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Gas turbine fault recognition trustworthiness

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1. Abstract

This paper examines three methods of gas turbine parametric diagnosing. The functioning methods are simulated in the identical conditions of gradually developing faults and random measurement errors. The objectives are to tune the methods, to compare them, and to choose the best one on basis of probabilistic criteria of class correct and incorrect recognition. So, main focus of the paper is a recognition trustworthiness problem. A previous research work in this direction is united with new results and they all together are presented in more systematic form as a common approach. Besides the method comparison and selection, other ways to enhance the trustworthiness are described and the perspectives to realize the methods in real condition monitoring systems are analyzed.

2. Resumen

Este artículo examina tres métodos del diagnóstico paramétrico de turbinas de gas. El funcionamiento de los métodos se simula en condiciones idénticas al desarrollo de fallas y errores aleatorios de medición. Los objetivos son afinar los métodos, compararlos y escoger el mejor con base en criterios probabilísticos del reconocimiento correcto e incorrecto de las clases de fallas. Así, el enfoque principal del artículo es el problema de autenticidad del reconocimiento. Algunos resultados de investigación previa en este campo se unen con nuevos resultados y todos se presentan en forma más sistemática como un enfoque común. Además de la selección del método mejor, se describen otros medios para mejorar la autenticidad y se analizan perspectivas de la realización de los métodos en los sistemas actuales de monitoreo.

Key words: Gas turbine fault classification, thermodynamic model, diagnosis methods, fault recognition trustworthiness

3. Introduction

Knowledge of machines' health through condition monitoring can allow reducing maintenance cost without risk of failure and give industries significant improvements in efficiency. With a new generation of high temperature and high output gas turbine engines the objectives of attaining a high availability and limiting degradation is of vital importance [1]. That is why advanced condition monitoring systems for critical turbomachines and auxiliary equipment are designed and maintained in recent decades.

To examine the wide range of common deterioration problems, a comprehensive monitoring system must integrate a variety of approaches. In addition to vibration analysis, there are other technologies to be employed such as gaspath analysis also known as aerothermal [1] or thermodynamic performance analysis. Gaspath analysis of turbomachinery presents advanced calculation techniques used to compute and correlate all performance variables of the gaspath. This technology applied in gas turbine monitoring in order to simulate and detect the failures also provides insight into how efficiently fuel is being utilized and so favours a fuel saving.

Gaspath analysis is a multidiscipline incorporating three interrelated disciplines [2,3]: common engine state monitoring, state prognostics, and concerned in this paper detailed diagnostics (fault localization or identification).

The faults exert influence on measured and registered gaspath variables (pressure, temperatures and consumptions of the gas flow, rotation speeds, fuel consumption, and any others). On the other hand, the influence of operational regime changes is much greater. That is why in the localization algorithms, raw measurement data should be subjected to a complex mathematical treatment to obtain final result identified faults of gas turbine modules (compressors, combustors, turbines). Besides the gaspath faults, control system and measurement system malfunctions can be also detected analyzing the gaspath variables [4].

However, a lot of negative factors, which are explained in more detail below, affect the diagnosing process and make difficulties for the correct detection. So, engine fault detection presents a challenging recognition problem.

To review common works on condition monitoring [1] and fault detection [5] as well as works applied to gas turbines [4,6], it can be stated that a simulation of analyzed systems is an integral part of their diagnostic process. The models fulfill here two general functions. The first one is to give a gas turbine performance baseline in order to calculate differences between it and current measurements. These differences (or residuals) do not practically depend on operational regime variations and so serve as good degradation indices. The second function is related with a fault classification. The models connect module degradation and the residual changes assisting with a fault class's description.

In the eighties and early nineties, any direct use of complex statistical recognition methods in an on-line capacity was prohibitively expensive in time and computer capacity. It was therefore often decided to simplify diagnostic techniques in order to reduce processing requirements. For instance, MacIsaac and Muir [6] used the method based on fault matrices where every class (fault signature) is presented by residual's signs only. Other example of a simplified technique can be found in [7]. To recognise the classes the author applies linear and non-linear discriminant analysis but he needs to minimize an axis set of the class's recognition space to reduce processing requirements. However, our statistical simulations of diagnosing process have shown [8] that the mentioned simplifications cause great recognition errors.

Over the last decade there have been significant advances in instrumentation and computer technology which resulted in more perfect approaches such as [4]. The authors propose some enhanced diagnosing methods based on non-linear gaspath models, statistical neural networks, and probabilistic fault identification that promise high confidence. However, this work as many other lacks for a numerical estimation of method's effectiveness and any comparison with other known approaches.

