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GAS TURBINE DIAGNOSABILITY AT VARYING OPERATING POINTS

The parametric diagnostics of gas turbine engines has been improved in the last decades due to computer technology development and better analysis methods such as artificial neural networks. It has demonstrated to be a very powerful tool providing an insight into an actual engine health condition and predicting possible future failures. On the basis of a thermodynamic model that relates monitored variables with operating conditions and fault parameters, it is possible to obtain healthy and faulted engine performances. This model allows calculating deviations between actual and baseline engine performances. Based on the deviations computed for all monitored variables, the diagnosis is made by pattern recognition techniques. These deviations include errors due to measurement uncertainty and model inadequacy. Since an engine operating point changes, the deviation errors change as well, resulting in varying diagnostic inaccuracy. In the present paper, two hypotheses on how the errors influence engine diagnosability at varying operating points are first investigated on simulated data and then verified with real information.

Key words: *gas turbine, parametric diagnostics, thermodynamic model, deviation errors.*

Introduction

Since the beginning of their practical application in the decade of the 1940's, gas turbine engines (GTE) have proven to be very powerful machines. In the last decades, the development of GTE has increased to inconceivable limits and its usage has extended to various areas such as civil and military aviation, electric energy generation, natural gas compression, and propulsion for land and maritime vehicles [1-3].

GTE are quite complex machines with very high operation parameters like temperature, pressure, and rotation speed and improper maintenance can provoke a catastrophic event. Because of these reasons, condition monitoring systems for GTE are extensively used. These systems are capable to monitor actual condition of the engine, identify the kind and place of a possible fault, predict its possible changes, and therefore reduce the risk and the economic impact of a serious failure or an unexpected engine stoppage [4].

The condition monitoring systems should use all the available information of a diagnosed GTE to cover the majority of its components and systems. Actually, the diagnostic techniques embrace all the primary systems of GTE, such as gas path, transmission, measurement system, fuel system, oil system, starting system, variable geometry systems, etc. Among all these techniques, the algorithms of parametric diagnostics that analyze gas path variables can be considered as essential. They provide a deep vision about the performance of the engine components and they also reveal different mechanisms of degradation. Besides the wear and faults in the gas path, these techniques can also detect malfunctioning of the engine measurement systems.

The gas path diagnostics embraces three mayor components: monitoring of the engine conditions, detailed diagnostics, and prognostic of the remaining life of the engine. The possible faults alter the monitored gas path variables but engine operating conditions (variables that determine the engine regime and ambient conditions) have a higher impact. For this reason, the three components are preceded by a preliminary phase where deviations, between actual and baseline values of the monitored variables are computed. These deviations will be explained in detail further in this paper.

The deviations are computed with random errors and measurement inaccuracy is one of their sources. Since final diagnostic reliability depends on the deviation accuracy and a gas turbine engine should be diagnosed at varying operating conditions, it is of practical interest to reveal how these conditions influence the deviation accuracy. Some investigations accept the hypothesis that the measurement random errors are constant for all engine operating points. In this case, as deviations and their errors have a relative form, the deviation errors increase when the engine descends and all variables go down.

In contrast, in basis of the analysis of real data-based deviations, we consider that their errors do not practically depend on operating points [10]. This is partly explained by the fact that, apart from measurement errors, the deviations have other and greater error components [5, 9].

On the basis of a gas path model, this paper analyses the influence of operating points on diagnostic reliability for both described error hypotheses. Additionally, using real data-based deviations, the paper tries to answer what the hypothesis is most likely.

The paper is structured as follows. A detailed explanation of the gas path model is presented in Section 1. Next, Section 2 summarizes the approach to fault recognition by a detailed description of the diagnostics process. Then, Section 3 describes in more details the two error hypotheses and their influence on diagnostic reliability. The hypotheses are verified on real data in Section 4. Finally, Section 5 presents a discussion of the results obtained.

