GAS TURBINES COMPRESSOR FAULT IDENTIFICATION BY UTILIZING FUZZY LOGIC-BASED DIAGNOSTIC SYSTEMS

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- Fuzzy Logic Systems Overview
- Implementation Issues
    - Input Data Preprocessing
    - Architecture of the developed FL systems
- Application of the method- Results
    - Examined Mechanical and Blade Faults
    - Results for mechanical faults
    - Results for blade faults
- Summary - Conclusions

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Why Use Fuzzy Logic?

- Fuzzy Logic can deal with uncertainty and ambiguous information.
- It lies very close to the human intuition and thinking.
- Easy incorporation of engineering experience.
- Versatile set-up even for a simple user.
- Mature methodology applicable to a wide variety of disciplines.
- An FL system is a universal function approximator.
- Constitutes a nonlinear mapping of an input space to an output space.

Fuzzy Logic Fundamentals

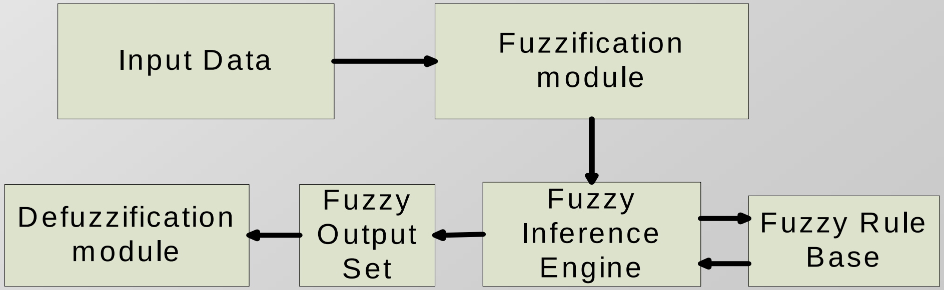
Nonlinear mapping of an input space to an output space

$$f : X \in R^n \rightarrow Z \in R$$

- Output is usually a scalar.
- X is an input vector while Z is the output scalar.
- f represents the FL system.

FL system is comprised of four basic components

- Fuzzification module
- Rule Base
- Fuzzy Inference Engine
- Defuzzification



Fuzzy Logic System structure

Fuzzy Logic Fundamentals

Fuzzification module

- Fuzzifier maps input data to fuzzy sets-Expansions of typical sets.
- Key elements of a fuzzy set:

  i) Universe of Discourse-U (equivalent of function domain).

  ii) Membership function (MF) $\mu(x)$, assigns membership values for input.
- Membership functions can overlap each other.

Fuzzy Rule Base

- Knowledge and conditional statements represented by ***IF-THEN*** rules.

IF x is A AND w is B ***THEN*** z is C

- ***IF*** part is called premise, ***THEN*** part is called conclusion.

  i) x, w are elements of U (linguistic variables), z is the output.

  ii) A, B fuzzy sets with corresponding MFs (linguistic values).
- Logical operators (e.g. AND, OR etc.) can be present.

Fuzzy Logic Fundamentals

Fuzzy Inference Engine

- Interaction with the rule base, "implements" the mapping between input-output.
- Key elements of inference engine:
  - i) Implication-Total membership value by premises is derived.
  - ii) Composition-Derivation of final output fuzzy set.
- Typical representatives: MIN-MAX and PRODUCT-SUM.

Defuzzification Module

- Extracts a scalar value by the final output fuzzy set.
- Defuzzification is performed according to the number of output variables.
- Typical representatives: MEAN-of-MAXIMA, CENTROID.

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Preprocessing of Input Data

- Performance and Fast Response data were available.
- Performance data originate from real test campaigns on a radial and an axial compressor.
- Performance data were different for the two compressors.
- Preprocessing of performance data was the same for both compressors.
- Fast Response data comprised by time signals of unsteady wall pressure and originated from simulation of the flow field over a blade row of known geometry in the axial compressor.
- Available data sets corresponded to healthy and faulty operation as well.

Preprocessing of Performance Data

- Data were available to 4 operating points.
- Corresponded to healthy and faulty operation as well.
- The notion of “fault signature” constitutes the utilized diagnostic parameter.

  Derived in the form of percentage deviations (deltas): $d = \frac{Y - Y_0}{Y_0} \times 100$

- Y_0 represented a measurement in ‘healthy’ state of the compressor.
- Y was the same measurement in the presence of a fault at the same operating point.
- Deltas were in the form of vectors.

