Tomasz GAŁKA

ODWZOROWANIE STANU TECHNICZNEGO MASZYNY W EWOLUCYJNYCH SYMPTOMACH DIAGNOSTYCZNYCH

REPRESENTATION OF MACHINE TECHNICAL CONDITION IN EVOLUTIONARY DIAGNOSTIC SYMPTOMS

Charakterystyki drganiowe stanowią ważne źródło informacji o stanie technicznym maszyny. W większości zastosowań dla złożonych maszyn diagnoza opiera się na widmach drgań, jednak wpływ na nie ma, oprócz parametrów stanu, wiele innych czynników. Prowadzi to niekiedy do nieuzasadnionych alarmów. Alternatywnym sposobem uzyskania informacji o stanie technicznym maszyny jest analiza trendów drgań. Można to zrealizować przez zastosowanie tzw. symptomów ewolucyjnych, opisujących ilościowo zależność poziomów drgań od czasu. Z modeli teoretycznych można wywnioskować, że zarówno szybkość narastania, jak i odstępstwo od liniowości mogą być przyjęte jako symptomy diagnostyczne. Ocena eksperymentalnych trendów drgań, uzyskanych dla turbin parowych, potwierdza ten wniosek i wykazuje, że tego rodzaju symptomy pod wieloma względami przewyższają typowe symptomy drganiowe, wykorzystywane w procedurach diagnostycznych.

Słowa kluczowe: *drgania, diagnostyka techniczna, stan techniczny, symptomy diagnostyczne*

Vibration patterns provide an important source of information on machine technical condition. In most applications for complex machines, diagnosis is based on vibration spectra, but they are influence by many factors other than condition parameters. Consequently false alerts can be triggered. Analysis of vibration trends is an alternative way to extract information on machine technical condition. This can be achieved by employing so-called evolutionary symptoms, which describe quantitatively the time dependence of vibration levels. From theoretical models we may conclude that both increase rate and departure from linearity can be accepted as diagnostic symptoms. Evaluation of experimental vibration time histories, obtained for steam turbines, has confirmed this conclusion and shown that such symptoms are in many aspects superior to typical vibration-based symptoms employed in diagnostic procedures.

Keywords: *vibration, technical diagnostics, technical condition, diagnostic symptoms*

1. Introduction

Vibration patterns are perhaps the most important source of information on technical condition, especially for complex rotating machines [1]. From the points of view of data acquisition and processing, vibration-based methods are well-developed and employed in both on-line and off-line modes for a wide variety of machines, in particular critical ones, where reliable technical condition assessment is of prime importance.

In most cases it is essential not only to find and identify malfunctions – if any – but also determine their extent or, more generally, evaluate lifetime consumption. This means that quantitative diagnosis is necessary. Quantitative description has to be based on some reference scale, which can be provided by critical symptom values (basic, limit and admissible); such approach is employed in many diagnostic systems. Of the above, limit value is the most important one, as its excess in general indicates condition deterioration to a level that calls for some remedial action [10]. Symptom limit values can be estimated e.g. from statistical analysis, on the basis of the energy processor model and symptom reliability concept (theory and model descriptions can be found in [10], while application example for steam turbines is reported in [4]).

Quantitative assessment of diagnostic symptoms can sometimes, however, become vague. As it shall be shown in the next chapter, for most practical applications symptoms depend not only on machine technical condition parameters, but also on a number of other factors. Sometimes influence of these factors becomes dominant and limit value can be exceeded without any significant change of the technical condition. False alarms can thus be triggered, which is unacceptable for large critical machines. In order to provide reliable diagnosis, alternative symptoms have to be employed.

According to [12], for the particular case of steam turbines, as many as 21 symptom types can be distinguished, of which ten are related to vibration or noise. This can be generalized for a broader class of large rotating machines. One of these types is referred to as 'vibration evolution' which can be more precisely given as 'parameters describing time dependence of vibration patterns'. As we shall see later, such symptoms have certain advantages that can be very important in some applications. We shall call them 'evolutionary symptoms', bearing in mind that they are in a way secondary to those provided directly by vibration patterns, in particular to vibration amplitudes in specific frequency bands.

2. General remarks on the evolution of diagnostic symptoms

2.1. Basic considerations

In order to deal with the evolution of diagnostic symptoms, we have to define the machine life cycle. Essentially it can be understood as a period between two events that change the machine structure, so that we can assume that during this cycle this structure remains unchanged. For a simple object, life cycle is equivalent to the entire life. For complex objects, individual cycles are determined by overhauls or repairs.

