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Gas Turbine Fault Diagnosis Using Fuzzy-Based Decision Fusion

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A two-step information fusion technique allowing the combination of fast response and performance data for the improvement of gas turbines diagnostic procedures is proposed. The proposed technique is derived from the notion of decision level fusion. Different diagnostic methods provide assessments for the condition of an engine, and the final decision is derived from a combination of these assessments. The diagnostic method of probabilistic neural networks acts independently and in parallel on data of a different nature. The conclusions are given for the first step of the fusion technique and are aggregated deriving the probability consensus. In a second step this consensus is classified within a set of examined faults using the fuzzy set theory and fuzzy logic, thus providing the final diagnostic decision. The effectiveness of the proposed technique is demonstrated through the application to data from a radial and an axial compressor.

Nomenclature

a_j	=	element of space H (hypothesis)
$\mathbf{F}$	=	probability distribution by each "expert" for fuzzy classification
$g_i(x)$	=	fuzzy membership function of fuzzy set for FCLF1
H	=	space of hypotheses (vector)
k	=	normalization constant for opinion pools
M	=	number of experts for fuzzy classification of consensus
N	=	number of hypotheses for fuzzy classification of consensus
nq	=	normalized probability consensus
p_i	=	probability distribution for ith expert
PSD(f)	=	power spectral density, dB
$\mathbf{Q}$	=	vector of probability consensus
q_j	=	element of vector $\mathbf{Q}$
$V_l(z)$	=	lth available fault signature for a fault
$V_R(z)$	=	reference fault signature
$\mathbf{W}_i$	=	vector of weights for ith expert
w_{ij}	=	element j of vector $\mathbf{W}_i$
$\mathbf{X}$	=	probability consensus for fuzzy classification
$\mathbf{X}'$	=	transformed probability consensus for fuzzy classification
ΔPSD(f)	=	spectral difference pattern, dB

Subscripts

Fault	=	faulty operation
Heal	=	healthy operation
i	=	index for experts
j	=	index for hypotheses
l	=	index for fault signatures
R	=	reference value (for fault signatures or input patterns)

Introduction

ENGINE health monitoring has become very crucial for today's gas turbines because of the benefits associated with its implementation. For that reason, numerous diagnostic methods and tools have been proposed in recent years. These tools and methods make use of both aerothermodynamic and fast response measurements.

Several tools and methods are coming from the area of artificial intelligence (AI), such as pattern recognition (Aretakis and Mathioudakis [1], Loukis et al. [2]), rule-based expert systems (Breese et al. [3], DePold and Gass [4]) and fuzzy logic (Healy et al. [5], Siu et al. [6], Verma et al. [7], Ganguli [8–10]). Other types of methods, also from the AI area, are the stochastic diagnostic methods, with common representatives such as the Bayesian belief networks (BBN) and the probabilistic neural networks (PNN). They perform probabilistic diagnosis rather than deterministic, which has the advantage of being much closer to real situations. BBNs have been used for component fault diagnosis (Romessis and Mathioudakis [11], Romessis et al. [12]), whereas PNNs have been used for both component and sensor fault diagnoses (Romessis et al. [13], Romessis and Mathioudakis [14]).

Although the above mentioned methods exhibit satisfactory performance, further improvement is possible by performing information fusion. A fusion process can be applied at different levels of the diagnostic process: on sensor data, at a feature level (combining features employed by individual diagnostic methods, e.g., health parameter deviations), at a decision level where outputs from several diagnostic methods can be combined to improve the confidence of the derived conclusion.

Dewallef et al. [15] presented a feature level fusion method for aircraft engine diagnostics, derived from the combination of a BBN and a constrained Kalman filter, which used deviations of gas path data. Volponi et al. [16] presented the development of an information fusion system for engine diagnostics and health management for the P&W F117 engine, which used data of a different nature, namely, gas path measurements, vibration signals, oil debris analysis, etc. Volponi [17] reported that this fusion system was not fully materialized due to data problems, and the fusion process addressed only gas path information. Finally, Turso and Litt [18] presented a fusion methodology which combined data of a different nature (gas path and vibration) with the aid of fuzzy logic in order to detect foreign object damage in turbofan engines. It was applied directly on raw data (sensor level) and the final diagnostic decision was derived through the Dempster–Schafer theory [19].

In this paper we describe a fusion methodology that combines data of a different nature and detects also different kinds of faults. It is coupled to stochastic diagnostic methods acting independently and

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fuses their outcomes. Two different fusion techniques derived directly from the notion of this methodology are described. Fast response data from various instruments and performance data are exploited. To the authors' knowledge, such an approach is presented for the first time.

Theoretical Background of Decision Fusion Methodology and Prerequisites

The proposed fusion methodology is derived from the notion of decision level fusion, where individual assessments of engine health condition are combined to provide a final diagnostic decision. The utilization of decision fusion is done within the framework of a generalized diagnostic system which consists of three main modules, shown in Fig. 1. This system can have input of several kinds of data, such as performance data, fast response, oil debris data, and even simulation data from engine models. The data must undergo a certain preprocessing in order to be exploited by the diagnostic procedure.

The preprocessing stage, which occurs in the first main module, refines the input raw data and extracts certain features, for example, performance data deviations that are used as first level diagnostic parameters. The output from the first module is fed to the second one, which comprises the individual diagnostic methods, each one producing an engine health condition assessment. These assessments come in different formats depending on the outputs of the individual diagnostic methods used. For the majority of cases they are in the form of probability distributions and this is the form considered for the purpose of this work. The probability distributions are fed to the third module, the decision level fusion mechanism, which composes the final diagnostic decision.

Description of Decision Fusion Methodology

The proposed decision fusion methodology uses assessments in the form of continuous probability distributions, as mentioned above. It comprises two steps:

1) All the outputs of the independent diagnostic methods are aggregated deriving the probability consensus.

2) The probability consensus is then classified to a fault, with the aid of fuzzy set theory and fuzzy logic.

