Gas Turbine Fault Diagnosis From Fast Response Data Using Probabilistic Methods and Information Fusion

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Gas Turbine Fault Diagnosis From Fast Response Data Using Probabilistic Methods and Information Fusion

- **The diagnostic problem**
- **Fast Response Data Preprocessing**
- **Probabilistic Methods applied**
- **Information Fusion Techniques**
- **Summary-Conclusions**

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The Diagnostic Problem

- Several Measurement Instruments.
- Fast Response Data obtained from them.
- Objective:
    1. Utilization of different diagnostic methods-techniques.
    2. Derivation of diagnostic information from each instrument.
    3. Combination of results from different diagnostic techniques (FUSION) in order to better improve the final diagnostic decision.

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Fast Response Data Preprocessing

- Fast Response Data consist of measurements of dynamic quantities (sound pressure, unsteady wall pressure and vibration)
- Data Acquisition is accomplished through various instruments:

  1. Accelerometers (ACCs) for vibration
  2. Pressure transducers (PTs) for wall pressure
  3. Microphones for sound pressure

- Time signals are Fourier analyzed to obtain their Power Spectral Density (PSD)

Fast Response Data Preprocessing

- Derivation of Spectral Differences

$$\Delta PSD(f) = PSD_F(f) - PSD_H(f)$$

$PSD_F(f)$ the power spectral density of the signal in faulty condition

$PSD_H(f)$ the power spectral density of the signal in healthy condition

$\Delta PSD(f)$ the resulting spectral difference pattern

- Derivation of Fault Signatures

Through filtering procedure at the harmonics of the shaft rotational speed

- Derivation of Reference Fault Signatures

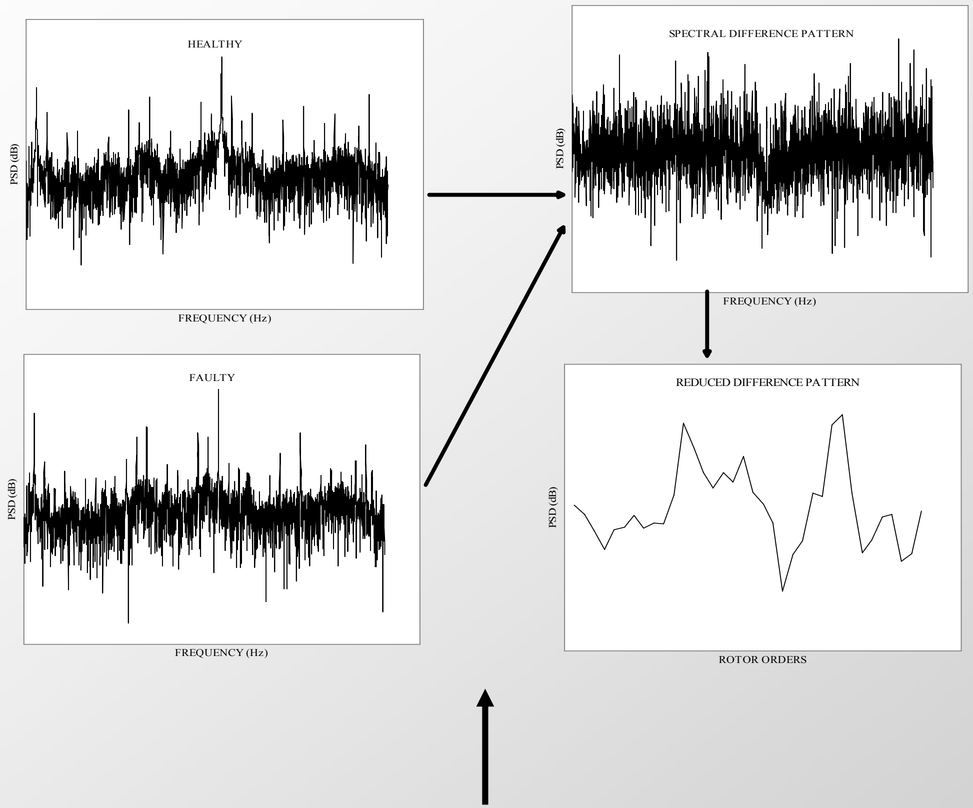
A normalization procedure to all fault signatures is applied firstly, according to the relationships:

$$V_{aver} = \frac{1}{n}\sum_{i=1}^{n} V_{init}(i) \qquad V(i) = \frac{V_{init}(i) - V_{aver}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(V_{init}(i) - V_{aver})^2}}$$

