THE GLOBAL AND PARTIAL SYSTEM CONDITION ASSESSMENT IN MULTIDIMENSIONAL CONDITION MONITORING[1]

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Summary

Machines have many faults which evolve during its life (*operation*). Observing some number of symptoms during the machine operation it is possible to capture needed fault oriented information. One of the methods to extract fault information from such symptom observation matrix (SOM) is to apply the singular value decomposition (SVD), obtaining in this way the generalized fault symptoms. The problem of this paper is to use the total damage symptom, being a sum of all generalized symptoms. Also we will use the first generalized symptom as the dominating fault symptom, to infer better on machine condition. There was some new software created for this purpose, and some cases of machine condition monitoring have been considered as examples. Considering these it seems to the author, that both generalized symptoms should be used for the inference on machine condition. They are complimentary each other in some way, and should be used together to increase the reliability of diagnostic decision.

Keywords: condition monitoring, multidimensional observation, singular value decomposition, generalized fault symptoms, grey models, forecasting, decision reliability.

CAŁKOWITA I CZĄSTKOWA OCENA STANU W WIELOWYMIAROWEJ DIAGNOSTYCE MASZYN

Streszczenie

Maszyny mają wiele uszkodzeń, które ewoluują w trakcie ich pracy. Jeśli obserwujemy pewną liczbę dobranych symptomów w trakcie życia obiektu możemy tą informację o uszkodzeniach wychwycić w zapisie symptomowej macierzy obserwacji (SOM). Ekstrakcja tej informacji uszkodzeniowej jest możliwa za pomocą procedury SVD, która wyodrębnia poszczególne uogólnione symptomy związane z niezależnymi uszkodzeniami w maszynie. Zazwyczaj mamy sytuacje jednego dominującego symptomu i nasze wnioskowanie diagnostyczne może być związane z tym dominującym symptomem, lub też z tzw. uszkodzeniem całkowitym jako suma wszystkich uogólnionych symptomów. Problemem pracy jest właśnie pytanie; czy wziąć pod uwagę jedynie dominujące uszkodzenie, czy też całkowite. Okazuje się z kilku przykładów, ze większą pewność decyzji diagnostycznej uzyskamy jeśli w weźmiemy pod uwagę oba symptomy, symptom całkowitego uszkodzenia jak i dominujący symptom.

Słowa kluczowe: nadzorowanie stanu, wielowymiarowa obserwacja, rozkład SVD, uogólnione symptomy, szare modele, prognozowanie, pewność decyzji.

1. INTRODUCTION

The most machines in operation, even performing simple operations, have many modes of failure. Hence their diagnostics have to be multidimensional. From the other side, the contemporary advancement in measurement technology allows us to measure almost any component of phenomenal field, inside or outside of the working machine. The only condition for symptoms in such multidimensional diagnostics is some kind of proportionality to gradual worsening of the machine condition which takes place during it operation. If it is so, we can name the measured component of machine phenomenal field as the **symptom**[2] of condition. In this way we are measuring a dozen of '*would be*' symptoms, and our condition monitoring is multidimensional from the beginning. Due to this situation, the application of multidimensional machine condition observation is now well established fact, see [1, 4, 5, 6] - for example. Moreover there exist some difference in application and processing of the multidimensional signals and/ or symptom observation matrix. For a diagnostic signals and symptoms one can apply also so called data fusion technique [4, 20, 21], and similar techniques developed lately.

[1]Paper presented at ISVR09 Cracow
[2]Measured physical quantity being proportional to the condition of the machine.

In case of multi symptom observation one can apply principal component analysis (PCA), or singular value decomposition (SVD), looking for principal or singular components, which may have some diagnostic meaning. For the case of SVD method (*Singular Value Distribution*), there exists the body of experimental evidence [2, 19], for example, that singular components and the quantities created from them can be treated as **generalized** fault symptoms having prescribed diagnostic meaning.

All these transformation and symptom processing starts from the data base called symptom observation matrix (SOM) acquired during the on line or off line machine monitoring. Let us explain now how this SOM is structured and how it may be obtained.

During the machine life θ we can observe its condition by means of several symptoms $S_m(\theta)$ physically different and measured at some moments of life θ_n , $n=0,1,\ldots p > r$, $\theta_p < \theta_b$, (θ_b – *anticipated breakdown time*). This creates sequentially the symptom observation matrix (SOM), the only source of information on condition evolution of machine in its life time $0 < \theta < \theta_b$. We assume additionally that real condition degradation is also multidimensional, and is described by semi independent faults $F_t(\theta)$, $t=1,..u < r$, which are evolving in the machine body, as the expression of gradual degradation of the overall machine condition. This degradation proceeds from the **not faulty condition**[3] up to its near breakdown state. Generalizing, one can say now, that we have m dimensional symptom space for condition observation, and $r < m$ dimensional fault space, which we try to extract from the observation space, by using SVD or PCA.

Moreover, some of '*would be'* symptoms contained in SOM are redundant; it means not carrying enough information on the evolving faults during the machine life. But of course there is not unique criterion of the redundancy. During the course of our research, several measure of redundancy has been applied, the volume of observation space (*Vol1)*, pseudo Frobenius norm (***Frob1***) of SOM [19], and others. But they seem to be not good enough with respect of the quality of the final diagnostic decision. This means additionally, when optimizing the observation space, we should take into account the adequate assessment of the **current** and the **future machine condition**. The paper considers this problem, and it is done on the level of previous SVD works of the author. As the forecasting technique with minimal error, the **grey system model** with rolling window [12] was adopted for diagnostic purposes, and has been applied here according to [19].

[3]We assume machine is new, or after the overhaul and repair process.

But having the multidimensional problem of fault assessment, it is important now what type of generalized symptom we use for the forecasting and condition inference. Do we use the overall degradation symptom of the machine, or some specified generalized symptom proportional to one fault only, or both these symptoms. The results of such new approach to multidimensional diagnosis presented here were verified on the real data of machine vibration condition monitoring. Concerning the software, some modification of last programs for the data processing was needed as well. As a result is was found ,that this approach seems to be promising enabling a better understanding of machine condition, and also the better current and future condition assessment.

