MULTI SYMPTOM CONDITION MONITORING OF A CRITICAL MECHANICAL SYSTEMS AS A FIRST APPROACH TO DESIGN CONDITION INFERENCE AGENT (CIA)

Czesław CEMPEL,

Poznań University of Technology, Institute of Applied Mechanics
Piotrowo 3 Street, 60-965 Poznań, Poland
Tel. +48 61 665 23 28, Fax: +48 61 665 23 07
E-mail: Czeslaw.Cempel@put.poznan.pl

Summary

The paper presents the introductory results in application to multi fault condition monitoring of mechanical systems in operation, in particular internal combustion engines. This generalization to multi dimensionality and multi fault condition monitoring is possible by utilizing transformed symptom observation matrix, and by successive application of singular value decomposition (**SVD**) and based on it principal component analysis (**PCA**). On this basis one can make full extraction of fault related information taken from symptom observation matrix, which can be created by traditional monitoring technology. Moreover, by **SVD**/**PCA** we can create some independent fault measures and indices, and of overall system condition. In another words, full utilization of **SVD**/**PCA** enable us to pass from multi dimensional - non orthogonal **symptom space**, to orthogonal generalized **fault space**, of much reduced dimension. This seems to be important, as it can increase the scope and the reliability of condition monitoring of critical system in operation. It enables also to maximize the amount of condition related information, and to redesign the traditional condition monitoring system. At the end of the paper some introductory consideration are presented leading to a design of **C**ondition **I**nference **A**gent (**CIA**), which will enable to infer in real time on condition of critical objects in operation.

Keywords: machine condition monitoring, vibration, faults, singular values, condition inference agent

1. SINGLE AND MULTI SYMPTOM MONITORING

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

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

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

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

system **condition** assessment, usually on the basis of: one symptom - one condition measure.

But the measuring technology of today enable to measure many life dependent operational and residual processes as symptoms. Hence we can have many condition related quantities, and a good possibility of creation of **symptom observation matrix** (SOM), when observing our system in a discrete moments of life θ. We can also include to our consideration some assessment of system logistic vector, proportional to the life time **θ** in a first approach. Such is the problem of this paper, to advance and apply the multi dimensionality of system condition observation, as it was initially proposed in already published papers [1], [2], [5]. Having **SOM** matrix measured we can apply **SVD** and **PCA** based algorithms to extract independent multi fault $F_t(\theta)$ related information. Next when we connect obtained in this way generalized fault symptoms with some techniques of symptom limit value calculation [9], to infer on system operational condition. In this way we may start to think on the design of **c**ondition **i**nference **a**gent (**CIA**), for critical mechanical systems.
The paper is illustrated also by some examples of symptoms taken from real machine condition monitoring practice, rail road Diesel engines in particular.

2. MULTIDIMENSIONAL OBSERVATION OF SYSTEMS IN OPERATION

Let us take into consideration machine in operation. During its life $0 < \theta < \theta_b$(–anticipated breakdown time), several independent faults are growing; $F_t(\theta)$, t = 1,2,..u. We would like to identify and assess these faults by forming and measuring the symptom observation vector; $[\mathbf{S_m}] = [\mathbf{S_1,...,S_r}]$, which may have components different physically, like vibration, temperature, machine load, etc. In order to track machine condition evolution (faults), we are making equidistant reading of above symptom vector in the life time moments; θ_n, n = 1, ... p, $\theta_p \le \theta_b$, forming in this way the rows of symptom observation matrix (SOM). From the previous papers [1], [5] we know that the best way of pre processing of SOM is to center it (remove), and normalize (divide) to symptom initial value; $\mathbf{S_m(0) = S_{0m}}$, of a given symptom (column of SOM). This gives us dimensionless symptom observation matrix in the form

