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MULTIDIMENSIONAL VIBRATION CONDITION MONITORING OF NONSTATIONARY MECHANICAL SYSTEMS IN OPERATION

Czesław CEMPEL, Maciej TABASZEWSKI

Poznań University of Technology
Ul. Piotrowo 3, PL-60-965 Poznań, Poland
czeslaw.cempel@put.poznan.pl

Abstract

The readings of vibration symptoms made in vibration condition monitoring should be done in stationary and standard load condition. But sometimes we have no control of operating load of critical machine. The multidimensionality of symptom observation can help a little in a such case, but much better is to apply the rescaling of a symptom readings to standard operating condition. This possibility is shown in the paper, giving some practical examples as well.

1. INTRODUCTION

The idea of multidimensional condition monitoring of critical machines, with the application of singular value decomposition (**SVD**), was formulated firstly in the paper of a first author [Cempel99]. Here the concept of symptom observation matrix (**SOM**) was used in order to extract by **SVD** the new fault related **generalized symptoms,** or fault indices. The latest development of this concept is presented in the last papers of the first author [Cempel03], [Cempel04]. In another development, it is known, that some symptoms of condition may depend on working and environmental condition of the machine, what was described in some papers of the first author as **logistic vector** concept [NatkeCempel97,s59]. For the final purpose of the machine diagnosis we need also some method of symptom limit value $\boldsymbol{S_l}$ determination, what can be done by the use of **symptom reliability** concept [CempelNatkeYao00]. But until now, there was no common connection and application of these three concepts in machine condition monitoring area.

2. RESCALING OF SYMPTOM OBSERVATION MATRIX

Let us take into consideration one of the component **S** of the symptom observation matrix, having the ordering number **n**. It is known already this symptom sensitivity to the logistic vector value ***L*,** hence its observation made in the life time θ_p will depend on both variables; $S_{pn}(\theta_p, L_p)$. If we know the standard value of the working load L_o , where the most of the observations has been made, we can perform the symptom rescaling operation.

By means of Taylor series expansion one can get as below

$$\mathbf{S}_{pn}(\theta_p, L_p) = S_{pn}[\theta_p, L_o(1 + \frac{\Delta L_p}{L_o})] \cong (1 + \frac{\Delta L_p}{L_o})\mathbf{S}_{pn}(\theta_p, L_o)\,, \qquad (1)$$

what is equivalent in a first approach to multiplicative influence of the logistic vector on the observed symptom value.

In this way, intending to bring **n**-th observation to the condition of the **standard load** L_o, it means to the rescaled value $S_{pn}(\theta_p, L_o)$, we should multiply it by the reverse rescaling coefficient taken from (1) in the form

$$l_p = (1 + \frac{\Delta L_p}{L_o})^{-1} \qquad (2)$$

It means, that for positive value of the load increment $\Delta L>0$ with respect to standard load L_o we should divide it by the coefficient greater than one. And vice versa, for the negative increment of the load ($\Delta L<0$ - decreased load) during the symptom observation we should divide by the coefficient less than one.

So much if we concern with rescaling of one symptom ***S*** only. Assuming now that the similar behavior can be a property of other symptoms in **SOM**, we can use the same coefficient for all observations taken in a time θ_p , it means to the whole ***p*** row of **SOM**. Let us assume now that our matrix notation will be the same as in a previous papers of the first author [Cempel03], with the **SOM** denoted as; $O_{pr} = [S_{mn}]$. It means with the maximal number of rows ***p***, with current observations *1, ...m* , and the maximal number of symptoms ***r*** (columns), succeeding from; *1,...n*. Hence, doing now rescaling of **SOM,** we should multiply the whole matrix row by rescaling coefficient (2). It follows from the matrix calculus [Gere65,p26], that it should be done by left hand side multiplication of the diagonal rescaling matrix having a rank equal to number of rows of current dimension of **SOM** matrix. In the light of the above, the rescaling operation of **SOM** to the standard load condition can be done as below

