GAS TURBINE FAULT DIAGNOSIS USING FUZZY-BASED DECISION FUSION

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GAS TURBINE FAULT DIAGNOSIS USING FUZZY-BASED DECISION FUSION

- **Description of the Fusion Method**
- **Aggregation theory-Probability Consensus**
- **Classification of Consensus**
- **Application Test Cases**
- **Summary-Conclusions**

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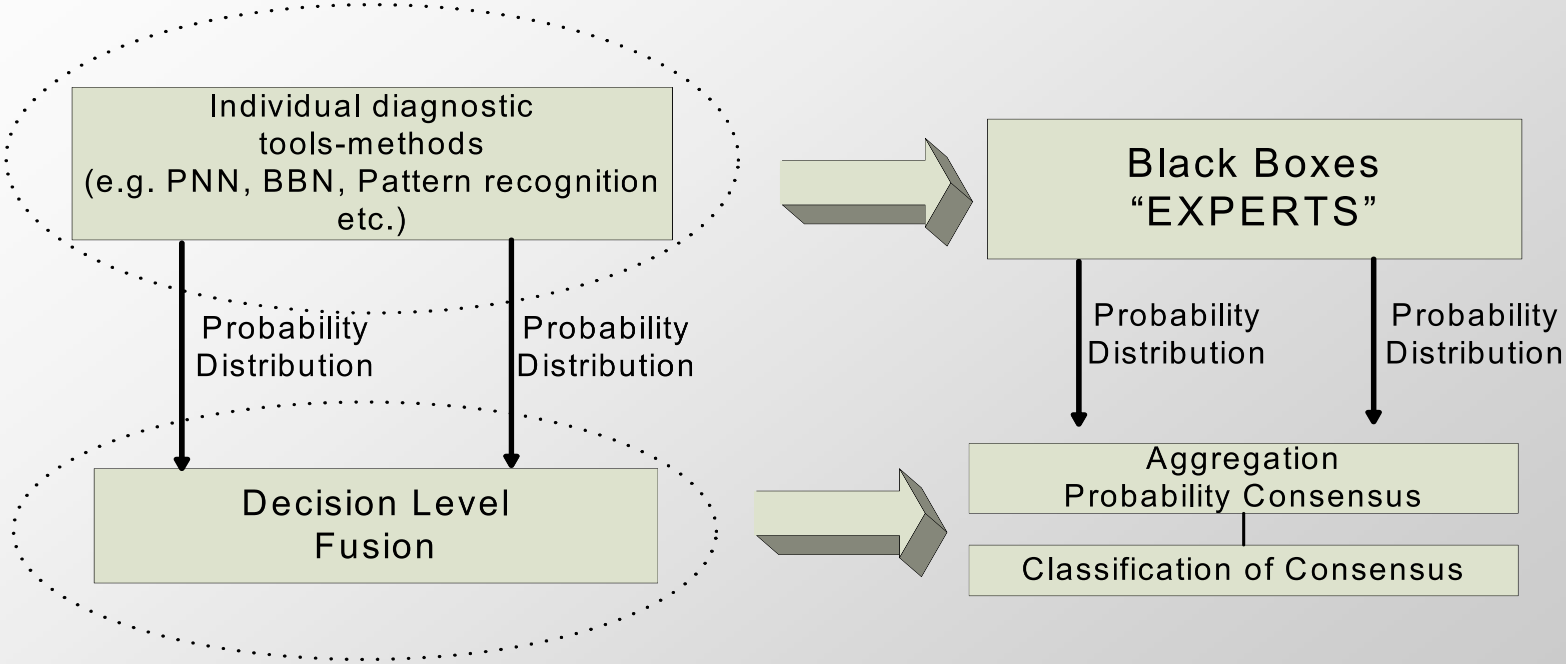
GENERAL DESCRIPTION

Two-Step Fusion Method for Decision Level Fusion



1. **All the outputs of the independent diagnostic methods are aggregated deriving the *probability consensus*.**
2. **The *probability consensus* is then classified to a certain fault with the aid of Fuzzy Set Theory and Fuzzy Logic**

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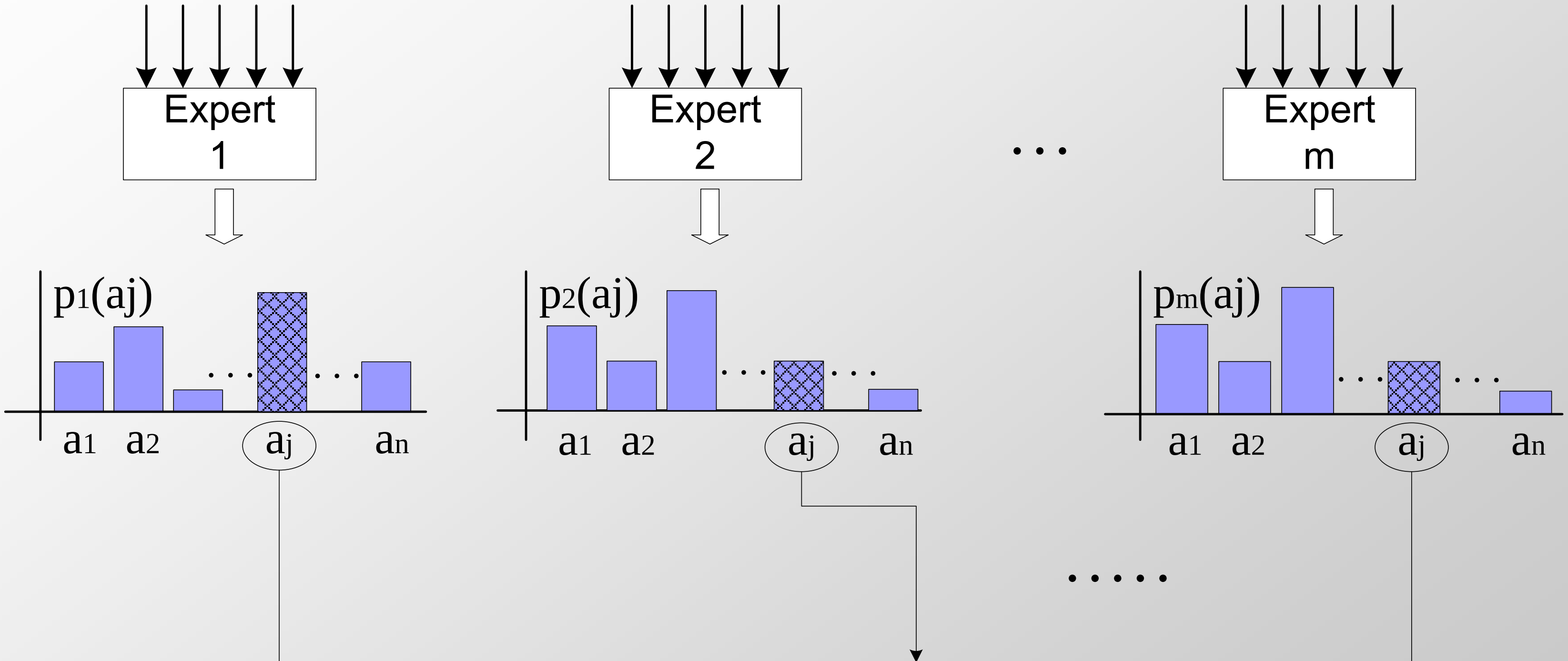
AGGREGATION THEORY

