Journal of Polish CIMAC
Gdansk University of Technology
The Faculty of Ocean Engineering and Ship Technology

NEW ELEMENTS IN THE TESTS PROGRAMMES OF MACHINE VIBRATIONS

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Abstract

This paper discusses selected issues of technical diagnostics and mechanics system status monitoring. The issues presented new elements in the test of quality vibrations machines in exploitation. Investigation of machinery destruction processes accompanying every machine just after its manufacturing until its liquidation. This gives a basis for rational maintenance of machines in newly created diagnostic maintenance systems. State evaluation depending on a good model and appropriate symptoms leads to entity-related technologies and the bionics of the existence of technical systems. The descriptors of diagnostic maintenance system enable to create modern maintenance strategies in enterprise systems, keeping modern machinery in motion.

Keywords: *signal processing, diagnostics, programmes test, vibrations, statistics optimization*

1. Introduction

The development of virtual technologies gives rise to many new solutions in the field of modelling, simulation, diagnostic information gathering and processing. Some of these possibilities were hinted at in this article, namely signal processing, statistical optimization of results and diagnostic inference.

The role and significance of technological diagnostics in every phase of machine life are extremely important. They were presented in numerous works against a background of tasks performed by a product in specific maintenance strategies [2,3,4,5,6,7,8,9,10,11,12]. The assessment of machines' technical state with the use of physical processes generated by them requires the gathering of crucial information on the state and proper association of functional parameters of an assessed item, along with a set of measures and evaluation of output processes.

In machinery diagnostics, tests of the evolution of technical state of a particular item occurring in a lifecycle and time $0 \leq \theta \leq \theta_b$ determined by the next planned or extorted item renovation in θ_b constitute a basis for many scientific initiatives. A diagnostic observation of the advancement of item's wear and tear is conducted through measuring various symptoms of technical state and comparing their values (strength, amplitude) with pre-determined allowed values – for a particular symptom and in a particular application.

The actual breakthrough in the valuation of contents and extraction of diagnostic information from the observation matrix occurred thanks to centring and regulating symptoms to their starting value, that is for a model item state with no wear and tear ($\theta = 0$).

A multi-dimensional symptomatic representation of item's technical state in programmed tests, already available, as well as the possibility to extract this information online gives new perspectives in item diagnosing. This in particular relates to new or modernized constructions and new start-ups of innovative items with no operating experience.

This paper presents the issues of redundancy reduction, the assessment of single measures of a diagnostic signal and multi-dimensional diagnostic information processing in program tests.

2. Initial data processing

In practical applications, the initial preparation of data obtained from measurements is a key stage in the classification of data influencing the effectiveness of state distinction, speed, easiness of construction and learning the cause and effect model, as well as its further generalization.
A registered time signal of an investigated process in an Excel spreadsheet is a basis for further processing, i.e. in the field of time, frequency and amplitudes, resulting in many measures enabling the decomposition of an output signal into the signals of specific failure in development. The decision-making process consists of a sequence of operations from the moment of obtaining the information on machinery state, its gathering and processing, until making a decision and forwarding it for implementation.

At the beginning, however, three types of initial data processing can be distinguished: data transformations, filling in the missing values and dimensionality reduction.

Data transformations

The analysis of experimental data is connected with the occurrence of different types of measuring scales, which can be symbolic or numeric. In the systems of diagnostic information processing usually all the features describing the analyzed items have to be numeric.

In the case of classification models making use of distances as similarity measures it is very common for specific features to characterize any physical state on the basis of various physical values, and as a result they influence distance differently. A few transformations unifying the influence of specific features in relation to distance values can be applied here. The most popular ones include normalization and standardization.

Normalization

Normalization is conducted according to the following formula:

$$X_N = \frac{x_i - x_{i\min}}{x_{i\max} - x_{i\min}} \qquad (1)$$

where: x_{imax} is a maximal value in the set for i-feature, and x_{imin} a minimal value for i-feature.

As a result of normalization, we obtain vectors with feature values in the range [0,1].