$${}^{R}O_{pr} = L_{pp} * O_{pr} = [L_{mm}]*[S_{mn}]\ ,\ m=(1,p)., \qquad (3)$$

where the left hand side superscript means rescaling, and a square bracket over matrices means current making of rescaling operation by logistic matrix L_{mn} . In the most general case the logistic rescaling matrix can have different multiplying coefficient for every row, as below;

$$L_{mm} = Diag\,(1 + \Delta L_m / L_o),\ m = (1,p), \qquad (4)$$

and if the rescaling operation for the given row is not needed, then the respective row in the logistic matrix becomes unity.

It seems to be reasonable, that the same rescaling operation can be applied to another components of a logistic vector **L**. The same can be done to variable environmental conditions, such as the gust of the wind in aero generator, the immersion and the pitch of the ship, etc. It is obvious now, that rescaling concept can be used not only to the load of machine, and environmental conditions, but also for the quality o maintenance where one can make rescaling of initial machine observation in **SOM**, just after the start up.

2. FAULT INFORMATION EXTRACTION AND INTERPRETATION OF RESCALED SYMPTOM OBSERVATION MATRIX

Just to remind ourselves, we are observing the condition of complex mechanical system, which can exhibit its wearing processes by means of a few dominating faults[1], described by generalized symptoms $F_t(\theta)$, $(t=1,2,...)$. Trying to catch and describe this multidimensional degradation process of the machine we observe multidimensional symptom space by means of symptom observation vector $\boldsymbol{S}$, and the successive life time realizations of this vector for θ_n $(n=1\ 2,\ ...)$ gives us **SOM**. As we have mentioned already, the best method to extract these information from rectangular **SOM** is the application of singular value decomposition (**SVD**), similar to the older method principal component analysis (**PCA**). It is good to know that, the last one is less sensitive to small energy components of **SOM** due to matrix multiplication inherent by definition in **PCA** [NatkeCempel02]. In our previous papers the original **SOM** was transformed column wise by centering and normalizing to the initial value ($\theta=0$) of each symptom (column). Hence our rescaled **SOM** can be written now as below;

$$ {}^{R}\boldsymbol{O}_{pr} = L_{pp} * O_{pr} = [L_{pp}] * [S_{nm}], \qquad S_{nm} = \frac{\mathbf{S}_{nm}}{\mathbf{S}_{0m}} - 1, \qquad (5) $$

where the bold letters means primary measured symptom values before its transformation.

The **SVD** procedure for any rectangular matrix gives us left hand and right hand side singular vectors U_i , V_i , and singular values σ_i , as below [Kiełbasiński92,s41], [Golub83];

$$ {}^{R}\boldsymbol{O}_{pr} = U_{pp} * \Sigma_{pr} * V_{rr}^{T}, \quad (\text{T- transposed matrix}), \qquad (6) $$

Where U_{pp} square matrix of left hand side singular vectors, and V_{rr} square matrix of right hand side singular vectors, and Σ_{pr} diagonal matrix of singular values as below;

$$ \Sigma_{pr} = diag\ (\sigma_1,\ ...,\ \sigma_l), \ and \ \ \sigma_1 > \sigma_2 > ... > \sigma_u > 0, \qquad (7) $$
$$ \sigma_{u+1} = ...\ \sigma_l = 0, \ \ l = max\ (p,\ r), \ \ u = min\ (p,\ r). $$

The diagnostic interpretation of **SVD** method elaborated so far in some papers of first author leads us to two quantities obtained from the above. The **generalized fault symptom** of order t which shows also the **time profile** of this fault $P_t\ (\theta)$;

[1] Faults can be different physically, have different spatial location in a machine, and even can be independent each other, at least at the beginning of wearing process.

$$SD_t = {}^{R}O_{pr} * v_t = \sigma_t \cdot u_t \quad \sim P_t\,(\theta)\,, \quad t = 1, ..., u. \tag{8}$$