1. Gas Path Model

A thermodynamic model of GTE can afford a lot of information useful for diagnostics that would be very difficult to obtain from a real engine. It is called thermodynamic because in basis of the thermodynamic laws, the model calculates the variables in the gas path from the air inlet until the output. The model determines how monitored gas path variables $\vec{Y}$ depend on engine operating conditions $\vec{U}$ (control variables such as rotation speed or fuel consumption and ambient conditions: air pressure and temperature). In the other hand, this model can simulate the degradation of each component of the engine. The vector of state parameters $\vec{\theta} = \vec{\theta}_0 + \vec{\Delta\theta}$ is included for describing an engine health condition. A vector $\vec{\theta}_0$ corresponds to an engine normal state, while a vector of fault parameters $\vec{\Delta\theta}$ shifts a little the performance maps of engine components (compressor, combustion chamber, turbine, etc.) and in this way allow simulating different deterioration mechanisms and faults. Thus, the structure of the thermodynamic model, which can be characterized as nonlinear and component-based, can be given by the following formula

$$\vec{Y} = F(\vec{U}, \vec{\theta}) . \quad (1)$$

From a mathematical standpoint, model (1) is a result of solving a system of nonlinear algebraic equations reflecting engine operation at steady states.

2. Diagnostic Approach

If a vector $\vec{\theta}_0$ corresponds to a healthy engine, a baseline model can be presented by an expression

$$\vec{Y}_0 = F(\vec{U}, \vec{\theta}_0) = F(\vec{U}) . \quad (2)$$

Using the thermodynamic model as a baseline, we can calculate for every monitored variable the relative change (deviation)

$$\delta Y_i = \frac{Y_i - Y_{0i}}{Y_{0i}} \quad (3)$$

between an actual value Y_i and a baseline value Y_{0i}.

The deviations are practically free of an influence of operating conditions and may serve as good GTE degradation indicators. That is why they are used for detection, diagnosis, and failure prediction [6-8]. To make the fault simulation process more realistic, random errors $\varepsilon\delta Y_i$ are included to the simulated deviations. The total deviation δY_i^* is presented for each monitored variable Y_i as:

$$\delta Y_i^* = \delta Y_i + \varepsilon\delta Y_i . \quad (4)$$

The random error $\varepsilon\delta Y_i$ for each variable has its own amplitude $a_{\delta Yi}$. This error has a normal distribution and 99.7% of its values are inside the interval $\left[-a_{\delta Yi}, +a_{\delta Yi}\right]$. To diagnose the engine in a uniform space, to simplify the description of the faults, and improve the diagnostic reliability, this deviations are normalized as follows:

$$Z_i^* = \frac{\delta Y_i}{a_{\delta Yi}} + \frac{\varepsilon\delta Y_i}{a_{\delta Yi}} = Z_i + \varepsilon_{Zi} . \quad (5)$$

The errors ε_{Zi} are generated randomly for all monitored variables according to the multidimensional normal distribution.

The deviations Z_i^* of all monitored variables form the vector $\vec{Z}^*$, that is considered a pattern. The fault classification will be presented on the basis of these patterns.

The GTE faults vary considerably and for the purposes of diagnosis, numerous gas turbine faults are divided into a limited number q of classes $D_1, D_2, ..., D_q$. Each class corresponds to one engine module and is described by its fault parameters $\vec{\Delta\theta}$.

Each class is determined by a representative sample of the deviation vector $\vec{Z}^*$, obtained in basis of expression (5). A totality $Z1$ of all classification's patterns is employed to train the used neural network, multilayer perceptron and is therefore called a learning set. It is illustrated by figure 1.

Afterwards, to validate the network, an additional data simple called a validation set $Z2$ is created in the same way as the learning set $Z1$. The only difference between these sets is that another random numbers are generated for the validation set. The network classifies each pattern of the set $Z2$ producing the diagnosis d_k. Comparing d_k with a known class D_j for all validation set patterns, probabilities of correct classification $\vec{P}$ are estimated for all fault classes. A mean value $\overline{P}$ of these probabilities characterizes engine diagnosis reliability (diagnosability).

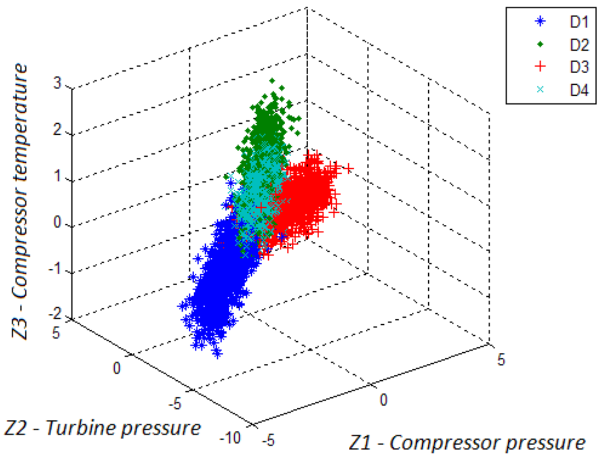

Fig. 1. Fault classification representation by patterns

3. Influence of operating points

Since the GTE monitored variables (pressures, temperatures, rotation speeds, etc.) strongly depend on an operating point, deviation errors can depend as well. Therefore, it is practically important to determine what happens with the engine diagnosability when the operating point changes.

