JET ENGINE SENSOR VALIDATION WITH PROBABILISTIC NEURAL NETWORKS

C. Romessis
Research Assistant

K. Mathioudakis
Associate Professor

Laboratory of Thermal Turbomachines
National Technical University of Athens

JET ENGINE SENSOR VALIDATION WITH PROBABILISTIC NEURAL NETWORKS

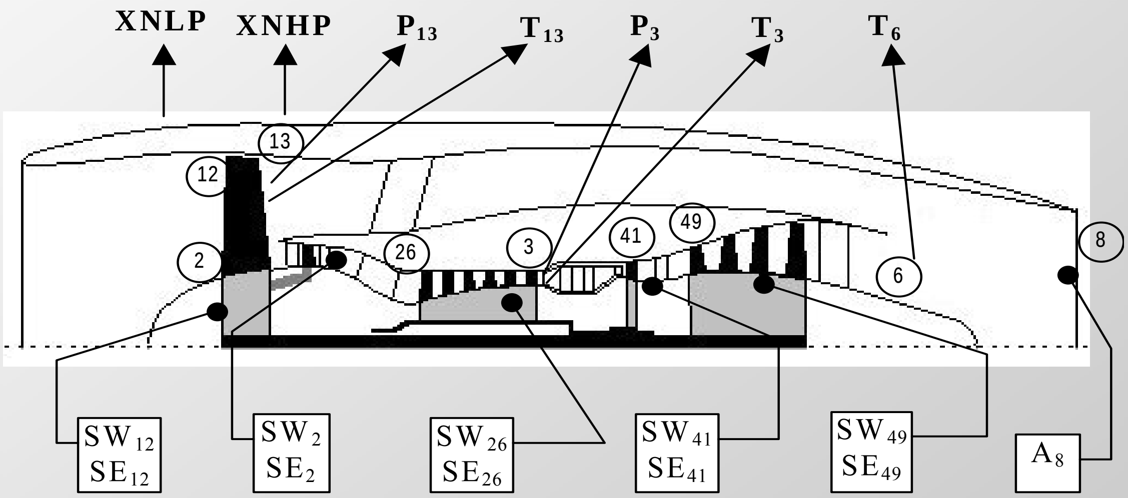
- Definition of the diagnostic problem
- Probabilistic Neural Network Architecture
- PNN sensor validation
  - o Sensor fault detection in a faulty engine
  - o Minimum detectable sensor biases
  - o Sensor fault detection in a deteriorating engine
  - o Sensor validation during a flight
  - o Multiple sensor faults
- Summary - Conclusions

JET ENGINE SENSOR VALIDATION WITH PROBABILISTIC NEURAL NETWORKS

- **Definition of the diagnostic problem**
- Probabilistic Neural Network Architecture
- PNN sensor validation
  - o Sensor fault detection in a faulty engine
  - o Minimum detectable sensor biases
  - o Sensor fault detection in a deteriorating engine
  - o Sensor validation during a flight
  - o Multiple sensor faults
- Summary - Conclusions