2. EXTRACTION METHOD OF PARTIAL FAULTS FROM THE SOM

As it was said in the introduction, our information on machine condition evolution is contained in $p \bullet r$ symptom observation matrix (SOM), where in r columns are presented p rows of the successive readings of each symptom, made at equidistant system lifetime moments θ_n, $t=1,2,\ldots p$. The columns of such SOM are next centered and normalized to three point average of the three initial readings of every symptom. This is in order to make the SOM dimensionless, to diminish starting disturbances of symptoms, and to present the evolution range of every symptom from zero up to few times of the initial symptom value $\mathbf{S}_{0n}$, measured in the vicinity of lifetime $\theta_1 = 0$.

After such preprocessing we will obtain the dimensionless symptom observation matrix (**SOM**) in the form;

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

where bold non italic letters indicate primary measured dimensional symptoms.

It was said in the introduction, we apply now to the dimensionless **SOM** (1), the Singular Value Decomposition (**SVD**), [22], to obtain singular components (*vectors*) and singular values (*numbers*) of **SOM** , in the form

$$O_{pr} = U_{pp} * \Sigma_{pr} * V_{rr}^T, \quad (T\text{- matrix transposition}) , \qquad (2)$$

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

$$\Sigma_{pr} = diag\,(\sigma_1, \ldots, \sigma_l), \text{ with nonzero s. v.: } \sigma_1 > \sigma_2 > \ldots > \sigma_u > 0, \qquad (3)$$

and zero **s. v.** ; $\sigma_{u+1} = \ldots \sigma_l = 0$, $l = \max(p, r)$,
$u \le \min(p, r)$, $u < r < p$.

In terms of machine condition monitoring the above (3) means, that from the ***r*** primarily measured symptoms (*dimension of **observation space***) we can extract only $u \le r$ nonzero independent sources of diagnostic information, describing the evolving generalized faults $F_t(\theta)$, $t=1,..u$, and creating in this way the less dimensional **fault space**. But only a few faults developing currently in a machine are making essential contribution to total fault information (*are enough developed*). The rest of potential generalized faults, symbolized here by small σ_u value, are usually below the standard 10% level of noise. What is important here, that such **SVD** decomposition can be made currently, after each new observation (*reading)* of the symptom vector $[S_m]$; $n = 1 \ldots p$, and in this way we can trace the faults evolution, and their advancement, in any operating mechanical system.

3. DIAGNOSTIC INTERPRETATION OF SVD

From the current research and implementation of this idea [2], one can say, that the most important fault oriented indices obtained from **SVD;** is the generalized fault symptom SD_t, $t=1,2,$ and also the sum of all generalized fault symptoms $SumSD_i$, as some equivalent symptom of total (*cumulated*) machine damage. In another way, the generalized fault symptom SD_t can be named also as discriminant, or the generalized symptom of the fault order ***t***, and one can obtain this as the **SOM** product and singular vector v_t, or in general in matrix notation as below:

$$SD = O_{pr} * V = U * \Sigma,$$
$$\textit{and in particular}; \quad SD_t = O_{pr} * v_t = \sigma_t \cdot u_t, \quad t=1,...u < r. \tag{4}$$

We know from **SVD** theory [22], that all singular vectors v_t, and u_t, as the components of singular matrices, are normalized to one, so the energy norm of this new discriminant (*generalized fault symptom*) gives simply the respective singular value σ_t:

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

The above defined discriminant $SD_t(\theta)$ can be also named as lifetime fault profile, and the respective singular value $\sigma_t(\theta)$ as a function of the lifetime seems to be its life advancement of damage (*energy norm*) and the same the measure of importance of the fault. That is the main reason why we use dimensional or dimensionless singular values for the ordering of importance of generalized symptoms (*faults*).

The similar fault inference can be postulated to the meaning, and the evolution of summation quantities, the total damage profile $SumSD_i(\theta)$ as below

$SD_t(\theta) \propto F_t(\theta)$, with: $//SD_t(\theta)// = \sigma_t$, $t=1,2,$

$$SumSD_i(\theta) = \sum_{i=1}^{u} SD_i(\theta) = \sum_{i=1}^{u} \sigma_i(\theta) \cdot u_i(\theta) \propto F(\theta)$$
with: $//SumSD_i(\theta)// \cong \Sigma\, \sigma_i(\theta)$ (6)

Currently it seems to be, that the condition inference based on the first summation damage measure; $SumSD_i$, (*total damage measure*) may stand as the first approach to multidimensional condition inference, as it was lately shown in the previous papers (*see for example* [1, 2, 7]). The similar inference based on the first (*dominating*) generalized fault SD_1 is valuable and complimentary, as it was shown lately [19].

$$SumSD_i(\theta) = SD_1(\theta) + \varepsilon(SumSD_i(\theta)). \tag{6a}$$

Going back to SVD itself it is worthwhile to show some mathematical metaphor of (5), that every perpendicular matrix has such decomposition, and it may be interpreted also as the product of three matrices [22], namely

$$O_{pr} = (\textbf{Hanger}) \times (\textbf{Stretcher}) \times (\textbf{Aligner}^T). \tag{7}$$

This is very metaphorical description of **SVD** transformation, but it seems to be useful analogy for the inference and decision making in our case. The diagnostic interpretation of formulae (7) one can obtain very easily. Namely, using its left hand side part we are stretching our **SOM** over the life (*observations*) dimension, obtaining the matrix of generalized symptoms as the columns of the matrix ***SD*** (*see below*). And using its right hand side part of (7) we are stretching **SOM** over the observed symptoms dimension, obtaining the assessment of contribution of every primary measured symptoms in the matrix ***AL***, assessing in this way the contribution of each primary symptom to the generalized fault symptom SD_i.

$$SD = O_{pr} * V_{rr} = U_{pp} * \Sigma_{rr};$$
$$\textit{and} \quad AL = U^T_{pp} * O_{pr} = \Sigma_{rr} * V^T_{rr}. \tag{8}$$

This means that ***SD*** matrix is stretched along the life coordinate giving us the life evolution of the weighted (σ_i) singular vectors. And AL matrix is aligned along the symptom dimension with the same way of weighting by σ_i, giving the assessment of information contribution of each primary symptom.

