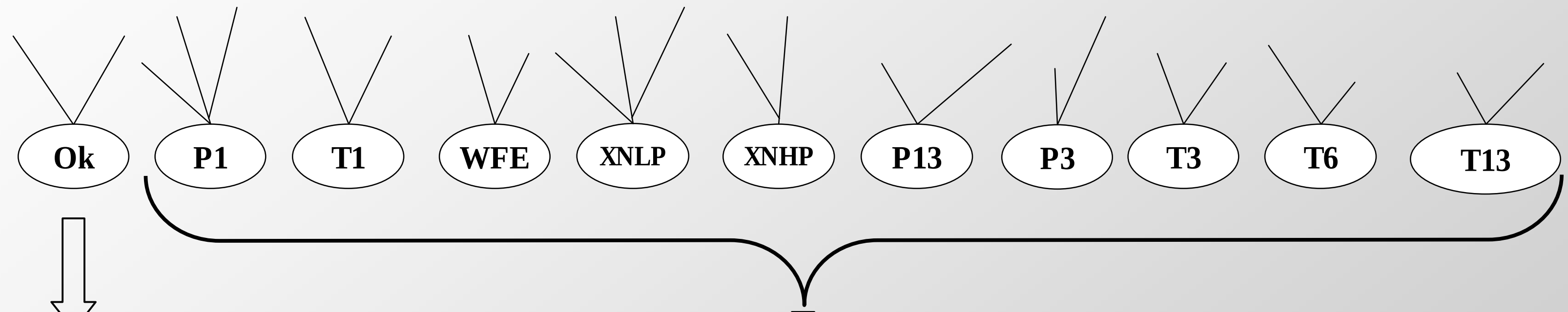
Hidden layer: Training patterns

m ~ 11,000 nodes



Each node: **A Noise-free pattern produced by simulation**

Output layer: Considered classes



No fault probability

probability that sensor is faulty

Example

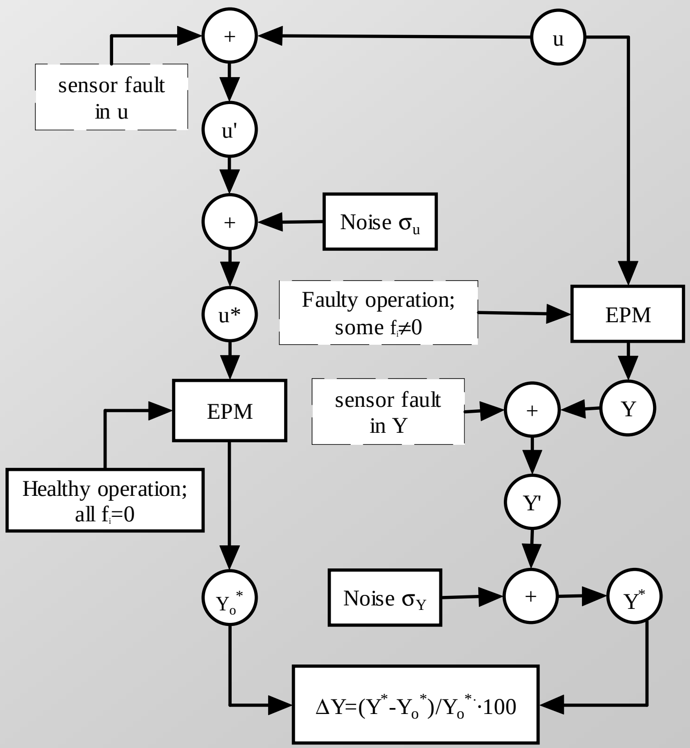
5.30%	2.20%	2.38%	68.30%	3.65%	4.56%	4.30%	1.58%	3.60%	2.90%	1.23%

Fuel flow reading is faulty

Materializing the Network

Generation of the patterns

Network once trained, then tested



Aspects Examined to Assess Diagnostic Potential

§ Effect of **Noise**

§ Diagnosis at different **Operating Conditions**

§ **Minimum detectable** sensor biases

§ **Multiple Sensor Faults** detection

§ Simultaneous presence of **Component Faults**

§ Drifting **Deterioration of Fault Parameters**

Aspects Examined to Assess Diagnostic Potential

Have been considered for:

A. **Patterns for training the network**

B. **Patterns for testing the network**

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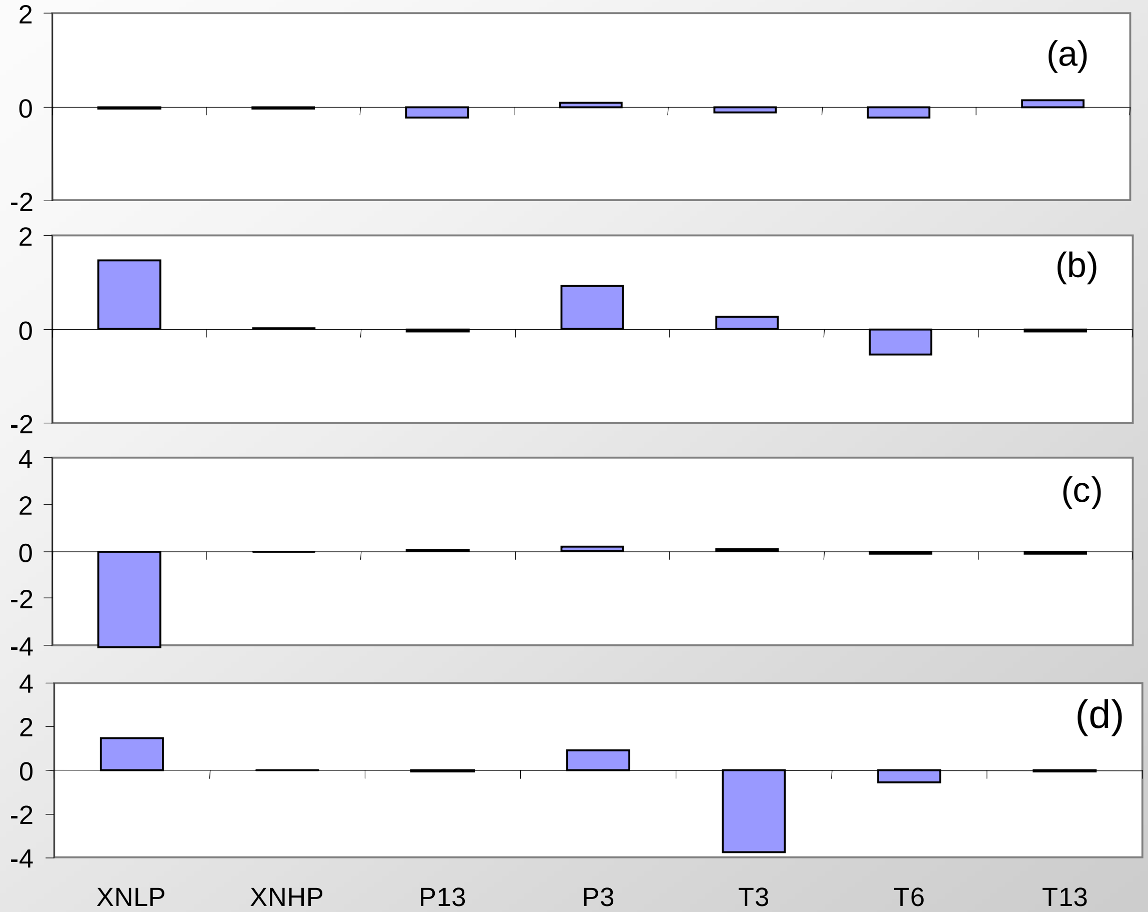
Examples of Test Patterns



Healthy engine,
Healthy sensors

Faulty engine,
Healthy sensors

Healthy engine,
Faulty sensor (XNLP)

Faulty engine,
Faulty sensor (XNLP)

PNN behavior in the presence of Noise

How the diagnostic ability is affected by the presence of noise?