Preprocessing of Performance Data

- From each operating point "fault signatures" were obtained.
- For each fault "fault signatures" were available in all operating points.
- A reference signature was obtained, as the average of all "fault signatures" available for a fault

$$\mathbf{d}_{\mathbf{ref}} = (1/NS) * \sum_{l=1}^{NS} \mathbf{d}_{\mathbf{l}}$$

- NS represented the number of "fault signatures" that corresponded to a specific fault.
- $\mathbf{d}_{\mathbf{l}}$ constituted the lth available signature.
- $\mathbf{d}_{\mathbf{ref}}$ was the derived reference signature.

Preprocessing of Fast Response Data

- Derived from simulated noise free patterns upon which noise was added.
- Two diagnostic parameters have been defined.
- Main characteristic is the reflection of the differentiations in the pressure signals due to changes in the geometry of the blades.
- These were:

1) Correlation Coefficient for Blade-To-Blade Pressure Distribution.

$$\alpha h_k = \frac{\overline{h(t)\cdot W(t)}}{\overline{W(t)^2}}$$

"Healthy" signal

$$\alpha f_k = \frac{\overline{f(t)\cdot W(t)}}{\overline{W(t)^2}}$$

"Faulty" signal

2) Passage Maximum Pressure Coefficient.

$$Ph_k = \max_{t_{k-1}\le t\le t_k} [h(t)]$$

"Healthy" signal

$$Pf_k = \max_{t_{k-1}\le t\le t_k} [f(t)]$$

"Faulty" signal

Preprocessing of Fast Response Data

- “Fault signatures” were also derived in this case.
- These were namely **Da** and **Dp**, defined as vectors.

$$Da_k = \frac{af_k - ah_k}{ah_k} \times 100 \qquad k = 1, 2, \ldots, Nb$$

$$Dp_k = \frac{Pf_k - Ph_k}{Ph_k} \times 100 \qquad k = 1, 2, \ldots, Nb$$

- *Nb* is the total number of the blades in the blade row.
- Equivalent definition with the “fault signatures” from performance data.
- No reference signatures were derived since data corresponded to a single operating point.

Architecture of the developed FL systems

- The developed FL systems handled the diagnostic task as a classification problem.
- Parametric studies have been performed regarding the basic elements of the systems

Structural elements of the deployed FL systems

- Input variables and Output.
- Fuzzy Sets of the Input and Output.
- Construction of the rule base.
- Inference Engine utilized.
- Defuzzification technique employed.

Architecture of the developed FL systems

Input variables and Output

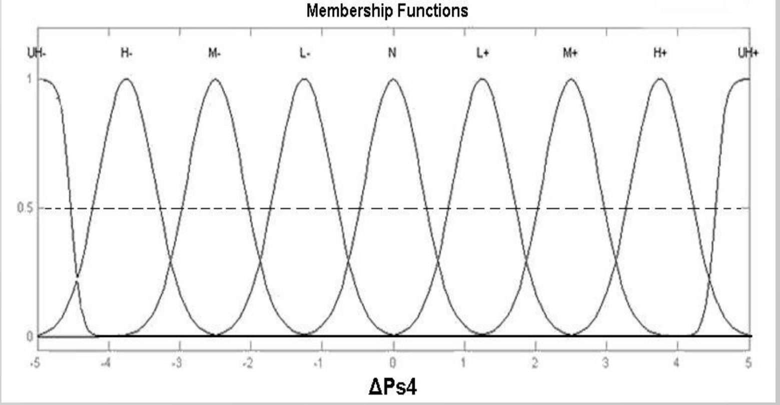
- Inputs were the extracted “fault signatures”.
- Outputs were the examined faults for each fault scenario.