As shown in [5, 9], there are four main sources of errors that affect the deviations. The first source of error is caused by measurement errors $(\varepsilon \vec{Y})$ in the monitored and registered variables. Second source of inaccuracy is the error $(\varepsilon \vec{U}_m)$ of the measured operating variables which are baseline function arguments. The third source is explained by the fact that the baseline function arguments do not include some variables (air moisture, valves positions, etc) that influence a real engine. The fourth (last) source of error is the inadequacy of the baseline function caused by some factors like algorithm and data sample for determining the baseline function in real conditions. All these error sources have a high impact on the final deviations.

In this section, we will focus our efforts in understanding the effects of the first source of error on the diagnosability at different operating points. To this end, eleven operating points given by successive reduction of a compressor rotor speed are analyzed. Point 1 (engine maximum power) is set by the rotation speed 10700 rpm and the speed decreases until 9700 rpm for point 11.

For the purpose of a better analysis, the deviation error from equation (4) can be expressed as a relative error

$$\varepsilon\delta Y = \frac{\Delta\varepsilon}{Y_0}, \tag{6}$$

where $\Delta\varepsilon$ is an absolute error.

Using this expression, we will analyze two schemes of error change along with the operating point.

The first scheme implies that the relative error $\varepsilon\,\delta\vec{Y}$ does not depend on the operating point i.e. it is constant for all points. Figure 2 illustrating this scheme shows the behavior of a monitored variable Y and its errors $\Delta\varepsilon$ and $\varepsilon\delta Y$ for the eleven analyzed regimes. As can be seen, when the relative error $\varepsilon\delta Y$ is constant, the absolute measurement error $\Delta\varepsilon$ reduces along with reduction of a monitored variable.

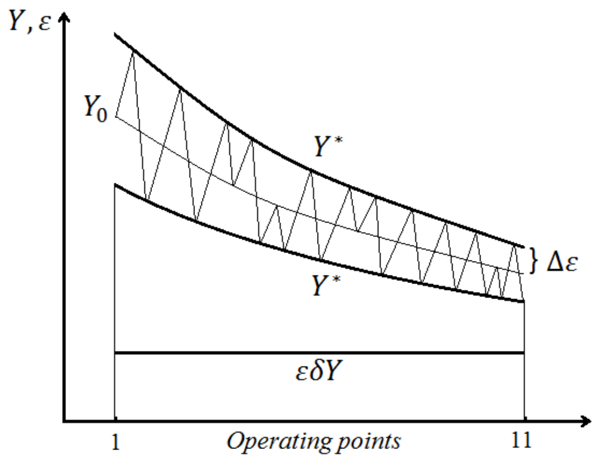

Fig. 2. Constant relative error scheme

The second scheme means that the absolute measurement error $\Delta\varepsilon$ is constant. Figure 3 illustrates this scheme using the same format as figure 2. It can be seen here and follows from equation 2 that the relative error $\varepsilon\delta Y$ increases when the absolute error is constant.

Summing up the analysis of figures 2 and 3, it can be concluded that the analyzed schemes result in significantly different errors at varying operating point. Consequently, using an improper error scheme can result in incorrect deviations and diagnostic inaccuracy. Let us now assess how significant this inaccuracy can be.

Using the two errors schemes, the respective resulting probabilities $\overline{P}$ were obtained. They are shown in figure 4 against the operating points. One can see here that the probabilities corresponding to the error schemes differ a lot. In this way it is of great importance to know what scheme takes place in reality.