We will calculate numerically the above matrices and use them for the better interpretation of monitoring results (***SD***), and optimization of dimension of the observation space (***AL***).

4. THE SOM INFORMATION MEASURE AND OPTIMIZATION

Having in mind the redundancy of some primary symptoms, i.e. the primary observation space, some additional considerations should be made concerning **SOM** information assessment. In terms of previous findings this can be done by calculating the Frobenius norm (***Frob***) of this matrix, and the volume (***Vol***) created by ***u***-dimensional generalized fault space identified by application of (**SVD**). One can calculate easily both information indices as the sum and the product of singular values in the following way:

$$Frob(SOM) \equiv \{\Sigma \sigma_i^2\}^{1/2};$$
$$\text{and } Vol(SOM) \equiv \Pi \sigma_i, \quad i = 1,\dots u.$$

But squaring the small singular values of σ_i (*less than one*) make them much smaller, giving seemingly smaller contributions to the matrix information asset, and to the volume of the observation space. Due to this we can propose to use not the exact Frobenius norm but its modification as below:

$$Frob1 = \Sigma \sigma_i; \text{ and: } Vol1 = \Pi \sigma_i. \quad i = 1,\dots u. \tag{9}$$

This will give us possibility to look for the small, just evolving faults, and not omit them when we try to reduce the redundancy of the observation vector. Consequently one can get less redundancy of new optimized SOM, with less number of columns but also keeping in observation the small just evolving fault information (σ_i).

The use of Frobenius measure for a matrix has also mathematical validation. In general, one can understand this as the problem of approximation of matrix ***B***, by so called k-rank approximation. Following the paper [9] we can make the quantitative assessment of such k-rank approximation of a matrix ***B*** as the difference below:

$$\| B - B_k \|_F = \{\sigma^2_{k+1} + \dots \sigma^2_u\}^{1/2}, \tag{10}$$

where the subscript ***u*** stands for maximal dimension of nonzero singular value, i.e. the rank of our primary **SOM.**

This means also, that instead of (9), we will write simplified measure of approximation of SOM in the form of deviation from primary **SOM** rank, as below

$$\Delta_k Frob1 \equiv Frob1_o - Frob1_k = \{\sigma_{k+1} + \dots \sigma_u\}. \tag{11}$$

Using this quality index of matrix approximation measure we, can form additional objective measure of the SOM redundancy. And minimization of **SOM** rank may be carried by excluding some primary measured symptoms S_m with low information contribution, which produce mainly small (*less than one*) singular vales σ_u.

Such criteria of redundancy minimization we have used quite recently. But following the last papers [19], one may notice that after some symptom rejection, which gives expected increase in the volume of information space (Vol1). Also the rank approximation of **SOM** gives only some drop in Frob1 measure, but the result of prognosis is not enough good, ***giving erroneous future values***, sometimes less than the previous one. How to avoid such errors in forecasting?

There seem to be one possibility more, to make the symptom rejection more objective and anticipating the goodness of the condition forecast. We have to consider the contribution of primary measured symptoms to the creation of first generalized symptoms SD_1, and also the creation of total damage generalized symptom ***SumSDi***. The first overall information contribution measure, can be calculated separately to each primary symptom, from the correlation matrix of our SOM (*with appended lifetime in the first column*), as the centered and normalized sum of column elements. The second measure one can obtain if we append additionally to the previous matrix the vector ***SumSDi***, as a first column. When calculating covariance matrix from these and in the first row we will have needed information. After needed normalization to the first element of this row this will give us the contribution of every primary symptom to the total damage symptom ***SumSDi***.

5. THE GLOBAL AND PARTIAL FAULT INFERENCE

We have gathered above all necessary analytical and inference knowledge concerning processing of symptom observation matrix, the extraction of fault information, and optimization of SOM rank. So, there is a right moment to validate these finding and proposal by some experimental data taken from real situations of vibration condition monitoring. In order to do this the last Matlab® program **svdopt1gs.m** presented in [19] has been modified to **svdoptInt.m**. The inference basis for the first program was the total damage generalized symptom ***SumSDi*** , while in the modified program such inference basis is the first generalized symptom SD_1. Just to catch the the way of inference and the followed diagnostic decision difference we will take some uneasy case of heavy fan (3MW) working in unstable and load uncontrolled regime (*random supply of the air to the mine shaft*), serving as the source of fresh air for ventilation at the deep copper mine. The main troubles with this fun were unbalance and nonalignment between the fan and the driving electric motor, due to that the unit was constantly monitored.

Figure 1 presents below the six pictures as the result of fan data processing by specially prepared program **svdoptint.m** made in the Matlab® environment, where the main stream of inference follows the evolution of the first generalized symptom SD_1. The first top left picture, gives the results of 30 weeks measurements of symptom life curves of vibration velocity at a five points located on the fan aggregate structure. One may notice here the great instability of symptom readings, symptom No 4 in particular. This is better seen at the picture middle left when data are centered and normalized to the average value of the three initial symptom readings. We can notice here the negative values of symptom as an effect of load instability and normalization. The picture bottom left presents the *generalized symptoms* as the result of SVD processing, indicating also the symptom limit value calculated for the generalized symptom of total damage ***SumSDi*** (*red line*) denoted there as $\mathbf{S_{lc}}$, and also symptom limit value $\mathbf{S_{l1}}$ calculated from the first generalized symptom $\boldsymbol{SD_1}$.

The picture top right shows the relative amounts of information obtained as percentage of given singular value $\boldsymbol{\sigma_i}$ normalized to the sum of all singular values. As it follows from (5) this indicates at the same time the advancement of the given fault evolution in the machine life. As the legend to this picture we have indication of two redundancy measure, the ***Frob1*** and the ***Vol1***, which will serve as some guidance in the optimization process of the observation space.

