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Innovative Developments in Systems Condition Monitoring

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Abstract

It is shown in this paper that classical approach to condition monitoring of critical systems can be supplemented by holistic models, which enable the best symptom of condition to be chosen and the evolution of the sytem condition to be simulated. When this is not possible, and where large symptom data base exist, we can apply singular value decomposition (SVD) as the newest data mining procedure to obtain symptom evolution model. By using SVD it is possible to have two additional independent fault discriminant: SD and SG, with the high dynamics of evolution. Moreover we can add life count as the first approximation of a logistic vector describing the unit life history. It is also possible to use the value of pseudo - determinant of a symptom observation matrix, and to correlate between this new discriminant and the symptom observation matrix to minimise the redundancy of symptom measuring space.

1 Introduction

Contemporary systems in operation, like machines, vehicles, and many structural systems, are growing in structural and functional complexity. On the other hand there is a constant demand from the users of these systems to increase their safety and reliability in operation. There seems to be only one solution, the **monitoring of condition**, of the critical systems in operation. Such systems are more and more mechatronic in nature, so being inteligent and synergetic combination of information technology and other branches of engineering, control, electric, mechanical, civil, etc. One of the challenges in development of condition monitoring of such contemporary system lies in their mechanical subsystem. This may be the critical task of determination of the structural integrity, the residual strength, the advancement of the wear processes, etc. Hence, the questions needed usually to be answered by the users are as below.

- What is the current condition of the system in terms of the safety and reliability ?
- What are the causes of such condition, and what actions are needed?
- What will be the evolution of the current condition, and what is the assessment of system residual life?

In order to answer these questions with the high confidence level we should have an identified and workable holistic model of a system in operation. It means, we need model which enable us to simulate.

- Short term dynamics of the system, like vibration, noise, etc, with the time -t.
- Long term evolution of system condition during its life (operation) with time θ.
- The influence of the system life history on its condition, in particular the history of the external influence, like severity of load, quality of maintenance / repair, etc.

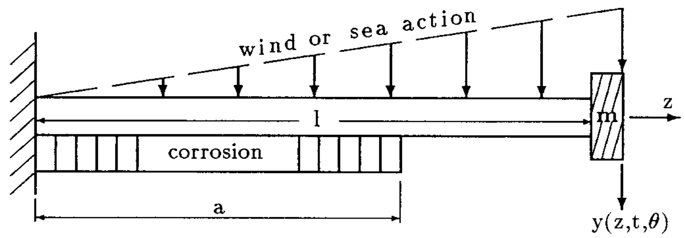

Figure 1: Simplified Model of Two Mechanical Systems under the Corrosion Action

As we can see, the challenge is as high as critical are systems in operation. With the sophisticated measuring technology of today in our possession now, this challenge concerns mainly modelling and identification of critical systems, and transforming this knowledge into condition monitoring purposses. In this paper we will address these issues, in some cases pointing only the problem and giving some references, if any. We will propose also a new method of condition discrimination in the symptom space, what enables to increase the accuracy and reliability of condition recognition, and to reduce the symptom measuring space i. e. the number of symptoms we observe.[2]

2 Holistic and Symptom Models

As it is known [1] there are two most important wearing processes, errosion and fatigue, which a system may undergo during its life time θ. Trying to establish the holistic model for a mechanical part of the system under such wearing processes we will start from the continuous description of the mechanical subsystem. There were many approaches to model the fatigue process in a structure in a simple way [14], [8], but they are correct in special narrow conditions, and so far need many improvements. Much better situation is in modelling of system errosion, with corrosion as the special case. As an example, let us take the steel chimney, or the platform leg, modelled as a beam under the action of wind and sea waving and the corrosion. The case is fully described in [9, 10], so here we will refer only to the most substantial moments of it. As we know the corrosion changes the mass - m, and the moment of inertia - I of the beam during the system life in the following way (see Fig 1).

$$\left.\begin{aligned} m[z, D(z,\theta)] &= m_0\{1 - \sigma_c \tfrac{\theta}{R}[H(z) - H(z-a)]\} \\ I(z, D(z,\theta)] &= I_0\{1 - \sigma_c \tfrac{\theta}{R}[H(z) - H(z-a)]\}^4. \end{aligned}\right\} \tag{1}$$

with the dynamic forcing term

$$f(z,t) = \frac{z}{l} f(t). \tag{2}$$

and the σ_c as the speed of the corrosion, and R critical radius of the beam, $H(*)$ is the Heaviside step function.
Hence the resulting holistic equation of beam vibration in 't' and condition evolution in 'θ' may be written as

$$\left.\begin{aligned} m_0\{1 - \sigma_c \tfrac{\theta}{R}[H(z) - H(z-a)]\}\tfrac{\partial^2 y(z,t)}{\partial t^2} + \alpha m_0\{1 - \sigma_c \tfrac{\theta}{R}[H(z) - H(z-a)]\}\tfrac{\partial y(z,t)}{\partial t} + \\ + EI_0\{1 - \sigma_c \tfrac{\theta}{R}[H(z) - H(z-a)]\}^4 \tfrac{\partial^4 y(z,t)}{\partial z^4} = \tfrac{z}{l} f(t). \end{aligned}\right\} \tag{3}$$

The decomposition of the solution of the equation into the eigenvalue and eigenvector domains will get

[2]Symptom is the measurable quantity covariable with condition of system in operation

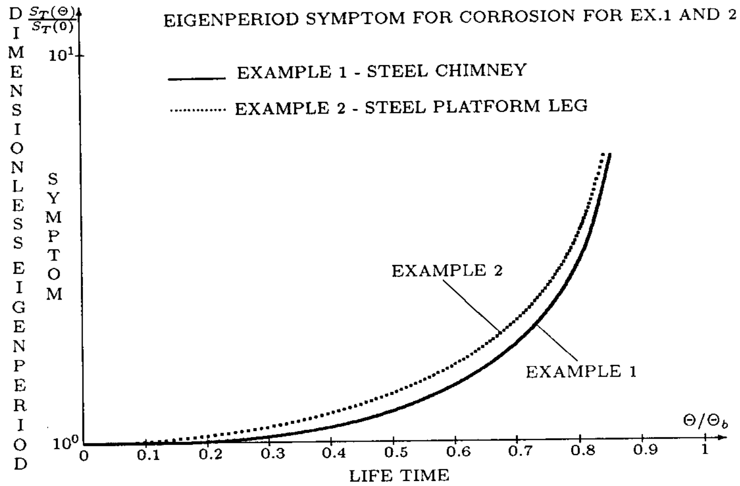

Figure 2: The course of the normalized fundamental vibration period as the symptom of condition for the structural part with corrosion