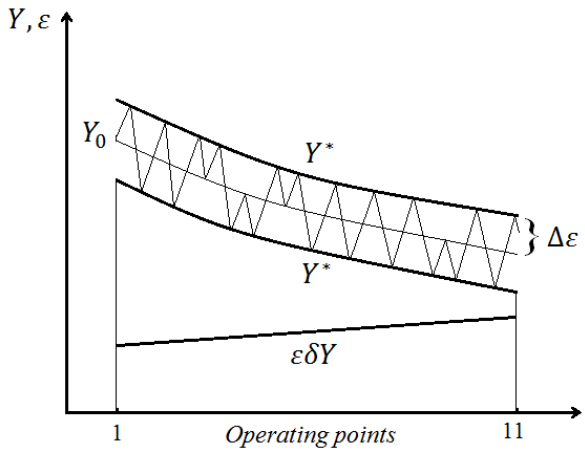

Fig. 3. Constant absolute error scheme

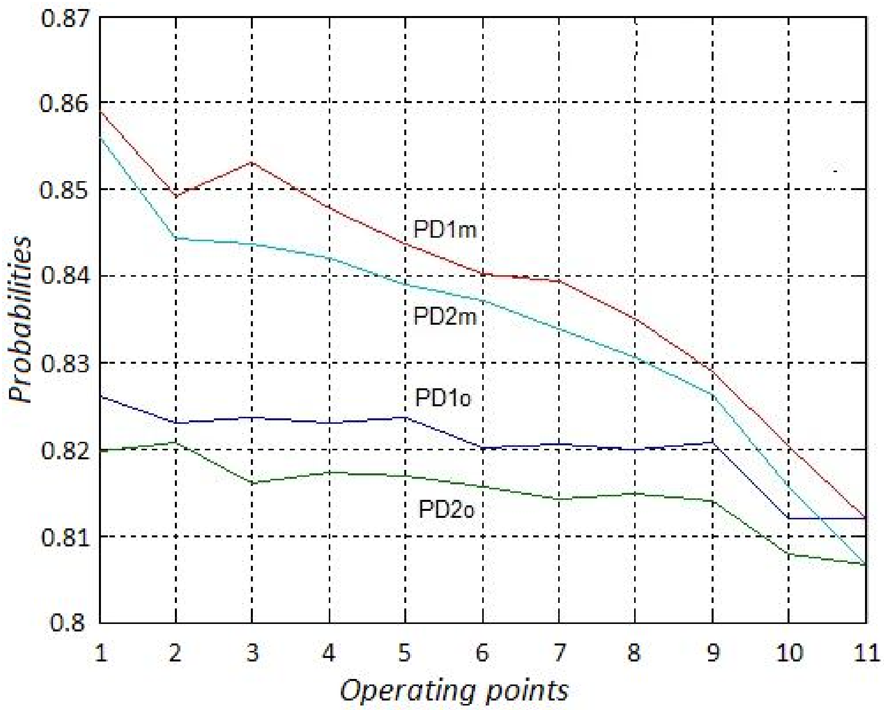

Fig. 4. Behavior of the probabilities:
PD1o – Constant relative errors, learning set;
PD2o – Constant relative errors, validation set;
PD1m – Constant absolute errors, learning set;
PD2m – Constant absolute errors, validation set

4. Real Data

Now, when we have revealed great influence of the deviation error scheme on the diagnostic reliability, it is important to find out how this error really changes due to operating conditions and what error scheme is more probable. To solve this issue, the present section uses deviations calculated on basis of real data.

Real data-based deviations have been computed for a two shaft free turbine engine for driving a natural gas centrifugal compressor. Its monitored variables were recorded every hour under field conditions.

Figure 5 illustrates the deviations of the exhaust gas temperature presented versus operation time. We can clearly see systematic tendencies: two periods of compressor fouling divided by the point of washing that recovers the temperature. However, random errors are also seen in the deviation plot presented.

Given the computed deviations, their errors have been determined using a degraded engine model as described in [7]. Figure 6 shows the deviation errors of the same exhaust gas temperature versus the operation time.

The aforementioned degraded engine mode was identified by the least square method using first 2608 data points. That is why the errors computed in this interval are minimal and more accurate. From here we will analyze only the errors of this interval. They are plotted in a greater scale in figure 7.

When an engine operating point goes down, all the monitored variables decrease as well. In this way an absolute variable value shows how high or low the corresponding operating point is. Therefore, to see the influence of the operating point, we can plot the same variable deviation as before, but now versus the monitored variable itself. Such a plot is given in figure 8. As can be seen, an error spread is practically the same for low and high temperatures, in other words, the deviation error does not practically depend on operating points.

The same error distributions plotted for all other monitored variables are given in figure 1A of Appendix I. Observing these plots, one can arrive to the same conclusion: in general, the hypothesis of the deviation errors independent on an operating point seems to be much more probable then the hypothesis of higher errors for low operating points.