The middle right picture presents the contribution of primary measured symptoms (*the first = lifetime*) to the creation of the dominating three generalized symptoms. One can notice here, that symptoms No 4 and 5 give minimal contribution and can be rejected in a process of optimization of the observation space. The last picture, the bottom right, of the Figure 1 shows the evolution of symptom limit value as calculated from the first generalized symptom SD_1, indicating also the value of symptom limit value as calculated from the sum of generalized symptoms ***SumSDi***. One can notice from the both bottom pictures, that in this case the difference between symptom limit values is a small one, but the value obtained from SD_1 gives better indication of the coming machine breakdown.

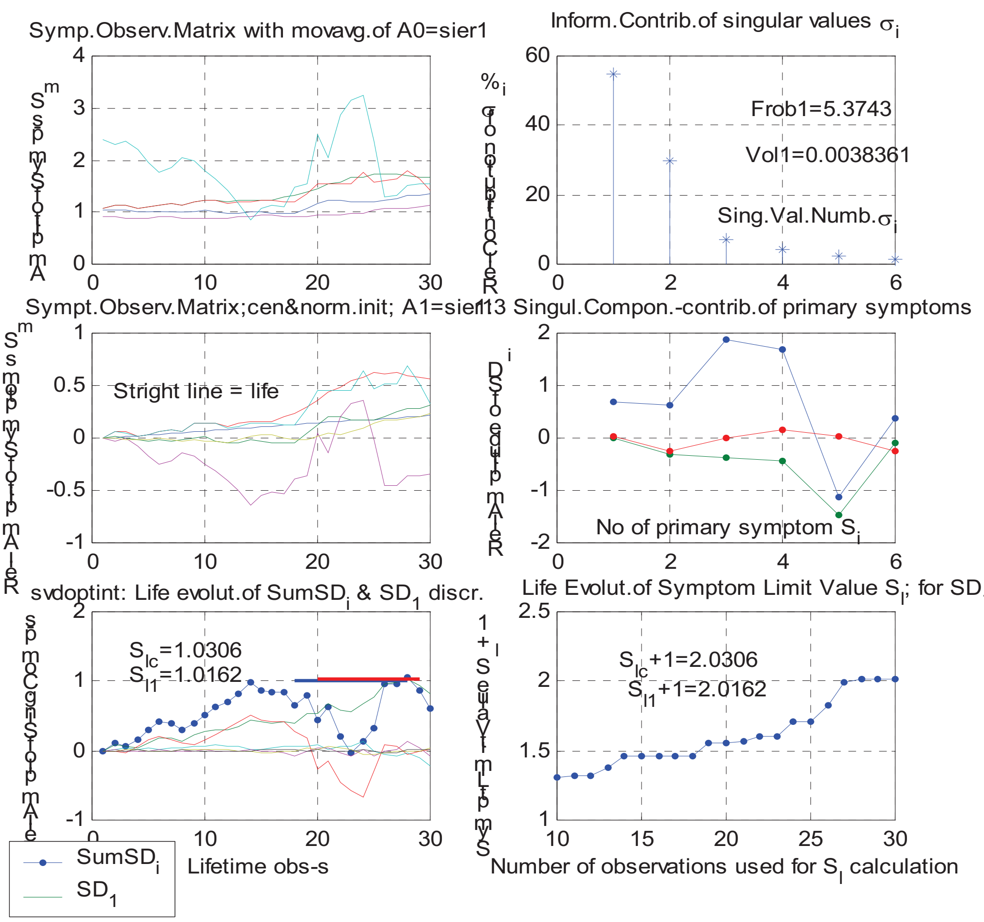

Fig. 1 The results of SVD processing of vibration data of a huge fan pumping air into the copper mine shaft, with the inference according to dominating generalized symptom SD_1

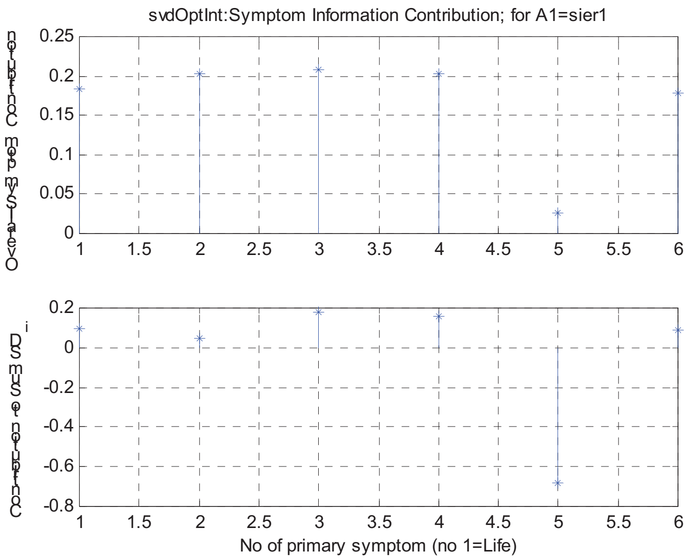

Fig. 2. The Correlation measure of overall and particular contribution of primary symptoms

As it was mentioned before, the program **svdoptint.m** contains not only the matrix ***AL*** (8) (*picture middle left*), but also some correlation assessment of individual and overall information contribution of every primary symptom in SOM. Figure 2 presents these data, and we can see there, really symptom No4 has minimal overall contribution, and a negative one to generalized symptom SD_1.

Having such strong indication of the two symptoms redundancy (*No 4 and No 5*), let us begin a gradual rejection of these symptoms contained in SOM. As a first step we rejected symptom No 4, however its contribution is not minimal in this case. The effect of such rejection is shown in a Figure 2, organized in the same manner as a previous one. Comparing the both we can notice the radical change in the symptom behavior, mainly we have rejected the most unstable primary symptom No 4. As the result of such rejection we have much clear situation of symptom evolution, primary symptom (*picture top left*) and generalized (*picture bottom left*), and the values of symptom limit values have change slightly, differing more than previously. Also the Frobenius redundancy measure drops significantly, and the volume of the fault space increased a little. But the most important effect of this rejection is the increased stationarity of remaining symptoms, the primary and generalized as well. Looking at the picture middle right one can notice very low contribution of primary symptom No 5. Hence next motion will be the rejection of this symptom together with previously rejected No 4. The results of such double rejection operation and subsequent processing one can find on the Figure 4.