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

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

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

$$O_{pr} = U_{pp} * \Sigma_{pr} * V_{rr}^T \qquad (2)$$

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

$$\begin{aligned} &\Sigma_{pr} = \mathrm{diag}(\sigma_1,\cdots,\sigma_L),\\ &\sigma_1 > \sigma_2 > \cdots > \sigma_u > 0\\ &\sigma_{u+1} = \cdots = \sigma_L = 0,\\ &L = \max(p,r),\ \ u = \min(p,r) \end{aligned} \qquad (3)$$

It means that from the r measured symptoms we can extract only u ≤ r independent sources of diagnostic information describing evolving generalized faults F_t (see Fig. 1). As it is seen from Fig. 1 upper left, only a few developing faults are making essential contribution to total fault information, the rest of the generalized faults are on the level of noise. Such SVD decomposition can be made currently after each new observation of the symptom vector; n = 1, … p, and in this way we can trace the faults evolution in a system (see Fig. 5). From the current research of this idea [1], [2], [3], we can say that the most fault oriented indices obtained from **SVD** is the first pair SD_t , σ_t , and the sum of them. The first indices SD_t can be named as discriminate of the fault t, one can get it as the SOM product and singular vector v_t , as below

$$SD_t = O_{pr} * \mathbf{v_t} = \sigma_t \mathbf{u_t}, \qquad (4)$$

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

$$\mathrm{Norm}(SD_t) \equiv \|SD_t\| = \sigma_t,\ \ t = 1,\cdots,u \qquad (5)$$

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

$$\|F_t(\Theta)\| \sim \|SD_t(\Theta)\| = \sigma_t(\Theta) \qquad (6$$

The above discriminant $SD_t(\theta)$ can be also named as fault profile, and in turn $\sigma_t(\theta)$ as its advancement. The similar inference can be postulated to the meaning, and the evolution, of summation quantities, what can mean the total damage profile SD(θ), and total damage advancement DS(θ),

$$\begin{aligned} SD(\Theta) &= \sum_{i=1}^{z} SD_i(\Theta) = \sum_{i=1}^{z} \sigma_i(\Theta) u_i(\Theta) = P(\Theta)\\ DS(\Theta) &= \sum_{i=1}^{z} \sigma_i(\Theta) = \sum_{i=1}^{z} F(\Theta)_i = F(\Theta) \end{aligned} \qquad (7)$$

It seems to, that the condition inference based on this summation measures $SD = \sum SD_i$ may stand for the first approach to multidimensional condition inference by condition inference agent (CIA) described latter.

3. EXAMPLES OF MULTI DIMENSIONAL DIAGNOSTIC OBSERVATION

In order to illustrate the diagnostic inference power of multi fault approaches, by **SVD**, some computational programs were prepared named **diaginfo.m**, based on SVD algorithm and **pcainfo.m** based on principal component analysis (PCA). Both were written in the MATLAB® computational system. By means of such software several real diagnostic cases were studied and reported below partially.
Let us take into consideration vibration condition monitoring of 12 cylinder railroad Diesel engines, where in some chosen point a dozen vibration symptoms (3 acceleration amplitudes, 3 velocity, 3 displacement, 3 Rice frequency) were measured, each ten thousand kilometer of mileage, from zero up to 250.000 km. So our SOM has altogether 12 columns and 25 rows. Also we can append life proportional column to the calculation, as the first approximation of logistic vector and wear. The results of such new vibration condition monitoring, applied to the engine **sil54d2** are presented in Figure 1. As it is seen from the top left picture, the 12 measured symptoms create dense brushwood, and nothing can be said from this picture. But after SVD/PCA computation, picture top right, one can say, that at least two independent generalized faults can be recognized . And the same one can say considering SD_i, σ_i indices of the lower picture of Fig. 1.