Definition of the Diagnostic Problem

Determine the bias of the readings from a number of instruments

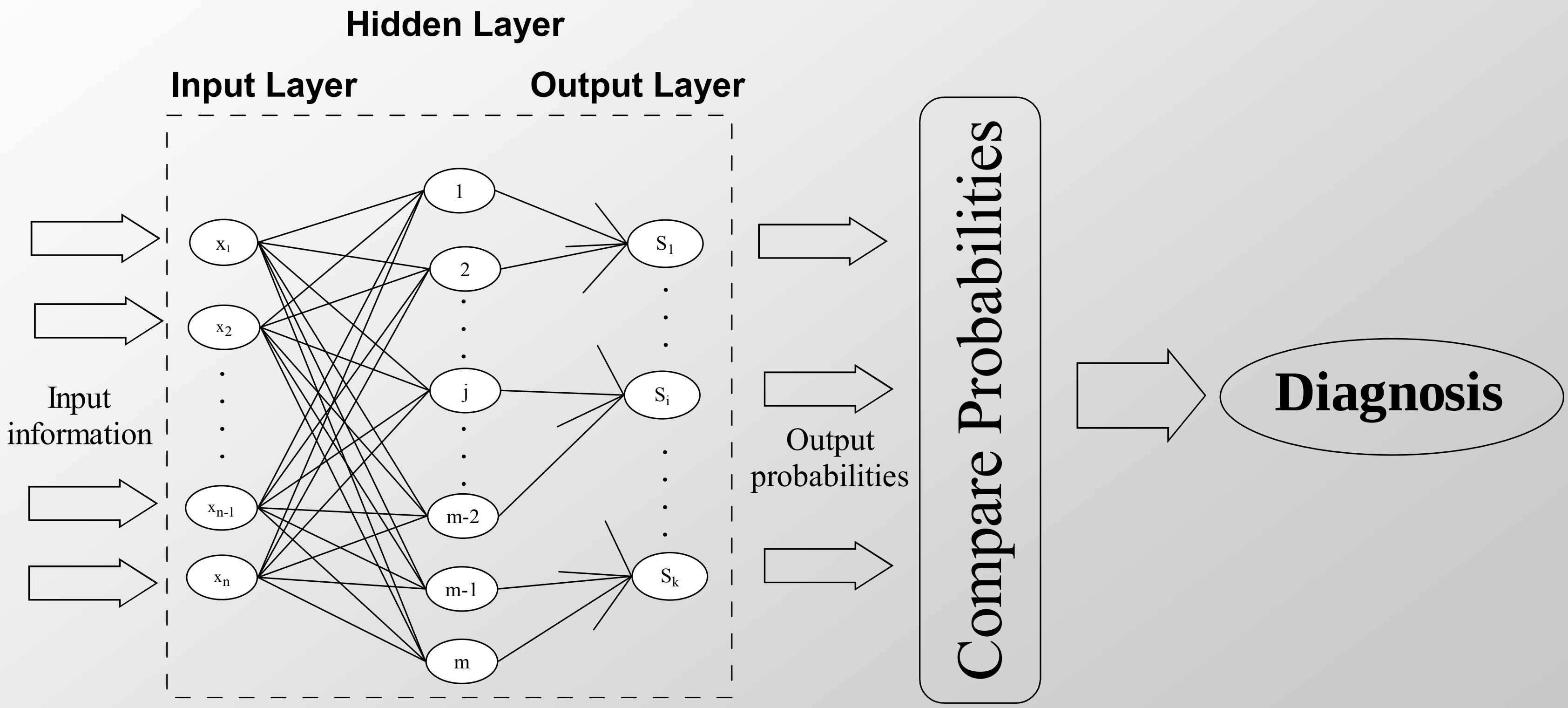


High-by-Pass ratio, partially mixed, turbofan engine used as a test case

JET ENGINE SENSOR VALIDATION WITH PROBABILISTIC NEURAL NETWORKS

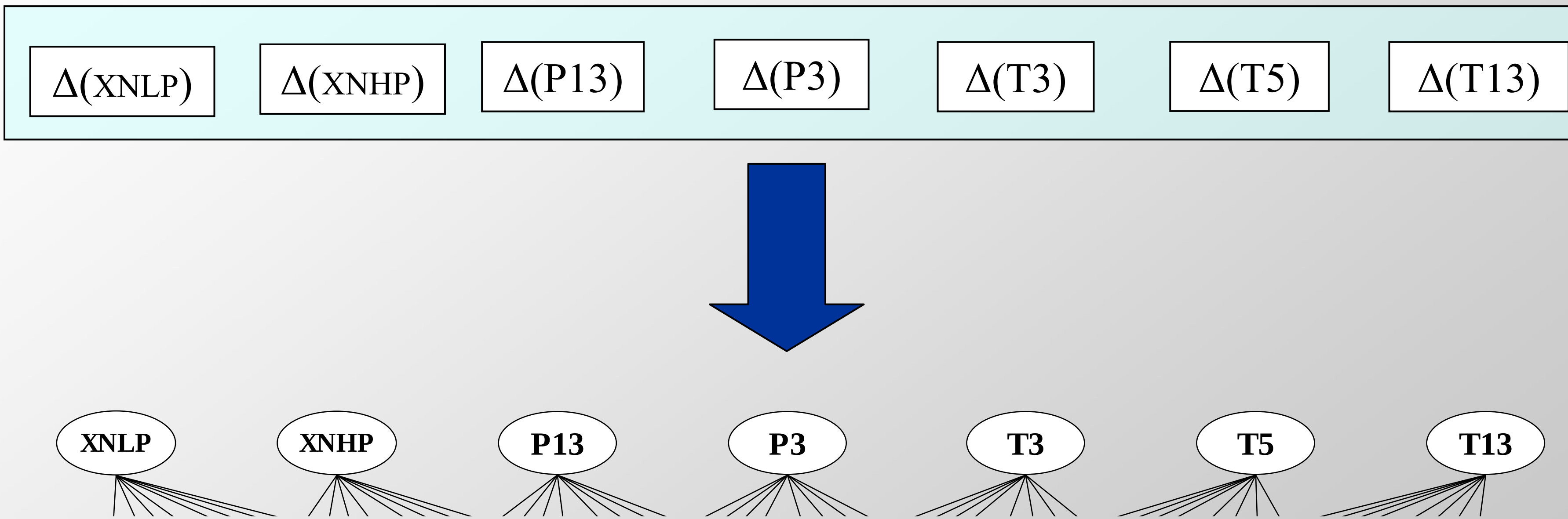
- Definition of the diagnostic problem
- **Probabilistic Neural Network Architecture**
- PNN sensor validation
  - o Sensor fault detection in a faulty engine
  - o Minimum detectable sensor biases
  - o Sensor fault detection in a deteriorating engine
  - o Sensor validation during a flight
  - o Multiple sensor faults
- Summary - Conclusions

Diagnosis with the Probabilistic Neural Network (PNN)



Structure of the PNN

Input layer: Deltas of the measurements



Pattern Generation from Measurements

XNLP, XNHP, P13, P3, T3, T5, T13

P_{amb}, P1, T1, WFE

EPM

Nominal values:
XNLP, XNHP, P13, P3, T3, T5, T13

$\Delta(Y)=(Y-Ynom)/Ynom$

Pattern

Δ(XNLP)	Δ(XNHP)	Δ(P13)	Δ(P3)	Δ(T3)	Δ(T5)	Δ(T13)

Turbofan Engine Modeling

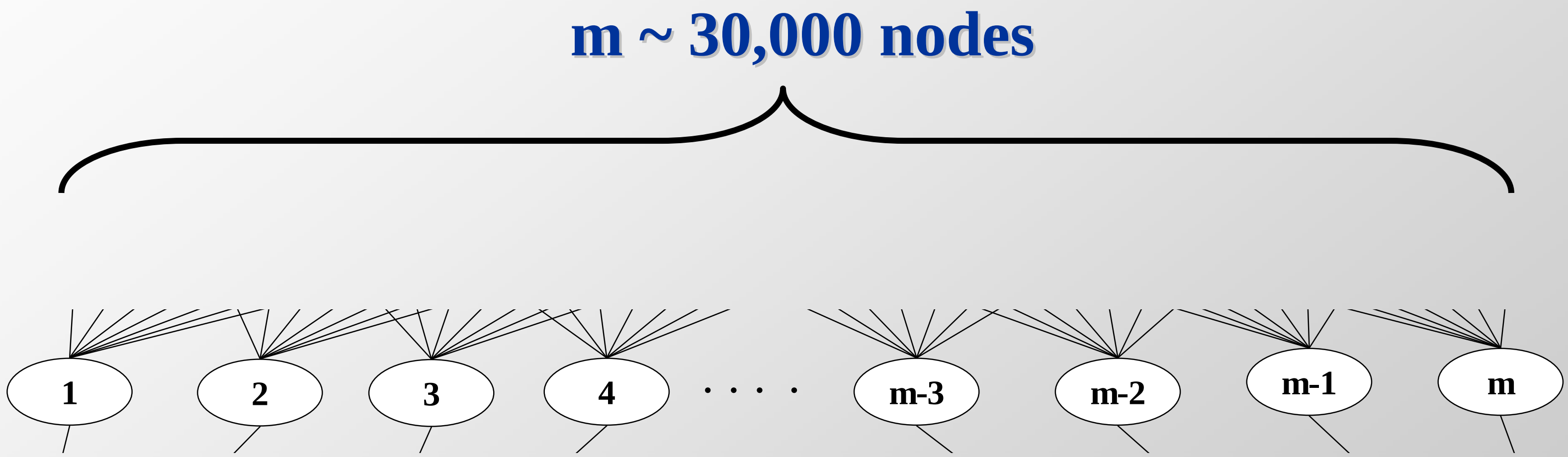
- **Quantities defining the operating Conditions:**
  - **Ambient Pressure**
  - **Fuel consumption**
  - **Engine Inlet Conditions (pressure, temperature)**
- **Fault Parameters:**
  - **Flow factors along the engine**
  - **Efficiency factors along the engine**
  - **Exhaust area**

