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Gas Turbine Condition Monitoring and Diagnostics

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1. Introduction

Gas turbine monitoring and diagnostics belong to a common area of condition monitoring (health monitoring) of machinery and mechanical equipment such as spacecrafts, aircrafts, shipboard systems, various power plants and industrial and manufacturing processes. They can be considered as complex engineering systems and become more sophisticated during their further development that results in potential degradation of system reliability. In order to keep reliability high, various diagnostic tools are applied. Being capable to detect and identify incipient faults, they reduce the rate of gross failures.

Considerable increase of industrial accidents and disasters has been observed in the last decades (Rao, 1996). Mechanical failures cause a considerable percentage of such accidents. Various deterioration factors can be responsible for these failures. Among them, the most common factors that degrade a healthy condition of machines are vibration, shock, noise, heat, cold, dust, corrosion, humidity, rain, oil debris, flow, pressure, and speed (Rao, 1996).

In these conditions, health monitoring has become an important and rapidly developing discipline which allows effective machines maintenance. In two last decades the development of monitoring tools has been accelerated by advances in information technology, particularly, in instrumentation, communication techniques, and computer technology.

Modern sensors trend to preliminary signal processing (filtering, compressing, etc.) in order to realize self-diagnostics, reduce measurement errors, and decrease volume of data for subsequent processing. So, sensors become more and more “intelligent” or “smart”. Development of communication techniques, in particular, wireless technologies drastically simplifies data acquisition in the sites of machine operation. Data transmission to centralized diagnostic centres is also accelerated. In these centres great volume of data can effectively be analyzed by qualified personnel. The personal computer has radically changed as well. Large numbers of powerful PCs united in networks allow easy sharing the measured data through the company, fast data processing, and suitable access to the diagnostic results. Development of the PC technology also allows many independent disciplines to be integrated in condition monitoring.

Success of monitoring not only depends on perfection of monitoring hardware and software themselves, but also is determined by tight monitoring integration with maintenance when the both disciplines can be considered as one multidiscipline. Behind this trend lies a well known concept of Condition Based Maintenance (CBM) as well as ideas of Condition Monitoring and Diagnostic Engineering Management (COMADEM) (Rao, 1996) and Prognostics and Health Management (PHM) (Vachtsevanos et al., 2006). As illustrated by many examples in (Rao, 1996), the proper organization of the total monitoring and maintenance process can bring substantial economical benefits. Numerous engineering systems, which considerably differ in nature and principles of operation, need individual techniques in order to realize effective monitoring. The variety of known monitoring techniques can be divided into five common groups: vibration monitoring, wear debris analysis, visual inspection, noise monitoring, and environment pollution monitoring (Rao, 1996). The two first approaches are typical for monitoring rotating machinery, including gas turbines.

A gas turbine engine can be considered as a very complex and expensive machine. For example, total number of pieces in principal engine components and subsystems can reach 20,000 and more; heavy duty turbines cost many millions of dollars. This price can be considered only as potential direct losses due to a possible gas turbine failure. Indirect losses will be much greater. That is why, it is of vital importance that the gas turbine be provided by an effective monitoring system.

Gas turbine monitoring systems are based on measured and recorded variables and signals. Such systems do not need engine shutdown and disassembly. They operate in real time and provide diagnostic on-line analysis and recording data in special diagnostic databases. With these databases more profound off-line analysis is performed later.

The system should use all information available for a diagnosed gas turbine and cover a maximal number of its subsystems. Although theoretical bases for diagnosis of different engine systems can be common, each of them requires its own diagnostic algorithms taking into account system peculiarities. Nowadays parametric diagnostics encompasses all main gas turbine subsystems such as gas path, transmission, hot part constructional elements, measurement system, fuel system, oil system, control system, starting system, and compressor variable geometry system. In order to perform complete and effective diagnosis, different approaches are used for these systems. In particular, the application of such common approaches of rotating machinery monitoring as vibration analysis and oil debris monitoring has become a standard practice for gas turbines.

However, the monitoring system always includes another technique, which is specific for gas turbines, namely gas path analysis (GPA). Its algorithms are based on a well-developed gas turbine theory and gas path measurements (pressures, temperatures, rotation speeds, and fuel consumption, among others). The GPA can be considered as a principal part of a gas turbine monitoring system. The gas path analysis has been chosen as a representative approach to the gas turbine diagnosis and will be addressed further in this chapter. However, the observations made in the chapter may be useful for other diagnostic approaches.

The gas path analysis provides a deep insight into gas turbine components' performances, revealing gradual degradation mechanisms and abrupt faults. Besides these gas path defects, malfunctions of measurement and control systems can also be detected and identified. Additionally, the GPA allows estimating main engine performances that are not measured like shaft power, thrust, overall engine efficiency, specific fuel consumption, and compressor surge margin. Important engine health indicators, the deviations in measured variables induced by engine deterioration and faults, can be computed as well.

The gas path analysis is an area of extensive studies and thousands of technical papers can be found in this area. Some common observations that follow from these works and help to explain the structure of this chapter are given below.

First, it can be stated that gas turbine simulation is an integral part of the diagnostic process. The models fulfil here two general functions. One of them is to give a gas turbine performance baseline in order to calculate differences between current measurements and such a baseline. These differences (or deviations) serve as reliable degradation indices. The second function is related to fault simulation. Recorded data rarely suffice to form a representative classification because of the rare and occasional appearance of real faults and very high costs of real fault simulation on a test bed. That is why mathematical models are involved. The models connect degradation mechanisms with gas path variables, assisting in this way with a fault classification that is necessary for fault diagnosis.

Second, a total diagnostic process can be divided into three general and interrelated stages: common engine health monitoring (fault detection), detailed diagnostics (fault identification), and prognostics (prediction of remaining engine life). Since input data should be as exact as possible, an important preliminary stage of data validation precedes these principal diagnostic stages. In addition to data filtration and averaging, it also includes a procedure of computing the deviations, which are used practically in all methods of monitoring, diagnostics, and prognostics.

Third, gas turbine diagnostic methods can be divided into two general approaches. The first approach employs system identification techniques and, in general, so called thermodynamic model. The used models relate monitored gas path variables with special fault parameters that allow simulating engine components degradation. The goal of gas turbine identification is to find such fault parameters that minimize difference between the model-generated and measured monitored variables. The simplification of the diagnostic process is achieved because the determined parameters contain information on the current technical state of each component. The main limitation of this approach is that model inaccuracy causes elevated errors in estimated fault parameters. The second approach is based on the pattern recognition theory and mostly uses data-driven models. The necessary fault classification can be composed in the form of patterns obtained for every fault class from real data. Since patterns of each fault class are available, a data-driven recognition technique, for example, neural network, can be easily trained without detailed knowledge of the system. That is why, this approach has a theoretical possibility to exclude the model (and the related inaccuracy) from the diagnostic process.

Fourth, the models used in condition monitoring and, in particular, in the GPA can be divided into two categories – physics-based and data-driven. The physics-based model (for instance, thermodynamic model) requires detailed knowledge of the system under analysis (gas turbine) and generally presents more or less complex software. The data-driven model gives a relationship between input and output variables that can be obtained on the basis of available real data without the need of system knowledge. Diagnostic techniques can be classified in the same manner as physics-based or model-based and data-driven or empirical.

Illustrating the above observations, Fig. 1 presents a classification of gas path analysis methods. Taking into the account the observations and the classification, the following topics will be considered below: real input data for diagnosis, mathematical models involved, preliminary data treatment, fault recognition methods and accuracy, diagnosis and monitoring interaction, and application of system identification methods for fault diagnosis.