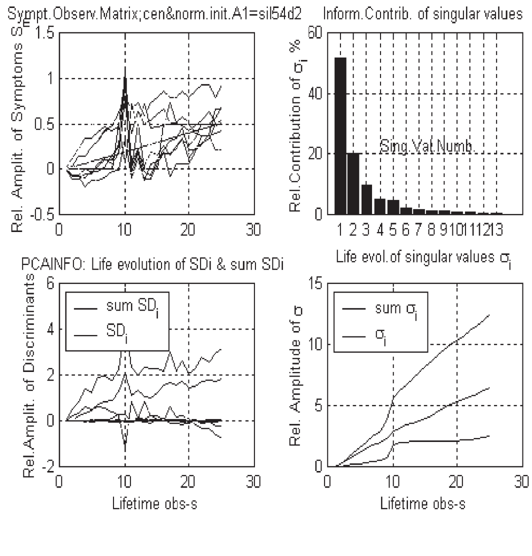

Fig. 1. The information contents of symptom observation matrix for a diesel engine **sil54d2**, and independent fault indices SD_i ,σ_I as discovered by SVD/PCA.

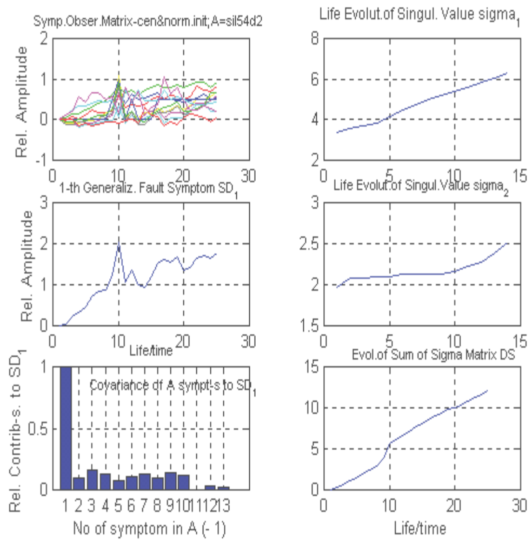

Fig.2. Contribution of primary measured symptom (bottom left) to the first fault discriminants; SD_i ,σ_i.

As it is seen from that, the first generalized fault SD_1 increases almost monotonic, while the second SD_2 is unstable, even in a higher engine mileage above 200.000 km. Looking for the total damage indices, denoted on the lower pictures as; **sumSD$_i$** and **sumσ_I,** one can say, they are similar to the first generalized fault discriminant SD_1 and σ_1, and seems to be more stable. Hence, there is great redundancy in our observation vector, and we are interested to diminish it. The next Fig. 2 answers partially this question, when looking to the bottom left pictures, giving the contribution of each measured symptom to the first generalized fault SD_1. We can see there, that three last symptoms (10 – 12, the Rice frequency) give low information contribution, and these symptoms can be omitted without substantial loss of monitoring quality.

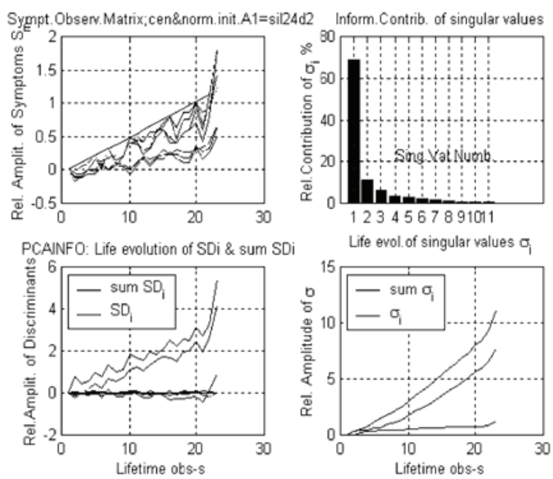

Fig. 3. Information contents and discriminants evolution for **sil24d2** diesel engine.

Next figure 3 present the result of application of this algorithms to another engine called **sil24d2**. As we can see from the figure and the picture top right, more than 60% of information contents concerns the generalized fault no 1, so SD_1 and σ_1. The next generalized fault SD_2 , σ_2 carries only 12 % of information contents. Looking at the bottom pictures in Fig. 3, one can say, that only the first generalized fault SD_1 , σ_1 gives the steady increase of both fault indices.