EPM

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

Structure of the PNN

Hidden layer: Training patterns

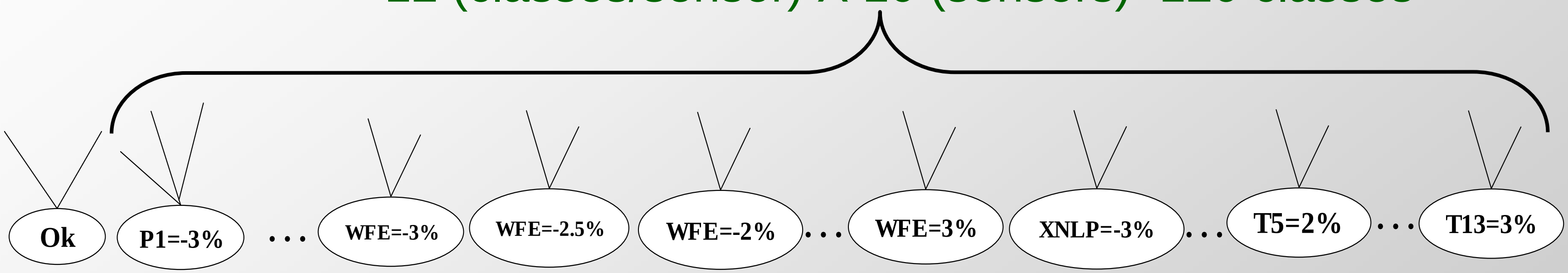


Each node: A Noise-free pattern produced by simulation

Structure of the PNN

Output layer: Considered classes

12 (classes/sensor) X 10 (sensors)=120 classes



No fault probability

probability of sensor biases

Example

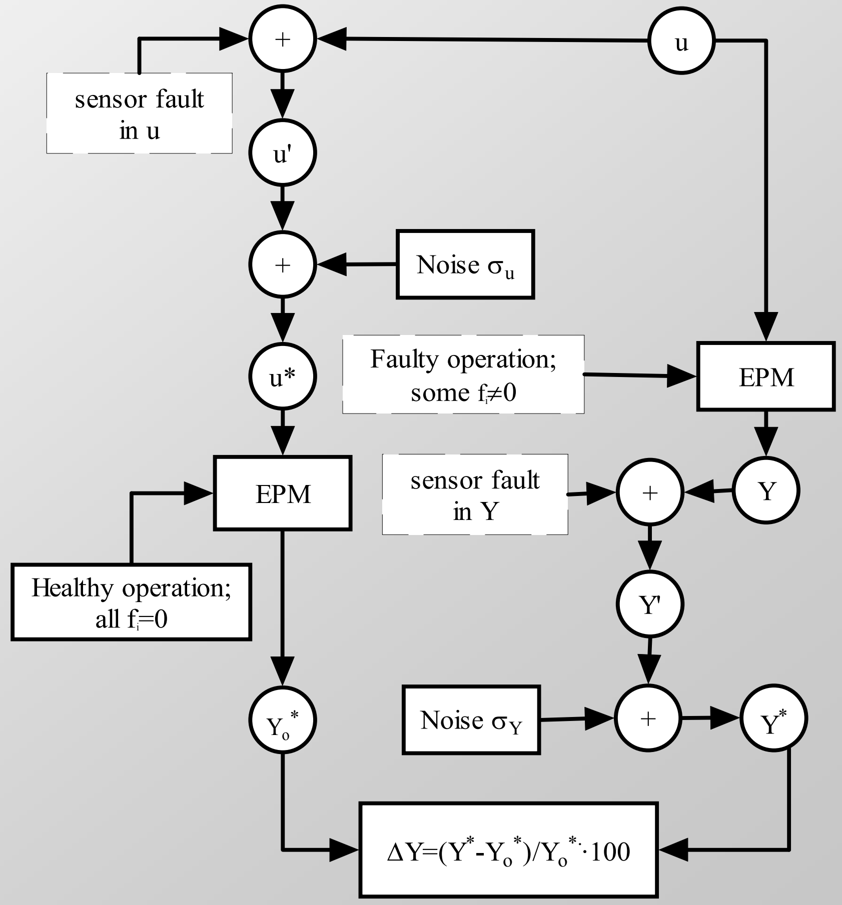
5.30%	2.20%	. . .	4.65%	3.65%	68.30%	. . .	1.58%	3.60%	. . .	1.23%	. . .	2.90%

Fuel flow reading has a bias of -2%

Materializing the Network

Generation of the patterns

Network once trained, then tested



Aspects Examined to Assess Diagnostic Potential

- Simultaneous presence of **Component Faults**
- **Minimum detectable** sensor biases
- Drifting **Deterioration of Fault Parameters**
- Diagnosis at different **Operating Conditions**
- **Multiple Sensor Faults** detection

Aspects Examined to Assess Diagnostic Potential

Have been considered for:

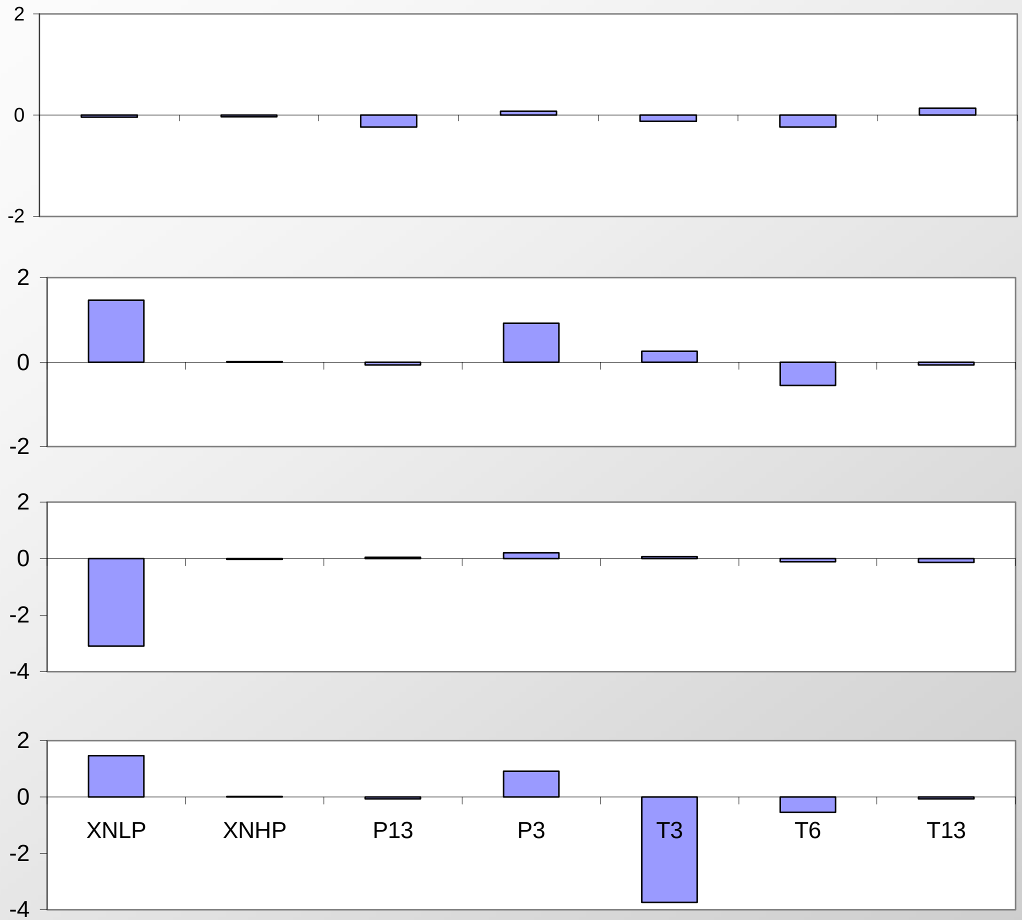
A. **Patterns for training the network**