Relation between symptoms and condition parameters in its simplest form is given by:

$$\mathbf{S}(\theta) = F[\mathbf{X}(\theta)] \quad (1)$$

where **S** and **X** denote vectors of measurable symptoms and condition parameters, respectively, and θ denotes time. F is an operator, assumed to remain unchanged during the entire object life (also on transition from one life cycle to another). Relation (1) holds only for very simple objects. More general description is provided by [11]:

$$\mathbf{S}(\theta) = F[\mathbf{X}(\theta), \mathbf{R}(\theta), \mathbf{Z}(\theta)] \quad (2)$$

where **R** and **Z** denote vectors of control and interference, respectively. For a given object, relation (2) is usually difficult to identify and simplifying assumptions are necessary.

On the other hand, from the energy processor (EP) model, we have [2]:

$$\left(\frac{V}{V_0}\right) = \left(1 - \frac{\theta}{\theta_b}\right)^{-1} \quad (3)$$

where V denotes the power of residual processes, $V_0 = V(\theta = 0)$ and θ_b denotes time to breakdown, which is determined by unchangeable object properties. V is related to a symptom S via:

$$S(\theta) = \Phi[V(\theta)] \quad (4)$$

where Φ is the symptom operator. With $D \equiv \theta/\theta_b$ this can be rewritten as:

$$S(\theta) = \Phi[V_0(1 - D)^{-1}] \quad (5)$$

D is a quantity important for these considerations, as it can be interpreted as damage advancement or alternatively dimensionless lifetime consumption. It is easily seen that equations (1) and (5) are equivalent if $\mathbf{S} = \{S\}$ and $\mathbf{X} = \{D\}$, i.e. only one symptom is considered and only one object condition parameter is taken into account. Basically, Eq. (5) can be developed to include other factors that influence symptom value, but for actual objects this results in complex and unwieldy formulae that are hardly suitable for applications (see e.g. [4]).

Eqs. (1) to (5) refer to a single life cycle and theoretical $S(\theta)$ function is smooth and monotonically increasing. Transition to the next cycle usually involves a stepwise change of S and basically can be understood as a creation of a new object, characterized by new V_0 and θ_b values. This corresponds to a modification of Eq. (2), where $\mathbf{X}(\theta)$ is replaced by:

$$\mathbf{X}'(\theta) = H[\mathbf{X}(\theta), \mathbf{L}(\theta)] \quad (6)$$

$\mathbf{L}(\theta)$, referred to as the logistic vector, includes all parameters that characterize individual cycles and change only on transition from one cycle to another; H denotes an operator. If the logistic vector is taken into account and a sequence of life cycles is analyzed, $S(\theta)$ becomes discontinuous and takes a form of the type given in Fig.1. Note the 'double' symptom dependence on time, which is very inconvenient in applications, but necessary with such approach, as θ goes down to zero at the beginning of a cycle. Note also that cycle length is determined by θ_0 rather than θ_b, as overhauls are basically performed before the final breakdown, so $\theta_0 < \theta_b$.[1]

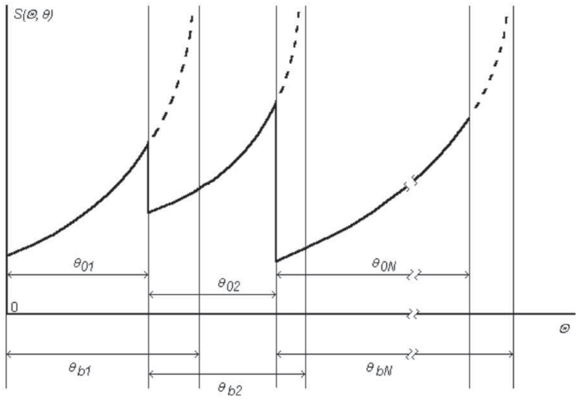

Fig.1. Sequence of life cycles

Discontinuity of the $S(\theta)$ functions and 'double' dependence on time can be eliminated by means of normalization. This will be described in Section 3.

2.2. Influence of control and interference

Basic EP model cannot, in principle, account for the influences of control and interference on the diagnostic symptom value. It can therefore be used for a given symptom S and a given condition parameter X only if we can assume that these influences can be neglected, which means that:

$$\bigwedge_i \frac{\partial S}{\partial R_i} << \frac{\partial S}{\partial X} \quad (7)$$

$$\bigwedge_i \frac{\partial S}{\partial R_i} << \frac{\partial S}{\partial X} \quad (8)$$

In many cases these assumptions do not hold. A good example is provided by the dependence of turbine vibration patterns on active power (load). Fig.2 shows two 23% CPB spectra, recorded at the same measuring point on a 16K260 turbine. It is easily seen that at 230 MW (which is a mere 11% below the rated load) the 50 Hz component, which corresponds to the rotational speed, is about 110 dB and blade components (above about 2 kHz) are moderate. Furthermore, there is a considerable 'hump' about 250 Hz (higher harmonic components). At 104 MW, i.e. 40% of the rated load, the 50 Hz component is higher by some 10 dB and the 'hump' is much less pronounced, but there is a dramatic increase in the blade frequency range, even by one order of magnitude. This is caused by uneven load imposed by steam flow. Close to the rated load, three of four control valves are almost completely opened and the fourth one is closed, while at 104 MW only two valves are opened by about 50% and two are closed. Load distribution changes and so do the vibration patterns. Account of these phenomena and some results of model calculations can be found in [7].