4. MULTI FAULT CONDITION INFERENCE

It seems to the author, that figures 1, 2 and 3 confirm fully the usability of singular value decomposition and principal component analysis, to extract multi fault information from symptom observation matrix. It is possible to create this during normal (routine) condition monitoring practice, and not only with vibration symptoms but some components of logistic vector too. We can also assess the information contribution of each primary symptom to any fault discriminants under our concern, and in this way to modify and diminish redundancy of symptom observation vector.

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

As was shown we can use for maintenance related inference, the first generalized fault, and some generalized fault idices as the measure of wear advancement. For the examples shown in the paper, (and it seems to be the general case also), good indices of overall condition seem to be the diagonal sum of singular values $DS(\theta)$, as the energy fault measure, and the sum of singular vectors $P(\theta) = \sum SDi$, as the fault profile measure.

In the view of theory and examples shown above we can present some life interpretation of Singular Value Decomposition (**SVD**). It seems to be valid for every generalized fault $F_t(\theta)$, t = 1, ... , as well as for total generalized fault profile $P(\theta)$, and the total generalized fault energy $DS(\theta)$.

This altogether means, that multi dimensional condition monitoring can give us real progress in on line assessment of condition of critical systems in operation. We can distinguish by this new method the momentary generalized fault profile $SD(\theta)$, as well as the generalized fault energy or its advancement $DS(\theta)$. The next additional step we need here in multi fault condition monitoring is to give limit values of chosen indices, measures, and generalized fault symptoms. And we can calculate this limit value by any method given in [3], [4], or by the latest proposal [9] based on symptom reliability, symptom hazard and Neyman - Pearson rule.

5 SVD/PCA IN DAMAGE EVOLUTION PROCESS TRACKING, FORE-CASTING AND LEARNING

One of the current aims of condition monitoring for critical systems in operation, vibration **CM** in particular, is to learn how to elaborate the software entity called condition inference agent (CIA) or simply **diagnostic agent**[2]. By definition (with supervision or by learning) it must be able to;

1. chose the set of condition related symptoms from the primary group of measured symptoms,
2. extract condition related information from the set of monitored symptoms,
3. to form generalized fault symptoms as the image of evolving faults in a system
4. to assess currently the limit values for each generalized fault
5. to make condition forecasting on the basis of acquired object related specific knowledge, some general knowledge, and to communicate it.

In the view of presented results of **SVD/PCA** application here, it seems to be possible to perform the first three tasks. The last two can be done by the use of additional knowledge flowing from theory of damage evolution, model of energy processor developed earlier [3], [4],[6], [9], mostly by present author, together with the associated software **cem8.m** and **dem8.m**, for condition assessment and forecasting.Just to see in what stage of design of CIA we are, the output result of just shown here program **pcainfo.m** was put into **dem8.m** [4p79], [9], for diagnostic assessment of overall condition measure SumSDi (Fig. 4a), and generalized symptom SD1(Fig. 4b), of a first generalized fault.

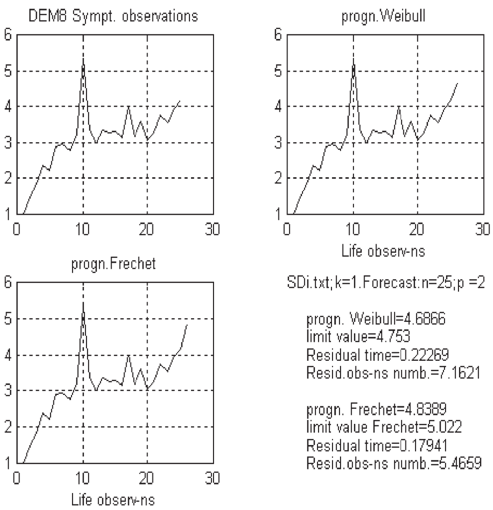

Fig. 4a.The results of condition inference program **dem8.m** applied to the generalized fault symptoms SumSDi (k=1), and SD1 (k=2), for the **sil54d2** diesel engine.

