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Two-shaft stationary gas turbine engine gas path diagnostics using fuzzy logic†

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Abstract

Our objective was to develop a Fuzzy logic (FL) based industrial two-shaft gas turbine gas path diagnostic method based on gas path measurement deviations. Unlike most of the available FL based diagnostic techniques, the proposed method focused on a quantitative analysis of both single and multiple component faults. The data required to demonstrate and verify the method was generated from a simulation program, tuned to represent a GE LM2500 engine running at an existing oil & gas plant, taking into account the two most common engine degradation causes, fouling and erosion. Gaussian noise is superimposed into the data to account measurement uncertainty. Finally, the fault isolation and quantification effectiveness of the proposed method was tested for single, double and triple component fault scenarios. The test results show that the implanted single, double and triple component fault case patterns are isolated with an average success rate of 96 %, 92 % and 89 % and quantified with an average accuracy of 83 %, 80 % and 78.5 %, respectively.

Keywords: Gas turbine; Component faults; Gas turbine performance; Fuzzy logic; Gas path diagnostics

1. Introduction

Failure or performance deterioration of a gas turbine engine strongly affects its operation. Gas turbine performance highly relies on the performance of the main gas path components, namely compressor and turbine [1, 2]. The gas path components' performance can be degraded due to different faults such as fouling, erosion, blade tip clearance, corrosion, and foreign/domestic object damage [3]. To avoid these faults and ensure a high level reliability and availability, an effective diagnostic system that can detect, isolate, and identify developing engine faults, at the earliest possible, is very critical. This will help the operators to take the appropriate maintenance action at the right time so that the engine can restore its best performance. Degradation can be manifested by changes in gas path parameters (pressure, temperature, fuel flow rate, shaft speed, etc.) from the established baseline. The deterioration extent of the engine gas path components is expressed in terms of efficiency (η) and flow capacity (Γ) deviations. For example, fouling results in a decrease in efficiency and flow capacity, while turbine erosion leads to a decrease in efficiency and an increase in flow capacity [4, 5].

In the field of gas path diagnostics, an accurate assessment of the actual health status of the engine is challenged by the small number of measurements available, measurement noise and sensor biases, and the presence of multiple faults at the same time. Concerning these issues, previously, several studies have been conducted and many diagnostic techniques with improved accuracy devised [6-8].

To confront the first problem, Ganguli [9] developed an FL based single fault isolation system for a jet engine. He examined the diagnostic effectiveness of different sets of measurements ranging from four to eight. The proposed method isolated 95 % of the fault signatures correctly using only four parameters. As the number of sensors increased, the accuracy increased and reached 100 % with eight sensors, even at high measurement noises. On another study, Ogaji et al. [10] discussed the possible optimal parameter combinations that are sufficient to perform both single and multiple fault diagnostics. A combination of GPA and measurement subset concept has also been applied to select appropriate instrumentation sets for multiple gas path component fault diagnostics [11]. Recently, the potential of Genetic algorithm (GA) on measurement selection was evaluated by Chen et al. [12].

A single fault detection and isolation effectiveness of Kalman filter (KF), ANN and hybrid ANN was investigated by Volponi et al. [13]. Although three of them were able to isolate more than 90 % of the fault signatures, the result from the hybrid system was the best. Ganguli [14] suggested trend shift detection mechanism using median filters and fuzzy logic. The measurement outliers were removed and noises were reduced before the fault detection process. However, it was limited to single component fault cases only. Similarly, Ogaji et al. [15] devised a fuzzy logic based fault identification tech-

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nique for a military turbofan engine application that can estimate single component faults with an accuracy of 92.5 %. Kyriazis et al. [16] proposed an FL based gas turbine compressor fault diagnostic system using performance data. Its diagnostics effectiveness was compared with pattern recognition and Probabilistic neural network (PNN) methods. They reported that the FL based method showed as good generality and effectiveness in fault diagnostics as the other two methods. The fault detection and identification performance of FLs in full-load and part-load engine operating condition was tested by Mohammadi and Montazeri-Gh [17]. The robustness towards measurement noise has been undertaken. Tsoutsanis et al. [18] proposed a component map tuning based performance diagnostics method for a GE's LM2500+ engine compressor. In this work a component curve fitting scheme and a gas turbine dynamic model are integrated.

Nevertheless, in practice, it is likely to have one or more affected components at the same time. Methods that are good in single component fault analysis would produce wrong diagnostic result, whenever multiple faults exist simultaneously. This may be due to the possible existence of similar patterns or fault indicators of different fault types [19]. In this regard, many different attempts were performed to develop methods that can deal with multiple fault diagnostics problems. For example, authors in Refs. [20-29] devised ANNs based methods and some other authors in Refs. [30-34] developed GPA based methods. The ANN based techniques can deal with measurement uncertainties and limited numbers of sensors. Whereas, the GPA based methods are suitable for multiple fault analysis although they are not coping with measurement uncertainties and require a large number of sensors [7]. Unlike the other Artificial intelligence (AI) methods, there are limited numbers of techniques utilizing an FL for quantitative multiple fault diagnostics [7]. The capability of FLs for multiple fault isolation and identification was evaluated by Marinai et al. [35, 36]. In this work, although the proposed method was able to quantify faults, it was limited to double component faults only, where in reality, there is a possibility that more than two components of the case engine could be affected at the same time. Simulated data sets for clean and faulty engine cases were used to test the fault detection performance of the model, and results showed that the detection based on filtered data was very accurate with negligible missed alarms and no false alarms. Recently, a multiple component fault diagnostic method based on a nonlinear component adaptation scheme was proposed by Tsoutsanis et al. [37] for a 2-shaft industrial gas turbine engine under transient operating conditions.