$$\left.\begin{array}{c}\ddot{q}_j(t) + \alpha_j(\theta)\dot{q}_j(t) + \omega_j^2(\theta)q_j(t) = \frac{1}{m_{gj}}\int_0^l \frac{z}{l} f(t)U_j(z,\theta)dz,\\ \text{with the eigenvibration equations}\\ -\omega_j^2(\theta)m_0\{1-\sigma_c\frac{\theta}{R}[H(z)-H(z-a)]\}U_j(z,\theta)+\\ +EI_0\{1-\sigma_c\frac{\theta}{R}[H(z)-H(z-a)]\}^4\frac{\partial^4 U_j(z,\theta)}{\partial z^4} = 0,\\ \text{and the abbreviation for model damping}\\ \alpha_j(\theta) = 2\xi_j(\theta)\omega_j(\theta),\ \ \omega_j = \frac{2\pi}{T_j(\theta)},\ \ j = 1,2,...,\end{array}\right\} \qquad (4)$$

where $q_j(t)$ is the principal (generalized) coordinate, $U_j(z,\theta)$ is the eigenfunction (normal mode), and m_{gj} the generalized mass, $\omega_j(\theta)$ eigenvibration frequency, $T_j(\theta)$ eigenperiod of vibration.
It was found by simulation that the reciprocity of the first eigenvalue, so the first eigenperiod of vibration of the beam model, will change much during the system life as it is shown in the figure 2. Here the first eigen period of system vibration changes almost ten times during the life of the system. Hence it can be applied for the condition monitoring as the good symptom of its condition under the influence of dynamical 't' forcing and the corrosion 'θ'.
For the discrete or lumped models of mechanical sytems we can apply the evolutionary models for its mass - m, stiffness - k, and damping - c, coefficients [9], [10]. Denoting there dimensionless life time as $D = \frac{\theta}{\theta_b}$ of a system (part), with breakdown time θ_b, we can write

$$\begin{aligned} m(D) &= m_o(1 \pm a_k D)^{\gamma_k},\\ k(D) &= k_o(1 \pm a_m D)^{\gamma_m},\\ c(D) &= c_o(1 \pm a_c D)^{\gamma_c}, \end{aligned} \qquad (5)$$

with the sign and coefficients $\pm, a_m, \gamma_m, a_k, \gamma_k, a_c, \gamma_c$ to be assumed or identified in the process of modelling and validation of a system model.
Putting the evolutionary parameter values into the model of a specific system, we can obtain as the solution of the ordinary differential equations (or a system of), the change in system condition in terms of the chosen symptom. This may mean its amplitude of vibration, the fundamental period of vibration, or some more appropriate measurable quantities, (more you can see in [8], [10]).
We can infer from the above that in some simple cases, like beam, or bridge as a beam system, etc. the evolutionary models of system dynamics, and system life, can be presented and solved succesfully. But for more complicated shapes and modes of parts interaction, like for ball or roller bearing, this

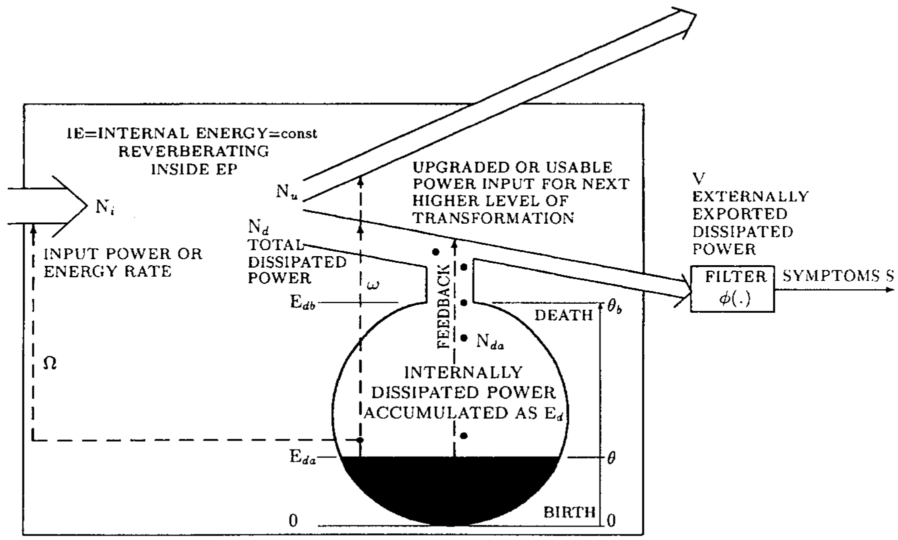

Figure 3: Energy Processor as the evolutionary model of systems in operation with destructive and ageing feedback

can not be done as yet (to the author knowledge).
However on the contrary, with the modern measuring and signal processing technology we can obtain a bunch of measurable quantities (symptoms like kurtosis for the ball bearings), presenting better or worse, the real system evolution, etc.
So instead of holistic model, we can present a model of symptom evolution in θ domain for the system in operation. If we model the system under consideration, or its part (ball bearing for example), as an Energy Processor (EP) evolving during its life (operation), we can obtain the bunch of symptom models describing the condition evolution of systems in operation. Refering to the newest book [10] and papers on this subject [16], we will present below only the essential moments of the EP model, the behaviour and resulting possibilities of EP as a model of systems in operation.

3 Energy Processor (EP) as a Symptom Model of Systems in Operation

The energy processor model of systems in operation concerns long term behaviour, i.e. evolution of system properties observed in its life time θ. It consists of one energy input and two outputs, one for upgraded energy and the other for the degraded (dissipated) energy. The incoming energy is transformed inside the system into the needed form (product), i.e. upgraded. The price for this transformation is internal dissipation and resulting system damage, and also external dissipation of the remaining part of energy. As it is known, every system, or even the bit of material, has finite damage capacity. On the other hand in many cases of system operation there exist so called **destructive feedback** - the worse condition of the system the more energy it dissipates, and the **ageing feedback** - the older the system is the less efficient are the energy income and upgrading processes. Under such assumptions we can present the model of EP as in the Figure 3.
There are four postulates (or constitutional equations) for the EP which must be fulfilled here. Firstly, the input power (energy time rate) N_i must be balanced by the upgraded power N_u and the dissipated power N_d. Also the dissipated power is divided into two streams of power: internally accumulated