The second quantity is the energy norm of the above, so it can represent the cumulative advancement of given generalized fault

$$Norm\,(SD_t) \equiv // SD_t // = \sigma_t. \sim F_t\,(\theta)\,, \quad t = 1, ..., u. \tag{9}$$

Of course, when tracing the fault evolution in the operating machine, both quantities will depend on a life time of the system $\boldsymbol{\theta}$, so we will have; $\boldsymbol{SD_t(\theta)}$ and $\boldsymbol{\sigma_t\,(\theta)}$. Finally, it seems to be good to monitor cumulative wear, so the advancement of all generalized faults in a machine, by means of summation quantities given below;

$$SumSD_i(\theta) = \sum_{i=1}^{z} SD_i(\theta) = \sum_{i=1}^{z} \sigma_i(\theta) \cdot u_i(\theta) = P(\theta)\,, \tag{10}$$

$$Sum\sigma_i(\theta) = \sum_{i=1}^{z} \sigma_i(\theta) \sim \sum_{i=1}^{z} F(\theta)_i = F(\theta)\;.$$

As it was shown in [Cempel04] such interpretation of generalized fault indices in operating system obtained by **SVD** seems to be correct, what allows us to use **symptom reliability** concept for determination of generalized symptom life curve a $\boldsymbol{S_u(\theta)}$ and symptom limit value $\boldsymbol{S_l}$ **.** Adding now **rescaling** capabilities to the above theory and related diagnostic programs, we will try to establish the validity and applicability of rescaling concept.

4. SYMPTOM RESCALING IN CONDITION MONITORING OF NONSTATIONARY MACHINES

The vibration condition monitoring was implemented in several ventilation fans of one Polish cooper mine, but due to the mining activity the demand for the air is unstable. On each fan five vibrational symptoms have been measured once a week, but with no information on the driving power or air flow demand and load ***L***. As symptoms of condition, the axial vibration velocity of two bearings, taken as all pass quantity, also they were filtered with rotational and blade frequencies, and one overall vibration velocity reading of the fan foundation. This gives altogether five symptoms plus linear life time measure, as the base for creation of symptom observation matrix (**SOM**). These observations were treated by special software **pcainfo.m**, based on **SVD** as above, and written in **Matlab®** environment. The results of introductory application of this software, without rescaling are shown on Figure 1 containing four pictures. As for now, there is no measurement of air flow ***(L)***, or momentary power of electric motors driving the fans. Hence, there is instability in some vibration readings, as it can be seen from picture upper left of Fig. 1, where symptom observation matrix (**SOM**) is graphically presented along 32 weeks life time. The upper right picture gives us the percent amounts of information for the independent components (σ_I) contained in **SOM**, what is equivalent to information distribution of independent generalized faults. The profiles of these faults $P_t\,(\theta)$, *I=123,* and the summation generalized symptom, calculated according formulae (8) – (10), are shown on the lower left picture of Fig.1.