If, for a given symptom S, functions $S = f(R_i)$ can be determined for all control vector parameters that influence the value of S, symptom normalization is possible. More detailed description can be found in [3,6]. Such study was performed for active power influence on absolute vibration patterns of K200 steam turbines [6]. Detailed account is beyond the scope of this paper; general

[1] In fact this assumption results from mathematical reasons, as $S \to \infty$ when $\theta \to \theta_b$, cf. Eq. (3).

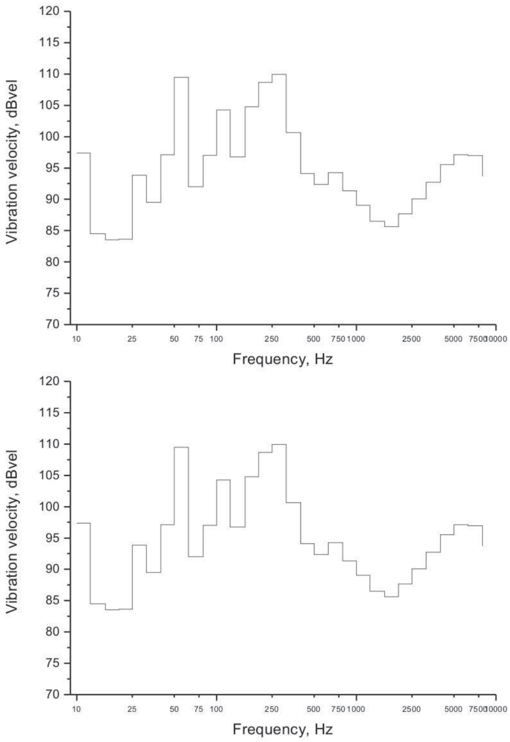

Fig. 2. Vertical absolute vibration spectra, recorded at the HP/IB bearing of a 16K260 turbine at 230 MW (upper) and 104 MW (lower)

conclusion is, however, that normalization procedures for such complex machines are inevitably approximate. Of course,

$$P_u(\theta) = P_u[\mathbf{R}(\theta)] \tag{9}$$

where P_u denotes active power, but various **R** vectors can give the same P_u values. This basically excludes precise normalization for real turbines.

Fig. 3 shows an example for the 50 Hz component of front HP bearing vertical vibration; symptom is given as the relative value S/S_{nom}, where S_{nom} refers to the rated load. It is easily seen that the $S(P_u)$ is by no means monotonic, which is the rule for steam turbines. Certainly, however, influence of the active power cannot be neglected.

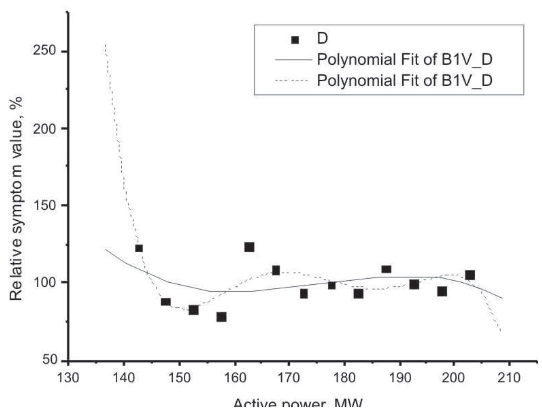

Fig. 3. Example of normalizing functions; 3th (solid) or 5th (dotted line) order polynomial fit; K200 turbine, front HP bearing, vertical vibration, 50 Hz component

As for interference vector **Z**, no normalization is possible. Proper measuring procedures can minimize the effect of interference, but not eliminate it. Therefore it is justified to conclude that normalization can alleviate the problem, but cannot solve it. In practice, cases of sudden stepwise symptom value increase are commonplace. Example is given in Fig. 4. Due probably to some interference (nature of which has not been clarified), vibration velocity amplitude in a frequency band in the blade range increased by one order of magnitude and exceeded the limit level, to return to its initial value almost immediately. No failure was found. Such occurrences are typical for this frequency range and are often caused by steam flow instability.