N_{da} and externally exported V. Hence we can write

$$N_i = N_u + N_d, \; N_d = N_{da} + V. \tag{6}$$

Secondly, there is a very important destructive feedback in the system, i.e. the accumulated dissipated energy E_{da} (which is the evidence of damage advancement in the system) controls the flow of dissipative power V exported outside, and vice versa: with more external output of V there is more dissipation intensity N_{da} and accumulation. Therefore, the differential increase of dE_{da} is proportional to the corresponding increase of dV. Hence it follows

$$dV(\theta) = \beta \; dE_{da}(\theta, V), \;\; \beta = const. > 0. \tag{7}$$

The accumulated internal part of the dissipated energy E_{da} is a function of the system lifetime θ, and may be calculated as the integral of N_{da}, and is of course limited by the dissipative capacity of the system E_{db}. So for the case of a system with limited damage potential it gives

$$E_{da}(\theta, V) = \int_0^\theta [N_d(\theta) - V(\theta)]d\theta \leq E_{db}. \tag{8}$$

Finally it is postulated, that the internal structure of the EP, (i.e. identity of the system), remains unchanged during its lifetime θ, which is expressed by identity realation

$$\frac{dN_d}{dV} = \alpha = const., \; \Rightarrow \; V = \alpha^{-1} N_d + const1, \;\; \alpha \gg 1. \tag{9}$$

After some calculations based on the above four assumptions we obtain the differential equation for externally exported dissipated power [4]:

$$\frac{dV}{V} = \frac{\beta(\alpha - 1)d\theta}{1 - \beta(\alpha - 1)\theta}. \tag{10}$$

Introducing [2] the breakdown time of the system, being here the time when the denominator approaches zero, and taking into account, that the dimensionless lifetime was proved to be the measure of damage advancement of the system [3], one can get

$$\theta_b^d = [\beta(\alpha - 1)]^{-1}, \;\; \alpha \gg 1, \;\; \text{and} \;\; D \equiv \frac{E_{da}(\theta)}{E_{db}} = \frac{\theta}{\theta_b^d} \leq 1 \tag{11}$$

Using this approach we obtain a very simple differential equation, and the solution for the dissipated power of Birth&Death energy processor as below

$$\frac{dV}{V} = \frac{dD}{1 - D}, \;\;\; \Rightarrow V = V_o(1 - D)^{-1}. \tag{12}$$

It is worthwhile remembering here, that according to the solution (12) the externally dissipated power V tends to infinity when the system approaches the breakdown ($\theta \Rightarrow \theta_b^d$, *or* $D \Rightarrow 1$). The same is true, of course, with respect to the total dissipated power N_d, according to the relation (9). But in reality there will be no infinite power at the system breakdown, because the balance of power (6) must be maintained and the destructive capacity of the system is limited. Hence, we can observe at the breakdown moment, that all power delivered to the system N_i will be almost entirely dissipated for the destructive process -N_d. This is exactly what one can observe in case of breakdown of some technical systems.

For such simple EP as the model of system (part) in operation it is possible also to present subsequent bunch of symptom models with associated symptom reliabilty and hazard models. These possibilities are shown in table 1 in an abbreviation, [4], [16]. The most important conclusion from this table are enumerated below.

Sympt.life curve $S_0 > 0$, $\frac{S(D)}{S_0} =$ for $D = \theta/\theta_b$	Sympt. reliability $R(S) =$, or Resid. Life $\Delta D =$	Sympt.hazard rate:$h(S) =$ S_o-norm.sympt.	Cumul. hazard $H(S) =$ $= -\ln R(S) =$	Remarks: γ-shape coeff. Symptom Model:
$[-\ln(1-D)]^{1/\gamma}$	$\exp -(\frac{S}{S_0})^\gamma$	$\frac{\gamma}{S_o}(\frac{S}{S_o})^{\gamma-1}$	$(\frac{S}{S_o})^\gamma$	**Weibull**, $S > 0$
$[-lnD]^{-1/\gamma}$	$1 - \exp -(\frac{S}{S_0})^{-\gamma}$	too complicated	$\simeq \exp -(\frac{S}{S_o})^{-\gamma}$	**Fréchet**, $S > 0$
$(1-D)^{-1/\gamma}$	$(\frac{S}{S_o})^{-\gamma}$	$\frac{\gamma}{S}$	$\gamma \ln \frac{S}{S_o}$	**Pareto**, $S \geq S_0 > 0$ Frechet asymptot.

Table 1: Models of the symptom life curves , the system's residual life, the respective hazard rate and the cumulative hazard, as generated by the theory of evolution of Energy Processors (EP).

1. We can chose analytical symptom models, from Weibull to Pareto, and make the best fit of some data taken from the real case of symptom condition monitoring.
2. For every chosen symptom model we have apprioprate symptom reliability and hazard models for further use.
3. Symptom relaibility in our model is equivalent to system residual life;

$$R(S) \equiv \Delta D(S) = 1 - D(S) = 1 - \frac{\theta(S)}{\theta_b}$$

This properties of EP model are very convenient in system condition assessment and forecasting. The example of this is shown in the Fig 4, for the case of vibration condition monitoring of group of diesel engines, where the peak vibration acceleration amplitude readings were taken each 10 thousand kilometers, with the life scale on the figure being equivalent to 300 thousands kilometers [2]. As it is seen from the graph the life assessment for the Weibull model (chosen) and Fréchet model differs a little. So in practice it is good to carry both assessments of life, one as **optimistic** and the other one as **pessimistic** with this respect, and to choose the best one with the **minimal risk** for the case under the consideration.

4 The Life History of Systems

As it was presented extensively in [12, 13,15], each unit in operation has its own history; beginning from the production stage of system life, its own history of operational load, maintenance and repair. So, beside the set of symptoms to describe the system condition we should have also in our data base so called logistic vector $\vec{L} = \{d, p, s, l, m, r, ...\}$ presenting the history of given unit. We should note also, that the nature of some explanatory variables as the components of L, will of course change over the set of units, but some may change even for the same unit, so being the function of the unit life θ. It seems that one of the most important components of the logistic vector is the value of the cumulative load (cl) applied to the unit till the given moment of life, when the symptom S was measured. If we denote the current load of the unit as $l(\theta)$, so cumulative load will be simply the integral of it, which may be approximated as

$$cl(\theta) = \int_0^\theta l(x)dx = \int_0^\theta (l_o + \frac{dl(x)}{dx}\delta x + ...)dx \simeq l_o \cdot \theta. \quad (13)$$

One can see from the above, the first approximation of the cumulative life can be the properly scaled (l_o) life count θ. When we now recollect ourselves the counting of life of turbosets or turboengines, used

