NOVEL INTUITIVE HIERARCHICAL STRUCTURE FOR CONDITION MONITORING SYSTEM OF WIND TURBINES

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Summary

The field of condition monitoring (CM) systems has developed significantly in recent decade. Due to constant improvement of embedded computing, complex vibration data processing can be now implemented for a much larger group of machines, e.g. wind turbines.

One of the key outcomes of this process is increase in the number of signal features calculated online. Instead of a dozen of broadband values, we now have more than a hundred for a typical wind turbine. Such a situation creates information overload for the operators. On one hand, it is now possible to detect machine failure at an early stage, but on the other – a person monitoring a few dozens of turbines, each generating over a hundred features is not able to properly organize all the information from CM systems.

Therefore, we have proposed the hierarchical informational structure for condition monitoring system of wind turbines, based on the data fusion methods. The information about feature values and statuses is combined into higher levels, e.g. main bearing, gearbox and generator together with the information about its severity and novelty.

Keywords: data fusion, condition monitoring, fault detection and identification, vibration, wind turbines

NOWATORSKA INTUICYJNA STRUKTURA HIERARCHICZNA SYSTEMU MONITOROWANIA STANU TURBIN WIATROWYCH

Streszczenie

Na przestrzeni ostatniego dziesięciolecia zaobserwować można było szczególny rozwój na polu monitorowania stanu maszyn i urządzeń. Stało się tak dzięki wykorzystaniu bardziej zaawansowanych systemów wbudowanych oraz skomplikowanych algorytmów przetwarzania sygnałów drgań, które obecnie mogą być zastosowane do oceny stanu znacznie większej grupy maszyn, takich jak np. turbiny wiatrowe.

Jednym z najważniejszych efektów tego procesu jest zwiększenie ilości wskaźników diagnostycznych, które mogą zostać obliczone w czasie rzeczywistym – zamiast kilkunastu wartości szerokopasmowych, obecnie otrzymuje się ich ponad sto dla typowej turbiny wiatrowej. W rezultacie prowadzi to do przeciążenia ilością informacji, jakie jest stanie przetworzyć wykwalifikowany pracownik utrzymania ruchu. Z jednej strony, istnieje obecnie możliwość wykrycia uszkodzenia maszyny w najwcześniejszym jego stadium, z drugiej natomiast – inżynier utrzymania ruchu monitorujący kilkadziesiąt turbin, z których każda generuje ponad sto wskaźników informujących o stanie maszyny, nie jest zdolny do właściwej oceny wszystkich informacji z systemu diagnostycznego.

W związku z tym, zaproponowana została hierarchiczna struktura informacyjna dla systemów monitorowania stany turbin wiatrowych oparta na metodach integracji danych. Informacja o wartościach oraz stanach wskaźników diagnostycznych łączy się na wyższych poziomach, tj. łożyska głównego, przekładni oraz generatora razem z informacją o ich o ważności oraz aktualności.

Słowa kluczowe: integracja danych, monitorowanie stanu, wykrywanie i identyfikacja uszkodzenia, analiza drgań, turbiny wiatrowe

1. INTRODUCTION

Nowadays condition monitoring (CM) systems are much more robust than, for instance, 10 years ago [1]. This is due to the accelerated development of complex signal processing techniques and computing effectiveness caused by demanding applications. Important field is wind power generation especially offshore [2, 3]. That in turn makes the diagnostic process of machinery more precise and quicker, since it enables the maintenance engineer to detect fault development at the earliest stage it occurs. Many researchers develop new fault detection methods using numerous approaches, ranging from knowledge-based methods [4, 5] to numerous natural/soft computing techniques [6, 7]. There are also practical approaches, using data available from SCADA systems [8]. Important review papers in this field is [9].

On the other hand, the rapid development of diagnostic capabilities causes the information overload.

For example, in wind turbine industry, the maintenance engineer typically is obligated to analyze more than a hundred different diagnostic features that describe the technical state of each turbine. Examples of such might be root mean square, peak to peak and kurtosis as broadband indicators, and ball passing frequency of outer ring and higher harmonics presence as the narrowband ones. Gears are probably the most important component of wind turbines, therefore several new methods have been recently proposed [10, 11, 12, 13]. Taking into account all the features calculated from 6-8 vibration signals, for a wind park consisting of few dozens of wind turbines the amount of information is overwhelming. Responding to individual threshold violations may as a consequence lead to the situation when alarms that are crucial for the operation of machine and thus should be analyzed in the first place are pushed to the side by the minor ones.