As opposed to the mentioned works, this paper is concentrated on a trustworthiness problem. On basis of proposed earlier probabilistic indices [9], three methods are optimized and compared in order to choose the best one and give recommendations for practical use. The method analysis is preceded in the paper by a description of developed and applied models.

4. Development

4.1 Models used

First of all the diagnosing process needs a base-line to calculate the residuals [5] which may be presented as relative changes of gaspath variables

$$\delta Y^* = \frac{Y^* - Y_0(\vec{U})}{Y_0(\vec{U})} \tag{1}$$

where Y^* is measured value, $Y_0(\vec{U})$ - base-line value, and $\vec{U}$ is the vector of control variables (for example, fuel consumption) and ambient conditions (ambient air pressure and temperature). So, the vectorial base-line function $\vec{Y}_0(\vec{U})$ may be interpreted as a model of gas turbine normal behavior.

Such a normal state model may be formed by any abstract function as well as a physical model. As an example of an abstract function, the second order four arguments full polynomial

$$\begin{aligned} Y_0(\vec{U}) = {} & c_1 + c_2U_1 + c_3U_2 + c_4U_3 + c_5U_4 + \\ & c_6U_1U_2 + c_7U_1U_3 + c_8U_1\,U_4 + \\ & c_9U_2U_3 + c_{10}U_2U_4 + c_{11}U_3U_4 + \\ & c_{12}U_1^{\,2} + c_{13}U_2^{\,2} + c_{14}U_3^{\,2} + c_{15}U_4^{\,2} \end{aligned} \tag{2}$$

is given which is able to describe correctly an engine behaviour [10]. To compute the coefficients $c_1 - c_{15}$ this model needs registered data inside a wide range of operational conditions.

Non-linear thermodynamic model [3], in which every module is presented by its full manufacture performance map as it is done in [6], demonstrates the option of a physical model. The capacity to reflect the normal behaviour is based on objective physical principles realized. Since the faults affect the module performances involving in the calculations the thermodynamic model has additional capacity to simulate gas turbine degradation.

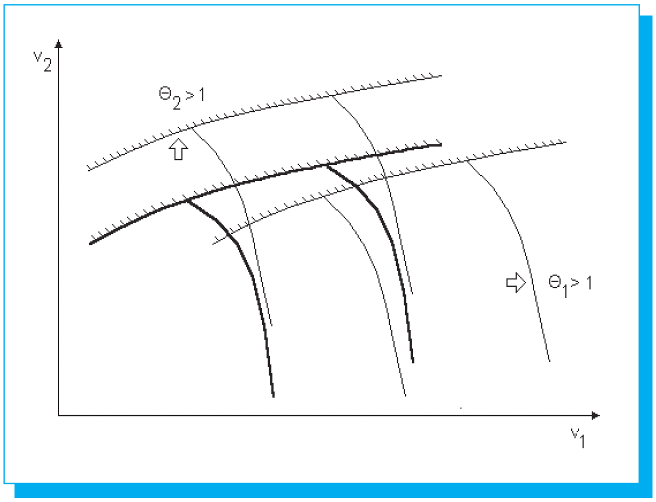

Fig. 1. Correction factor effects.

To have a possibility to displace the module maps of performances $\vec{v}$ (corrected flow parameters or efficiency parameters) for a fault development introducing into the model, the correction factors

$$\Theta_j = {}^{v_j}\!/_{v_{j0}} \qquad (3)$$

are introduced as a relative performances, where v_{j0} is a nominal value. Fig.1 gives a schematic representation of correction factor actions.

So, in the thermodynamic model, the gaspath variables relate with the control variables and the correction factors i.e. present a vector function of the view

$$\vec{Y}(\vec{U},\vec{\Theta}) \qquad (4)$$

This function is computed as a solution of an algebraic equations system reflecting the conditions of a gas turbine modules combined work. The software consists of approximately 60 subprograms, most of them are universal. Thermodynamic models of more than 20 gas turbine engines of various schemes were elaborated and applied in health monitoring systems [3].

It is known that typical gaspath faults cause relatively small residuals (4-6%). That is why a linearization of the functional dependence $\vec{Y}(\vec{\Theta})$ is possible and the linear model:

$$\delta\vec{Y} = H\delta\vec{\Theta} \qquad (5)$$

is widely used in diagnostics. It connects the small relative changes $\delta\vec{\Theta}$ of correction factors with the relative deviations $\delta\vec{Y}$ of gaspath variables by the matrix of influence coefficients H. The thermodynamic model software is capable to generate the matrices H for any operational conditions determined by the vector $\vec{U}$.

