

THEORY OF ENERGY TRANSFORMING SYSTEMS AND THEIR APPLICATION IN DIAGNOSTICS OF OPERATING SYSTEMS

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In this paper the theory of energy transforming systems (ETS) with finite dissipation capacity was presented and applied to condition assessment of operating systems (OS). It was shown that externally dissipated energy transformed into life-symptom of OS has direct equivalence with its reliability, and the remaining life. It was shown also, that ETS modules can serve as building block for creating the diagnostic and reliability models of any OS. These models have very important fractal-like property which enables us to apply this line of reasoning to every level of energy transforming hierarchy of any OS. The explanatory properties of such fractal-like modeling can be used for better understanding of life evolution of OS. The diagnostic and reliability consideration were illustrated and validated by the computer program applied to Diesel engine vibration condition monitoring.

1. Introduction

In the author's early work in the area of vibroacoustical condition monitoring (see Cempel, 1991) the tribovibroacoustical (TVA) machine model has been given describing the link between the evolution of the machine condition, (i.e. its degradation advancement), and its measurable vibrational symptoms of condition. The inference power of this energy dissipation model (TVA) enables its further development and generalization the domain of operating systems of mechanical engineering (Cempel, 1992), and of mechanical origin (Cempel and Natke, 1992), and evolutionary systems at all (Winiwarter and Cempel, 1992; 1993). In particular the latter concept of hierarchical fractal-like structure of energy transforming processes and systems seems to have great explanation power. But so far it has not been applied in the area of mechanical systems. The aim of this paper is to enlighten all what has been done in the area of modeling of the operating systems (see also Cempel, 1992; 1992b), by this new concept of fractal-like energy transforming systems (ETS) and processes. And also to show the diagnostic, prognostic and modeling abilities of this ETS approach.

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2. Evolution of Condition of Energy Transforming Systems

Operating systems of mechanical origin such as machines, vehicles, engineering structures, etc. are working on the basis of transformation of the input energy supplied to perform the necessary action or to keep necessary condition or state. Here the input stream of material is also treated as the input energy. In such approach all operating systems can be treated as open energy transforming dissipative systems. They are dissipative in the sense of Prigogine (Prigogine, 1971), as they are all subject to wearing processes (Cempel, 1992). After thorough consideration we can come to the conclusion, that all the essential parts of the operating system (metasystem) can be treated as dissipative Energy Transforming Systems (ETS), and the nature of their energy transformation by its dissipation is the same. Due to that it is convenient for further consideration to present the behavior of the base unit, or the ETS building module (Winiwarter and Cempel, 1993) separately. Following the notations and the explanations of the Figure 1 we can present this theory as follows.

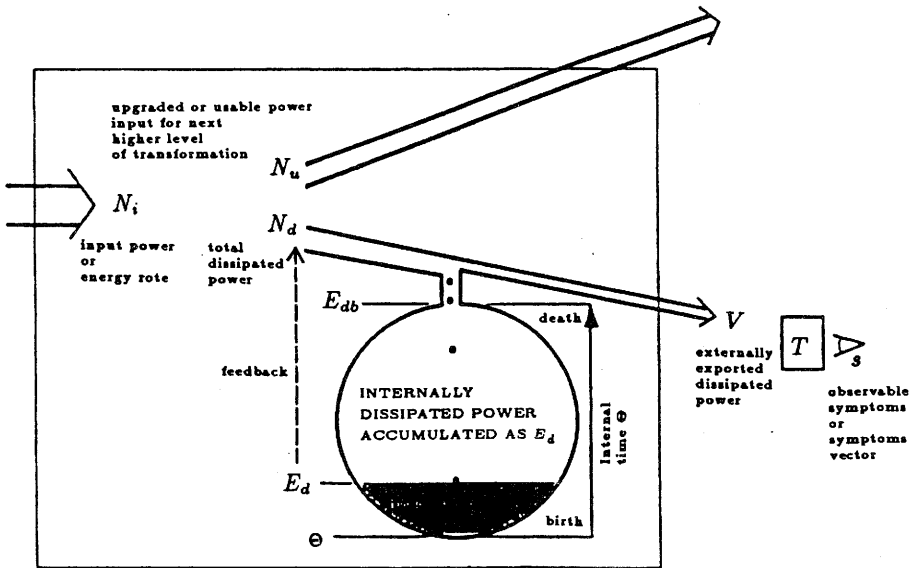


Fig. 1. Elementary energy transformation module, the building block of the self-similar hierarchical energy transformation process and system.