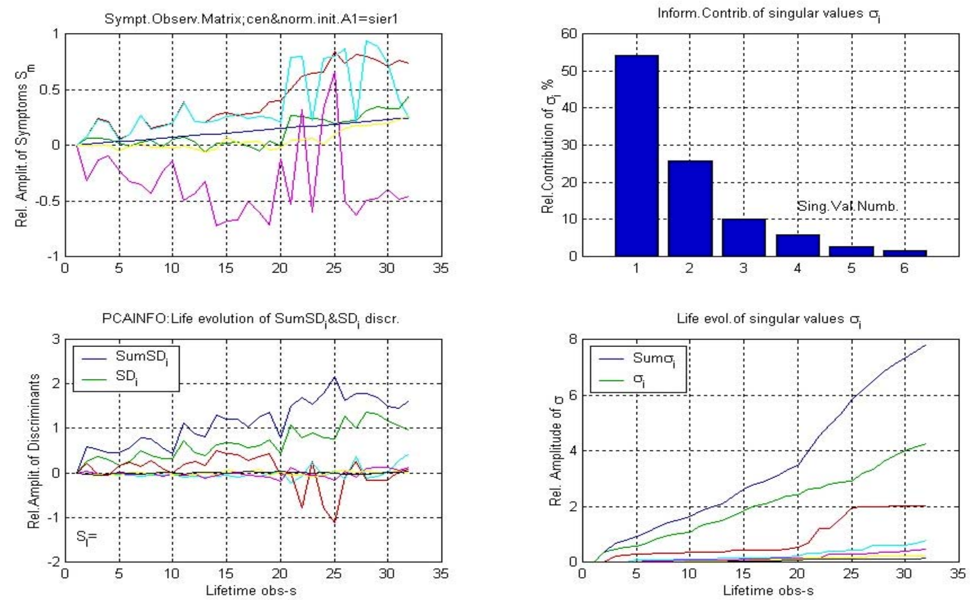

Fig. 1. Multi symptom vibration condition monitoring of a huge fan used to supply air into the deep mining shaft, and the results of ***SVD*** *performed on* ***SOM****.*

Comparing now the upper and the lower left pictures one can notice that **SVD** decomposition stabilizes the course of generalized symptoms, because $\boldsymbol{SD_i}$ oscillation due to air flow variability are much smaller. Hence, one can conclude, that multidimensional symptom observation can lead us to much better condition assessment than by means of one symptom only. And the best generalized symptom for further condition assessment seems to be the upper curve and the second one on the lower left picture, what corresponds in our calculation to summation quantity $\boldsymbol{SumSD_i}$, and the first generalized fault $\boldsymbol{SD_1}$.

As there was no rescaling in all calculations of Fig. 1, let us assume, that the first observation of our symptom vector (first row of **SOM**) was performed during the high demand of air in the ventilation system, so during $\boldsymbol{\Delta L>0}$. Corresponding rescalling coefficient (2) must be less than one, and the rest of the observations in **SOM** we leave unchanged. Due to this assumption, our rescaling diagonal matrix will be: $\boldsymbol{L_{pp} = Diag(0.9;1;1;....)}$.

Following this only change in **SOM** let us perform all calculations again by means of similar software with rescaling, namely: **pcainfo3.m** The results of such calculations are presented on Fig.2, where one can notice that every of four pictures has some relevant change. The left upper picture presents much smaller oscillations of previously (Fig.1) negative value symptom (negative after standardization of column), and the information amount prescribed to generalized fault No 1 has grown up almost to 60%. One can notice much more on the picture lower left, where almost all oscillations of previously negative generalized symptom has changed to positive valued, and the dynamics of summation generalized symptom $\boldsymbol{SumSD_i}$ and the first one $\boldsymbol{SD_1}$, is much larger than before. In a similar way one can observe the increase of dynamics for a symptoms $\boldsymbol{Sum\sigma_i}$ and $\boldsymbol{\sigma_1}$.