Therefore there is a need to organize the diagnostic analyses (i.e. features) into the reasonable order (also referred as structure) to improve embracing diagnosis of machinery with growing number of diagnostic features by maintenance engineer. The proposed structure shall be both intuitive and accessible in order to increase proper justification of a problem and simplify the further maintenance steps.

The paper is organized as follows. After the introductory part the wind turbine design is briefly discussed along with typically used wind turbine diagnostic hierarchical structures that are used to describe technical state of the machine. Next, the proposal of more intuitive approach is presented. The block diagram is described together with new way of categorizing alarm level violations. Ideas of data fusion, alarm novelty and severity are discussed in the separate subsections. The results are described and followed by the conclusions.

2. STATE OF THE ART

Since organization of diagnostic features is supposed to be easily interpretable for the maintenance engineer it shall be based on the scheme of turbines operation. Such arrangement is aimed at proper justification of machine operation, easier fault recognition and proper planning of further actions. Thus it is important to describe the kinematic chain of a typical wind turbine.

Such a kinematic scheme is presented in Fig. 1. The main rotor is driven by three blades and supported by the main bearing. It passes the torque to the planetary gearbox. Second bearing supporting the rotor is incorporated into the gearbox. The planetary gear has three planets, which are driven by the planet carrier. The planets transmit the torque to the sun gear, in the same time increasing the rotational speed. The sun shaft passes the torque from the planetary gear to the two-stage parallel gear. The parallel gear contains three shafts: the slow shaft clutched to the sun shaft, the intermediate (sometimes called middle) shaft and the high speed shaft, which drives the generator.

Typical requirement for wind turbine drive-train condition monitoring systems is to measure vibrations with six measurement channels that each covers separate area of drive-train [1, 3]. Namely: main bearing, planetary gearbox, 1st stage of parallel gearbox, 2nd stage of parallel gearbox, front of the generator (driven end – DE) and back of the generator (non-driven end – NDE).

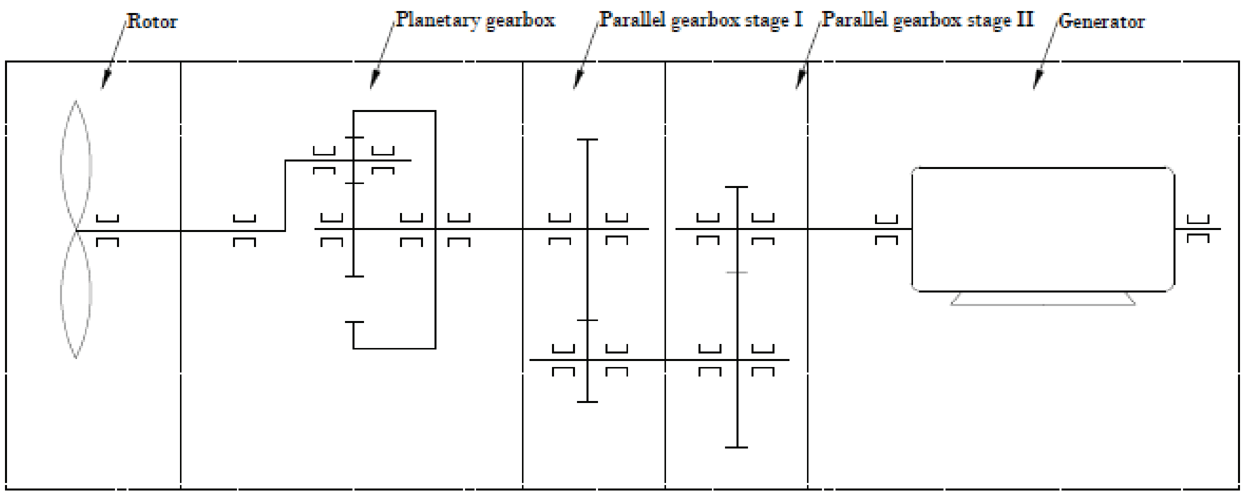

Figure 1. Kinematic scheme of a typical geared wind turbine

Additional required measurement covers rotational speed in order to asses acquired vibration data to proper operational state. In majority of condition monitoring systems dedicated for wind turbines value of generated power and wind speed are measured along with calculation of the diagnostic features.