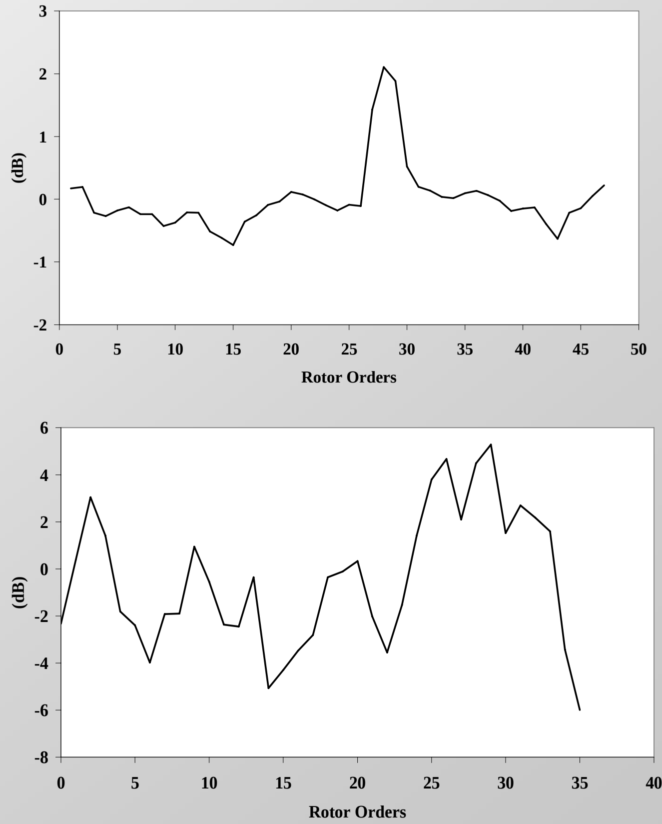
The reference signature results from the mean average according to:

$$V_R(i) = \frac{1}{N}\sum_{j=1}^{N} V_j(i)$$

Fast Response Data Preprocessing



Schematic representation of the procedure for deriving fault signatures



Examples of Reference Fault Signatures

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Probabilistic Methods Applied

Probabilistic Methods: (1) Pattern Recognition methods

Methods

1. **Geometrical (Geo)**
2. **Statistical (Stat)**
3. **Statistical with optimal directions (Opt)**

Procedure

1. **Derivation of fault signatures from fast response data**
2. **Utilization of two types of feature vectors, namely A and B**
    - **Components A:** **Euclidean distance and the correlation coefficient of every fault signature with each reference signature of the faults being examined.**
    - **Components B:** **The available signatures themselves**