B. **Patterns for testing the network**

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 sensor validation**
  - Sensor fault detection in a faulty engine
  - Minimum detectable sensor biases
  - Sensor fault detection in a deteriorating engine
  - Sensor validation during a flight
  - Multiple sensor faults
- Summary - Conclusions

Examples of Test Patterns



Healthy engine, Healthy sensors

Faulty engine, Healthy sensors

Healthy engine, Faulty sensor (ΔXNLP=-3%)

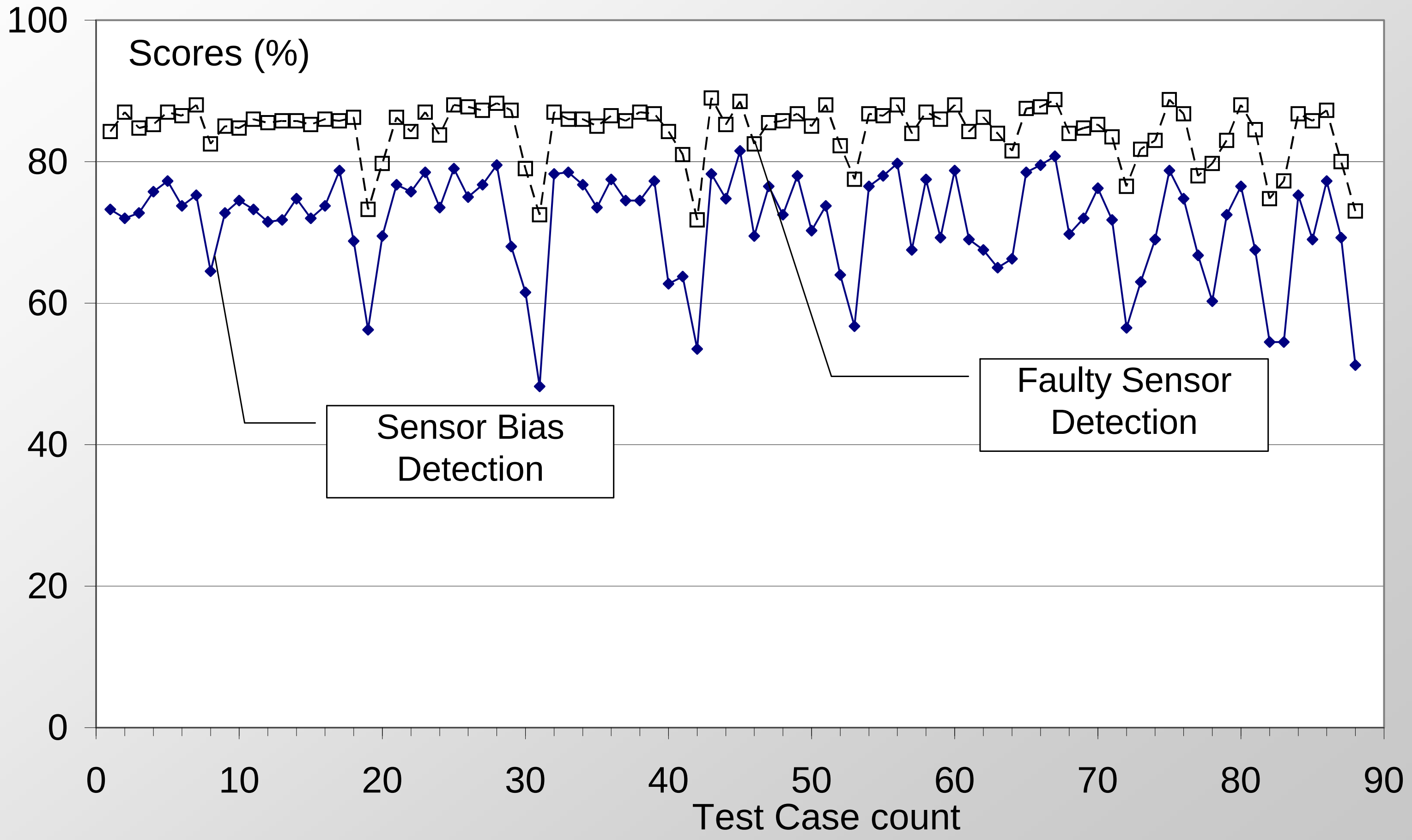
Faulty engine, Faulty sensor (ΔT3=-3%)

Simultaneous presence of Component Faults

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

Sensor Biases are detectable in almost all cases of faulty operation of the engine (deviation of 1%-2% of the fault parameters)