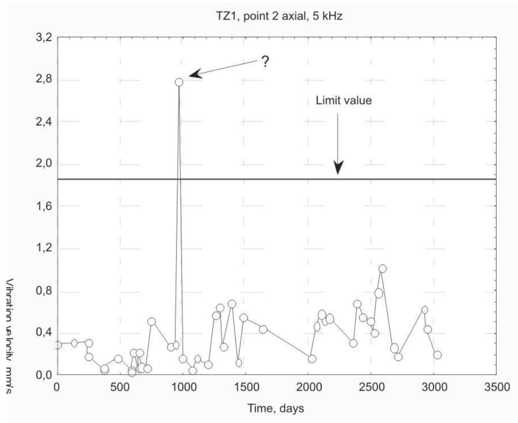

Fig. 4. Sudden increase of vibration amplitude (13CK230 turbine, HP/IP bearing, axial direction, 5 kHz band)

From these considerations we may conclude that there is a need for an alternative approach that could eliminate some of the shortcomings of standard quantitative assessment. Such approach can be based on so-called evolutionary symptoms.

3. Evolutionary symptoms

Before proceeding further, it is necessary to point out that the very term ‘evolutionary symptom’ is just a proposition. We can define it as a parameter that describes the time history of a diagnostic symptom. All examples refer to vibration-based symptoms, but in the following considerations no particular type is assumed and results can thus be generalized.

Basic assumption can be summed up by stating that information on machine technical condition is contained not only in symptom values (i.e. components of the vector **S**), but also in their time histories. In general, six types of symptom evolution can be distinguished [1,9], namely:

- simple evolution (linear or nearly linear),
- complex evolution (usually variations superimposed on a monotonically increasing curve),
- discontinuous evolution (stepwise changes),
- exponential or almost exponential increase,
- cyclic or nearly cyclic variations,
- rapid random variations.

Moreover, each of these types can be characterized by a ‘time constant’, which for complex machines designed for long operational life can range from second to months.

From Eq. (6) we can see that a symptom history that we really observe is in fact a combination of two functions:

− continuous evolution resulting from lifetime consumption, which produces a monotonically increasing function, and
− stepwise changes resulting from the logistic vector influence,

if control and interference vectors are neglected. By definition, the logistic vectors characterizes the entire cycle, so that:

$$\bigwedge_i L_i(\theta) = const, 0 \le \theta \le \theta_b \qquad (10)$$

This facilitates relatively simple normalization, as reference measurements can be performed for each cycle at $\theta = 0$. Details of relevant procedures can be found in [5] and example is given in Fig. 5. Possibility of such normalization is important, as discontinuity of the $S(\Theta)$ function and 'double' time dependence (cf. Fig. 1) are eliminated and entire life of the object can be treated as a single cycle.

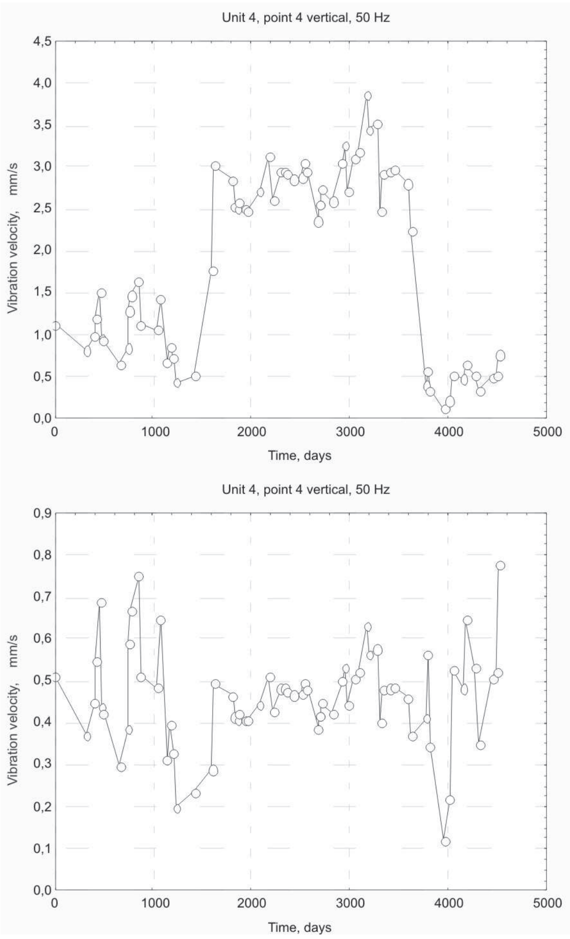

Fig. 5. Symptom time history before (upper) and after (lower) normalization of the logistic vector influence

In the following, we shall consider vibration amplitudes in individual 23% CPB spectral bands (cf. Fig. 2). Amplitudes in bands determined from the vibrodiagnostic model shall be adopted as diagnostic symptoms. Such approach is in particular suitable for rotating machines (turbines, fans, compressors) which generate vibration as a result of both rotating motion and interaction between fluid-flow system and flow of the medium. Vibrodiagnostic model of a steam turbine is described in detail in [11].

