A PARAMETRIC INVESTIGATION OF THE DIAGNOSTIC ABILITY OF PROBABILISTIC NEURAL NETWORKS ON TURBOFAN ENGINES

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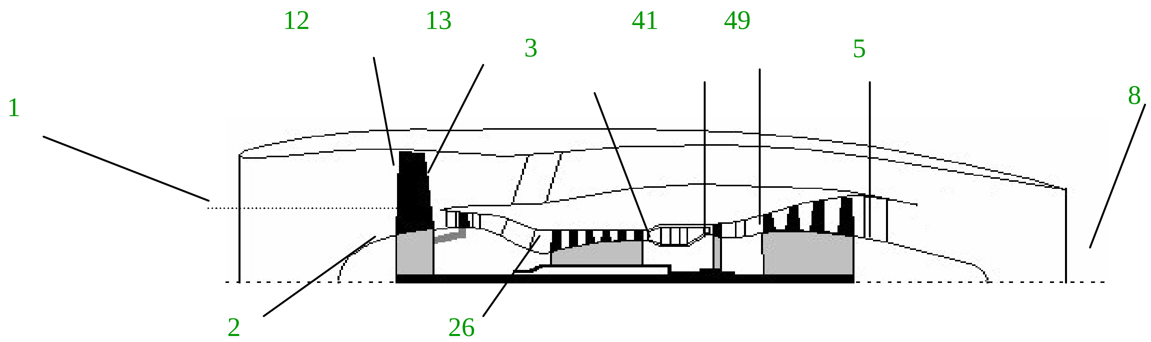
A PARAMETRIC INVESTIGATION OF THE DIAGNOSTIC ABILITY OF PROBABILISTIC NEURAL NETWORKS ON TURBOFAN ENGINES

- Formulation of the diagnostic problem
- Features of Probabilistic Neural Networks
- Study of factors affecting diagnostic performance of PNN
  - Effect of Training Set
  - Effect of Measurements' noise
  - Effect of the severity of a fault
  - Effect of the operating conditions
  - Effect of the selected diagnostic parameters
- Summary - Conclusions

Formulation Of The Diagnostic Problem (I)

OBJECTIVE: PNN to diagnose component faults of High-by-Pass ratio, partially mixed, TURBOFAN engine



Layout of a turbofan engine and

station numbering for positions of interest.

Formulation Of The Diagnostic Problem (II)

ØInformation Provided

- §**Quantities defining operating Condition (4)**
  - §Ambient Conditions
  - §Flight Speed
  - §Set Point Variable (Fuel flow rate)
- §**Quantities for Deducing Engine Condition (7)**
  - §Shaft speeds
  - §Pressure, Temperatures

ØInformation Required

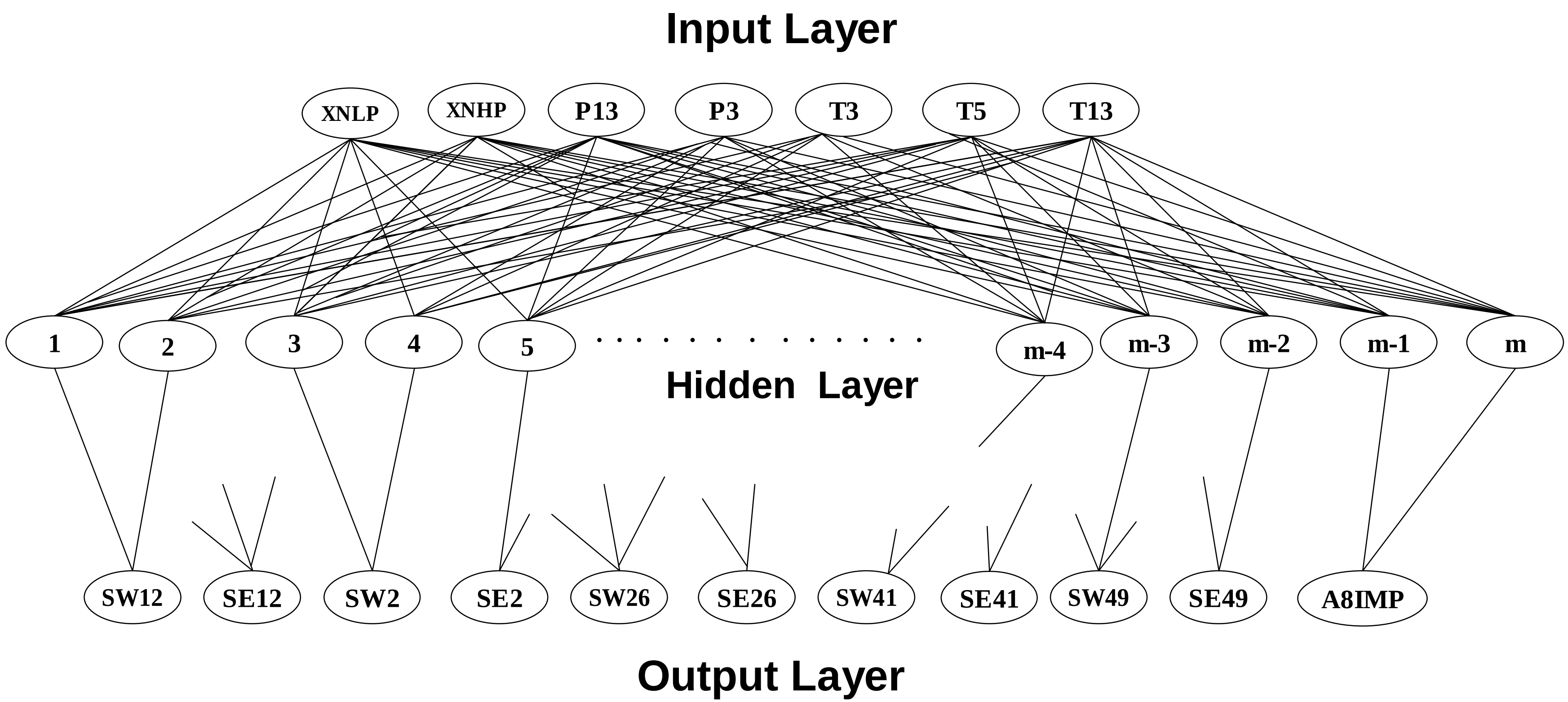
- §**Condition of individual engine components**
  - §Kind, Location, Severity (magnitude) of faults

