ICSV13 - Vienna
The Thirteenth International Congress on Sound and Vibration
Vienna, Austria, July 2-6, 2006

AVERAGING THE SYMPTOMS IN MULTIDIMENSIONAL CONDITION MONITORING FOR MACHINES IN NONSTATIONARY OPERATION

Czeslaw CEMPEL*[1], Maciej TABASZEWSKI[1]

[1]Institute of Applied Mechanics, Poznań University of Technology
ul. Piotrowo 3, PL-60-962 Poznań, Poland
czeslaw.cempel@put.poznan.pl

Abstract

The paper concerns the case of multidimensional condition monitoring of unstable running machines, which work for example with stochastic environment, where the load can not be easy controlled. It was shown on the example of same real data, that the averaging operation applied to the symptom observation matrix can be a valuable help, enabling to smoothen the life course of generalized faults obtained from the singular value decomposition. It enables also a better calculation of the symptom limit value S_l needed for the diagnostic decision.

INTRODUCTION

The idea of multidimensional diagnostics of machines by the use of symptom observation matrix (**SOM**) and application of the singular value decomposition (**SVD**) has been proposed some years ago [Cempel99]. It enables to extract the information on the developing machine faults using m component symptom observation vector, which by successive readings ($m\Delta\theta$) in a machine life time θ creates n by m perpendicular **SOM**, the only source of our fault information. The application of **SVD** enables to observe the evolution of a few generalized faults of the diagnosed machine, starting from the fault of maximal severity. Applying next to such extracted generalized fault symptoms, the concept of symptom reliability [CempelNatkeYao00] one can calculate the symptom limit value S_l, the basis for any diagnostic decision. However, the loadings of machines by the production process or the environment is not a constant one, so the resultant symptom readings can have some disturbances influencing the assessment of machine condition. This disturbing influence is most important at the start up of the new machine, as normally we are normalizing symptoms to a starting healthy values.

One of the possibilities of reducing the errors is rescaling the current symptom reading to a standard load if such load assessment is possible. It can be made by some measurements of the quantity connected with a production process, the wind load, or the sea waving, depending on the nature of disturbance. It was shown in one of the paper [CempelTabaszewski05] that such idea of symptom rescaling is workable, giving the possibility of better assessment of machine condition working in a nonstationary loading regime. However, when the assessment of the load parameter is not possible we can use with the success the averaging of few starting symptom readings, as it was shown in the last paper of the main author [CempelKrakowiak05].

These promising results in reducing operational instabilities and random disturbances of observed symptoms, lead us towards **SVD** application to the averaged symptom observation matrix (**SOM**), instead of primary **SOM**, as it has been done already from the beginning. Of course we mean moving average of the whole **SOM**, and in this approach it will encompass the last trial of averaging the few starting values of **SOM** [CempelKrakowiak05]. Such is the aim of our paper, and we will verify this concept taking into account the real cases of machine condition monitoring with operational instabilities and random disturbances of readings.

REDUCTION OF SYMPTOMS DISTURBANCES

Unstationary load of the machine, and subsequent symptom readings, is the effect of uncontrollable load change. This may be due to the work of the machine on account of some large production system, with its own rules of loading, etc. Some examples of such objects can be large ventilation systems with many fans, and ship engine driving the propeller in the presence of sea waving, or wind turbine producing electric power. In a such cases one can often measure the change of load in a some way, and according to this can rescale the previous symptom reading. Such idea was presented already in one of the paper of present authors, and we can summarize this as below.

Let as take into account one of the component $\boldsymbol{S_n}$ of symptom observation vector, which produces the $\boldsymbol{n}$-th column in our **SOM**. Any symptom value depends in the first approach on the life time $\boldsymbol{\theta}$ and the machine load $\boldsymbol{L}$. Hence the symptom reading at the life time $\boldsymbol{\theta_p}$, when the machine load value was $\boldsymbol{L_p}$ can be written as $\boldsymbol{S_{pn}(\theta_p, L_p)}$. Trying to rescale this reading to the nominal load condition $\boldsymbol{L_o}$, at the beginning of monitoring, and assuming that the resultant load deviation is small we can use Taylor series expansion as below

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

what is equivalent to multiplicative model of the load influence on the symptom value.