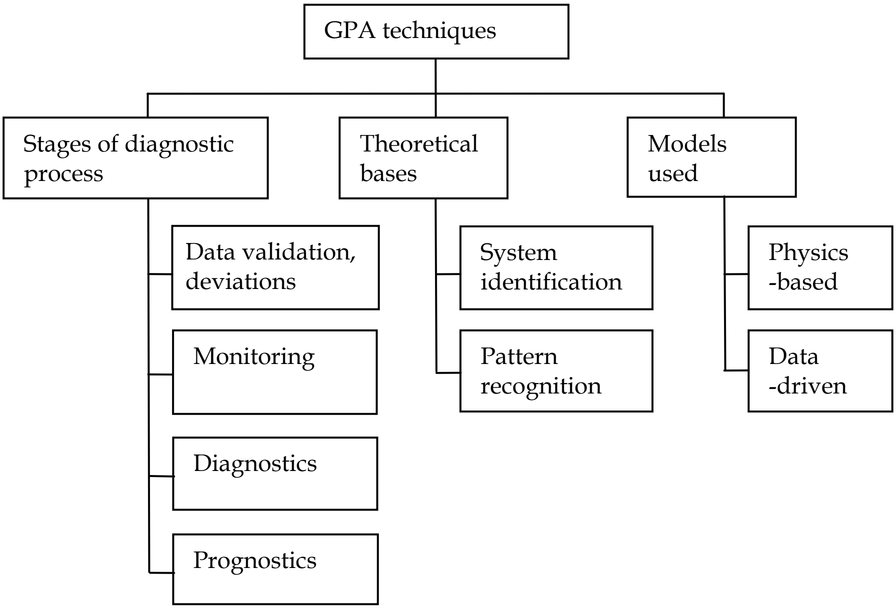


Fig. 1. Classification of gas path analysis techniques

2. Diagnostic models

2.1 Nonlinear static model

In the GPA the physics-based models are presented by thermodynamic models for simulating gas turbine steady states (nonlinear static model) and transients (nonlinear dynamic model). Since the studies of Saravanamuttoo et al., in particular, (Saravanamuttoo & MacIsaac, 1983), application of the thermodynamic model for steady states has become common practice and now this model holds a central position in the GPA. Such a model includes full successive description of all gas path components such as input device, compressor, combustion chamber, turbine, and output device. Such models can also be classified as non-linear, one-dimensional, and component-based.

The thermodynamic model computes a (m×1)-vector $\vec{Y}$ of gas path monitored variables as a function of a vector $\vec{U}$ of steady operational conditions (control variables and ambient conditions) as well as a (r×1)-vector $\vec{\Theta}$ of fault parameters, which can also be named health parameters or correction factors depending on the addressing problems. Given the above explanation, the thermodynamic model has the following structure:

$$\vec{Y} = F(\vec{U}, \vec{\Theta}) \; . \tag{1}$$

There are various types of real gas turbine deterioration and faults such as fouling, tip rubs, seal wear, erosion, and foreign object damage whose detailed description can be found, for example, in the study (Meher-Homji et al., 2001). Since such real defects occur rarely during maintenance, the thermodynamic model is a unique technique to create necessary class descriptions. To take into account the component performance changes induced by real gradual deterioration mechanisms and abrupt faults, the model includes special fault parameters that are capable to shift a little the components' maps.

Mathematically, the model is a system of nonlinear algebraic equations reflecting mass, heat, and energy balance for all components operating under stationary conditions.

The thermodynamic model represents complex software. The number of algebraic equations can reach 15 and more and the software includes dozens of subprograms. The most of the subprograms can be designed as universal modules independent of a simulated gas turbine, thus simplifying model creation for a new engine.

System identification techniques can significantly enhance model accuracy. The dependency $\vec{Y} = f_1(\vec{U})$ realized by the model can be well fitted and simulation errors can be lowered up to a half per cent. Unfortunately, it is much more difficult to make more accurate the other dependency $\vec{Y} = f_2(\vec{\Theta})$ because faults rarely occur. The study presented in (Loboda & Yepifanov, 2010) shows that differences between real and simulated faults can be visible.

As mentioned before, the thermodynamic model for steady states has wide application in gas turbine diagnostics. First, this model is used to describe particular faults or complete fault classification (Loboda et al., 2007). Second, the thermodynamic model is an integral part of numerous diagnostic algorithms based on system identification such as described in (Pinelli & Spina, 2002). Third, this nonlinear model allows computing simpler models (Sampath & Singh, 2006), like a linear model (Kamboukos & Mathioudakis 2005) described below.

2.2 Linear static model

The linear static model present linearization of nonlinear dependency $\vec{Y} = f_2(\vec{\Theta})$ between gas path variables and fault parameters determined for a fixed operating condition $\vec{U}$. The model is given by a vectorial expression

$$\delta\vec{Y} = H\delta\,\vec{\Theta}\,. \tag{2}$$

It connects a vector $\delta\,\vec{\Theta}$ of small relative changes of the fault parameters with a vector $\delta\vec{Y}$ of the corresponding relative deviations of the monitored variables by a matrix H of influence coefficients (influence matrix).

Since linearization errors are not too great, about some percent, the linear model can be successfully applied for fault simulation at any fixed operating point. However, when it is used for estimating fault parameters by system identification methods like in study (Kamboukos & Mathioudakis, 2005), estimation errors can be significant. Given the simplicity of the linear model and its utility for analytical analysis of complex diagnostic issues, we can conclude that this model will remain important in gas turbine diagnostics.

The matrix H can be easily computed by means of the thermodynamic model. The gas path variables $\vec{Y}$ are firstly calculated by the model for nominal fault parameters $\vec{\Theta}_0$. Then, small variations are introduced by turns in fault parameters and the calculation of the variables $\vec{Y}$ is repeated for each corrected parameter. Finally, for each pair Y_i and Θ_j the corresponding influence coefficient is obtained by the following expression

$$H_{ij} = \frac{\delta Y_i}{\delta\Theta_j} = \frac{Y_i(\vec{\Theta}_j) - Y_i(\vec{\Theta}_0)}{Y_i(\vec{\Theta}_0)} \Bigg/ \frac{\Theta_j - \Theta_{0j}}{\Theta_{0j}}\,. \tag{3}$$

2.3 Nonlinear dynamic model

Although methods to diagnose at steady states are more developed and numerous than the methods for transients, current studies demonstrate growing interest in the gas turbine diagnosis during dynamic operation (Loboda et al., 2007; Ogaji et al., 2003). A thermodynamic gas path model (dynamic model) is therefore in increasing demand. As distinct from the static model (1), in the dynamic model a time variable t is added to the argument set of the function $\vec{Y}$ and the vector $\vec{U}$ is given as a time function, i.e. a dynamic model has a structure

$$\vec{Y} = F(\vec{U}(t), \vec{\Theta}, t) . \tag{4}$$

A separate influence of time variable t is explained by inertia nature of gas turbine dynamic processes, in particular, by inertia moments of gas turbine rotors. The gas path parameters $\vec{Y}$ of the model (4) are computed numerically as a solution of the system of differential equations in which the right parts are calculated from a system of algebraic equations reflecting the conditions of the components combined work at transients. These algebraic equations differ a little from the static model equations, that is why the numeric procedure of the algebraic equation system solution is conserved in the dynamic model. Therefore, the nonlinear dynamic model includes the most of static model subprograms. Thus, the nonlinear static and dynamic models tend to be united in a common program complex.

2.4 Neural networks

Artificial Neural Networks (ANNs) present a fast growing computing technique in many fields of applications, such as pattern recognition, identification, control systems, and condition monitoring (Rao, 1996; Duda et al., 2001). The ANN can be classified as a typical data-driven model or black-box model because it is viewed solely in terms of its input and output without any knowledge of internal operation. During network supervised learning on the known pairs of input and output (target) vectors, weights between the neurons change in a manner that ensures decreasing a mean difference (error) e between the target and the network output. In addition to the input and output layers of neurons, a network may incorporate one or more hidden layers of nodes when high network flexibility is necessary.

The multilayer perceptron (MLP) has emerged as the most widely used network in gas turbine diagnostics (Volponi et al., 2003). Its foundations can be found in any book devoted to ANNs and we give below only a brief perceptron description. The MLP is a feed-forward network in which signals propagate through the network from its input to the output with no feedback. The diagram shown in Fig.2 helps to understand better perceptron operation. The presented network includes input, hidden, and output layers of neurons. For each hidden layer neuron, the sum of inputs of a vector $\vec{p}$ multiplied by waiting coefficients of a matrix W_1 is firstly computed. The corresponding bias from a vector $\vec{b}_1$ is added then, forming a neuron input. Finally, inputs of all neurons are transformed by a hidden layer transfer function f_2 into an output vector $\vec{a}_1$. The described procedure can be written by the following expression

$$\vec{a}_1 = f_1(W_1 \vec{p} + \vec{b}_1) . \tag{5}$$

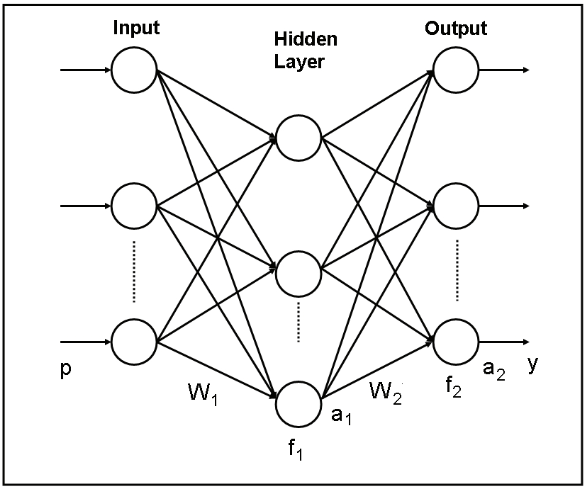


Fig. 2. Perceptron diagram

The same procedure is then repeated for the output layer considering $\vec{a}_1$ as an input vector. Similarly to formula (5), the output layer is given by

$$\vec{y} = \vec{a}_2 = f_2(W_2 \vec{a}_1 + \vec{b}_2) . \quad (6)$$

Before the use the network should be trained on known pairs of the input vector and the output vector (target) in order to determine unknown waiting coefficients and biases. The MLP has been successfully applied to solve difficult pattern recognition problems since a back-propagation algorithm had been proposed for the training. It is a variation of so called incremental or adaptive training mode that changes unknown coefficients after presentation of every individual input vector. In the back-propagation algorithm the error between the target and actual output vectors is propagated backwards to correct the weights and biases. The correction is repeated successively for all available inputs and targets united in a training set. Usually it is not sufficient to reach a global minimum between all targets and network outputs and a cycle of calculations with learning set data is repeated many times. That is why this algorithm is relatively slow. To apply the back-propagation algorithm, a layer transfer function should be differentiable. Generally, it is the tan-sigmoid, log-sigmoid, or linear type.