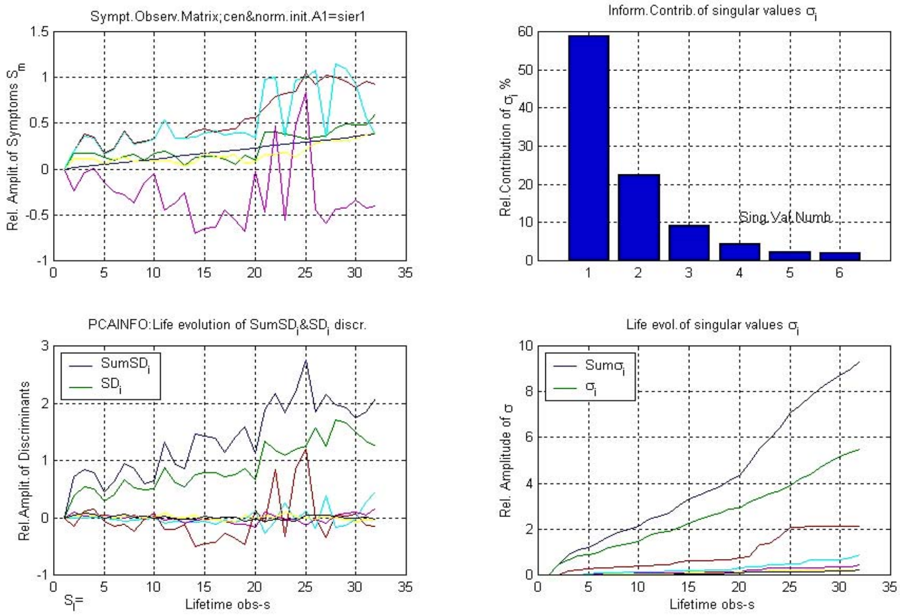

*Fig. 2. Data the same as on Fig 1, but with rescaling of the first raw of **SOM**, with rescaling matrix: **L_{pp}=Diag(0.9;1;1...).***

Considering once more the oscillations of symptom values in case without rescaling (Fig. 1 upper left) one can find, that these oscillations have larger amplitudes after observation No 20, having large maximal and minimal values. This may mean that primary cause of this vibration instability was the change of the fan load. Let us take this into account and change the respective rescaling coefficients, this time increasing them up to l_p = 1.1. Hence in the next approach we will put this rescaling coefficient into the rows of **SOM** No; 23; 26; 30; 31; 32, together with the l_p = 0.9 for the first observation, as before. The results of a such recalculations with above defined rescaling matrix are shown on Fig. 3.

Comparing now the results of latest calculations (Fig. 3), with unmodified case of Fig. 1, one can notice successive decrease in symptom oscillations, and the increase of the dynamics of generalized symptoms ***$SumSD_i$*** and ***SD_1***. What is more to notice here, it is increase of information contribution of the main component ***σ_1*** up to 60%, and the increase in the dynamics of generalized symptoms ***$Sum\sigma_i$*** and ***σ_i***, up to the value of **10**. Concluding this positive change in the life course of generalized symptoms one can suppose, that by the rescaling operation of symptom values it is possible to decrease symptom variability, making them more monotonic, like in case of continuous running with the same system load. Also, by the same rescaling operation one can increase the dynamics of the generalized fault symptoms. Maybe the same is true for the generalized symptom life curve.

It is worthwhile to analyze more the influence of rescaling, in particular the influence on the quantities shaping the final maintenance and operational **go/ no go** decisions. The key quantity is here symptom limit value ***S_l*** calculated from generalized fault symptoms ***SD_1*** lub ***$SumSD_1$***. As it was mentioned during introduction, this quantity can be calculated using the concept of symptom reliability [CempelNatkeYao00]. This quantity can be calculated continuously by the software of **pcainfo3.m**, and on the Fig. 4 one can find the coarse of symptom limit value S_l for the above shown cases of the fan **sier1**, marked here as **case1** till **case 3**. This means that **case 1** is without rescaling , and **case 2** and **3** concerns respectively Fig. 2 and 3.