The individual diagnostic methods are regarded as "black boxes" (or experts) in the functionality of the fusion process. For the purpose of the current work the independent diagnostic method used (PNNs) is well established for its performance as shown by Romessis et al. [13] and Romessis and Mathioudakis [14]. The execution of these two steps is considered as a single task inside the frame of the third module of Fig. 1, as shown in Fig. 2.

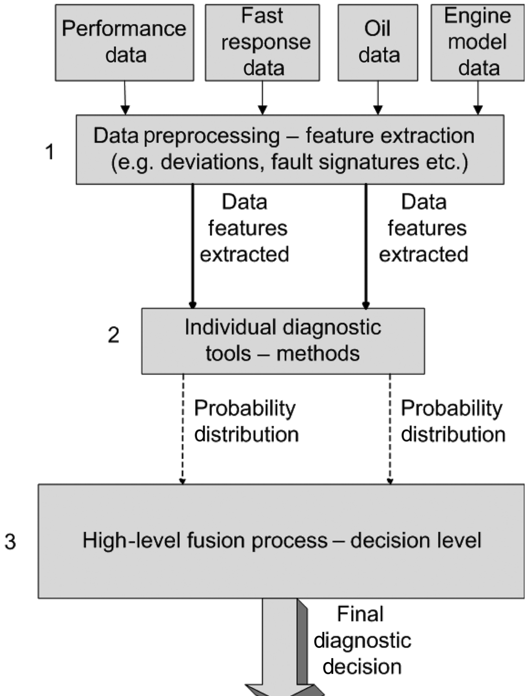

Fig. 1 Generalized diagnostic system architecture.

Aggregation Theory: Probability Consensus

Let $H = \{a_1, a_2, \ldots, a_n\}$ be the finite space of hypotheses with mutually exclusive and exhaustive elements. We also assume to have m experts, with every one producing a probability distribution on the hypothesis set H. To obtain the probability consensus of these m experts, an aggregation function f must be applied upon the m probability distributions. It is possible that each expert assumes credibility degrees regarding each hypothesis, represented in the form of a vector of weights. In that case the aggregation function f is applied upon m probability distributions and m weight vectors.

The probability distribution across the hypothesis set H for expert i is defined as p_i, $i = 1, 2, \ldots, m$, where $p_i(a_j)$ represents the probability assigned to hypothesis j, $j = 1, 2, \ldots, n$. Also the weight vector for expert i is defined as $\mathbf{W}_i = (w_{i1}, w_{i2}, \ldots, w_{in})$, where w_{ij} represents the credibility (weight) assigned to hypothesis j and $0 \le w_{ij} \le 1$ (in the case of normalized weights adding up to 1).

The probability consensus (combination of the experts' opinions) is derived by application of the aggregation function f, producing a single vector defined as $\mathbf{Q} = (q_1, q_2, \ldots, q_n)$, where $q_j = f(w_{1j}, w_{2j}, \ldots, w_{mj}, p_1(a_j), p_2(a_j), \ldots, p_m(a_j))$ and $j = 1, 2, \ldots, n$. The vector $\mathbf{Q}$ represents the probability consensus. A normalizing procedure to the elements of $\mathbf{Q}$ can also be performed to derive a final normalized consensus nq:

$$nq_j = \frac{q_j}{\sum_{k=1}^{n} q_k}, \qquad j = 1, 2, \ldots, n \tag{1}$$

This normalization is optional and does not need to be applied in all cases.

The aggregation function can take many forms as shown by Moral and Sagrado [20] and Genest and Zidek [21], but the majority of them imply complex analysis, interactivity among the experts, utilization of cognitive psychology principles, etc. On the other hand, the purely mathematical forms of the linear opinion pool and logarithmic opinion pool for the aggregation function f seem to have better performance in practice, as shown by Ng and Abramson [22]. For the purpose of the current work the form of the *linear opinion pool* has been used and examined for its effectiveness. This scheme is also known as the weighted average. The probability consensus for hypothesis j is derived according to the relation:

$$\mathbf{Q}\,(j) = k * \frac{\sum_{i=1}^{m} w_{ij} \cdot p_i(a_j)}{\sum_{i=1}^{m} w_{ij}} \tag{2}$$

k is an optional normalization constant for altering the scale of the probability consensus. When the weights w_{ij} are normalized (with a sum equal to unity) then Eq. (2) is slightly changed and the form of the linear opinion pool becomes

$$\mathbf{Q}\,(j) = k * \sum_{i=1}^{m} w_{ij} p_i(a_j) \tag{3}$$

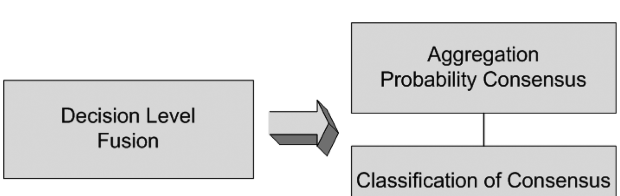

Fig. 2 Structure of the module 3 of Fig. 1.

Classification of Consensus

The classification of consensus constitutes the second step to the proposed fusion technique and is performed with the aid of fuzzy set theory and fuzzy logic. For details of fuzzy set theory and fuzzy logic the reader is referred to Jang et al. [23] and Ross [24].

This second step is performed with two alternative approaches, termed FCLF1 and FCLF2 in the following. They use the same input, the probability consensus derived from the aggregation function, but employ different classification mechanisms.

Suppose now that in a specific diagnostic problem we have M experts (diagnostic methods) and N hypotheses (examined faults). Each expert produces as output a probability vector, say $\mathbf{F}$, for a given test case (data set). This vector $\mathbf{F}$ has as many elements as the hypotheses and their values represent the probability for a test case to "belong" to each fault. The elements of $\mathbf{F}$ are normalized to 100 (they are adding to 100), so each one of them is a value between 0 and 100. Upon application of the linear opinion pool a probability consensus can be produced, say $\mathbf{X}$, according to Eq. (2). The normalization constant k has not been accounted for (or else set equal to 1).

Fuzzy Classifier 1 (FCLF1)

The first approach uses the principles of fuzzy set theory by constructing two fuzzy sets, namely, PROBABLE and NOT_PROBABLE. PROBABLE is defined through the z-shaped membership function $g_2(x)$ with valid range A and NOT_PROBABLE is defined through the z-shaped membership function $g_1(x)$ with valid range A.

