FUZZY LOGIC RULES FOR TURBOMACHINE MONITORING INSTRUMENTATION

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Abstract - *Turbomachines' maintenance diagnostic procedures are generally performed manually by expert engineers and technicians. However, there is a strong interest for expert systems to assist them in these complex fault identification procedures. The purpose of this paper is to describe and evaluate the implementation of a Fuzzy Logic (FL) system for fault diagnosis based on thermodynamic measurements of temperature and pressure. The measurements were taken in regular aerodynamic stations located lengthwise the engine. These stations are placed adequately in order to facilitate its performance monitoring.*

Keywords - Fuzzy C- Means, Neural Networks, Diagnostic system, Thermodynamic measurements.

1. INTRODUCTION

The current research aims to identify the advantages of Fuzzy Logic rules technology in turbine engine fault diagnosis. The CFM56–3 engine is a dual spoon turbofan designed and manufactured by CFM International. The engine incorporates a single-stage fan (A) and three-stage (L.P.C.) low-pressure compressor (B) driven by a four-stage (L.P.T) low-pressure turbine (F). A nine-stage axial flow (H.P.C.) high-pressure compressor (C) is driven by a single-stage (H.P.T.) high-pressure turbine (E). The inlets and outlets of the above engine components (2,25,3,4,45,5) are the most suitable stations for placing monitoring instruments on a jet engine like the CFM56-3 [1]. These stations are indicated in Figure 1.

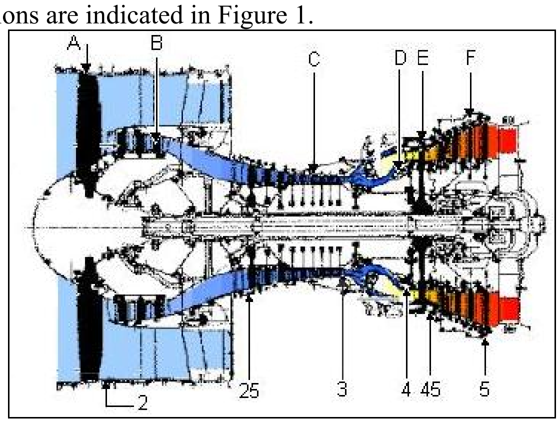

Figure 1. The thermodynamic stations of the CFM 56-3 jet engine.

2. NATURE OF THE PROBLEM

Within automatic control of technical systems, supervisory functions serve to indicate undesired or unpermitted process states and to take appropriate actions in order to maintain the operation and to avoid damages or accidents [2]. The following aspect are met in the fuzzy system proposed in this paper, which was built on Matlab 5.2 by Mathworks Inc:

a) M*onitoring using fuzzy rules:* measurable variables are checked with regard to specific tables and accepted tolerances.

b) F*ault diagnosis:* based on measured variables, features are calculated, a fault diagnosis is performed and decisions are made for counteractions.

Due to the fact that fuzzy set theory has the potential capability to efficiently represent input/output relationships of dynamic systems, this theory has gained popularity, especially in pattern recognition and classification [3],[4],[5],[6]. An increasing activity can be observed in the field of fuzzy control systems and neural networks, for fault diagnosis in rotating machinery and jet engines. In some cases the combination of fuzzy logic and neural networks integrates the advantages of both approaches in one controller [7],[8],[9]. Controllers can be designed in the fuzzy sense using heuristic knowledge. On the other hand, they can be trained from learning data by means of algorithms developed for neural networks. In any case, there is structural equivalence between certain types of fuzzy systems and artificial neural networks [10],[11]. This paper aims also to perform a comparison between the Fuzzy Logic System and the Neural Network classifier trained on the same dataset [12].

The basic concept in FL, which plays a central role in most of its applications, is that of a fuzzy if-then rule or, simply, the fuzzy rule. In the proposed system measurements taken during the take-off operation point of the engine's cycle and then clustered using a specific membership grade. These membership functions (MF) formed the basis for the definition of the fuzzy logic rules. These if-then rule statements are used to formulate the conditional statements that comprise the fuzzy logic-based turbomachine monitoring system.

The purpose of this paper is to describe the implementation of Fuzzy Logic (FL) system and evaluate its performance with real –life thermodynamic measurements during various operating points of the machine. The input of the system is the measurement set consisting of thermodynamic patterns such as temperature and pressure. Additionally the structural elements of the system are discussed analytically.

3. METHODS OF RESEARCH

Clustering of numerical data forms the basis of many classification and system modeling algorithms. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior.

Fuzzy c-means (FCM) is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade.