There are two standard types of condition monitoring structural trees used in industrial condition monitoring systems that cover typical vibration analysis used in diagnostic process. The main idea in each of them is to reveal the information about the state of machine from the analysis level in the most convenient way.

2.1. Sensor based hierarchy

The first type of a structure is based on the measurement channels. It is presented in Fig. 2. As each of the hierarchical structures, it consists of information levels (or layers), which narrow down from the vibration signal analyses via the channel layer to the machine which is monitored, i.e. wind turbine. It is easy to notice that the channel layer corresponds with the (typically) six vibration sensors used for CM of wind turbine. First, the vibration data should be validated, as it was shown than wind turbines vibration depend highly on the operational state and are prone to multiple noise sources [14, 15]. Data acquired from the sensor is a subject of numerous analyses concerning energy levels, the character of its fluctuation and presence of particular frequency components in signals. The number of such signal features, and therefore elements on the analysis level, is typically in range of 150 as presented in Tab.1. The analyses most commonly used in wind turbine diagnostics are listed in the table attached at the end of the article (Tab. 2).

Tab. 1 Summary of basic commonly used wind turbine diagnostic features

Kinematic elements	Number of features per kinematic element	Total number of kinematic elements
Broadband	8	48
Narrowband bearings	4	72
Narrowband shafts	3	15
Narrowband gears	3	9
Total	-	144

In practice, the information about violated threshold limit on particular analysis is propagated directly to the higher level, i.e. to the channel layer and then to the examined machine. Such an approach impede quick defect diagnosis and is time consuming.
It is due to the fact that the condition monitoring engineer receives information about raised level of one or more analyses located in the 'analyses layer'. The features are not divided into segments regarded to the kinematic elements (whether it concerns gears, shafts or bearings) they indicate about. Therefore in such situation, one has to refer the particular (raised) analysis to the appropriate fault-susceptible element and estimate the severity of the problem by himself. Moreover, in the presented approach there is no separation between crucial alarms and simple informative warning. Similarly, such structure suffers lack of indication of novelty of the alarm. For example, if the engineer decides to deal with some major alarm at first, the remaining alarms verified as less important after time will still be unmarked, just as new ones, what might be misleading afterwards. As a result, the hierarchy presented in the Fig. 2 looks transparently, however it does require additional substantial time and effort to identify the severity of information