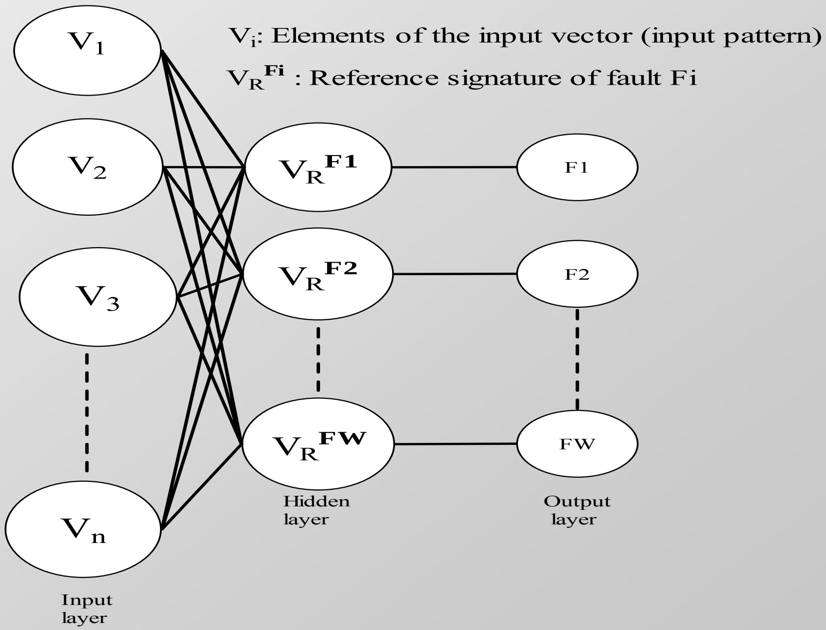
Probabilistic Methods Applied

Probabilistic Methods: (2) Probabilistic Neural Network -PNN

Features of the Probabilistic Neural Network

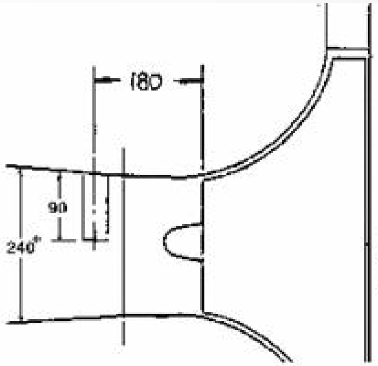
- **Input Layer:**
  Inputs are the available fault signatures. Each node represents an element of the vector consisting the fault singature.
- **Hidden Layer:**
  Training patterns are the reference fault signatures.
- **Output Layer:**
  Each node (class) represents a certain mechanical fault.

Structure of the Probabilistic Neural Network-PNN

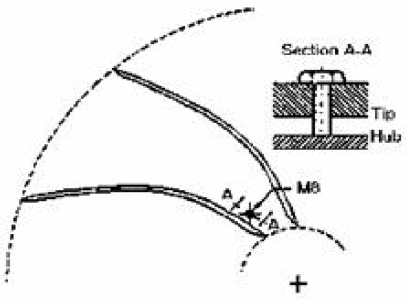


Probabilistic Methods Applied

Mechanical Faults: Radial Compressor Test-Cases



Inlet Distortion-M3



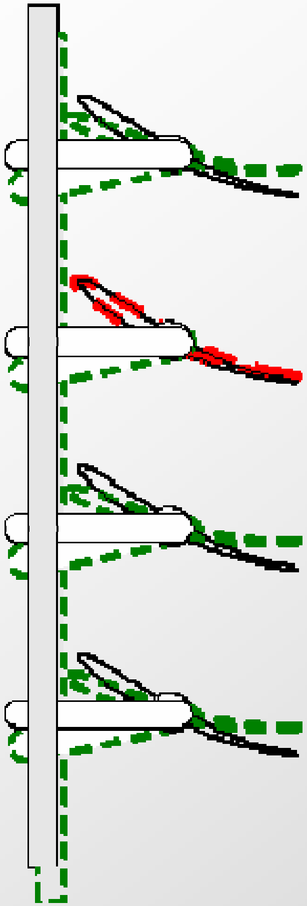
Diffuser Fault-M1

Impeller Fouling-M2

Radial Compressor:
Mechanical faults introduced
Diffuser Fault (M1)
Impeller Fouling (M2)
Inlet Distortion (M3)

Probabilistic Methods Applied

Mechanical Faults: Axial Compressor Test-Cases



Mistuned stator vanes

Twisted blade

Axial Compressor:

Mechanical faults introduced

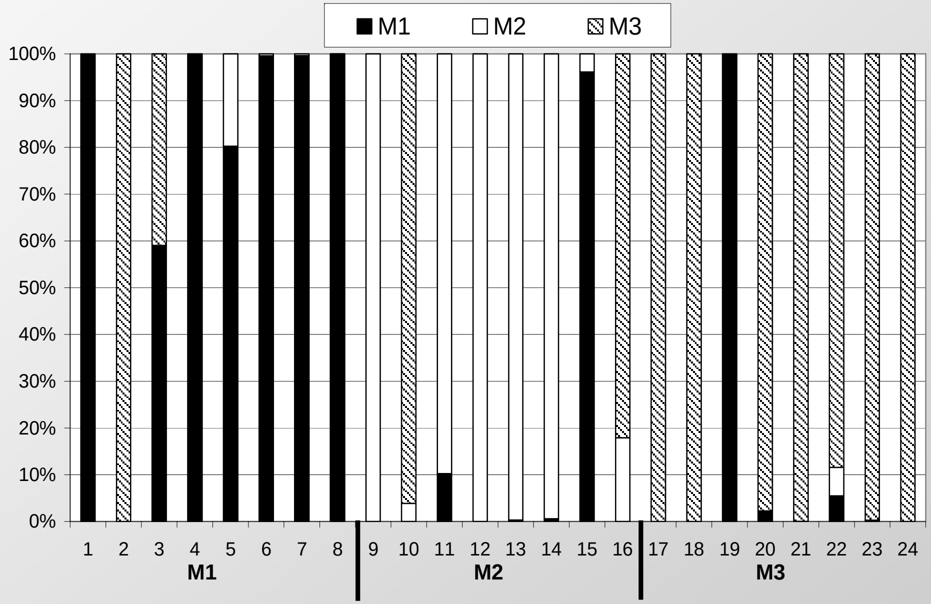
Severe Rotor Fouling (F-2)

Slight Rotor Blade Fault (F-3)

Severe Rotor Blade Fault (F-4

Severe Stator Fault (F-53)

Probabilistic Methods Applied



An example performance of PNN for radial compressor test-cases

Probabilistic Methods Applied

		Pattern recognition methods					PNN
Faults	Test cases	Geo	Stat-A	Stat-B	Opt-A	Opt-B	PNN
M1	1	x	x	x	x	x	x
	2	●	●	x	●	x	●
	3	x	●	●	x	x	x
	4	x	x	x	x	x	x
	5	●	x	x	x	x	x
	6	x	x	x	x	x	x
	7	x	x	x	x	x	x
	8	x	x	x	x	x	x
M2	9	x	x	x	x	x	x
	10	●	●	x	x	x	●
	11	x	x	x	x	x	x
	12	x	x	x	x	x	x
	13	x	x	x	x	x	x
	14	x	x	x	x	x	x
	15	●	●	x	x	x	●
	16	●	●	x	x	x	●
M3	17	x	x	x	x	x	x
	18	x	x	x	x	x	x
	19	●	●	●	●	x	●
	20	x	x	x	●	x	x
	21	x	x	x	x	x	x
	22	x	x	x	x	x	x
	23	x	x	x	x	x	x
	24	x	x	x	x	x	x

x Correct classification ● Incorrect classification

Performance of all diagnostic methods on radial compressor's data sets

		Pattern recognition methods					PNN
Faults	Test cases	Geo	Stat-A	Stat-B	Opt-A	Opt-B	PNN
F-2	**1**	X	X	X	X	X	X
	2	X	X	X	X	X	X
	3	X	X	X	X	X	X
	4	X	X	X	X	X	X
F-3	**5**	X	X	X	X	X	X
	6	X	X	X	X	X	X
	7	X	X	X	X	X	X
F-4	**8**	X	X	X	X	X	X
	9	X	X	X	X	X	X
	10	X	X	X	X	X	X
	11	X	X	X	X	X	X
F-53	**12**	X	X	X	X	X	X
	13	X	X	X	X	X	X
	14	X	X	X	X	X	X
	15	X	X	X	X	X	X
F-3	**16**	X	●	●	X	●	X

X Correct classification ● Incorrect classification

Performance of all diagnostic methods on industrial turbine's data sets for instrument PT2

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Information Fusion Techniques