Noise 'blurs' the diagnosis

A simple filtering procedure 'narrows' the region of ineffective diagnosis

Effect of Noise Level

Noisy Data

-1					●	●				
-0.8		●	●		●	●	●			
-0.6		●	●			●		●		
-0.4		●	●	●		●		●	●	
-0.2	●	●	●	●	●	●	●	●		●
0		●	●	●	●	●	●	●	●	●
0.2	●		●	●	●	●	●	●	●	●
0.4			●	●	●	●	●	●	●	●
0.6	●	●	●		●	●	●	●	●	
0.8	●		●		●		●			
1					●	●		●		●
ΔY	T1	P1	WFE	XNLP	XNHP	P13	P3	T3	T6	T13

Filtered Data

-1										
-0.8										
-0.6							●			
-0.4			●	●	●	●				
-0.2		●	●	●	●	●	●	●	●	●
0	●	●	●	●	●	●	●	●	●	●
0.2		●	●	●	●	●	●	●	●	
0.4			●		●		●		●	
0.6										
0.8										
1										
ΔY	T1	P1	WFE	XNLP	XNHP	P13	P3	T3	T6	T13

● Not Diagnosed

(blank) Diagnosed

Diagnosis at different Operating Conditions

How the diagnostic ability is affected at different operating conditions?

Diagnostic ability unaffected for 'neighboring' operating conditions

Effect of Operating Conditions

Trained OP

-1										
-0.8										
-0.6							●			
-0.4			●	●	●	●				
-0.2		●	●	●	●	●	●	●	●	●
0	●	●	●	●	●	●	●	●	●	●
0.2		●	●	●	●	●	●	●	●	
0.4			●		●		●		●	
0.6										
0.8										
1										
ΔY	T1	P1	WFE	XNLP	XNHP	P13	P3	T3	T6	T13

Not Trained OP

-1										
-0.8										
-0.6										
-0.4				●	●					
-0.2		●	●	●	●	●		●	●	●
0	●	●	●	●	●	●	●	●	●	●
0.2	●			●	●	●	●	●	●	●
0.4			●		●					
0.6									●	
0.8										
1										
ΔY	T1	P1	WFE	XNLP	XNHP	P13	P3	T3	T6	T13