[2] Complex autonomous software entity, communicative and perceptive, with different level of competence [8].

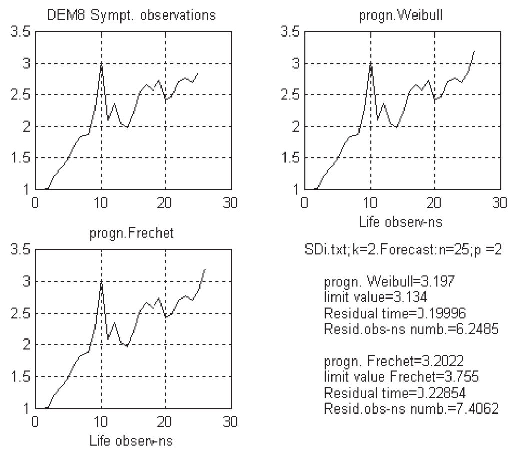

Fig. 4b.The results of condition inference program **dem8.m** applied to the generalized fault symptoms SumSDi (k=1), and SD1 (k=2), for the **sil54d2** diesel engine.

As it is seen from the both pictures, the maximal determination coefficient (R^2) of the distribution of symptom values in each case belongs to the Weibull symptom distribution, not to the Frechet, Pareto, and the like. In each case also for k=1=sumSDi, k=2=SD1 and life point n=25, forecasting step p=2, Weibull symptom prognosis, is over passing the symptom forecasted value.

We should remind here, that these **CIA** tasks (1-5) must be made during the wear and fault evolution in an operating critical system, what is not an easy task. In order to look even partially for this problem, let us look on the fig. 5 presenting the evolution of fault discriminant SD1, when the number of symptom observations is ascending from a few at the start of engine, up to the final number 25, for the case of already known **sil54d2** engine.

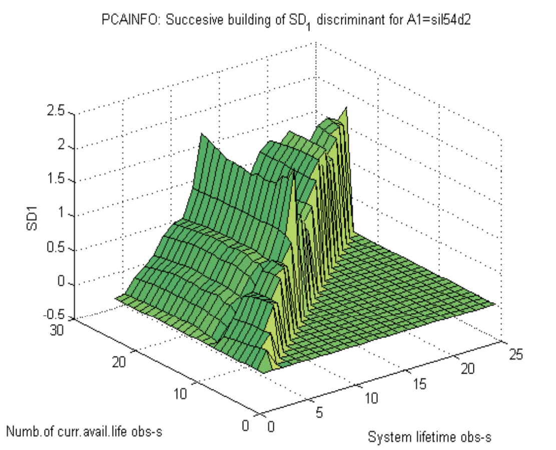

Fig.5. The evolution of fault discriminant SD1 during the life operation of some diesel engine.

One can see from the Fig. 5 the shape of SD1 discriminant is stabilizing steadily, when number of available information number increases (left scale). And after about 10 available observations, what means less as ½ life of the engine. One can say, that SD1 discriminant is really describing some evolving fault. Of course it depends on the case under consideration, and relative contribution of fault No1 in an information share in symptom observation matrix. This is seen clearly on Fig.1 picture upper right, for this case. Also, when generalized fault No1 is prevailing like for the engine **sil24d2** (fig.2, upper right), the SD1 discriminant is stabilizing quickly, after a few available observations. So basing on the current result of processing, we can say, which discriminant is representing the real fault in an operating critical system. And more importantly, when to start to determine the limit values of the generalized fault and discriminant SD1. We should think for each case, if to use only fault discriminant SD1, or overall fault measure as a sum of SDi, (upper curve on the picture lower left of Fig. 1 and Fig. 3). It seems to be more safely to start first time from the sum SDi, and in the next system run from a specific discriminant SD1.

Just to show what may be the line on reasoning and inference in a future diagnostic agent, intelligently monitoring some critical system in operation, one can study Fig. 6, where the general idea of critical system diagnostic observation, and information flow in a future diagnostic agent is shown. We can see also, that there is a place and need to take into consideration some other information concerning the system operation like; load **L**, current system life **θ**, and also some previous records on system history contained in the maintenance data base.