There is another training mode called a batch mode because a mean error e between all network targets and outputs is computed and used to correct the coefficients. In this mode the training comes to a common nonlinear minimization problem in which the error $e(W_1, b_1, W_2, b_2)$ should be minimized in a multidimensional space of all unknown coefficients, waits and biases. This error can be reduced but should not be vanished because the network must follow general systematic dependencies between simulated variables and should not reflect individual random errors of every input and output.

Though the trained network is ready for practical use in a gas turbine diagnosis, an additional stage of network verification is mandatory. There is a common statistical rule that a function determined on one portion of the random data should be tested on another. Consequently, to verify the MLP determined on a training set, we need one more data portion called a validation set. If the neural network describes well training data but loses its accuracy on validation data it is a clear indication of an overlearning effect. The network begins to take into account training set random peculiarities and therefore loses its capability to generalize data.

In addition to the MLP described above, some other network types are also used in the gas path analysis, in particular, Radial Basis Networks, Probabilistic Neural Networks (Romessis & Mathioudakis, 2003; Romessis et al., 2007), and Bayesian Belief Networks (Romessis & Mathioudakis, 2006; Romessis et al., 2007). Foundations of these particular recognition and approximation tools can be found in any book in the area of ANNs, for instance, in (Haykin, 1994). The language of technical computing MATLAB developed by the MathWorks, Inc. offers convenient tools to experiment with different neural networks. It contains a neural networks toolbox that simplifies network creation, training, and use. MATLAB also allows choosing between various training functions and calculation options.

With respect to diagnostic problems where the ANNs are used, it can be concluded that in most cases networks are employed for gas turbine fault identification, in particular, to form fault classification (Ogaji et al., 2003) and to estimate fault parameters (Romessis & Mathioudakis, 2006). However, the ANNs not only are applied for recognition problems, but they also are famous as good function approximators in many fields including gas turbine monitoring (Fast et al., 2009). In addition to ANNs, other and simpler data-driven models like polynomials can be successfully applied to simulate gas turbine performances.

2.5 Polynomials

It is proven in (Loboda et al., 2004) that complete second order polynomials give sufficient approximation of healthy engine performance (baseline). For one monitored gas path variable Y as a function of three arguments u_i, such polynomial is written as

$$Y_0(\vec{U}) = a_0 + a_1u_1 + a_2u_2 + a_3u_3 + a_4u_1u_2 + a_5u_1u_3 + a_6u_2u_3 + a_7u_1^2 + a_8u_2^2 + a_9u_3^2 . \tag{7}$$

The polynomials for all monitored variables can be given in the following generalized form:

$$\vec{Y}_0^T = \vec{V}^T \mathbf{A} , \tag{8}$$

where $\vec{Y}_0^T$ is a (1×m)-vector of monitored variables, $\vec{V}^T$ is a (1×k)-vector of components $1, u_1, u_2, ...u_2^2, u_3^2$, and $\mathbf{A}$ presents a (k×m)-matrix of unknown coefficients a_i for all m monitored variables. Since measurements at one steady-state operating point are not sufficient to compute the coefficients, data collected at n different points are included into the training set and involved into calculations. With new matrixes $\mathbf{Y}$ (n×m) and $\mathbf{V}$ (n×k) formed from these data, equation (8) is transformed in a linear system

$$\mathbf{Y} = \mathbf{VA} . \tag{9}$$

To enhance estimations $\hat{a}_i$, large volume n>>k of input data is involved and the least-squares method is applied to solve system (9), resulting in the well known solution:

$$\hat{\mathbf{A}} = (\mathbf{V}^T\mathbf{V})^{-1}\mathbf{V}^T\mathbf{Y}\,. \tag{10}$$

As can be seen, polynomials present a typical data-driven model because only input and output data are used to compute polynomials' coefficients. In the below sections that describe the stages of a total diagnostic process, we will return to polynomials and other described above models considering their particular applications in the GPA methods.

3. Data validation and preliminary processing

3.1 Deviations

Modern instrumentation and data recording tools allow collecting a great volume of test bed and field data of different types. Typically, historical engine sensor data are used in diagnostics that were previously filtered, averaged, and periodically recorded (once per flight, day, or hour) at steady states. Every measurement section (snapshot) includes engine operational conditions $\vec{U}$, which set an engine operating point, and monitored variables $\vec{Y}$. When recorded over a long period of time, these snapshots can provide valuable information about the deterioration and faults. The most common cause of stationary gas turbines' deterioration is compressor fouling and the data with fouling and washing cycles are widely used in order to verify diagnostic techniques.

By direct analysis of the variables themselves it is difficult to discriminate performance degradation effects from great changes due to different operating modes. To draw useful diagnostic information from raw recorded data, a total gas turbine diagnostic process usually includes a preliminary procedure of computing deviations. The deviations, also known as residuals and deltas, are defined as differences between measured and engine baseline values. As the baseline depends on an engine operating condition, it can be written as function $\vec{Y}_0(\vec{U})$ usually called a baseline function or model. With this model the deviations for each monitored variables $Y_{i,i=1,m}$ is computed in a relative form

$$\delta Y_i^* = \frac{Y_i^* - Y_{0i}(\vec{U})}{Y_{0i}(\vec{U})}, \tag{11}$$

where Y_i^* denotes a measured value.

The deviation consists of the systematic influence (signal) induced by engine degradation or faults and a noise component, which is explained by sensor errors and a baseline model inadequacy. When properly computed, the deviations can have relatively high quality (signal-to-noise ratio) and can potentially be good indicators of engine health. Since success of all principal diagnostic stages directly depends on the deviations' quality, best efforts should be applied to keep deviation errors to a minimum.

Figure 3 exemplifies the exhaust gas temperature (EGT) deviations of a gas turbine for natural gas pumping stations. Let us call this engine GT1. The deviations are plotted here against an operation time *t* (here and below a variable *t* is given in hours). As can be seen, the presented data cover approximately 4.5 thousand hours. The deviations δY^* computed on real measurements with noise are marked by a grey colour while a black line denotes ideal deviations δY without noise. A compressor washing at the time point *t* = 7970 as well as fouling periods before and after the washing are well-distinguishable in the figure.

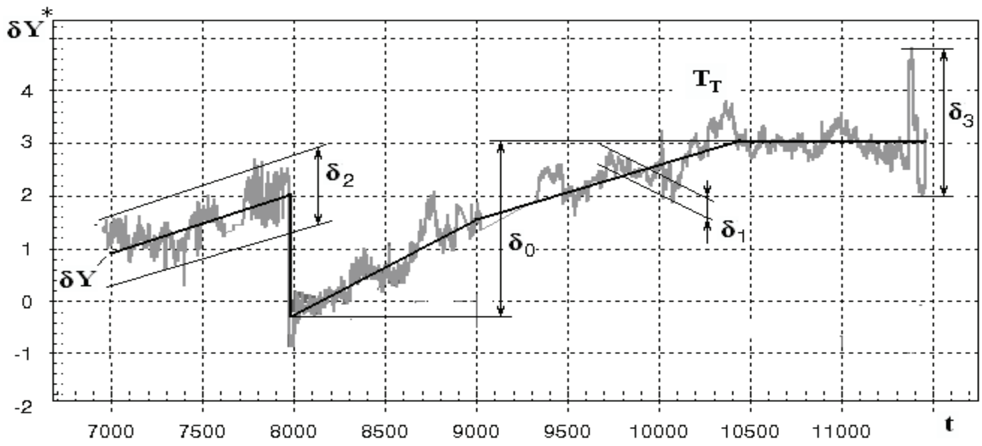


Fig. 3. Deviations' characteristics

A difference $\varepsilon_\Sigma = \delta Y^* - \delta Y$ can be considered as an error. If we designate the maximum deviation δY as δ_0, the signal-to-noise ratio

$$\bar{\delta}_0 = \delta_0 / \sigma(\varepsilon_\Sigma)\,, \tag{12}$$

where $\sigma(\varepsilon_\Sigma)$ is a standard deviation of the errors, will be an index of diagnostic quality of the deviations δY^*. To enhance the quality we should reduce the errors ε_Σ. According to Fig.3, there are three elemental errors given here by error intervals δ_1, δ_2, and δ_3. Total error ε_Σ consists correspondingly of three components and can be given by the formula:

$$\varepsilon_\Sigma = \varepsilon_1 + \varepsilon_2 + \varepsilon_3\,, \tag{13}$$

where ε_1 is a normal noise smaller than 0.2% that is observed at every time point,
ε_2 presents slower fluctuations of the amplitude limited by 0.8%, and
ε_3 means single outliers with the amplitude greater than 0.8%.