● Not Diagnosed

(empty) Diagnosed

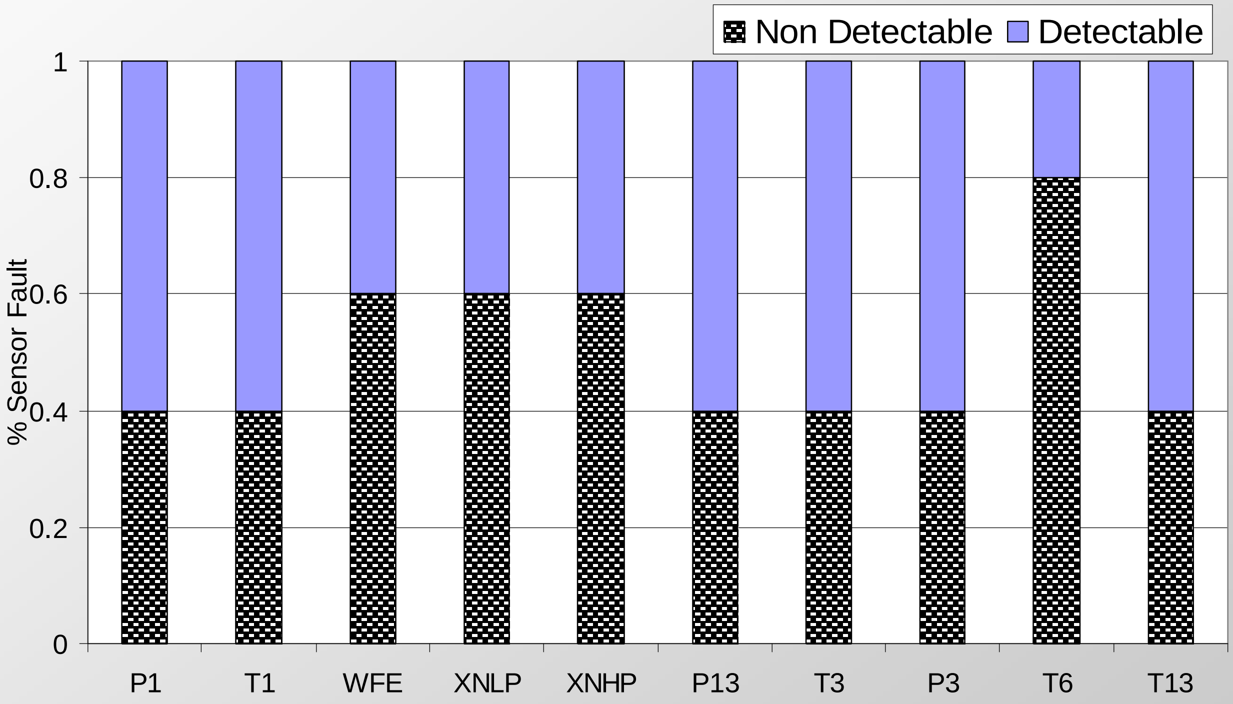
Minimum detectable sensor biases

Which are the minimum sensor biases that can be detected?

Biases greater than 0.4% - 0.8% are detected for all sensors

Bias Levels usually represent 2-4 times the considered noise levels

Minimum detectable sensor biases



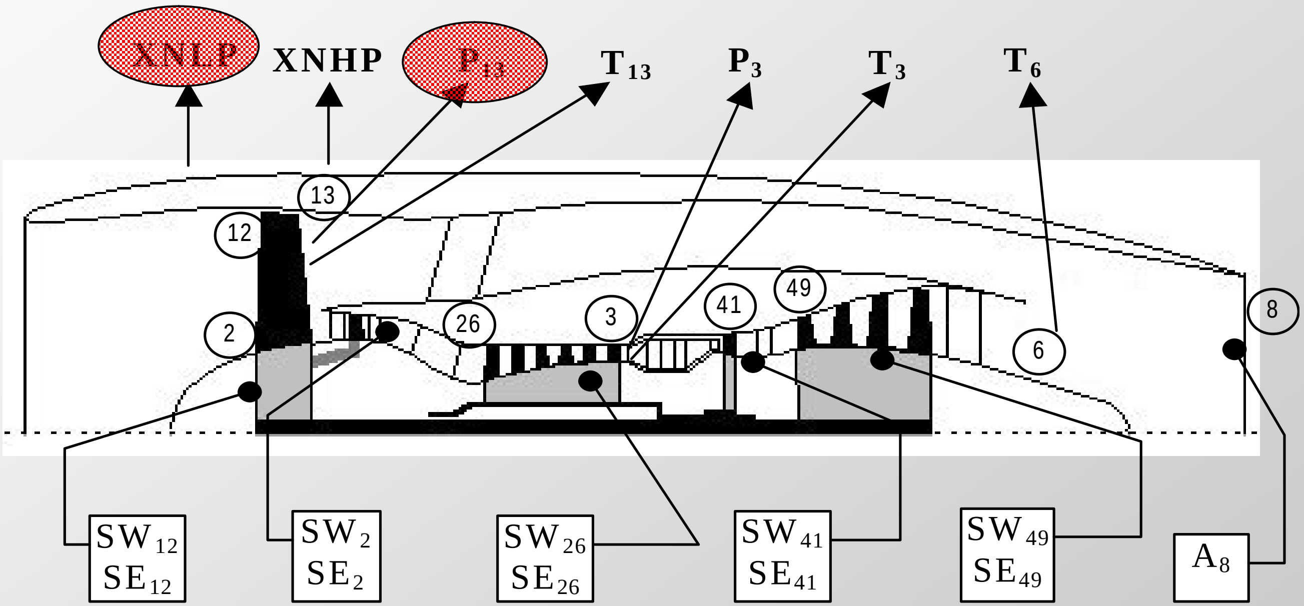
Multiple Sensor Faults detection

How, possibly, multiple sensor faults can be detected?