This technique was originally introduced by Jim Bezdek in [13] as an improvement on earlier clustering methods. It provides a method of how to group data points that populate some multidimensional space into a specific number of different clusters.

An initial guess for the cluster centers is calculated randomly, which is intended to mark the mean location of each cluster. The initial guess for these cluster centers is most likely incorrect.

Additionally, a membership grade for each cluster is assigned in every data point. By continuously updating the cluster centers and the membership grades for each data point, the cluster centers are moved to the "right" location within a data set. This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data grade.

Table 1. Engine's parameters corresponding to its conditions

Engine Parameter	**Devia-tion (%)**	**Engine Condition**
FAN Pressure Ratio (P.R.)	1-3	Health
Low Pressure Comp. P.R.	1-3	Health
High Pressure Comp. P.R.	1-3	Health
BURNER Pressure	1-3	Health
FUEL Consumption	1	Health
High Pressure Turbine P.R.	1	Health
Low Pressure Turbine P.R.	1	Health
FAN P.R.	4-16	Fan fault
Low Pressure Comp. P.R or High Pressure Comp. P.R	4-16	Compressor Fault
FUEL Consumption	4-16	Burner Fault
High Pressure Turbine P.R or Low Pressure Turbine P.R.	3-9	Turbine Fault

The system was originally built on the basis of the Fuzzy Logic Toolbox of MATLAB 5.2 by Mathworks Inc. The whole system was based on the initial training of the system in order to create successfully membership functions to represent the fuzzy qualities of each cluster. After this training it can be assumed that the membership functions represent successfully the statistical nature of the if-then rules of the problem.

4. EXPERIMENTAL RESULTS

The Fuzzy C- Mean method has clustered thermodynamic patterns –namely temperature (°C) and pressure (bar)- measured in aerodynamic stations, during the take-off operation point of the engine's cycle [14]. The training set was created with values corresponding to "healthy" instances, along with cases of engine malfunction. The malfunction cases represent insignificant, moderate or severe faults in the compressor, combustion chamber and turbine part of the engine [14], as shown in Table 1.

For the current ANN the target vectors are the following:

- Healthy operation
- FAN fault
- Compressor fault
- Burner fault
- Turbine fault

The system's input is a 6-dimensional vector, which should be classified in the above 5 clusters.

4.1 Training the FCM system

A fuzzy set, or cluster, is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. This concept describes the malfunction cases met in the CFM –56 jet engine [14].

The training set consists of 255 patterns. Each pattern is a 6-dimensional vector containing the temperature and pressure value of the three aerodynamic stations 3,4 and 5 as indicated in Figure 1 during the phase of take-off. As mentioned above the 4 target clusters represent malfunction in one part of the jet engine, plus the one cluster, which corresponds to the healthy operation of the engine. Table 2 indicates the correlation of patterns and clusters.

Table 2. Training Set of the fuzzy system

Number of patterns	**Engine's Condition**
64	Health
12	Fan fault
49	Compressor fault
49	Burner fault
81	Turbine fault
255	

The clusters are also visualized in a 3D plot, which is presented in Figure 2. As it is obvious the boundaries of the clusters, which represent the condition of the engine are not always crisp.

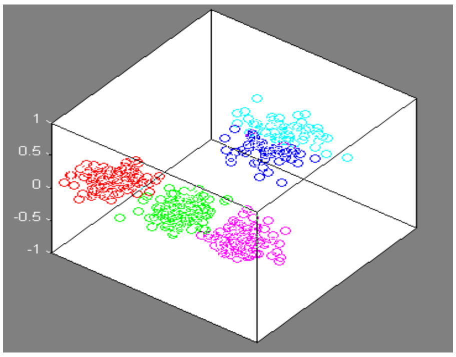

Figure 2. A 3D visual representation of the way that the Fuzzy C Mean algorithm grouped the patterns in 5 clusters.

4.2 Calculation of the membership functions

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. These mathematical functions, which encapsulate the fuzziness of the problem were calculated and chosen accordingly in order to built the Fuzzy Inference system for the assessment of the CFM56-3 jet engine.

A 3D representation of the membership functions is presented in the Figures 3,4,5,6 and 7.