Hence, going to rescale the load influence on the symptom value of nominal load $\boldsymbol{S_{pn}(\theta_p, L_o)}$ we should divide the current reading by the rescaling coefficient

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

This means, that for the load increase $\Delta L > 0$ we will divide the current symptom readings by the correction factor less than one, and vice versa, for the load decrease we will divide by the factor less than one. Of course this model is valid only when the load increase increases the symptom readings, what is right almost in any case of condition monitoring.

So much if we are observing only one symptom, but having multidimensional case of **SOM** we may assume in the first approach that the other symptom have similar behavior. It means that the same correction factor can be applied to the given row of the **SOM**, as it was shown already in [CempelTabaszewski05].

But having the case that symptom readings can not be simple linked to the load fluctuation, we may assume that any symptom has some small probabilistic component, which can be diminished by an averaging operation carried out on some neighbour readings of the symptom and **SOM** as well. Currently, almost any calculation or simulation package contains such moving average operation, like for example in Matlab® one can use for the whole **SOM** the function ***movavg(SOM,q)*** using ***q=3,5..*** neighboring points only. The extent of averaging (***q***) depends on the case under the consideration, and of course should be carefully studied at the place of its implementation. As it follows from the introductory simulation carried out on our condition monitoring data, the value ***q=3*** seems to be satisfactory in many cases.

EXTRACTION OF FAULT INFORMATION

Having said all of this, let us take into consideration the primary symptom observation obtained by the set of observation of symptom observation vector, it means we have **SOM=** $^{*}S_{nm}$. As previously, before the application of **SVD** to the **SOM** matrix, every column is centered and normalized to the initial symptom value $^{*}S_{mo}$, it means for the symptom value in healthy condition.
In this way one can obtain the dimensionless symptom observation matrix of the shape

$$O_{nm} = [S_{nm}];\ S_{nm} = (^{*}S_{nm} / ^{*}S_{no}) - 1 \tag{3}$$

Also, aiming to apply the rescaling operation we will multiply left hand side the already dimensionless symptom observation matrix by rescaling matrix L_{pp} , which rows are the coefficients defined by relation (2). Applying now the moving average operation to the above dimensionless symptom observation matrix, and replacing the numbering of column by the ***r*** index, and rows by ***p,*** we have

$$O_{pr} = [movavg(S_{nm}, q)]. \tag{4}$$

Using now rescaling operation one can get finally

$$^{R}O_{pr} = L_{pp} * O_{pr} \quad . \tag{5}$$

The singular value decomposition **SVD** of the above transformed **SOM** matrix gives us the left hand side and right hand side singular vectors with respective matrices, and singular values σ_l, as below [Kiełbasiński92,s41]

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

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

$$\Sigma_{pr} = diag\ (\sigma_1, \ldots, \sigma_l),\ and\ \ \sigma_1 > \sigma_2 > \ldots > \sigma_u > 0, \tag{7}$$

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

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 first is **generalized fault symptom** of order t which shows also the **time profile** of this fault $P_t(\theta)$;

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

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

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

Of course, when tracing the fault evolution in the operating machine, both quantities will depend on a life time of the system θ, so we will have; $SD_t(\theta)$ and $\sigma_t(\theta)$. Finally, it seems to be good to monitor cumulative wear of all types, so one can get 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 symptoms in operating system obtained by **SVD** seems to be correct, what allows us to use the **symptom reliability** concept for the determination of generalized symptom life curve $P(\theta)$, and next the symptom limit value S_l.

So far, this methodology of decomposition and fault interpretation was used only to primary **SOM**, but now we will try to apply the same approach to the moving average data. And we will try to compare new obtained results with the data not averaged, and also with the averaging of initial value, as it was done lately in [CempelKrakowiak05].

EXAMPLES OF SYMPTOMS AVERAGING IN REAL CASES OF MACHINE CONDITION MONITORING

One of the critical activity in deep mining is the ventilation of shafts, obtained by continuous running of huge fans, with mass of the rotor of several tones. But due to the mining activity the demand for the air is unstable, and it influences strongly the vibration amplitudes measured by vibration condition monitoring subsystem. Beside that instabilities, the vibration condition monitoring was implemented in several fans of one Polish copper mine, as it gives some additional insight into the rotor unbalance, the condition of the slide bearings, and some other faults. On each fan five vibrational symptoms have been measured once a week, but with no information on the driving power or the air flow demand, and the load ***L*** as well. As symptoms of fan condition, the radial vibration velocity of two bearings were taken as all pass quantity, also they were filtered with rotational and blade frequencies, and also one overall vibration velocity reading of the fan foundation was used, too. 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 **pcarescavg.m** (*written in **Matlab**® environment*) based on **SVD** as above, but for comparison without **SOM** averaging.