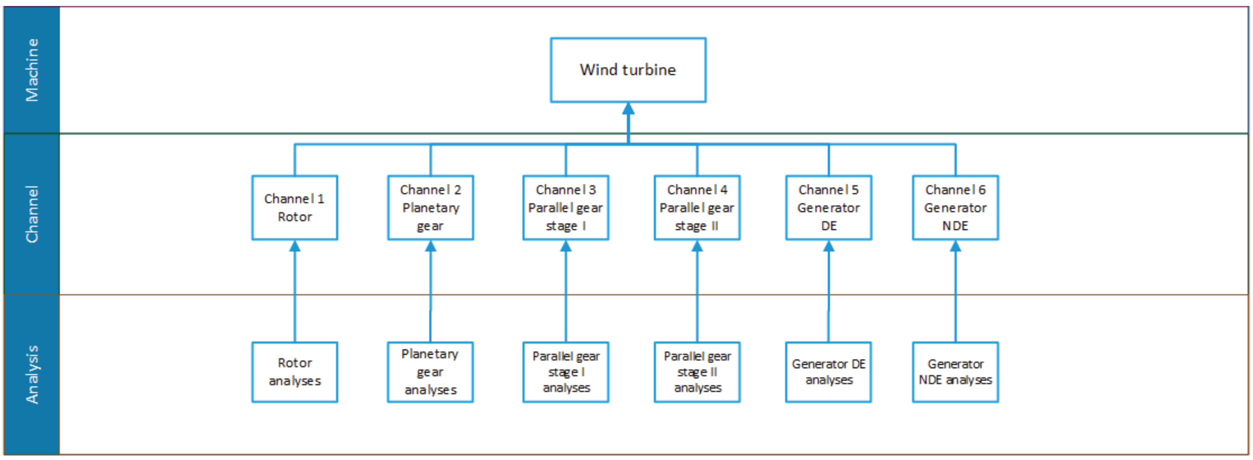

Figure 2. Hierarchical structure based on measurement channels

2.2. Component based hierarchy

The second standard type of condition monitoring hierarchy is based on the real mechanical elements in wind turbine, i.e. gears, shafts, bearings and rotor. It is intuitive from the practical point of view. It is presented in Fig. 3. For a single wind turbine the structure is divided into 5 main layers, namely:

- the machine that is being monitored,
- types of kinematic elements, i.e. gears, shafts, bearings and rotor,
- particular kinematic elements, e.g. planetary gear, generator shaft or main bearing,
- location of a sensor, one of six typically used sensor locations used for wind turbines, as mentioned above,
- signal features (i.e. analyses), used for fault detection of particular kinematic element at particular sensor location.

The main advantage of this approach is the ability to localize fault development according to the kinematic element, however it is hindered as well. Practically, the maintenance engineer has to deal with mix of the sensor locations within the structure. In fact it does not concern the engineer from which sensor the faulty signal used for the particular feature comes from. It is important whether the analysis level is high, its dynamic changes rapidly over time and whether the machinery may run for the time necessary for preparation of the repair or it has to be stopped immediately to prevent more serious breakdown.

It is always worth mentioning that early detection and preventing crash of machinery is one of the basic objective of CM systems. For instance, if the alarm threshold violates for the middle shaft harmonic analysis, the system informs of the exceeding within the group of shafts, then on the middle shaft. Next the structure of the system reveals that the violation is obtained from signal measured on either stage I or II of parallel gearbox. Finally, the analysis related to particular harmonics of the shaft rotation are obtained. Such diffuse can be confusing. Separating shafts or bearings without placing them within the kinematic scheme makes finding the reason of potential fault more complex. Furthermore, the described structure does not carry information about the severity nor about the novelty of the alarm, similarly to the first type of hierarchy.

3. NEW HIERARCHICAL STRUCTURE

The proposed hierarchical structure aims to overcome problems and difficulties related to previously described structures. As presented in Fig. 4 the information about feature values and statuses is combined into higher levels, i.e. rotor, gearboxes and generator that correspond with the kinematics of a wind turbine. If diagnosis concerns bigger kinematic element it is categorised under such label, e.g. a malfunction of one of middle shaft's bearings falls into the following sections: middle shaft bearing, middle shaft, parallel gearbox, gears generally. It is because, at the first place, defect of the bearing affects operation of this particular shaft, subsequently parallel gearbox (it is not important which stage of the gearbox), and gears altogether.