The input N_i , the usable (or upgraded) N_u and dissipated N_d streams of power in the module are balanced, that is

$$N_i = N_u + N_d \tag{1}$$

The price for input energy transformation or upgrading is the dissipated power N_d , and the whole flow is divided into two streams: accumulated internally A and exported externally V . There is always the finite dissipation capacity for accumulated energy inside the ETS i.e. $E_d(\Theta) \leq E_{db}$. Here, Θ is the life time measure of the module and the E_{db} is the breakdown value of internally dissipated energy, (by analogy to the volume of the tank in Figure 1).

$$E_d(\Theta, V) = \int_0^\Theta A(\Theta, V) d\Theta \leq E_{db} \quad (2)$$

There is also a destructive feedback between the current value of internally dissipated energy and the intensity of externally dissipated (exported) power, for example, the more vibration the more fatigue and wear. Hence, we can write the second constitutive equation of ETS in the differential form:

$$dV(\Theta) = \alpha dE_d(\Theta, V) \quad (3)$$

The third postulate for ETS model building concerns its internal structure, i.e. it has to be invariant during the life of the module, so the internal energy streams (piping) can not be changed

$$\frac{dN_d(\Theta, V)}{dV} = \text{const} \quad (4)$$

Basing on these three postulates the differential equation of the evolution of the externally exported power, i.e. system degradation (see the second postulate), during the ETS life can be obtained and solved. This solution gives two colinear power streams:

the total dissipated power

$$N_d(\Theta) = N_{d_0}(1 - \Theta/\Theta_b)^{-1} \quad (5)$$

the externally dissipated power stream

$$V(\Theta) = V_0(1 - \Theta/\Theta_b)^{-1} \quad (6)$$

As it can be observed they are colinear and have the same asymptote at the breakdown time Θ_b , which can be also defined analytically as

$$\Theta_b \equiv \frac{dN_d}{dE_d} \quad (7)$$

To complete the theory of ETS module, the energy base definition of damage advancement is necessary. It was defined in (Cempel and Natke, 1990) as physically validated composition of two simple measures

$$D \equiv \begin{cases} \Theta/\Theta_b & - \text{for uniform continuous wear} \\ \frac{n}{N_b} & - \text{for uniform cyclic wear} \\ & - \text{any linear and/or stepwise combination of the above} \end{cases} \quad (8)$$

However, the trouble is that no one can observe or measure directly any of the above quantities D, N_d, V describing the ETS life. As it is shown in Figure 1 we can only observe some T -filtered part of externally exported power V . It means the vibration amplitude for the dynamic processes, the temperature for the heat, etc. Hence, let us assume that we are observing the life symptom S of our ETS evolution being the function of $V(\Theta)$

$$\frac{S}{S_0} \equiv \Phi \left(\frac{V}{V_0} \right) = \Phi \left[\left(1 - \frac{\Theta}{\Theta_b} \right)^{-1} \right] = \Phi [(1 - D)^{-1}] \equiv \Phi [(\Delta D)^{-1}] \quad (9)$$

Here as the above $S_0 = \Phi(1)$ is initial value of the symptom, $D = \Theta/\Theta_b$ is the dimensionless life of the ETS, $\Delta D \equiv 1 - D$ is residual life, and $\Phi(*)$ is life symptom operator. We can conclude that by the observation of the ETS life symptom values we can assess its residual life ΔD of the module or of the system. Of course, it is true only if we know the symptom operator $\Phi(*)$. The forms of this symptom operator can be different in dependence on the wear participation factors for the given ETS. In the simple case we can try the exponential form of the symptom operator $S/S_0 = (\Delta D)^{-1/\gamma}$, $\gamma > 0$, that means Pareto life curve. We shall discuss these problems later on.

3. Behavior of the Population of ETS

At this moment a very important applicational question can arise namely, how the knowledge of the life symptom behavior can be used in diagnostics of operating system? For the simple operating system it may be the simple equivalence: *one fault - one life symptom*. For more complicated OS we can apply this in accordance with the reliability theory—to look for the weakest element. Hence, we should look for such symptom which will describe only the technical condition of the weakest element in OS. However, the other question remains unanswered. How to find the life symptom operator for this case? It is possible to answer this question by observing the life behavior of population of ETS of the same type, assuming that each one is in a different stage, or advancement, of its damage evolution process. Thus, the distribution of the individual life will begin from the birth ($\Theta = 0, D = 0$) until the death ($\Theta = \Theta_b, D = 1$). There is another reason for observing the population of ETS of the same type. It is easy to imagine that each module having the same design goal can be implemented by different enterprises, with different quality merit dq , produced by another enterprise with the quality pq , installed at some factory site with dynamic standard sq , running with the different load lq , being maintained with mq quality, and repaired with quality rate rq . Of course at the running site of ETS nothing is usually known concerning this quality ratings. Hence, we can say that logistic vector of the OS

$$L = \{dq, pq, ds, lq, mq, rq, \dots\} \quad (10)$$

is not known, and we have to use some population statistics to overcome the lack of this knowledge. Owing to this, the dissipated power N_d , the dissipated energy

E_d , the breakdown energy E_{db} , and the breakdown time Θ_b in our ETS model will be also the function of this logistic vector, i.e. we will have: $N_d(\Theta, V, L)$, $E_d(\Theta, V, L)$, $E_{db}(L)$, $\Theta_b(L)$.