Sensor fault detection in a faulty engine



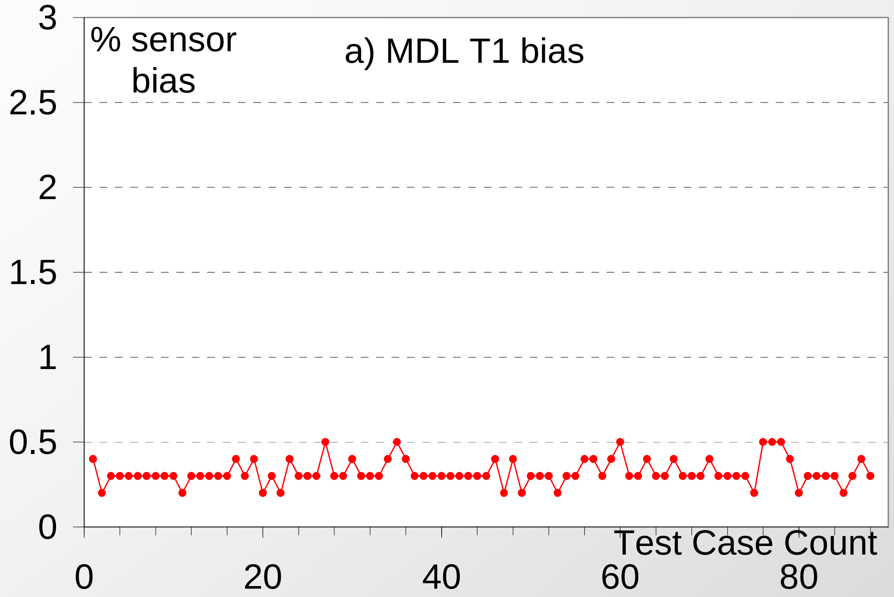
Minimum detectable sensor biases

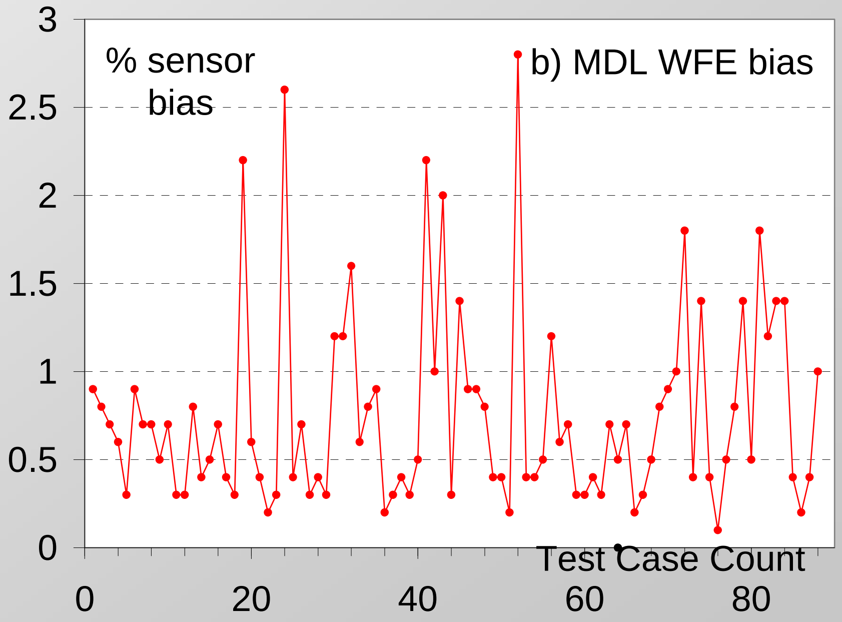
Which are the minimum sensor biases that can be detected?

Biases greater than 0.4% - 1.0% are almost always detected for all sensors

Bias Levels usually represent 2-6 times the considered noise levels

Minimum detectable sensor biases



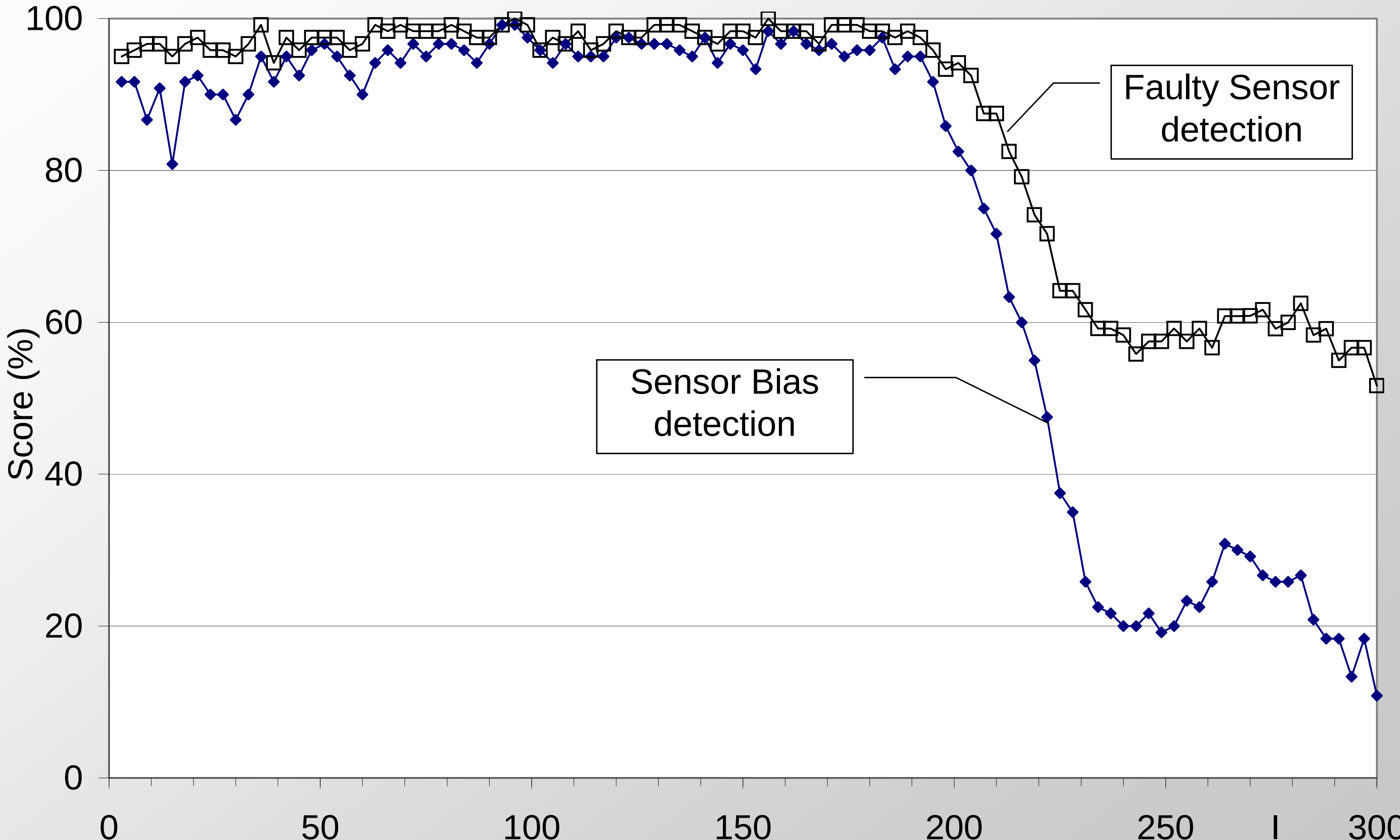


Drifting Deterioration of Fault Parameters

How the diagnostic ability is affected in a deteriorated engine?