Faults in up to three different sensors are detected efficiently

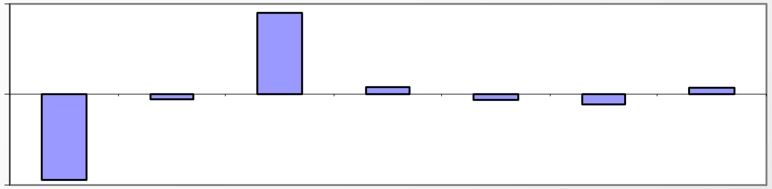
Sensors of measurements for condition monitoring

Multiple sensor faults



Multiple sensor faults: Diagnostic procedure

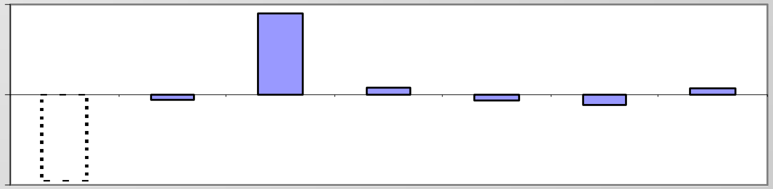
Initial Pattern



Diagnosis

P(XNLP)>50%

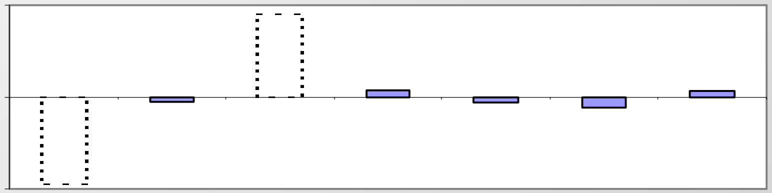