The errors can be induces by both sensor malfunctions and baseline model inadequacy. Let us analyse separately these error sources.

3.2 Sensor malfunction detection

Developed graphical tools of monitoring systems can promote a successful exploration of abnormal sensor behaviour. In particular, different deviation plots can be applied because the deviations are very sensitive to sensor errors. However, these plots can not sometimes explain a true cause of detected abnormal fluctuations in the deviations. Additional plots like the time plot of some parallel measurements of the same variable assist to identify the problem. For special cases theoretical analysis can also be applied to make clear the origin of the fluctuations. Some examples of sensor malfunctions revealed by the described graphical tools are given below.

It was found in (Loboda & Santiago, 2001) that great outliers δ_3 at the end of the analysed time interval of Fig.3 are related with wrong measurement of a gas turbine inlet temperature t_{in}. As a result of numerical analysis it was found that the inlet temperature error influences

the deviations according to the following mechanism: [increasing of temperature t_{in} due to the errors] → [drop of the calculated value of a corrected rotation speed] → [reducing an inlet guide vane angle by the control system] → [gas flow decreasing and the corresponding power drop below the setting level] → [feeding the additional fuel by the control system to reach the power setting] → [the increase of gas path variables due to the compressor condition change and the regime raising] → [deviation increase]. Thus, the input temperature errors resulted in wrong control system operation and undesirable EGT increase.
Another example of input temperature sensor errors is described in (Loboda et al., 2009). It was found in the data recorded in a gas turbine driver for an electric generator. Let us call this engine GT2. Figure 4 illustrating this case presents the plots of the variables T_{in} and T_H and EGT deviations dTt. As can be seen, the T_H curve changes a little but the T_{in} curve shows frequent spikes and shifts that are synchronous with anomalies in the dTt curve. The explanation is that an abnormal increase in the variable T_{in}, which is a baseline function argument, results in a function increment for all monitored temperatures and the corresponding fall in the deviations dTt, which is about -5%. Such errors are capable to hide degradation and fault effects completely and to render useless gas turbine monitoring.

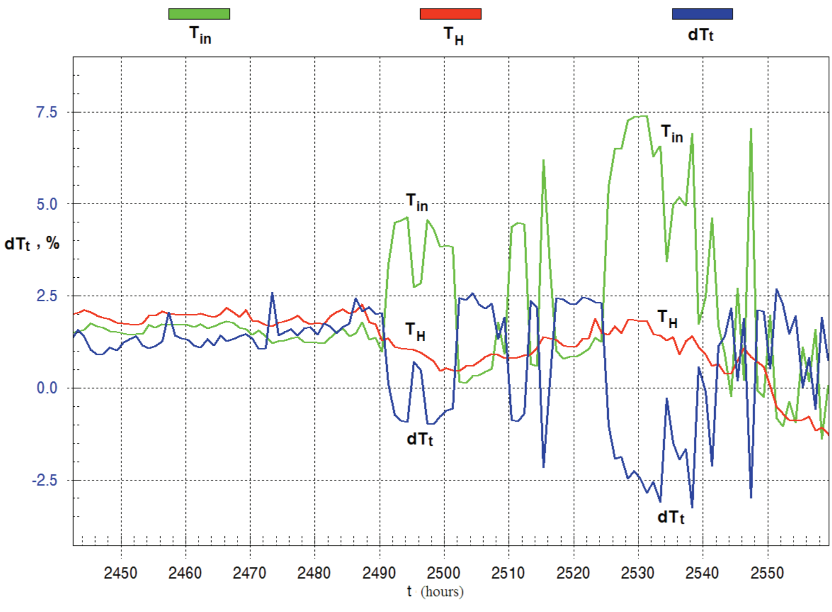


Fig. 4. GT2 inlet temperature sensor faulty operation

The next example of sensor data anomalies is related with a fuel consumption, which can be regarded as one of the most important variables for control and monitoring systems. In fuel consumption deviations dGf computed for one of the units of the GT2, an unusual decrease of approximately 7% over a prolonged period of time was found and described in (Loboda et al., 2009). Analyzing data from two other units, similar prolonged shifts in the consumption deviations were also revealed. The idea arose about a possible common cause of the consumption deviation shifts in different gas turbine units. Figure 5 helps to verify this idea. The deviations dGf are plotted here vs. a calendar time for all three units. The deviation shifts are well visible from the end of January to the beginning of April and they begin and end at the same time for different units. What reasonable explanation can there be to the puzzling fact that independent fuel consumption sensors have a common source of errors? The answer was related with a variable chemical structure of fuel gas supplied from a common source that produces synchronous fluctuations of a gas calorific value in the units.

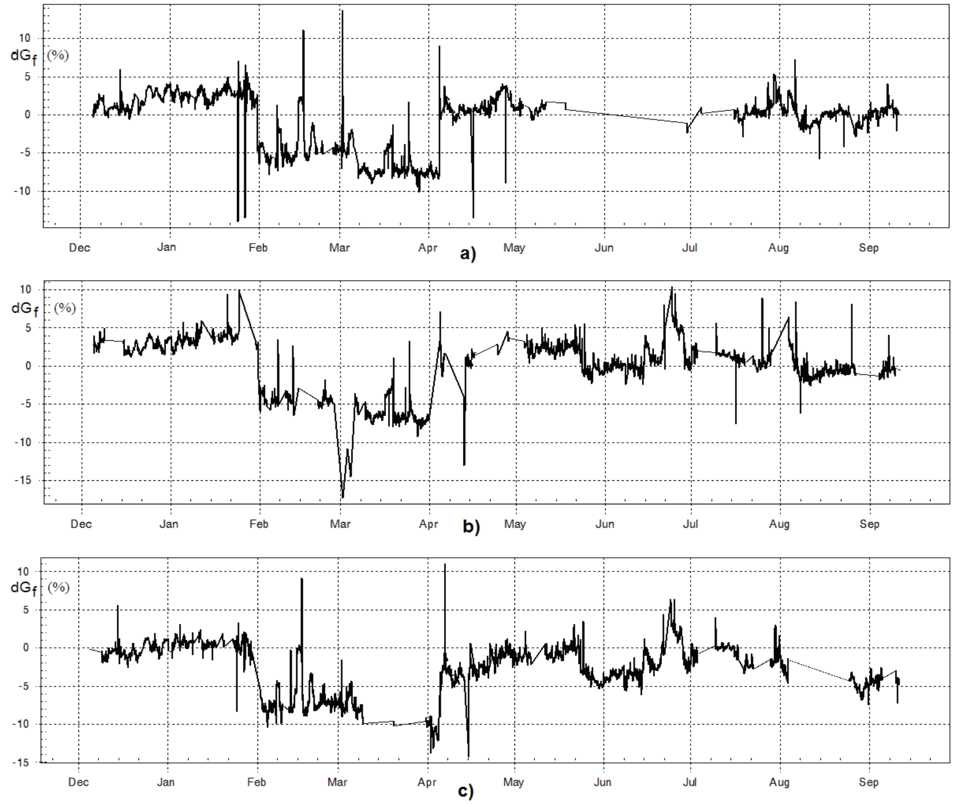
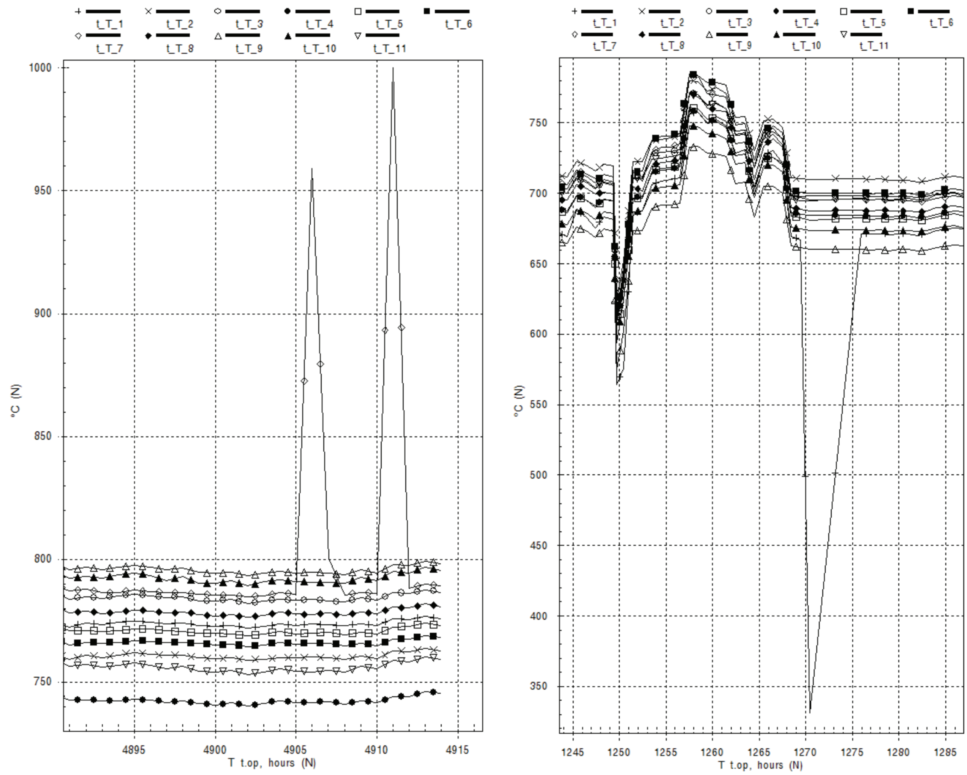