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

Sensor fault detection in a deteriorating engine



Diagnosis at different Operating Conditions

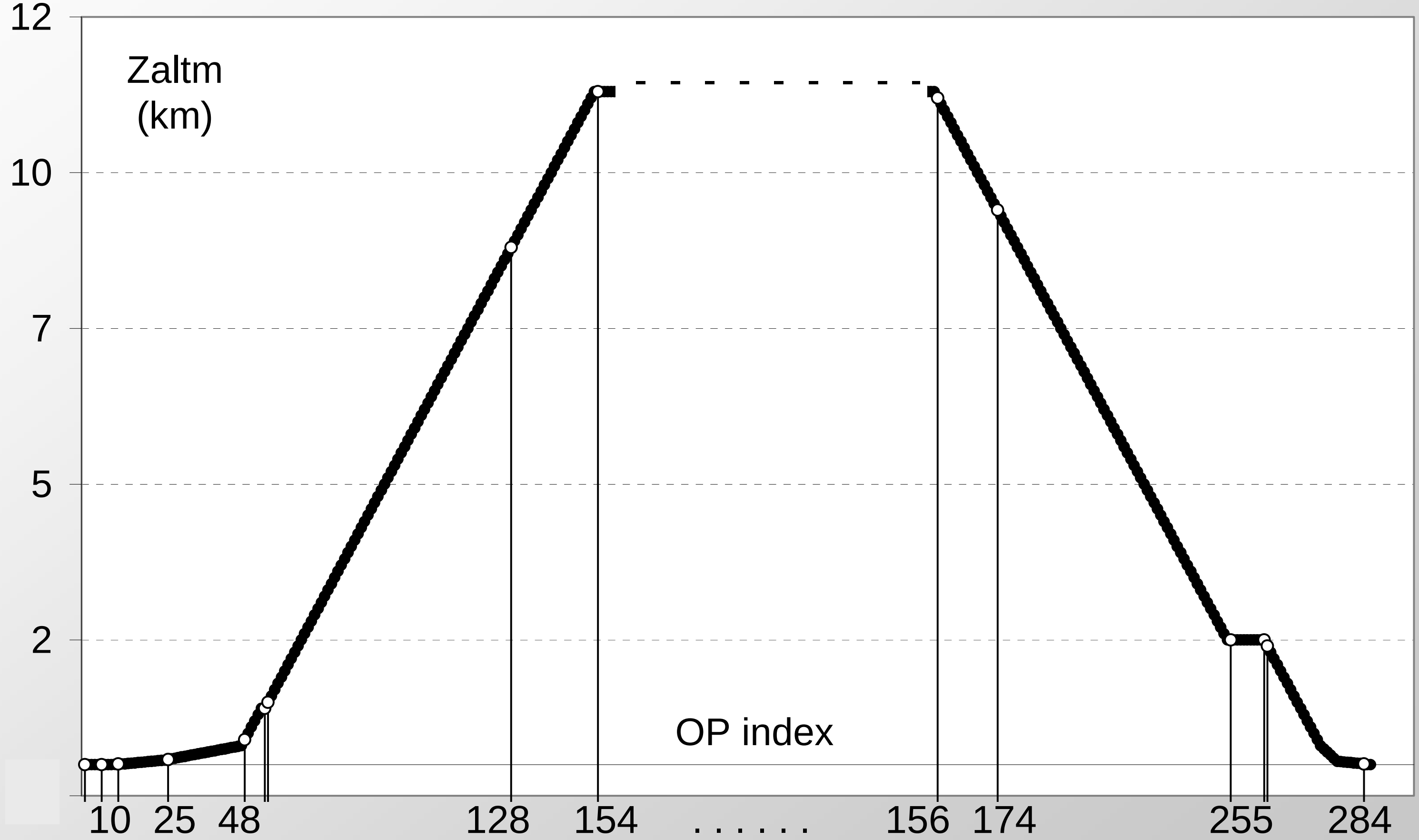
How the diagnostic ability is affected at different operating conditions?

Diagnostic ability unaffected for a region of operating conditions

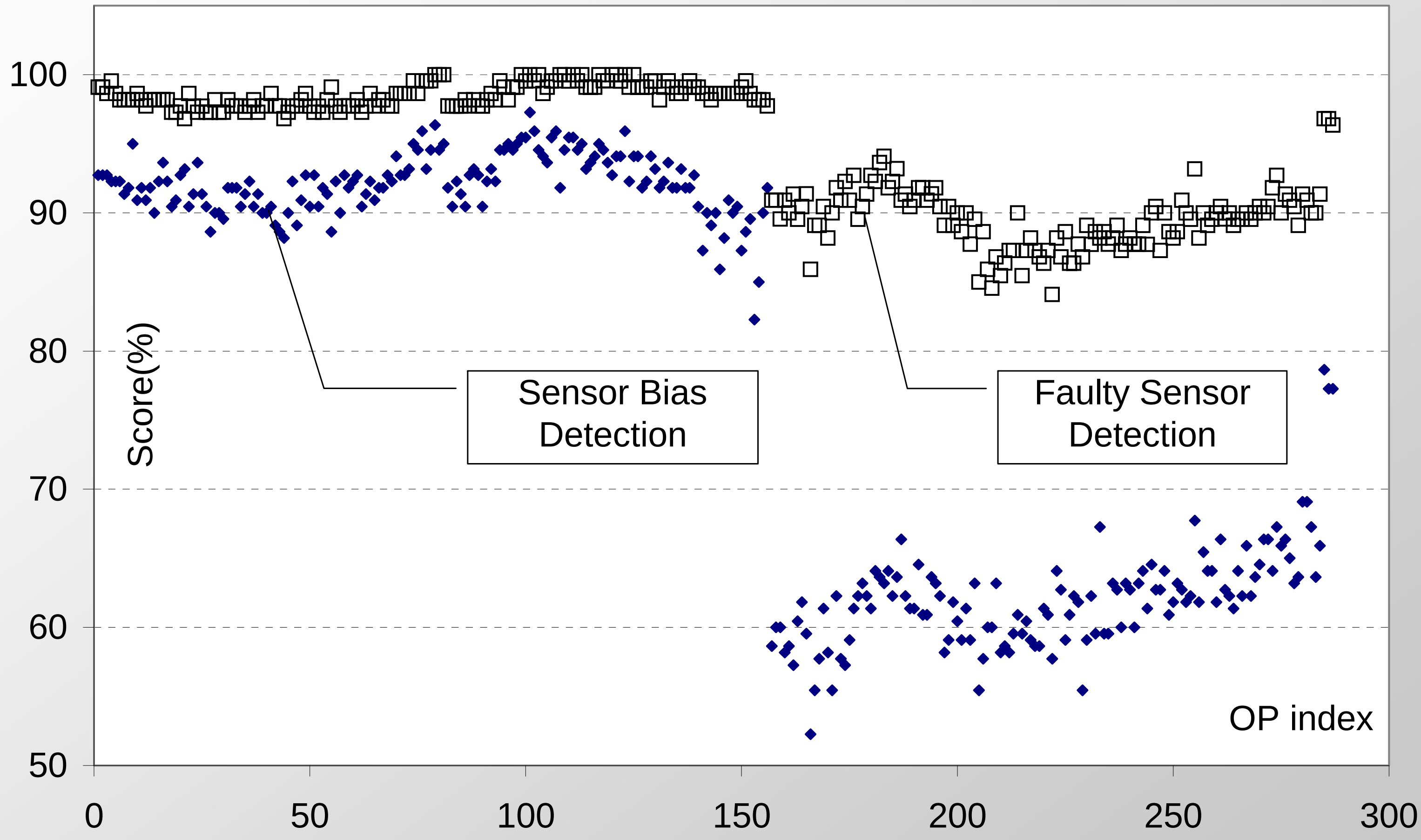
A whole flight envelope can be covered by two PNNs