PNN Generation

(I) Architecture

- **Input Layer:**
  Each node represents a measured quantity
  (Inputs :$\Delta Y = [(Y - Y_{ref}) / Y_{ref}]\ 100\%$)
- **Hidden Layer:**
  Each node represents a training pattern
  (a-priori given information)
- **Output Layer:**
  Each node represents a fault parameter
  (probability values derived by NN)

Structure of a Probabilistic Neural Network



PNN Generation

(II) A priori information

- **Training Patterns**

- **Generated by Engine Performance model**
  - **Reference information ("healthy" - Y_{ref})**
  - **Faulty Engine Information (Y)**

Turbofan Engine Modeling

ØQuantities defining the operating Conditions (4):

- § *Ambient Pressure*
- §*Fuel consumption*
- §*Engine Inlet Conditions (pressure, temperature)*

ØFault Parameters (11):

- § **Flow factors of positions of interest:** $SW_i = \dfrac{W_i \cdot \sqrt{T_i}}{p_i} \Big/ \left(\dfrac{W_i \cdot \sqrt{T_i}}{p_i} \right)_{ref}$
- §**Efficiency factors of positions of interest:** $SE_i = \dfrac{h_i}{(h_i)_{ref}}$
- §**Exhaust area (numbered station 8)**

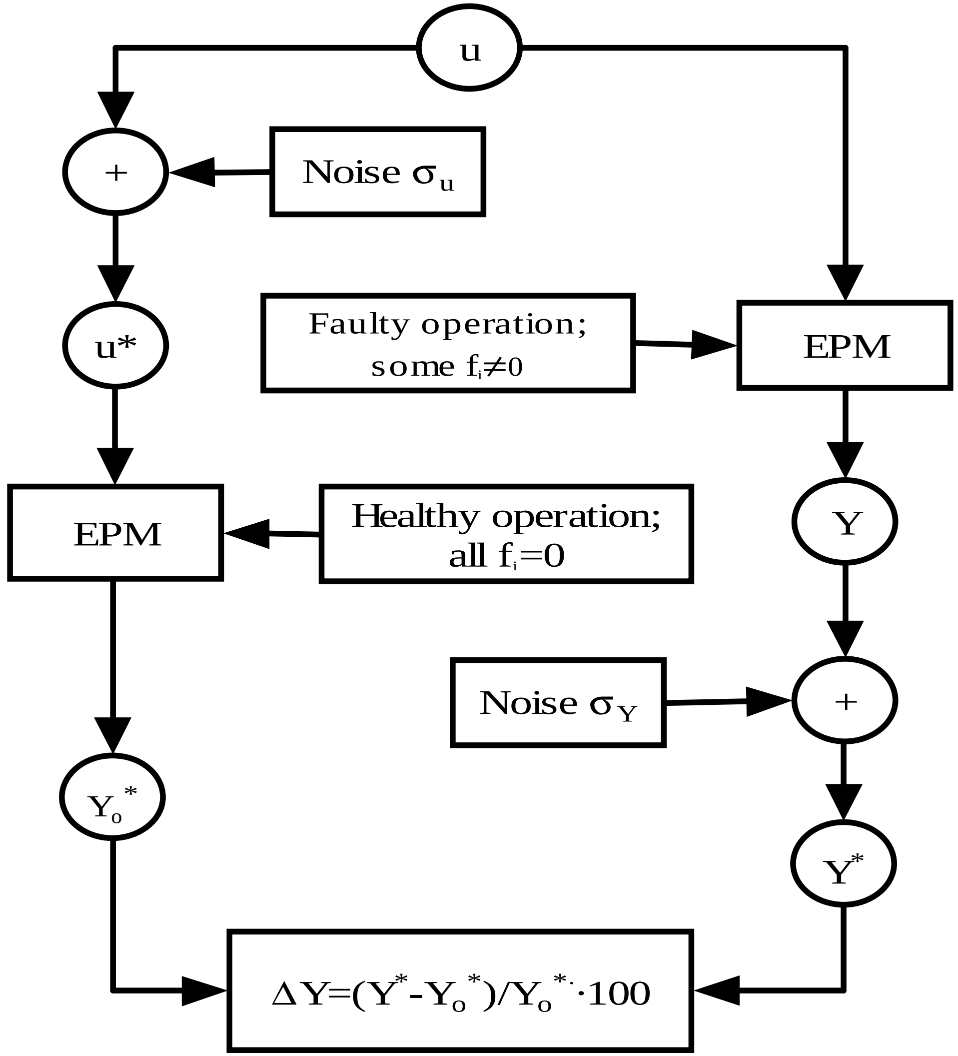
Ø Measured quantities (7):