The results of introductory application of this software, being the basis of comparison for further calculations, is shown in Figure 1 containing six pictures.

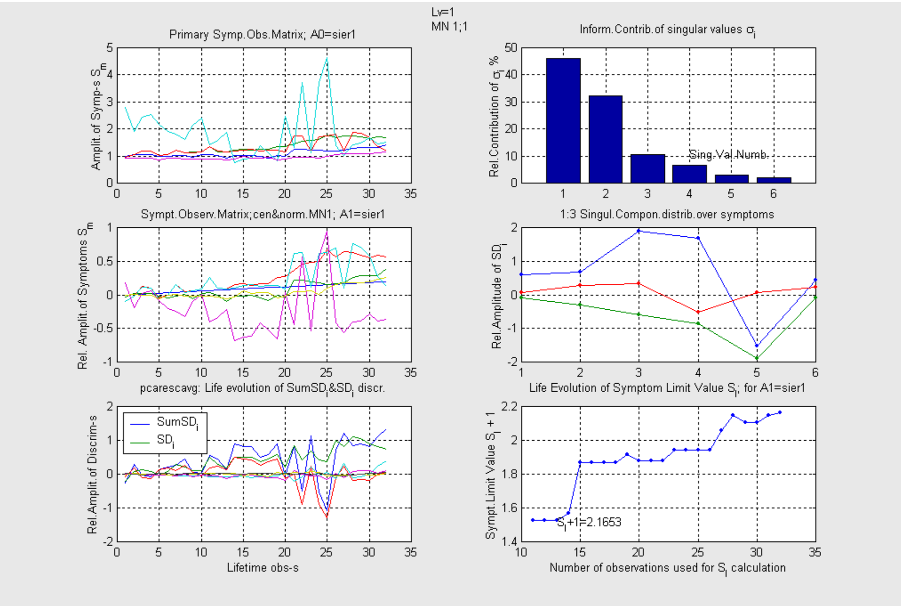

*Fig. 1. Multi symptom vibration condition monitoring of a huge fan used to supply air into the deep mining shaft, and the results of **SVD** performed on **SOM**.*

The first picture, left top one, shows us primary symptom observation matrix of fan called here **sier1.txt**. As it can be seen the symptom readings are very unstable, even one vibration symptom is falling down what may mean that first reading was taken at the peak of the system load. The middle left picture shows already dimensionless **SOM** (*after centering and normalization*), where the variability of observed symptoms are fully shown, together with the straight line of the system life θ. The left bottom picture shows the generalized faults (*after **SVD***) in accordance to formulae (8) and (10). We can see here that multidimensionality of observation and application of **SVD** gives some smoothing in the course of generalized symptoms and their sum. This property of multidimensional observation enables to make diagnostic decision with better accuracy and safety, even in nonstationary running. The top right picture shows us the intensity of information sources or generalized faults in **SOM**, with one fault prevailing others at almost 50% of total information resource. The right middle picture shows the importance of primary measured symptom in the creation of first three singular components SC_i. One can notice that symptoms number 3 and 4 are the most important in the creation of the first singular component, it means first generalized fault, too. The last picture, the right bottom one, shows us the creation of symptom limit value S_l, calculated by means of symptom reliability concept [CempelNatkeYao00]. One may notice here, that even with such great instability of symptom readings this concept of symptom reliability seems to be working, as it enables the assessment of symptom limit value $S_l=1.165$. If we take a look to the left bottom picture this limit value seems to be a good assessment of generalized symptom variability, giving the basis for the diagnostic decision.

Now, it is time to introduce the averaging concept into **SOM** before its decomposition. This was made by similar program called **pcasvdavg.m**, where the only difference is the running average operation introduced at the beginning to our **SOM sier1.txt**. Again, the same primary **SOM** have been used but with three point moving average ($q=3$), and the result of such calculations are shown on the figure 2. Comparing this figure with previous one, one can notice the great difference on the left hand side. The variability of symptoms is smaller, but their smoothness is far greater. One can notice comparatively, that these pictures can serve much better for the purpose of condition monitoring. This concerns the dimensionless symptoms (*picture middle left*) and generalized symptoms (*picture bottom left*) as well. Going now to compare right hand side pictures in Fig.1 and Fig. 2 one can notice small differences only, the fault information contribution is with no difference, as well as primary symptom contribution to the singular components is almost the same. The only difference is the course and the value of symptom limit vale $S=1.0306$, but if compared to the smallest variability of generalized symptoms, (*picture bottom left*), this seems to be also the good assessment for the diagnostic decision.