The same philosophy should be used if we apply the theory of ETS to other evolutionary systems of natural, or social origin (see Winiwarter and Cempel, 1992; 1993). As an example for the social systems the meaning of the logistic vector L can be; the social standard of a family where a human being was born, a country, its geographic location, its socioeconomic system, etc.

Having enough reasons for the population observation, let us assume that in our passive experiment the life symptom value is measured and classified for each operating ETS. In this way we can obtain the probability of symptom exceedance $P(S \geq S_t)$ of ETS being in operation (GOOD condition). Such empirical assessment of this probability is an equivalent to operational reliability (or survival function), which can be also expressed as

$$P(S \geq S_t) \equiv R(S) = \frac{n(S \geq S_t)}{M} \tag{11}$$

where $n(S \geq S_t)$ is the number of ETS which symptom value overpasses threshold S_t , and M is the total number of ETS population. On the other hand, the symptom reliability $R(S)$ can be calculated analytically (O'Connor, 1985)

$$R(S) \equiv P(S \geq S_t) = \int_S^\infty p(S_e) dS_e \tag{12}$$

Here, $p(S)$ is the probability density of symptom observation for ETS being in GOOD condition. From the observation of population reliability $R(S)$ we will know the behavior of the ETS set in the symptom domain S . Hence, let us transform this knowledge to the life time domain Θ or the damage D domain. On the basis of probability theory (Papoulis, 1965) it is known how to exchange these domains

$$p(S) = p(D) \frac{dD}{dS} = p(D) \left(\frac{dS}{dD} \right)^{-1} \tag{13}$$

The first term gives us the density of ETS life distribution in our population, and the second describes its life symptom evolution, what we have already found by means of equations (8) and (9). For the damage allocation density $p(D)$ in a population of ETS we can propose alternatively

$$p(D) = \begin{cases} \left(\frac{S(D)}{S_0} \right)^k, & k \geq 0, \text{ for symptom value related density} \\ \sum_{n=0}^k \left(\frac{S(D)}{S_0} \right)^n, & \text{for arbitrary density approximated} \\ & \text{by polynomial} \end{cases} \tag{14}$$

We have found already the life symptom evolution of our ETS module (8), (9), so we can also calculate the required derivative dS/dD being alternatively

$$\frac{dS}{dD} = \begin{cases} \frac{1}{\gamma} \left(\frac{S_0}{S}\right)^{-\gamma+1}, & S \geq S_0, \gamma \geq 0 & - \text{for Pareto type} \\ & & \text{life curve} \\ \frac{d\Phi[(1-D)^{-1}]}{dD} \cong \frac{d}{dD} \left[\sum_{l=1}^k a_l (1-D)^{1-l} \right] & & - \text{polynomial} \\ & & \text{approximation of} \\ & & \text{general case of} \\ & & \text{life curve} \end{cases} \quad (15)$$

Putting now the first alternative of equation (14) and equation (15) into the reliability integral (12) we will have

$$R(S) = \int_S^\infty p(S_e) dS_e = \int_S^\infty \gamma \frac{S_0}{S_e} \left(\frac{S_0}{S_e}\right)^{\gamma-k-1} = \frac{\gamma}{\gamma-k} \left(\frac{S_0}{S}\right)^{\gamma-k} \quad \gamma, k \geq 0 \quad (16)$$

And for the second alternative of the life distribution (14) in ETS population again

$$R(S) = \gamma \sum_{n=0}^k \frac{1}{\gamma-n} \left(\frac{S_0}{S}\right)^{\gamma-n}, \quad \gamma > k \geq 0 \quad (17)$$

In both cases we have obtained the Pareto type of reliability or survival function. It is shown directly in (16) with the accuracy of normalization coefficient. It is true also for the reliability (17), as it can be shown (Roehner and Winiwarter, 1985) that the sum of Paretian distributions maintains its property. So, for the both cases of life distribution in our population we obtain Pareto reliability, if, of course, the life symptom is of Pareto type. Hence, we can assume for the both cases

$$R(S) \equiv P(S_e > S) = \left(\frac{S_0}{S}\right)^\gamma, \quad \gamma > 0 \quad S \geq S_0 \quad (18)$$

For the Paretian reliability we can prove more valuable relationship. Putting here Paretian life curve

$$\frac{S}{S_0} = (1 - D)^{-1/\gamma}$$

we can have

$$R(S) = \left(\frac{S_0}{S}\right)^\gamma = 1 - D \equiv \Delta D \quad (19)$$

So, knowing the symptom reliability $R(S)$ for a given population of ETS, or operational systems, and measuring the symptom value for a given unit we can determine the *residual life* of that unit because

$$\Delta D = 1 - D = \begin{cases} 1 - \frac{\Theta}{\Theta_b} = \frac{\Delta\Theta}{\Theta_b}, & \text{for continuous wear (life)} \\ 1 - \frac{n}{N_b} = \frac{\Delta n_b}{N_b}, & \text{for cyclic wear (life) or for uniform} \\ & \text{spacing of measurement along} \\ & \text{the life symptom curve} \end{cases} \quad (20)$$

This possibility is a great advantage of ETS theory. Moreover, we can prove the validity of relations (19), (20) for other types of reliability function, Weibull, Fréchet and Uniform. It is possible to recalculate the symptom operator $\Phi(\frac{V}{V_0})$, and the life symptom curve $\Phi[(1 - D)^{-1}]$, (see relation (9)) for each reliability model mentioned above, as it is shown in Table 1.