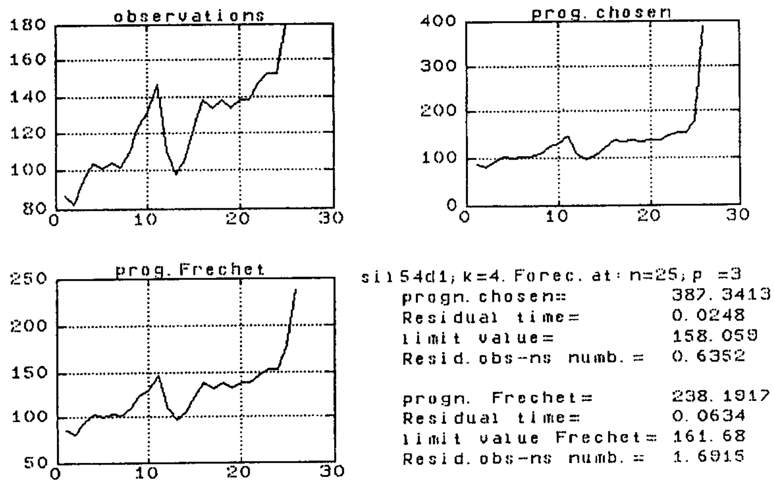

Figure 4: Condition determination and residual life assessment of the diesel engine by the computer program basing on the EP model

extensively long ago, we can see now it has the deep motivation. Acknowledging this, we must append at first the additional column - life count 'cl' to our symptom data base and symptom observation matrix,

$$X_{nm} = [S_1 ... S_m] = [S_{jk}]$$

In another words if the symptom readings are $S_j(\theta_k)$, (k - rows, j - columns of observation matrix), we will append new column $cl(\theta_k)$. This means that each row of the new column will consist of value $l_o\theta_k$ with l_o as the scaling factor. This is for keeping the same order of the magnitude of new variable as for the other symptoms. In some cases it will give us the life in days, months, or any other equidistant units (like for example the ordering number of measuremnets).
Of course, if we are fortunate that in our data base, outside of symptom readings, are also the cumulative counts of units life, we should use this data with more benefit than from life counter.

5 Fault Space and Symptom Space in Condition Monitoring

When we perform vibration condition monitoring (VCM) of a critical system or its part, we normally measure signals in some few locations, and by proper signal processing we can obtain more symptoms of condition, sometimes 5 -15, to characterize the condition evolution of our critical system. Creating the symptom space in such a way we have great redundancy, which means that the dimension of symptom observation matrix and the dimension of fault space differ very much.
The assumption is here, that principial components of the observation matrix carries information about independent faults in the system. But anyway, symptoms may be multicorrelated, and some may carry little or nothing of differentiating or distinct information, and we are looking for trend of condition evolution of each particular fault with minimal redundancy. This means, if system is in continuous operation, giving continuous degradation of condition, i.e each particular fault and symptom must be more or less **monotonous growing**. What is also important, that such newly created symptoms of condition should be sensitive only to one fault, so should be discriminants [1] and with the greatest dynamics of symptom evolution.
This problem of symptom space redundancy and its reduction, the search for fault discriminant with good dynamics were recognized by the author as early as in 1980, when the paper 'Reduction of Data Set in Vibration Condition Monitoring' was published [17] and 10 years later in abbreviated

version in the book form translated to English [1]. As we know the symptom observation matrices are rectangular not quadratic, so the principial components decomposition of symptom observation matrix must be done by its covariance matrix. If we define the reading of each measured symptom at the life θ_k as $S_j(\theta_k)$ or column vector S_j with $k = 1,...n$ rows, and $j = 1,...,m$, so our symptom observation matrix X_{nm} will be

$$X_{nm} = [S_1...S_m] = [S_{jk}], \tag{14}$$

and its quadratic matrix analogously to covariance matrix will get(T-transposed matrix)

$$Q = X_{nm} * X_{nm}^T. \tag{15}$$

That was the basis for the eigenvalue decomposition of information contained in symptom observation matrix X_{nm}, and principial component decomposition of covariance matrix Q. In the problem of minimizing of redundancy of the symptom observation matrix X_{nm} one step more is important, it follows from the fact that the determinant of the covariance matrix Q equals the square of the volume of m - dimensional perpendicular streched over our symptom observation matrix, i.e. $V_{nm}^2 = det(Q)$. Hence, if in the symptom observation matrix X_{nm} there are some dependent symptoms, then some sides of m - dimensional perpendicular will not be orthogonal, even some are close to zero and vice versa. That was the basis for rejection rule of some symptoms in primary symptom observation matrix eighteen years ago. This idea works good with specially written computer program [17], but we must remember that such decomposition concerns not the symptom observation matrix X_{nm} but its covariance matrix Q. At the time of paper writing (1979) not so much was known on singular value decomposition (SVD) for perpendicular matrices, and MATLAB computing system was not known too.
Applying now SVD method to our symptom observation matrix one can get decomposition [18]

$$X_{nm} = U_{nn} * \Sigma_{nm} * V_{mm}^T, \tag{16}$$

with U_{nn} and V_{mm} unitary singular vector matrices of respective order, and diagonal singular value matrix

$$\Sigma_{nm} = diag(\sigma_1, ...\sigma_l), with\ \sigma_1 \geq \sigma_2 \geq ...\sigma_r > 0, \quad \sigma_{r+1} = ...\sigma_l = 0, \quad l = max(n, m).$$

Another form of decomposition, much convenient to us is

$$X_{nm} = U_{nn} * \Sigma_{nm} * V_{mm}^T = \Sigma_{j=1}^r \sigma_j * (u_j * v_j^T), \tag{17}$$

with the singular values σ_j and u_j, v_j singular vectors as columns of respective matrices.
Using the SVD properties fully we can use another form of decomposition [18], non - normalized singular vector of the information source σ_j i.e. associated with the fault number 't', which may be called as fault discriminant

$$SD_t \equiv X_t(\sigma_t) = X_{nm} * v_t = u_t \sigma_t, \ t = 1, ...r. \tag{18}$$

In another words it is the total vectorial information contained in the symptom observatiom matrix X_{nm}, which concerns the fault 't'.
As each singular value σ_t is the measure of the information contents, so we can define the relative measure of information content as concerning the given fault in the form

$$IC_t \equiv IC(\sigma_t) = \frac{\sigma_t}{\Sigma_{i=1}^r \sigma_i}, \ t = 1, ...r. \tag{19}$$