***m* experts provide a probability distribution over the *n* possible faults**



$$X(j)=f\left(p_1(a_j), p_2(a_j),..., p_m(a_j)\right)$$

Probability consensus

PROBABILITY CONSENSUS

The probability consensus (combination of the experts' opinions) is derived by application of the aggregation function X (weighted average of probability density functions)

$$X(j) = k \cdot \frac{\sum_{i=1}^{m} w_i \cdot p_i(a_j)}{\sum_{i=1}^{m} w_i} \quad , j = 1,..,n$$

- k is a normalization factor (optional)
- When $0 \leq w_i \leq 1$ (normalized weights adding up to 1) denominator is omitted

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CLASSIFICATION OF CONSENSUS

Two different approaches for fuzzy classification

$$X(j) = k \cdot \frac{\sum_{i=1}^{m} w_i \cdot p_i(a_j)}{\sum_{i=1}^{m} w_i}$$

Appr1

(principles Fuzzy Set Theory)

Appr2

(principles Fuzzy Logic and reasoning)

(complete FIS system)

CLASSIFICATION OF CONSENSUS

Appr1

Fuzzy sets

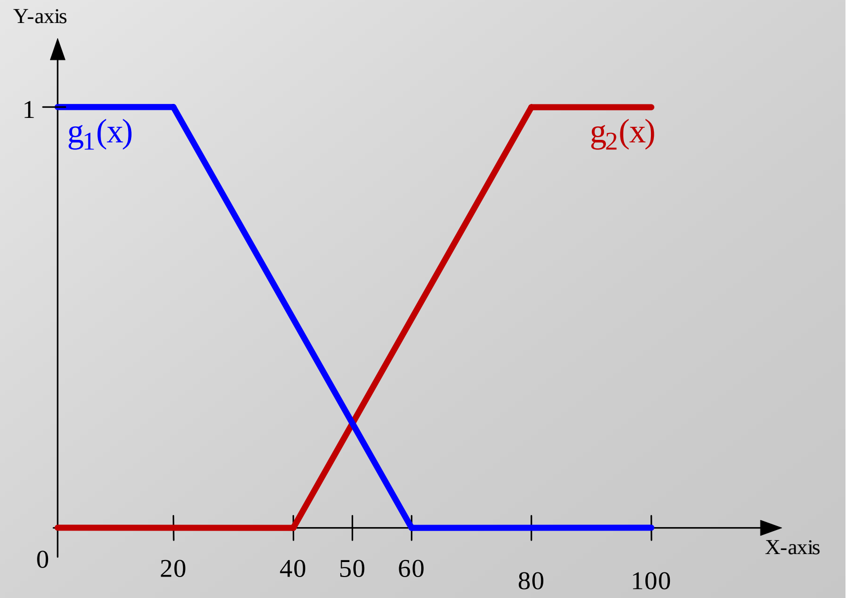
1.PROBABLE = {x, g2(x) / x∈A}

2.NOT_PROBABLE = {x, g1(x) / x ∈A}

$$g_1(x)=\begin{cases} 1, & x<=20 \\ -\frac{1}{40}x+\frac{3}{2}, & 20<x<60 \\ 0, & x>=60 \end{cases}$$

$$g_2(x)=\begin{cases} 0, & x<=40 \\ \frac{1}{40}x-1, & 40<x<80 \\ 1, & x>=80 \end{cases}$$