Fuzzification and Fuzzy Sets

- Fuzzy Output sets number according to the number of examined faults.
- Fuzzy Sets of inputs represented fuzzy values and spanned U into regions.
- Spanning was variable in size leading to a parametric study regarding adopted number of input fuzzy sets.
- Input fuzzy sets defined by Gaussian MF: $\mu(x) = e^{-\frac{(x-m)^2}{2\sigma^2}}$

	MIDPOINTS						
LINGUISTIC VALUES	ΔW1(%)	ΔWf (%)	ΔPs4(%)	ΔT4(%)	ΔPs9(%)	ΔT9(%)	ΔT12(%)
UH-	-5	-5	-5	-5	-5	-5	-5
H-	-3.75	-3.75	-3.75	-3.75	-3.75	-3.75	-3.75
M-	-2.5	-2.5	-2.5	-2.5	-2.5	-2.5	-2.5
L-	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25	-1.25
N	0	0	0	0	0	0	0
L+	1.25	1.25	1.25	1.25	1.25	1.25	1.25
M+	2.5	2.5	2.5	2.5	2.5	2.5	2.5
H+	3.75	3.75	3.75	3.75	3.75	3.75	3.75
UH+	5	5	5	5	5	5	5

Names of Gaussian Fuzzy Sets



Gaussian MFs for ΔPs4

Architecture of the developed FL systems

Construction of Rule Base

- Rule base was constructed based on training by the available data.
- Each delta was applied to all MFs that spanned U into regions.
- The highest membership degree assigned by a MF was tied with this delta that activated it.
- The same applied for all available delta of the measurements.
- The activated fuzzy sets were joined by AND operators and assigned to a certain fault class.
- A filtering procedure was established in order either to eliminate mismatched rules among different fault classes or to reduce to 1 all the same rules in one fault class.
- Training was performed either by the “fault signatures” or by the reference signatures that derived from the first.

	MEASUREMENTS						
FAULT CLASS	ΔW_1(%)	ΔW_f(%)	ΔPs_4(%)	ΔT_4(%)	ΔPs_9(%)	ΔT_9(%)	ΔT_{12}(%)
F2	L-	N	L-	N	L-	N	L+
F2	L-	M-	L-	L-	L-	N	N
F2	L-	N	L-	N	L-	N	N
F2	L-	L-	L-	N	L-	N	N
F3	L-	L-	L-	L-	L-	L-	N
F3	N	M-	N	L-	N	L-	N
F3	L-	M-	L-	L-	L-	L-	L-
F4	N	L-	L-	N	L+	N	N
F4	N	H-	L-	N	N	L-	L-
F4	N	H-	N	N	N	M-	L-
F53	UH-	UH+	UH-	N	H-	H+	UH+
F53	UH-	L+	H-	N	H-	H+	UH+
F53	UH-	N	H-	N	H-	H+	M+
F53	UH-	UH-	UH-	N	UH-	L+	L+

Exmaple of Fuzzy Rules for the axial compressor

Architecture of the developed FL systems

Inference Engine utilized

- FL systems utilized both MIN-MAX and PRODUCT-SUM pairs.

Defuzzification Technique

- MEAN-of-MAXIMA technique was adopted.
- More appropriate for diagnostic tasks that handle the diagnostic problem as a classification problem.

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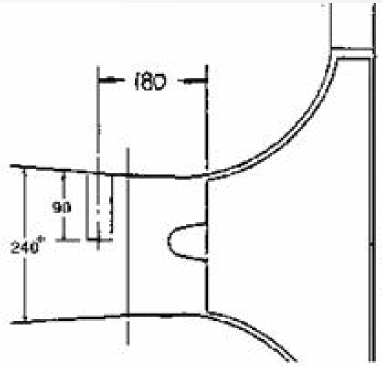
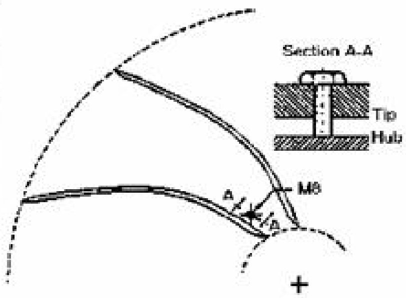
Examined Mechanical Faults