This transformation does not take into account the distribution of values of a specific symptom; consequently, in the case of the occurrence of a few symptoms with considerably different values, most values are pressed in a very narrow range as a result of normalization.

Standardization

Making use of the distribution of values in specific symptoms leads to a transformation known as standardization, as per the following relations (2).

$$X_S = \frac{x_i - \bar{x}_i}{\sigma_i(x)}; \quad \bar{x} = \frac{1}{n}\sum_j^n x_j^i$$

$$\sigma_i(x) = \frac{1}{n-1}\sum_j^n (x_i^j - \bar{x}_i)^2 \qquad (2)$$

As a result of this transformation symptoms with an average value of x=0 are obtained, while a standard deviation equals σ=1, thanks to which all the symptoms have identical input in information value.

Precision constant – takes into account the range of changeability and an average value of measured parameters, as well as ensures non-dimensionality, as per the following relation:

$$p_i = \frac{\bar{x}_i}{w_i} \qquad (3)$$

Symptom sensitivity w_i contained together with an average value in one number ensures non-dimensionality and changeability range:

$$w_i = \frac{x_{i\max} - x_{i\min}}{\bar{x}_i} \qquad (4)$$

Giving the possibility of further mutual consideration of data of comparable weight obtained in measuring is an important and necessary step.

3. Ideal point method - *OPTIMUM*

Measured diagnostic signals reflect in various ways the observation space, and indirectly also failure development in a machine - fig.1. With the use of optimization techniques, it is possible to characterize measured symptoms' sensitivity to state changes on the basis of measured distance. Distinguishing failure is possible after projecting symptoms onto respective axes: *x, y, z.*

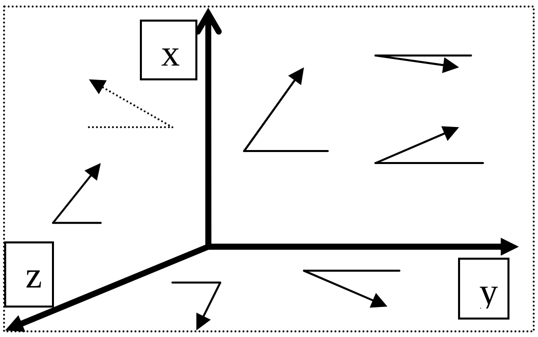

Fig.1. Multi-dimensional observation space

The algorithm below enables to statistically assess individually elaborated diagnostic signals, resulting in a ranking list of their sensitivity and usefulness. The next steps of such proceedings are as follows:

1. The creation of an observation matrix of measured symptoms: $s_1, s_2, s_3, \ldots, s_m$;

2. The results of measuring symptoms for various states are subject to statistical evaluation with the help of different criteria, i.e.

- the changeability of symptoms:

$$f_1 = \frac{s_j}{\bar{y}} \qquad (5)$$

where: S_j – standard deviation, $\bar{y}$ - average value.

- the assessment of symptom sensitivity to state changes:

$$w_i = \frac{x_{i\max} - x_{i\min}}{\bar{x}_i} \qquad (6)$$

- the correlation with technical state, mileage (determining the coefficient of symptom-state correlation):

$$f_2 = r\,(y,w); \qquad r_{xy} = \frac{1}{n-1} \frac{\sum_{i=1}^{n} (x_i - x_{ir})(y_i - y_{ir})}{\sigma_x \; \sigma_y} \qquad (7)$$

In order to make the considerations easier and the results possible to present on a plane, two selected quality indicators are sufficient.

3. Performing the maximization and normalization of assumed indicators of signal quality further, the statistical descriptions of their sensitivity are obtained (f_1^*, f_2^*), which further enables to determine the coordinates of the ideal point. Then, the determination of distances of specific signal measures from the ideal point is possible, as per the following relation (7):

$$L = \sqrt{(1 - f_1^*)^2 + (1 - f_2^*)^2} \qquad (8)$$

4. General sensitivity coefficients (weights) for each tested signal are determined on the basis of the following relation:

$$w_i = \frac{1}{\frac{1}{L_i} \cdot \sum_{i=1}^{n} L_i}, \qquad \text{where: } \sum w_i = 1 \qquad (9)$$

The presented algorithm can be easily realized in Excel, giving a qualitative arrangement of measured symptoms. Fig.2 presents a final result of the effect of the described procedure on sample measuring data. Distance points of specific measures form the ideal point (1,1) prove the sensitivity of the assessed signal measures, with the nearest points (1,1) being the best symptoms.