- § **Shafts' speed (low and high pressure)**
- § **Pressures and temperatures at stations along the engine**

Creating Fault Patterns

(Containing noise)

Procedure for generating noise-free patterns by EPM and adding noise on them



Generating the Training – Testing patterns

Patterns (generated by EPM)

Deltas of measurements for a specific set of deltas of the fault parameters

Considered faults

- **11 Single faults: Delta of 1 fault parameter deviates within a range of +/- 3%**

- **5 Combined faults: Deltas of 2 fault parameters, of the same module,deviate.**

*** Delta of a value Y: $\Delta Y = [(Y - Y_{ref}) / Y_{ref}]\ 100\%$**

Noise Situations Considered

(reproduce realistically the data collected from an actual engine)

5 noise levels considered

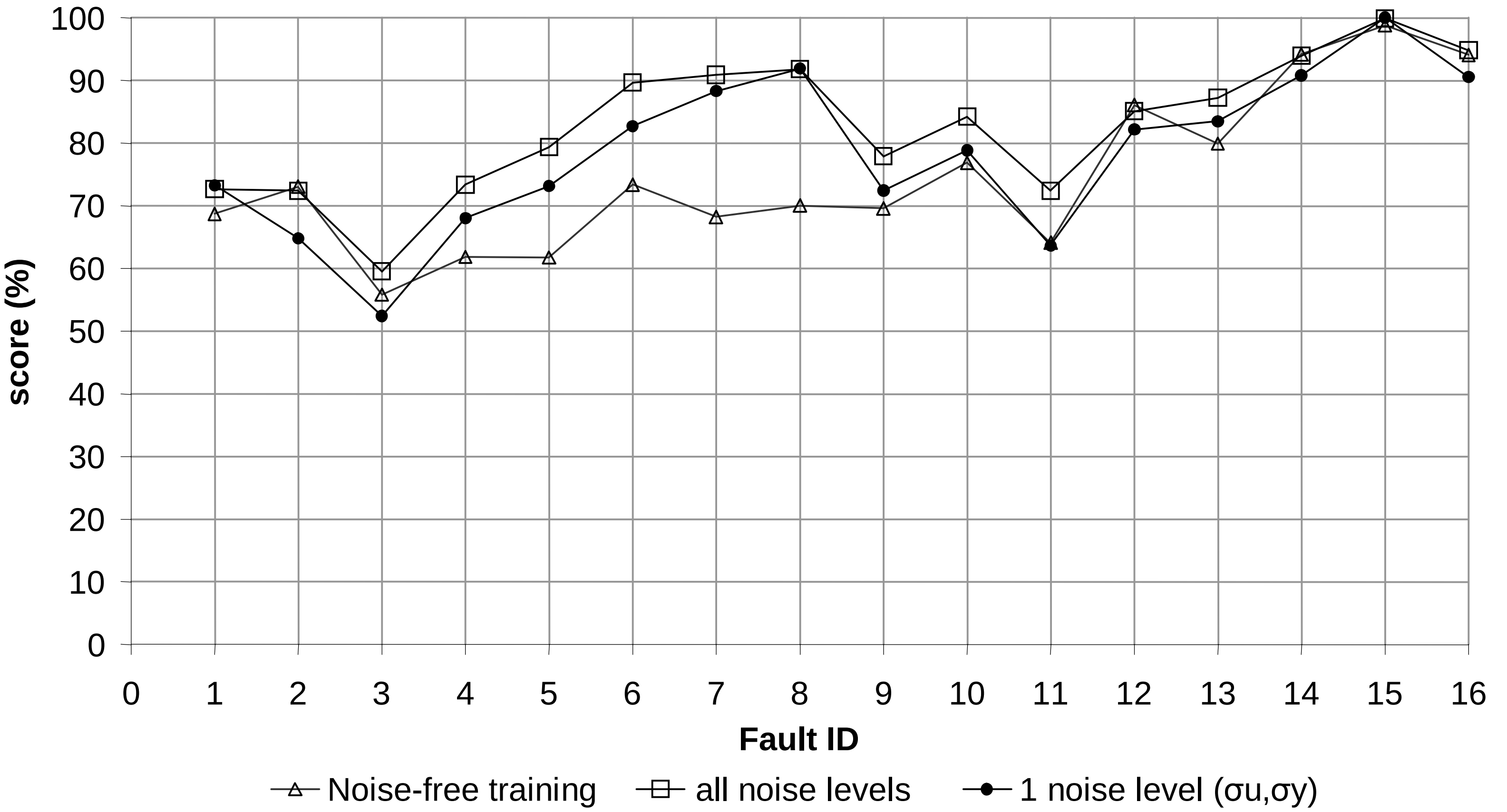
noise level	noise in u	noise in y
1	0	$\sigma_y/2$
2	0	σ_y
3	0	$3\sigma_y/2$
4	0	$2\sigma_y$
5	σ_u	σ_y