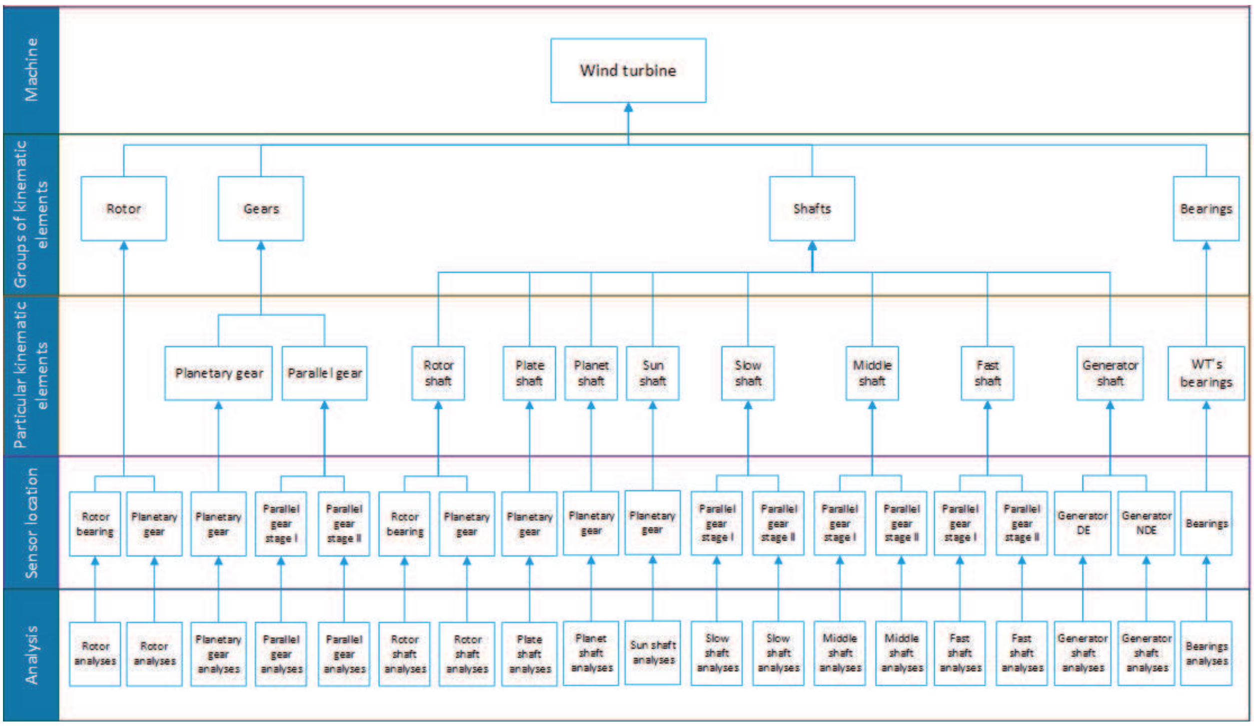

Figure 3. Hierarchical structure based on groups of kinematic elements

The significant amount of techniques performed within the analysis layer may be reduced using data fusion methods with no harm or even with a benefit to the correctness of evaluation. It is discussed in the subsections below along with procedures used to define the severity and novelty of alarms. The propagation of the alarm in the proposed structure assumes its flexibility and is described afterwards.

3.1 Severity

The main reason for introducing the severity feature is to help to distinguish the important information from not-so-important. The main approach to avoid the information overload is extension of signal parameters by adding the field of priority, which we will later call severity. The severity parameter should inform the operator how important is the message about a violation of an alert threshold. There should be 4-6 levels of severity, e.g.:

- critical,
- important,
- early warning,
- information

For example, the increase in the overall signal energy with dominant first harmonic component on the generator should be treated with the upmost priority. This can be a sign of an unbalance, leading to a catastrophic failure. On the other hand, a relatively small increase on the BPFO frequency is typically not critical. It should be monitored, but there is no need to stop the machine and perform a maintenance action.

Severity should also depend on the rate of change of the feature. For a majority of mechanical faults in wind turbines, the process of the development is relatively slow and takes weeks or even months. If a situation is detected when the rate of change suggests a problem within a shorter time, e.g. hours, the user must be notified with much higher priority.

3.2 Novelty

The next extension of signal parameters, which we propose to take into account is the novelty of the information. Such an approach shall create a dynamic system, which uses the rules of human perception. In a live situation, when a small team must supervise several hundred machines, generating all together many thousands of features it is a normal situation that many threshold violations are active in the same time. There must be a method to attract the attention of operators to newly detected events. This should be achieved by increasing the weight of the information right after it is detected and decreasing it as it gets older.

One way to implement at least a part of this mechanism is to adopt the acknowledgement of events. The operator must manually acknowledge the information from the system about the threshold violation. The system shall store the time of detection and the time of acknowledgment. This is, however, only the basic level of such an approach.