What is a difference between the simulated deviations $\delta\vec{Y}$ and the residuals $\delta\vec{Y}^*$ based on real measurements? Ideally, they should be equal however every vector has its own errors.

As described before, either the non-linear model (4) or the linear one (5) are capable to simulate the fault development and for this reason can be classified as diagnostic models. However, fault modeling accuracy presents a separate problem and this is not an object of current study. In this paper, the hypothesis is accepted that the diagnostic models adequately describe the mechanisms of gaspath deterioration; consequently, the vector $\delta\vec{Y}$ does not contain errors. In section 4.6, some arguments are given to support the hypothesis.

As regards the vector $\delta\vec{Y}^*$, its errors occur due to measurement errors in $\vec{Y}$ and $\vec{U}$ as well as possible inherent inaccuracy of the function $\vec{Y}_0(\vec{U})$. It is supposed that a systematic component of these errors does not depend on a deterioration development and a random component is normally distributed due to various factors affecting the accuracy of the residuals. As a consequence, the residuals $\delta\vec{Y}^*$ can be presented as a sum of the deviations $\delta\vec{Y}$ and the standard normal distribution vector $\vec{\varepsilon}_n$ multiplied by the diagonal matrix Σ_Y of maximal dispersions. In this way,

$$\delta\vec{Y}^* = \delta\vec{Y} + \Sigma_Y\vec{\varepsilon}_i \qquad (6)$$

Inside the following approach to gas turbine diagnostics and methods' comparison in basis of trustworthiness criteria, the described models aid to form a gas path fault classification.

4.2 Recognition trustworthiness: common approach

The pattern recognition theory supposes three principle stages of total recognition process: a classification forming, a recognizing itself, and a trustworthiness estimating. These stages are concretized below in application to a gas turbine diagnostics.

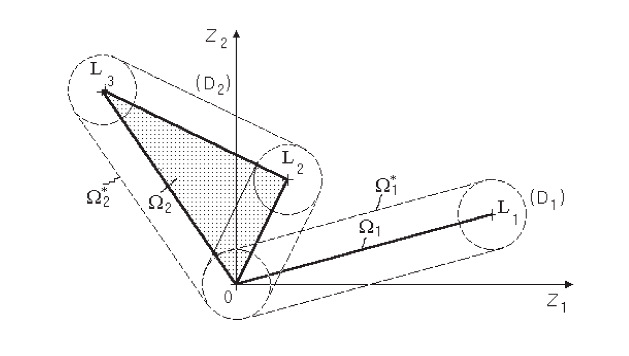

Fig. 2. Single and multiple fault classes.

4.2.1 Classification

Many gaspath faults are known from scientific literature. For instance, Meher-Homji *et al*. [11] give an excellent discussion of performance degradation mechanisms. Existent fault variety is too great to distinguish all possible gas turbine degradation states, moreover a maintenance personnel does not need such a detailed diagnosing. That is why the degradation states should be divided into limited number of classes.

There are many difficulties to form a representative classification based on real fault appearances only. The faults appear rarely and their displays depend on a fault severity, engine type and operational conditions. A few degradation modes only, for instance, a compressor contamination of stationary gas turbines and compressor erosion of helicopter engines, can be interpreted as a permanent problem.

As a result, the real classification could be theoretically made up only for a great engine fleet maintained over a long period of time and model-based classifications are widely used in diagnostics [2,6].

In this paper, applying the models (4) and (5) the classification is made up in the multidimensional space of the corrected residuals

$$Z_i = \frac{Y_i - Y_{0i}(\vec{U})}{\sigma Y_i}, i = 1 - m \quad (7)$$

and a diagnostic decision about the actual state is taken in the same space. Here σY_i is a maximal random error amplitude of the deviation $[Y_i - Y_{0i}(\vec{U})]$ and m is a number of measured variables. So, the residual vector $\vec{Z}$ corresponds to the vector $\vec{Y}$. The vector $\vec{Z}$ corresponding to the measure $\vec{Y}^*$ is formed in the same way.

The hypothesis is accepted that an object (engine) state D can belong to one of q determined beforehand classes

$$D_1, D_2, \ldots, D_q \quad (8)$$

only, as it is often supposed in the pattern recognition theory. Consequently,

$$\sum_{j=1}^{q} D_j = 1 \quad \text{and} \quad \underset{j \neq l}{P}(D_j / D_l) = 0$$

We consider two types of classes: single and multiple.

