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MULTI FAULT CONDITION MONITORING OF MECHANICAL SYSTEMS IN OPERATION

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Abstract. The paper presents the introductory results in application to multi fault condition monitoring of mechanical systems in operation, in particular internal combustion engines. This generalization to multi dimensionality and multi fault condition monitoring is possible by utilizing transformed symptom observation matrix, and by successive application of singular value decomposition (SVD). On this basis one can make full extraction of fault related information from symptom observation matrix created by traditional monitoring technology. Moreover, by SVD we can create several independent fault measures and indices, and some combined measures of overall system condition. In another words, full utilization of SVD enable us to pass from multi dimensional - non orthogonal **symptom space**, to orthogonal generalized **fault space**, of much reduced dimension. This seems to be important, as it can increase the scope and the reliability of condition monitoring of critical system in operation. It enables also to maximize the amount of condition related information, and / or to minimize redundancy in the primary symptom observation matrix, and the same, to redesign the traditional condition monitoring system.

Keywords: machine condition monitoring, vibration, faults, singular value decomposition.

1.SINGLE AND MULTI FAULT MONITORING

Contemporary systems of mechanical and civil engineering are becoming more complex in design, function, and maintenance. Often they are mechatronic in nature, and their mechanical part is usually less reliable, creating comparatively the greatest risk in system operation. This is particular important when operation of system is critical in terms of human life, economy, or both. As examples of such critical systems we may take a bridge, or its part for civil engineering, a turboset for power generation, or huge fan supplying air for the deep mining, in the case of mechanical engineering.

One of the method of risk minimization for such critical systems is permanent installation of condition monitoring subsystem, in order to monitor the integrity and other operational characteristics of mechanical part (structure) of the complex system. Mechanical structures and machines in operation are vibrating, sometimes in a high amplitude and with wide spectrum. As it is known, the vibration process is a good carrier of many structural and condition related information. Hence we are measuring vibration signals, and transforming by filtering and some fast time averaging operation, to obtain a set of **symptoms** of condition[1]. Symptoms are evolving (usually growing) during the system life θ, giving good mapping of operational condition of a system.

The condition of a system itself is usually expressed in terms of some measure of evolution of some few separate faults – $F_t(\theta)$, t= 1,2..$, or as some measure of overall operational condition. As it is known they are contained in some symptoms of condition, like for example the vibration amplitude of machine casing. Having some additional historical records of observed symptom values, we can create condition inference rules concerning reliability and risk issues of our system. As end result we are able to elaborate "**go / repair**" maintenance decision set, usually separate for each symptom, controlling in this way the operation of a given critical system, and lowering the risk of operation. Such is the idea standing behind the condition monitoring of a critical systems; from **signals** to **symptoms** and to system **condition** assessment, but usually on the basis of: one symptom - one condition measure.

The measuring technology of today enable to measure many life dependent operational and residual processes as symptoms. Hence we can have many condition related quantities, and a good possibility of creation of **symptom observation matrix**, when observing our system in a discrete moments of life θ. We can also include to our consideration some assessment of system logistic vector, the life time in a first approach. Such is the problem of this paper, to apply the multi dimensionality of system condition observation, as it was initially proposed in already published papers [1], [2], [5].

[1] Symptoms are measurable quantities covariable with system condition.

Briefly, we investigate here the multi dimensional symptom space of systems in operation, and try to elaborate some independent measures and indices of systems condition, for further inference with a higher confidence level. This is illustrated here by some examples taken from real condition monitoring practice of machines, rail road Diesel engines in particular.

2. MULTIDIMENSIONAL OBSERVATION OF SYSTEMS IN OPERATION

Let us take into consideration machine in operation, where during its life $0 < \theta < \theta_b$, several independent faults are growing; $F_t(\theta)$, t = 1,2,..u. We would like to identify and assess these faults by forming and measuring the symptom observation vector; $[\mathbf{S_m}] = [\mathbf{S_1,...,S_r}]$, which may have components different physically, like vibration, temperature, machine load, etc. In order to track machine condition evolution (faults), we are making equidistant reading of symptom vector in the life time moments; θ_n, n = 1, ... p, $\theta_p \leq \theta_b$, forming in this way the rows of symptom observation matrix (SOM). From the previous papers (see for example [1]) we know that the best way of pre processing of SOM is to center it (remove), and normalize (divide) to symptom initial value; $\mathbf{S_m(0) = S_{0m}}$, of a given symptom (column of SOM). This gives us dimensionless symptom observation matrix in the form

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

where bold letters indicate primary dimensional symptoms as taken from measurements.