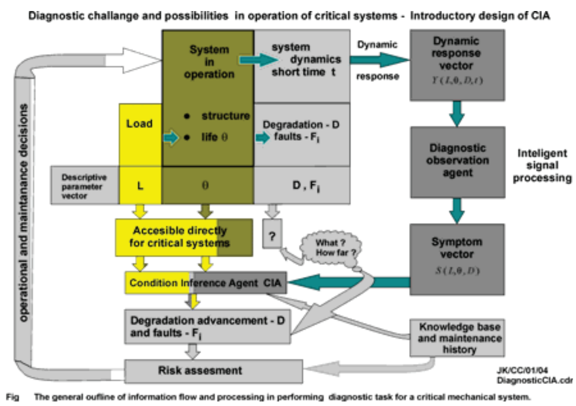

Fig.6. The information flow and processing in an operating system and intelligent condition monitoring subsystem.

6. CONCLUSIONS

The paper starts with some summary of research concerning application of singular value decomposition to the problem of extraction of multifault information from symptom observation matrix **SOM**. It was shown, that basing on **SVD**/**PCA** we can describe the condition evolution in terms of some independent fault discriminants. And one must interpret these new indices in term of machine damage and operational data. The whole idea is illustrated by the data taken from the real diagnostic experiment on some Diesel engines. Having generalized symptoms determined for each case we can calculate symptom limit values, by already known methods and programs in order to infer on systems condition. On this basis some new idea how to design condition inference agent (**CIA**) was presented for further consideration .

Acknowledgment Author acknowledges the financial support of this research, made possible in part by; KBN grant, as well as the support of the Faculty of Mechanical Engineering and Management of Poznań University of Technology.

REFERENCES

[1] Cempel C., Innovative Developments in Systems Condition Monitoring, Keynote Lecture for DAMAS '99, Damage Assessment of Structure Conference, Dublin, June 1999.
[2] Natke H. G., Cempel C., Symptom observation matrix for monitoring and diagnosis, Journal of Sound and Vibration, Vol.248, No 4, 2001, pp 597 - 620.
[3] Cempel C., 1991, Vibroacoustical Condition Monitoring, Ellis Horwood Ltd., Chichester - New York, p 201.
[4] Natke H. G., Cempel C., 1997, **Model - Aided Diagnosis of Mechanical Systems**, Springer Verlag, p 300.
[5] Cempel C., 2003, Multi Dimensional Condition Monitoring of Mechanical System in Operation, Mechanical Systems and Signal Processing, 2003, Vol. 17, No 6, pp 1291 –1303.
[6] Cempel C., 1990, Limit Value in Practice of Vibration Diagnosis, **Mechanical Systems and Signal Processing**, Vol 4, No 6, 1990, pp 483 – 493.
[7] Kiełbasiński A., Schwetlick H., 1992, Linear Numerical Algebra, WNT, Warsaw, chapt., 1, (in Polish), p 502.
[8] Agent Builder, Build it smarter, Internet; http://n….com/Documentation/whyAgent.html
[9] Cempel C., Natke H. G., Yao J.P.T., Symptom Reliability and Hazard for System Condition Monitoring, **Mechanical Systems and Signal Processing**, 2000, Vol. 14, No 3, pp 495 – 505.

Czeslaw CEMPEL, Poznań University of Technology, Applied Mechanics Institute, ul Piotrowo 3, PL-60-965 Poznań, Poland,
fax; +48.61.6652307, email; czeslaw.cempel@put.poznan.pl ,web; http://neur.am.put.poznan.pl .

Full professor of mechanics, vibroacoustics and machinery diagnostics. Cofounder of vibroacoustics and diagnostics in Poland, member of the Polish Academy of Sciences, and Engineering Academy in Poland, elected member of State Research Committee in Poland (KBN) since 1991.