As mentioned above, analysis of the EP model leads to relatively simple description, given by Eqs. (3) and (4). As the power of residual processes V is not measurable, some assumptions on symptom operator Φ have to be made. Several operator types have been suggested (see e.g. [10]). For the particular case of steam turbines, it has been shown [4] that:

− for harmonic (low-frequency) components Weibull operator is appropriate, which yields:

$$S(\theta) = S_0\{ln[1/(1 - \theta/\theta_b)]\}^{1/\gamma} \qquad (11)$$

− for sub-harmonic and blade (high-frequency) components exponential operator is appropriate, which yields:

$$S(\theta) = S_0 exp[(1/\gamma)(\theta/\theta_b)] \qquad (12)$$

In both these expressions, $S_0 = S(\theta = 0)$; γ is the shape factor that has to be identified.

For a given symptom S, with adequate database (covering sufficiently long period) it is possible to obtain an approximation of $S(\theta)$ and fit an analytical function given by Eq. (11) or (12) (or, more generally, derived from the corresponding symptom operator). Such approach has an important advantage, as influences of control and interference are virtually eliminated, so normalization with respect to them is no longer necessary. In fact, both control and interference vector components have in general no monotonic time trends[2] and it is justified to assume that if $\Delta\theta = \theta - \theta_b$ is sufficiently large, the for each i-th component:

$$\Delta\theta \to \infty \Rightarrow$$
$$\Delta R_i/\Delta\theta = [R_i(\theta_0 + \Delta\theta) - R_i(\theta_0)]/\Delta\theta \to 0 \qquad (13)$$
$$\Delta\theta \to \infty \Rightarrow$$
$$\Delta Z_i/\Delta\theta = [Z_i(\theta_0 + \Delta\theta) - Z_i(\theta_0)]/\Delta\theta \to 0 \qquad (14)$$

Thus, R_i and Z_i will not affect approximation and fitting results to a substantial degree. Moreover, instantaneous $S(\theta)$ peaks of the type shown in Fig. 4 will be 'smoothed' and their effect on results will be negligible.

There is, however, one fundamental problem. The final goal is to determine D, which describes damage progress and allows for a prognosis. Thus, θ_b has to be estimated. Eqs. (11) and (12), however, both contain two unknowns, θ_b and γ, and what is actually determined is their product. Therefore, until γ can be independently estimated with adequate accuracy, no estimation of D can be made.

For small D values we can, however, expand $S(\theta)$ into Taylor power series and truncate higher- order terms. This gives:

$$S(\theta) \approx S_0(\theta/\theta_b)1/\gamma \qquad (15)$$

for the Weibull operator and

$$S(\theta) \approx S_0[1 + \theta/(\gamma\cdot\theta_b)] \qquad (16)$$

for the exponential operator. $S(\theta)$ should thus be linear or almost linear, if $D << 1$ or $\theta << \theta_b$. This suggests that as long as $S(\theta)$ can

[2] This assumption is, to a certain extent, controversial. For example, some older turbines are shifted from base-load to peak operation and are often operated well below rated load. In such cases, $P_u(\theta)$ may exhibit long-term decreasing trend.

be well approximated by a straight line and its slope does not tend to increase, lifetime consumption ratio is small.

The above condition can alternatively be given by $dS/d\theta \approx$ constant or $d^2S/d\theta^2 \approx 0$. This is particularly suitable for on-line diagnostic systems, wherein approximation of $S(\theta)$ derivatives is a relatively simple task. At this point it seems justified to suggest these derivatives, and any other measure of departure from linearity, as evolutionary diagnostic symptoms.

4. Application examples

All examples presented in this section refer to large condensing steam turbines, operated by utility power plants. As mentioned above, some conclusions can be generalized over a broader class of critical rotating machines.

4.1. IP turbine rotor bow

Vibration components from the harmonic (low) frequency range are very sensitive to even small changes of rotor balancing, shaft alignment, bearing position etc. As these parameters are changed during every overhaul or repair, differences between individual life cycles can be very large (cf. Fig. 5).

The following example refers to two comparatively new 13CK230 turbines. Immediately after commissioning, their dynamic behavior was very good. Shortly afterwards, however, one of them (Unit 1) began to exhibit rather intensive increase of the 1st harmonic component (50 Hz) of rear intermediate-pressure (IP) bearing vertical vibration. In the course of approximately three years this component increased by one order of magnitude. The other turbine (Unit 3) behaved in a completely different fashion: although initial level of this component was substantially higher, there was no increase and in fact net trend over a period of over six years has been a decreasing one. Both time histories are shown in Fig.6 (note vertical scales difference).

Due to insufficient database, no symptom normalization could be performed. As we can see, Unit 3 exhibits a short initial ‘running-in’ stage; then, after a period of very low values (most probably caused by problems with load distribution between individual bearings) increase rate is low. Linear approximation slope is about 6.1×10^{-5} (mm/s)/day, which can be considered typical for a turbine in good technical condition.