But looking for decomposition (17) one can say, that each submatrix of this decomposition possess also all the information concerning one fault only. Hence if we sum up all rows of the submatrix $\sigma_t * (u_t * v_t^T)$, we obtain also the column vector with n rows presenting another approach to extraction

of fault related information from symptom observation matrix by its SVD.
We may call this new column vector as generalized fault symptom (SG) of given fault 'j' as below

$$SG_t \equiv SG(\sigma_t) = \sigma_t * \Sigma_{rows}(u_t * v_t^T),\ t = 1, ...r. \tag{20}$$

where Σ_{rows} means summation over the rows of matrix $(u_t * v_t^T)$.
As the source of information for both discriminant types is the same it is hard to say now that SD_j and SG_j must be equal. Frankly speaking the generalized discriminant SG_j was created first, and symptom discriminant being the formal use of SVD properties as SD_j as the second. Hence, having no help with current state of SVD theory we will observe the common properties of SD_t and SG_t on the data taken from Vibration Condition Monitoring (VCM) practice.
One word more concerning the redundancy minimization of symptom observation matrix X_{nm}. As we remember from the author previous work it was possible to do this by maximization of the determinant value of the covariance matrix: $det(Q) = \prod \lambda_i$.
By the analogy we can define a pseudo - determinant of symptom observation matrix, being the product of its nonzero singular values: $\sigma_1 ... \sigma_r > 0$.

$$V_{nm} = PsDet(X_{nm}) \equiv \prod_{j=1}^{r} \sigma_j,\ j = 1...r. \tag{21}$$

Hence minimizing the measuring space by looking for the $Max_m(V_{nm})$ we can cancel redundant symptoms from the measurement and processing procedures, if it maximize the value of the above pseudo - determinant of symptom observation matrix X_{nm}.
There is another possibility to do this on the basis on new derived generalized symptoms SG. To complete our task of reduction of symptom observation space we need to know the contribution of each symptom $S_k,\ k = 1, ...n$, to the detected fault represented by the pair σ_j, SG_j. Hence we need to calculate covariance or corelation coefficients among the given SG_j and the symptom observation matrix X_{nm}, where columns are individual symptoms. As we know usually the first two faults are dominating with respect of information amount, i.e. singular value $\sigma_1 > \sigma_2 \gg ...\sigma_r$. So, it may be enough to calculate this correlation coefficients, only for two faults σ_1, σ_2. Doing this and analyzing the first row of normalized covariance matrix with respect to minimal contributuion it may be easy to decide which symptom we can cancel from the observation matrix (space).

6 Modelling and Information Flow for Innovative Condition Monitoring

It seems to be a time to summarize just given approach to VCM for complex systems in operation with critical mechanical part lowering significantly the system's safety and reliability indices. The whole approach is illustrated in Fig 5 in two rows of information and action flow. As we can see in the Figure the system in operation can be observed by its processes taking place in the measuring space of the system. Basing on this information we can postulate some holistic model, and by system identification procedures we can verify and validate the model. Later we can solve the model and find system beahaviour by some eigenmode method, if the system model is linear. Having this, we can simulate the short time dynamics and long term life behaviour, to look for improvement in the design and to specify areas not possible to redesign, so in the areas where we need permanent condition monitoring.
When this step is done, we need symptoms of condition to describe the damage evolution of the given subsystem to design the entire condition monitoring subsystem. To do this we need the symptom data base gathered during the life testing phase of the system, or if it is not possible due to high cost of testing or physiscal impossibility to build the test stand, (like in case of turboset), we have to build the symptom data base observing a set of units of the same type in the real operating condition. In this way we obtain symptom observation matrix $[S_j(\theta_k)] = [S_{jk}]$, where symptom create columns

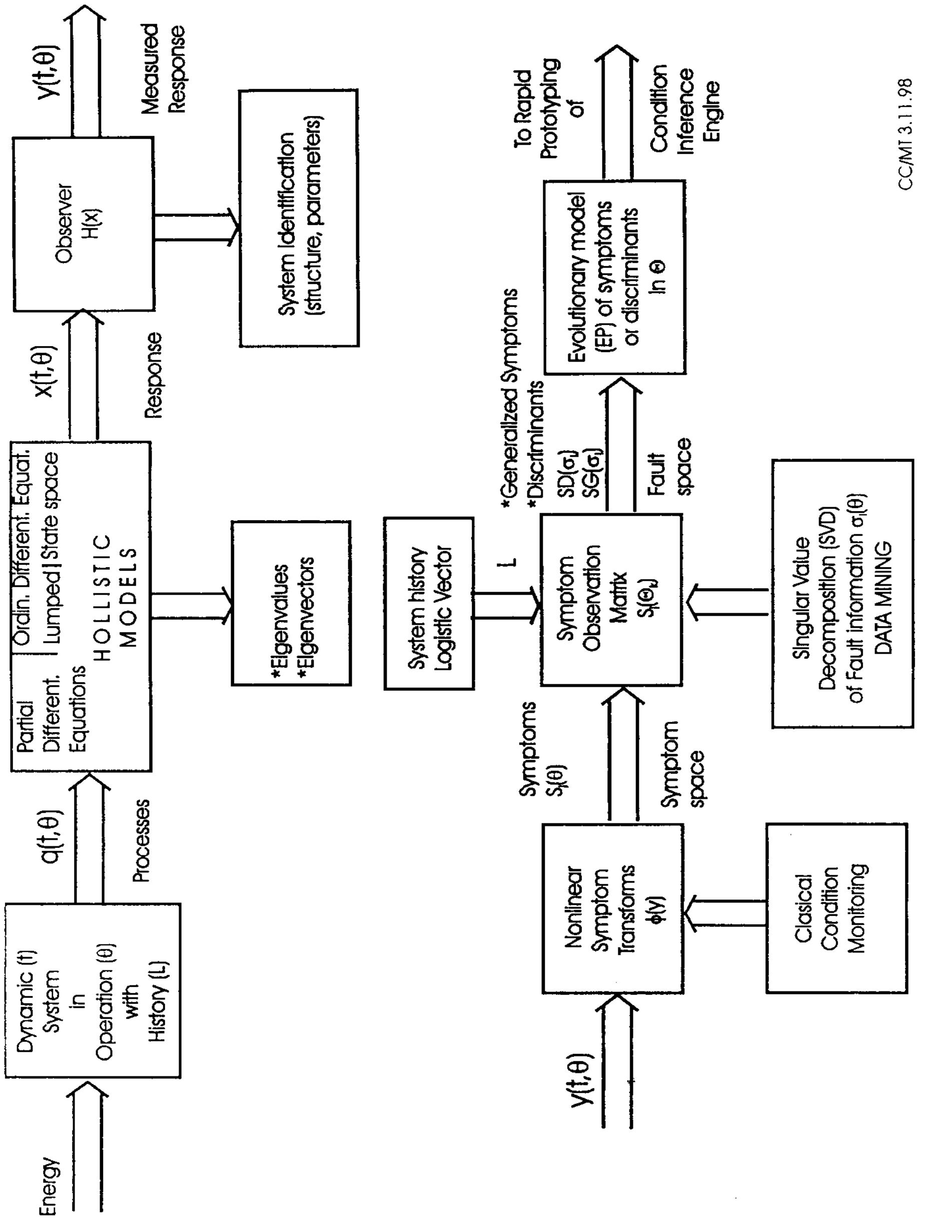

Figure 5: Modelling and Information Flow in Innovative Condition Monitoring of Complex System in Operation