The single type class has one independent parameter of fault severity, for example, one correction factor or some correction factors changed proportionally. This type is convenient to describe any known permanent fault of variable severity. In Fig. 2, the class D_1 demonstrates this type. The point O corresponds here to an engine normal state. The figure Ω_1 presented by the line O-L_1 reflects theoretical changes of the residuals $\vec{Z}$ while fault severity increasing to a limiting engine state in the point L_1. The figure $\Omega_1{}^*$ presents the residuals $\vec{Z}$ incorporating their random components induced by measurement errors. To complete class forming, any residuals sample or distribution function inside the region $\Omega_1{}^*$ is required.

In contrast to the single type class, the multiple type class has more than one independent parameter, for example, some correction factors to be changed independently. This class may be useful to combine some faults when their own displays and descriptions are uncertain. The class D_2 in Fig. 2 is formed by independent changes of two correction factors, that is why the region Ω_2 presents a surface and the region $\Omega_2{}^*$ has more complex form.

4.2.2 Recognition

A nomenclature of possible diagnosis

$$d_1, d_2, \ldots, d_q \quad (9)$$

corresponds with the accepted classification $D_1, D_2, \ldots, D_q$.

To make a diagnosis d a method dependent criterion

$$R_j = R(\vec{Z}^*, D_j) \quad (10)$$

is introduced as a closeness measure between current residual vector $\vec{Z}^*$ (pattern) and every item of the classification (8) and a decision rule

$$d = d_l \text{ if } R_l = \max\ (R_1, R_2, ..., R_q) \qquad (11)$$

is established.

4.2.3 Trustworthiness

Various negative factors affect the diagnosing process and the final recognition. So, to ensure the diagnosis d it needs to be accompanied by any trustworthiness assessment. Unfortunately, few probabilistic recognition methods only are capable to compute a confidence parameter for a current diagnostic action. On the other hand, such a particular parameter depending on the current measure $\vec{Y}^*$ can not serve as a criterion of average method reliability, engine controllability, and general diagnosing effectiveness.

For this reason mean trustworthiness characteristics are determined for every analyzed method by a statistical testing procedure. This procedure repeats numerously cycles of a method action. In every cycle, the procedure generates random numbers of the current class, fault severity, and measurement errors according chosen distribution laws, then computes actual pattern $\vec{Z}$, and finally takes a diagnostic decision d corresponding to this vector. A square diagnosis matrix Dd (see Table 1) accumulates diagnosing results according the rule

$$Dd_{lj} = Dd_{lj} + 1, \text{ if } (D \equiv D_j) \wedge (d = d_l) \qquad (12)$$

All simulated patterns $\vec{Z}$ compose a testing sample $\vec{Z}^*t$. Its volume Nt corresponds to a total cycle number. After a testing cycle's termination and diagnosis accumulation, the matrix Dd is transformed into a diagnosis probability matrix Pd of the same format by a normalization rule

$$Pd_{lj} = Dd_{lj} \Big/ \sum_{l=1}^{q} Dd_{lj} \qquad (13)$$

The diagonal elements Pd_{ll} forming a probability vector $\vec{P}t$ of true diagnosis represent indices of distinguishing possibilities of the classes. Mean number of these elements - scalar $\vec{P}t$ - characterizes the total controllability of the engine with its measurement system. No diagonal elements give probabilities of false diagnosis and their great values help to identify the causes of bad class distinguishability. These elements make up probabilities of false diagnosis

$$Pe_j = 1 - Pt_j \text{ and } \overline{P}e = 1 - \overline{P}t \qquad (14)$$

also applied in comparative analysis.

Table 1. Diagnosis matrix.

Diagnosis	Classes			
	D_1	D_2	...	D_q
d_1	Dd_{11}	Dd_{12}	...	Dd_{1q}
d_2	Dd_{21}	Dd_{22}	...	Dd_{2q}
...	...	...	...	...
d_q	Dd_{q1}	Dd_{q2}	...	Dd_{qq}

The number Nc that determines computational precision of the described indices is chosen as a result of compromise between a time T to execute the procedure and diagnosing accuracy requirements. In any case, uncertainty in the probabilities should be less than studied effects of changes of the method or diagnosing conditions.

4.2.4 Methods

Three recognition techniques which present different approaches in a recognition theory have been chosen for diagnosing. The first technique is based on the Bayesian approach [12], the second operates with the Euclidian distance to recognize gas turbine fault classes, and the third applies the neural networks which present a fast growing computing technique expanding through many common fields of applications. The techniques have been adapted for the diagnosing and statistically tested by the above procedure. While the testing the settings of these diagnosing methods were adjusted and the methods were compared in equal conditions.