In order to reduce vibration to an acceptable level, rotor balancing was performed. Results can be clearly seen in Fig. 6, but improvement was only temporary. Both before and after balancing linear approximation slope was about 3×10^{-3} (mm/s)/day. During the overhaul, IP rotor bow was detected. After rotor repair, vibration decreased to the initial level.

Identification of the problem was fairly straightforward, as increase rate was high. We can, however, note that the very form of symptom time dependence can also be an important symptom. As mentioned in the previous section, the ‘time constant’ of vibration-based symptoms can vary within a broad range. In this particular case, this parameter is of the order of months, which excludes a number of possible malfunction causes (e.g. water ingress into turbine, which is the most frequent rotor bow cause). In fact, foundation distortion was initially suggested, as these processes are usually characterized by symptom time histories of similar type.

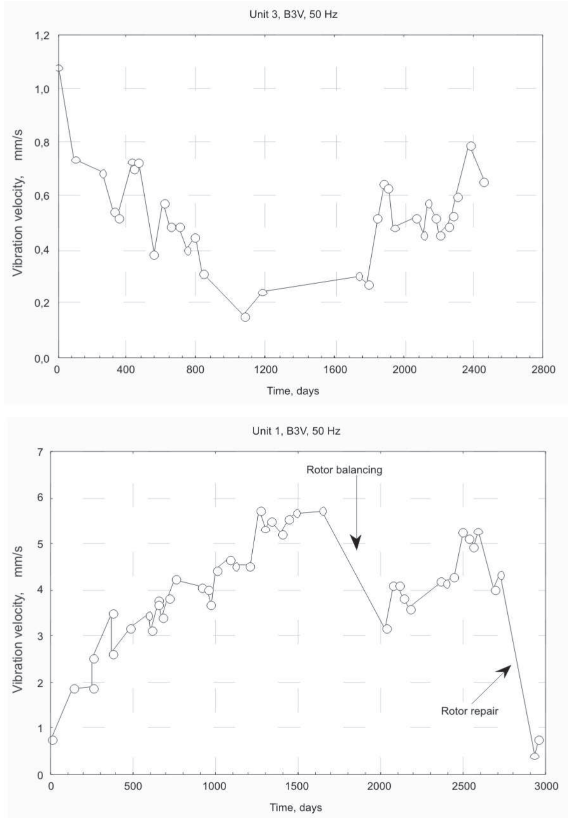

Fig. 6. Time histories for two 13CK230 turbines: Unit 3 (upper) and Unit 1 (lower); rear IP bearing, vertical vibration, 50 Hz component

4.2. Fluid-flow system condition deterioration

Analysis of a large number of symptom time histories has shown that overhauls involving no operations on the fluid-flow system do not affect vibration patterns in the blade frequency range. Therefore histories of the type similar to that shown in Fig. 5 are rare. Life cycles for such symptoms are determined by major overhauls that involve fluid-flow system replacement or repair.

Components from this frequency range are very sensitive to certain interference types, which is usually manifested through behavior similar to that shown in Fig. 4. They are also sensitive to control parameters, like active load (cf. Fig. 2) and, to a lesser extent, condenser vacuum. Due to these factors, $S(\theta)$ values often fluctuate intensively from one measurement to another, but an increasing trend can be traced.

Time histories shown in Fig. 7 for two K200 turbines (both with about 150,000 hours of operation at the starting moment) can be considered typical for the blade frequency range. Despite fluctuations, linear approximation gives good results. Slopes of the order of 10^{-6} – 10^{-5} (mm/s)/day are typical for this range with satisfactory technical condition; it should be kept in mind, however, that they should be evaluated individually for each symptom.

Evolution of the fluid-flow system condition in condensing steam turbines is usually rather slow. It accelerates when θ_b is approached and such phenomenon can be observed in old turbines. Fig. 8 shows two examples for K200 units. In both cases an accelerated increasing tendency can be observed before rotor re-