- σ_u: noise due to Operating Condition uncertainty
- σ_y: noise due to sensor inaccuracies

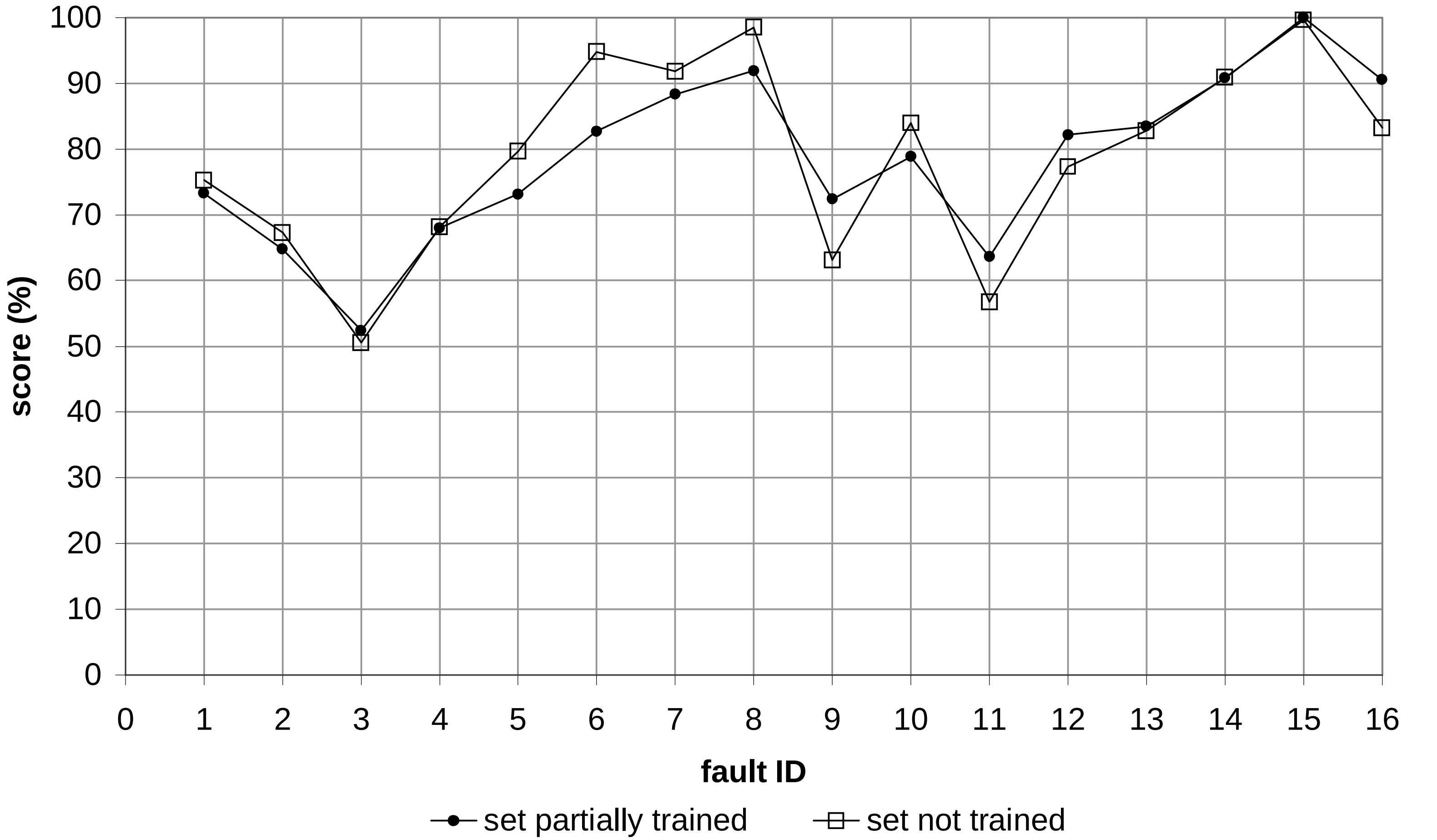
Considered Probabilistic Neural Networks

ID	No. of input nodes	Training patterns			No. of output nodes
		Operating point	Noise level included	No. of training patterns	
1	7	cruise	No noise	112	11
2	7	cruise	1st,2nd, 3rd, 5th	2240	11
3	7	cruise	5th level	1120	11
4	7	take-off	1st,2nd, 3rd, 5th	2240	11
5	7	take-off	5th level	1120	11
6	7	cruise	5th level	1120	5
7	14	cruise & take-off	5th level	2240	11