Fig. 5. Fuel consumption deviations vs. calendar time (a – unit 1, a – unit 2, a – unit 3)

The described above cases of sensor abnormal behaviour were found with the use of deviation plots. Nevertheless, parallel measurements of the same variable, for example, a suite of thermocouple probes installed in a high pressure turbine discharge station of the GT2, can also be useful to detect sensor problems. Although the thermocouple data were filtered and averaged before recording, some cases of single thermocouple probe faults have been found. Graphs (a) and (b) in Fig. 6 illustrate them. Observing two 25% spikes in graph (a) and a 50% spike in graph (b), we can conclude with no doubt that they are results of probe faults. Opposite spike directions in the graphs probably indicate different thermocouple fault origins. The outliers are well visible in the figure and the used filtering algorithm should be modified to exclude them.



a) b)

Fig. 6. EGT probes' errors: a – single gross errors, unit 1; b – a single gross error, unit 3

In this way, the deviation quality can be enhanced by the sensor malfunction detection and data cleaning from wrong data. The next mode to improve deviations is to make the baseline model as adequate as possible.

3.3 Baseline model improvement

The baseline model adequacy considerably depends on the learning set but the problem to compose a proper set for model determination seems to be challenging. On the one hand, to satisfy approximation requirements, the learning set must incorporate extensive data collected at all possible operating conditions. On the other hand, a technological process requires certain gas turbine power and does not allow arbitrary changes of an operating point. Moreover, data collection period is limited by a short time when a gas turbine condition can be considered as healthy and invariable. As a result, the baseline model is not adequate at the operating conditions not presented in the learning set. Two described below methods overcome mentioned difficulties. In the first method, the thermodynamic model is applied.

To demonstrate the possibility and advantages of the baseline model created on the basis of the thermodynamic model (see Loboda et al., 2004), two learning set variations are formed.

Variation 1. The learning set is created from 694 consecutive recorded operating points of the

GT1. As can be seen in the Fig.7a, the learning set points occupy only two limited zones of the operating space "G_f - n_{PT} - T_H" (n_{PT} denotes power turbine rotation speed). To overcome this obstacle, it is suggested to apply the thermodynamic model for learning set generation.
Variation 2. The learning sample includes 270 operating points generated by the thermodynamic model. With the help of Fig.7b one can see the advantages of such a model based learning set: the points are uniformly distributed in a much greater zone than in the case of real data.
On the basis of the described data sets two corresponding polynomial baseline models have been calculated as explained in section 2.2. The deviations were computed then for each model and with the same real data that are shown in Fig.3. Figure 8 illustrates these two series of the EGT deviations and helps to compare two concerned modes to calculate the baseline model. As can be seen, the model based learning set allow computing the deviations with notably lower errors. Thus, the use of the thermodynamic model can be recommended.

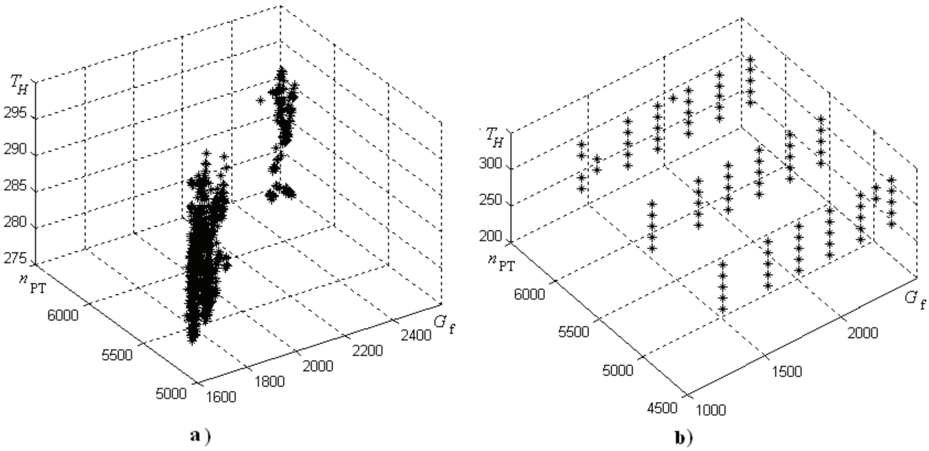
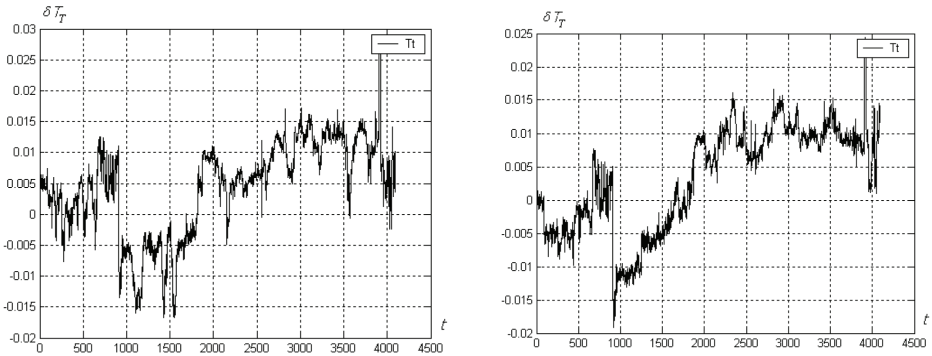


Fig. 7. Learning set points (a – real data; b – thermodynamic model data)



a) b)

Fig. 8. EGT deviations (a – data based learning set; b – model based learning set)

The second method overcoming the learning set difficulties is related with a degraded engine model (Loboda et al., 2009), from which the necessary baseline model can be derived. Since a compressor fouling severity depends on the engine operation time $\overline{t}$ after the last washing, it is natural to add this variable to the arguments of the baseline function (7) in order to describe a degraded engine. Consequently, the degraded engine model can be given by

$$Y(\vec{U}_m, t) = Y_0(\vec{U}_m) + c_{15}\overline{t} + c_{16}\overline{t}^2 . \quad (14)$$

Once computed, such model can be easily transformed into the necessary baseline model by putting $\overline{t}$ equal to zero. Since model (14) takes into consideration a varying deterioration level, all recorded data could be used to compute unknown coefficients.

To examine the idea, the data recorded in unit 1 of the GT2 during the second and third periods of fouling (1800 points in total) have been included in the learning set. With the baseline model found in this way, the deviations were computed then for all available unit 1 data and considerable deviation enhancement was achieved.

The method can be further improved. To that end, for each analyzed fouling period a particular model of a degraded engine is computed using all data recorded during the period. The resulting baseline model is then determined by averaging the particular baseline functions. Traditional and new methods for baseline model formation are illustrated in Fig.9. One can see significant deviation improvement provided by the new method. Consequently, the idea of a degraded engine model seems to be promising for computing the deviations in practice.