In this paper, an FL based multiple fault isolation and identification system is proposed for a twin-shaft stationary gas turbine engine application. The capability of the proposed method to isolate and quantify single, double and triple component faults has been evaluated. To model and demonstrate the method, the necessary data was generated from a performance simulation program, tuned to represent GE LM2500 engine running at oil & gas industries. The performance of the method towards measurement non-repeatability was also tested by superimposing standard Gaussian white noise values to the performance data. Compressor fouling (CF), Gas generator turbine erosion (GGTE), and Power turbine erosion (PTE) were considered as the gas path component faults that exist individually or together. The major contribution of this paper can be summarized as follows:

- The problem of multiple gas path component fault diagnostics of an industrial two-shaft engine was investigated using an FL-based method. As discussed in the literature review, most of the previous works have only focused on SCFs and DCFs diagnostics. In our method, we included the Triple component fault scenario (TCF). In addition to this, some others, as in Refs. [22-28], have considered the effects of component faults on efficiencies and flow capacities separately or independent of one another. Meaning that efficiency and flow capacity performance parameters are considered as SCFs taking them individually and as DCFs taking them concurrently. Conversely, in the new method, a more appropriate and reasonable consideration, as considered in Ref. [38], i.e., taking two performance parameters together as a SCF, four parameters as a DCF and six parameters as a TCF was made.
- In this paper a quantitative assessment of the health condition of a gas turbine engine based on a FL approach using rules generated from the engine performance model has been provided. In this regard, unlike the other AI methods, there are a very limited FL based techniques available in the literature that have tried to solve the diagnostic problem quantitatively, and they are limited to SCFs [15, 17] and DCFs [36]. Unlike most of these systems, in our method, the most effective MFs are created for each input parameter by a careful study of the nature of the training data and dividing into N_j (where j = 1, 2, …, k and k is the number of measurement parameters) number of subsets and taking the center of each subset as a midpoint of the associated MF. This enhanced the isolation and quantification capability of the method significantly with an increased training time.
- Finally, we tested the performance of our method in the case of measurement noises, and showed good isolation success rate even though the TCF estimation accuracy is relatively low, especially when compared with the ANN based result reported in Ref. [38]. It was due to the small amount of data we used for training.

2. Engine physical problems

Gas turbine performance can be degraded temporarily or permanently. The former can be partially recovered during operation and/or engine overhaul while the latter requires replacement [39]. Fouling, erosion, corrosion, blade tip clearance and object damage are among temporary degradation causes. Whereas, airfoil untwist and platform distortions lead to permanent deterioration [40]. The discussion of the most common degradation causes is available hereafter.

Fouling: Fouling is the adherence of contaminants such as sand, dust, dirt, ash, oil droplets, water mists, soot, carbon particles, hydrocarbons and industrial chemicals [39, 40]. It results in increased surface roughness and change in airfoil shapes [41]. Performance deterioration due to compressor fouling can be represented by a decrease in flow capacity and isentropic efficiency [42]. Different studies [1, 43] indicated that about 70-85 % of the gas turbine performance loss is due to compressor fouling. Fouling-based performance deterioration can be reversed by online and offline compressor washing using water and/or detergents [40, 44].

Erosion: Erosion is the gradual loss of material from the surface of gas path components caused by sand, dust, dirt, ash, carbon particles, and water droplets [1]. The influence of erosion is less for industrial gas turbines than aircraft engines due to the presence of an inlet air filtration system. Performance deterioration subjected to erosion can be expressed in terms of component flow capacity and isentropic efficiency changes. Isentropic efficiency decreases during both compressor and turbine erosions. While flow capacity decreases for compressor erosion and increases for turbine erosion [45].

Corrosion: Corrosion is the deterioration of gas path components as a result of oxidation reaction or chemical interaction with inlet air contaminants (sodium and potassium salts and mineral acids) and combustion gases (for instance sulfur oxides) [39]. It leads to a decrease in compressor flow capacity, compressor efficiency, and turbine efficiency and an increase in turbine flow capacity [1, 39].

Blade tip clearance: It is an increase in the clearance between moving blades' tips and stationary blades' tips or moving blades' tips and the casing because of particulate ingestion [39]. It results efficiency and flow capacity reduction [2].

Object damage: Gas path components are subjected to damage due to foreign objects (objects enter into the system with the inlet air such as birds, stones, and runway gravel) or domestic objects (i.e., broken out engine parts due to other problems) [46].

In general, since the majority of the gas turbine performance deterioration belongs to compressor fouling and turbine erosion [1, 4], in this study, the effects of compressor fouling, Gas generator turbine (GGT) erosion and Power turbine (PT) erosion were considered.

3. FL based gas turbine fault diagnostic system

Fuzzy logic (FL) is one of the most commonly used computational intelligence methods, which used to map an input feature vector into scalar output [47]. It allows computers to make decisions using imprecise quantities working more like a human brain. It consists of four basic components: Fuzzy rules (sets of if-then statements), fuzzifier (the mechanism which maps numbers of input signals into the fuzzy set), inference engine (the technique used to determine the ways in which the fuzzy sets are combined with each other), and de-