Membership functions

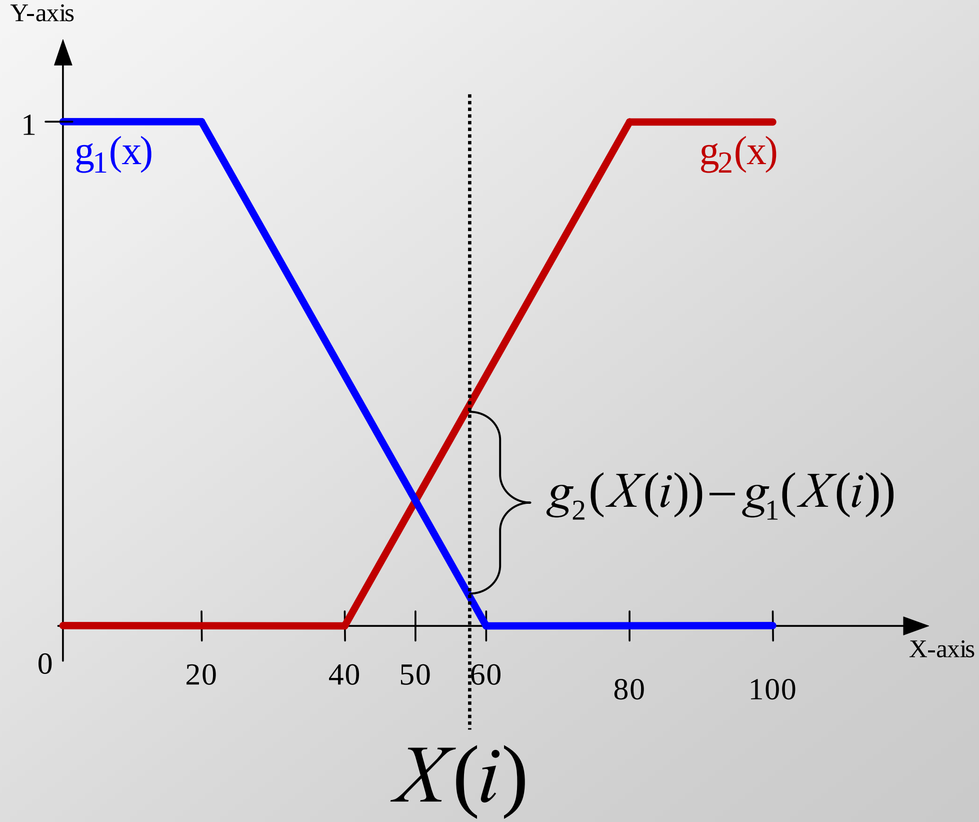


Universe of Discourse:

$A = x \in [0,100]$

CLASSIFICATION OF CONSENSUS

Appr1



Diagnostic criterion

$$j:\ \left[g_2\left(X\left(j\right)\right)\text{-}g_1\left(X\left(j\right)\right)\right]>\left[g_2\left(X\left(i\right)\right)\text{-}g_1\left(X\left(i\right)\right)\right],\ i\neq j$$

CLASSIFICATION OF CONSENSUS

Appr2

SCALING PROCEDURE:
$$X'(j) = \begin{cases} X(1), & j = 1 \\ [(j-1)\bullet 100] + X(j), & j = 2, 3, \ldots, N \end{cases}$$

Two Fuzzy Sets

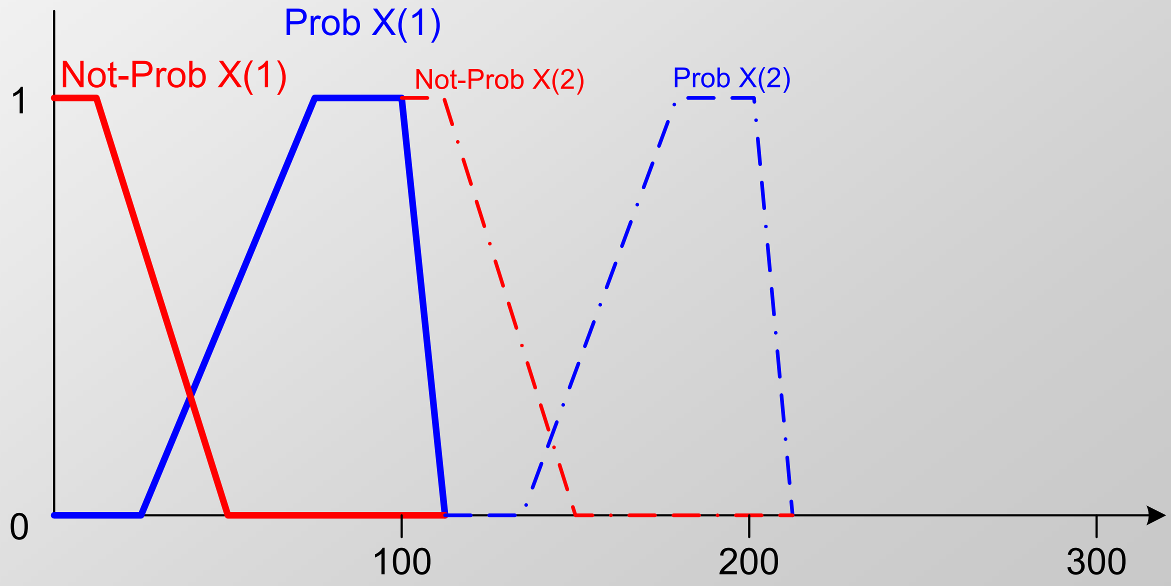
(for each element of X´):

1.ProbX$_i$

2.Not-ProbX$_i$

Universe of Discourse:

$A = x \in [0, N \bullet 100]$



MFs for the first two elements of X´

CLASSIFICATION OF CONSENSUS: Appr2

- **A set of fuzzy "if-then" rules equal to number of faults are defined over the membership functions**

- **For the FIS, the *Mamdani Model* of implication and the *max-min method of composition* have been considered.**
- **For the deffuzification process *mean of maximum (mom)* method has been selected**

- **Output is a** $crisp\_value$

Diagnostic criterion

$$j : \left[(j-1) \cdot 100 \right] < crisp\_value \leq \left[j \cdot 100 \right]$$

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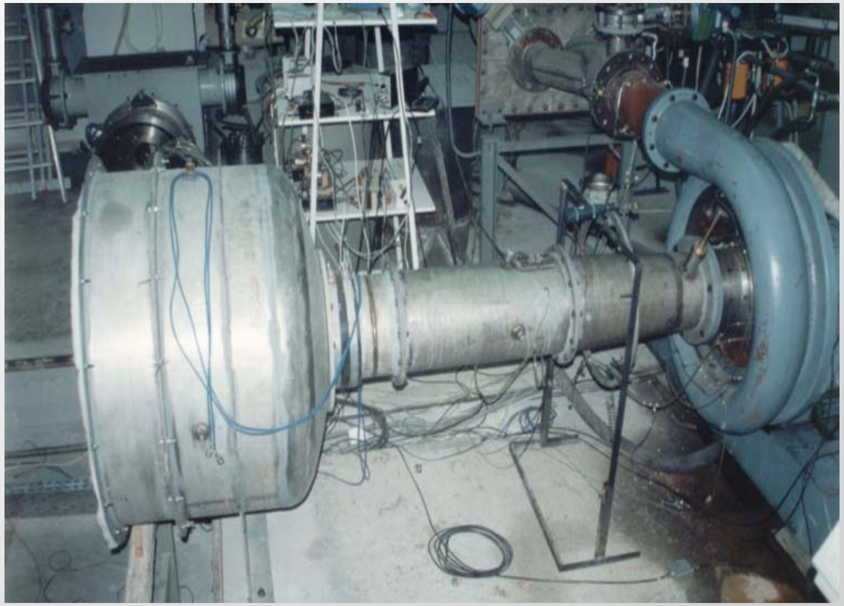
TEST CASE APPLICATIONS