Tabl. 1. The life symptom operators, life symptom curves, and the respective models of symptom reliability as generated by the theory of ETS.

Symptom operator $V > V_0, \gamma > 0$ $\Phi(\frac{V}{V_0}) =$	Symptom life curve $S_0 > 0, \frac{S(D)}{S_0} =$	Symptom reliability $R(S) =$	Remarks
$(\ln \frac{V}{V_0})^{1/\gamma}$	$[-\ln(1 - D)]^{1/\gamma}$	$\exp -(\frac{S}{S_0})^\gamma$	Weibull, $S \geq 0$
$[-\ln(1 - \frac{V_0}{V})]^{-1/\gamma}$	$[-\ln D]^{-1/\gamma}$	$1 - \exp -(\frac{S}{S_0})^{-\gamma}$	Fréchet, $S \geq 0$
$(\frac{V}{V_0})^{1/\gamma}$	$(1 - D)^{-1/\gamma}$	$(\frac{S}{S_0})^{-\gamma}$	Pareto, $S \geq S_0$ (asymptotics of Fréchet)
$1 + (1 - \frac{V_0}{V}) \cdot \frac{1}{\gamma}$	$1 + \frac{1}{\gamma} D$	$1 + (1 - \frac{S}{S_0}) \cdot \gamma$	Uniform, $S \geq S_0$ $S \sim S_0$ (approximation of Pareto)

In Table 1 we can notice that all proposed symptom operators $\Phi(*)$ give monotonous growth of the life symptom curves, mostly with asymptotic behavior at $D = 1$, (Weibull, Fréchet, Pareto). The life sensitivity of symptoms $S(D)$ depends reciprocally on the value of the γ exponent, being maximal for the Fréchet reliability and its life curve. The respective reliabilities in Table 1 belong to the long tailed distributions generated by the densities with right-hand skewness. It concerns in particular the Fréchet and its asymptotic expansion - Pareto, typically used in a statistics of evolutionary systems (Winiwarter and Cempel, 1992).

Summarizing the consideration of this paragraph we have shown here that by observing the life of the ETS population we can find its symptom reliability $R(S)$. This has a direct analytical link with the life symptom operator and the individual ETS life curve. Moreover, there is a direct equivalence between symptom reliability and ETS residual life of a given unit, i.e. $R(S) = 1 - D \equiv \Delta D$. We have also indicated the possibility of, general Pareto-like, polynomial expansion of life symptom curve and the reliability. This seems to be promising but we will not go into details here with it.

4. Operating Systems as Energy Transforming Systems

Operating systems are mostly of complex design, function, energy flow, etc. So the problem arising is, how the theory of ETS can be used for their condition

assessment ? In order to understand this, the possible interdependence, and the structure of the ETS set modelling the OS, let us start from the example of a simple machine with rotor supported by two bearings inside the machine casing. As the casing does not usually create the maintenance and reliability problems, our OS (machine) can be modelled only by the three ETS as shown on Figure 2.