4.2.5 Comparison conditions

Fixed conditions in which the diagnosing methods are simulated and compared are described below.

A. Gas turbine operational conditions determined by the vector $\vec{U}$ are: a maximal gas turbine regime established by the compressor rotation speed variable and standard ambient conditions.

B. Measured parameters structure and accuracy correspond to a gas turbine regular measurement system that includes 6 gaspath parameters to be included in the vector $\vec{Y}$. It is assumed that fluctuations of the residuals (7) mainly induced by measurement errors are normally distributed.

C. Classification parameters. Two classification variants are considered.

Table 2. Trustworthiness indices (case of single class type).

Pd								
.861	.001	.012	.0	.0	.008	.001	.002	.059
.0	.759	.001	.139	.025	.004	.020	.009	.0
.014	.002	.871	.002	.006	.036	.0087	.020	.010
.0	.096	.0	.745	.016	.004	.005	.004	.0
.0	.030	.003	.033	.856	.017	.014	.014	.0
.063	.057	.089	.028	.056	.828	.084	.139	.099
.001	.014	.008	.023	.017	.017	.834	.020	.001
.004	.040	.012	.030	.024	.059	.032	.788	.013
.057	.001	.004	.0	.0	.027	.003	.004	.818
$\vec{Pt}$								
.861	.759	.871	.745	.856	.828	.834	.788	.818

$\vec{Pt} = 0.8178$

The first incorporates nine single classes and every one is constituted by a variation $\delta\Theta_j$ of one correction factor (inlet pressure losses factor increase and flow and efficiency factors decrease for four principle engine modules: compressor, combustion chamber, compressor turbine, power turbine).

The second includes four multiple classes corresponding to the principle modules. Every multiple class is formed by independent variations of two correction factors of the same engine module and describes possible faults of the module. This classification corresponds to maintenance needs – to know engine condition to every module to be able to repair faulty one.

All variations $\delta\Theta_j$ which present here fault severities are uniformly distributed within the interval [0,5%]. The classes also have a uniform distribution, so every class is equally probable.

D. Testing sample volume. Analyzing precision of the averaged probabilities, the sample volume was established as a function of class number Nt=1 000 q.

In that way, section 4.2 embraces explanations of the approach involved (formation of the fault classification, fault recognition rule, and diagnosis trustworthiness indices) as well as gives common conditions to compare the methods. So, we have all necessary general information to begin presentation of every method. In the following three sections, the methods and their adjustment are described in more details and some trustworthiness characteristics computed in the described conditions are given.

Table 3. Trustworthiness indices (case of multiple class type)

Pd			
.891	.062	.016	.003
.045	.784	.016	.072
.050	.038	.940	.042
.014	.116	.028	.883
$\vec{Pt}$			
.891	.784	.940	.883

$Pt = 0.8744$

4.3 Method 1: Bayesian recognition

For actual measurement Y^* and corresponding Z the Bayes formula permits to determine a posteriori probabilities:

$$\underset{j=1-q}{P(D_j/\vec{Z}^*)} = \frac{f(\vec{Z}^*/D_j)P(D_j)}{\sum_{l=1}^{q} f(\vec{Z}^*/D_l)P(D_l)} \tag{15}$$

where
$P(D_j)$ is a priory probability of the class D_j and
$f(\vec{Z}^*/D_j)$ is its pattern density function

Density function assessment is a principle problem of statistics. To simplify it the function $f(\vec{Z}^*/D_j)$ was presented by elemental distributions $f(\vec{Z}/D_j)$ and $f(\vec{Z}^*/\vec{Z})$.

$$f(\vec{Z}^*/D_j) = \int_{\Omega_j} f(\vec{Z}^*/\vec{Z}) f(\vec{Z}/D_j) d\vec{\Theta} \tag{16}$$

and the following assumptions were taken: 1) adequacy of the linear model (5) applied to simulate faults, 2) uniform distribution $f(\vec{Z}/D_j)$ of the model values $\vec{Z}$ with a different fault severity, 3) normal distribution $f(\vec{Z}^*/\vec{Z})$ of residual errors.

Pointed assumptions considerably simplified the calculation of the sought function: for single fault classes, an analytical formula to take the integral (16) has been obtained as well as a simple numerical algorithm for multiple ones.