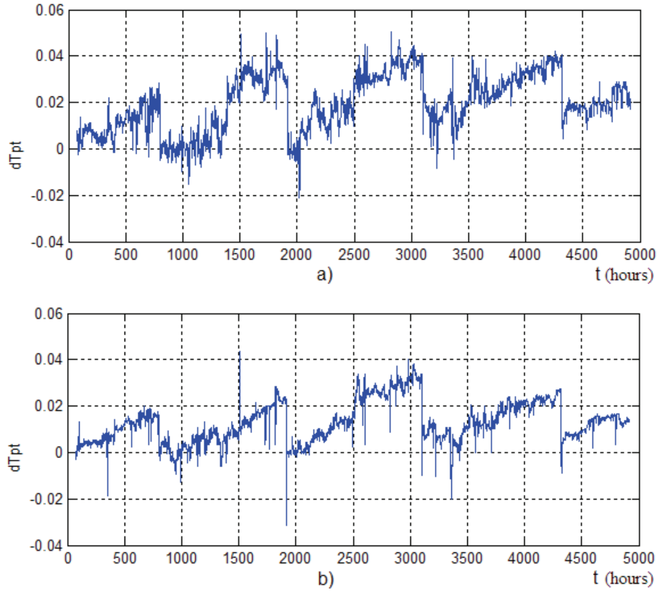


Fig. 9. Unit 1 power turbine temperature deviations for two methods of baseline model computation (a - model determined with 200 successive operating points, b - averaged model with the use of a time variable)

Choosing the best baseline function arguments (Loboda et al., 2004) can also improve the deviations. Unlike a real engine, the baseline model allows to change parameters setting an operating point (function arguments). This gives the possibility to examine all measured variables as such parameters. The numeric experiment has been conducted with the GT1 real data included 2608 operating points. The results are given in Table 1, which contains averaged errors of each deviation and their mean number presented for all possible arguments and ranged according to this mean number. At the first glance, the variable n_{hp} of high pressure rotor speed measured with high accuracy could be the best argument. However, it can be seen from the table that the parameters n_{hp} and G_f are situated in the lower part of the table while the parameter T_T occupies the first place. The explanation is that argument quality not only depends on its measurement accuracy, but also is defined by its influence on the gas turbine behaviour which is great for the parameter n_{hp}.

Argu-ment	Deviations								
	T_T	T_{PT}	P_C	P_T	G_f	T_C	n_{hp}	N_e	mean
T_T	-	0.12	0.07	0.08	0.13	0.12	0.39	0.17	0.108
T_{PT}	0.18	-	0.11	0.11	0.17	0.11	0.13	0.15	0.127
P_C	0.08	0.08	-	0.66	0.18	0.45	0.17	1.20	0.141
P_T	0.09	0.08	0.74	-	0.16	0.92	0.19	6.11	0.143
G_f	0.12	0.10	0.15	0.16	-	0.67	0.31	0.51	0.157
T_C	0.12	0.08	0.36	0.33	0.86	-	0.27	1.10	0.167
n_{hp}	0.35	0.14	0.19	0.21	0.36	0.26	-	0.29	0.216
N_e	0.17	0.11	1.42	1.69	1.01	1.41	0.25	-	0.224

Table 1. Deviation errors for different arguments

In all described above methods improving the baseline model, polynomials and the least square method have successfully been applied. The resulting model adequacy was sufficient for reliable monitoring gas turbine deterioration effects. Nevertheless, artificial neural networks are also famous as good function approximators in many fields including gas turbine monitoring. Investigations report wide use of artificial neural networks as a tool to describe an engine baseline, for example, for a stationary gas turbine (Fast et al., 2009) and an aircraft engine (Volponi et al., 2007).

The growing network application in gas turbine monitoring on the one hand and, on the other hand, our own positive experience with the use of polynomials have encouraged us to conduct a thorough comparative study of these two techniques. The paper (Loboda & Feldshteyn, 2010) verifies whether the application of such a powerful modelling tool as artificial neural networks (ANN) instead of polynomials yields higher adequacy of the baseline model and better quality of the corresponding deviations. The variety of analyzed neural network structures were considered and extensive field data of two different gas turbines were involved to compute and validate both techniques in order to draw sound conclusions on the network applicability to approximate healthy engine performance. In a part of the considered cases, polynomials were better in accuracy and, in the other cases the compared techniques were practically equal. However, no manifestations of network superiority were detected. Thus, this study shows that a polynomial baseline model can be successfully used in real monitoring systems instead of neural networks. At least, it seems to be true for simple cycle gas turbines with gradually changed performance, like the turbines considered in the study.

Concluding section 3, we would like to note that the considered here stage of data validation and computing deviations has received increased attention because this preliminary stage has utmost importance for subsequent general stages of a total diagnostic analysis. Among these stages, detailed diagnosis or fault identifications can be considered as a principal stage and it is addressed in the most of studies in the area of gas turbine diagnostics. A considerable part of these studies are based on the pattern recognition theory.

4. Diagnosis by pattern recognition methods

4.1 Technical approach to diagnosis at steady states

As mentioned in sections 2 and 3, models are used in gas turbine diagnostics to describe engine performance degradation and faults and the deviations are employed to reveal the degradation influence. That is why, a fault classification necessary to apply pattern recognition methods is usually constructed in a deviation space using nonlinear or linear static models.

Employing the nonlinear model, the normalized deviations induced by a change $\Delta\vec{\Theta}$ in fault parameters can be written as

$$Z_i = \frac{Y_i(\vec{U},\vec{\Theta}_0+\Delta\vec{\Theta}) - Y_i(\vec{U},\vec{\Theta}_0)}{Y_i(\vec{U},\vec{\Theta}_0)a_{Yi}} + \varepsilon_i, i = 1,m \,, \tag{15}$$

where coefficients a_{Yi} are employed to normalize deviations. In expression (15) amplitudes of random errors ε_i are equal to one for all monitored variables Y_i. Such normalization simplifies fault class description and enhances diagnosis reliability. The deviation vector $\vec{Z}^*$ is considered as a pattern to be recognized and a fault classification is presented as a set of such patterns.

Engine faults vary considerably. Hence, for the purposes of engine diagnostics this variety has to be broken down into a limited number of classes. In the pattern recognition theory, it is often supposed that an object state *D* can belong only to one of *q* preset classes

$$D_1, D_2, ..., D_q \,. \tag{16}$$

We accept this hypothesis for a gas turbine fault classification. It is also assumed that each class corresponds to one engine component and is described by the correction factors of this component. Two types of classes are simulated: a single fault class and a multiple one. The single fault class is formed by changing one fault parameter. The multiple fault class has two independently changed parameters for the same component, namely, a flow parameter ΔA and an efficiency parameter $\Delta\eta$.

Each class is given by a representative sample of the deviation vectors $\vec{Z}^*$ computed according to expression (15). During the calculations a variable fault severity is determined by a uniform distribution and errors are generated according to a normal distribution. The whole classification is a composition of these samples **Z1** called a learning set.

A nomenclature of possible diagnoses $d_1, d_2, ..., d_q$ corresponds to the accepted classification (16). To make a diagnosis *d*, a method-dependent criterion $R_j = R(\vec{Z}^*, D_j)$ is introduced as a measure of membership of a current pattern $\vec{Z}^*$ to class D_j. To determine the functions $R_j = R(\vec{Z}^*, D_j)$, the learning set is used. After calculating all values R_j, j = 1,q , a decision rule

$$d = d_l \text{ if } R_l = \max(R_1, R_2, ..., R_q) \quad (17)$$

is applied.

To verify a diagnostic algorithm determined with the help of the learning set, one more set is required. The necessary set $\mathbf{Zv}$, called a validation set, is created in the same way as the set $\mathbf{Zl}$. The only difference is that other series of random numbers is generated to simulate fault severity and errors in the deviations. Every pattern in the validation set pertains to a known class. That is why, comparing this class D_j with the diagnosis d_l, we can compute probabilities $Pd_{lj} = P(d_l / D_j)$ and compose a known confusion matrix **Pd**. Its diagonal elements Pd_{ll} form a vector $\vec{P}$ of true diagnosis probabilities that are indices of classes' distinguishability. Mean number of these elements – scalar $\overline{P}$ – characterizes total engine diagnosability. No diagonal elements help to identify the causes of bad class distinguishability. These elements make up probabilities of false diagnosis $Pe_j = 1 - P_j$ and $\overline{Pe} = 1 - \overline{P}$.