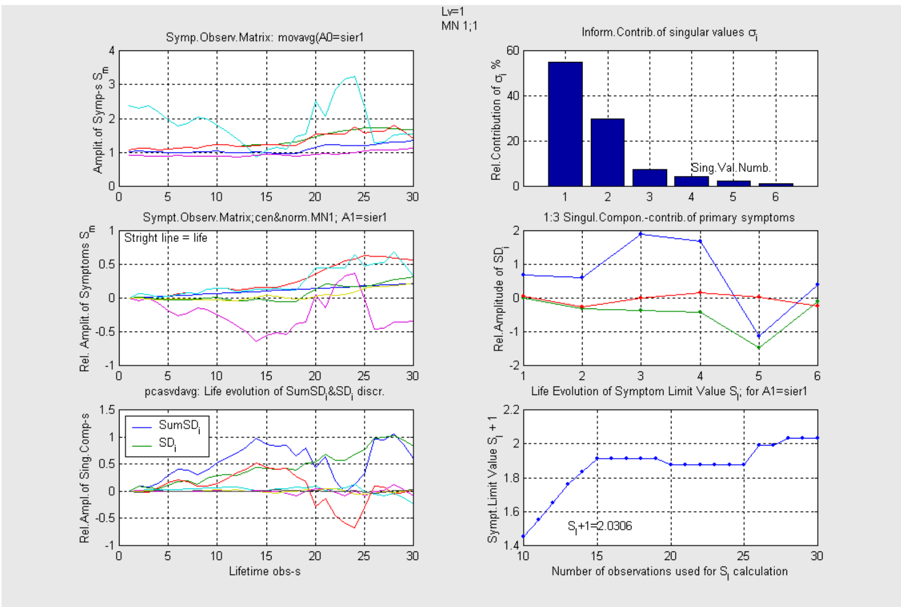

*Fig.2. Multi symptom vibration condition monitoring of the fan as above, but with moving average of primary **SOM**.*

Summing up the introduction of the moving average formulae to the fun data it seems to be a good idea, in particular for the machines with unstable operation.

As we have noticed at the beginning of this point, the values of one symptom are falling down as it would be the symptom of decreasing load of the fan. Let us assume this for the moment in rescaling matrix $\boldsymbol{L_{pp}}$ introducing here the coefficient ***0.9*** into its first row. All the other data of **SOM** and the moving average are the same as before (see Fig. 2), and the results of rescaling are shown in the diagrams of Fig. 3.

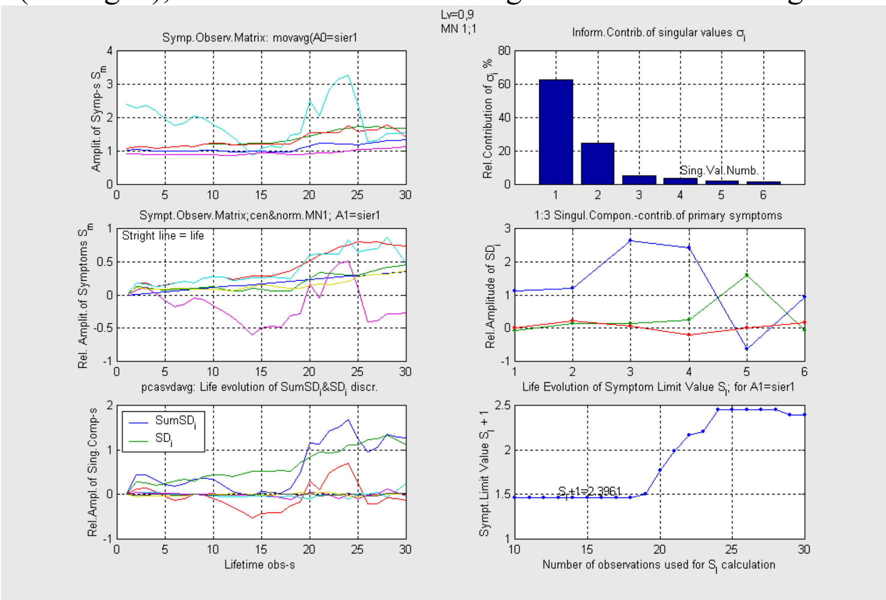

Fig. 3. Data the same as Fig 2(sier1.txt), but with rescaling in the first raw of ***SOM****, with rescaling matrix:* $\boldsymbol{L_{pp}}$***=Diag(0.9;1;1...).***