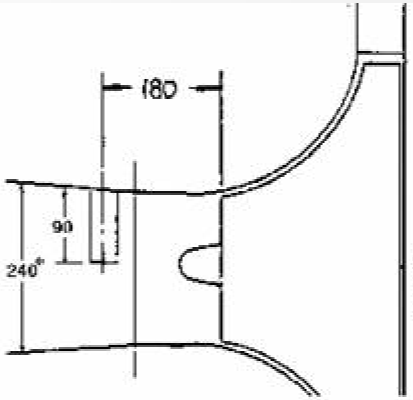
- **Two cases have been examined:**
  - **The case of a radial compressor**
  - **The case of an axial compressor**
- **In both cases the goal is to detect deliberately implemented mechanical faults**
- **The available information is two sets of measurements, in each case:**
  - **A set of fast response data (vibrations, sound pressures, etc…)**
  - **A set of performance data (pressures, temperatures, etc…)**
- **In each case two independently acting diagnostic methods have been applied:**
  - **The method of PNN for diagnosis over fast response data**
  - **The method of PNN for diagnosis over performance data**

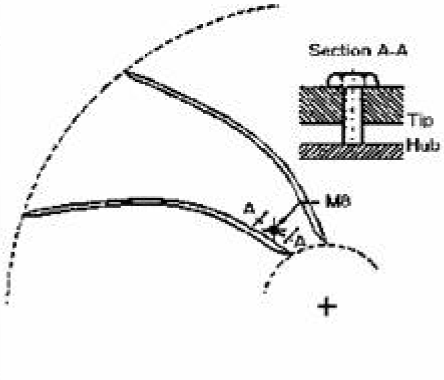
The case of radial compressor



The case of radial compressor

Examined faults





Inlet Distortion-M3

Diffuser Fault-M1

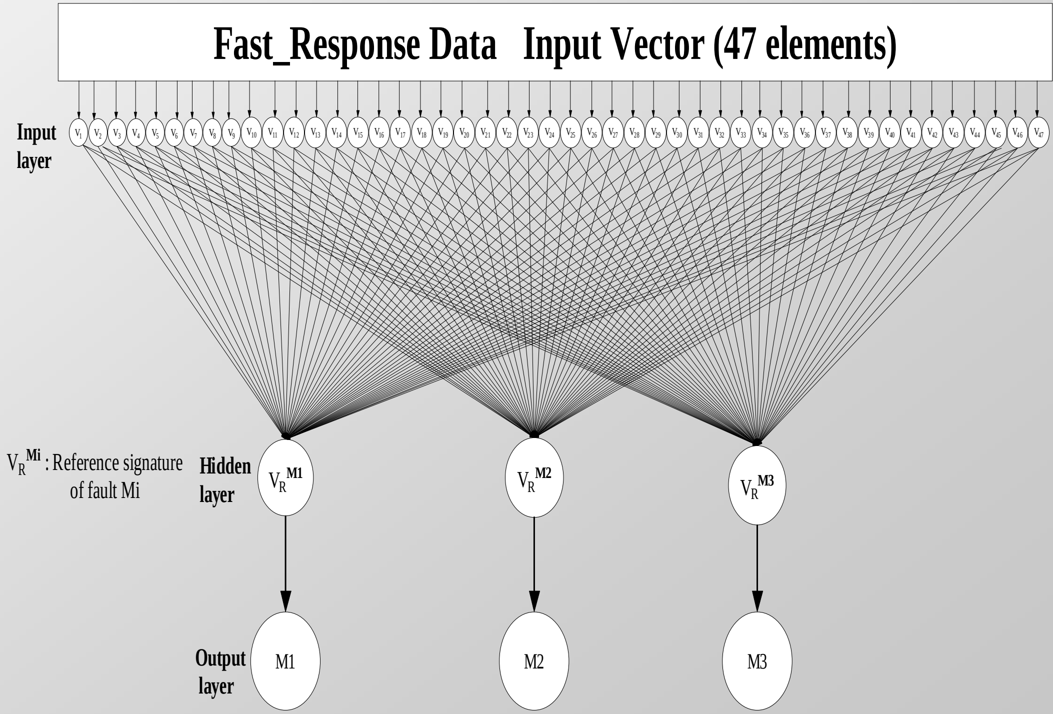
Impeller Fouling-M2

The case of radial compressor

Probabilistic Neural Network (PNN) for Fast Response Data

Features of the Probabilistic Neural Network

- **Input Layer:**
  Inputs are the available fault signatures. Each node represents an element of the vector consisting the fault signature.
- **Hidden Layer:**
  Training patterns are the reference fault signatures.
- **Output Layer:**
  Each node (class) represents a certain mechanical fault.



PNN Architecture for radial compressor case

The case of radial compressor

Probabilistic Neural Network (PNN) for Performance Data

Features of the Probabilistic Neural Network

- **Input Layer:**
  Inputs are the 7 deviations (deltas) of aerothermodynamic measurements according to type:

$$d_i = \frac{Y^i - Y_0^i}{Y_0^i}, i = 1, 2, \ldots 7$$

where Y^i is the value of a measurement for the i[th] fault and Y_0^i is the value for a "healthy" engine