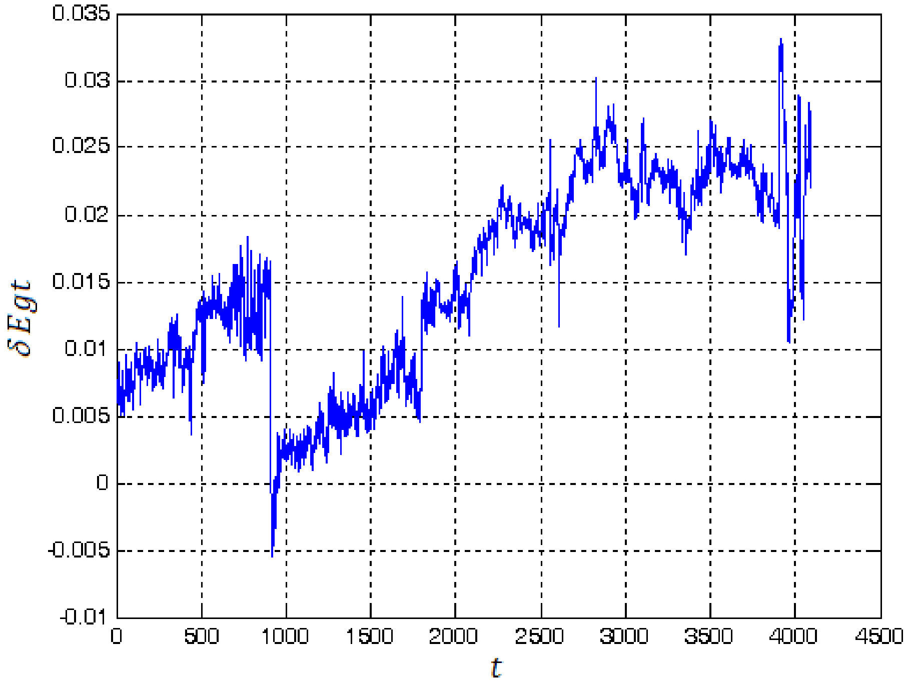

Fig. 5. Engine performance degradation due to compressor fouling (exhaust gas temperature deviation)

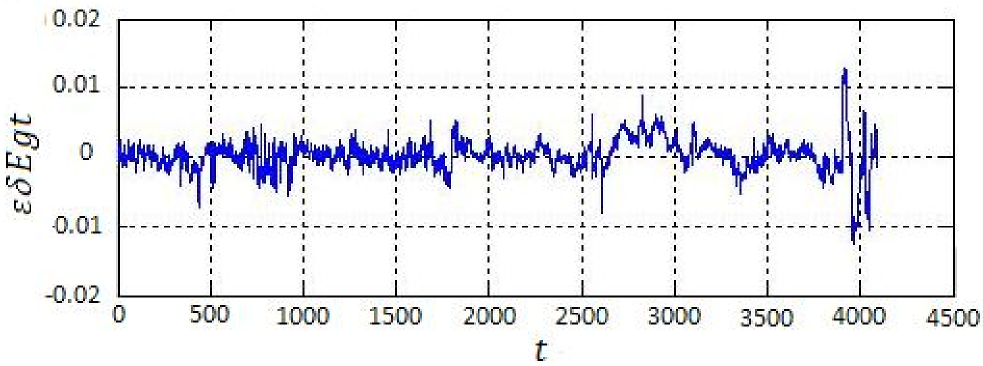

Fig. 6. Errors of the exhaust gas temperature deviation (whole time interval)