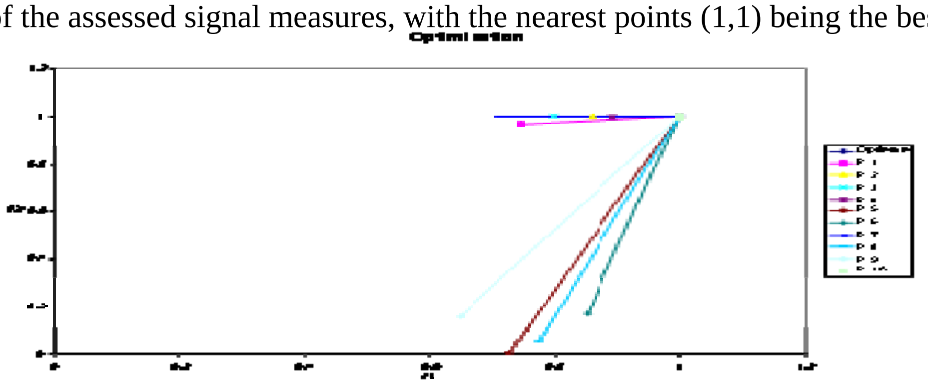

Fig.2. The result of ideal point method - OPTIMUM

With highlighted, statistically good symptoms, cause and effect models can be built on them at the stage of state inference. The quality of the model depends, however, on the number of measures taken into account, which indirectly can be evaluated with the determinance coefficient R^2 in the simplest regressive models.

4. Multi-dimensional observation of the system - SVD

SVD (Singular Value Decomposition) is a numeric procedure for the multi-dimensional monitoring of item's state changes. It detects failure in development and selects maximally informative state symptoms in a given situation.

Let us take a complex mechanical item operating in time into consideration; $0 < \theta < \theta_b$, where evolutionarily a few independent **failures** are progressing, $F_t(\theta)$, t=1,2,..u. Their development can be understood through observing the phenomenon field, making a linear vector of technical state symbols; $[\mathbf{s_m}] = [\mathbf{s_1,...,s_r}]$, of various physical nature. In order to monitor the changes in item's technical state, several dozens of equally distant readings of vector value in time are made; θ_n, n=1,...p, $\theta_p \leq \theta_b$. In this way, the following lines of the symptomatic observation matrix (SOM) are obtained. We already know [Cempel01], [Cempel02] that the maximum of diagnostic information can be obtained from the matrix if all the readings are initially centred (distracted) and normalized to the initial value $\mathbf{S_m (0) = S_{0m}}$ of a given symptom. In this way we obtain a non-dimensional symptomatic matrix of observation:

$$O_{pr} = [S_{nm}], \qquad S_{nm} = \frac{\mathbf{S}_{nm}}{\mathbf{S}_{0m}} - 1 \qquad (10)$$

where: bold lettering symbolizes original dimensional values of symptoms.

Hence, for describing a system's lifecycle there is a non-dimensional observation matrix O_{pr} with **r –** columns resulting from the number of observed symptoms and **p** – lines resulting form the total number of subsequent observations. A procedure of decomposition in respect of singular values can be applied for this non-dimensional observation matrix:

$$O_{pr} = U_{pp} * \Sigma_{pr} * V_{rr}^T, \qquad (11)$$

where: (T- transposition) U_{pp} is a p - dimensional orthogonal matrix of left-sided singular vectors, and V_{rr} is an r – dimensional orthogonal matrix of right-sided singular vectors, and in the centre – a diagonal matrix of singular values Σ_{pr} of the following properties:

$$\Sigma_{pr} = diag\ (\sigma_1, \ldots, \sigma_l), \ \ where: \ \sigma_1 > \sigma_2 > \ldots > \sigma_u > 0 \qquad (12)$$

and: $\sigma_{u+1} = \ldots \sigma_l = 0, \ \ l = max\ (p, r), \ \ u = min\ (p, r).$

This means that of r – measured symptoms only $u \leq r$ independent information on failure in development can be obtained. Such a distribution of SVD observation matrix can be conducted after finishing each observation; n= 1, ..., p, and in this way monitor the evolution of failure $F_t(\theta_n)$ in an item.