As it was already said in the introduction, we apply now Singular Value Decomposition (SVD) [2], [3], [7], to the dimensionless SOM (1), in the form

$$O_{pr} = U_{pp} * \Sigma_{pr} * V_{rr}^T, \text{ T- transposition }, \tag{2}$$

where U_{pp} is p dimensional orthogonal matrix of left hand side singular vectors, V_{rr} is r dimensional orthogonal matrix of right hand side singular vectors, and the diagonal matrix of singular values Σ_{pr} is as below

$$\Sigma_{pr} = \mathrm{diag}\,(\sigma_1, \ldots, \sigma_l), \text{ and } \sigma_1 > \sigma_2 > \ldots > \sigma_u > 0, \tag{3}$$
$$\sigma_{u+1} = \ldots \sigma_l = 0, \quad l = \max\,(p, r), \quad u = \min\,(p, r).$$

It means that from the r measured symptoms we can extract only $u \leq r$ independent sources of information describing evolving generalized faults F_t . Such decomposition by SVD can be made currently after each new observation of the symptom vector; n = 1, … p, and in this way we can trace the faults evolution in a system. From the current research of this idea [1], [2], [3], we can say that the most fault oriented indices obtained from SVD is the pair SD_t , σ_t , and the sum of them. The first indices SD_t can be named as discriminate of the fault t, one can get it as the SOM product and singular vector v_t , as below

$$SD_t = O_{pr} * \mathbf{v_t} = \sigma_t \cdot \mathbf{u_t}\,. \tag{4}$$

We know that all singular vectors v_t are normalized to one, so the energy norm of new discriminant is simply

$$\mathrm{Norm}\,(SD_t) \equiv || SD_t || = \sigma_t\,, \; t = 1, ...,u. \tag{5}$$

In this way, for the given life time value θ the damage advancement of the fault $F_t(\theta)$ can be described by $\sigma_t(\theta)$, and its momentary evolution by the discriminate $SD_t(\theta)$. Hence we can present the following working hypothesis $SD_t(\theta) \sim F_t(\theta)$, with the energy norm;

$$|| F_t(\theta)|| \sim || SD_t(\theta|| = \sigma_t(\theta)\,. \tag{6}$$

The discriminate $SD_t(\theta)$ can be also named as fault profile, and $\sigma_t(\theta)$ as its advancement. The all concept observed in the system life time can be presented in Fig 1.

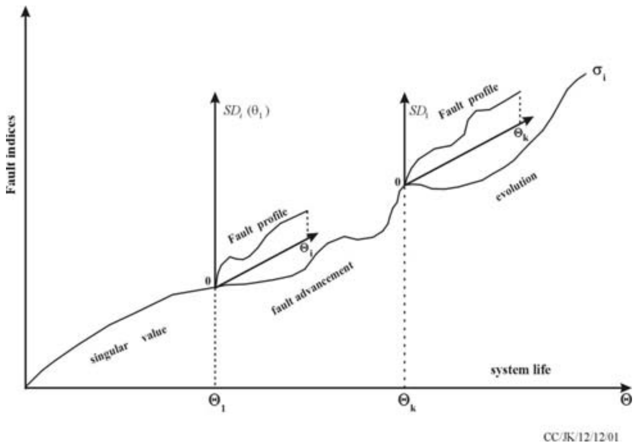

Fig.1 Postulated lifetime meaning of SVD indices SD_i, σ_i.

The similar inference can be postulated to the meaning, and the evolution, of summation quantities, what can mean the total damage profile SD(θ), and total damage advancement DS(θ), as below

$$SD(\theta) = \sum_{i=1}^{z} |SD_i(\theta)| = \sum_{i=1}^{z} |\sigma_i(\theta) \cdot u_i(\theta)|$$

$$\sim \sum_{i=1}^{z} |F_i(\theta)| = P(\theta)$$

$$DS(\theta) = \sum_{i=1}^{z} |\sigma_i(\theta)| \sim \sum_{i=1}^{z} |F(\theta)_i| = F(\theta)\,. \tag{7}$$

3. EXAMPLES OF SVD APPLICATION

In order to illustrate the diagnostic inference power of multi fault approaches, by SVD, some computational programs were prepared named **diaginfo.m**, based on SVD algorithm, and written in the MATLAB® computational system. By means of such software several real diagnostic cases was studied with a success.