Effect of noise level on the training patterns

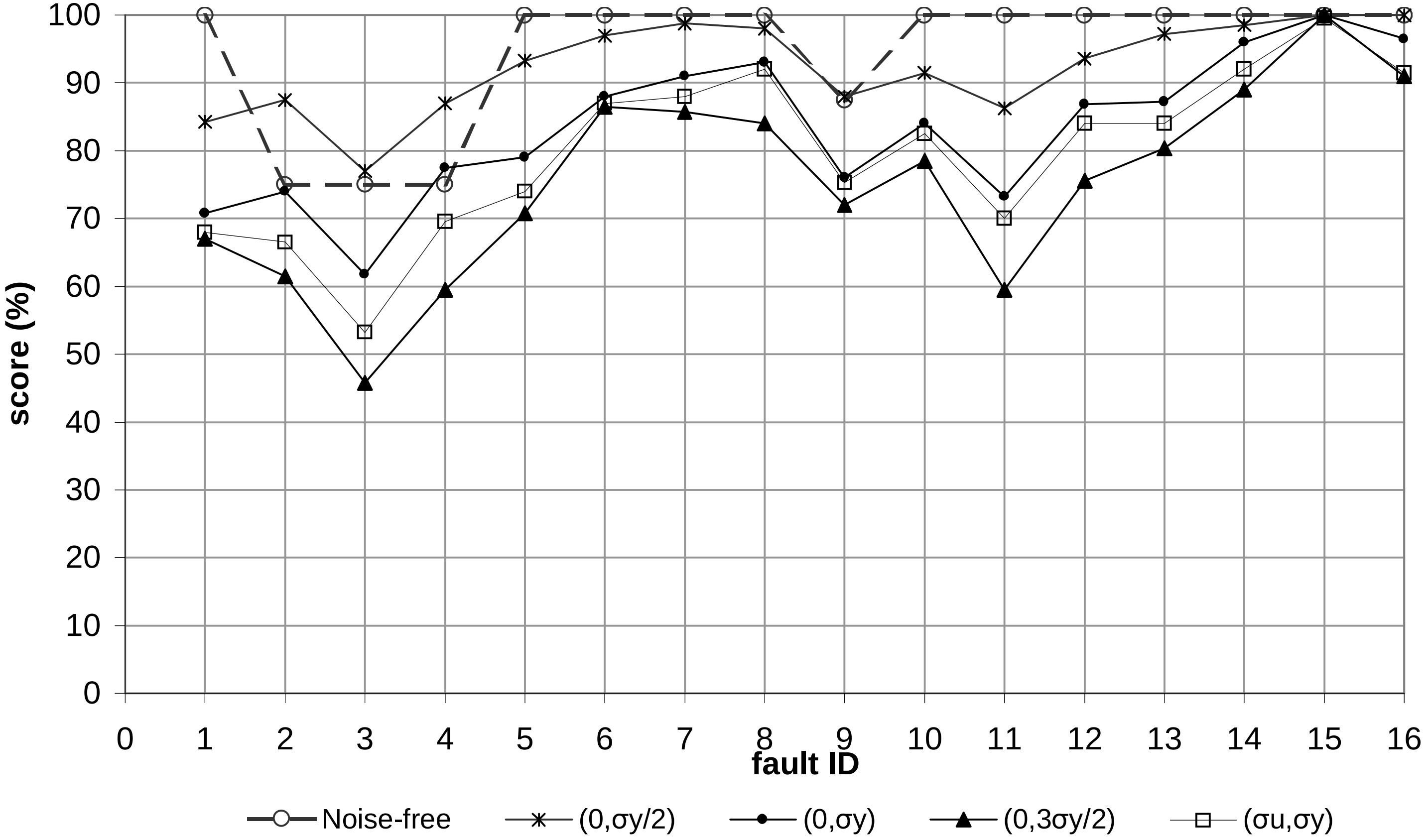


Performance of a network tested on patterns partially used for training and on non-training patterns