1) PROBABLE $= \{x, g_2(x)/x \in A\}$.
2) NOT$_{\text{PROBABLE}} = \{x, g_1(x)/x \in A\}$.

A is also called the universe of discourse and is defined according to the kind of output from experts. Because this output is given in the form of a probability vector $\mathbf{F}$, with elements normalized to 100, it is clear that $A = x \in [0, 100]$. A schematic representation of these functions is given in Fig. 3.

The two membership functions $g_1(x)$ and $g_2(x)$ produce two different membership values for each element of the probability consensus vector $\mathbf{X}$. The value from $g_1(x)$ is subtracted from the value of $g_2(x)$ for each element of vector $\mathbf{X}$. The final classification criterion chooses as the final hypothesis $Hfinal$ (final fault), the one with the highest difference value, according to the equation:

$$Hfinal = \arg\max[g_2(X(j)) - g_1(X(j))] \tag{4}$$

An example representation for the diagnostic process employing FCLF1 is presented in Fig. 4. In this example, the diagnostic method of PNN provides the experts for the proposed technique. Two PNNs are used with different inputs, one suited for performance data and one for fast response data.

Fuzzy Classifier 2 (FCLF2)

The second approach uses the principles of fuzzy logic and fuzzy reasoning by constructing a complete fuzzy inference system (FIS system). As previously, we have M experts and N hypotheses. A transformation is performed upon the elements of consensus vector $\mathbf{X}$, deriving a new consensus vector $\mathbf{X}'$. This is done to make the constructed fuzzy sets more distinguishable. Otherwise the overlapped areas among the fuzzy sets would be of considerable size. This would lead to a difficulty of defining appropriate fuzzy rules and later inferencing. The transformation is performed according to the relation:

$$X'(j) = \{[(j-1)\cdot 100] + X(j), j = 1, 2, \ldots, N\} \tag{5}$$

This new consensus vector $\mathbf{X}'$ has the same number N of elements as $\mathbf{X}$, that is, the same number of hypotheses, and is used as the input information to the FIS system. For every element of $\mathbf{X}'$ two fuzzy sets are defined: ProbXj and Not-ProbXj, $j = 1, 2, \ldots, N$. Therefore a total of $2 * N$ fuzzy sets is constructed. Each fuzzy set is defined through a trapezoid membership function with universe of discourse of the space $A = [0, N * 100]$. This space is defined as in FCLF1 taking into account also the transformation of Eq. (5). In Fig. 5 an example of the membership functions regarding the first element of $\mathbf{X}'$ is shown for $N = 2$.

The number of fuzzy "if-then" rules is set to be equal to the number of hypotheses, in this case N. Each fuzzy rule has the following general form:

$$\text{if } (X'(j) \text{ is Prob}Xj) \text{ and } (X'(h) \text{ is Not-Prob}Xh) \text{ then } Y \text{ is } Hj$$

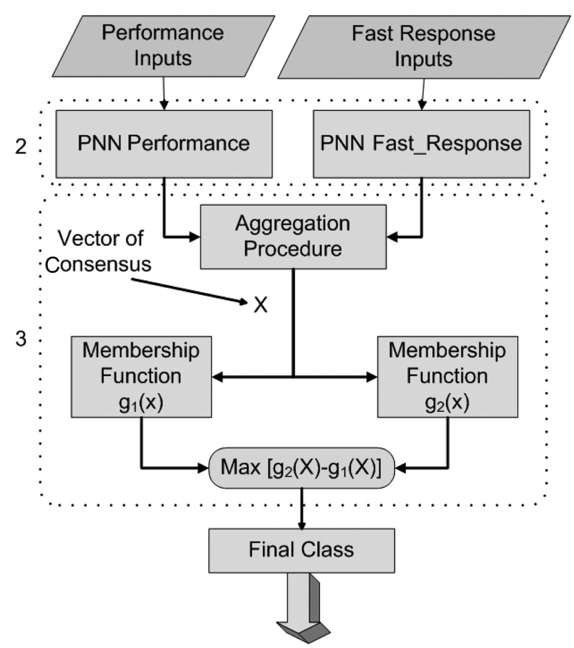

Fig. 4 Schematic representation of fusion technique FCLF1.

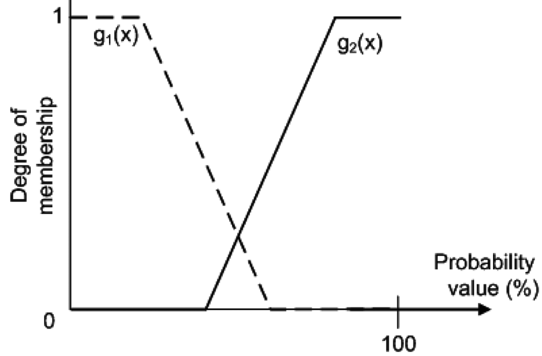

Fig. 3 Membership functions for fuzzy sets PROBABLE and NOT_PROBABLE.

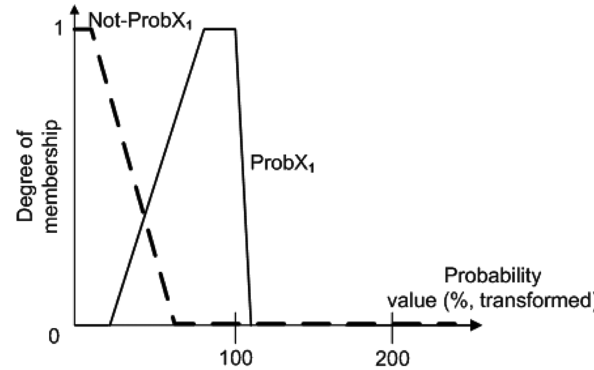

Fig. 5 Membership functions for first element of X′.

where $j = 1, 2, \ldots, N$ and $h = 1, 2, \ldots, N$ with $h \neq j$. Y is the selected hypothesis Hj by each rule and is defined through N fuzzy sets with trapezoid membership functions. It is noted that in each fuzzy rule j index takes only one value and h index the rest $N - 1$ different values. The proposed FIS system is using the Mamdani model of implication and max–min composition (see Jang et al. [23] and Ross [24]) to produce a final fuzzy output set, say C. For the defuzzification process, where a crisp value from the final output fuzzy set C is derived, the mean of maximum (*mom*) method has been selected, given by the following relation:

$$mom = \frac{\int_{A'} Y \, \mathrm{d}Y}{\int_{A'} \mathrm{d}Y} \tag{6}$$

In this relation $A' \subseteq A$, $A' = \{Y | \mu_C(Y) = \max\}$, where C is the final output fuzzy set and $\mu_C(Y)$ is the membership degree.