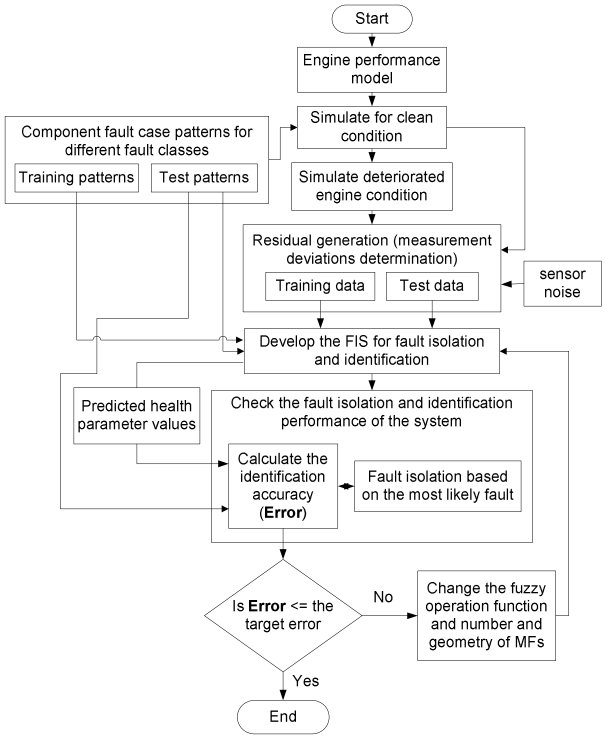

Fig. 1. FL based GT fault diagnostic procedure using simulation data.

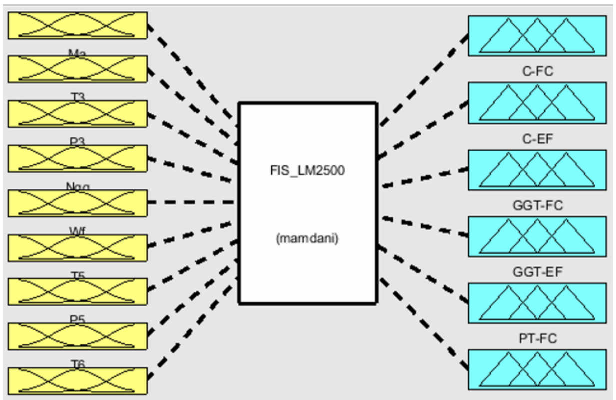

Fig. 2. Schematic illustration of the FIS.

fuzzifier (the mechanism used to predict the output values). The measurable parameters (temperature, pressure shaft speed, and flow rates) and the performance parameters (efficiency and flow capacity) deltas are inputs and outputs of the Fuzzy inference system (FIS), respectively. In this work, nine engine parameters were selected as input and six performance parameters as output. Figs. 1 and 2 illustrate the general procedure to develop engine fault diagnostic system using simulation data and the proposed FIS, respectively.

3.1 Dataset generation

Due to the difficulty of obtaining operational data in the required quality and quantity [48], in this work, the necessary data used to model and verify the diagnostic system was gen-

Table 1. LM2500 design point specifications.

Parameter	Value
Power output (KW)	20163
Mass flow (Kg/s)	66
Compressor pressure ratio	17.5
Cycle efficiency	0.39
Max cycle temperature (K)	1400
Compressor isentropic efficiency	0.88
Gas generator turbine isentropic efficiency	0.915
Power turbine isentropic efficiency	0.915

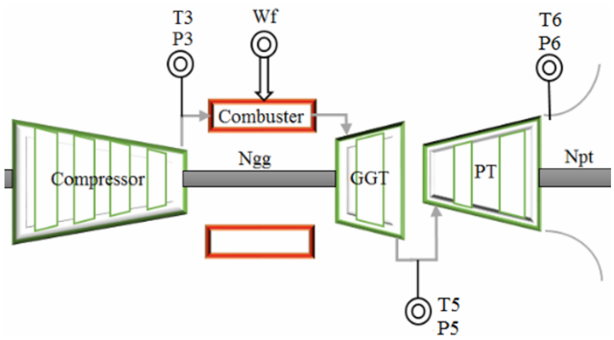

Fig. 3. Double shaft engine gas-path measurements.

erated from a GT simulation software called GSP. GSP is an off-line component based user friendly performance simulation tool composed at National Aerospace Laboratory. The target engine GE LM2500 is a double-shaft industrial gas turbine consisting of 16-stage axial compressor (C), 2-stage GGT and 6-stage PT that can produce 23.3 MW power output. Fig. 3 illustrates the schematics of the basic engine components with its gas path parameters. Its design point specifications are given in Table 1. At first, the clean condition steady state simulation was performed followed by establishing the baseline for gas-path measurements. Next, the deteriorated engine measurements were predicted by implanting different component fault cases, intentionally. Finally, the engine parameter deltas, which are input to the diagnostic system, were determined using Eq. (1). Single component faults (two parameters at a time), dual component faults (four parameters at a time) and triple component faults (six parameters at a time) were considered to generate the data. As a result, 700 and 341 fault case patterns were used to develop and test the FIS, respectively. Table 2 presents the implanted component fault cases and the search space. To account for sensor non-repeatability, white Gaussian noise, as given in Table 3, was added to the data.

$$\Delta Z_b = \frac{Z_p - Z_b}{Z_b} \times 100 , \tag{1}$$

where ΔZ_b is the measurement delta from the established baseline, Z_p is the predicted value, and Z_b is the baseline value.

Table 2. Implanted fault cases to develop the FIS.

Case	Fault type	Range of deviation		No. of cases	
		Γ	η	Training	Test
1	CF	0 → -5	0 → -2.5	100	49
2	GGTE	0 → +5	0 → -2.5	100	49
3	PTE	0 → +5	0 → -2.5	100	49
4	CF+GGTE	-	-	100	49
5	CF+PTE	-	-	100	49
6	GGTE+PTE	-	-	100	49
7	CF+GGTE+PTE	-	-	100	47

Table 3. Engine measurement uncertainty standard deviation (STD).