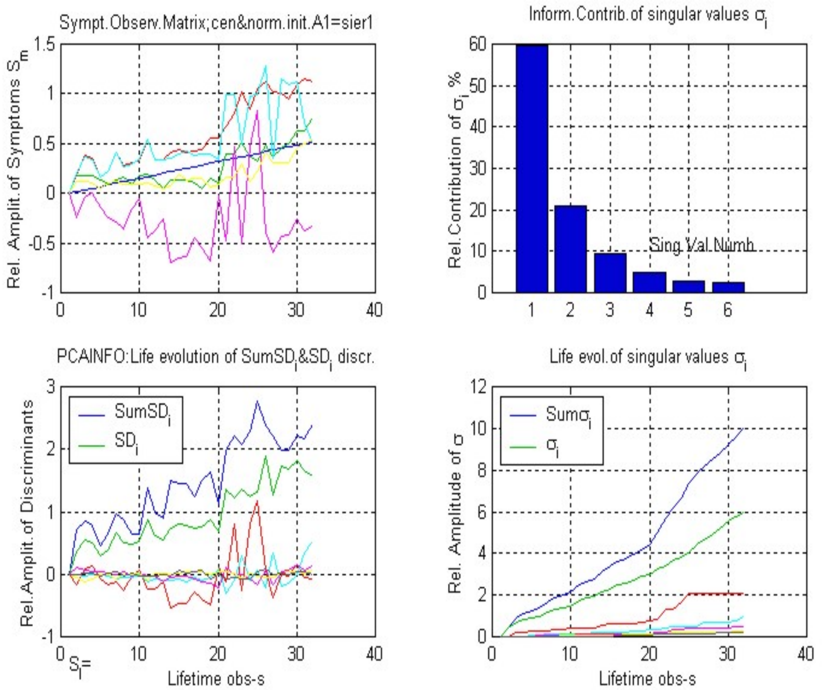

Fig.3. Multidimensional CM of a huge fan as on Fig 1 and 2 but with another rescaling L_{pp}*; for the observations No: (1)=0.9; (23)=1.1; (26)=1.1; (30-32)=1.1.*

One can conclude from the coarse of S_l on Fig. 4, that slight rescaling modification of case 2 gives almost no change in S_l , but rescaling of several symptom observation as in case 3 give a change of the coarse and the value of S_l **.**

This is all what can be said at this introductory stage of this concept concerning the symptom rescaling in multidimensional condition monitoring, and its influence on some decisive quantities. The more can be said when we will have sensor data concerning the change of the machine load and / or environmental conditions.

5. CONCLUSIONS

It follows from the above consideration supported by the real condition monitoring data, that the idea of rescaling of **SOM,** in multidimensional condition monitoring seems to be sound and practical in application to real critical machine with unstable loading. It was shown, that primary unstable symptoms with much oscillations are more stable after application of **SVD,** and much more monotonic with greater dynamics, when rescaling of some observation was in use. Also the influence of rescaling to the assessment of symptom limit value S_l is not a large Hence, having some sensor of a machine load, or its unstable external air supply in our condition monitoring subsystem, we can use it, and next to learn iteratively how to calculate rescaling coefficients for every case of symptom observation in non standard load / environment condition.

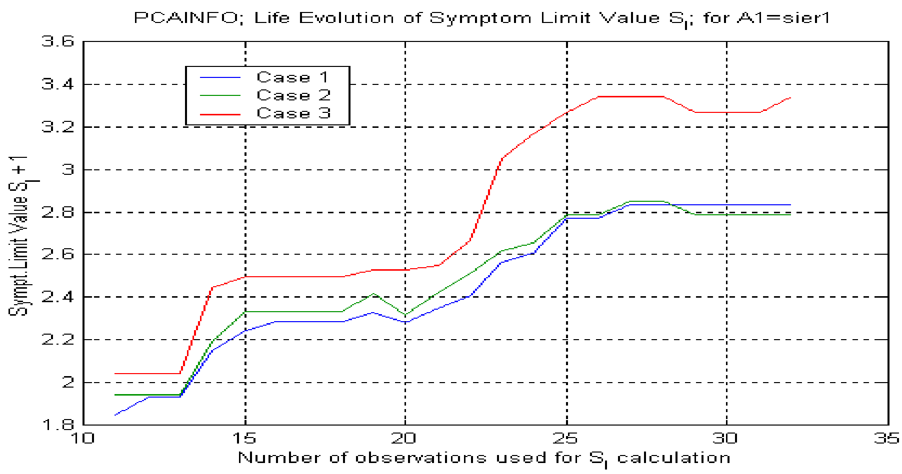

Fig. 4. Rescaling influence on the value and the life coarse of symptom limit value $\boldsymbol{S_l}$ *calculations, for the generalized fault symptom of the fan* ***sier1*** *according to different rescaling as on Fig.1 (case 1) up to Fig. 3 (case 3).*

6. REFERENCES

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