The final classification criterion takes into account this crisp value and chooses as a final hypothesis the one whose index j satisfies the following relationship:

$$Hfinal = Hj, \quad \text{where } (j - 1) * 100 < \text{crisp}_{\text{value}} \leq j * 100 \tag{7}$$

A flow diagram of the proposed FIS system is shown in Fig. 6, and the fusion approach FCLF2 embedding it is shown in Fig. 7.

Fusion Method Implementation on Test Data

To illustrate applicability and effectiveness of the proposed method, data from test campaigns on a radial (see Aretakis and Mathioudakis [1,25]) and an axial compressor (Mathioudakis et al. [26]) have been used. The employed experimental data consist of individual performance and fast response (sound pressure, unsteady wall pressure, and vibration) data sets. Each data set comes from an operation with a certain fault under examination and corresponds to a unique operating point on the compressor map. Before presenting the results, it is worth briefly describing the preprocessing applied on the data corresponding to module 1 of Fig. 1.

Data Preprocessing for Fault Diagnosis

The first level diagnostic method used, as mentioned earlier, is the probabilistic neural network. The PNN is a form of feed-forward neural network with three layers whose output is given in terms of a probability distribution (the reader is referred to Bose and Liang [27] for more details). This probability distribution expresses the result of a classification for a given data set (test case) among several examined faults. Preprocessing of the raw test data is done to derive inputs to the PNN diagnostic method.

Fault Signatures for Fast Response Data

Fast response data come from various instruments, such as accelerometers for vibration, pressure transducers for wall pressure, and microphones for sound pressure. Time signals for fast response data were Fourier analyzed to obtain their power spectral density (PSD). Establishment of an automated procedure for fault classification from fast response data can be based on fault signatures produced as spectral differences:

$$\Delta\mathrm{PSD}(f) = \mathrm{PSD}_{\mathrm{Fault}}(f) - \mathrm{PSD}_{\mathrm{Heal}}(f) \tag{8}$$

$\mathrm{PSD}_{\mathrm{Fault}}(f)$ is the power spectral density of the measured signal in the presence of a fault, $\mathrm{PSD}_{\mathrm{Heal}}(f)$ is the power spectral density during a healthy operation, and $\Delta\mathrm{PSD}(f)$ is the resulting spectral difference pattern. An example application of the above procedure is presented schematically in Fig. 8.

Once a number of fault signatures for a specific fault at different operating points are available, we can derive its reference signature, as the average of all signatures available for this fault:

$$V_R(z) = (1/N) * \sum_{l=1}^{\mathrm{NS}} V_l(z), \qquad z = 1, 2, \ldots, V \tag{9}$$

NS is the number of all signatures of a specific fault, $V_l(z)$ is the lth available signature, and V is the set of values that constitute one signature. More details are given by Aretakis and Mathioudakis [1,25] and Kyriazis et al. [28].

Notion of Fault Signatures for Performance Data

For the radial compressor, the performance data are as follows: corrected mass flow rate, impeller pressure ratio, impeller efficiency, compressor pressure ratio, compressor efficiency, mass coefficient Φ, and load coefficient Ψ. For the axial compressor, they are as follows: static pressure in the exit of the diffuser, temperature in the exit of the diffuser, corrected mass flow, static pressure in the entrance of the power turbine, temperature in the entrance of the power turbine, temperature in the exit of the power turbine, and fuel flow. These data are available at four operating points (the same as for fast response data) for healthy operation and faulty operation as well. From these data fault signatures are derived in the form of deviations (d_z) defined as

$$d_z = (Y^z - Y_0^z)/Y_0^z, \qquad z = 1, 2, \ldots, V \tag{10}$$

Y_0^z represents a measurement in the "healthy" state of the compressor, Y^z is the same measurement but now in the presence of a fault at the

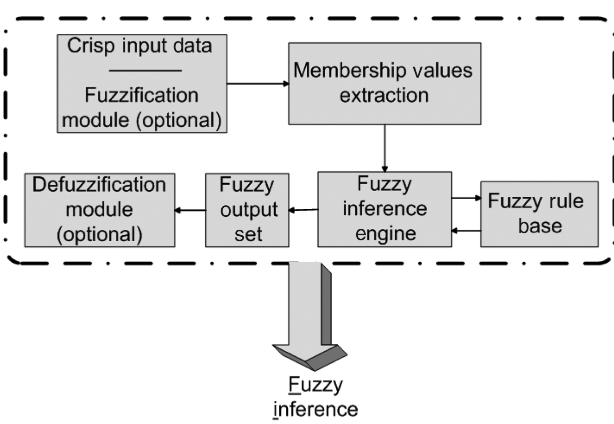

Fig. 6 Fuzzy inference system structure.