Radial compressor



Inlet Distortion-M3

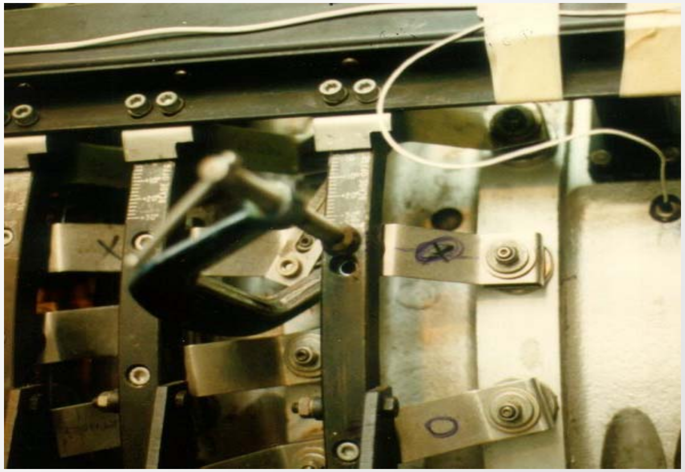


Diffuser Fault-M1

Impeller Fouling-M2

Examined Mechanical Faults

Axial compressor

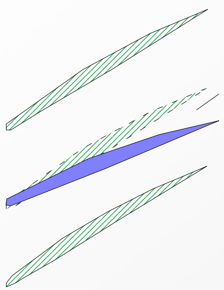


Mistuned stator vanes

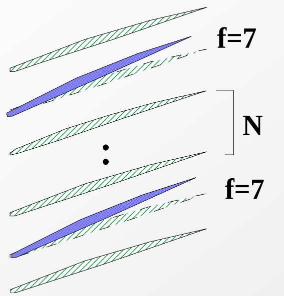
Twisted blade

- **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**

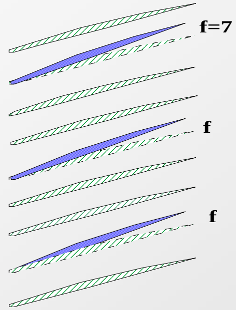
Examined Blade Faults



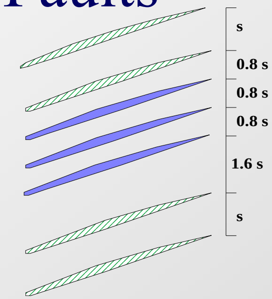
Mf (f=1,3,5,7,9)



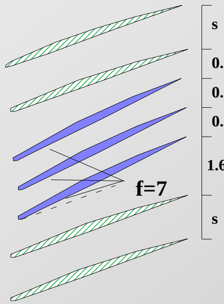
2TN (N=1,3,5)



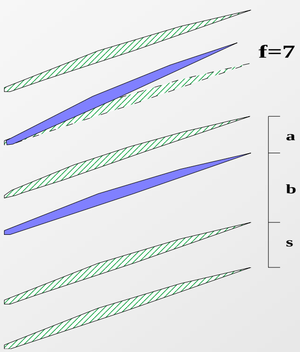
3T2



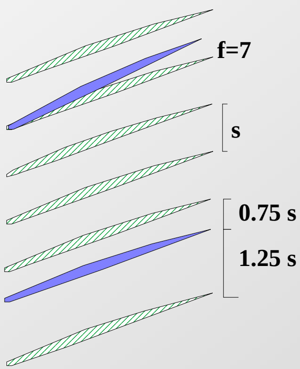
3D



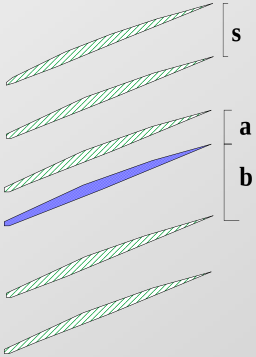
3DT



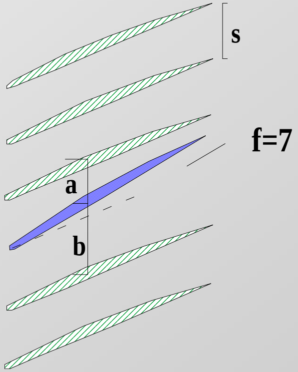
A_(1,2.3)



A4



A_(6,7,8)



A_(9,B,C,D)

A1: (a=0.75s, b=1.25s)
A2: (a=0.50s, b=1.50s)
A3: (a=0.25s, b=1.75s)
A6: (a=0.75s, b=1.25s)
A7: (a=0.50s, b=1.50s)
A8: (a=0.25s, b=1.75s)
A9: (a= b = s)
AB: (a=0.75s, b=1.25s)
AC: (a=0.50s, b=1.50s)
AD: (a=0.25s, b=1.75s)

Individual Diagnostic Methods

- Individual Diagnostic Methods validated in previous researches have been considered.
- Their results were compared with those from FL systems in order to derive the effectiveness and the applicability of the developed systems.