According to the Bayesian rule the recognition decision d_l is taken when $P(D_l/\vec{Z}^*)$is maximal in the set $P(D_j/\vec{Z}^*)$, $j=1-q$

that corresponds with the general criterion (10) and rule (11) if we put $R_j(\vec{D}_j/Z^*)$.

To assess average trustworthiness of this method (method 1), the diagnosing algorithm based on Bayesian recognition has been elaborated and inserted inside the testing procedure described above. The resulting probabilities (see section 4.2.3) corresponding to a single type classification are placed in Table 2 and the same data for a multiple type classification are included in Table 3.

From Table 2 it can be seen that the classes D_2 and D_4 have the lowest distinguishability according $\vec{Pt}$ and the elevated magnitudes Pd_{42} and Pd_{24} explain the cause – a great mutual intersection of these classes.

Comparison of Table 2 and Table 3 shows individual (for every class by the vector $\vec{Pt}$) and total (by $\bar{Pt}$) trustworthiness growth for the multiple classification that is a result of two opposite tendencies. On one hand, the replacement of a single type by a multiple one generally leads to more close class intersection and lower trustworthiness. On the other hand, the significant reduction of class total quantity (from nine to four) has a contrary influence. In our case, the second tendency dominates. Of course, another diagnosing method will change the presented probabilities and, probably, the conclusions.

This is an advantage of the method 1 that every diagnosis made for actual measurement may be accompanied by a confidence probabilistic estimate and, on average, such estimates will be maximal.

However, the method is not without its difficulties. It seems to be too complicated to restore density functions of a general form in a multi-dimensional recognition space utilizing real measurements (patterns). Therefore, simple type classes based on the linear model and ordinary theoretical distributions may be described only.

That is why a class representation directly by pattern sets is considered too as well as the methods 2 and 3 capable to treat them.

4.4 Method 2: Euclidian distance

Such a simplification as density functions replacement on the pattern sets permits simulating a fault severity growth by the more exact nonlinear thermodynamic model and forming complex multiple classes described by three and more correction factors. Furthermore, this permits forming real data based classes of general type without any model assistance

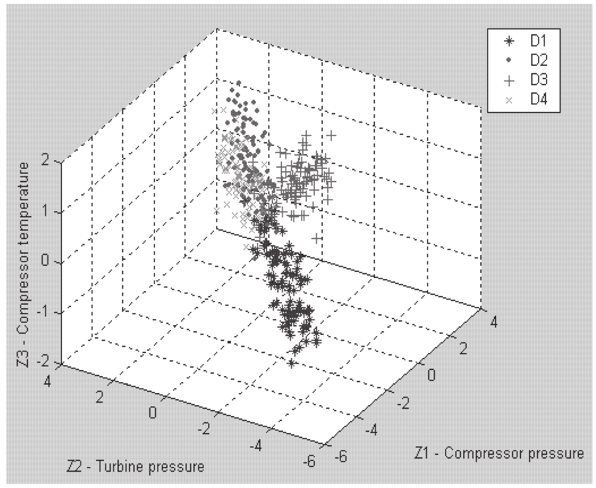

Fig. 3. Classes representation by the pattern sets

and consequently without negative influence of model proper errors. Fig. 3 demonstrates new class representation; pattern sets of four classes are given here in the three-dimensional space $\vec{Z}$.

The recognition space $\vec{Z}$ of residuals can be classified as uniform since all residuals have the same dispersion according to the transformation (7). That is why it will be correctly to introduce a geometrical measure of closeness between the current vector $\vec{Z}$ and the class D_j to be used as the recognition criterion R_j (10). For concerned method, this measure is based on the Euclidian distance between two points in a multidimensional space.

The computational algorithm has been realized inside the testing procedure and incorporates the following items. Firstly, outside the testing procedure, a reference sample Zr of the volume Nr incorporating the pattern sets Zr_j for all classes is composed. Secondly, inside the testing procedure, the criteria R_j are calculated for actual $\vec{Z}^*$ of the testing sample and every Zr_j^* of the reference set. Thirdly, the diagnosing decision d_l is accepted by the general rule (11). The trustworthiness indices (13) and (14) are calculated then according to the general scheme (see section 4.2.3).