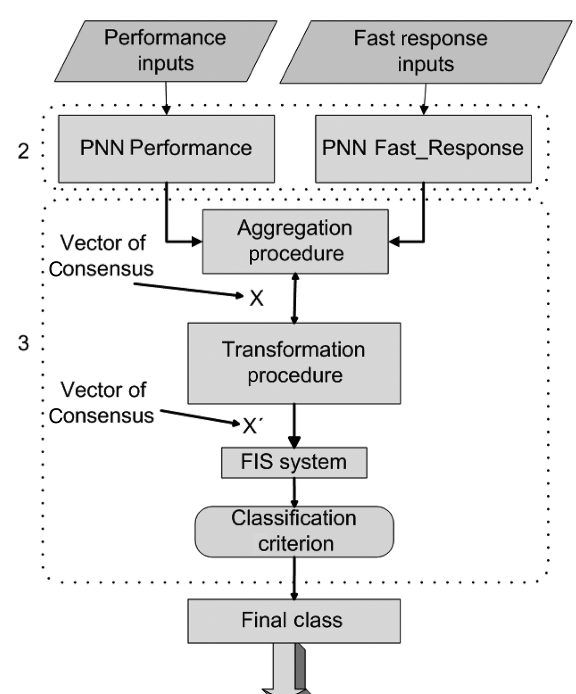

Fig. 7 Schematic representation of fusion technique FCLF2.

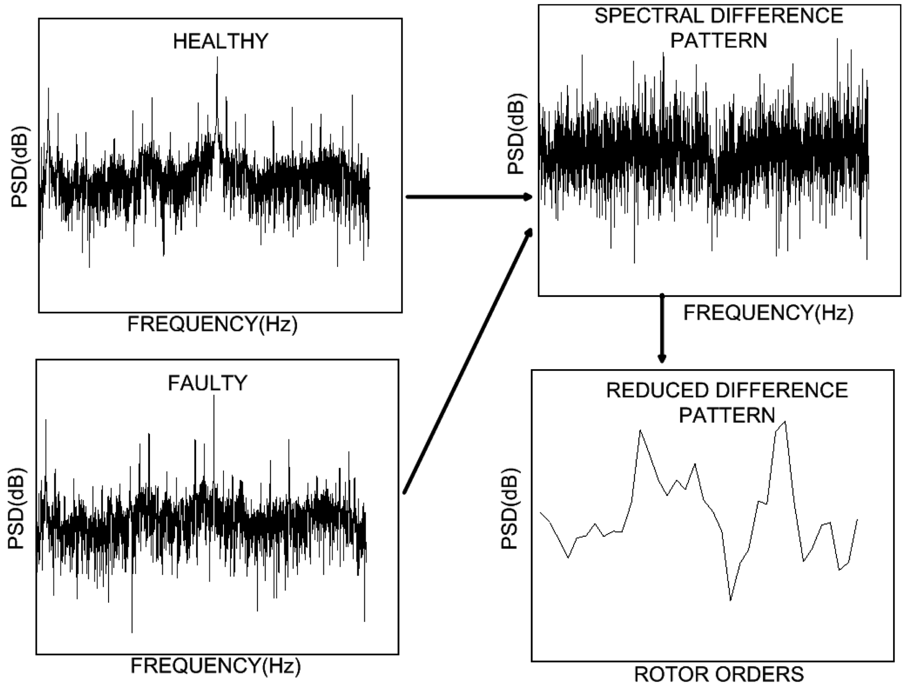

Fig. 8 Derivation of a fault signature.

same operating point, and V is the number of the performance measurements.

Each fault signature is in the form of a vector of seven elements (the number of performance measurements) and corresponds to a certain operating point. As earlier, it is feasible to derive a reference signature, once a number of fault signatures from different operating points for a specific fault are available. The method for the derivation of reference signature is exactly the same as before and it is described by Eq. (9). Finally, each fault signature refers to a single test case, which in turn refers to a single operating point.

Probabilistic Neural Network, Fusion Technique, and Final Results

In this section, application of the first level diagnostic method of the PNN network and the proposed fusion technique alongside the final results is presented. The current work used, as mentioned before, real data from two different turbomachines, a radial and an axial compressor. Therefore two different cases of application are presented next. For both cases the structure of the diagnostic procedure is the one given as an example in Figs. 4 and 7.

Radial Compressor Case

The faults considered were a diffuser fault, an impeller fouling, and an inlet distortion, referred to as M1, M2, and M3, respectively. Four test cases, one from each operating point, were considered for each fault, leading to a total of 12 test cases. Based on that, two different sets of fast response data (set A1 and set A2) were produced (each having 12 test cases) and one set of performance data (also with 12 test cases). The instrument used for the fast response data was a pair of double layer microphones.

The first layers of these PNN networks are the input layers which contain the input vectors. Those are the available fault signatures for both performance and fast response data. Each node of the input layers corresponds to an element of the input vector. The nodes of the second layers (or hidden layers) contain the training vectors, which consist of the reference fault signatures, as explained previously. Each training vector has the same dimension as an input vector and each node of the hidden layer corresponds to one training vector. The nodes of the third layers (output layers) represent the examined classes of faults. The value derived from each third level node is the probability that each examined input vector (fault signature) is classified among the classes of faults. As there is only one training vector (reference signature) corresponding to a single fault, the number of nodes in the output layers is equal to those of the hidden layers in each PNN network. Finally every node of the hidden layer is fully linked to every node of the input layer, whereas each node of the hidden layer is linked only to the node of the output layer that represents the corresponding class (fault) of the training vector.

In the case of the radial compressor, the first layer of the PNN network for fast response data consisted of 47 nodes while the first layer of the PNN regarding performance data consisted of seven

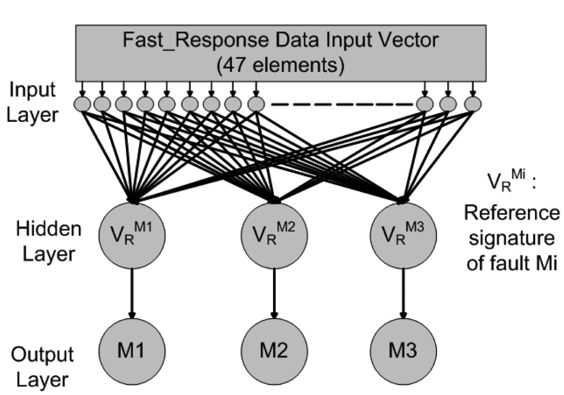

Fig. 9 PNN architecture for fast response data from radial compressor.