Diagnostic Methods :

1. ***Geo***: Geometrical Pattern Recognition.
2. ***Stat-A***: Statistical Pattern Recognition with feature vector A.
3. ***Stat-B:*** Statistical Pattern Recognition, same as 2 but now with feature vector B.
4. ***Opt-A:*** Statistical with Optimal Directions Pattern Recognition with feature vector A.
5. ***Opt-B***: Statistical with Optimal Directions Pattern Recognition, same as 4 but now with feature vector B.
6. ***PNN***: Probabilistic Neural Network.

Results of Individual Diagnostic Methods in Mechanical Faults

Axial compressor

	1st Training Procedure	2nd Training Procedure
Geo	0/4	0/16
Stat-A	1/4	0/16
Stat-B	0/4	0/16
Opt-A	0/4	0/16
Opt-B	0/4	0/16
PNN	1/4	1/16

Radial compressor

	1st Training Procedure	2nd Training Procedure
Geo	0/3	1/12
Stat-A	1/3	1/12
Stat-B	0/3	0/12
Opt-A	0/3	0/12
Opt-B	0/3	0/12
PNN	2/3	1/12

Results given in terms of incorrect classifications versus total test-cases

Results of FL systems in Mechanical Faults (parametric studies)

Axial compressor

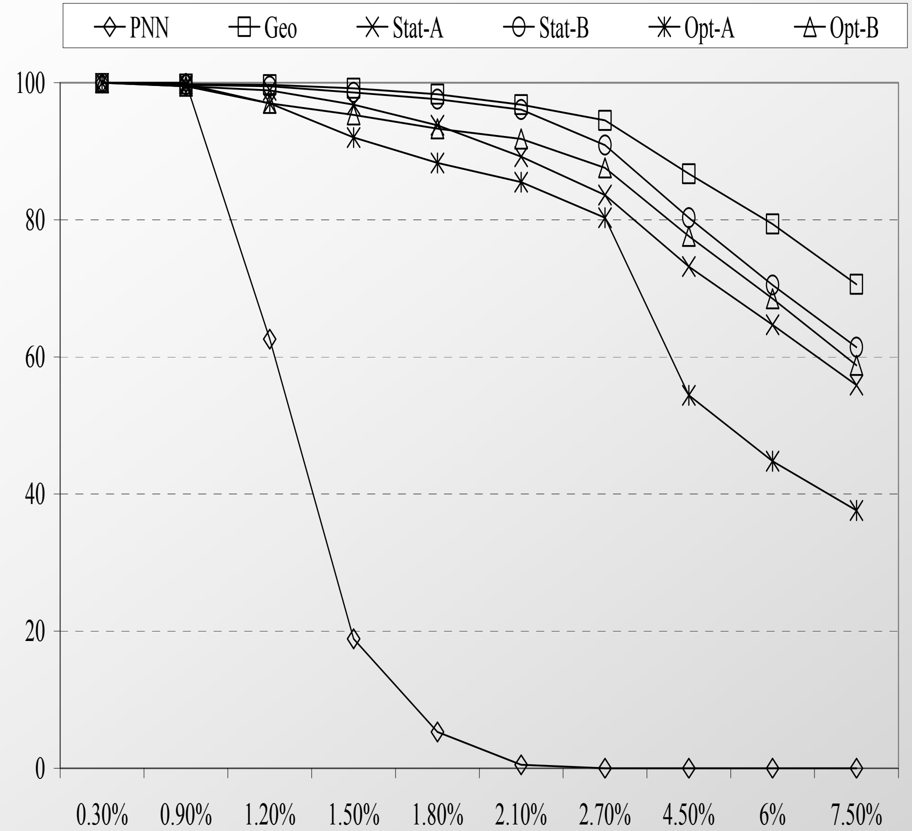
	1st Training Procedure						2nd Training Procedure					
	MIN-MAX			PROD-SUM			MIN-MAX			PROD-SUM		
	σ=0.2	σ=0.4	σ=0.6	σ=0.2	σ=0.4	σ=0.6	σ=0.2	σ=0.4	σ=0.6	σ=0.2	σ=0.4	σ=0.6
5 MFs	1/4	1/4	1/4	2/4	2/4	2/4	8/16	8/16	8/16	8/16	7/16	7/16
9 -//-	1/4	1/4	1/4	1/4	1/4	1/4	3/16	3/16	3/16	3/16	3/16	3/16
15-//-	1/4	1/4	1/4	1/4	1/4	1/4	3/16	3/16	3/16	2/16	2/16	2/16