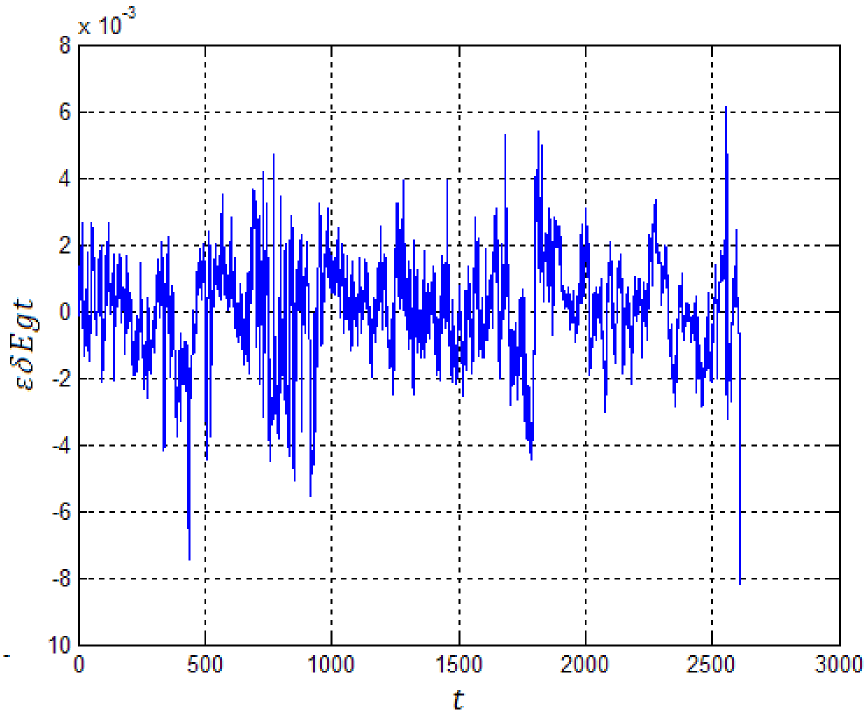

Fig. 7. Deviation errors vs. operation time (first 2608 data points)

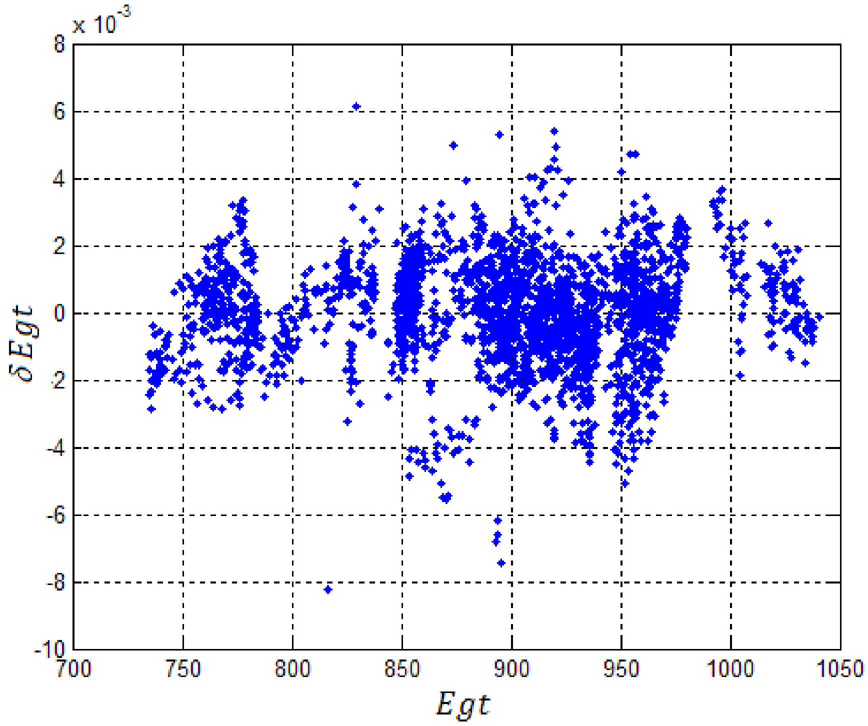

Fig.8. Deviation errors vs. monitored variable

Discussion

Clearly, the selection of a proper hypothesis on deviation error distribution will allow us to simulate the diagnostic process with greater exactitude.

Additionally, the accepted hypothesis demonstrates that the diagnostic reliability does not change a lot with the regime (See figure 4). This means that whichever operating point is equally important for diagnostics. The accepted hypothesis confirms the importance of the multi-point option as well.

This hypothesis also proves the manner of forming a fault classification described in [9]. Because the deviation error is independent of operating points, it can be extracted from real date recorded at different operating point and added to fault-induced deviations in class description.

Furthermore, the accepted hypothesis supports the principle of a generalized classification introduced in [11]. It unites fault manifestations obtained at different operational conditions and allows diagnosis under any conditions. The generalized classification is very useful because it drastically simplifies the gas turbine diagnosis because: once formed, this classification is used later without changes. The deviation errors that are independent of operating conditions present an additional justification for applying the generalized classification.

Conclusions

This paper examines two hypotheses for the deviation calculus in the GTE parametric diagnosis. They were analyzed with the thermodynamic model as a basis for calculating the deviation. It was found that the hypotheses result in very different diagnostic reliability that is why it is important to choose the proper hypothesis.

Also, an analysis is presented, in which errors were extracted from real data-based deviations. The plots of these errors have allowed us to choose the most probable hypothesis that the deviation error is constant (independent of operating point).

Not only acceptance of this hypothesis enhances diagnosis reliability, but it also validates some useful principles that make diagnostic algorithms more realistic and vital.

