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

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

- 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:
  - Universe of Discourse-U (equivalent of function domain).
  - 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.
  - $x, w$ are elements of $U$ (linguistic variables), $z$ is the output.
  - $A, B$ 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

\[ d_{\text{ref}} = \frac{1}{NS} \sum_{l=1}^{NS} d_l \]

- NS represented the number of “fault signatures” that corresponded to a specific fault.
- \( d_l \) constituted the \( l^{th} \) available signature.
- \( d_{\text{ref}} \) 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.

\[
\alpha h_k = \frac{h(t) \cdot W(t)}{W(t)^2}
\]

"Healthy" signal

\[
\alpha f_k = \frac{f(t) \cdot W(t)}{W(t)^2}
\]

"Faulty" signal

2) Passage Maximum Pressure Coefficient.

\[
P h_k = \max_{t_{k-1} \leq t \leq t_k} \left[ h(t) \right]
\]

"Healthy" signal

\[
P f_k = \max_{t_{k-1} \leq t \leq t_k} \left[ f(t) \right]
\]

"Faulty" signal
Preprocessing of Fast Response Data

- “Fault signatures” were also derived in this case.
- These were namely \( D_a \) and \( D_p \), defined as vectors.

\[
D_{a_k} = \frac{af_k - ah_k}{ah_k} \times 100 \quad k = 1, 2, ..., Nb
\]

\[
D_{p_k} = \frac{Pf_k - Ph_k}{Ph_k} \times 100 \quad k = 1, 2, ..., Nb
\]

- \( Nb \) 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:
  \[
  \mu(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-m)^2}{2\sigma^2}}
  \]

<table>
<thead>
<tr>
<th>LINGUISTIC VALUES</th>
<th>ΔW1(%)</th>
<th>ΔWf (%)</th>
<th>ΔPs4(%)</th>
<th>ΔT4(%)</th>
<th>ΔPs9(%)</th>
<th>ΔT9(%)</th>
<th>ΔT12(%)</th>
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<td>5</td>
</tr>
</tbody>
</table>

*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.

![Example of Fuzzy Rules for the axial compressor](image)
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*

- 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

Mistuned stator vanes

Twisted blade
Examined Blade Faults

- **Mf (f=1,3,5,7,9)**
- **2TN (N=1,3,5)**
- **3T2**
- **3D**
- **3DT**

- **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**

<table>
<thead>
<tr>
<th>Method</th>
<th>1st Training Procedure</th>
<th>2nd Training Procedure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geo</td>
<td>0/4</td>
<td>0/16</td>
</tr>
<tr>
<td>Stat-A</td>
<td>1/4</td>
<td>0/16</td>
</tr>
<tr>
<td>Stat-B</td>
<td>0/4</td>
<td>0/16</td>
</tr>
<tr>
<td>Opt-A</td>
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<td>0/16</td>
</tr>
<tr>
<td>Opt-B</td>
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**Radial compressor**

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<td>0/3</td>
<td>0/12</td>
</tr>
<tr>
<td>PNN</td>
<td>2/3</td>
<td>1/12</td>
</tr>
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Results given in terms of incorrect classifications versus total test-cases.
**Results of FL systems in Mechanical Faults (parametric studies)**

### Axial compressor

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>MIN-MAX</td>
<td>PROD-SUM</td>
</tr>
<tr>
<td>$\sigma=0.2$</td>
<td>$\sigma=0.4$</td>
</tr>
<tr>
<td>5 MFs</td>
<td>1/4</td>
</tr>
<tr>
<td>9 -/-</td>
<td>1/4</td>
</tr>
<tr>
<td>15-/-</td>
<td>1/4</td>
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<tr>
<td>8/16</td>
<td>8/16</td>
</tr>
<tr>
<td>3/16</td>
<td>3/16</td>
</tr>
<tr>
<td>2/16</td>
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</table>
Results of Individual Diagnostic Methods in Blade Faults

\textit{Da vectors}

\textit{Dp vectors}

\begin{align*}
\text{Noise levels}
\end{align*}
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.