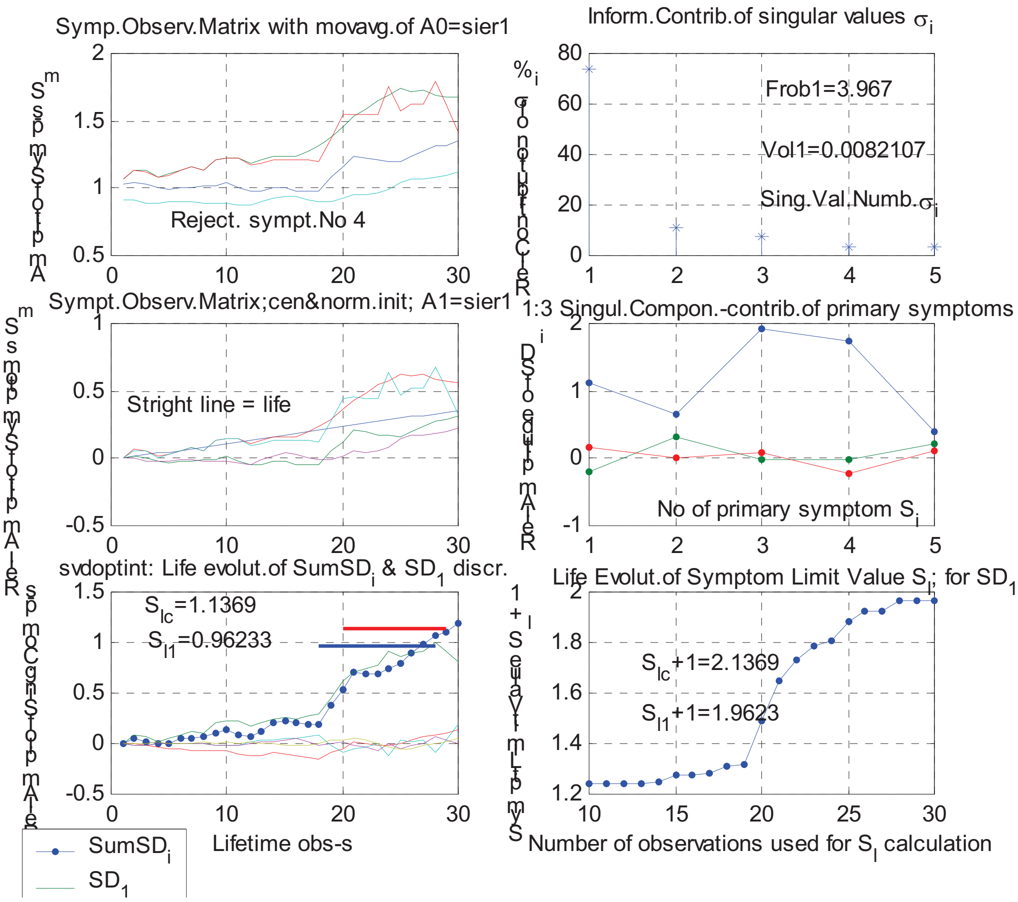

Fig. 3. The vibration symptom observation matrix of the huge fan (see Fig.1) after the rejection of unstable symptom No 4

Looking at the difference between Figures 3 and 4 one can notice much more clear situation on the right hand pictures of Fig. 4. Now we can infer on fan condition using both symptom limit values S_{lc} and S_{l1}, however with S_{l1} diagnosis seems to be more reliable. The top right picture indicate that Frobenius measure does not change much, but the volume of fault space increases almost ten times. This may mean that for the condition inference of the fan we should take into consideration the remaining three primary symptoms No 1, 2, 3, and due to this we will have the relative stable and reliable situation for the inference. This conclusion is validated more by the picture middle right, where one can see that the contribution of all remaining symptoms and the life symptom to the generalized symptom SD_1 is valuable, being almost of the same order.

One can notice also that the calculation of limit value using first generalized symptom ***SD₁*** gives us lower value and this can give us more safe assessment of lifetime moment for machine shut down and renewal. From the point of view of diagnostic **decision reliability**, this seems to be important to have two different sources of symptom limit vale assessment, and to confront these values and the associated knowledge.