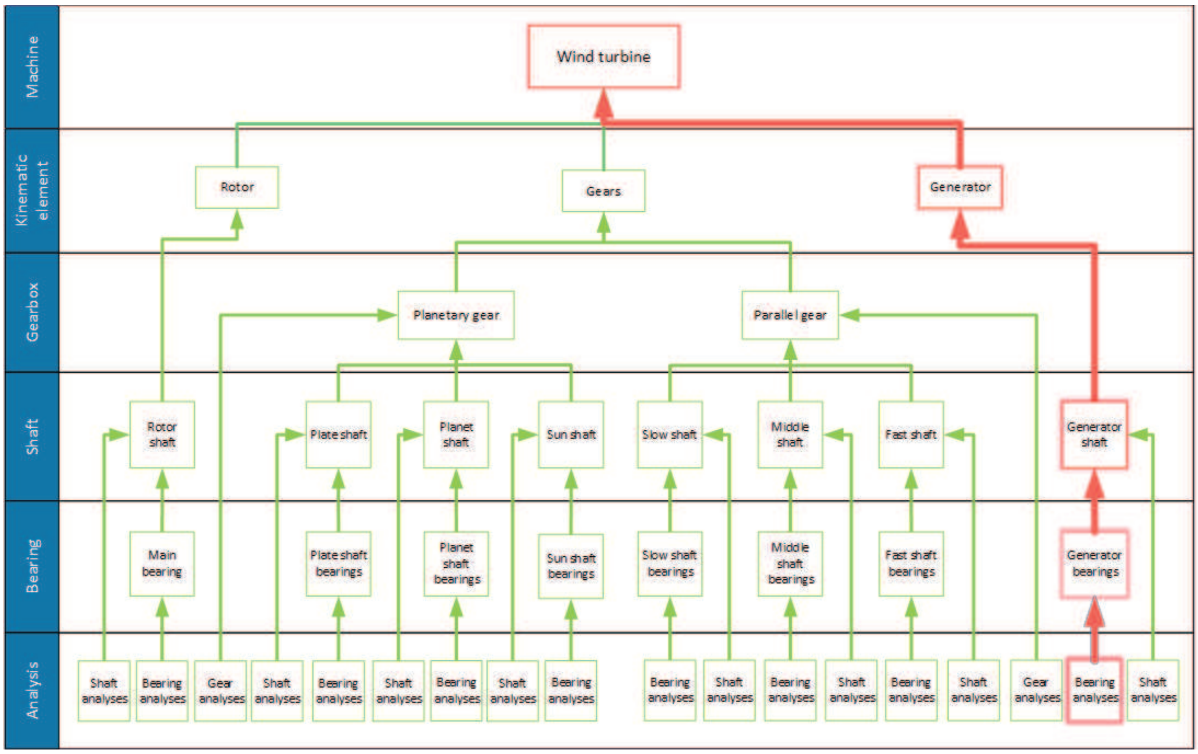

Figure 4. Hierarchical structure based on kinematic elements

3.3 Data fusion

The main reason to use the data fusion method is to decrease the amount of information [16, 17, 18]. The idea of employing data fusion methods for diagnostics of wind turbine comes from two facts. Firstly, for a single wind turbine one may distinguish more than a hundred diagnostic features, which creates information overload for the operators. Secondly, one does not need to know, for instance, which particular component of a rolling bearing generates an alarm, because the maintenance staff will replace the whole bearing anyway. Thus, information should be integrated to a form comprehensible for people without detailed diagnostic knowledge.

The integration of data is carried out at the analysis level. Its block design, presented in Fig. 5, enables synthesis of the features regarding to particular kinematic element of the machine.

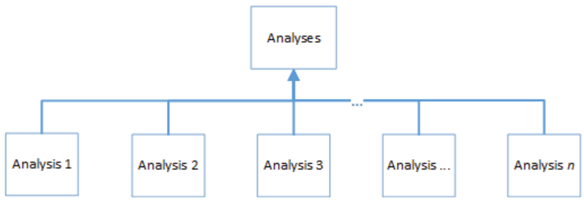

Figure 5. Hierarchical structure based on kinematic elements

The most efficient method available for data fusion is the weighted average of lower level signal features. It can be used for a single estimator of a gearbox state and it can be obtained from integration of harmonics using weighted average [19]:

$$\bar{x} = \frac{\sum_{i=1}^{n} w_i n_i}{\sum_{i=1}^{n} w_i} \qquad (1)$$

where n_i represents i^{th} analysis and w_i stands for weight assigned to the i^{th} analysis. Such an approach does not need to follow exact model, where all the analyses are only at the lowest level. It is possible that more complex features, e.g. referring to modulations coming from the gearbox or from faulty bearings [20] or even to the whole machine [21, 22] can be integrated at a higher level.

Such a simple approach may also be used for combining information related to shaft's rotational speed harmonics or gear mesh harmonics.