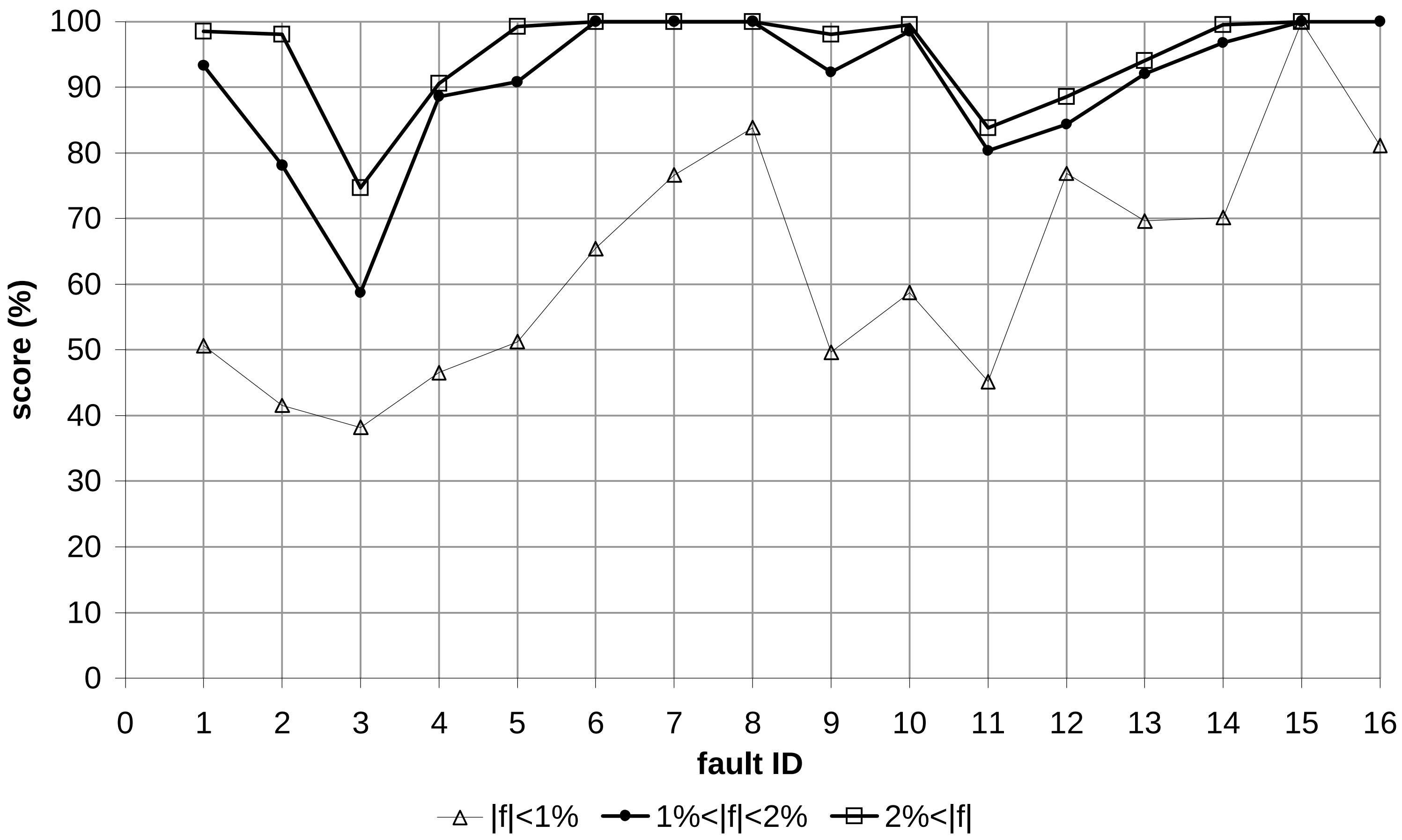


Effect of noise level in the patterns presented to the network.

Network trained using data from all noise situations.