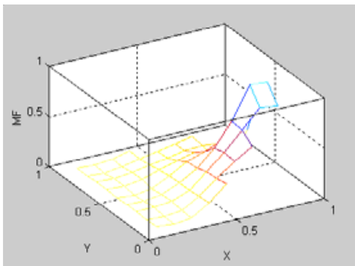

Figure 3. MF for FAN fault

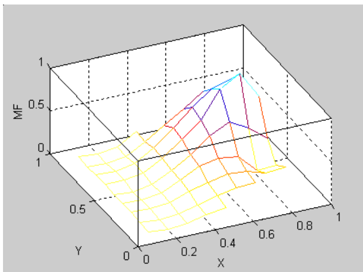

Figure 4. MF for Compressor fault

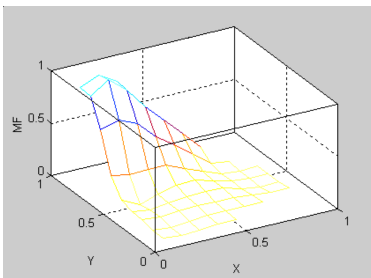

Figure 5. MF for Burner fault

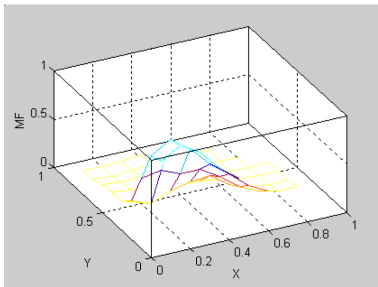

Figure 6. MF for Turbine fault

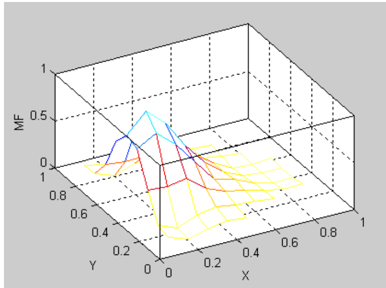

Figure 7. MF for "healthy" operation

4.3 The Fuzzy Inference System (FIS)

The first step for building a FIS is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. Once the inputs have been fuzzified, the fuzzy logical operations must be implemented. For this application we used the OR operator (max). The aggregation method for the rules is the maximum value. Finally, the defuzzification method is the middle of maximum (the average of the maximum value of the output set.

The fuzzy rules were successfully applied to a Fuzzy Inference System (FIS), using the Fuzzy Logic Toolbox of Matlab 5.2 by MathWorks Inc. The inputs of the FIS program are the temperature and pressure values taken during the take-off operation point of the CFM 56-3 jet engine.

4.4 Testing the Fuzzy Inference System (FIS)

The performance of the FIS was tested with a set of 3883 patterns covering almost all the possible conditions of the jet engine during the take-off phase [14]. The system successfully identified the malfunctions occurred in the burner and the turbine with high accuracy (98.2% and 97.9%). The compressor faults were successfully identified from the system (100% of the test patterns).

The system presented the lowest performance in the classification of the Fan malfunctions. Specifically, in these the performance reached the 95%, while the further cases (6%), were misclassified as healthy patterns.

Additionally, the patterns, which correspond to healthy instances, have been identified successfully by the FCM system in a great extend (95.9 %). The remaining patterns were assigned to the class of Fan (1.7 %), or Turbine (2.4 %)

malfunction. Table 3 presents the performance of the system.

Table 3. Performance of the Fuzzy Logic System

	Health	FAN Fault	Comp. Fault	Burner Fault	Turbine Fault
Health	982 /1024 **95.9%**	17/1024 1.7%	-	-	25/1024 2.4%
FAN Fault	6/120 5.0 %	114/120 **95.0%**	-	-	-
Comp. Fault	-	-	169/169 **100.0%**	-	-
Burner Fault	-	-	3/169 1.8%	166/169 **98.2%**	-
Turb. Fault	9/2401 0.4%	-	24/2401 1.0%	17/2401 0.7%	2351 /2401 **97.9%**

5. COMPARISON WITH A LEARNING VECTOR QUANTIZATION (LVQ) NEURAL NETWORK

For the same data set an Artificial Neural Network was trained and then tested for a similar classification application in thermal turbomachines [12]. The results in this case were slightly better in most cases. However, with the Fuzzy C-Mean method there is a slight improvement in the cool parts of the engine and especially in the patterns belonging to the FAN fault as shown in Tables 3 and 4.

Table 4. The performance of the LVQ network

	Health	FAN Fault	Comp. Fault	Burner Fault	Turbine Fault
Health	1000 /1024 **97.6%**	8/1024 0.8%	-	-	16/1024 1.6%
FAN Fault	10/120 8.3%	110/120 **91.7%**	-	-	-
Comp. Fault		3/169 1.8%	166/169 **98.2%**	-	-
Burner Fault	-	-	-	169/169 **100.0%**	-
Turb. Fault	-	-	-	-	2401 /2401 **100.0%**

The plot, which is indicated in Figure 8, is a visual representation of the way, which the FCM system clusters the data. It also shows that the weights of the LVQ1 networks (circles) are fairly close to their respective patterns (crosses). The classification groups are mapped in different non-overlapping clusters. However, there is an overlapping area between the boundaries of the compressor and fan regions. That explains the misclassification cases in the experimental results.