Thus, the described approach to gas turbine diagnosis under stationary conditions includes the fault classification stages, formation of a diagnostic algorithm, and estimation of diagnosis reliability indices. With several small corrections this approach is also applicable for diagnosis at transients (Loboda et al., 2007). A transient interval is divided into T time points and, with measurements at these points, a generalized deviation vector is computed. It is a pattern to be recognized in diagnosis under transient conditions.

Following the presented approach, some studies have been conducted for the GT1 chosen as a test case. In these studies steady state operation is determined in the thermodynamic model by a fixed gas generator speed and standard ambient condition. Eleven full and part-load steady states are set by the following speeds: 10700, 10600, …, 9800, 9700 rpm. Six simulated gas path variables correspond to a standard measurement system of the GT1. The single type fault classification consists of nine classes, which are simulated by nine fault parameters. The multiple type classification comprises four items corresponding to four main components: an axial air compressor, a combustion chamber, a gas generator turbine, and a power turbine. The learning and validation sets include 1000 patterns for each class that are sufficient to ensure the necessary computational precision. The first conducted study (Loboda & Yepifanov, 2006) compares different recognition tools.

4.2 Comparison of recognition techniques

Three recognition techniques that present different approaches in a recognition theory have been chosen for diagnosing. The first technique is based on the Bayesian approach (Duda et al., 2001), in which each fault class D_j should be described by its probability density function $f(\vec{Z}^* / D_j)$ and a posteriori probability $P(D_j / \vec{Z}^*)$ is employed as a decision criterion. Difficulty of this method is related with the function $f(\vec{Z}^* / D_j)$ as far as density function assessment is a principal problem of mathematical statistics, that is why this function can be determined only for a simplified class description. The second technique operates with the Euclidian distance to recognize gas turbine fault classes. The criterion R_j for this technique is an inverse averaged distance between an actual pattern and all patterns of a fault class D_j. The third technique applies the neural networks, in particular, a multilayer perception.

The resulting diagnosis reliability indices – the probabilities of false diagnosis Pe_j and $\overline{Pe}$ for the multiple faults – are placed in Table 2. The given indices demonstrate that probabilities of erroneous diagnosis by methods 1 and 3 are approximately equal and significantly lower than the corresponding probabilities of method 2. The calculations for single faults have confirmed this conclusion. It is important that neural networks are not inferior in diagnosis accuracy to the Bayesian approach, because the latter in its turn is known as the best recognition technique if we use the criterion of a correct decision probability. Additionally, neural networks do not need the simplifications of the fault class description required for Bayesian approach. In this way, neural networks can be recommended for the use in real condition monitoring systems.

Neural networks will also be used in the next study. It proposes and verifies the idea of the generalized fault classification (Loboda, Yepifanov et al., 2007; Loboda & Feldshteyn, 2007) that drastically simplifies practical realization of diagnostic algorithms.

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	0.127
$\overline{P}e$		0.1256	0.1790	0.1293

Table 2. False diagnosis probabilities (multiple type classification)

4.3 Generalized fault classification

The approach presented in subsection 4.1 implies that a laborious procedure of fault classification formation is repeated for every new operating condition. It will be difficult to realise this approach in practice because an engine frequently changes its operating mode. The same problem arises for diagnosis at transients but existing works do not answer how to overcome it.

Diagnosing the considered gas turbine (GT1) at different operating modes, it has been found out that the class presentation in the diagnostic space $\vec{Z}$ is not strongly dependent on a mode change. Therefore we intended to draw up the classification that would be independent from operational conditions. This classification has been created by incorporating patterns from all 11 steady states into each class of the reference and testing sets. Such generalized classification was successively applied to diagnose at each steady state. In the classification, a region occupied by any class is more diffused that induces greater class intersection, which in its turn leads to losses in the diagnosis reliability. But how significant are these losses?

Numeric experiments with traditional and new classifications helped to quantify such losses. To ensure firm conclusions, the classification comparison was drawn for both single and multiple class types. Table 3 contains the results for the single class type. In this table, the row "Conv." means the probabilities for the conventional classification averaged over all steady states. The row "Gen." contains the probabilities for the generalized classification created for, and applied at, the same steady states. It can be noted that differences of the probabilities $\vec{P}_e$ between the considered classifications are small for the both class types. The mean probability $\overline{P}_e$ also rises just a little, by about 0.5%, in the row "Gen.". So the diagnosis reliability losses resulting from the classification generalization are insignificant.

Classification	$\vec{P}_e$									$\overline{P}_e$
	ΔA_c	$\Delta\eta_c$	ΔA_{hpt}	$\Delta\eta_{hpt}$	ΔA_{pt}	$\Delta\eta_{pt}$	$\Delta\sigma_{cc}$	$\Delta\eta_{cc}$	$\Delta\sigma_{in}$	
Conv.	0.166	0.266	0.132	0.265	0.146	0.172	0.154	0.174	0.168	0.1827
Gen.	0.156	0.275	0.131	0.269	0.148	0.190	0.161	0.184	0.180	0.1883

Table 3. Diagnosis errors for single faults (indices of fault parameters ΔA and $\Delta\eta$ mean compressor, high pressure turbine, power turbine, combustion chamber, and input device)

For additional verification of the generalized classification, the previous analysis was also carried out for real operational conditions. Two sets of 25 operating points were made up from a six-month database of gas turbine performance registration at different operational field conditions. The points of each set correspond to the maximally different conditions. The results show (Loboda, Yepifanov et al., 2007) that differences between two classifications are small and can be considered as random calculation errors. Consequently, the proposed classification does not cause additional accuracy losses. This still holds true when the classification is used at the operating points different from the points of classification formation. So, the generalized classification can be applied not only to the steady state points used for its creation but also to any other points.

The principle of a generalized classification was also examined for transient operations. In (Loboda, Yepifanov et al., 2007) the examination is conducted at 16 transients with different transient profiles and ambient temperatures. The resulting accuracy losses due to the classification use did not exceed 3.5%. More cases of transient operation are considered in (Loboda & Feldshteyn, 2007). The losses are estimated at the level of 2% and it is shown that they could be lower in practice.

In this way, the proposed classification principle was verified separately for steady states and transients. In both cases, the results have shown that the generalized classification practically does not reduce the diagnosis accuracy level. On the other hand, the suggested classification drastically simplifies the gas turbine diagnosis because it is formed once and used later without changes. Therefore, the diagnostic technique based on the generalized fault classification can be successfully implemented in gas turbine health monitoring systems.

The next study briefly described below also deals with networks-based diagnosis under variable operating conditions. In contrast to the previous study, the data from different operating points (modes) are grouped to set only a single diagnosis. Such multipoint diagnosis promises considerable accuracy enhancement.

4.4 Multipoint diagnosis

Although some works deal with the influence of operating conditions on the diagnostic process (Kamboukos & Mathioudakis, 2006), no full-length analyses are yet available. It is known that multipoint methods, which group the data registered at different operating points in order to make a single diagnosis, ensure higher accuracy when compared with conventional one-point (one-mode) methods. However, questions arise as to how significant this effect is and what its causes are. The diagnosis at transient operation (Ogaji et al., 2003) poses the similar questions. To make one diagnosis, this technique joins data from successive measurement sections of one transient and in this regard looks like multipoint diagnosis. From a theoretical and practical standpoint, it would be interesting to find out how much these two approaches differ in accuracy.

The investigation to answer the questions has been conducted in (Loboda, Feldshteyn et al., 2007) for the GT1 and an aircraft engine, called GT3. The following conclusions were drawn. First, a total diagnosis accuracy growth due to switching to the multipoint diagnosis and data joining from different steady states is significant. It corresponds to a decrease in the diagnosis errors by 2-5 times. Second, the main effect of the data joining consists in an averaging of the input data and smoothing of the random measurement errors. It is responsible for the main part of the total accuracy growth. If variations in fault description at different operating points are slight as for the GT1, the averaging effect is responsible for the whole growth. Under these conditions, the generalized classification has a certain advantage as compared to the conventional one-point diagnosis. Third, if the variations are considerable (GT3), they give new information for the fault description and produce an additional accuracy growth for the multipoint option. This part depends on the class type but in any case it is essentially smaller than the principal part. The diagnosis at transients may cause further accuracy growth of this type. However, it will be limited and the averaging effect will be a principal part of the total accuracy growth relative to the one-point diagnosis.

We complete here the descriptions of the studies in the area of diagnosis (fault identification) based on pattern recognition. In the next section it will be shown how to extend the described approach on the problem of gas turbine monitoring (fault detection).