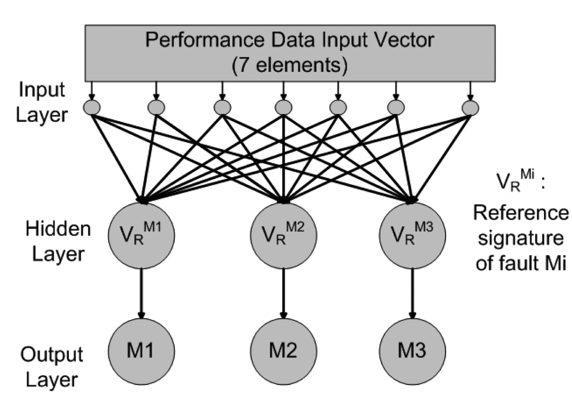

Fig. 10 PNN architecture for performance data from radial compressor.

nodes. On the other hand, the hidden layers for both PNNs consisted of three training vectors (three nodes) regarding fast response and performance data, as we had three examined faults. In Figs. 9 and 10 the structures of the developed PNN networks are presented. The two architectures are similar, because they differ only in the number of input layer nodes. To demonstrate how the method acts on the data, results of the individual PNNs for fast response and performance data are shown first, while the outcome of probability aggregation and fuzzy classification follows.

Indicative results of PNNs for fast response data and performance data, respectively, are presented in Figs. 11 and 12. Three incorrect classifications occur for the data of Fig. 11. For test case 2, the highest probability is assigned to fault M3 which is the fault diagnosed, although it actually belongs to M1. For test case 6, M3 is also diagnosed while M2 occurs and for test case 11, M1 is diagnosed instead of the correct M3. Diagnosis from performance data, Fig. 12, misses case 9 which is assigned to M1 although belonging to M3.

The fusion approach termed FCLF1 is then applied to the outputs of the two PNNs. In Fig. 13 the derivation of probability consensus from the results of data sets in Figs. 11 and 12 is presented. The values of probability consensus, according to Eq. (2), are equal to the arithmetic mean of the corresponding test cases, because the utilization of the linear opinion pool considered equal weights for both PNNs. Inspection of this figure shows that the highest probabilities are always attributed to the right fault.

The results of the FCLF1 classification of consensus [differences of Eq. (4)] are presented in Fig. 14. The fuzzy differences for each fault, concerning each test case, are the results of the subtraction between the membership values of each element of the consensus vector. The maximum of them, for each test case, is chosen to be our final diagnostic decision. It is observed that the highest value corresponds to the right fault for all cases, confirming the above mentioned observation of the highest probability in Fig. 13. In Fig. 15 an example of application for the FCLF2 classification is presented. In this example the consensus values of test case 8 were used. In this figure each row represents graphically the used fuzzy rules, mentioned before, and the shaded areas are the *firing strength* of each. The last column, corresponding to the first three rows, shows graphically the degree of satisfaction for the conclusion part (the "then" part) of each rule. The last box, bottom right, presents the final output fuzzy set from which the final crisp value is derived according to Eq. (6).

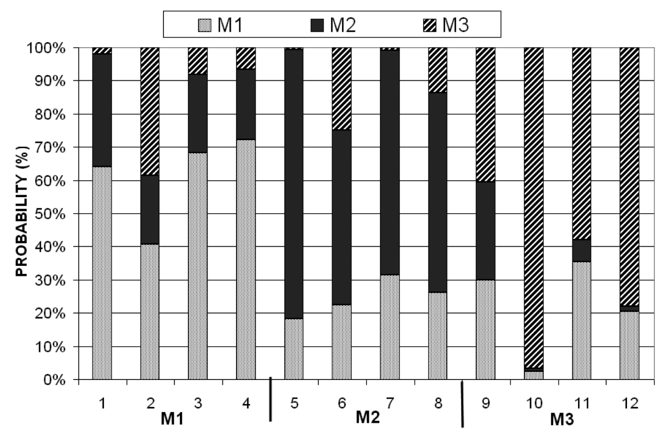

Fig. 13 Aggregation-probability consensus results.

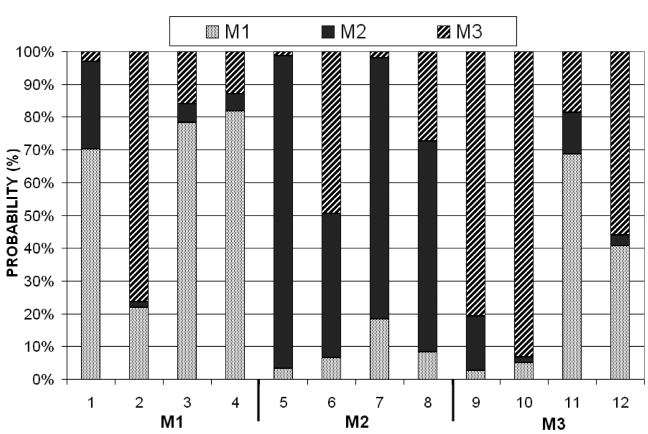

Fig. 11 Fast response data, three incorrect classifications (radial compressor test cases 2, 6, and 11).

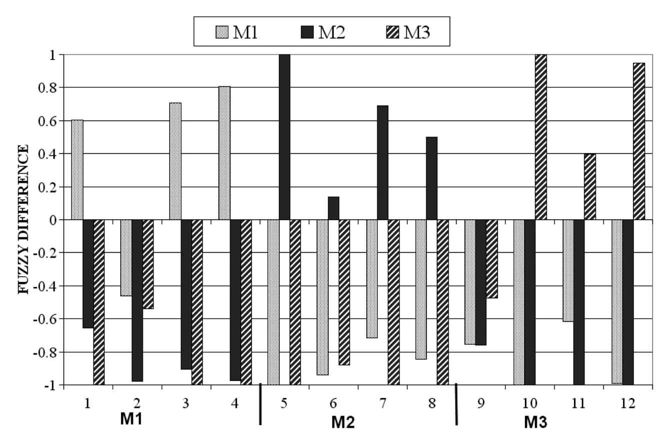

Fig. 14 Fuzzy classification regarding FCLF1.