information on two faults, and the values of pseudo determinant equal 1531 is not high in comparison to the symptom amplitude scale (top right). At the top right picture two dominant symptoms can be seen, and the highest one does not look like fault symptom, because of its lack of asymptotic growths needed by definition of symptom of condition of system in continuous operation. It is clearly seen, looking for symptom discriminant SD1 or generalized symptom SG1 (bottom left), that they do not carry fault information at all, but the noise. The second symptom discriminant SD2 and the generalized symptom SG2 look similar to second dominant symptom of the observation matrix, with the correlation coefficient of SG1 and SG2 equal 0.2193. It is seen also from the last row of the pictures that SG2 is created mainly by the first three symptoms, and SG1 mainly by the dominant not fault like symptom H_v.

Summarizing Fig 6 it is clearly seen we should exclude the dominant not fault like symptom (harmonic ratio H_v). Hence the next Figure 7 shows the application of SVD to the same case but the number of columns of X_{nm} were cut to four only, three acceleration amplitudes and one velocity or cumulative life cl. As the result of this cutt of observation space, from 13 to 4 symptoms, we can see now quite different and very clear fault information, with the high value of $PsDet = 1.007 * 10^5$, very clear symptom discriminant SD1, and generalized symptom SG1, with much higher dynamics, and lower correlation between SG1 and SG2 equal 0.1096 only, and clear contribution of measured symptoms to SG1 (last row of pictures).

It is important to note here much higher dynamics of generalized symptom SG1 than symptom dyscriminant SD1, or original symptom in top right picture. How it is possible that SD1 and SG1 have correlation coefficient value 1, and much different dynamics is not clear from the theory of SVD, but one is sure it is much better to use for VCM generalized symptom SG1, than the others.

Next Figure 8 with the case of VCM of a big industrial fan shows the effect of introduction of cumulative life count 'cl'. Here there were measurements of 5 symptoms, three all pass band velocity amplitudes measured on the bearing pedestals, and the blade band velocity measured on both bearing pedestals. For such symptom observation matrix (with pseudo determinant value equal 9.1 only) it was very hard to find even good generalized symptom SG1 for the further use. Quite different situation can be seen when we append life count according to succession of measurement from 1 to 33 and comparable to symptom dynamics in the form $cl = 0.1, ..., 3.3$, with the scaling $l_o = 0.1$ here. As it is seen from the Figure 8 the information amount rises twicely up to $PsDet = 18.47$, and the dynamics of symptom discriminant SD1 and generalized symptom SG1 increased significantly with much lower intercorrelation between SG which dropped from 0.73 till 0.16. Also the contribution of observed symptoms and the life count to SG1 and SG2 is quite visible. Now one can be safe to infer on the fan condition having good generalized symptom SG1 for condition determination and forecasting, with initial and final values differing more than twice.

Concluding the advantages of SVD application to symptom observation matrix X_{nm} we can formulate them as below.

1. We may now know (in the demonstrated example), how many independent faults are represented in our symptom observation matrix X_{nm}, and we can say qualitatively which singular value represents which dominant symptom in observation matrix.
2. In case of low information contents in X_{nm} we can reject an unwanted symptom from the symptom primary data base X_{nm}, obtaining clear increase in information content, and have the generalized symptom similar to one of the dominant symptoms in observation matrix X_{nm}.
3. It was possible to elaborate two new types of fault discriminant, the first SD being directly a singular vector of the symptom observation matrix (18), and the other one a generalized symptom SG with the unit correlation to SD but with much greater dynamics.
4. Introduction of the life counter cl as the additional column appended to the symptom observation matrix increases its information contents (the value of pseudo determinant), decreases intercorrelation of SG components, and increases much the dynamics of generalized symptom SG1 prescribed to the first singular value σ_1.

$j = 1...m$, and its rows are created by the measuring sequence of life time $\theta_k, k = 1...n$, and usually we have the relation $n > m > 1$.
At this moment of information flow diagram (see Fig 5) there is a time to append some additional information on the history of each individual system unit, i.e. the components of the logistic vector L. At the first approach we will use cumulative load: $cl = l_o\theta_k$, (13). To such extended symptom observation matrix $X_{nm} = [S_{jk}, cl]$ we will apply singular value decomposition (SVD), while looking for fault discriminants SD or SG, or for other succesfull algorithm of data mining procedures [19].
Also for minimization of redundancy of measuring space in terms of minimal number of symptoms in X_{nm}, or minimal symptom contribution reflected by normalized covariance coefficients, we will do it by looking for the maximal value of pseudo determinant of X_{nm}. Such elaborated information. in terms of evolution of fault discriminant of a good sensitivity, can then go to the next step of the diagnostic subsystem, i. e. to the condition inference engine, not shown in the picture. This may be in the form of fuzy logic, some clasifier, expert system, or the neural net for the condition determination and forecasting, made for example by rapid prototyping of condition inference engine. But here we will not develop it more, because more and more one can buy it in special combined modules, (see for example Data Engine of MIT gmbh [19]).