Parameter	Description	Unit	STD (%)
Ma	Air mass flow rate	Kg/s	1
T3	Compressor discharge temperature	K	0.4
P3	Compressor discharge pressure	bar	0.25
Ngg	Gas generator spool speed	rpm	0.05
T5	GGT exit/PT inlet temperature	K	0.25
P5	GGT exit/PT inlet pressure	bar	0.25
T6	PT exit temperature	K	0.4
P6	PT exit pressure	bar	0.25
Wf	Fuel flow rate	Kg/s	0.4

3.2 Fuzzy rules

To use FLs in decision making, determining the fuzzy sets and constricting the fuzzy rules are the two most important steps. The knowledge that can be obtained from fuzzy sets is combined using fuzzy rules to make decisions based on this information. Fuzzy rules take partially true facts, find out to what degree they are true and then take another fact, making it true to that degree. A number of fuzzy rules can then be combined and the final decision made. Suppose that $\boldsymbol{I_{ij}}$ and $\boldsymbol{O_{ij}}$ represent the input and output matrixes of the FIS, respectively, where I_{ij} is the i^{th} observation of input j, O_{ij} is the i^{th} observation of output j, n and p are the number of input and output parameters and m is the number of observations. Then the fuzzy rules for the FIS can be expressed as:

- Rule 1: IF $I_1 = I_{11}$ AND $I_2 = I_{12}$ AND … AND $I_n = I_{1n}$ THEN $O_1 = O_{11}$ AND $O_2 = O_{12}$ AND … AND $O_n = O_{1p}$
- Rule 2: IF $I_1 = I_{21}$ AND $I_2 = I_{22}$ AND … AND $I_n = I_{2n}$ THEN $O_1 = O_{21}$ AND $O_2 = O_{22}$ AND … AND $O_p = O_{2p}$
- Rule m: IF $I_1 = I_{m1}$ AND $I_2 = I_{m2}$ AND … AND $I_n = I_{mn}$ THEN $O_1 = O_{m1}$ AND $O_2 = O_{m2}$ AND … AND $O_p = O_{mp}$

$$I_{ij} = \begin{bmatrix} I_{11} & I_{12} & \cdots & I_{1n} \\ I_{21} & I_{22} & \cdots & I_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ I_{m1} & I_{m2} & \cdots & I_{mn} \end{bmatrix},$$

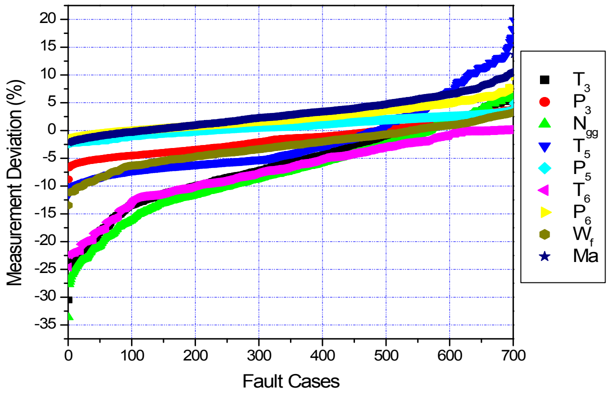

Fig. 4. Range of measurement deltas for 700 fault cases.

$$O_{ij} = \begin{bmatrix} O_{11} & O_{12} & \cdots & O_{1n} \\ O_{21} & O_{22} & \cdots & O_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ O_{m1} & O_{m2} & \cdots & O_{mn} \end{bmatrix}.$$

Accordingly, to design the FIS, 701 rules, 100 from each fault type and 1 for the clean engine, have been generated.

3.3 Membership functions (MFs) construction

Prediction accuracy of fuzzy systems highly depends on geometry and number of fuzzy sets. So in FL based algorithms the optimal selection of fuzzy sets with the appropriate MFs is the critical step. As far as geometry is concerned, the most commonly used types are linear, triangular, trapezoidal and Gaussian. Regarding the number of fuzzy sets, there is no standard for a specific application, rather it is expert based. Applying imprecise qualitative measures such as, high, low, hot, cold, etc. to create MFs is one of the most commonly used techniques [49]. Ogaji et al. [15] and Ganguli [47] used 15 qualitative features to generate fuzzy sets for each input and output parameters of the diagnostic system. Another approach is to use the engine measurement deltas as midpoints of the MFs and identifying the most accurate geometry of the sets by trial and error. Using this method, acceptably good results can be obtained, but the complexity of the algorithm and computational time will be high. Marinai [35] applied this approach and created 500 MFs from 1771 parameter deltas by taking the mean of the measurement deltas, having very small difference, and by discarding the overlapped values, except the one.

In this paper, the MFs for each input parameter were created by a careful study of the nature of the entire data and dividing into N_j, where j = 1, 2, 3…9, number of subsets and taking the center of each subset as midpoint of the associated MF. Fig. 4 shows variations of the measurement parameters sorted from the minimum to the maximum (taking the sign into account), to create the associated fuzzy sets. As explained in Sec. 3.1, in this analysis, SCFs, DCFs and TCFs are considered and represented by two, four, and six performance parameters together, respectively. The highest deviation for each measurement, like the 30 % drop in Ngg, was obtained in the case of TCF scenario, at the maximum severity level of the combined faults. Likewise, the output fuzzy sets were created by subdividing the range of the deterioration, at different steps. Gaussian and triangular MFs were used for input and output fuzzy sets.

3.4 Antecedent and consequent evaluation

Antecedent, the IF part of the inference system, and consequent, the THEN part of the inference system, can be evaluated using the following procedures.

Fuzzification: The degree of membership, $\mu(x)$, of each input exemplars' values is determined from the associated MFs.

Logical operator: It is the process of implementing the AND operator and determining the degree of activation of each rule by using the corresponding degree of membership values of each exemplars obtained from the fuzzification and taking the minimum or the product. In matrix form it can be expressed as:

$$H_{ij} = \begin{bmatrix} \mu_{11} & \Lambda & \mu_{12} & \Lambda & \cdots & \Lambda & \mu_{1n} \\ \mu_{21} & \Lambda & \mu_{22} & \Lambda & \cdots & \Lambda & \mu_{2n} \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ \mu_{m1} & \Lambda & \mu_{m2} & \Lambda & \cdots & \Lambda & \mu_{mn} \end{bmatrix} = \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_m \end{bmatrix}.$$

Implication: Refers to the step of integrating the antecedent and the consequent using the logical implication functions.