Effect of Operating Conditions

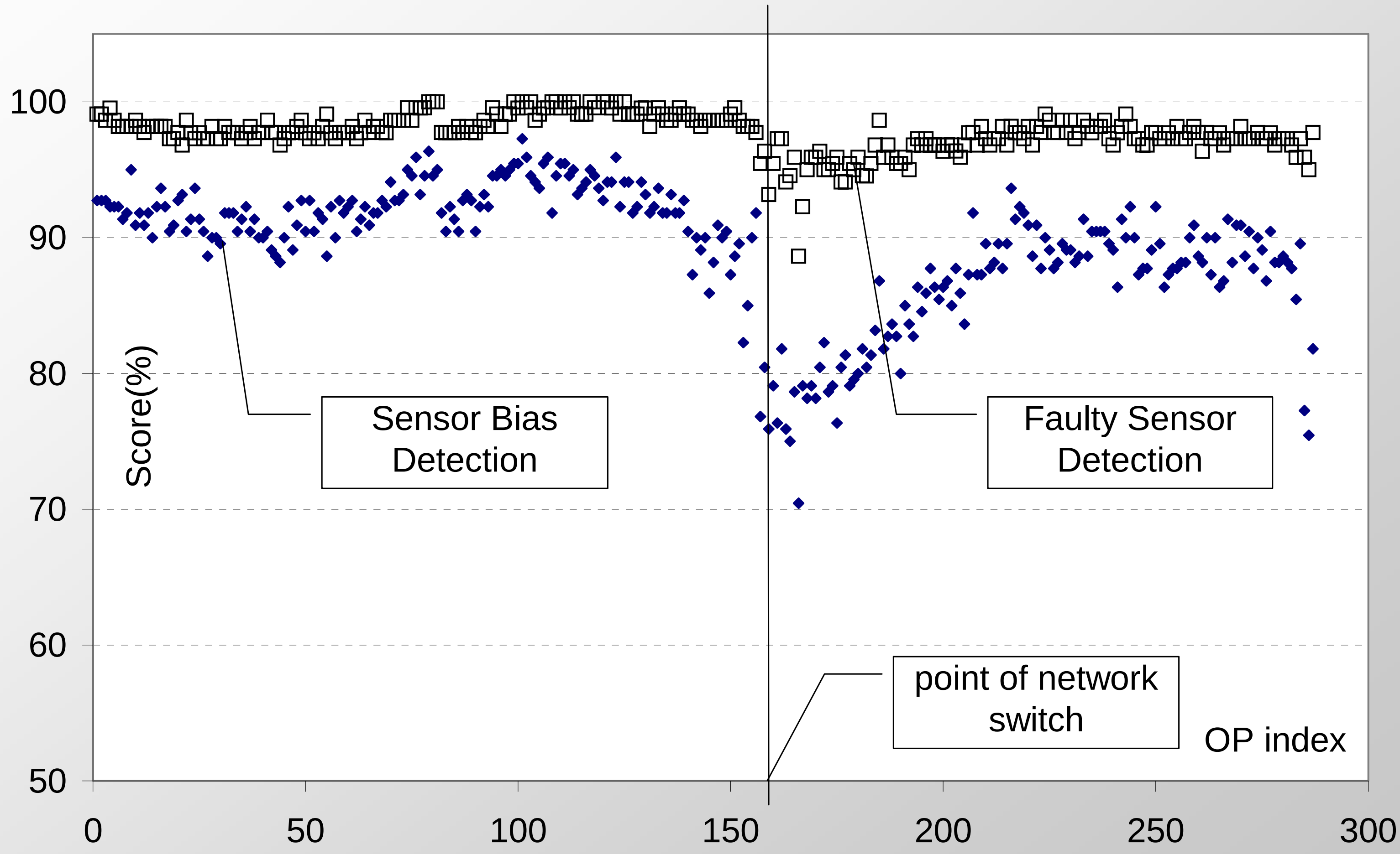
Representation of a flight envelope



Effect of Operating Conditions



Effect of Operating Conditions

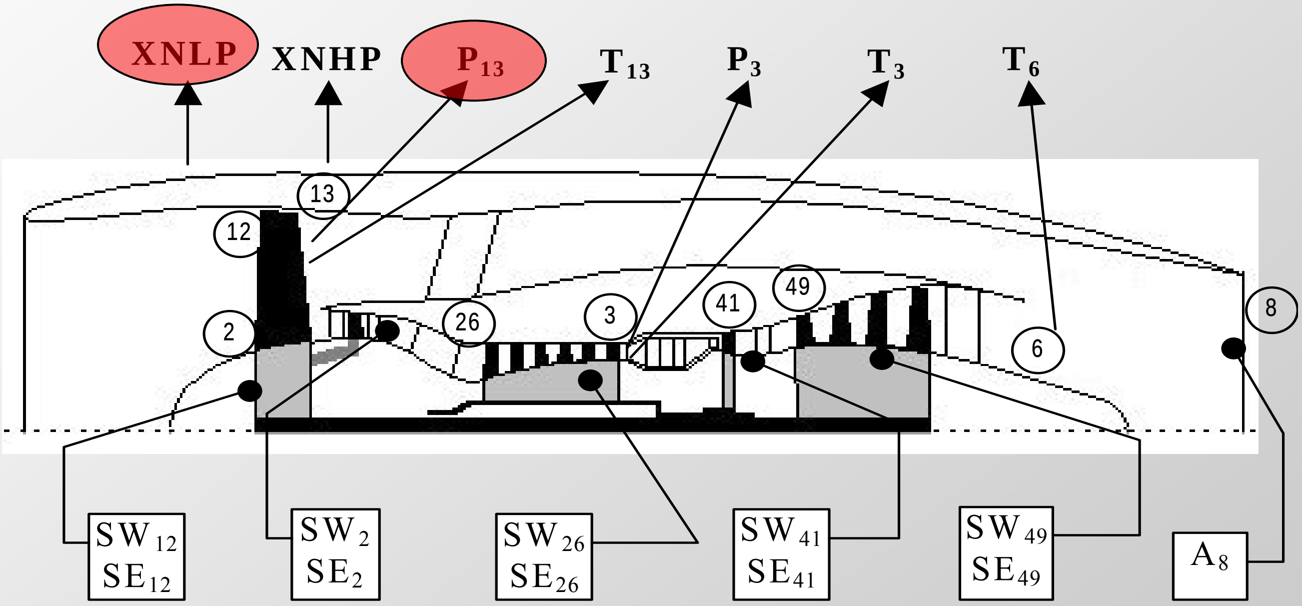


Multiple Sensor Faults detection

How, possibly, multiple sensor faults can be detected?

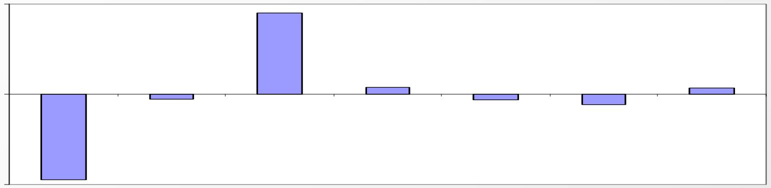
Faults in up to two different sensors are detected efficiently

Multiple sensor faults



Multiple sensor faults: Diagnostic procedure