Let us take into consideration vibration condition monitoring of 12 cylinder railroad Diesel engines, where in some chosen point a dozen vibration symptoms (3 acceleration amplitudes, 3 velocity, 3 displacement, 3 Rice frequency) were measured, each ten thousand kilometer of mileage, up to 250.000 km. So our SOM has altogether 12 columns and 25 rows. The results of such new vibration condition monitoring, applied to the engine **sil54d2** are presented in Figure 2. As it is seen from the top left picture, the 12 measured symptoms create dense brushwood, and nothing can be said from this picture. But after SVD computation, picture top right, one can say, that at least two independent generalized faults can be recognized . And the same one can say considering SD_i , σ_i indices of the lower picture, in Fig. 2.

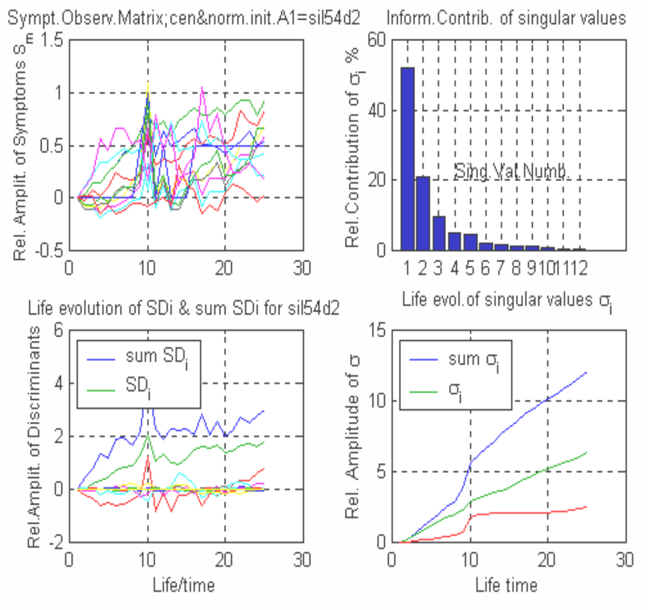

Fig. 2. The information contents of symptom observation matrix for a Diesel engine **sil54d2**, and independent fault indices SD_i ,σ_I as discovered by SVD.

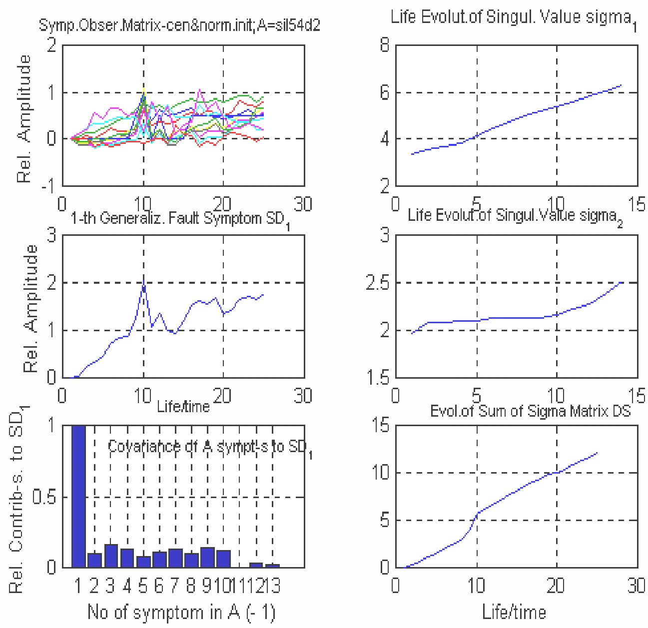

Fig.3. Contribution of primary measured symptoms (bottom left) to the first fault discriminants; SD_i ,σ_i.

As it is seen from that, the first generalized fault SD_1 increases almost monotonic, while the second SD_2 is unstable, and it begins to grow really in a higher engine mileage above 200.000 km.

Looking for the total damage indices, denoted on the lower pictures as; **sum** $\mathbf{SD_i}$ and **sum** $\boldsymbol{\sigma_I}$**,** one can say they are similar to the first generalized fault discriminant SD_1 and σ_1 . Hence, there is great redundancy in our observation vector, and we are interested to diminish it. The next Fig. 3 answers partially this question, when looking to the bottom left pictures, giving the contribution of each measured symptom to the first generalized fault SD_1. We can see there, that three last symptoms (10 – 12, the Rice frequency) give low information contribution, and these can be omitted without substantial loss of monitoring quality.