7 Examples of Singular Value Decomposition of a Symptom Observation Matrix

The symptom observation matrix X_{nm} is the rectangular matrix with n - rows (observations) greater than number of different symptoms (columns)- m. These are the symptoms applied usually in vibration condition monitoring (VCM) like average, root mean square and peak amplitudes of vibration acceleration, velocity, displacement, measured in the whole frequency band or in some chosen band, like rotational or blade frequencies. It may be also specially calculated symptoms like Rice frequency of vibration velocity or displacement,as well as harmonic index of these processes, etc (more see [1]). In dependence on the given monitoring case alltogether it can give 12 - 15 vibration symptoms as columns of the matrix X_{nm}. Normally the symptom observation matrix of our diesel engine data base begins with three amplitude measures of vibration acceleration, then velocity or cumulative life counter 'cl'. In the case of such appended matrix we have extention 'a' for the data file and vibration velocity as a symptom is shifted to next place. This can be seen in diesel engine data file 'sil54d1a', or 'sier1a' in VCM of huge industrial fan.
To such VCM data base SVD was applied and the results are presented in Fig 6 and 7 for the same diesel engine, and in Fig 8 for industrial fan. Each figure presents 8 pictures of the same type: and begining from the top left we have: the relative information contribution IC contained in the symptom observation matrix (19), and also the value of pseudo determinant (21) indicated here as PsDet of X_{nm}.
The next top right picture shows the life course of dominant symptoms in the X_{nm} matrix, where one can see their relative significance and their dynamics. The next layer of pictures show two symptom discriminants calculated by SVD for the two dominant singular values SD1 and SD2 calculated according to formula (18). The third row of pictures gives the life course of the new generalized symptoms SG1 and SG2 calculated by formula (20), respectively for σ_1 and σ_2 faults. Finally, the last row gives normalized covariance coefficients of new generalized symptoms SG1, SG2, to the symptom observation matrix X_{nm}. In the same it presents real contribution (similarity and information content) of each particular symptom to the given discriminants SG1 and SG2.
The figures shown here are typical for many cases calculated, and we can see here some average behaviour and possibility of SVD in application to symptom observation matrix. In general we can say that the correlation coefficients between SD and SG discriminants are ± 1, and the correlation coefficient between SD1 and SD2 is zero by definition. But let us analyze obtained results in detail.
Figure 6 presents the SVD results for diesel engines VCM carried by 13 measured and calculated symptoms of just described nature. One can see here at the top left picture that X_{nm} matrix carries