- **Hidden Layer:**
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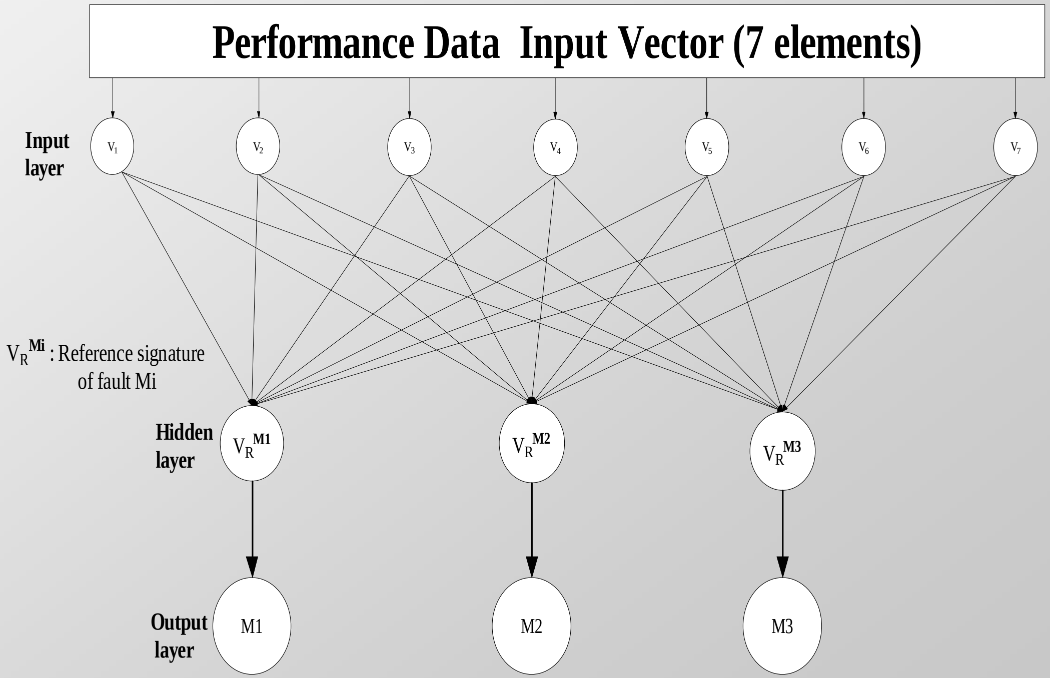
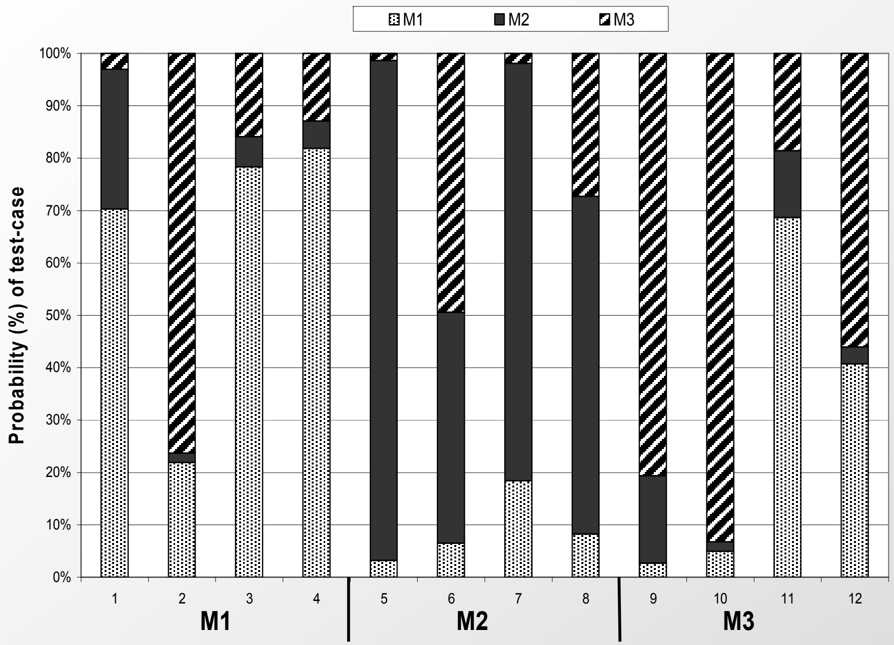
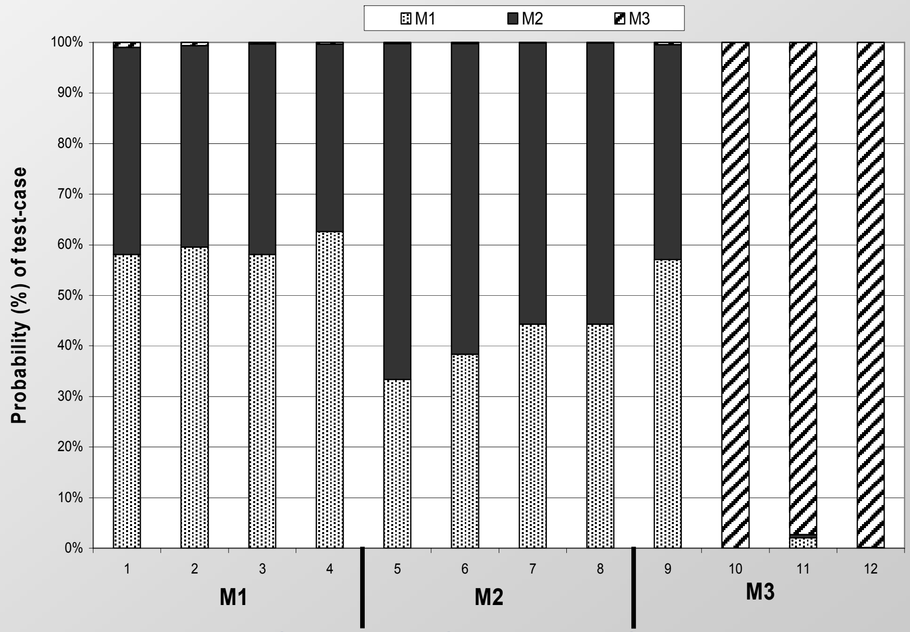