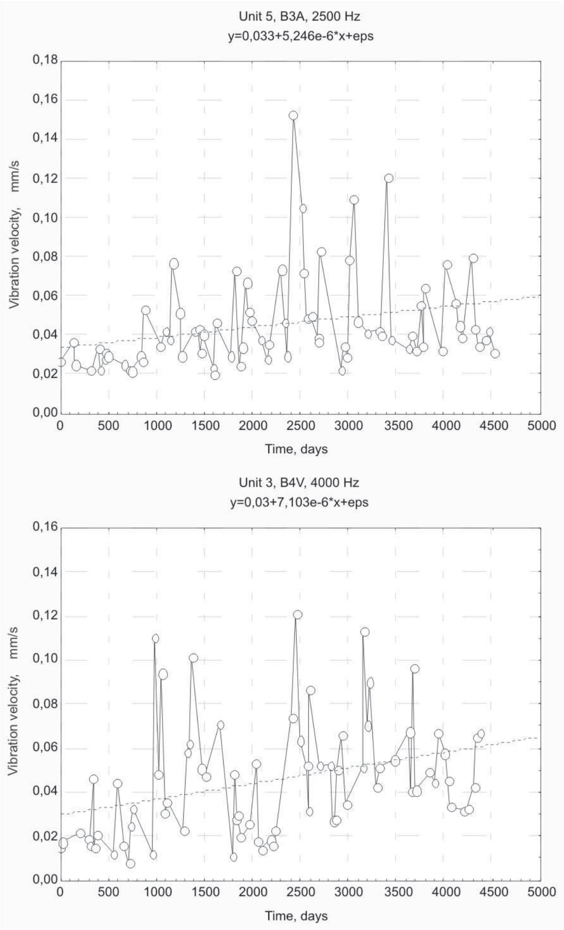

Fig. 7. Time histories for two K200 turbines: Unit 5, rear IP bearing, axial direction, 2.5 kHz band (upper) and Unit 3, front LP bearing, 4 kHz band (lower); broken lines show linear approximations

placement (upper graph refers to the HP rotor and lower to the LP one). It can be easily seen that linear approximation is no longer valid and relevant sections of the *S(θ)* curves are best approximated by exponential functions. In both cases, technical condition deterioration would have certainly been detected with the aid of evolutionary symptoms before limit value was exceeded (in the first case, it was not exceeded before rotor replacement and is above the maximum value on the vertical axis).

Both examples shown in Fig. 8 refer to cases when no damage had occurred and rotors were replaced after a routine examination during a major overhaul. Fig. 9 shows time histories for a 13K215 unit that has suffered a minor damage of the IP rotor last stage. In some preliminary studies on the possibilities of fluid-flow condition assessment with vibration-based symptoms [8], it was

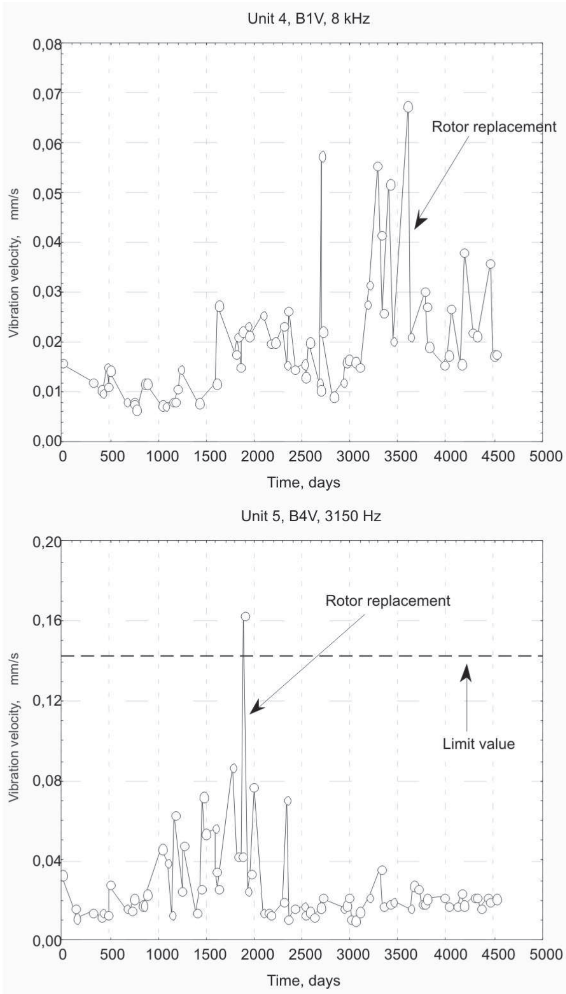

Fig. 8. Time histories for two K200 turbines: Unit 4, front HP bearing, vertical direction, 8 kHz band (upper) and Unit 5, front LP bearing, 3.15 kHz band (lower)