Aggregation: It is the process of combining MFs of each output parameter, corresponding to each rule, to a single MF. This can be done by associating each output parameters' MFs with the respective degree of activation of the antecedent. Output MFs which are corresponding to zero degree of activation are zero. Then, the remaining MFs are connected by using either the fuzzy intersection (function –'min') or fuzzy union (function –'max').

Defuzzification: In this stage a crisp value for the aggregated output is estimated. Different defuzzification methods are available in the literature. For instance, center of area or centroid, where the defuzzified value is the center of gravity of the aggregated fuzzy set, center of maxima, finds the crisp value at the center of the MF with the highest activation, and mean of maxima, finds the mean of the crisp values corresponding to the maximum fuzzy values, are the most commonly used ones. For this analysis a center of area (centroid) scheme was implemented.

Accordingly, the proposed FIS chose the functions 'prod' (i.e., product) for AND operator and implication, 'sum' (i.e., summation) for aggregation and centroid for defuzzification as the best combination.

4. Results and discussion

The fault diagnostic performance of the proposed FIS was evaluated using the generated test data sets presented in Table

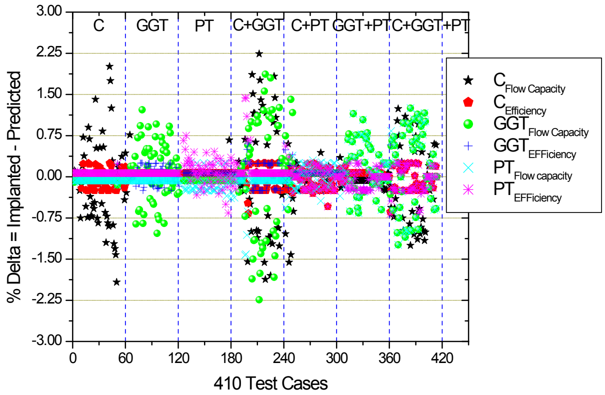

Fig. 5. The gas path component fault diagnostic accuracy of the proposed FIS againest 410 noisy test cases.

2. First, the model was demonstrated on the training dataset. Then, in order to evaluate the generalization capability of the method a new dataset called the test data was used. The test data represents the so-called blind-test-case that the system "unseen" during training. In principle, if the method can categorize the new dataset into the corresponding main fault classes and estimate their magnitude correctly, then its generalization ability would be confidential.

In fault isolation the fault with the highest degree of fulfillment was taken as the most likely fault. A fault classification is wrong whenever the method grouped the test input pattern with other fault categories. Accordingly, the component level as well as the overall fault isolation Success rate (SR) of the proposed method has been computed using the following equation.

$$SR = \left[\frac{NCCP}{TNTP}\right] \times 100\%, \tag{2}$$

where NCCP is the number of correctly classified patterns and TNTP is the total number of test patterns.

Isolation and identification accuracy of the method is clearly illustrated in Fig. 5. The first three sections present results of Single component faults (SCFs) (Cases 1-3 of Table 2), the next three sections of Double component faults (DCFs) (Cases 4-6 of Table 2), and the last section presents Triple component faults (TCFs) (Case 7 of Table 2). SCFs were isolated with negligible wrongly classified patterns. But, in the case of DCFs and TCFs, there were reasonable numbers of fault patterns classified wrongly. Meaning that, for example, in the case of DCFs, when small amount of deterioration was considered for any one of the two components, the method recognized some of the patterns as SCF, and vice versa. Likewise, in the case of TCFs, when small amounts were considered for any one of the three faults, while the rest two were suffering high level of performance deterioration, the method wrongly classified some of the TCF patterns as DCF, and vice versa. In general, SCFs were isolated with an average success rate of 96 %, DCFs with 92 % and multiple component faults with 89 %. Specifically, when the SR values associated with the three SCFs are compared to each other, the value for the PTE is the highest, followed by GGTE, and finally by CF. While, in the case of DCFs, the order of accuracy when sorted in descending order is CF+PTE, GGTE+PTE and CF+GGTE.

As far as identification is concerned, in general, there was a significant difference in the fault approximation accuracy of the different fault scenarios, assumed in this analysis. If we consider component faults in general or parameter values in particular, PT faults and efficiencies showed better accuracy for all scenarios. Specifically, in the first section (fault case 1), the target values of the health parameters for the other fault types were zero. Similarly, in the second section (fault case 2), the target values of the corresponding health parameters for the remaining fault cases were zero. Same was true for the rest fault scenarios. But, as shown in this figure, the RMS error deviates from the target value by some range of threshold. The average estimation accuracy was 83.5 %, 80 % and 78.5 % for single, double and triple component faults, respectively. In both the fault isolation and identification cases, the accuracies decrease as the number of concurrent fault increases, and that is what was basically expected. Moreover, we observed that as high severity fault levels are considered the prediction accuracy was reduced.

To improve the prediction accuracy of the proposed method, we suggest the following techniques:

(1) Increasing the size of the training data: In fact, FL system's estimation performance highly depends on the amount of the training data and its domain [7]. Conversely, in this analysis a small amount of performance data has been used;

(2) Integrating it with other AI based optimizing methods like genetic algorithm, in order to select the most appropriate MFs and fuzzy sets automatically [50];

(3) Integrating the proposed method with an AI based denoising method prior to the fault diagnostics [51].