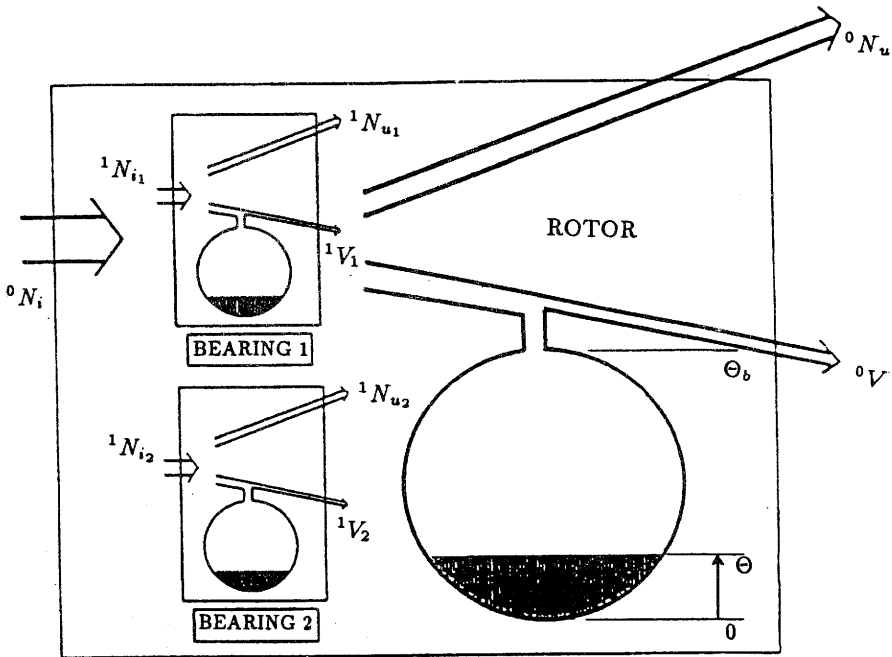


Fig. 2. The simplified two level decomposition of rotor machine into the hierarchy of ETS.

In this figure we can see that in order to describe the life evolution of the machine it is necessary to observe the following life-symptoms of OS:

For bearing No.1

$${}^1S(\Theta) = \Phi[{}^1V_1(\Theta)]$$

bearing No.2

$${}^2S(\Theta) = \Phi[{}^1V_2(\Theta)] \tag{21}$$

and for the rotor (the whole machine as well)

$${}^0S(\Theta) = \Phi[{}^0V(\Theta)]$$

It is also seen in the Figure 2 that the information describing the condition of the whole machine is contained in the shaft condition symptom ${}^0S(\Theta)$, but it may be hard to decode it. Such situations are very often observed in vibration condition monitoring practice, where casing vibration signals contain a mixture of all diagnostic information, but hard to decipher. The Figure 2 as well as the machine condition monitoring practice make it clear, that the behavior of these three ETS in terms of energy flow and dissipation may be quite different. It gives quite different life span (Θ_b), different type of symptom, its sensitivity, etc. But having the life symptom value of given ETS module, and its statistics we can apply the theory of ETS condition evolution to assess the residual life of every component.

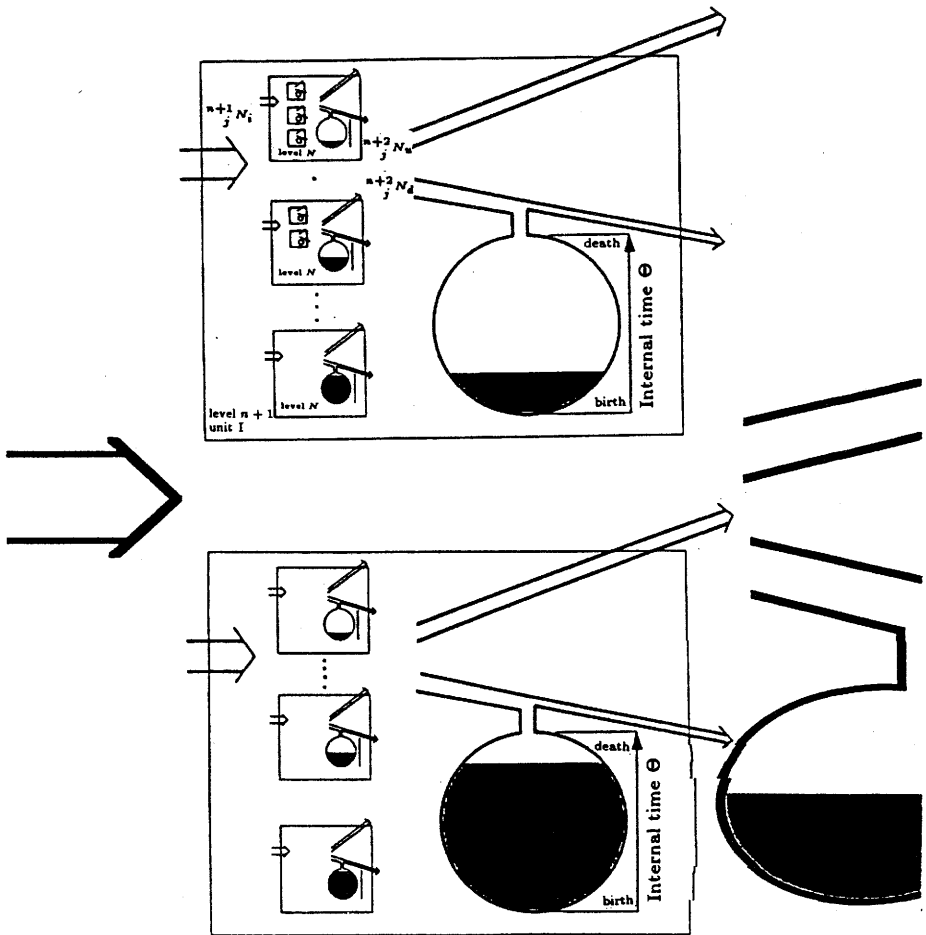


Fig. 3. Operating system diagnostic model as self-similar (fractal-like) hierarchy of ETS.