PNN Architecture for radial compressor case

Classification Probabilities for radial compressor faults



Fault classification from fast response data

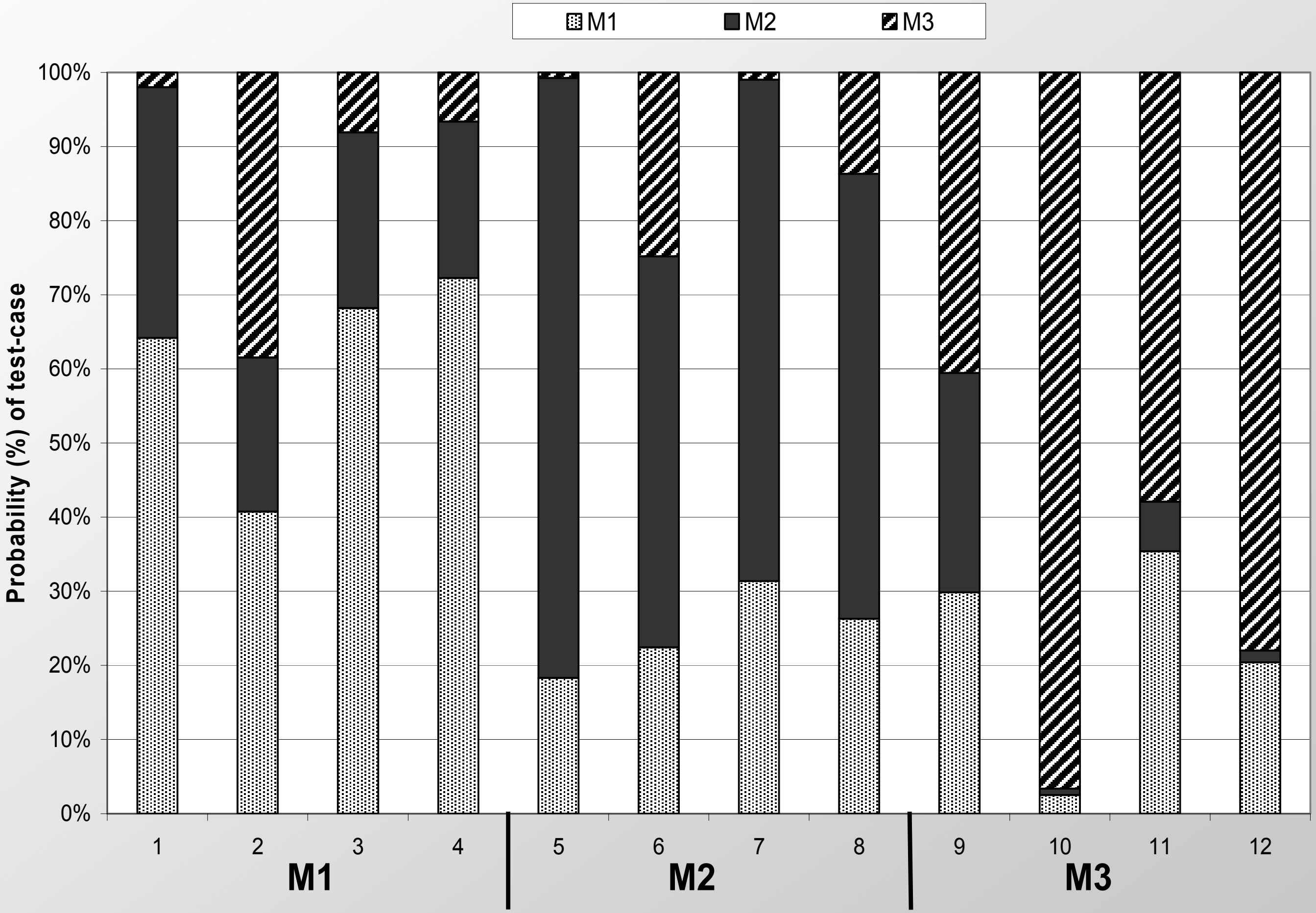


Fault classification from performance data

$$X(j) = k \cdot \frac{\sum_{i=1}^{m} w_i \cdot p_i(a_j)}{\sum_{i=1}^{m} w_i}$$

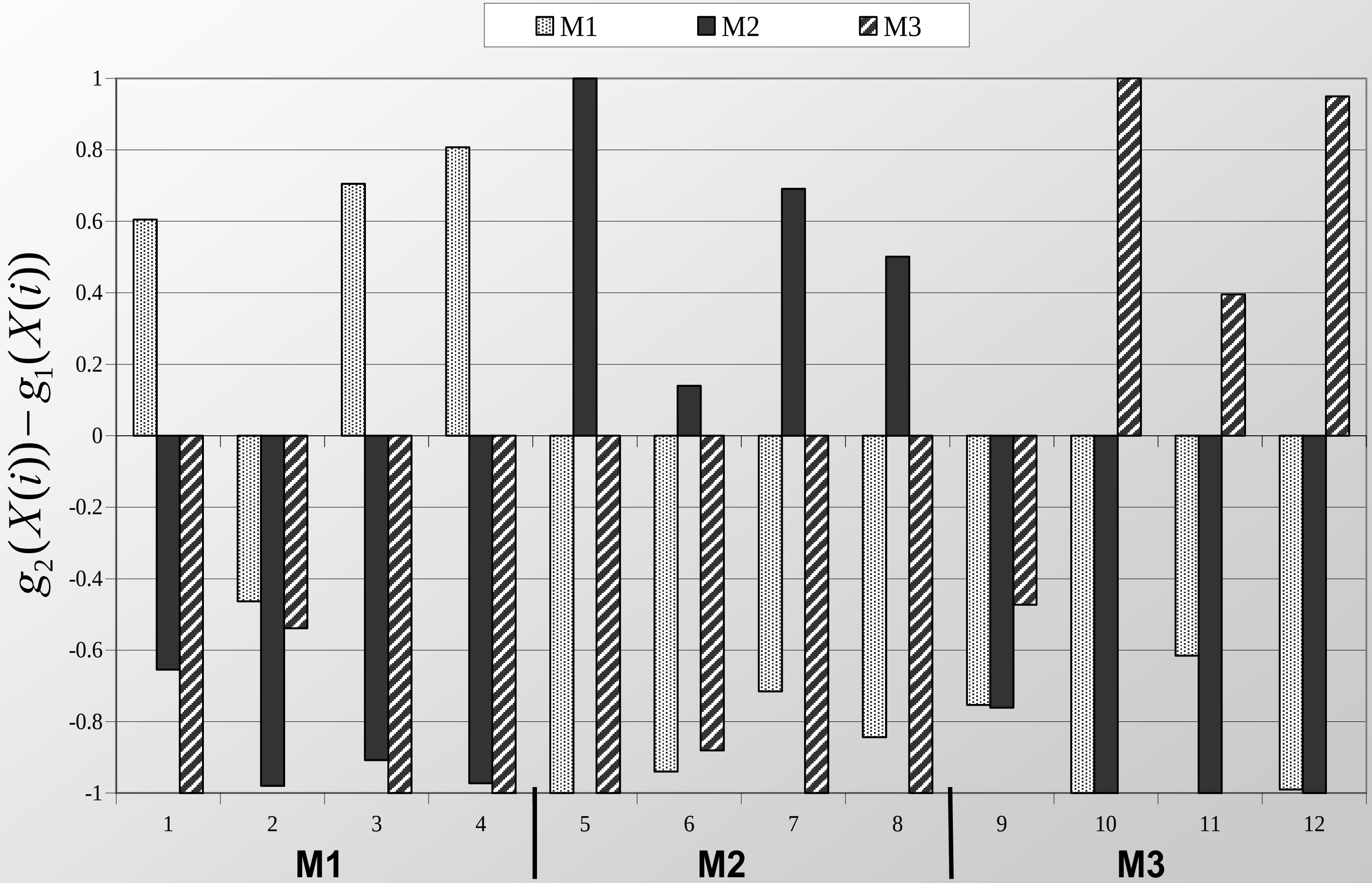
The case of radial compressor

Aggregation – Probability consensus results



The case of radial compressor

Fuzzy classification regarding Appr1



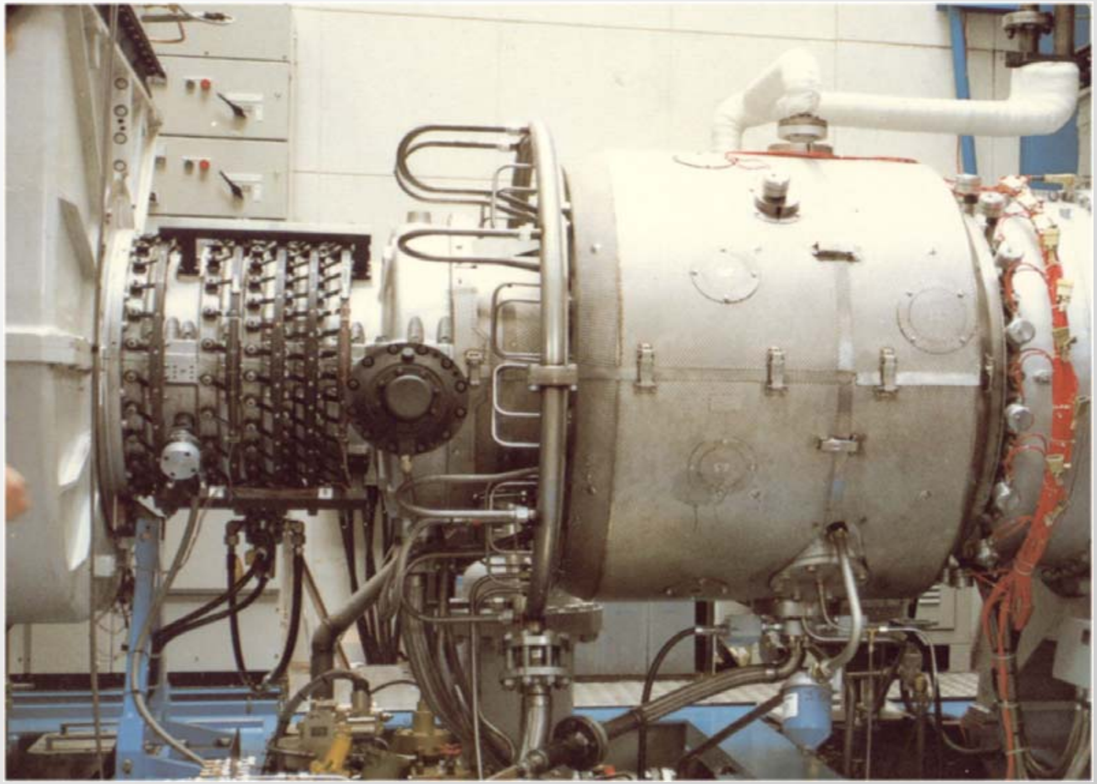
The case of radial compressor