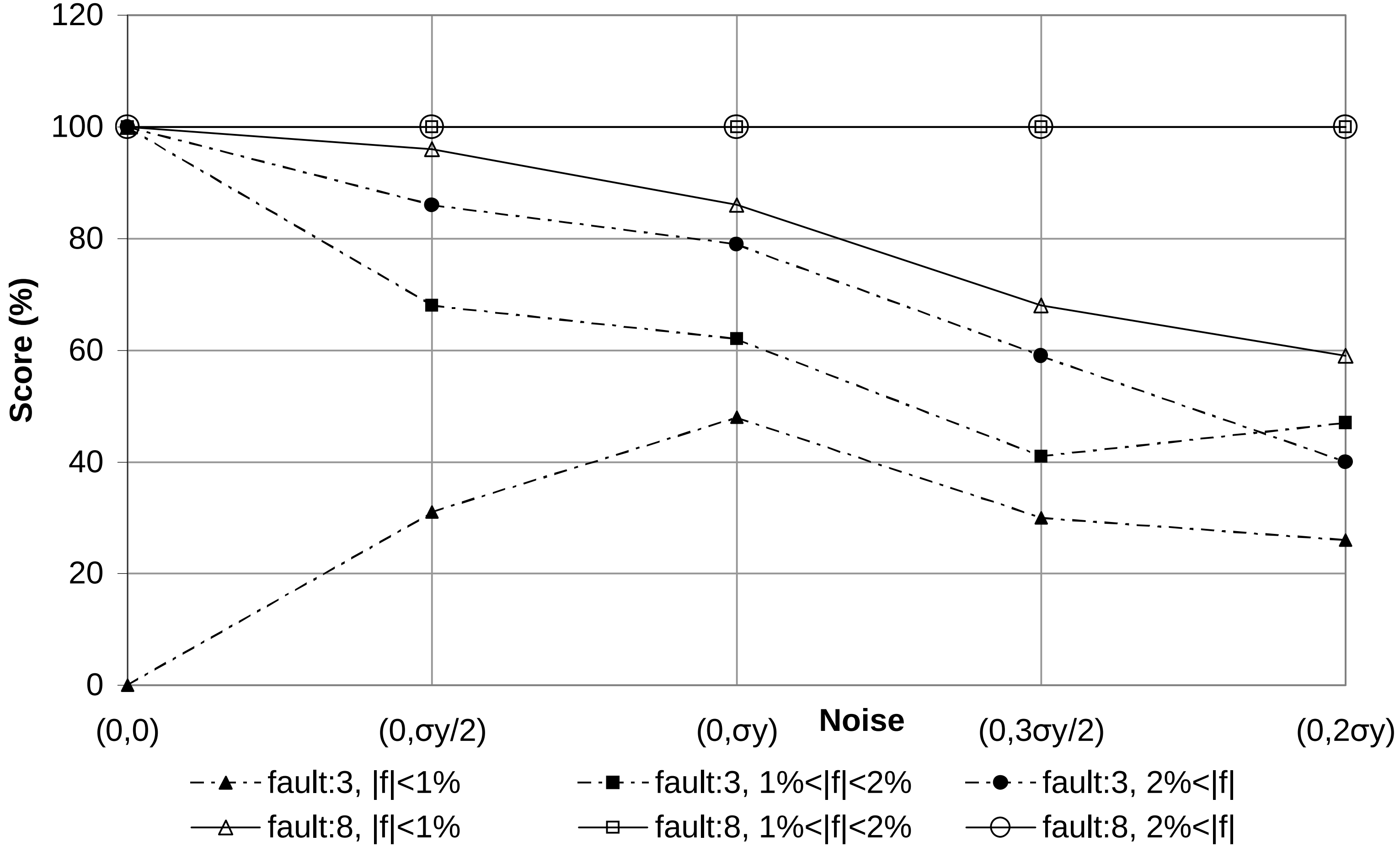


Effect of magnitude of fault on the diagnostic performance of PNN.