Because of normalization to the smallest value of our symptom the amplitudes of pictures middle left and the bottom left are larger now. What is more remarkable is the course of the second singular component $\boldsymbol{SD_2}$ (*picture bottom left*), now it has mostly positive values against previously negative in Fig.2. Due to that, the contributions of primary symptoms in creation of the first singular components are little bigger (*picture middle right*), and also the symptom limit value has a greater value $\boldsymbol{S_l=1.3961}$ than before. But again, it is the good assessment of limit value in comparison to course and values of generalized symptom of picture bottom left. Hence, one can say that rescaling operation seems to be workable as shown in the paper [CempelTabaszewski05], also this time with the moving average of primary **SOM**.

Finally, it has been also shown the usefulness of **SOM** averaging idea for some another data taken from the vibration condition monitoring of the diesel engines, and also from vibrational observation of ball bearing life testing stand. But for the sake of place here we are not showing them in this paper. They confirm fully the conclusions drawn from the above presented examples.

In summary one can say, that the moving averaging of **SOM** is a valuable diagnostic tool, especially for the real data taken from the objects working with unstable environment. It gives the effect of smoothing the normalization of initial values, as well as smoothing the course of the dimensionless and generalized symptoms, what makes easy the final diagnostic decision and symptom limit value S_l calculation as well. What is more to say, this additional operation on **SOM** does not change the information contribution and the meaning of primary symptoms.

CONCLUSIONS

The paper concerns again the case of multidimensional condition monitoring of unstable running machines, which work for example with stochastic environment, where the load of machine can not be simply controlled. It was shown on same real data, that averaging operation applied to the symptom observation matrix, can be a valuable help enabling to smoothen the life course of generalized fault, and much better calculate the symptom limit value S_l needed for the diagnostic decision.

REFERENCES

1. Cempel C., Innovative developments in systems condition monitoring, Keynote Lecture, **DAMAS'99**, Dublin, June 1999.
2. Natke H. G., Cempel C., **Model Aided Diagnosis of Mechanical Systems**, Springer Verlag, Berlin, 1997, p248.
3. Cempel C., Multidimensional Condition Monitoring of Mechanical Systems in Operation, **Mechanical Systems and Signal Processing,** 2003, Vol. 17, No 6, pp1291 – 1303.
4. Cempel C, Implementing Multidimensional Inference Capability in Vibration Condition Monitoring, Proceedings of Conference: **Acoustical and Vibratory Surveillance,** Senlis - France, October 2004; *improved version* see *also* **Diagnostyka,** No 34, 2005, s7-14.
5. Gere G. M., Weawer W., **Matrix Algebra for Engineers**, Van Nostrand, Princetown, 1965, p168.
6. Natke H. G., Cempel C., The symptom observation matrix for monitoring and diagnosis, **Journal of Sound and Vibration,** 2002, 248, pp597 – 620.
7. Kiełbasiński A., Schwietlick H., **Numeryczna Algebra Liniowa**, WNT, Warszawa, 1992, s502.
8. Cempel C., Natke H. G., Yao J. P. T., Symptom Reliability and Hazard for Systems Condition Monitoring, **Mechanical Systems and Signal Processing,** Vol. 14, No 3, 2000, pp 495-505.
9. Cempel C., Tabaszewski M**.,** Multidimensional vibration Condition Monitoring of Nonstationary Mechanical System in Operation**, 12 ICSV Lisbon,** July2005, *full text in:*, **Diagnostyka,** 2005, No 34, s23-30.
10. Cempel C., Krakowiak M., Unstable and probabilistic behavior of symptoms in multidimensional condition monitoring, (*in Polish) paper prepared to* **Conference on Machine Diagnostics**, Węgierska Górka, March 2006.