5. Integrated monitoring and diagnosis

Detection algorithms deal with two classes, a class of healthy engines and a class of faulty engines. In multidimensional space of the deviations they are divided by a healthy class boundary (internal boundary). The healthy class implies that small deviations due to usual engine performance degradation can certainly take place, although they are not well distinguishable against a background of random measurement and registration errors. The faulty class requires one more boundary, namely, faulty class boundary (external boundary) that means an engine failure or unacceptable maintenance costs.

Classification (16), created for the purpose of diagnosis and presented by the learning set, corresponds to a hypothetical fleet of engines with different faults of variable severity. To form a new classification necessary for monitoring, we suppose that the engine fleet, the distributions of faults, and their severities are the same. Hence, patterns of the existing learning set can be used for a new classification but the classes should be reconstructed. The paper (Loboda et al., 2008) thoroughly investigates such approach considering monitoring and diagnosis as one integrated process. Below we only give a brief approach description and the most important observations made.

Each former class D_j is divided into two subclasses $DM1_j$ and $DM2_j$ by the healthy class boundary. There is an intersection between the patterns $\vec{Z}^*$ of these subclasses because of the errors ε in patterns. A totality of subclasses

$$DM1_1, DM1_2, \ldots, DM1_q \tag{17}$$

constitutes the classification of incipient faults for the diagnosis of healthy engines, while subclasses

$$DM2_1, DM2_2, \ldots, DM2_q \tag{18}$$

form the classification of developed faults for the diagnosis of faulty engines.
To perform the monitoring, the subclasses $DM1_1$, $DM1_2$, …, $DM1_q$ compose a healthy engine class M_1, while the subclasses $DM2_1$, $DM2_2$, …, $DM2_q$ make up a faulty engine class M_2. Thus, the classification for monitoring takes the form of

$$M_1, M_2. \tag{19}$$

It is clear that the patterns of these two classes are intersected, resulting in α- and β-errors.
Figure 10 provides a geometrical interpretation of the preceding explanations. The former and the new classifications are presented here in the space of deviations Z_1 and Z_2. A point "O" means a baseline engine; lines OD_1, OD_2, …, and OD_q are trajectories of fault severity growth for the corresponding single classes; closed lines B1 and B2 present boundaries of a healthy class M_1 (indicated in green) and faulty class M_2 (indicated in yellow).

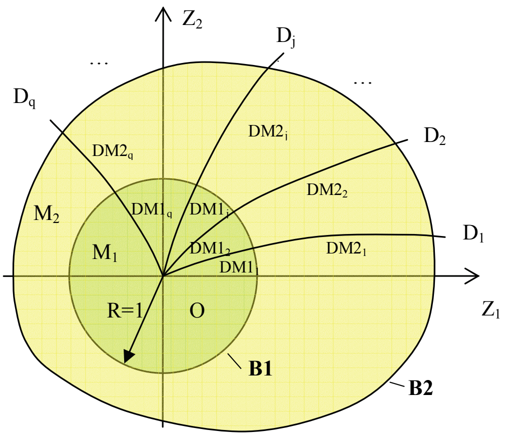


Fig. 10. Schematic class representation for integrated monitoring and diagnosis

With these three classifications, monitoring accuracy and diagnosis accuracy were estimated separately for healthy and faulty classes and some useful results were obtained. First, the recognition of incipient faults was found to be possible and advisable before a gas turbine is recognized as faulty by fault detection algorithms. Second, the influence of the boundary on the monitoring and diagnosis accuracy was also investigated. Third, it has been shown that the introduction of an additional threshold, which is different from the boundary, can reduce monitoring errors. Fourth, it was demonstrated that a geometrical criterion, which is much simpler in application than neural networks, can provide the same results and thus can also be used in real monitoring systems.
The pattern recognition-based approach considered in this section is not however without its limitations. The diagnoses made are limited by a rigid classification and fault severity is not estimated. The second approach maintained in gas turbine diagnostics and based on system identification techniques can overcome these difficulties.

6. Diagnosis by system identification methods

This approach is based on the identification techniques of the models (1), (2) or (4). These techniques compute estimates $\hat{\vec{\Theta}}$ as a result of distance minimization between simulated and measured gas path variables. In the case of model (1) this minimization problem can be written as

$$\hat{\vec{\Theta}} = \arg\min \left\| \vec{Y}^{*} - \vec{Y}(\vec{U},\vec{\Theta}) \right\| . \tag{20}$$

It is an inverse problem while a direct problem is to compute $\vec{Y}$ with use of known $\vec{\Theta}$. The estimates contain information on the current technical state of each engine component therefore further diagnostic actions will be simple. Furthermore, the diagnosis will not be constrained by a limited number of determined beforehand classes.

Among system identification methods applied to gas turbine diagnostics, the Kalman filter, basic, extended, or hybrid, is mostly used, see, for example (Volponi et al., 2003). However, this method uses a linear model that, as shown in (Kamboukos & Mathioudakis, 2005), can result in considerable estimation errors. Moreover, every Kalman filter estimation depends on previous ones. That is why abrupt faults are detected with a delay.

Other computational scheme is maintained in (Loboda, 2007). Independent estimations are obtained by a special inverse procedure. Then, with data recorded over a prolonged period, successive independent estimation are computed and analyzed in time to get more accurate results.

Following this scheme, a regularizing identification procedure is proposed and verified on simulated and real data in (Loboda et al., 2005). The testing on simulated data has shown that the regularization of the estimated state parameters makes the identification procedure more stable and reduces an estimation scatter. On the other hand, the regularization shifts mean values of the estimations and should be applied carefully. In the conditions of fulfilled calculations, the values 0.02-0.03 of the regularization parameter were recommended. The application of the proposed procedure on real data has justified that the regularization of the estimations can enhance their diagnostic value.

Next diagnostic development of the gas turbine identification is presented in (Loboda, 2007). The idea is proposed to develop on the basis of the thermodynamic model a new model that takes gradual engine performance degradation in consideration. Like the polynomial model of a degraded engine described in section 3.3, such a model has an additional argument, time variable, and can be identified on registered data of great volume. If we put the time variable equal to zero, the model will be transformed into a good baseline function for diagnostic algorithms. Two purposes are achieved by such model identification. The first purpose consists in creating the model of a gradually degraded engine while the second is to have a baseline function of high accuracy. The idea is verified on maintenance data of the GT1. Comparison of the modified identification procedure with the original one has shown that the proposed identification mode has better properties. The obtained model taking into account variable gas path deterioration can be successfully used in gas turbine diagnostics and prognostics. Moreover, this model can be easily converted into a baseline model of a high quality. Such a model can be widely used in monitoring systems as well.

Another novel way to get more diagnostic information from the estimations is to identify a gas turbine at transients as shown in (Loboda & Hernandez Gonzalez, 2002). However, this paper is only the first study, which needs to be continued.

7. Conclusions

In this chapter, we tried to introduce the reader into the area of engine health monitoring. The chapter contains the basis of gas turbine monitoring and a brief overview of the applied mathematical techniques as well as provides new solutions for diagnostic problems. In order to draw sound conclusions, the presented studies were conducted with the use of extended field data and different models of three different gas turbines.

The chapter pays special attention to a preliminary stage of data validation and computing deviations because the success of all subsequent diagnostic stages of fault detection, fault identification, and prognostics strongly depends on deviation quality. To enhance the quality, the cases of abnormal sensor data are examined and error sources are identified. Different modes to improve a baseline model for computing the deviations are also proposed and justified.

On the basis of pattern recognition, the chapter considers monitoring and diagnostic stages as one united process. It is shown that the introduction of an additional threshold, which is different from the boundary between healthy and faulty classes, reduces monitoring errors.

Many improvements are proposed, investigated, and confirmed for fault diagnosis by pattern recognition and system identification methods, in particular, generalized fault classification, regularized nonlinear model identification procedure, and model of a degraded engine.

We hope that the observations made in this chapter and the recommendations drawn will help to design and rapidly tailor new gas turbine health monitoring systems.

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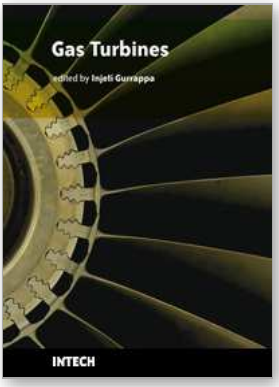

Gas Turbines

Edited by Gurrappa Injeti

ISBN 978-953-307-146-6

Hard cover, 364 pages

Publisher Sciyo

Published online 27, September, 2010

Published in print edition September, 2010

This book is intended to provide valuable information for the analysis and design of various gas turbine engines for different applications. The target audience for this book is design, maintenance, materials, aerospace and mechanical engineers. The design and maintenance engineers in the gas turbine and aircraft industry will benefit immensely from the integration and system discussions in the book. The chapters are of high relevance and interest to manufacturers, researchers and academicians as well.