Modified Pattern



Diagnosis

P(P13)>50%

Modified Pattern

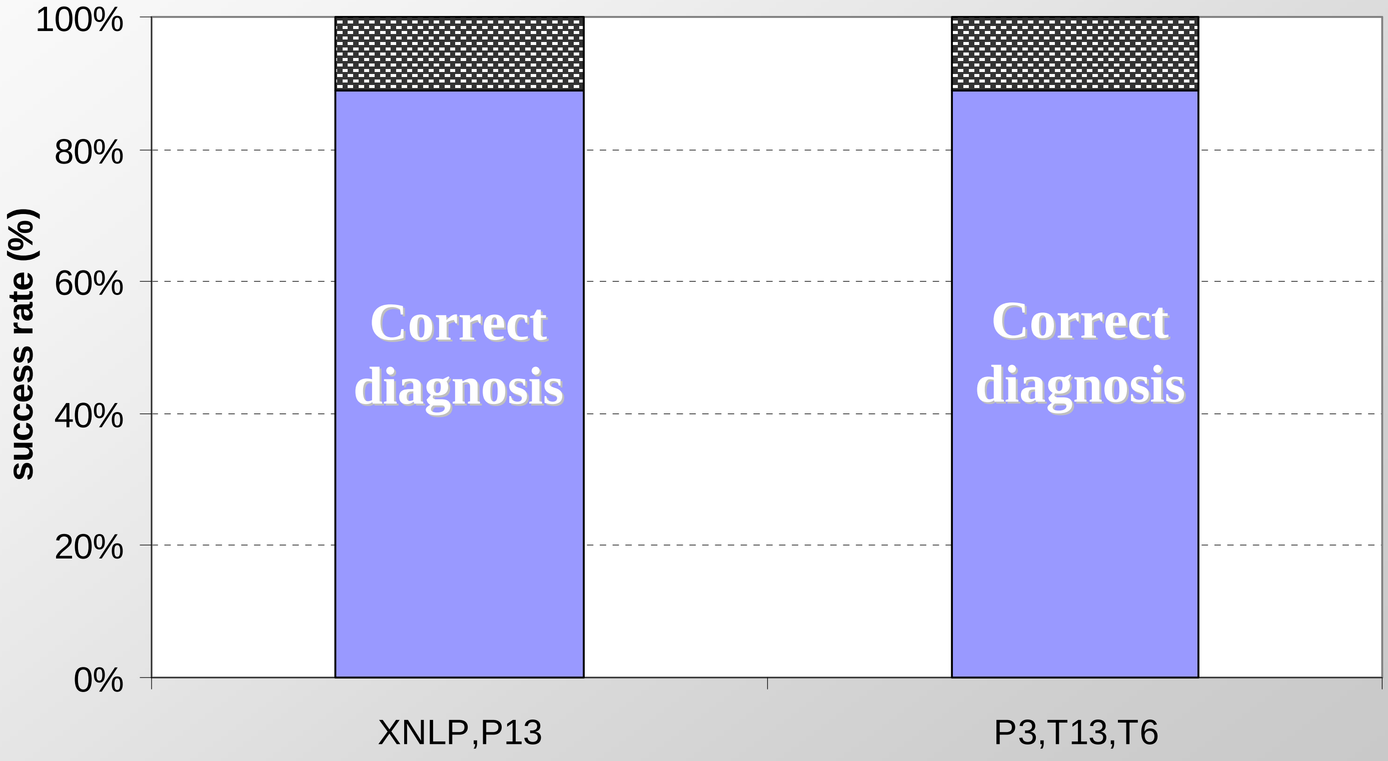


Diagnosis

P(Ok)>50%

Sample result

Success rate for Multiple sensor faults



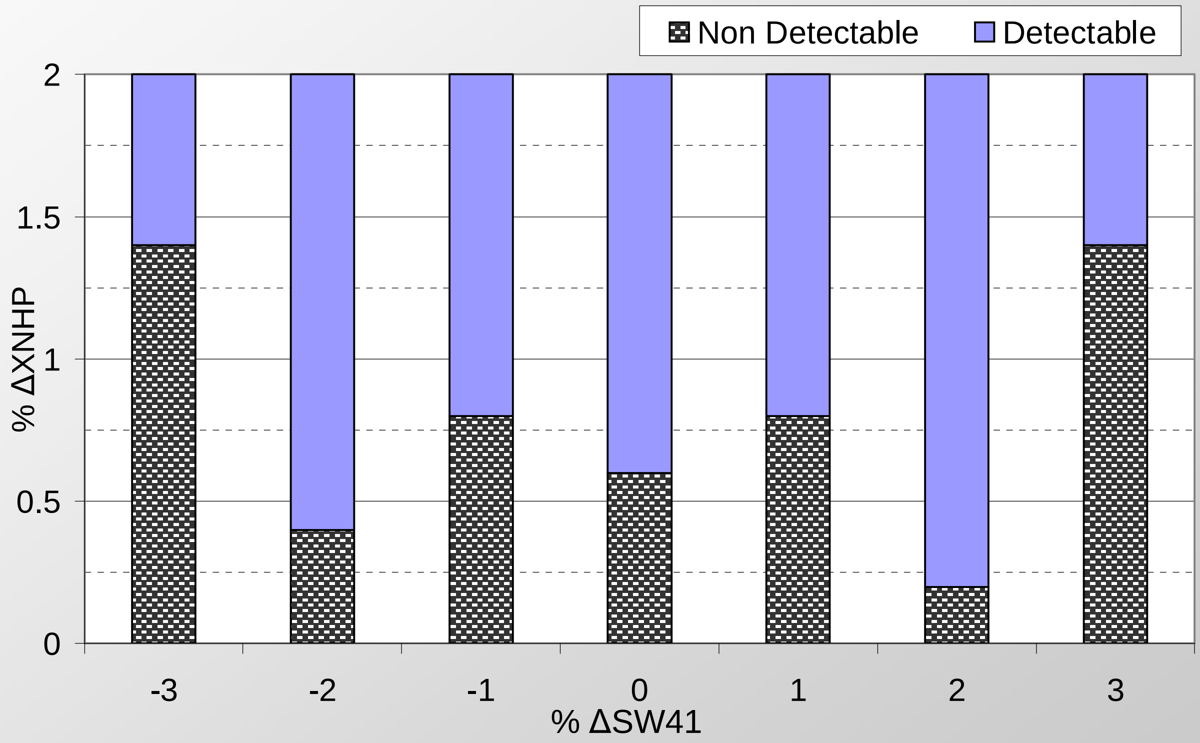
Simultaneous presence of Component Faults

How the diagnostic ability is affected at the simultaneous presence of Component Faults ?

