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GEAR WEAR MECHANISMS, MONITORING TECHNIQUES AND THEIR POTENTIAL USE IN GEAR PREDICTIVE MAINTENANCE

In order to ensure the undisturbed operation of gear transmissions, avoid their unplanned downtimes and secondary damage to them, their condition needs to be monitored and their failures need to be diagnosed. Currently, there is no commercial and universal diagnostic system for predictive analysis of gear wear. There are also no limit values of wear indicators defining individual causes of wear. The article presents problems related to various mechanisms of gear wear. Different methods of monitoring the condition of the gear are presented. They are presented. Thermal methods, analysis of wear residues, and measurements and analysis of vibrations and acoustic emissions are described. The usefulness of these techniques for predictive maintenance of gear movement is indicated. It is proposed to extend gear diagnostics by using machine learning methods to detect their faults, and in particular critical states of gear wear.

1. INTRODUCTION

In order to ensure the high availability of machines and mechanical devices, one should see to that the response to incipient machine faults is the quickest possible. Thus the early detection of the initiation of faults is of key importance for the early planning and execution of repair actions [1]. This helps to minimize downtimes and increase the availability of the machines. Modern gears in high-performance equipment, especially in the manufacturing and power industries, must meet high requirements as regards their rated load, working properties and operating stability. The assurance of the undisturbed operation of gears and the avoidance of unplanned downtimes and secondary damage to gears require the monitoring of their condition and the diagnosis of their faults [2].

Currently, there is no commercial, universal, and at the same time comprehensive diagnostic system available for sale that would allow for connecting any type of measuring sensors measuring various physical quantities, and then, based on the synthesis of the received

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processed measurement signals, performing predictive analysis of the gear. Therefore, each time a measurement system must be built and algorithms for signal conditioning and synthesizing measurement results must be developed, and ultimately for diagnosing the condition of the gear. In addition, there are no limit values defining the individual causes and methods of gear wear, which is a significant scientific gap for issues related to predictive maintenance.

The paper presents problems related to various mechanisms of gear wear. Various methods currently used to monitor the condition of the gear and their advantages and limitations are presented. Some guidelines for predictive maintenance of the gear are presented. The potential application of machine learning methods in the diagnosis of gears, together with the possibilities of detecting their faults, is indicated.

2. GEAR WEAR MECHANISMS

The wear mechanism of a tribological couple formed by the surfaces of interacting gear wheels is determined by many factors, including the relative motion (e.g. rolling or sliding) of the contact surfaces, the rubbing speed, the load acting on the contact surface, the hardness and roughness of the surfaces and the lubrication [3]. In gear transmissions the above factors result in various tooth profile wear mechanisms. Wear is accompanied by material loss. Various types of tooth wear, including abrasive wear, fatigue wear and adhesive wear (Fig. 1), are distinguished.

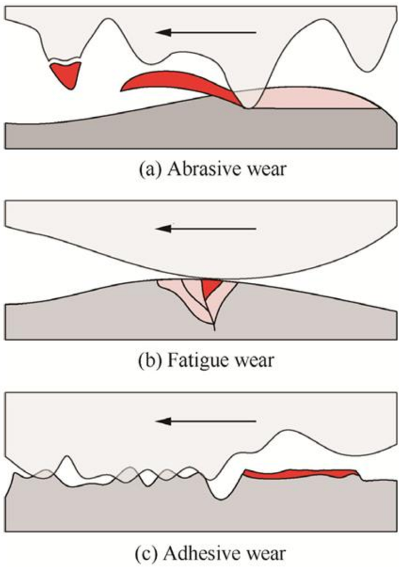

Fig. 1. Three wear mechanisms [1]

Generally, three stages occur in the process of material wear, i.e. running-in wear, steady wear and catastrophic wear. Figure 2 shows changes in wear rate in each of the stages.

The running-in stage occurs in the initial period of the interaction between the contact surfaces during which the peaks of surface asperities deform and diminish. The geometry of the surfaces changes and the material structure undergoes texturing towards the contact. As the peaks of asperities are continuously removed, the direct contact between the sliding surfaces increases whereby the surface pressures decrease and the rate of wear drops markedly.

Friction characteristics, including the coefficient of friction, the degree of wear and the temperature, on average have constant values in the stage of steady wear. The surface geometry on the micro level is continuously and stably reproduced, as evidenced by constant average roughness values.

The beginning of the stage of catastrophic wear becomes visible after a rapid rise in the level of friction. The factors which trigger this phenomenon are: the overheating of the contact surfaces, the exceedance of the material's fatigue strength due to overloading, insufficient lubrication, etc. From the wear process assessment point of view is essential to reveal the beginning of this stage so as to be able to respond on time to the gear operation issue. The terminology relating to the wear of and damage to teeth in gears, particularly in steel gear wheels, is contained in international standard ISO 10825-1:2022 [4].