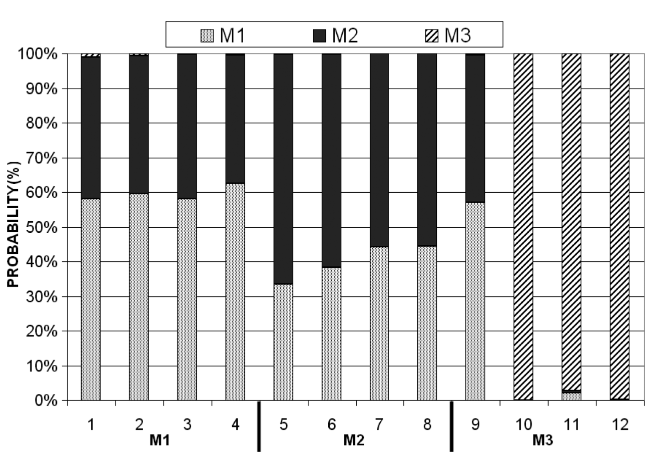

Fig. 12 Performance data, one incorrect classification (radial compressor test case 9).

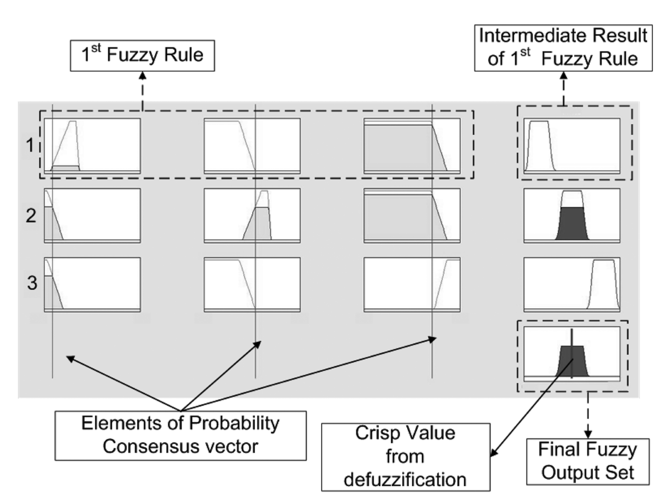

Fig. 15 FCLF2 classification example.

Table 1 Fusion results for examined radial compressor test cases (fast response data + performance data)

Data employed		
Technique	Set A1 + performance	Set A2 + performance
PNN_fast response	3/12	1/12
PNN_performance	1/12	1/12
FCLF1	0/12	1/12
FCLF2	0/12	1/12

In Table 1 the performance of the proposed fusion technique over the test cases examined is summarized. The results concern both alternative approaches of the fusion technique as discussed above, while the diagnoses of the individual PNN methods are also given for comparison.

Table 1 shows the number of incorrect classifications next to the total number of test cases. The last two rows present the results of the fusion technique regarding both approaches. For set A1 of fast response data, PNN had three incorrect classifications out of 12 regarding test cases 2, 6, and 11. For set A2 PNN had one incorrect classification out of 12 for test case 7. For performance data, PNN had one incorrect classification regarding test case 9 (only one set of performance data was available). FCLF1 and FCLF2 had one incorrect classification, regarding set A2 and performance, both for test case 9. This is mainly due to the same input information for FCLF1 and FCLF2. From this table we can see that the fusion technique improves diagnostic ability in comparison to its constituent PNN method.

Axial Compressor Case

In the case of the industrial gas turbine, the test engine was a Ruston Tornado and the experimental investigation is described by Mathioudakis et al. [26]. The examined faults were the following: F-2, where all blades of stage 2 rotor were coated with textured paint in order to simulate a severe rotor fouling; F-3, where two blades of stage 1 rotor separated by five intact were painted in order to simulate a slight rotor blade fault; F-4, where a single blade of stage 1 rotor was twisted in order to simulate a severe rotor blade fault; F-53, where three stage 1 stator vanes were mistuned in order to simulate a severe stator fault. The instruments used for the fast response data were three accelerometers, ACC1, ACC2, and ACC3, and a pressure transducer PT-2. For each fault, four test cases, one from each operating point, were considered leading to a total of 16 test cases.

As in the radial compressor case, two PNNs, one for fast response data and one for performance data, were developed. The principles concerning the development and the final structure of the PNNs that applied before also hold for the axial compressor case. The only difference lies on the number of nodes for the input and the hidden layers. In this case the input layer of the PNN for fast response data consists of 36 nodes while the first layer of the PNN for performance data consists of seven nodes. On the other hand, the hidden layers for both PNNs consist of four training vectors (four nodes), as we had four examined faults. In Figs. 16 and 17 the structures of the developed PNN networks are presented.

Indicative results of PNNs for fast response data and performance data, respectively, are presented in Figs. 18 and 19. These figures can be interpreted in the same way as Figs. 11 and 12 of the radial compressor and thus give a first level diagnosis, based on each individual data set. Aggregation and fuzzy inference are then applied here to produce the final diagnosis.

In Table 2 the performance of the proposed fusion technique over the test cases and data sets examined is summarized. The results concern both approaches of the fusion technique as discussed previously.

Table 2 shows the number of incorrect classifications over the total number of test cases. The last two rows present the results of the fusion technique regarding both approaches. FCLF1 and FCLF2 had two incorrect classifications, regarding ACC1 and performance, both

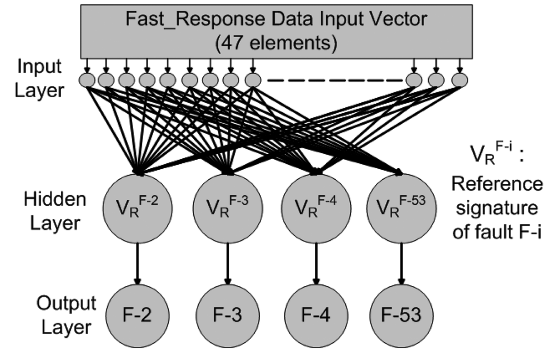

Fig. 16 PNN architecture for fast response data (axial).