The average identification accuracy of the FIS can be determined using Eq. (3).

$$\%Error = implanted - predicted\ . \tag{3}$$

Table 4 reports the percentage distribution of the estimation errors with in the given standard Confidence interval (CI) values. It can be seen that the average estimation errors are contained within the standard CI values.

Table 5 shows the fault quantification results of sample test fault cases corresponding to each fault type listed in Table 2. The sample test fault cases were selected randomly to verify the prediction accuracy of the method at different fault levels.

Table 6 presents the advantages and limitations of the method. Most of the advantages and limitations are from the nature of the FL used in developing the diagnostic system.

As far as practical aspects are concerned, a maintenance decision through diagnostics requires three basic activities: Data acquisition, data processing and diagnostics. Data acquisition

Table 4. Test estimation error mean, standard deviation (STD), and confidence interval (CI) values.

		Γ_C	η_C	Γ_{GGT}	η_{GGT}	Γ_{PT}	η_{PT}	
	Mean	-0.024	0.004	0.047	0.032	0.01	0.038	
	STD	0.572	0.153	0.545	0.157	0.654	0.211	Average
% of error fall between the given CI	CI90±	88.85	90.24	86.6	87.8	97.56	94.63	90.95
	CI95±	91.5	98.8	92.7	97.8	98.3	96	95.85
	CI99±	96.83	99.02	97.56	98.3	99.51	97.1	98.05

Table 5. Test results of sample component faults.

Component (s)	Implanted fault (%)						Predicted fault (%)					
	C		GGT		PT		C		GGT		PT	
	Γ	η	Γ	η	Γ	η	Γ	η	Γ	η	Γ	η
C	-3.9	-1.3	-	-	-	-	-3.86	-1.27	-	-	-	-
	-5	-3	-	-	-	-	-4.95	-2.98	-	-	-	-
GGT	-	-	4.4	-2.2	-	-	-	-	4.69	-2.03	-	-
	-	-	5	-3	-	-	-	-	4.89	-3.03	-	-
PT	-	-	-	-	4	-2	-	-	-	-	4.02	-1.83
	-	-	-	-	5	-3	-	-	-	-	4.95	-3.06
C+GGT	-4	-2	4	-2	-	-	-3.73	-1.92	3.76	-1.97	-	-
	-5	-3	5	-2	-	-	-4.86	-2.98	4.86	-1.94	-	-
C+PT	-4	-2	-	-	4	-2	-3.88	-1.79	-	-	4.2	-1.75
	-5	-3	-	-	5	-3	-4.86	-2.91	-	-	5.18	-3.11
GGT+PT	-	-	4	-2	4	-2	-	-	3.9	-1.83	3.91	-2.09
	-	-	5	-3	5	-3	-	-	4.89	-2.94	4.77	-3.08
C+GGT+PT	-4	-2	4	-2	4	-2	-3.82	-1.85	3.56	-1.76	4.4	-2.05
	-5	-3	5	-3	5	-3	-4.86	-2.87	5.3	-2.88	4.75	-2.92

Table 6. Advantages and limitations of the method [2, 7, 15, 49, 52, 53].

Advantages	Limitations
Fuzzy rules are derived from the available data; this makes them particularly suited for finding solutions to problems for which there are no exact solutions.	They cannot recognize new data sets that the model "unseen" during training, a huge amount of training data is required.
It is capable of handling problems which are difficult to be described and solved mathematically.	Fuzzy rules depend on the knowledge of subject expert, and diagnostic accuracy depends on the available rules.
It can deal with the non-linear nature of the gas path problems.	For a better accuracy large quantity of rules are essential.
It is robust towards measurement uncertainties.	Inefficient in fault diagnostics with a very limited data
It can undertake multiple component fault diagnostics.	Difficult to define exact queries that identify specific faults
The rule generation process is fast and observable.	High memory requirement
High computational speed	High model complexity
It has good explanation facility about the nature of the faults.	-
It is flexible to be integrated with other AI based methods.	-

is the process of collecting and storing the necessary data from the engine under monitoring. The data processing task, involves the activities of data cleaning followed by validating, through appropriate screening technique, and extracting the data patterns according to the requirements of the diagnostic technique for the decision-making. Finally, the fault diagnostics method will detect, isolate and quantify the available faults based on the extracted data patterns and suggest the appropriate maintenance action to the engine operators at the right time. Though, the proposed method incorporated with a data acquisition and processing system could be employed to a gas turbine gas path fault diagnostics.

5. Conclusions

We investigated the use of FL for single and multiple component fault isolation and identification using gas path measurement variations. The study focused on stationary GT engines under steady-state operating conditions. The FIS was developed based on 701 fuzzy rules derived from 9 gas path and 6 performance parameters' deviations. The data required to develop and illustrate the inference system was generated from simulation software, called GSP, tuned to represent LM2500 engine running at an existing oil & gas plant. The fault isolation and assessment performance of the system was examined for single double and triple component faults. The main component faults, compressor fouling, gas generator turbine erosion and power turbine erosion were considered one at a time and simultaneously. As shown in the result, the FIS is capable to isolate single, double and triple component faults with an average accuracy of 96 %, 92 % and 89 %, respectively. It can also identify single, double and triple component faults with an average accuracy of 83.5 %, 80 % and 78.5 %, respectively. Since the FIS was developed from only 700 fault case patterns (100 fault case patterns for each fault type) and diagnostic accuracy of fuzzy logic based methods depend on the data size, the obtained success rate was promising. Eventually, the performance of the proposed method could also be evaluated for other stationary GT engines under transient operating conditions or with different configurations; it needs only a small modification.