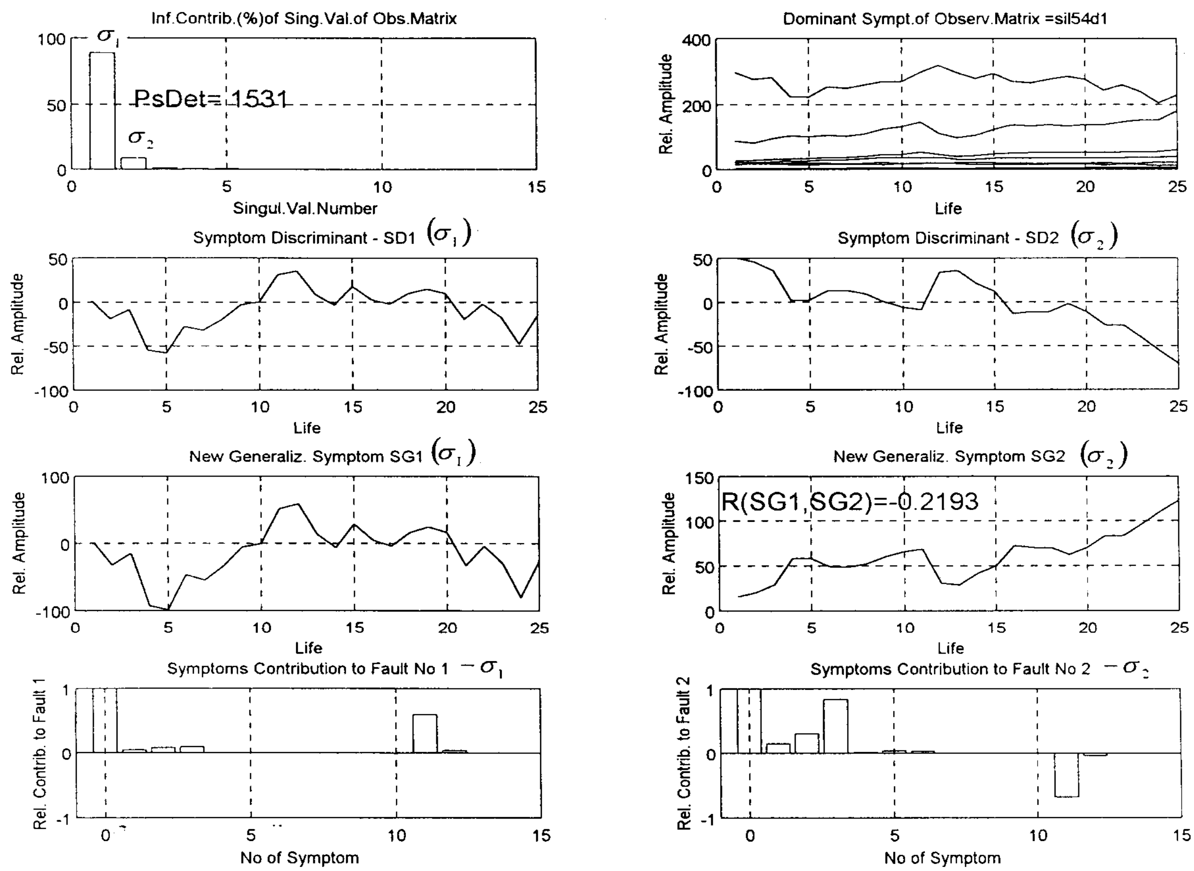

Figure 6: Results of SVD Use for One of the Engine in Diesel Engine Data Base

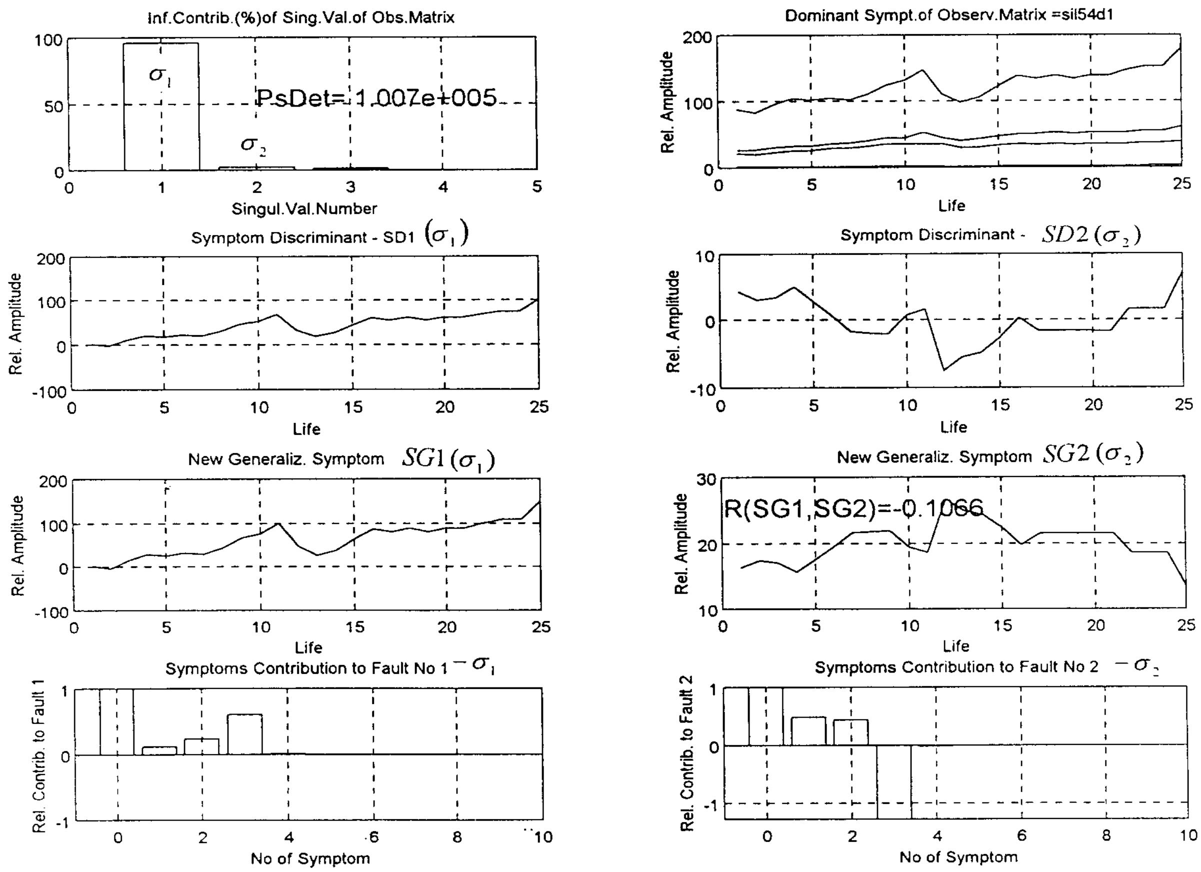

Figure 7: Abbreviated Version of Symptom observation Martix for the Same Engine as Above

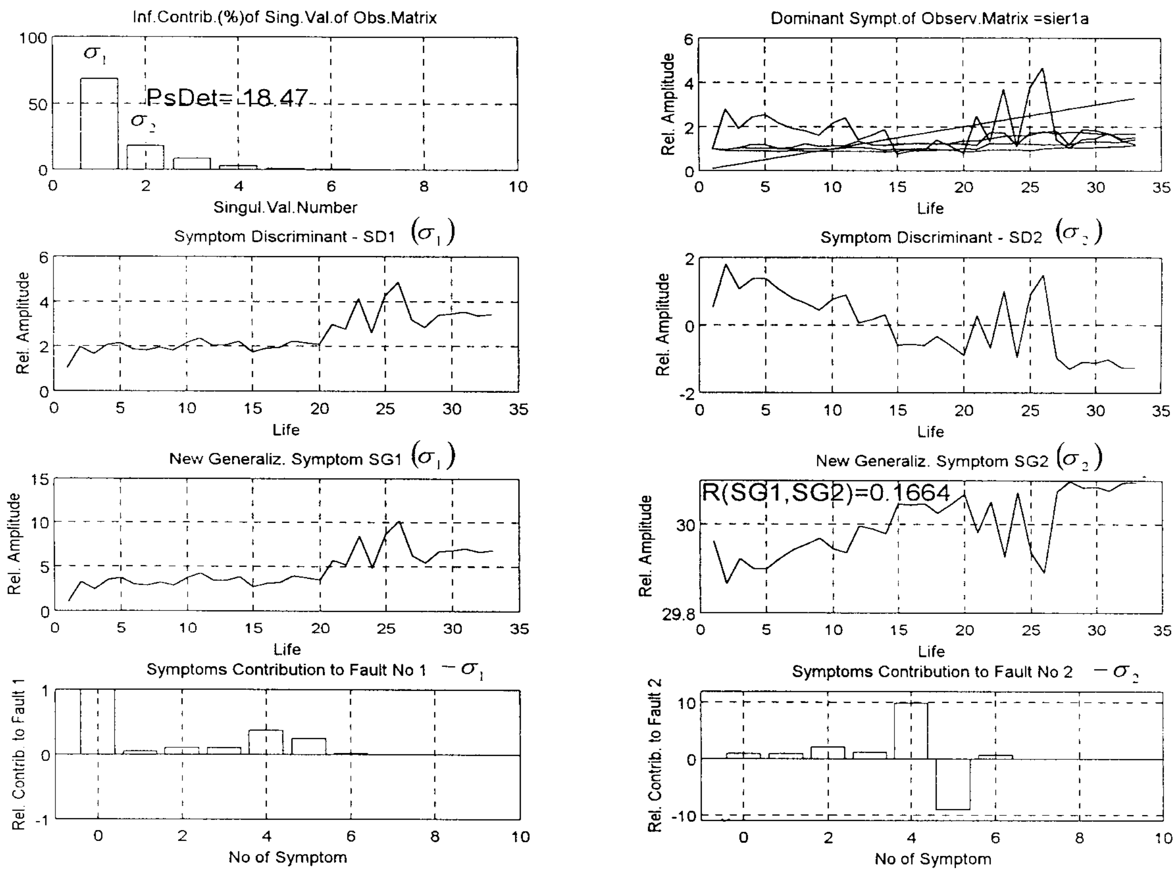

Figure 8: SVD of Observation Matrix with Appended Life Counter for Huge Industrial Fan

5. Covariance coefficients (normalized) between generalized symptoms SG1, SG2, and columns of symptom observation matrix X_{nm} determine clearly the contribution of each individual symptom to given fault discriminant SG1 and SG2, being the good indication for reduction of symptom space redundancy.

6. In view of these an automatic procedure using SVD seems to be possible. This will cut redundancy of observation matrix, and use the resultant generalized symptom SG for further condition recognition and forecasting.

8 Conclusions

Considering the condition monitoring (CM) of critical systems in operation it was shown here, that a clasical CM approach can be well supplemented and extended. First, when we can elaborate the holistic model of a system, we can simulate the life behaviour and choose the best symptom for subsequent use. Such models, as shown on Fig 5, can be identified and validated by some identification procedures.
Even when holistic modelling is not possible it is still possible to model long term evolution of system by the Energy Processor model. This model gives possibility of modelling of evolution of symptoms of condition of a system in operation, and to chose the best one for condition recognition and forecasting basing on EP theory.
Having syptom observation matrix for the given case of CM of critical system we can aply SVD looking for fault discriminants. By this new data mining procedure we can create two new discriminants of faults SD and SG,with much greater dynamics of evolution than before.
When the redundancy of the symptom observation matrix is great, we can use the value of pseudo discriminant and covariance coefficients of SG and X_{nm}, to cancel some redundant primary symptom. We can also add a new column of life count as the first approximation of the logistic vector representing the life history of the given unit. This additional information increases the differences between fault discriminants and their dynamics too, so enabling much better condition recognition and forecasting.
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