Overall Results

	Radial compressor	
	Fast Response data + Performance data	
	Set A1 + Performance	Set A2 + Performance
PNN_Fast Response	3/12	1/12
PNN_Performance	1/12	1/12
Appr1	0/12	1/12
Appr2	0/12	1/12

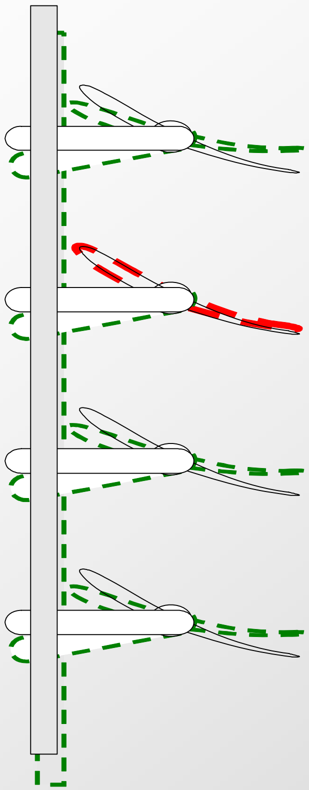
test-cases of incorrect classification / total test-cases

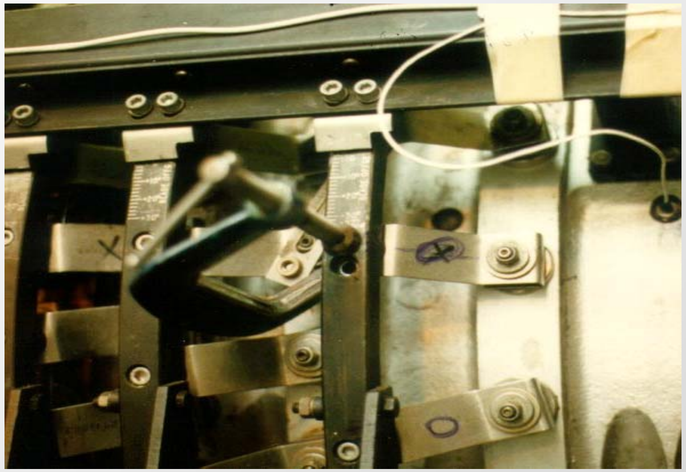
The case of axial compressor



The case of axial compressor

Examined faults





- F-2: Fouled Rotor of Stage 2
- F-3: Two blades of Rotor 1 fouled
- F-4: Twisted blade of Rotor 1
- F-53: Three mistuned stator vanes