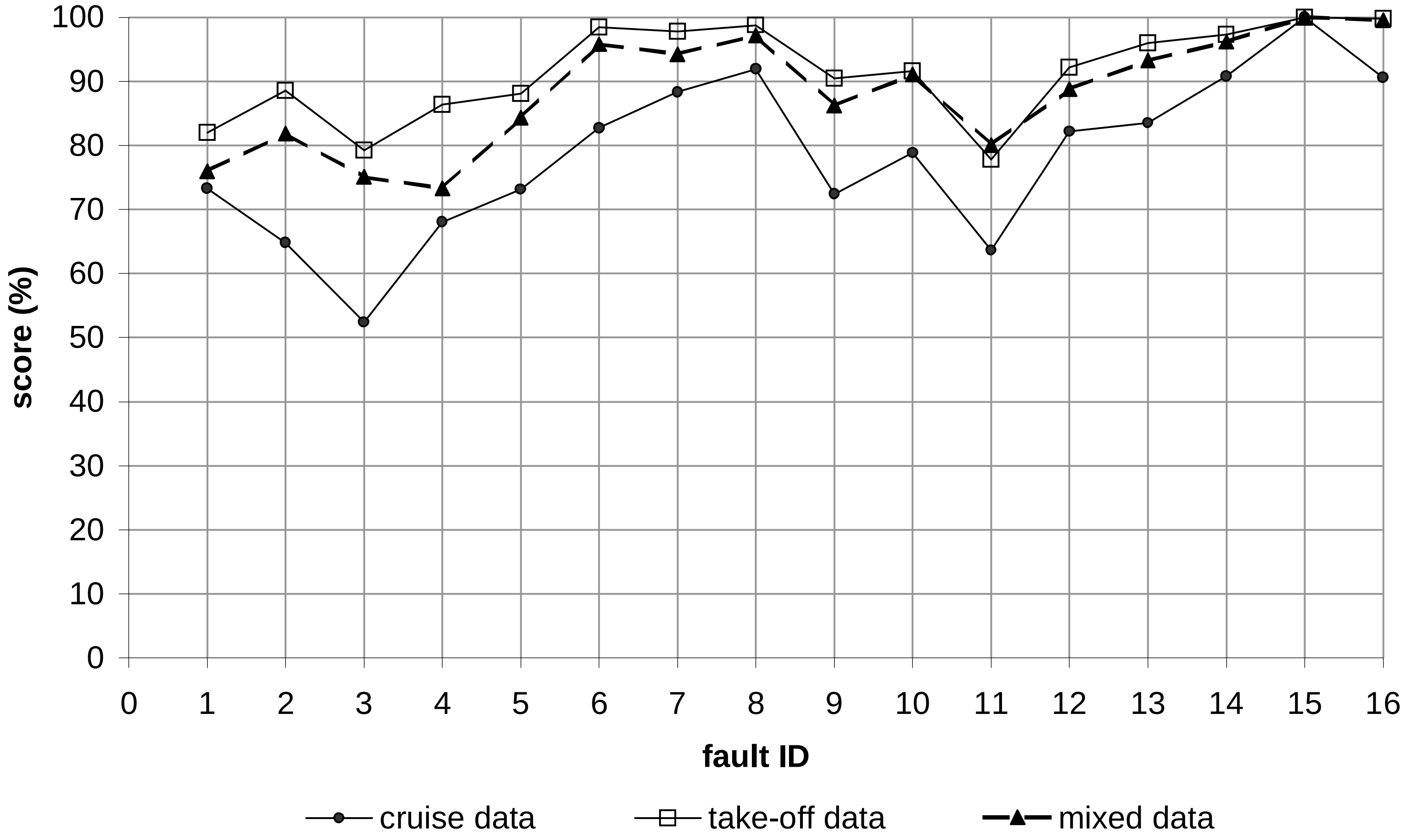


Effect of noise magnitude on test patterns

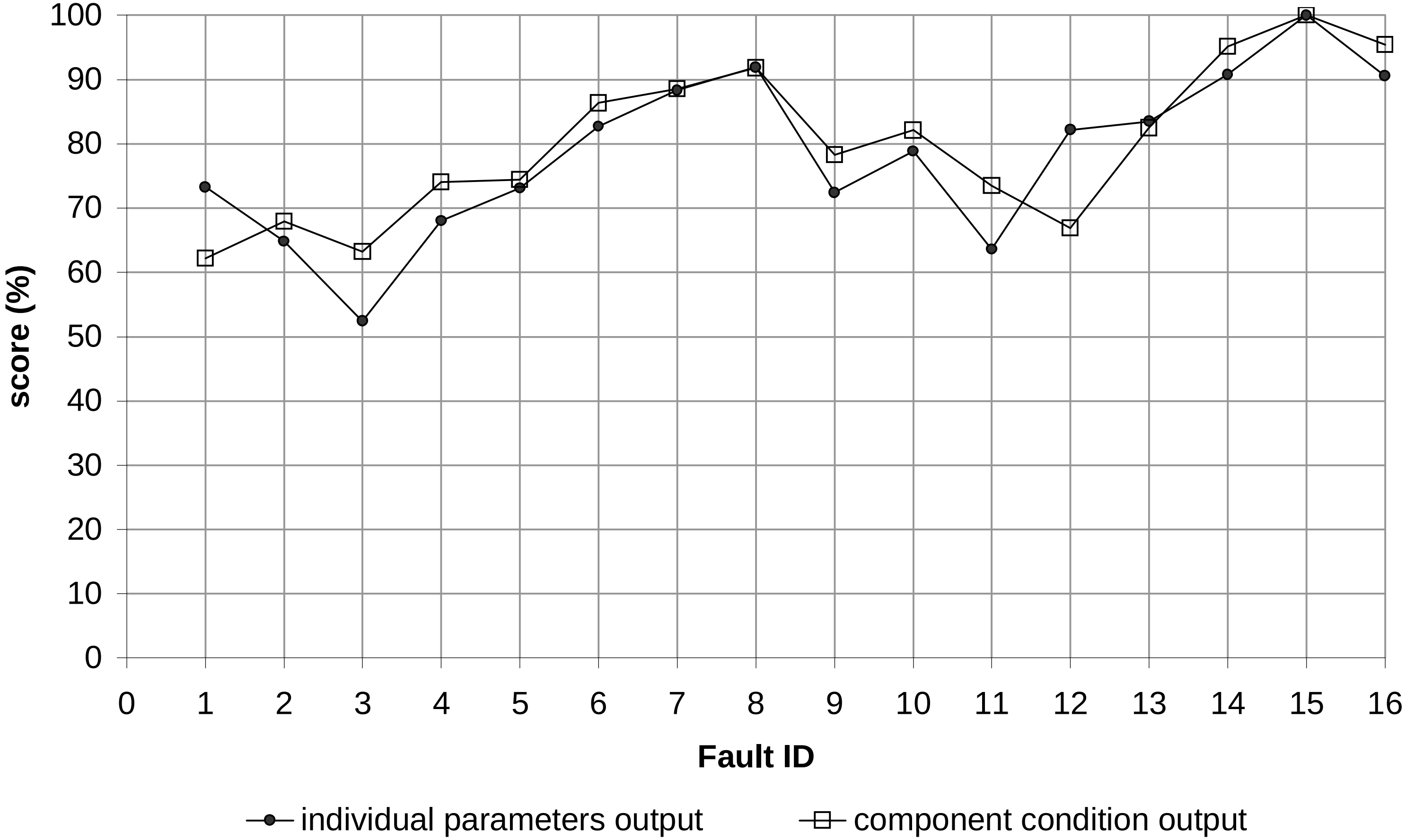
Fault 3: SW2 Fault 8: SE41



Diagnostic performance of three networks, each one trained and tested at a different operating point.



Diagnostic performance of two networks with different output configuration.



Conclusions

•The influence of noise is important. Training with noisy data improves the performance.

•When a network is used, the performance is better for less noise in the data. Filtering procedure of measurements before they are fed to such a network may thus be beneficial.

•Possibility of correct detection of a fault is better for more severe faults, namely when the magnitude of deviation is bigger.

•It is safer to make diagnosis based on observations at higher power settings (e.g. take-off versus cruise conditions).