One failure F_t can be described by new values; SD_t and σ_t. The first one is a generalized symptom of failure **t**, which can be called a discriminant of this failure and obtained as a right-sided product of an observation matrix and vector $\mathbf{v_t}$ [4]:

$$SD_t = O_{pr} * \boldsymbol{v_t} = \sigma_t \cdot \boldsymbol{u_t} \qquad (13)$$

Since vectors v_t and u_t are normalized to entity, the length of vector SD_t equals its energetic norm, as follows:

$$Norm\ (SD_t) \equiv //SD_t// = \sigma_t \qquad (14)$$

Thus, for an assigned lifetime θ, utility advancement of failure F_t can be reflected by a singular value $\sigma_t(\theta)$, whereas its momentary evolution by the discriminant $SD_t(\theta)$. The equivalence of new measures obtained form SVD to the descriptions of failure spaces id postulated in the whole lifecycle θ of an item:

$$SD_t(\theta) \sim F_t(\theta), \text{ with the norm } /F_t(\theta)/ \sim /SD_t(\theta/ = \sigma_t(\theta) \qquad (15)$$

$SD_t(\theta)$ could also be called a failure profile, whereas $\sigma_t(\theta)$ its advancement. Fig.2 visualizes the idea of SVD.

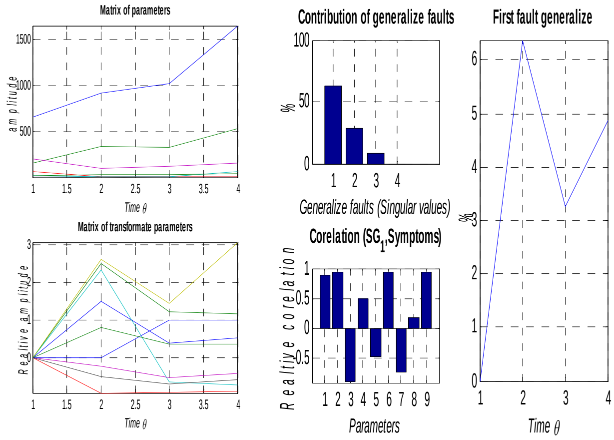

Fig.2 The contents of diagnostic information with independent failures in the symptomatic matrix of observation and the detected discriminants SD_i and measure of advancement σ_i

The aim of SVD also includes the selection of maximally informative symptoms measured in a given instance of diagnostic observation.

From the matrix of observation $O_{pr} = [S_{nm}]$, we can define two square covariance matrices **r** and **p** dimensional, as shown below ($*^T$ – matrix, vector transponing):

$$W_1 = (O_{pr})^T * O_{pr}, \text{ and; } W_2 = O_{pr} * (O_{pr})^T \quad (16)$$

The solution of this issue of such matrices (EVD) shows that singular vectors in demand obtained from SVD observation matrix, as well as squares of singular values can be obtained:

$$W_1 * v_\nu = \sigma^2_\nu * v_\nu, \ \nu = 1,...r; \text{ and; } W_2 * u_i = \sigma^2_i * u_i, \ i = 1,...p. \quad (17)$$

Hence, solving two own issues (Eigen Value Decomposition - EVD) of both matrices of covariance defined on the observation matrix, we obtain the exact result as from the procedure SVD; the only difference is the squares of singular values instead of their original values. It is commonly known that squaring favours the biggest values, which can thus cause a different evaluation of information input significance by different symptoms, but the rejection of the ones with the lowest values is obvious.