3.4 Flexibility

If an informational hierarchy should be efficient, it also needs to be flexible. The hierarchy should take into account all the three proposed features. In such a system, if a threshold violation is detected on a lowest level, the information is propagated up to the top level of the wind turbine (see Figure 4). The different groups of users will move from the top to the level, which gives sufficient information for the observer. On the Fig. 4, such levels are:

- wind farm: the turbine number X has a problem
- single WT level: there is a problem with generator
- component: the generator bearing has a problem
- analysis: one of bearing parts (e.g. outer race) is damaged

In order to achieve the flexibility, users should be able to view the data from different angles. For example, one may need to see the most critical events, the most recent events, all the events referring to the generator etc.

4. CONCLUSIONS

In the paper we have proposed transparent, expanded and unequivocal hierarchical structure that simplifies diagnostic process for the maintenance engineer and enhances the correct fault recognition. The structure is built based on the approaches of severity and novelty were presented. Data fusion algorithms are proposed in order to limit diffuse of diagnostic information. Only relatively simple elements of the proposed hierarchy were shown in this paper, this issue is our main area of research.

Further research are necessary in this field. Main directions should be:

- determine the detailed structure for certain wind turbine types
- selection of more efficient data fusion techniques
- definition of normal states and a method to calculate the distance between one of "good" states and the current one

The real data (laboratory data, real wind turbines) should be applied to the proposed structure in order to fine tune the proposed information system.

The ultimate goal is implementation of the proposed method in a real world condition monitoring system.

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Appendix

Tab. 2 Diagnostic features assigned to kinematic elements of a typical wind turbine

Kinematic element	Bandwidth	Feature	Formula
General	Broadband	RMS – root mean square	$u_{rms} = \sqrt{\frac{1}{T} u^2(t)dt}$ (2)
	Broadband	PP – peak to peak	$u_{pp} = \max\limits_{0<t<T}(u(t)) - \min\limits_{0<t<T}(u(t))$ (3)
	Broadband	ZP – zero to peak	$u_{zp} = \max\limits_{0<t<T}(u(t))$ (4)
	Broadband	Crest factor	$C = \frac{u_{zp}}{u_{pp}}$ (5)
	Broadband	Kurtosis	$K = \frac{\mu^4}{\sigma^4} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}}$ (6)
Bearing	Narrowband	BPFO – ballpass frequency of outer race	$f = \frac{n}{2} f_r \left(1 - \frac{d}{D} cos \propto\right)$ (7)
	Narrowband	BPFI – ballpass frequency of inner race	$f = \frac{n}{2} f_r \left(1 + \frac{d}{D} cos \propto\right)$ (8)
	Narrowband	FTF – fundamental train frequency	$f = \frac{1}{2} f_r \left(1 - \frac{d}{D} cos \propto\right)$ (9)
	Narrowband	BSF (RSF) – ball (roller) spin frequency	$f = \frac{D}{2d}\left(1 - \left(\frac{d}{D} cos \propto\right)^2\right)$ (10)
	Narrowband	Cepstrum	$C_A(\tau) = F^{-1}\{\log A(f)\}$ (11)
	Narrowband	Bispectrum	$bisp(f_1, f_2) = \frac{1}{M}\sum_{m=1}^{M} X_m(f_1) \cdot X_m(f_2) \cdot X_m^*(f_1 + f_2)$ (12)
Shaft	Narrowband	Higher harmonics of rotational speed	$f = f_r$, $f = 2f_r$, $f = 3f_r$. (13)
Gear	Narrowband	TSA – time synchronous averaging	$y_a(t) = \frac{1}{N}\sum_{n=0}^{N-1} y(t + nT)$ (14)
	Narrowband	GMF – gear meshing frequency	$f_{GMF} = GMF = f_1.v_1 = f_2 \cdot v_2$, $f_{GMF} = 2GMF$, $f_{GMF} = 3GMF$ (15)
	Narrowband	Cepstrum	As above
	Narrowband	Bispectrum	As above

Notation in the table:

u – time domain signal, f_r - shaft speed, n - number of rolling elements, $\propto$ - the angle of the load from the radial plane, d - ball diameter, D - pitch diameter (distance between opposing balls in a bearing); F - Fourier transform ,A – Amplitude, f – narrowband frequency; f_1 – fundamental frequency, f_2 – first harmonic frequency, X_m - short-time Fourier transform, t – time, T – time interval for avering.