Next figure 4 present the result of application of this algorithm to another engine called **sil24d2**. As we can see from the figure and the picture top right, more than 60% of information contents concerns the generalized fault no 1, so SD_1 and σ_1. The next generalized fault SD_2 , σ_2 carries only 12 % of information contents. Looking at the bottom pictures in Fig. 4, one can say, that only the first generalized fault SD_1 , σ_1 gives the steady increase of both fault indices.

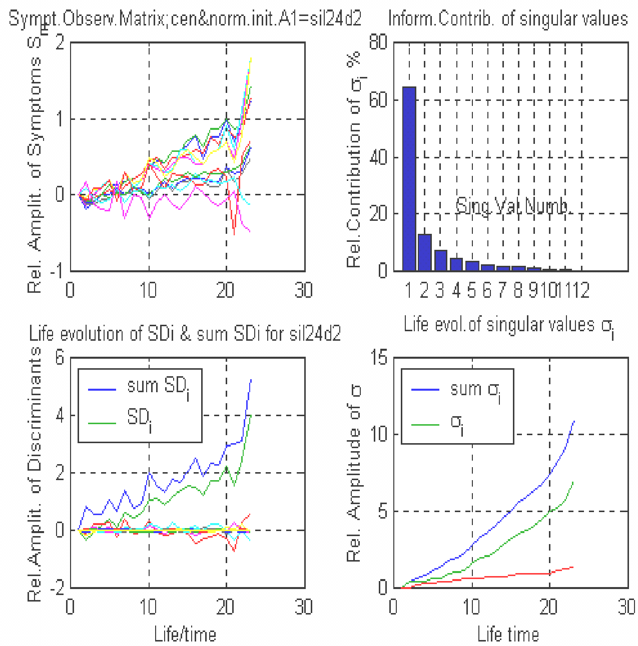

Fig. 4. Information contents and discriminants evolution for **sil24d2** Diesel engine.

It seems to the author, that figures 2, 3 and 4 confirm fully the usability of singular value decomposition, to extract multi fault information from symptom observation matrix. It is possible to create this during normal (routine) condition monitoring practice, and not only with vibration symptoms. We can also assess the information contribution of each primary symptom to any fault discriminants under our concern, and in this way to modify and diminish redundancy of symptom observation vector.

Commenting commonly the results obtained by using SVD, as the method of multi dimensional condition monitoring shown in the paper, one can summarize them as follows.

The proposed method of analysis of symptom observation matrix (SOM) enable to optimize its information contents, and to reject or include some primary symptoms of condition. When transformed symptom readings are load sensitive, with the use of SVD we can obtain stable fault related indices with much higher range of life evolution, when compared to primary measured symptoms.

We can use for further maintenance related inference, any of fault indices - for the first generalized fault, and some generalized fault idices as the measure of wear advancement. For the examples shown in the paper, (and it seems to be the general case also), good indices of overall condition seem to be the diagonal sum of singular values DS(θ), as the energy fault measure, and the sum of singular vectors P(θ), as the fault profile measure.

In the view of theory and examples shown above we can present some life interpretation of Singular Value Decomposition (SVD). It seems to be valid for every generalized fault F_t (θ), t = 1, ... , as well as for total generalized fault profile P(θ), and the total generalized fault energy DS(θ). This was shown on the Fig. 1 of the paper, and we can see there again, that for every life value of generalized fault energy or its advancement, we can draw the associated generalized fault profile $SD(\theta)_t$, on the perpendicular axis. The same maybe true for the total fault profile and generalized fault energy.

This altogether means, that multi dimensional condition monitoring can give us real progress in on line assessment of condition of critical systems in operation. We can distinguish by this new method the momentary generalized fault profile SD(θ), as well as the generalized fault energy or its advancement DS(θ). The next additional step we need here in multi fault condition monitoring is to give limit values of chosen indices, measures, and generalized fault symptoms. And we can calculate this limit value by any method given in [3], [4], or by the latest proposal [6] based on symptom reliability and Neyman - Pearson rule.

4.CONCLUSIONS

Paper starts with some summary of research concerning application of singular value decomposition to the problem of extraction of multifault information from symptom observation matrix. It was shown, that basing on SVD we can describe the condition evolution in terms of some independent fault discriminants. And one must interpret these new indices in term of machine damage and operational data. The whole idea is illustrated by the data taken from the real diagnostic experiment on some Diesel engines. It is good to mention here, that modern principal component analysis (PCA) is basing also on SVD, but giving much faster way of symptom processing and calculation. Hence it is postulated to use this modern tool. Also at the end of the paper, one can postulate some generalization of SVD, (GSVD), in order to include some other operational data and matrices concerning the external and internal condition of machine operation.

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