Radial compressor

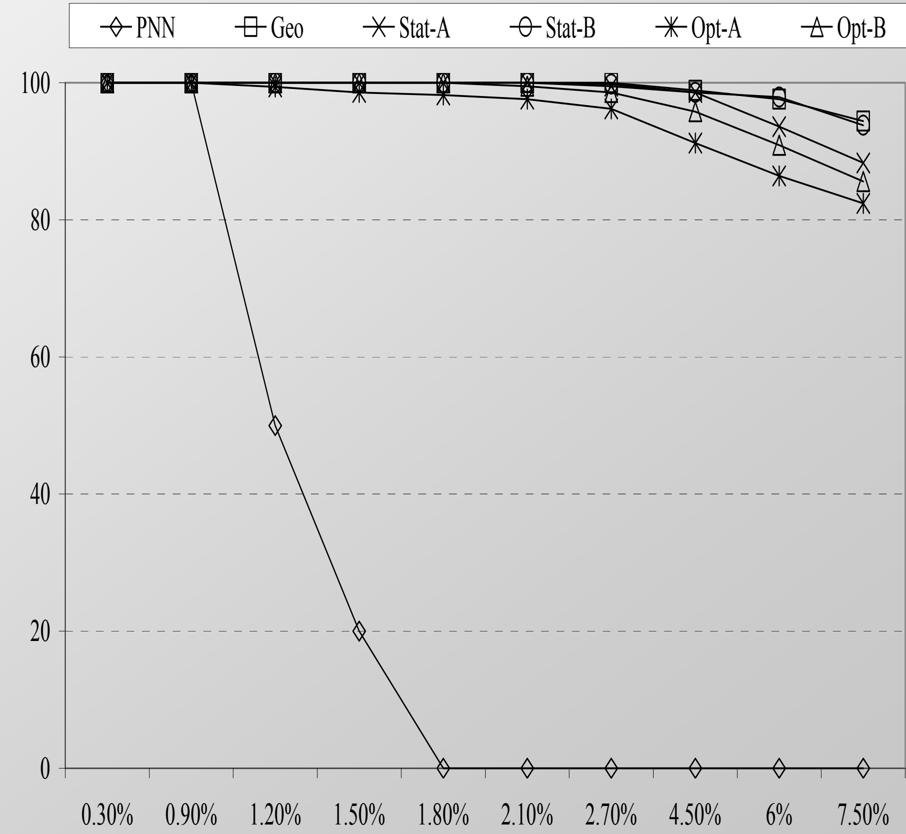
	1st Training Procedure						2nd Training Procedure					
	MIN-MAX			PROD-SUM			MIN-MAX			PROD-SUM		
	σ=0.2	σ=0.4	σ=0.6	σ=0.2	σ=0.4	σ=0.6	σ=0.2	σ=0.4	σ=0.6	σ=0.2	σ=0.4	σ=0.6
5 MFs	1/3	1/3	1/3	1/3	1/3	1/3	4/12	4/12	4/12	1/12	1/12	1/12
9 -//-	0/3	0/3	0/3	0/3	0/3	0/3	1/12	1/12	1/12	1/12	1/12	1/12
15-//-	0/3	0/3	0/3	0/3	0/3	0/3	1/12	1/12	1/12	1/12	1/12	1/12