Acknowledgments

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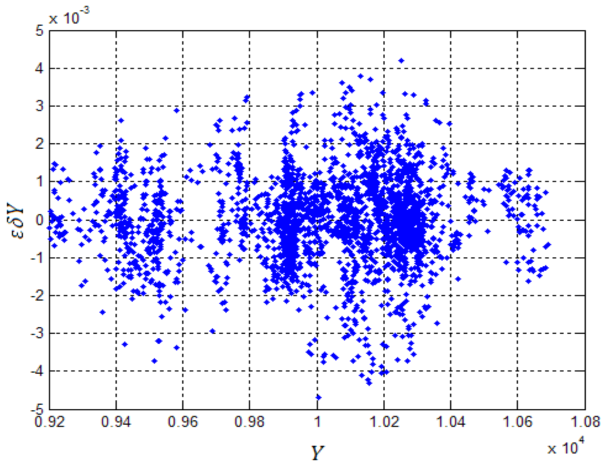
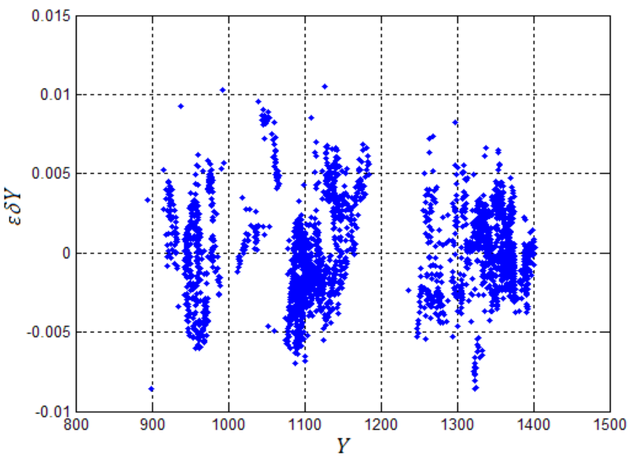
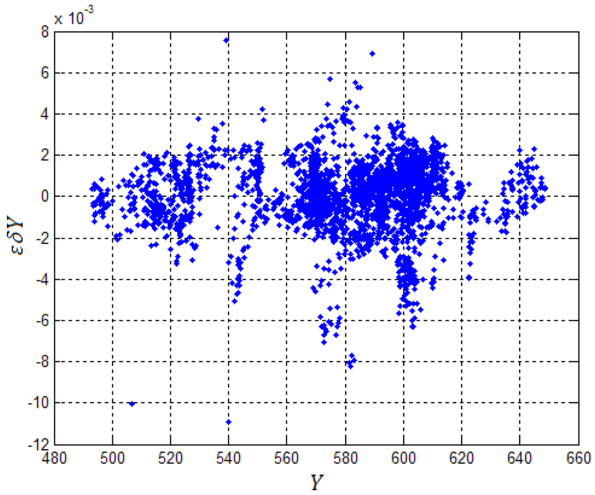
Appendix I