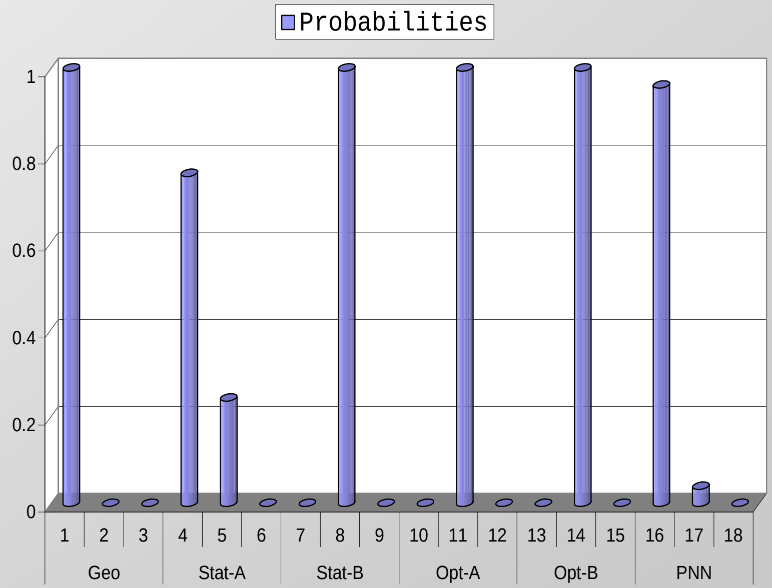
- **Implementation of feature level fusion**
- **Diagnostic outcomes of 6 first level diagnostic methods are utilized**
  1. **Pattern recognition techniques (Geo, Stat-A, Stat-B, Opt-A and Opt-B)**
  2. **PNN network**
- **Each of them has a vector D $\in$ R^W as an output**
- **Elements of D are probabilities and W is the number of faults**
- **The new fusion schemes are based on PNN networks and BBN (Bayesian Belief Networks) networks (*PNN-fusion* and *BBN-fusion*)**

Information Fusion Techniques

- ***Input pattern Q:*** **derives from the 6 first level diagnostic methods in terms of a vector with probabilities as components.**
- **Formed by concatenating vectors D with the following order of diagnostic methods**

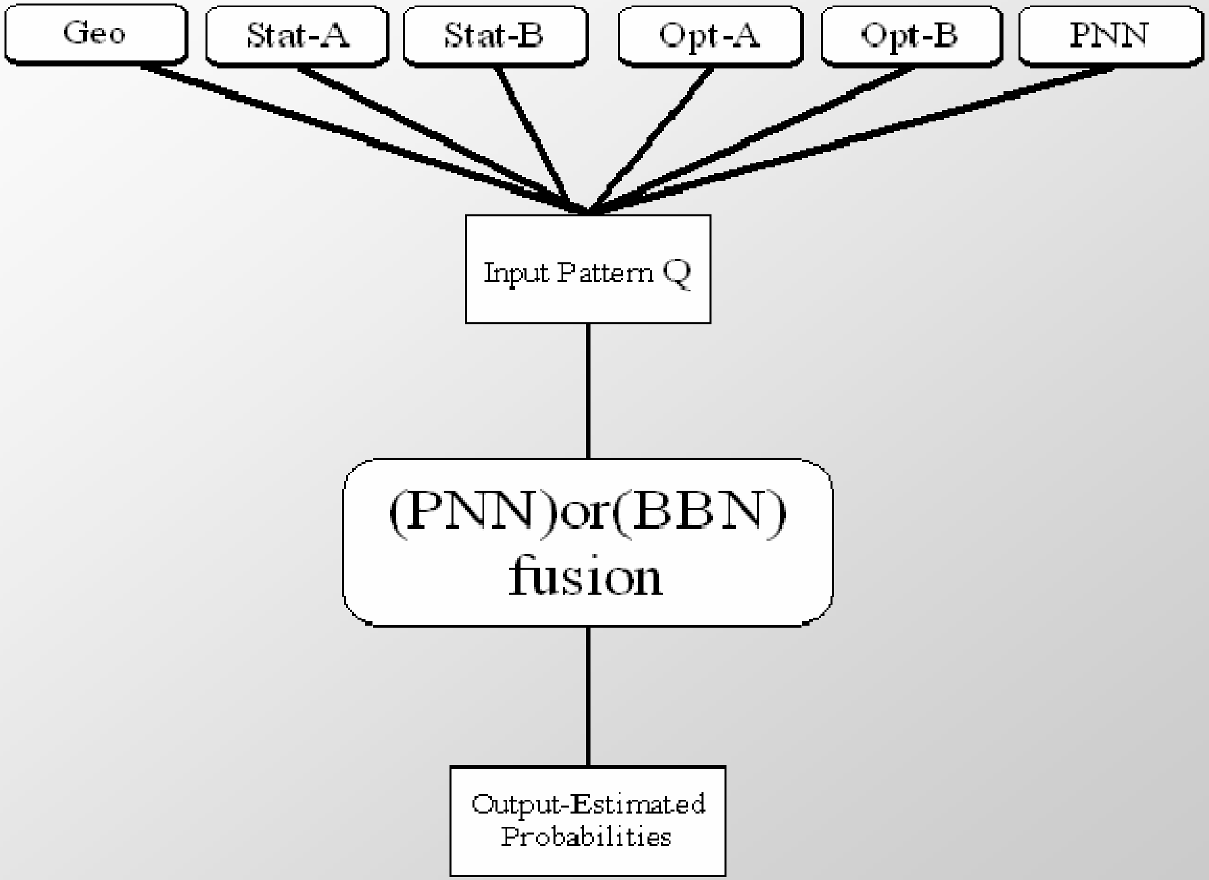
$$Q(i) = \begin{cases} i = 1, \ldots, W & \textit{for Geo} \\ i = (W+1), \ldots, 2 \cdot W & \textit{for Stat}-A \\ i = (2 \cdot W + 1), \ldots, 3 \cdot W & \textit{for Stat}-B \\ i = (3 \cdot W + 1), \ldots, 4 \cdot W & \textit{for Opt}-A \\ i = (4 \cdot W + 1), \ldots, 5 \cdot W & \textit{for Opt}-B \\ i = (5 \cdot W + 1), \ldots, 6 \cdot W & \textit{for PNN} \end{cases}$$