A good example illustrating the application of these considerations is a diagnostic observation of a twelve-cylinder traction Diesel engine, where in one chosen point measurements of a dozen vibration symptoms in the whole lifecycle were made every $\Delta\theta$ = 10 thousand km. In total, the amplitudes of 3 accelerations, 3 speeds, 3 displacements and 3 Rice frequencies were measured.

The upper-left corner image shows 12 measured symptoms forming an abundance of information, which, however, after being processed by SVD, is easily decoded into two main failure types due to the fact that σ_1 and σ_2 constituting approximately 50% and 20% of the total amount of diagnostic information in an observation matrix (upper right corner) measured as a quotient of the value of a given σ_i to the sum of all singular values. On top of that, the first failure SD_1 (lower left corner) rises almost monotonically, whereas the second one is unstable and starts to rise only after the twentieth measurement (200 thousand km), which is shown in the course of failure intensity σ_2 in the lower right corner of Fig.3.

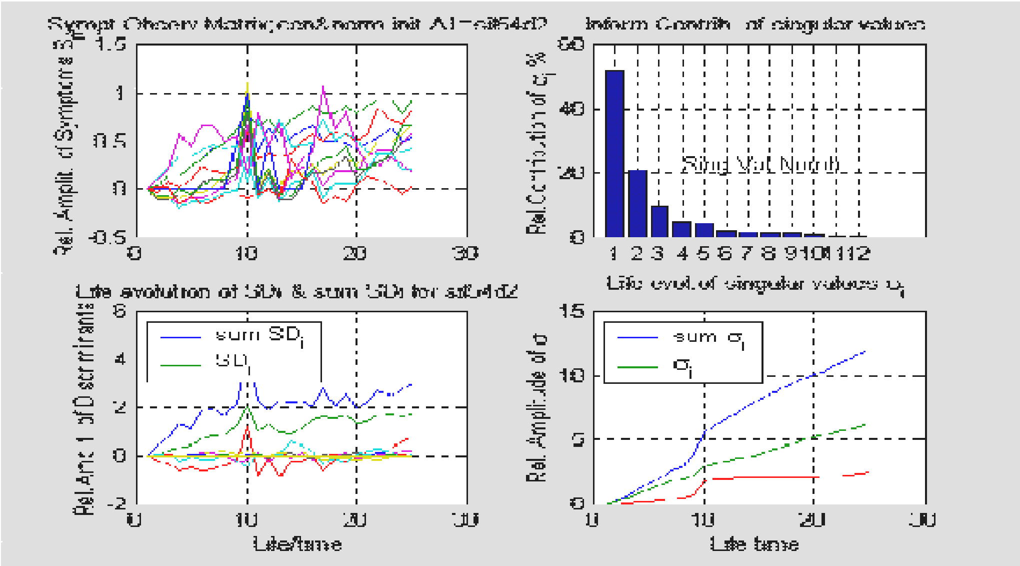

Fig.3 SVD applied in engine tests

Hence, the SVD procedure in the latest program implementations is of base character and contains only approximately 70 lines. Naturally, the algorithm can be further expanded, automatically searching for superfluous measuring symptoms for a given diagnostic issue. It was presented in Fig.3 in a simplified form – in the image in the upper right corner, where the participation of specific symptoms in discriminant SD_1 is clearly visible.

5. CONCLUSIONS

The issues related to diagnosing complex technological items are constantly developed, and the procedures of obtaining and processing diagnostic information constantly improved. This paper deals with reduction redundancy for single state symbols and a multi-dimensional state test.

A new, simple and effective method of the assessment of sensitivity of single state measures was proposed – the *OPTIMUM* method, as well as the core of the *SVD* method. The latter is applied and still improved for the needs of multi-dimensional diagnostics.

The GSVD procedures are already implemented in the majority of advanced calculation systems, i.e. in *MATLAB*®. Thus, a diagnostic interpretation, calculation details concerning additional knowledge accumulated in matrices describing an item and measuring environment are worth considering. Such additional data do not always have to be digital; in many cases linguistic or fuzzy variables are sufficient.

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