The case of axial compressor

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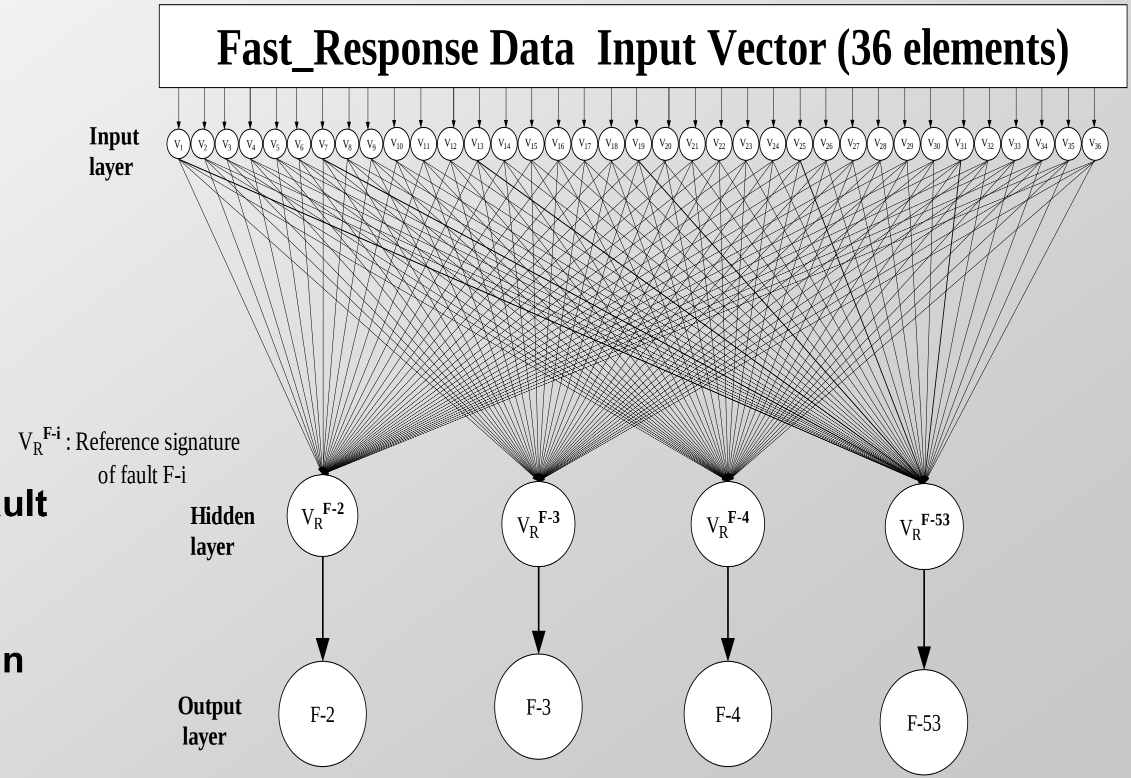

PNN Architecture for axial compressor case

The case of axial compressor

Probabilistic Neural Network (PNN) for Performance Data

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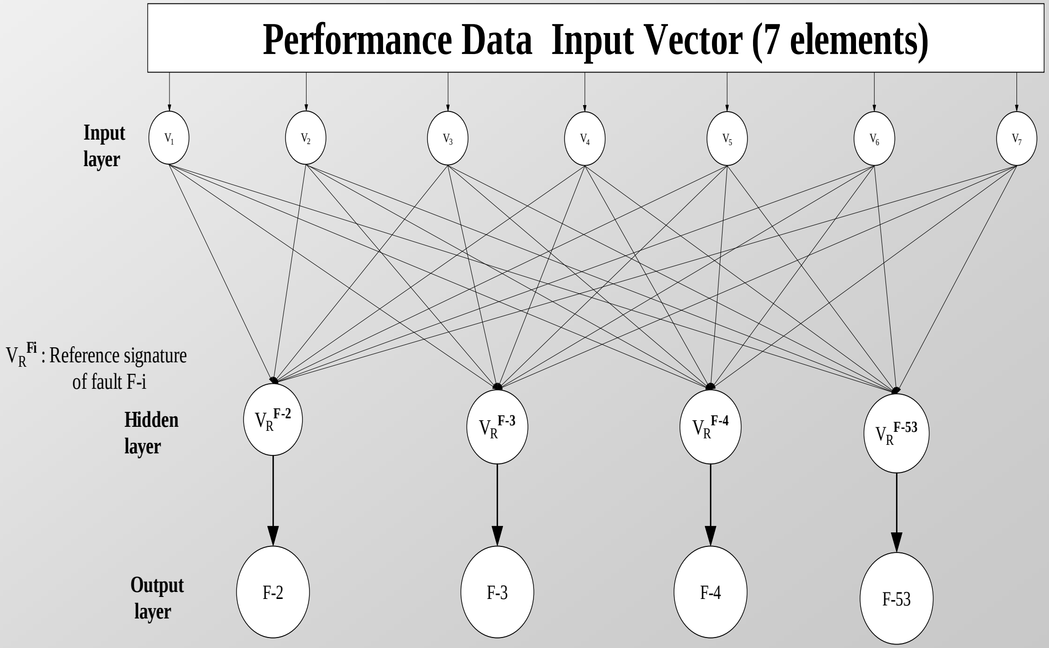

PNN Architecture for axial compressor case

The case of axial compressor

Overall Results

	Axial compressor			
	Fast Response data + Performance data			
	ACC1+ Performance	ACC2+ Performance	ACC3+ Performance	PT2+ Performance
PNN_Fast Response	1/16	0/16	0/16	0/16
PNN Performance	4/16	4/16	4/16	4/16
Appr1	2/16	0/16	0/16	0/16
Appr2	2/16	0/16	0/16	0/16

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- A new approach for information fusion by combining data of different nature has been demonstrated
- It utilizes the concepts of Aggregation Theory, Fuzzy Set theory and Fuzzy Logic principles
- PNN networks act as first level diagnostic techniques (“experts”).
- Improvement to the final diagnostic decision by the proposed fusion method has been presented by application to test-cases of faults from a radial compressor and an axial compressor