For the general case of OS diagnostics it is now easy to imagine, that we have here multi-level self-similar (fractal-like) hierarchy of ETS, as it is shown in Figure 3 (Winiwarter and Cempel, 1993). It may be noticed now from the both figures, that the best diagnostic description of our OS must have the life-symptom vector with the components created from ${}^k V_i(\Theta)$ of every ETS, of every level of OS hierarchy. Of course, it is usually not possible and we are taking into account the principle of the weakest element, to account only for the first few, with the greatest probability of damage.

It is clear again now, that every output process (signal) contains all information from the lower level. Also the technical condition, or the damage advancement, (the amount of internally dissipated and accumulated energy) of the lower level influences the technical condition of the higher level. It means the condition of the rotor (see Fig. 3) is also determined by the condition of both bearings. When one of the bearings is more damaged it gives the bigger stream of dissipated energy to the higher level at first, and secondly the other bearing must take some part of local energy stream, so it will be damaged much quicker. This example makes it obvious that ETS hierarchical model of OS allows us to understand the interrelations between the elements of the OS, within the given hierarchy level and between the neighbouring levels. It also allows building hierarchically the diagnostic and reliability model of OS basing on the simple rule, *the greater the energy flow the more important and critical is the element or the part*.

Summing up, we can say, that the diagnostic and the reliability model of OS can be build as a hierarchy of ETS. Due to a self-similarity of processes we can apply the results of ETS theory to each level of OS hierarchy, looking for the residual life of each critical part of the operating system.

5. Condition Assessment of Operating Systems

One of the goals of diagnostics of operating systems is the assessment of the present and future condition of the system, within the forecasting life horizon. Due to advantages of ETS theory we can perform it in two domains, in the symptom and the life domains. To assess the OS condition in symptom domain we need some symptom limit or standard value for the comparison. And in the life domain we will assess the residual or remaining life, as it was shown already by relation (20). But in order to determine the symptom limit value, for the breakdown S_I , or the alarm S_a , we should apply the same bit of statistical decision theory (Birger, 1979), namely the Neyman-Pearson rule of risk assessment. If we known the availability of the OS population (or the machine group), $0 < G < 1$, and will specify the allowable risk, $0 < A \ll 1$, of false condition assessment, we can calculate our limit values (breakdown and alarm) as follows.

$$G \cdot R(S_I) = A$$

$$G \cdot R(S_a) = cA \tag{22}$$

As it can be seen the symptom reliability $R(S)$ is used here again, and we should specify only the allowable probability of unnecessary repair A (false decision), and the coefficient c value. Usually, in dependence on the age and maintainance quality of OS; $A = 0.02 - 0.1 = (2 - 10)\%$ and the alarm coefficient $c = 2 - 4$. It means we are ready to repair needlessly $(2-10)\%$ of our machinery stock in order not to allow the breakdown condition. This rule of symptom limit value calculation gives good results in vibration condition monitoring of machines (Cempel, 1990).

Concerning the residual life assessment we will start from the relation (20). Having measured the life symptom value S_e of our OS we can write accordingly

$$R(S_e) = 1 - D_e \equiv \Delta D_e \quad (23)$$

On the other hand, and the above, we can set also the safety limit of the remaining life, because

$$R(S_l) = \frac{A}{G} \equiv \Delta D_l \quad - \text{limit remaining life.}$$

Now, we are ready to write the basic relation for the condition assessment of the OS

GOOD condition

$$\text{If} \quad S_e < S_l$$

$$\text{or} \quad \Delta D_e < \Delta D_l$$

FAULTY condition

$$\text{If} \quad S_e \geq S_l$$

$$\text{or} \quad \Delta D_e \geq \Delta D_l$$

(24)

Knowing the assessment of system remaining life ΔD_e , made during periodic system monitoring with the life step $d\Theta$ for its n_e -th measuring step, we can calculate by the analogy to relation (20)

$$\Delta D_e \equiv R(S_e) = 1 - \frac{\Theta_e}{\Theta_b} = 1 - \frac{n_e \cdot d\Theta}{N_b \cdot d\Theta} = 1 - \frac{n_e}{N_b} \quad (25)$$

Basing on this we can calculate the system breakdown time

$$\Theta_b \equiv N_b d\Theta = \frac{n_e}{1 - \Delta D_e} \quad (26)$$

and the residual number of measurements before system breakdown

$$\Delta N_b \equiv N_b - n_e = \frac{n_e \Delta D_e}{1 - \Delta D_e} \quad (27)$$

This is the assessment of the remaining life, but we can make prognosis of the next symptom value S_p . Basing on the relation (9) and Table 1, for the specific chosen symptom operator model and the forecasting step $\Delta D_p \leq \Delta D_e$, we can write

$$\frac{S_p}{S_0} \equiv \frac{S(D_e + \Delta D_p)}{S_0} = \Phi [(1 - D_e - \Delta D_p)^{-1}] = \Phi \left[\left(1 - \frac{n_e + p}{N_b} \right)^{-1} \right] \quad (28)$$

where $\Delta D_p = pd\Theta/N_b d\Theta$ is the dimensionless forecasting step transformable to the number of observations p , if condition monitoring is periodic. Having such possibilities of diagnosis and prognosis of OS condition we can use the computer software for a detailed calculation, what will be referred to the next section.