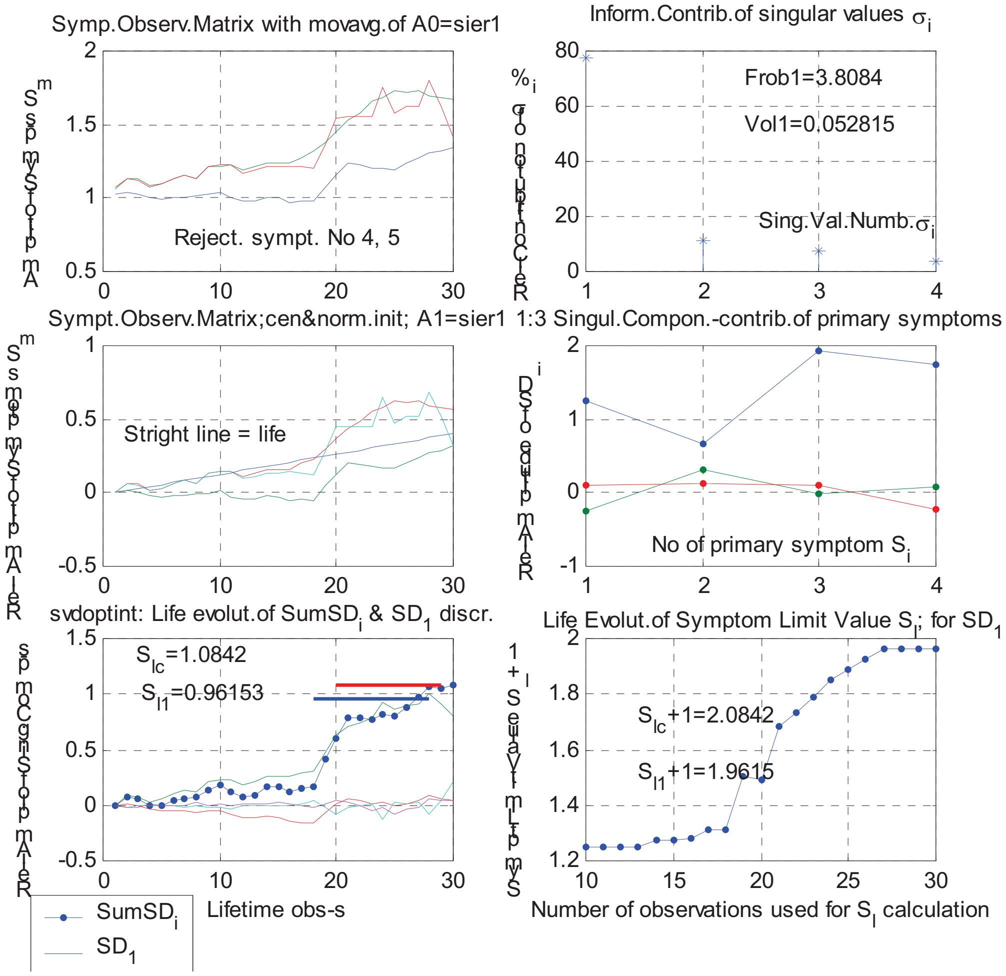

Fig. .4. The vibration symptom observation matrix of the huge fan (see Fig.1) after the rejection of unstable and the redundant symptoms No 4 and No 5

6. FORECASTING OF GLOBAL SYSTEM DAMAGE AND PARTIAL FAULTS ADVANCEMENT

The final quality of diagnostic decision one may judge making the forecast of the future condition in terms of total damage symptom ***SumSDi*** , and the first generalized fault symptom ***SD₁***. It was said in the introduction, that the forecast will be made by grey system theory (**GST**) [13], together with the rolling window method using the first order grey model **GM**(1,1) [12].

In general **GST** assumes that our incomplete and uncertain observation can be the output of some dynamic multi input system of high order, described by the grey differential or difference model [20]. In condition monitoring, we assume it is enough to take the first order system described by the grey differential equation, and one forcing or control input only. This simplest case in **GST** is denoted as **GM**(1,1), means the grey model of order 1 with one input only. The output of the system is the series of discrete observations (*our symptom readings*) denoted here as:

$$\mathbf{x^{(0)}}=\{x^{(0)}(1),x^{(0)}(2),\ldots x^{(0)}(n)\}, \qquad (12)$$

where $n \geq 4$ is the number of observation made on a system (*machine*).

We will not present GST theory here, but only using the final formulae for the forecasting, and the rolling window concept, which is implemented into the forecasting software.

The application of GST to the above symptom readings gives the possibility to forecast the future one step symptom value, starting from very small number observation, and using the formula:

$$\hat{x}^{(0)}(k+1) = \left[x^{(0)}(1) - u/a\right]\left(e^{-ak} - e^{-a(k-1)}\right), \quad k=2,3,..n, \qquad (13)$$

where $\boldsymbol{u}$ and $\boldsymbol{a}$ are parameters to be estimated by special least square matrix procedure using the observed data (12), and the hat ^ in (13) means future value of the forecasted quantity.

This concept was adjusted to the purposes of vibration condition monitoring in one of the earlier paper [18, 19]. One can notice here from the bottom left picture of Fig. 3 and 4, that the total damage generalized symptom ***SumSDi*** (*line with dots*) is evolved well after rejection the primary symptom No **4 and 5**, enabling to undertake good diagnostic decision on the basis of these two symptom limit vales (*see Fig. 4 bottom left*). Moreover it enables good forecast even without the rolling window (*see* *fig. 5*). But of course, as usually in case of grey system modeling, the rolling windows forecast gives the smallest error. This error can be even smaller if we diminish the span of window (***w***), as it is clearly seen from the picture bottom right of the Fig. 5. It is worthwhile also to analyze the other pictures of this figure. Picture top left presents clearly, that the rejection of symptom No 4 was a good idea allowing us to determine symptom limit value $\boldsymbol{S_{l1}}$ and having this information do act properly to shut down the fan ahead of breakdown time. The top right picture present the total forecast of dominating damage symptom $\boldsymbol{SD_1}$ with the grey model ***GM(1,1)***. It seems to be good forecast with the small average error, but the picture bottom left with the rolling windows forecast, have he smaller error and the actual forecast adapts smoothly to the course of $\boldsymbol{SD_1}$, (*see curve with asterisk on the picture bottom right)*.

It is seen from the Fig. 5 left top picture, that the course of $\boldsymbol{SD_1}$ generalized symptom is decreasing at the end of fan life, but the both assessed symptom limit values $\boldsymbol{S_{lc}}$ and $\boldsymbol{S_{l1}}$ warns in advance enough to undertake shut down decision, just on time. However, comparing the both symptom limit values shown on the picture top right of the last figure, and Fig.4, it is good to know that the global damage symptom limit value $\boldsymbol{S_{lc}}$ can be used only with a global damage symptom ***SumSDi*** , in other case it can give erroneous decision. But the limit value of the first generalized symptom $\boldsymbol{SG_1}$ (*dominating fault*) warns us enough in time when to shut down the machine safely. And this is the **most important message** for using partial and global condition inference simultaneously in order to increase the reliability of diagnostic decision, as proposed in this paper.

To illustrate this idea more, let us consider another object, railroad diesel engine monitored by vibration measurement, each ten thousand kilometers of mileage. Here 12 vibration symptoms were initially monitored at the top of one of the engine cylinder. With this data using the software similar as previously (Fig.1-4), two primary symptoms have been found as redundant. As it is seen from the vibration course on the next figure 6, at 210 thousand kilometers of the engine mileage some minor repair was done without overhauling the engine, what reduced greatly the generalized symptom of total engine damage $\boldsymbol{SumSD_i}$.