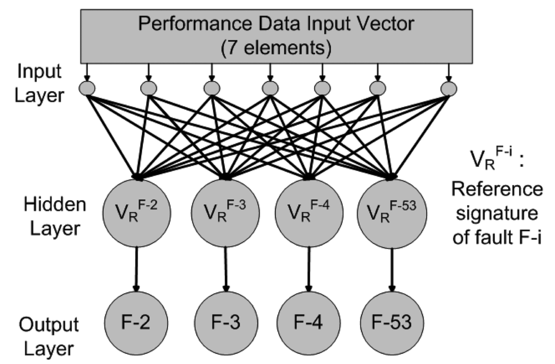

Fig. 17 PNN architecture for performance data (axial).

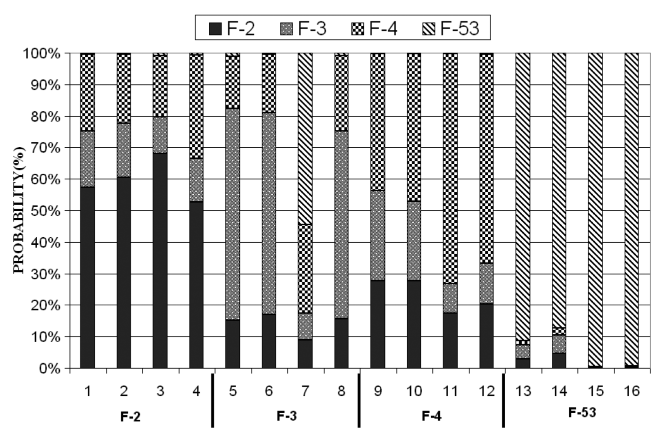

Fig. 18 Fast response data, one incorrect classification (test case 7). Data from accelerometer ACC1.

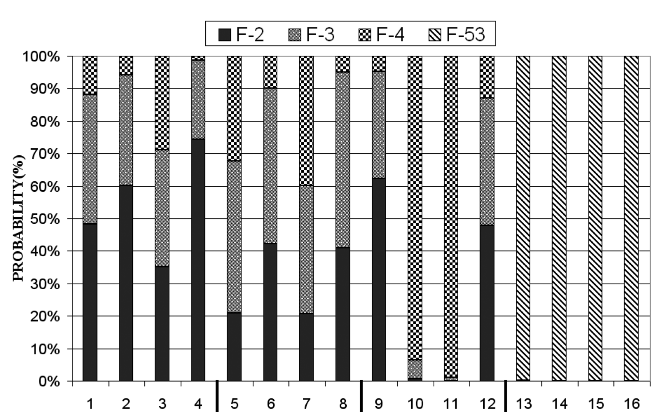

Fig. 19 Performance data, four incorrect classifications (test cases 3, 7, 9, and 12). Data from accelerometer ACC1.

Table 2 Fusion results for examined axial compressor test cases

Data employed	ACC1 +	ACC2 +	ACC3 +	PT2 +	All fast response +
Technique	performance	performance	performance	performance	performance
PNN_fast response	1/16	0/16	0/16	0/16	——
PNN_performance	4/16	4/16	4/16	4/16	——
FCLF1	2/16	0/16	0/16	0/16	0/16
FCLF2	2/16	0/16	0/16	0/16	0/16

for test cases 7 and 9. This is mainly due to the same input information for FCLF1 and FCLF2. We note that test case 7 was incorrectly classified by PNNs so the fusion method also misclassifies it. Concerning all the other instruments, the fusion technique verified the correct classification of the test cases and reinforced the final diagnostic conclusion. Finally when fast response data from all instruments are fused with performance, a 100% rate of success with zero misclassifications is observed.

Conclusions

A fusion methodology for gas turbine fault diagnosis, using decision fusion in the framework of a generalized diagnostic system, has been presented. It employs the concepts of aggregation theory, fuzzy sets, and fuzzy logic, and it is materialized by two different approaches concerning the fuzzy classification task. The first approach, FCLF1, is based solely on fuzzy set theory and is much simpler than the second approach, FCLF2, in which a whole fuzzy inference system is constructed, based on fuzzy logic theory. The developed method follows the trend of hybridization in soft computing which permits improvement in diagnostic performance. Although hybrid systems present increased complexity due to the combination of several different methodologies, the presented method is rather simple. FCLF1 is based on only two membership functions, independent from the input data to the diagnostic problem, as they employ only the fuzzy membership values of the outputs from individual experts. FCLF2 is also simple, because it is also independent of the input data and has an easy-to-build set of rules.

The processing and exploitation of the input data is a task assigned to the experts, which are responsible for a first diagnostic assessment. The developed fusion method is only responsible for the improvement of these diagnostic assessments, so it can be used to a variety of different engine applications. A possible drawback concerns the selection of appropriate and effective experts in order for the fusion task to be able to improve the overall results. In the case of poor experts, then the developed fusion method will also present poor results. Another feature is the requirement for a predefined set of fault classes for the diagnosis. This can be handled with the definition of an extra class which can compensate for all the unknown fault cases.

FCLF2 has been developed mainly as it is expected to have a potential for better diagnostic performance against FCLF1, because it uses the whole theory of fuzziness. The application of both approaches to the examined fault cases presented in the previous sections has shown equivalence in the final effectiveness, providing flexibility on selection among them considering the fusion mechanism. This happened because both approaches had the same input information in the form of crisp valued probability consensus. Input information in the form of vague (or imprecise) probability distributions might reveal the superiority of FCLF2, because it uses the whole structure of a FIS system, but further studies have to be performed to fully ascertain this. For the aggregation procedure the selection of the linear opinion pool has been based on purely mathematical criteria. Future research could include the separate definitions for the fuzzy membership functions of FCLF1 (different shapes, etc.), different sets of fuzzy rules for FCLF2, another defuzzification method for FCLF2, application of a different aggregation function rather than the linear opinion pool, automation of the procedure for selecting weights for the aggregation function, etc.

Application of this fusion methodology yielded significant and encouraging results by examining two different approaches of the proposed fusion procedure concerning the classification of consensus. It was shown that fusion of diagnosis based on fast response and performance data can provide higher effectiveness. The proposed technique is considered to provide a reliable tool for fault classification.

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