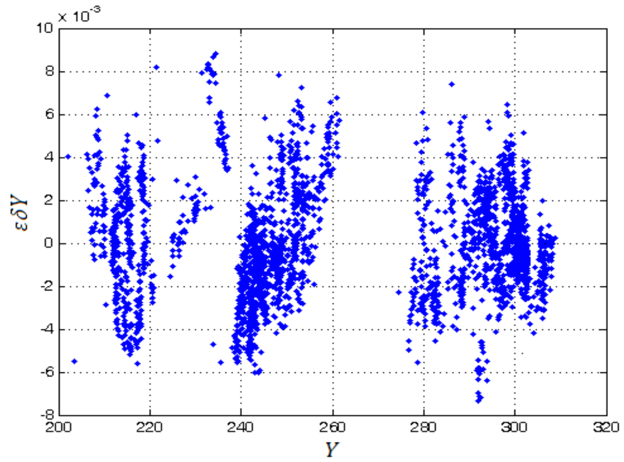
a) Compressor rotor speed



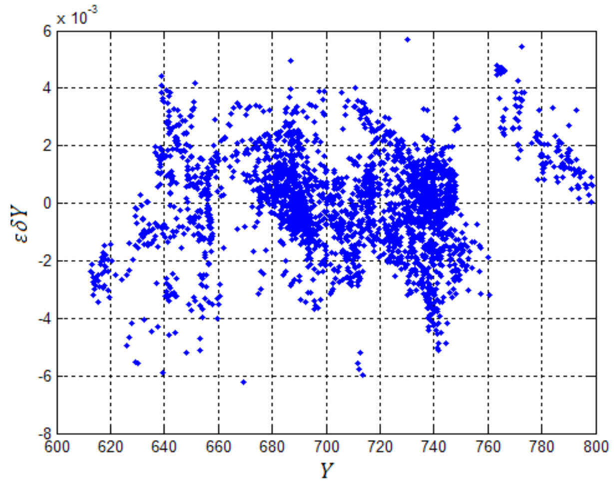
b) Compressor pressure



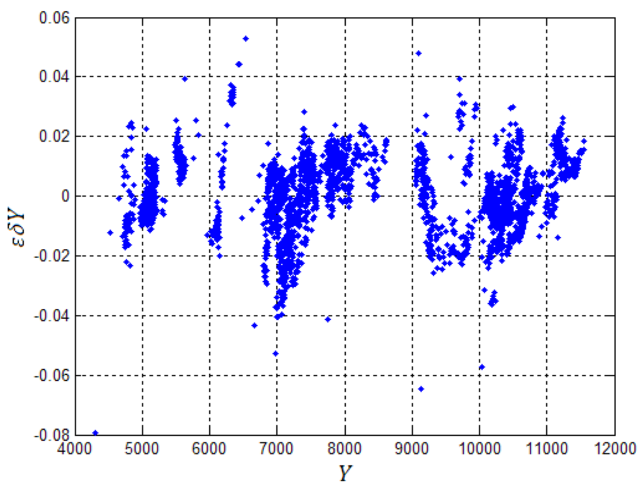
c) Compressor temperature



d) Exhaust gas pressure



e) Power turbine temperature



f) Power turbine output

Fig. 1A. Deviation errors of all monitored variables

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ДІАГНОСТОВАНІСТЬ ГТД НА ЗМІННИХ СТАТИЧНИХ РЕЖИМАХ

І. І. Лобода, Л. А. Миро Сарате

Параметрична діагностика ГТД суттєво покращала в останні десятиліття завдяки розвитку обчислювальної техніки і кращим методам аналізу, таким як нейронні мережі. Вона показала себе досить ефективним засобом оцінки внутрішнього стану двигуна і передбачення його можливих відмов. Необхідні для діагностики характеристики справного і несправного двигуна можна отримати на основі термогазодинамічної моделі двигуна , яка пов'язує контрольовані параметри двигуна з параметрами режиму і параметрами дефектів. Ця модель дозволяє розраховувати відхилення поточних параметрів двигуна від номінальних параметрів двигуна. Діагностування ГТД проводиться методами розпізнавання образів на основі відхилень, розрахованих для всіх контрольованих параметрів. Ці відхилення включають помилки, викликані неточністю вимірювань і неадекватністю моделі. Дані помилки змінюються разом із зміною режиму, приводячи до змінюваної достовірності діагностування. У даній роботі питання впливу помилок на діагностованість двигуна, що працює на змінних режимах, спочатку досліджується на модельованих даних і потім перевіряється на реальній інформації.

Ключові слова: ГТД, параметрична діагностика, термогазодинамічна модель, помилки відхилень.

ДИАГНОСТИРУЕМОСТЬ ГТД НА ПЕРЕМЕННЫХ СТАТИЧЕСКИХ РЕЖИМАХ

И. И. Лобода, Л. А. Миро Саратэ

Параметрическая диагностика ГТД существенно улучшилась в последние десятилетия благодаря развитию вычислительной техники и лучшим методам анализа, таким как нейронные сети. Она показала себя достаточно эффективным средством оценки внутреннего состояния двигателя и предсказания его возможных отказов. Необходимые для диагностики характеристики исправного и неисправного двигателя можно получить на основе термогазодинамической модели двигателя, которая связывает контролируемые параметры двигателя с параметрами режима и параметрами дефектов. Эта модель позволяет рассчитывать отклонения текущих параметров двигателя от номинальных параметров двигателя. Диагностирование ГТД производится методами распознавания образов на основе отклонений, рассчитанных для всех контролируемых параметров. Эти отклонения включают ошибки, вызванные неточностью измерений и неадекватностью модели. Данные ошибки меняются вместе со сменой режима, приводя к изменяемой достоверности диагностирования. В данной работе вопрос влияния ошибок на диагностируемость двигателя, работающего на переменных режимах, сначала исследуется на моделируемых данных и потом проверяется на реальной информации.

Ключевые слова: ГТД, параметрическая диагностика, термогазодинамическая модель, ошибки отклонений.

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