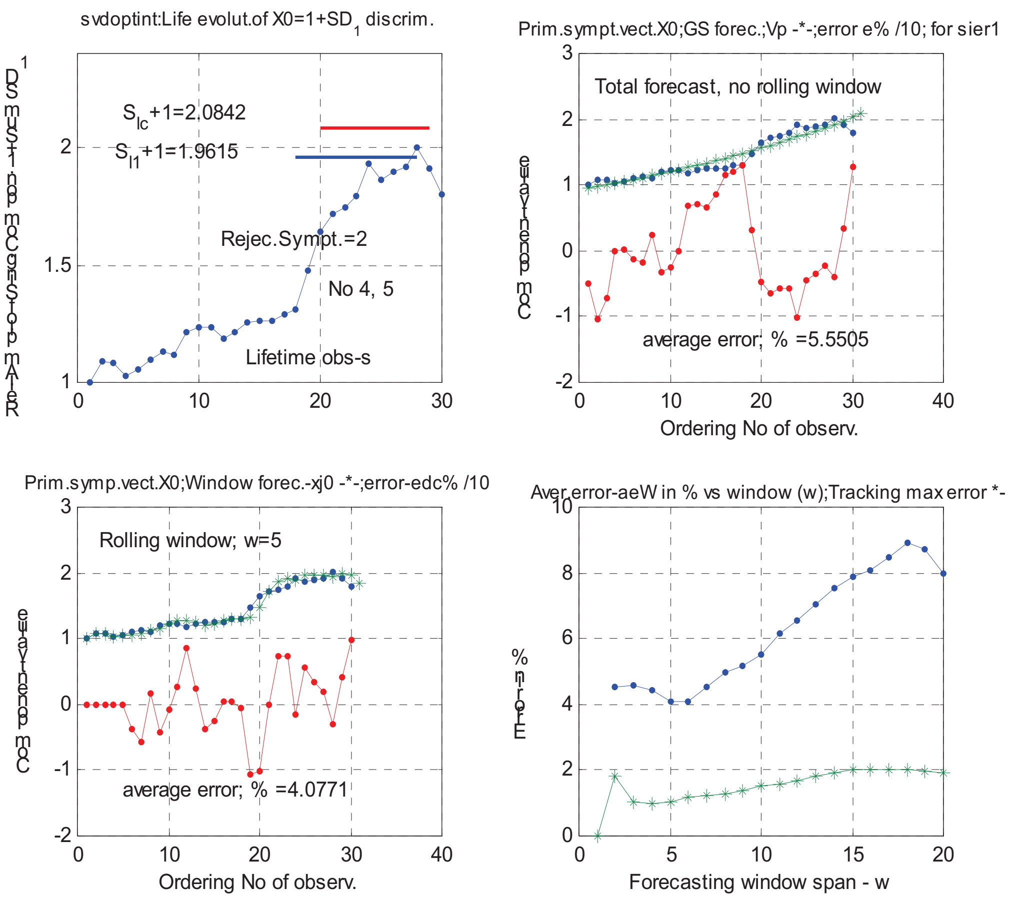

Fig. 5. Grey rolling forecast of the fan condition using the first generalized symptom $\boldsymbol{SD_1}$ *, together with the both symptom limit values and the errors of the forecasts, with and without rolling window*

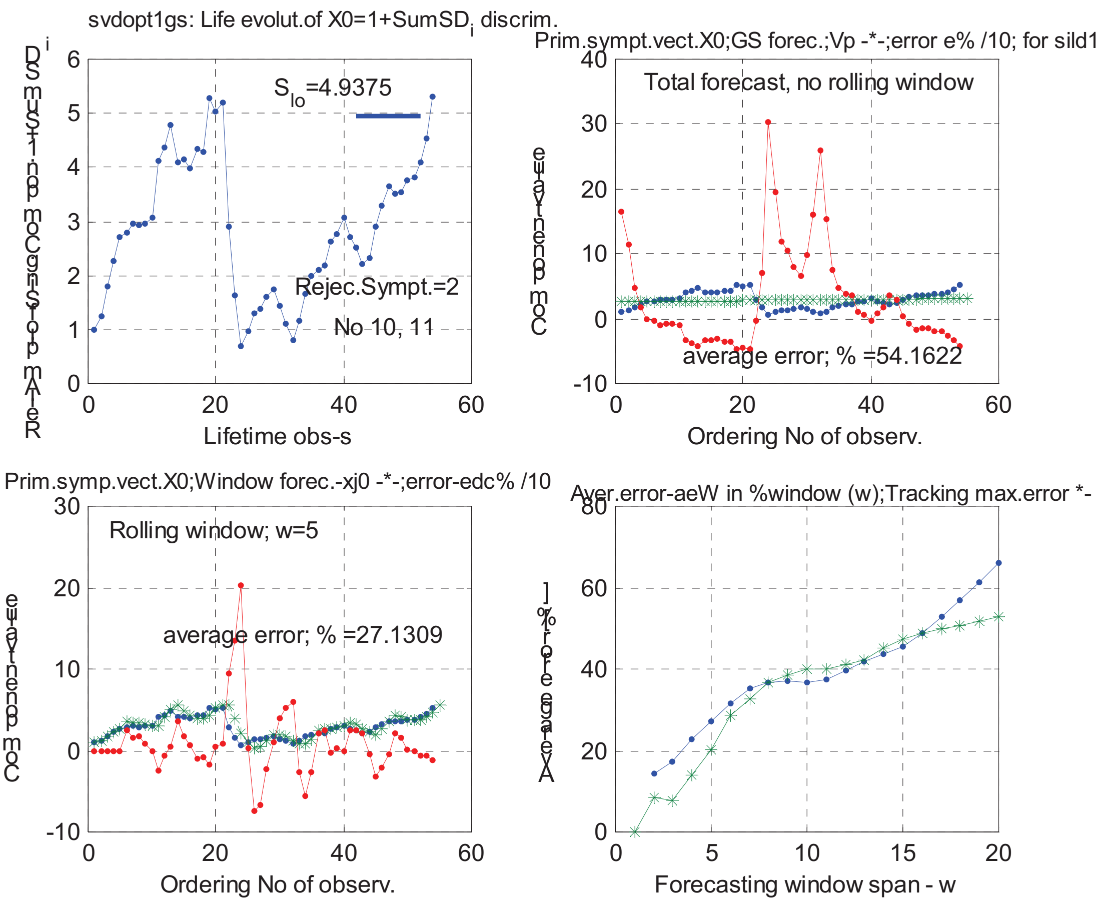

Fig. 6. Vibration based total damage forecast by grey system theory for the railroad diesel engine

The resultant forecast with the use of grey system model **GM(1,1)** has a great jump in the magnitude of error at the vicinity of this point, but assessed symptom limit vale $\boldsymbol{S_{lo}}$ gives enough lead time to warn us on the impending engine failure.