Detectable biases are larger

Sensor Biases larger than ±1% are detectable for usual component faults

Sensor fault detection in a faulty engine

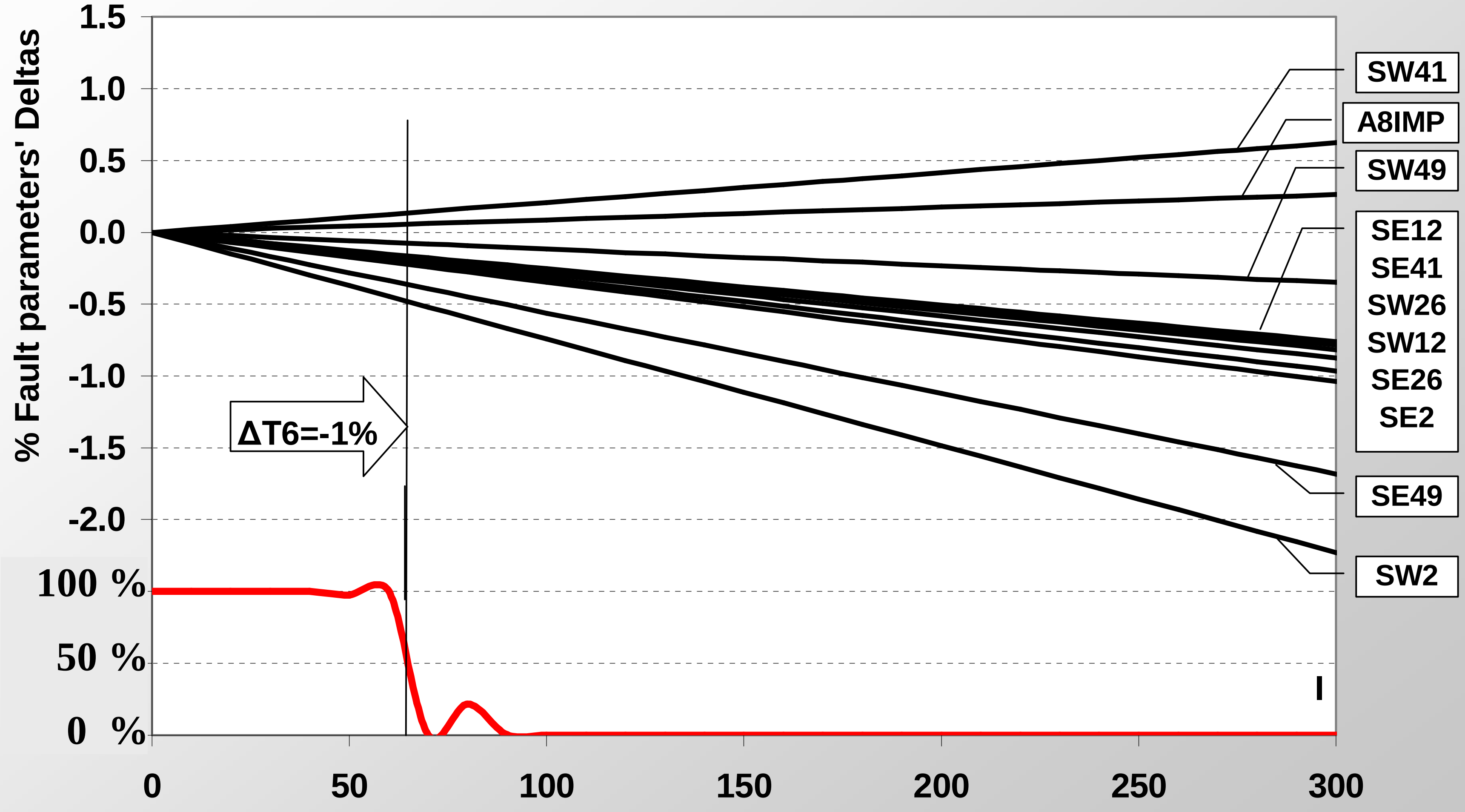


Drifting Deterioration of Fault Parameters

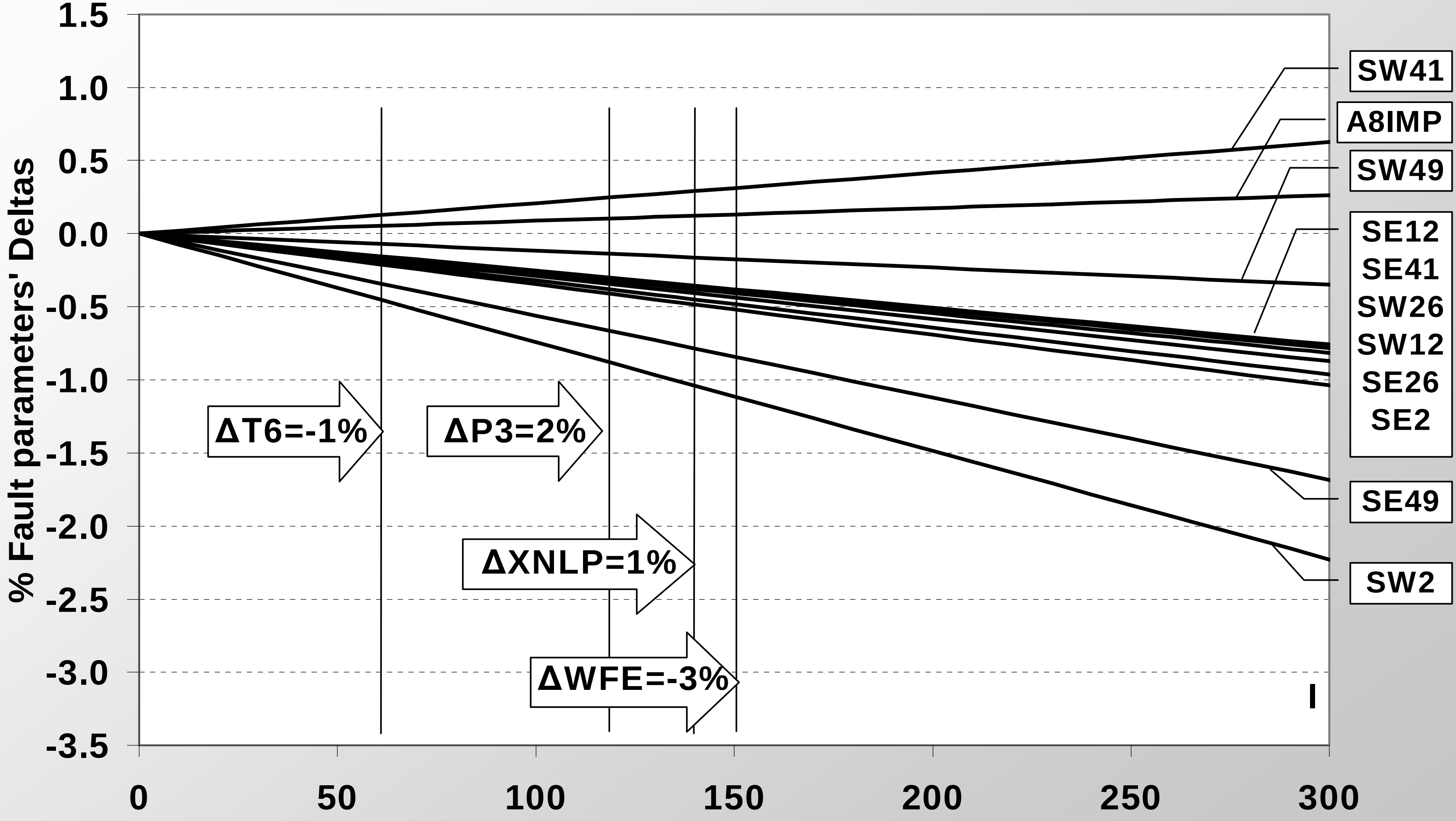
How the diagnostic ability is affected in a deteriorated engine?

The general trend is that ±1% biases are detectable for deterioration levels of up to ±0.5% fault parameters deviation

Sensor fault detection in a deteriorating engine



Sensor fault detection in a deteriorating engine



Conclusions - Results

- Flexible and easy to built network
- Wide range of effective diagnosis
- Cases of Multiple sensor faults handled efficiently
- Robustness in the presence of component faults or deterioration

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