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Nomenclature

AI : Artificial intelligence
ANN : Artificial neural network
C : Compressor
CF : Compressor fouling
CI : Confidence report
DCF : Double component fault
FIS : Fuzzy inference system
FL : Fuzzy logic
GA : Genetic algorithm
GE : General electric
GG : Gas generator
GGT : Gas generator turbine
GGTE : Gas generator turbine erosion
GPA : Gas path analysis
GSP : Gas turbine simulation program
GT : Gas turbine
KF : Kalman filter
I : Input
MF : Membership function
NCCP : Number of correctly classified patterns
O : Output
TNTP : Total number of test patterns
PT : Power turbine
PNN : Probabilistic neural network
PTE : Power turbine erosion
RMS : Root mean square
SCF : Single component fault
SR : Success rate
STD : Standard deviation
TCF : Triple component fault

References

[1] I. S. Diakunchak, Performance deterioration in industrial gas turbines, *J. of Engineering for Gas Turbines and Power*, 114 (1992) 161-168.

[2] M. Tahan, E. Tsoutsanis, M. Muhammad and Z. A. Karim, Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: A review, *Applied Energy*, 198 (2017) 122-144.

[3] C. B. Meher-Homji and A. Bromley, Gas turbine axial compressor fouling and washing, *33rd Turbomachinery Symposium*, Houston, TX, September (2004) 20-23.

[4] A. N. Lakshminarasimha, M. P. Boyce and C. B. Meher-Homji, Modelling and analysis of gas turbine performance deterioration, *ASME 1992 International Gas Turbine and Aeroengine Congress and Exposition*, GT 1992 (1992).

[5] R. Kurz and K. Brun, Degradation in gas turbine systems, *J. of Engineering for Gas Turbines and Power*, 123 (2000) 70-77.

[6] Y. G. Li, Performance-analysis-based gas turbine diagnostics: A review, *Proceedings of the Institution of Mechanical Engineers, Part A: J. of Power and Energy*, 216 (2002) 363-377.

[7] L. Marinai, D. Probert and R. Singh, Prospects for aero gas-turbine diagnostics: A review, *Applied Energy*, 79 (2004) 109-126.

[8] A. J. Volponi, Gas turbine engine health management: Past, present, and future trends, *J. of Engineering for Gas Turbines and Power*, 136 (2014) 051201.

[9] R. Ganguli, Application of fuzzy logic for fault isolation of jet engines, *J. of Engineering for Gas Turbines and Power*, 125 (2003) 617-623.

[10] S. O. T. Ogaji, S. Sampath, R. Singh and S. D. Probert, Parameter selection for diagnosing a gas-turbine's performance-deterioration, *Applied Energy*, 73 (2002) 25-46.

[11] M. S. Jasmani, Y.-G. Li and Z. Ariffin, Measurement selections for multicomponent gas path diagnostics using analytical approach and measurement subset concept, *J. of Engineering for Gas Turbines and Power*, 133 (2011) 111701.

[12] M. Chen, L. Quan Hu and H. Tang, An approach for optimal measurements selection on gas turbine engine fault diagnosis, *J. of Engineering for Gas Turbines and Power*, 137 (2015).

[13] A. J. Volponi, H. DePold, R. Ganguli and C. Daguang, The use of Kalman filter and neural network methodologies in

gas turbine performance diagnostics: A comparative study, *J. of Engineering for Gas Turbines and Power*, 125 (2003) 917-924.

[14] R. Ganguli and B. Dan, Trend shift detection in jet engine gas path measurements using cascaded recursive median filter with gradient and laplacian edge detector, *J. of Engineering for Gas Turbines and Power*, 126 (2004) 55-61.

[15] S. O. T. Ogaji, L. Marinai, S. Sampath, R. Singh and S. D. Prober, Gas-turbine fault diagnostics: A fuzzy-logic approach, *Applied Energy*, 82 (2005) 81-89.

[16] A. Kyriazis, I. Helmis, N. Aretakis, I. Roumeliotis and K. Mathioudakis, Gas turbines compressor fault identification by utilizing fuzzy logic-based diagnostic systems, *9th European Conference on Turbomachinery: Fluid Dynamics and Thermodynamics, ETC 2011 - Conference Proceedings* (2011) 865-878.

[17] E. Mohammadi and M. Montazeri-Gh, A fuzzy-based gas turbine fault detection and identification system for full and part-load performance deterioration, *Aerospace Science and Technology*, 46 (2015) 82-93, 10.

[18] E. Tsoutsanis, N. Meskin, M. Benammar and K. Khorasani, A component map tuning method for performance prediction and diagnostics of gas turbine compressors, *Applied Energy*, 135 (2014) 572-585.

[19] D. F. Amare, T. B. Aklilu and S. I. Gilani, Effects of performance deterioration on gas path measurements in an industrial gas turbine, *ARPN J. of Engineering and Applied Sciences*, 11 (2016) 14202-14207.

[20] S. O. T.-O. Ogaji, Advanced gas-path fault diagnostics for stationary gas turbines, *Ph.D. Thesis*, Cranfield University (2003).

[21] R. B. Joly, S. O. T. Ogaji, R. Singh and S. D. Probert, Gas-turbine diagnostics using artificial neural-networks for a high bypass ratio military turbofan engine, *Applied Energy*, 78 (2004) 397-418.

[22] R. Mohammadi, E. Naderi, K. Khorasani and S. Hashtrudi-Zad, Fault diagnosis of gas turbine engines by using dynamic neural networks, *2011 IEEE International Conference on Quality and Reliability*, ICQR 2011 (2011) 25-30.

[23] S. Sina Tayarani-Bathaie and K. Khorasani, Fault detection and isolation of gas turbine engines using a bank of neural networks, *J. of Process Control*, 36 (2015) 22-41.

[24] S. Sina Tayarani-Bathaie, Z. N. Sadough Vanini and K. Khorasani, Dynamic neural network-based fault diagnosis of gas turbine engines, *Neurocomputing*, 125 (2014) 153-165.