Input pattern Q to the BBN-fusion or PNN-fusion schemes



Example input pattern Q

Information Fusion Techniques



Flowchart of the fusion process

Information Fusion Techniques

PNN-fusion Network

Features of the PNN-fusion Network

- **Input Layer:**
  Inputs are now the patterns Q regarded as a new type of fault signature. Each node represents an element of the vector Q.
- **Hidden Layer:**
  Training patterns are the mean averages P_R of all patterns Q corresponding to a specific fault. P_R derive from the following relationship:

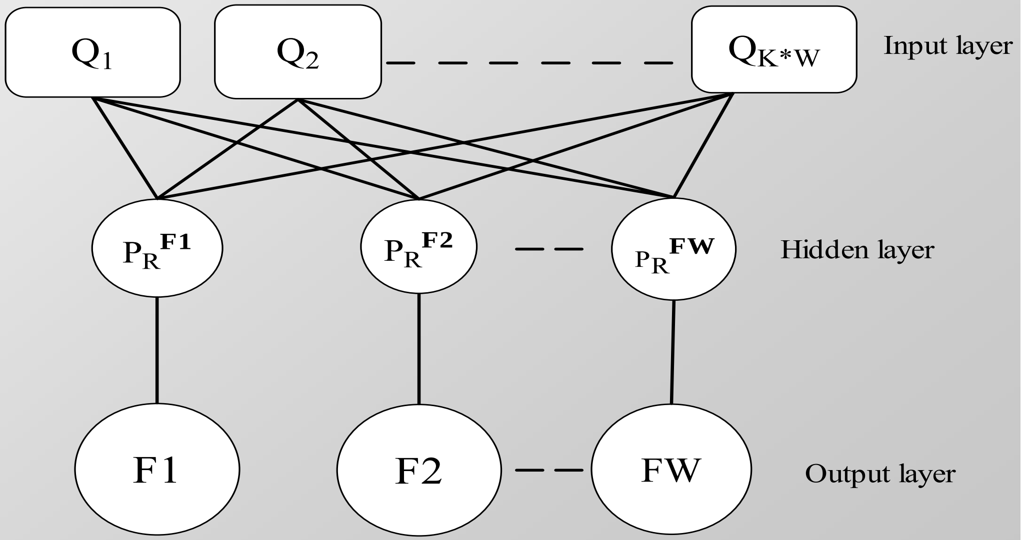
$$P_R(i) = \frac{1}{N}\sum_{j=1}^{N} Q_j(i)$$

- **Output Layer:**
  Each node (class) represents a certain mechanical fault.