Results of Individual Diagnostic Methods in Blade Faults

Da vectors



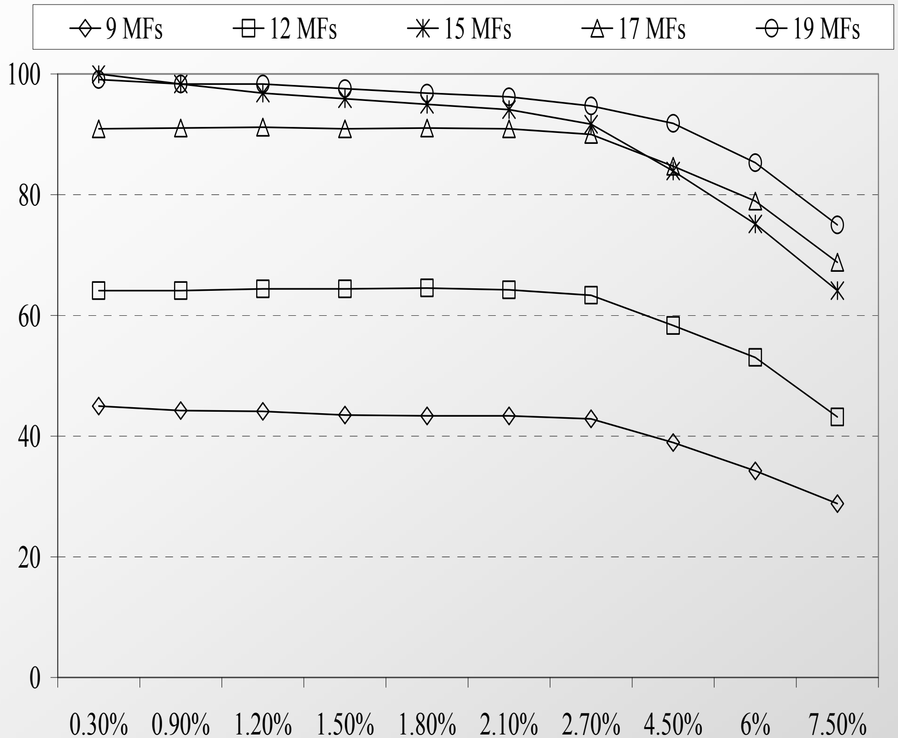
Dp vectors



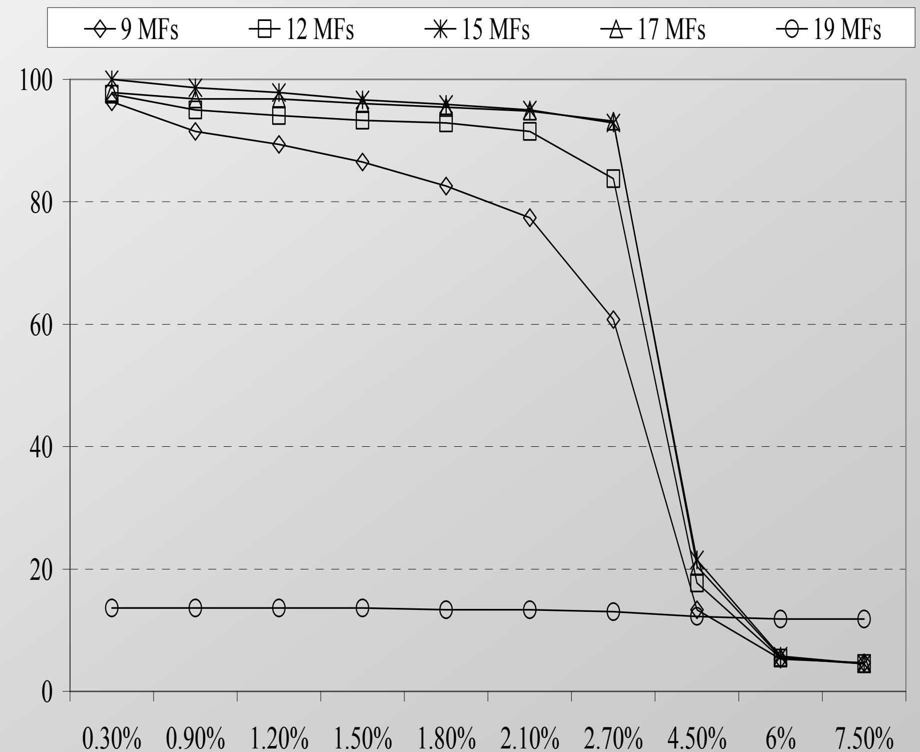
Noise levels

Results of FL systems in Blade Faults

Da vectors



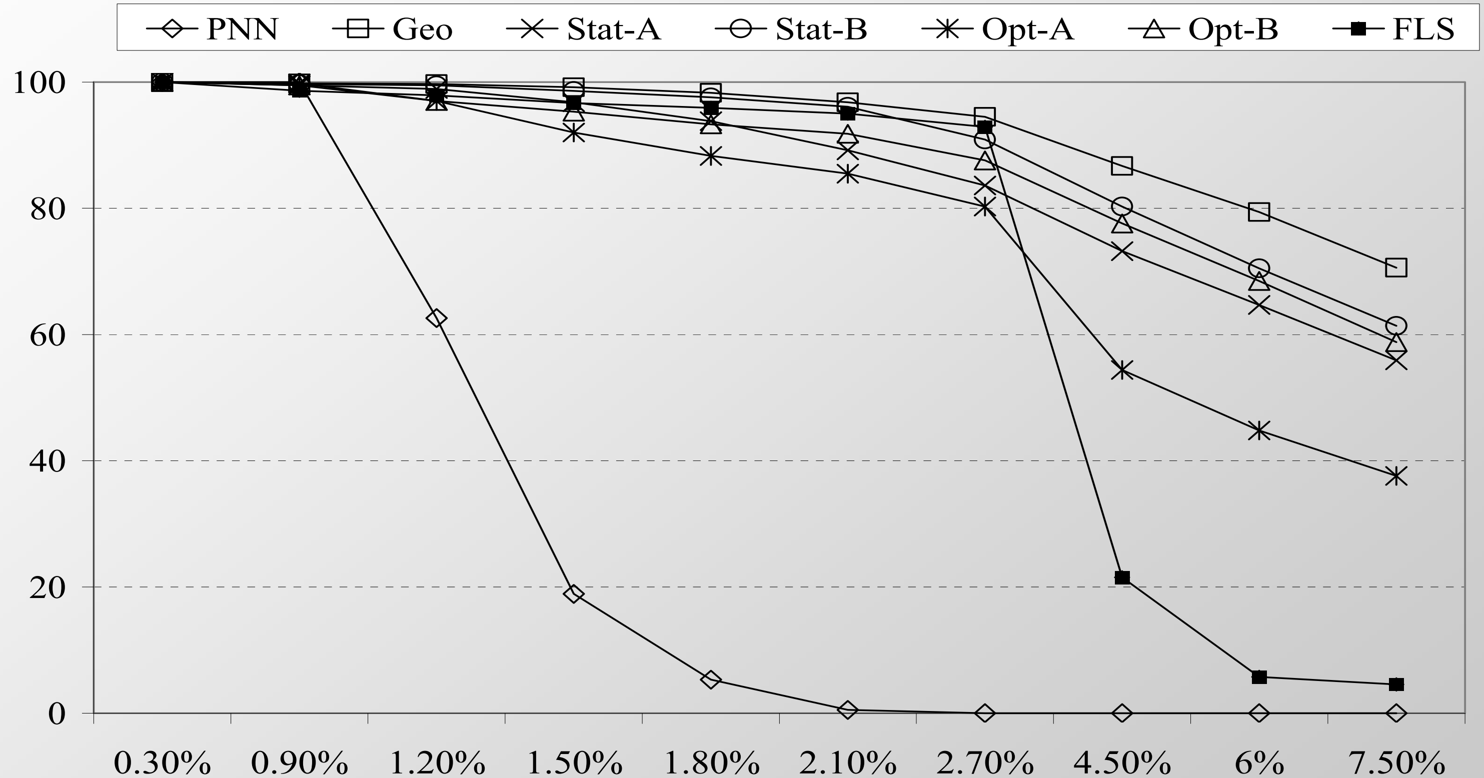
Dp vectors



MIN-MAX pair *Noise levels* *PROD-SUM pair*

Compared results of FL systems and Individual Methods in Blade Faults

Dp vectors, FL system with 15 MFs, PROD-SUM pair



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Summary - Conclusions

- **An implementation of FL systems oriented for gas turbine diagnostics has been presented.**
- **Key structural element of such systems is the number of defined fuzzy sets. Parametric studies have been performed in the current work to investigate the degree of significance.**
- **In general increased number of fuzzy sets (and corresponding MFs) led to better performance but the optimal number was bounded by the overlapping areas between the MFs.**
- **A filtering module which permitted the elimination of similar or mismatching rules was developed, optimizing thus the final rule base.**
- **No significant difference was found in the effectiveness of the FL systems regarding the selected inference engine.**
- **Generality of the method demonstrated by application to different fault scenarios and by the utilization of different type of data.**
- **Overall, the developed FL systems have found to constitute an alternative and effective tool for diagnostic purposes.**