[25] Z. N. Sadough Vanini, K. Khorasani and N. Meskin, Fault detection and isolation of a dual spool gas turbine engine using dynamic neural networks and multiple model approach, *Information Sciences*, 259 (2014) 234-251.

[26] Z. N. Sadough Vanini, N. Meskin and K. Khorasani, Multiple-model sensor and components fault diagnosis in gas turbine engines using autoassociative neural networks, *J. of Engineering for Gas Turbines and Power*, 136 (2014) 091603-091603.

[27] S. S. Tayarani-Bathaie, Z. S. Vanini and K. Khorasani, Dynamic neural network-based fault diagnosis of gas turbine engines, *Neurocomputing*, 125 (2014) 153-165.

[28] M. Amozegar and K. Khorasani, An ensemble of dynamic neural network identifiers for fault detection and isolation of gas turbine engines, *Neural Networks*, 76 (2016) 106-121.

[29] D.-H. Seo, T.-S. Roh and D.-W. Choi, Defect diagnostics of gas turbine engine using hybrid SVM-ANN with module system in off-design condition, *J. of Mechanical Science and Technology*, 23 (2009) 677-685.

[30] F. Lu, J.-Q. Huang, C.-S. Ji, D.-D. Zhang and H.-B. Jiao, Gas path on-line fault diagnostics using a nonlinear integrated model for gas turbine engines, *International J. of Turbo & Jet-Engines*, 31 (2014).

[31] A. Stamatis, K. Mathioudakis, K. Papailiou and G. Berios, Jet engine fault detection with discrete operating points gas path analysis, *J. of Propulsion and Power*, 7 (1991) 1043-1048.

[32] A. G. Stamatis, Evaluation of gas path analysis methods for gas turbine diagnosis, *J. of Mechanical Science and Technology*, 25 (2011) 469-477.

[33] L. A. Urban, Gas path analysis applied to turbine engine condition monitoring, *J. of Aircraft*, 10 (1973) 400-406.

[34] Y. Ying, Y. Cao, S. Li, J. Li and J. Guo, Study on gas turbine engine fault diagnostic approach with a hybrid of gray relation theory and gas-path analysis, *Advances in Mechanical Engineering*, 8 (2016) 168781401562776.

[35] L. Marinai, Gas-path diagnostics and prognostics for aero-engines using fuzzy logic and time series analysis, *Ph.D. Thesis*, Cranfield University (2004).

[36] L. Marinai and R. Singh, A fuzzy logic approach to gas path diagnostics in Aero-engines, *Computational Intelligence in Fault Diagnosis,* Springer (2006) 37-79.

[37] E. Tsoutsanis, N. Meskin, M. Benammar and K. Khorasani, Transient gas turbine performance diagnostics through nonlinear adaptation of compressor and turbine maps, *J. of Engineering for Gas Turbines and Power*, 137 (2015) 091201-091201-12.

[38] S. O. Ogaji and R. Singh, Advanced engine diagnostics using artificial neural networks, *Applied Soft Computing*, 3 (2003) 259-271.

[39] C. B. Meher-Homji, M. Chaker and H. Motiwalla, Gas turbine performance deterioration, *Proceedings of the 30th Turbomachinery Symposium* (2001) 17-20.

[40] K. Brun, W. C. Foiles, T. A. Grimley and R. Kurz, *Experimental evaluation of the effectiveness of online water-washing in gas turbine compressors* (2014) V03BT25A002.

[41] R. Kurz and K. Brun, Degradation of gas turbine performance in natural gas service, *J. of Natural Gas Science and Engineering*, 1 (2009) 95-102.

[42] A. Lakshminarasimha, M. Boyce and C. Meher-Homji, Modelling and analysis of gas turbine performance deterioration, *ASME 1992 International Gas Turbine and Aeroengine Congress and Exposition* (1992) V004T10A022-

V004T10A022.
[43] M. Morini, M. Pinelli, P. R. Spina and M. Venturini, Influence of blade deterioration on compressor and turbine performance, *J. of Engineering for Gas Turbines and Power*, 132 (2009) 032401-032401.
[44] R. Kurz, G. Musgrove and K. Brun, *Experimental evaluation of compressor blade fouling* (2016) V009T24A002.
[45] R. Kurz and K. Brun, Gas turbine performance—What makes the map, *29th Texas A&M Turbomachinery Symposium*, Houston, TX, September (2000) 18-21.
[46] I. S. Diakunchak, *Performance improvement in industrial gas turbines* (1993) V001T01A005.
[47] R. Ganguli, Fuzzy logic intelligent system for gas turbine module and system fault isolation, *J. of Propulsion and Power*, 18 (2002) 440-447.
[48] M. Tahan, M. Muhammad and Z. A. Karim, Performance evaluation of a twin-shaft gas turbine engine in mechanical drive service, *J. of Mechanical Science and Technology*, 31 (2017) 937-948.
[49] R. Ganguli, *Gas turbine diagnostics: Signal processing and fault isolation*, CRC press (2012).
[50] R. Verma, N. Roy and R. Ganguli, Gas turbine diagnostics using a soft computing approach, *Applied Mathematics and Computation*, 172 (2006) 1342-1363.
[51] C. Raikar and R. Ganguli, Denoising signals used in gas turbine diagnostics with ant colony optimized weighted recursive median filters, *INAE Letters*, 1-11.
[52] A. D. Fentaye, S. I. U.-H. Gilani and A. T. Baheta, Gas turbine gas path diagnostics: A review, *MATEC Web of Conferences* (2016) 00005.
[53] S. Sampath, Fault diagnostics for advanced cycle marine gas turbine using genetic algorithm, *Ph.D. Thesis*, Cranfield University (2003).

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