To select the best criterion type, the following variants were considered:

- variant 1 - mean inverse distance $M(1/d_i)$ between a testing sample point and reference points;

Table 4. Training algorithms. "Cycles" refers to the total cycle number of training process. $\vec{Pt}$ and $\vec{Pt}$' mean probabilities of truthful diagnosis obtained on the teaching and testing samples correspondingly.

e	Algorithm	Cycles	Time, s	$\vec{Pt}$	$\vec{Pt}$"
0.0300	1	383	110	0.8174	0.8132
	2	65	37	0.8132	0.8090
	3	111	70	0.8174	0.8172
0.0290	1	485	127	0.8211	0.8157
	2	95	44	0.8168	0.8126
	3	114	71	0.8213	0.8181
0.0285	1	598	158	0.8234	0.8173
	2	118	49	0.8196	0.8149
	3	122	75	0.8209	0.8180
0.0280	1	836	201	0.8264	0.8197
	2	149	56	0.8242	0.8159
	3	134	80	0.8234	0.8214
0.0275	1	1616	370	0.8276	0.8194
	2	212	70	0.8269	0.8198
	3	178	100	0.8267	0.8228

- variant 2 - mean inverse quadratic distance $M(1/d_i^2)$ between the testing point and the reference points;
- variant 3 - mean distance $M(d_i)$ between the testing point and the reference points;
- variant 4 - distance between the testing point and a reference sample gravity center.

In preliminary statistical testing, the variant 2 ensured the best class distinguishability and has been selected for further use.

Because the reference sample volume Nr influences the computational accuracy and executing time in the same mode as it does Nt, the value $Nr = Nt = 1000q$ has been accepted to carry out next calculations.

4.5 Method 3: neural networks

Neural networks consist of simple parallel elements called neurons. According to the common scheme of supervised learning networks are trained on the known pairs of input and output (target) vectors. The connections (weights) between the neurons change in such a manner that ensures decreasing a mean difference (error) e between the target and network output. Many such input/target pairs are used to adapt a network to a particular function.

Above an input layer and output layer of neurons a network may incorporate one or more hidden layers of computation nodes when high network flexibility is necessary. To solve difficult pattern recognition problems multilayer feedforward networks or multilayer perceptrons are successfully applied [13] since a back-propagation algorithm had been proposed to train them. So, a back-propagation network promises reliable fault recognition and we also included it in the comparative analysis.

Table 5. False diagnosis probabilities (single type classification).

Indices		Methods 1	2	3
$\vec{Pe}$	d_1	0.139	0.266	0.170
	d_2	0.241	0.248	0.252
	d_3	0.129	0.219	0.137
	d_4	0.255	0.390	0.250
	d_5	0.144	0.224	0.145
	d_6	0.172	0.015	0.170
	d_7	0.166	0.212	0.143
	d_8	0.212	0.243	0.173
	d_9	0.182	0.215	0.160
$\overline{Pe}$		0.1822	0.2258	0.1772

The network realized in the method 3 has the next composition depending on the measurement system and fault classification structures.

The input layer vector includes 6 elements since network inputs are residuals. The output vector presents the concerned classes and therefore incorporates 9 elements for the single type classification and 4 elements for the multiple one. Network complexity and resolution capability are in close relation with hidden layers quantity and their nodes numbers and, to a first approximation, the network has one hidden layer of 12 nodes.

Differentiable layer transfer functions are of sigmoid type. In the hidden layer, a tan-sigmoid function is applied; it varies from -1 to 1 and is typical for internal layers of a back-propagation network. A log-sigmoid function operates in the output layer; it varies from 0 to 1 and is convenient to solve recognition problems.

To put the compared methods under equal conditions the same reference and testing samples as used before are applied now as data sources in network training and verifying processes. Firstly, the training algorithm is performed on the sample $\vec{Zr}^*$. Secondly, the trained network passes a verification stage to compute the probabilistic trustworthiness indices (see section 4.2.3) corresponding to the samples Zr^* and Zt^*.

There are a number of variations on the basic back-propagation training algorithm. In order to choose the best one under concrete conditions of fault recognition, twelve variations were tested under fixed given accuracy e (mean discrepancy between all targets and network outputs) and compared by execution time. Three more perspective algorithms - variable (adaptive) learning rate algorithm (algorithm 1), resilient back-propagation (algorithm 2), and scaled conjugate gradient algorithm (algorithm 3) - were verified additionally for the different accuracy levels $e = 0.03$-0.0275, where the value 0.0275 is close to the final obtainable accuracy. The results given in Table 4 show that the algorithm 1 obviously loses the competition, the algorithm 2 seems to be a little more rapid than the algorithm 3 while the last is more reliable on the testing sample. Taking into account our priority - recognition trustworthiness - the scaled conjugate gradient algorithm is selected for next calculations.