6. Prognostic Assessment of Life Symptom Reliability Models

According to our theory of ETS evolution we should have at first the symptom data base for the selection of the best fit of reliability model (see Tabl. 1). Then according to this results we can transform the symptom reliability to the average symptom-life curve. Of course, we will assess the goodness of fit of the model by the determination coefficient and χ^2 test. Having chosen the best fit of reliability model, and having the last measurement of symptom for given OS we will calculate the symptom value forecast and the remaining life.

Such computer programs were made in MATLAB environment (cem7.m; dem7.m) under the author's supervision as the master thesis (Generalczyk, 1992), and project work (Mietki, 1992), using the vibration symptom data base gathered during the PhD preparation for the population of Diesel railroad engines (Tomaszewski, 1985). The example of calculation results for the data base 'sild1' with $M = 56$ readings, and the condition assessment of engine 'sil54d1' by root mean square vibration acceleration amplitude A_{rms} as the life-symptom are shown in Figure 4 and Figure 5.

It is seen here that statistically (in this case) the best reliability models are Uniform and Weibull, and Pareto model gives usually the first warning before the breakdown. However, the statistical treatment of these models made by similar program 'dem9.m' for the data base of 7 symptom and 9 measuring points has proved, that Frechet model and Weibull model have the best forecasting ability. The best symptoms with respect to forecasting accuracy (all four engines in data base broke down) are the rms and the peak values of vibration velocity, and acceleration as the second. The best measuring points out of d1,...,d9 were chosen as d4 and d1. Of course, it is all true with respect to observed fault, i.e. the breakdown of the engine crankshaft.

It is known that Pareto model is the asymptotic expansion of Frechet model (for $S \geq S_0$), hence for further consideration we can exclude Pareto and Uniform models basing in future only on Frechet and Weibull models for condition assessment and forecasting.

The polynomial representation of the symptom reliability indicated here as the next possibility (see equation (17)) is currently under the study. It follows from this that polynomial model with ascending exponents is very sensitive, and sometimes unstable for small values of reliability. It means also that this will be very sensitive

for the censoring effects inherent for vibration condition monitoring. Such censoring effects have no place when we choose the proper analytical model of symptom reliability. This inconvenience can be reduced when we create the polynomial with reverse of symptom (S^{-1}) as it is the case for Pareto-like distributions (see equation (17)), being in accordance with physics of wear and ETS theory.

Database sild1	k=3	A=0.1	G=0.9	c=3	cem7.m	
distrib	gamma	beta	R%	kappa	Sl/S0	Sa/S0 (S0=beta*Smin)
Weibull	3.34	1.976	96.8%	9.101	1.2658	1.0286
Frechet	4.109	1.55	85.1%	16.896	1.683	1.2457
Pareto	2.921	1.037	72%	16.91	2.1218	1.4566
Uniform	0.608	1	98.9%	7.597	2.4615	2.0961

Prognosis

Name of the input file for prognosis = 'sil54d1'

Loading from: sil54d1.mat

Number of column (symptom) k=3 = Arms [ms^{^(-2)}]

Starting point of forecast n=25 (last measurement before breakdown)

Forecast step = 2

*** CHOSEN UNIFORM RELIABILITY ***

** *FORECASTED VALUE (Weibull) = 67.7001

** *LIMIT VALUE (Weibull)= 65.036

** *RESIDUAL TIME (Weibull)=0.1866* *RESIDUAL OBSERV. NUMB.=5.7363

** *FORECASTED VALUE (Frechet) = 66.594

** *LIMIT VALUE (Frechet)= 67.834

** *RESIDUAL TIME (Frechet)=0.1772* *RESIDUAL OBSERV-NS

NUMB.=5.3831

** *FORECASTED VALUE (Pareto) = 75.3327

** *LIMIT VALUE (Pareto)= 57.235

** *RESIDUAL TIME (Pareto)=0.0968* *RESIDUAL OBSERV. NUMB.=2.6795

** *FORECASTED VALUE (Uniform) = 70.5715

** *LIMIT VALUE (Uniform)= 63.998

** *RESIDUAL TIME (Uniform)=0.1866* *RESIDUAL OBSERV-NS

NUMB.= 6.4324

*****Symptom reached limit value !!!!

*!*Residual time reached limit value*!*!

!!!Weibull forecast reached dangerous symptom value !!!!

!!!Pareto forecast reached dangerous symptom value !!!!

!!!Uniform forecast reached dangerous symptom value !!!!

Next forecast ? (yes=1, no <>1) ?