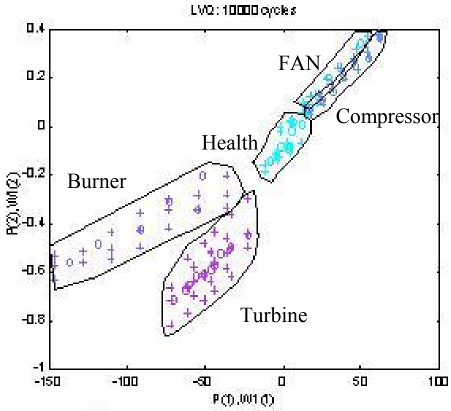

Figure 8. LVQ pattern map

6. PROPOSED SYSTEM FOR ON-LINE MONITORING

A diagnostic system architecture is proposed of several different components as shown in Figure 9. The Computer Unit provides an assessment of the engine's condition on the basis of previous training on the CFM56-3 operation map. As a standard the operator console and the archive subsystem are an integrated part of the analysis computer. The data stored in the database subsystem can be used for further training of the Fuzzy Logic system.

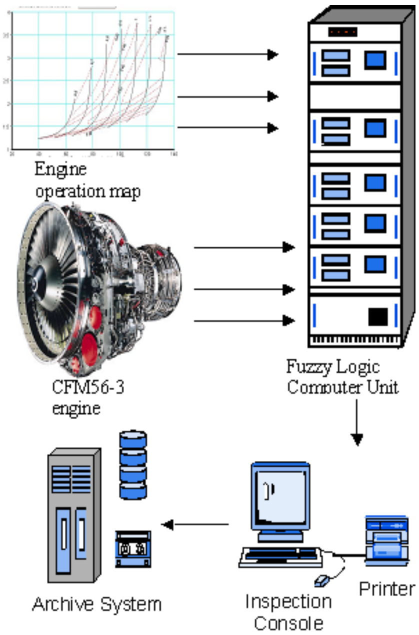

Figure 9. A proposed system for on-line assessment of the turbomachine.

7. CONCLUSIONS

This paper contributes to the state of the art techniques for fault diagnosis, with particular regard to rotating machinery. It has been seen that new model-based fault diagnosis systems are being developed rapidly in order to meet with the demand for increasingly intelligent condition monitoring systems for the maintenance of modern industrial processes. It is anticipated that future developments in fault diagnosis systems will be heavily concerned with the improved design of expert systems and neural networks for the continuous monitoring of machinery.

The results indicate that this approach for maintenance and diagnostics will save time and improve performance. The Fuzzy Logic system's capability to correctly classify patterns into specific classes, on the basis of measurements taken from the aerodynamic stations, will save time and increase diagnostic accuracy considerably. It is very interesting to note, that both the Fuzzy Logic System presented in this paper and the ANN in [12], featured not only structural equivalence but also comparable performances.

Thermodynamic patterns are extensively used for jet engine performance assessment and monitoring. However, due to the complexity of the problem, real-time diagnostic systems are needed to act as intelligent assistants in jet engines fault detection.

In this paper, it has been proved that, if enough input data from the aerodynamic stations are provided, Fuzzy Logic based systems are able to identify jet engine malfunctions with a high level of accuracy.

In the short term, it would reduce the amount of man-hours spent on diagnosing de facto failures. Further, it would decrease the requirement for additional Testing and Diagnostic Equipment as the predictive maintenance system is based on internal information. In addition, a robust maintenance system would decrease the probability of incorrect replacement of operational components due to poor initial diagnosis.

In the long term, computer-based maintenance technology would be a powerful and valuable tool to design engineers as well as the system operator and maintainer [3]. Once a robust and viable FIS-based maintenance system is developed, it would allow for a system design to be qualitatively analyzed across a range of operational parameters. This would enable design flaws to be corrected before the system is fabricated. In addition, it would enable the operator and maintainer to query the system about its relative operational state prior to the onset of any sustained operation. Any identified flaws could be detected and corrected.

Moreover, a further development of the system could incorporate additional parameters from the auxiliary units of the engine as well as measurements from more aerodynamic stations.

Thus, in spite of being in an early development stage, the application of Fuzzy Logic or Neural Network technology appears to be a promising tool for enhancing the effectiveness of jet engines maintenance practices.

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