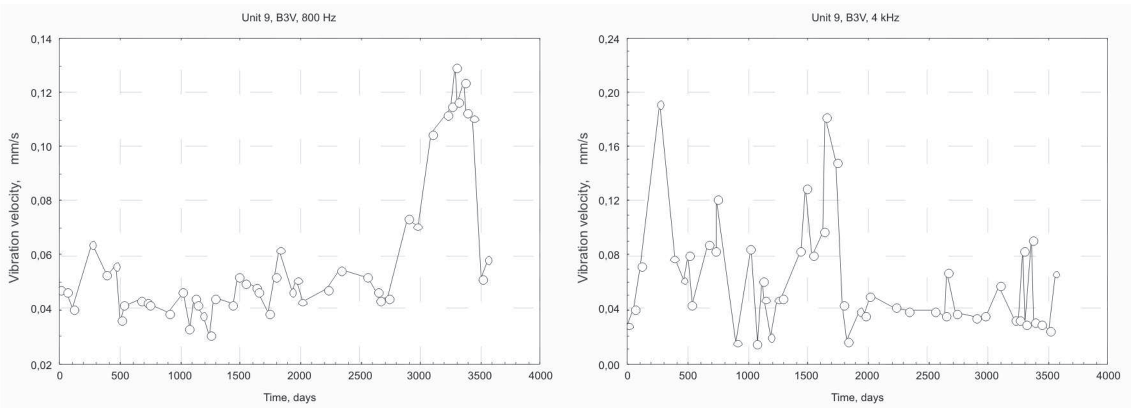

Fig. 9. Time histories for a 13K215 turbine, rear IP bearing, vertical direction: 800 Hz band (left) and 4 kHz band (right)

argued that components produced by interaction between rotor stages and bladed diaphragms are the first to react to condition deterioration. This is confirmed by this case. Vibration velocity amplitude in the 800 Hz band (which contains the component produced by the interaction between last rotor stage and preceding bladed diaphragm) had been increasing rather fast before the fault occurred, which is easily seen in the upper graph. On the other hand, component produced directly by the last stage, apart from fluctuation caused probably by some interference, had shown virtually no significant increase (see lower graph).

4. Conclusion

At the present stage it can be concluded that evolutionary symptoms should provide a useful tool to supplement diagnostic reasoning based on the 'traditional' approach. This refers mainly to the fluid-flow system condition assessment in large rotating machines. In normal operation, repair or replacement of the fluid-flow system components is performed only during some major overhauls, so often the entire machine life can be treated as a single cycle. This eliminates a need for symptom normalization. It should be kept in mind that, for example, in steam turbines fluid-flow system failures are responsible for roughly 50% of forced outages [12]; moreover, repairs of such failures are usually very costly and time-consuming. Any method that would allow for a reliable condition assessment is thus, at least, worth considering.

Further development of diagnostic techniques based on evolutionary symptoms shall certainly include determination of limit values. As mentioned above, in some cases symptom values typical for good technical condition have been estimated, but these are just preliminary observations. Much research, both theoretical and experimental, is still necessary.

5. References

[1] Cempel C.: *Vibroacoustic Condition Monitoring*, Ellis Horwood, Chichester, 1991.
[2] Cempel C.: *Theory of energy transforming systems and their application in diagnostics of operating systems*. Applied Mathematics and Computer Science, 1993, vol.3, No.3, pp.533-548.
[3] Cempel C.: *Multidimensional condition monitoring of mechanical systems in operation*, Mechanical Systems and Signal Processing, 2003, vol. 17(6), pp.1291-1303.
[4] Gałka T.: *Application of energy processor model for diagnostic symptom limit value determination in steam turbines*, Mechanical Systems and Signal Processing, 1999, vol.13(5), pp.757- 764.
[5] Gałka T., Orłowski Z.: *Logistic vector in steam turbines diagnostics*. Diagnostyka, vol. 25/2001, pp.49-56 (in Polish).
[6] Gałka T.: *Normalization of vibration measurements: Unnecessary complication or important prerequisite?*, Proceedings of the Second International Symposium on Stability Control of Rotating Machinery ISCORMA-2, Gdańsk, 2003, pp.722-731.
[7] Lampart P., Szymaniak M., Kwidziński R.: *Investigation of circumferential non-uniformity in a partial admission control stage of a large power turbine*, [in] Technical, Economic and Environmental Aspects of Combined Cycle Power Plants, ed. Z. Domachowski, Politechnika Gdańska, 2004, pp.261-271.
[8] Methods of fault detection and location in steam turbines. Report of the Institute of Power Engineering, 1983-85 (unpublished, in Polish).
[9] Morel J.: *Vibrations des machines et diagnostic de leur état mécanique*, Eyrolles, Paris, 1992.
[10] Natke H. G., Cempel C.: *Model-Aided Diagnosis of Mechanical Systems*, Springer-Verlag, Berlin-Heidelberg-New York, 1997.
[11] Orłowski Z.: *Vibrodiagnostics of Steam Turbines*, Proceedings of the Institute of Power Engineering, Warszawa, 1989 (in Polish).
[12] Orłowski Z.: *Diagnostics in the Life of Steam Turbines*, WNT, Warszawa, 2001 (in Polish).

Dr inż. Tomasz GAŁKA
Instytut Energetyki
Pracownia Diagnostyki Urządzeń Cieplnych Elektrowni
01-330 Warszawa, ul. Mory 8, Poland
tel. (022) 3451 431, fax (022) 642 8378
tomasz.galka@ien.com.pl