An influence of the hidden layer node number was examined too. Above the chosen number 12, the numbers 8, 16, 20 were also verified for options of the chosen back-propagation algorithm and fixed cycle number 200. The reduction of the node number from 12 to 8 has demonstrated visible changes for the worse of the obtainable accuracy Äe=0.00103 and the probabilities $\overline{Pt'}$=–0.0068 and $\overline{Pt''}$=–0.0068. On the other hand, the augmentation to 16 and 20 nodes has not improved the algorithm's characteristics. That is why the node number 12 remains for further calculations.

4.6 Methods comparison

To compare all three methods, the statistical testing of the methods 2 and 3 preliminarily checked and adjusted has been performed under the conditions of the method 1 testing and for the same two classification configurations. The resulting trustworthiness characteristics - the probabilities of false diagnosis (14) – are placed in Table 5 (single type classification) and Table 6 (multiple type classification). For the method 1 these probabilities correspond to the data of Table 2 and Table 3.

Firstly, the methods 2 and 3 are compared. They operate with the same input and output data representation and, from this point of view, do not have any significant advantages/limitations one against the other. So, the trustworthiness level and execution time are only arguments to choose the best method.

The indices presented in Tables 5 and 6 demonstrate significantly lower probabilities of false diagnosing by the

Table 6. False diagnosis probabilities (multiple type classification)

Indices		Methods 1	2	3
$\vec{P}e$	d_1	0.109	0.237	0.104
	d_2	0.216	0.373	0.214
	d_3	0.060	0.051	0.072
	d_4	0.117	0.051	0.217
$\overline{Pe}$		0.1256	0.1790	0.1293

method 3. Since calculating accuracy for the probability $\overline{Pe}$ works out at 0.01, the effect of trustworthiness enhancement is not a result of statistical simulation errors. The comparative calculations repeated for other gas turbine operating conditions prove the conclusion about superiority of the method 3.

As to the methods 1 and 3, the differences between them in diagnosis trustworthiness are lower. As it can be seen in Tables 5 and 6, these methods differ in the probability by 0.0037-0.0050. As the differences are opposite by the sign and smaller then the calculating inaccuracy, the trustworthiness levels of the methods 1 and 3 are considered as equal.

However in contrast to the methods 2 and 3, the method 1 applying the Bayesian approach has an advantage to accompany every diagnosis by its confidence estimation. Therefore the diagnostic method based on the Bayesian approach may be recommended for practical application always when we are able to describe the classes by density functions; for example, in the case of model-based classification concerned in this paper. Otherwise, the techniques like neural networks should be used.

4.7 Perspectives of practical application

Above the current work focused on a method comparing, numerous investigations were fulfilled by means of a diagnosing process statistical testing and trustworthiness indices analysis in order to study other factors that also affect the gas diagnosing trustworthiness.

The variety of these factors includes
- measurement system structure;
- measured parameters accuracy;
- number and structure of gas turbine operational regimes including dynamic regimes;
- classification structure and type;

- joint recognition of gaspath faults and measurement system proper defects.

Presented trustworthiness analysis may be classified as model-based since gas turbine models describe a normal behavior and fault influence. That is why a reasonable question appears how we could ensure that the obtained results be correct in practice.

To guarantee the results of model-based calculations the statistical testing is carried out for a wide range of possible diagnosing conditions and the conclusions are generalized. In addition, important results are confirmed on real data, if any. For instance, a practical mode has been proposed [10] to enhance the base-line function $\vec{Y}_0(U)$ and reduce the deviation errors σY_i by maintenance data analysis; the method based on Bayesian approach was adapted for recognition of physically simulated gas turbine faults and a real compressor contamination and has demonstrated a satisfactory accuracy of the previous model-based realization of the method.

The idea appears of a combined classification: to start a health monitoring system development and operation with model-based classes and later, along with maintenance information accumulation, to introduce one by one the classes formed by real fault description.

5. Conclusions

In this paper, we discuss a statistical testing of gas turbine diagnosing process in order to determine and elevate recognition trustworthiness indices which are averaged probabilities of true/false diagnosis. A thermodynamic model serves to simulate gas turbine degradation modes and form a faults classification. To conduct the trustworthiness analysis in more general form, two types of gas turbine fault classes called single and multiple are considered.

Three diagnosing methods functioning inside the statistical testing procedure are adjusted, verified, and finally compared. Two of them – the method utilizing Bayesian rule and the method applying neural networks - have demonstrated an equally high trustworthiness level and are recommended for the use in condition monitoring systems.

The presented investigation is a part of total work focused on the trustworthiness growth of gas turbine diagnosing; the other investigation lines including an analysis of maintenance data are noted.

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