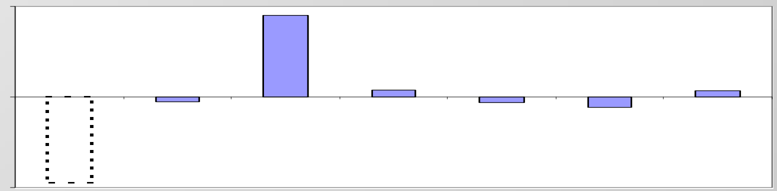
Initial Pattern



Diagnosis

P(XNLP=-2%)>50%

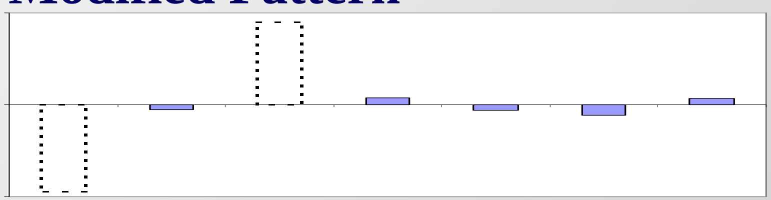
Modified Pattern



Diagnosis

P(P13=1%)>50%

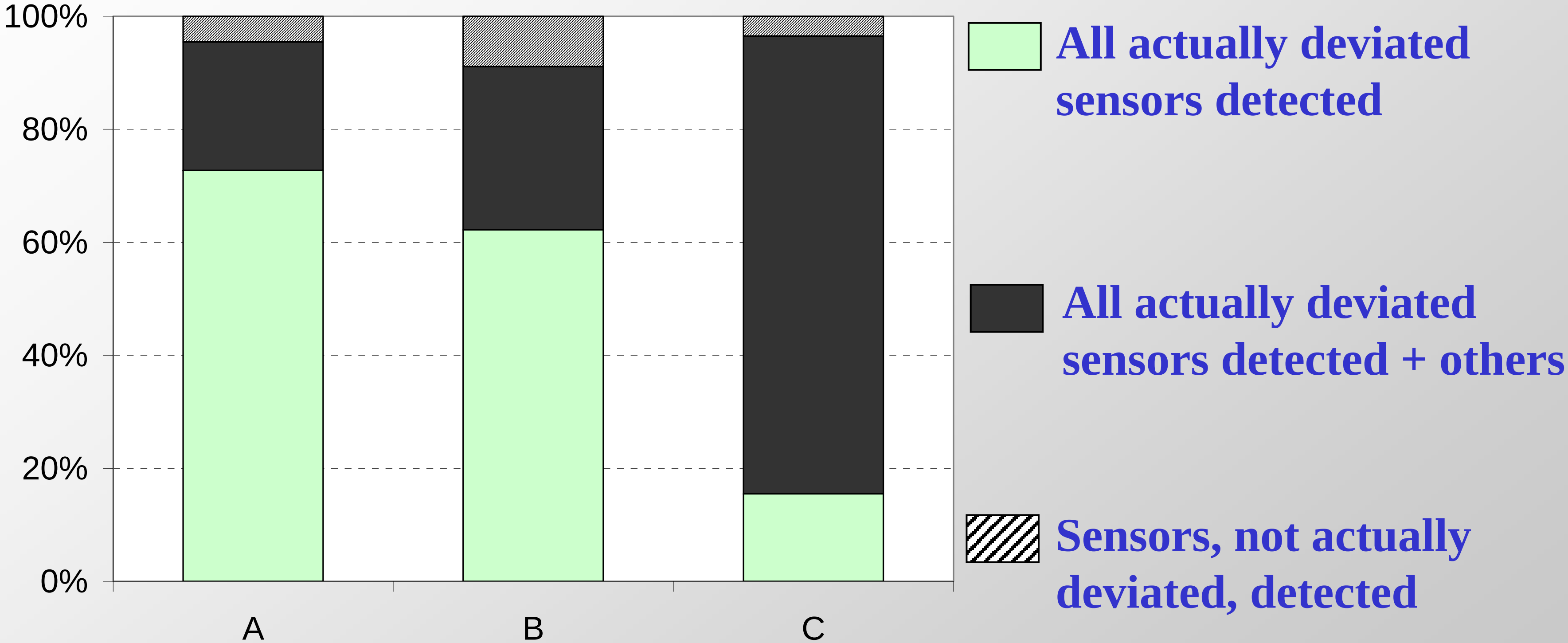
Modified Pattern



Diagnosis

P(Ok)>50%

Success rates for Multiple Sensor Faults



A: SF on 2 monitoring sensors
B: SF on 2 set-point or monitoring sensors
C: All combinations of SF on 2, 3, 4 sensors

Conclusions - Results

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