Much better situation with this respect one can note when the same engine data has been processed for the dominating generalized symptom $\boldsymbol{SD_1}$ instead of total damage symptom $\boldsymbol{SumSD_i}$, as it was done for the fan vibration data (Fig. 1-5). One can see from the figure 7 that symptom limit vale $\boldsymbol{S_{l1}}$ calculated for the dominating generalized symptom $\boldsymbol{SD_1}$ gives us much better lead in warning before impending failure. Also the tracking error of the forecast (*asterisk curve on picture bottom right*) is smaller than its average error.

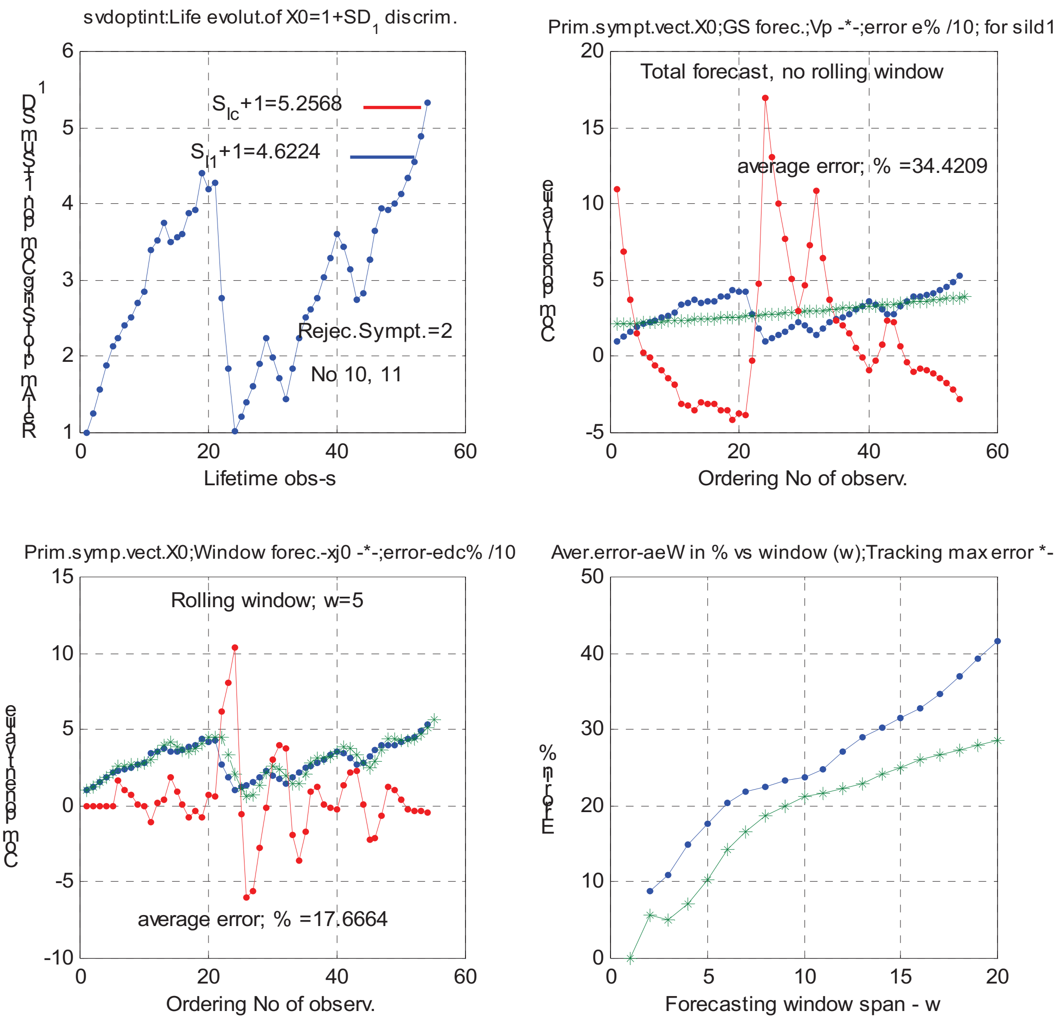

Fig. 7. Dominating fault method and vibration base forecast for the same diesel engine as above (Fig. 6)

Summing up all the results of our illustrative calculation for the two different objects one can say that the idea of calculating two symptom limit values simultaneously; for the global damage symptom ***SumSDi***, and for the first dominating generalized symptom SD_1 has proved its usefulness in increasing the reliability of diagnostic decision. Moreover, this integration of inference seems to be needed both in the main calculation in fault space and observation space optimization (Fig. 1-4), as well as in the grey system forecasting (Fig. 5, 6, 7).

7. CONCLUSIONS

The premise to write this paper was the supposition that the integral inference basing on the first generalized dominating fault symptom SD_1 and the total damage generalized symptom ***SumSDi*** of machine condition, can bring us valuable and reliable diagnostic information. As usually in multidimensional condition monitoring we have used the singular value decomposition to extract the fault information from the symptom observation matrix. After the first round of calculation it was possible to optimize observation space using some measures of fault space, such as ***Frob1*** and *Vol1* and reject some redundant symptoms. Having just mentioned generalized symptoms calculated, the symptom reliability and the symptom limit values S_{lc} , S_{l1} were assessed on that basis for the total damage symptom ***SumSDi***, and for the dominating generalized symptom SD_1. The last stage of inference was the forecast of the future value of the both symptoms made by grey system theory and **GM(1,1)** model. As an example we have used the most unstable case of condition monitoring, of the huge fan working in ventilation system of deep copper mine, and the railroad diesel engine. It was shown here that the optimization procedure can reject unstable symptom, and more over we are able to calculate two symptom limit values, and infer more effectively on the basis of such integral software.

It means also the global and partial inference do not exclude each other, both they are valuable expansion of our inference capability.

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