Fig. 4. The data base best fit and the engine condition and forecasting assessment.

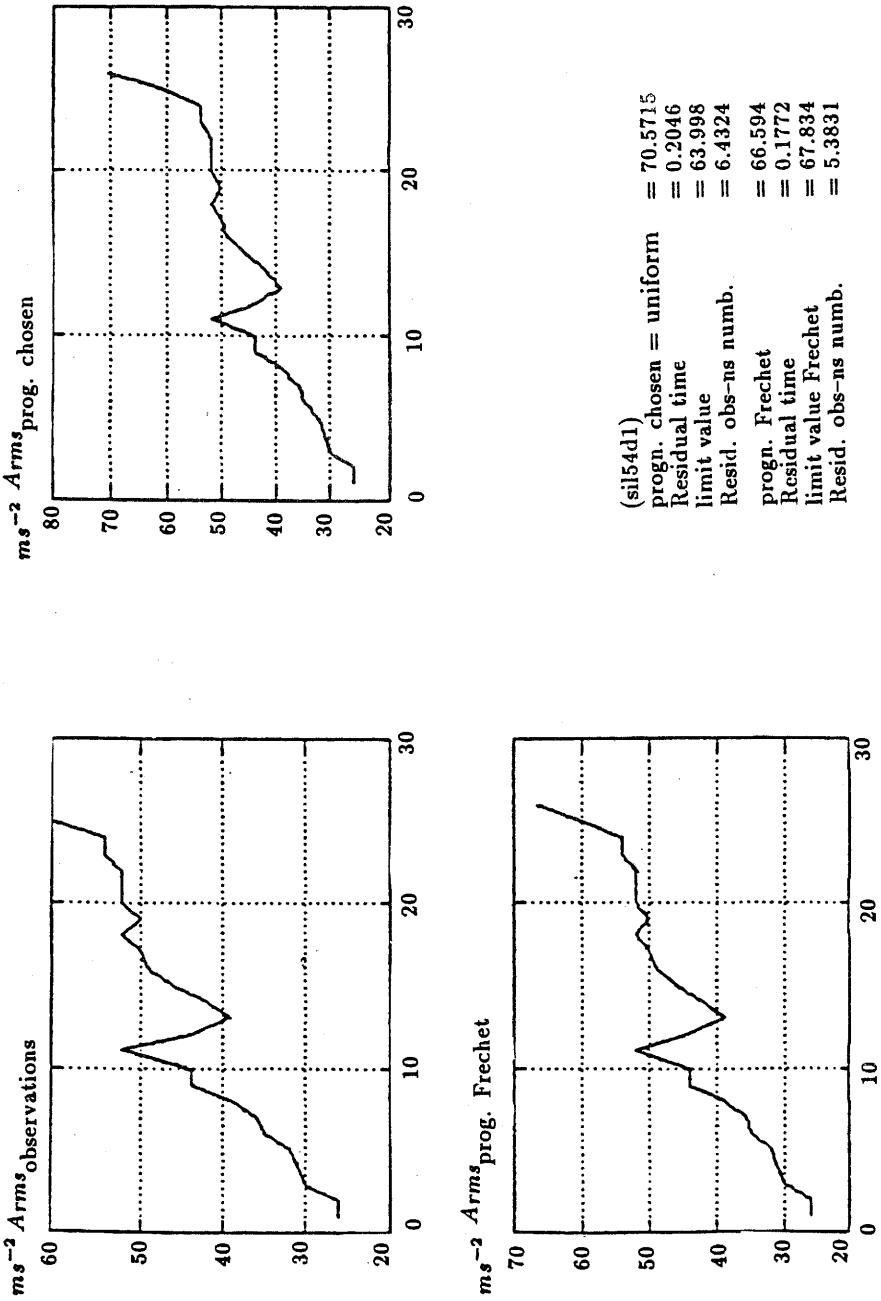


Fig. 5. The graphic presentation of actual acceleration course and its forecasts by the Uniform and Frechet models for the engine 'sil54d1'.

7. Conclusions

The generalization the author's tribovibroacoustical (TVA) machine model into the theory of energy transforming systems (ETS) with finite dissipation capacity has enabled to present the life behavior of every operating system. The processes of energy transformation depicted in ETS theory have fractal-like features that enable us to use ETS units for diagnostic and reliability modeling of any OS, including the design of optimal symptom vector for condition monitoring. Using this theory we can assess the current and the future condition of the OS, as well as its remaining life. This was possible due to newly found equivalence between the symptom reliability and the system remaining life. This theory can be used for the condition assessment of the whole OS, as well as for its any particular weak part or fault.

This approach was verified by specially created computer software applied to the Diesel engine vibration monitoring data base. It was found that for prognostic assessment of Diesel engines Frechet and Weibul symptom reliability models give the minimal errors. These results confirm numerically, (in the first approach) the line of reasoning in ETS theory and give the necessary condition for its further development.

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