Structure of the PNN-fusion network

Q_i: Elements of the input vector (input pattern)

P_R^{Fi}: Mean average pattern corresponding fault Fi



Information Fusion Techniques

BBN-fusion Network

Elements of BBN-fusion network

•NODES:

- 'Root' (or parent) nodes representing the mechanical faults examined. (variable **F** in BBN-fusion network)
- 'Leaf' (or child) nodes representing an input pattern of probabilities (variable **Q** in BBN-fusion network)

•LINKS:

Fully linked network

•BAYESIAN INFERENCE:

According to following relationships:

$$P[Q(1),...,Q(K*W),F1,...FW]=\prod_{i=1}^{W}P(Fi)\prod_{j=1}^{K*W}P[Q(j)\,|\,F1,...,FW]$$

$$P[Fi=X\,|\,Q(1),...,Q(K*W)]=\max_{i=1}^{W}\{P[Fi=X\,|\,Q(1),...,Q(K*W)]\}$$

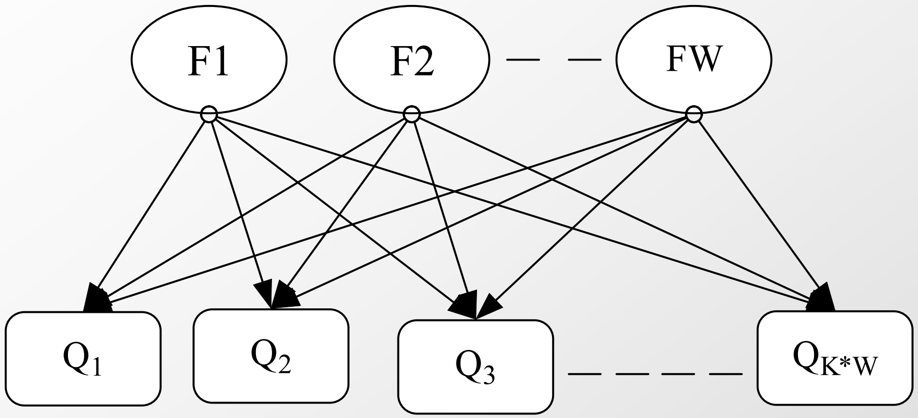
•DISCRETE STATES AND CONDITIONAL PROBABILITY TABLES (CPT) OF 'ROOT' NODES:

•5 discrete states forming corresponding regions of interest

•CPT table contains a-priori probability (uniform distribution)

Information Fusion Techniques

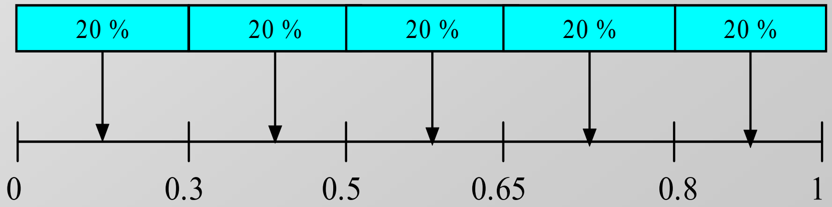
BBN-fusion Network



Q_i: Elements of the input vector (input pattern)

Fi: Fault i

BBN-fusion architecture



States of a 'root' node (regions of interest) and a-priori probabilities

Information Fusion Techniques

Performance of Fusion Techniques

	Radial Compressor	Axial Compressor				
	Number of incorrect classifications	Number of incorrect classifications				
	Microphones	ACC1	ACC2	ACC3	PT2	Mic-1
Geo	6	1	0	0	0	0
Stat-A	6	1	0	0	1	0
Stat-B	2	1	0	1	1	1
Opt-A	3	0	0	0	0	0
Opt-B	0	0	0	0	1	0
PNN	5	1	0	0	0	0
PNN-fusion	2	1	0	0	0	0
BBN-fusion	2	1	0	0	0	0
Improvement	YES	NO	——	YES	YES	YES

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Summary - Conclusions

- **Possibilities offered by implementation of probabilistic methods for fault diagnosis in compressors has been demonstrated.**
- **Probabilistic neural networks utilizing fast response data revealed an alternate tool for fault classification**
- **A new approach for information fusion by combining the outcomes of those diagnostic methods has been presented.**
- **Fusion methods introduced provide a significant tool for effective fault classification.**