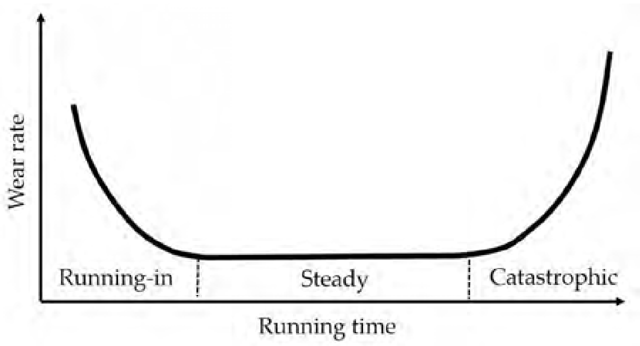

Fig. 2. Change in degree of wear in each stage of wear

2. 1. ABRASIVE WEAR

Abrasive wear is a critical kind of wear in the lubricated mechanisms of machinery [5]. This type of wear usually occurs due to the sliding contact between hard material particles and the soft surfaces. Abrasive wear can be divided into two subclasses: two-body abrasion and three-body abrasion [6]. In the former case a single surface with harder microasperities cuts into or scrapes a soft surface. This usually happens in insufficient lubrication conditions or in the case of excessively large surface microasperities (a rough surface) when the oil film does not separate the interacting surfaces. Solutions preventing this kind of wear comprise lubrication with higher viscosity oil and contact surface hardening.

Three-body abrasion is caused by the hard particles of impurities which during lubrication get between the interacting surfaces. The source of the particles can be dirt in the lubricating medium or abrasive impurities arising during wear. These particles deposit on one of the contact surfaces and make scratches or grooves on the interacting surface during the relative motion of the surfaces. The effect of this type of wear can be minimized through oil filtration.

The teeth of gears are subjected to sliding motion along the tooth profile, except for the pitch line area in which the relative rubbing speeds of the driving and driven gear teeth are equal to zero. For comparison, the maximum rubbing speeds occur at the tooth root/tip contact. Abrasive wear in a gear usually occurs in the running-in period during which a smoothing effect due to the removal of the peaks of surface asperities is observed. In the steady wear stage abrasive wear in the form of scratches and parallel grooves can be clearly seen at the tips and roots of teeth. This is due to the highest rubbing speeds, intensifying abrasive wear, which occur in these regions. Examples of abrasive wear on gears are shown in Fig. 3.

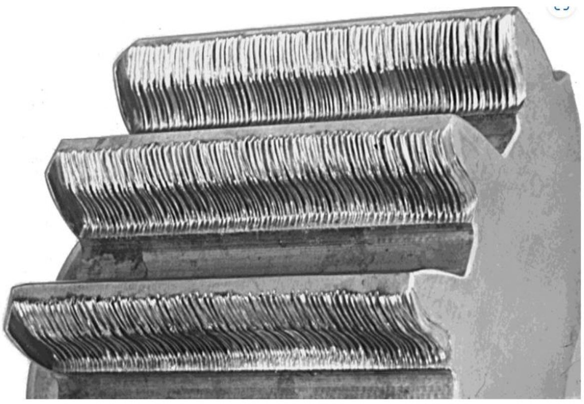

Fig. 3. Traces of excessive wear in form of grooves in gear wheel surface [7]

2. 2. FATIGUE WEAR (PITTING)

Surface fatigue often occurs in cyclically mechanically loaded rolling contacts. The main consequence of this mechanism is pitting. Wear of this type usually begins with dents made by particles in the contact surfaces. The dents cause an increase in local stresses on the surfaces. The repeated loads acting on the contact surfaces lead to material degradation and pitting.

Fatigue spots usually appear in the initial period of tooth work and then usually disappear as a result of the grinding in of the active surfaces. The spots appear in the vicinity of the pitch diameter and do not pose a significant danger. In the tooth root region, where the highest surface pressures prevail, pitting in the form of craters on the active surfaces appears. The craters often merge into larger bands, resulting in considerable pits with sharp edges. As the inter-tooth contact surface decreases, pitting increases, leading to the total destruction (breaking) of the tooth.

Depending on the location of the initial fatigue source, surface fatigue can be divided into two types: subsurface fatigue and fatigue initiated on the tooth's surface [3]. Subsurface fatigue occurs when a full lubricating film is present and there is no metallic contact between the interacting surfaces. Due to concentrated local stresses, microcracks are first generated under the surface of the metal and then spread onto the surface causing its damage (pitting). This kind of fatigue is usually mild and seldom leads to a machine failure, and it can be avoided by using mechanical components made of hard materials.

Fatigue initiated on the surface is a frequent cause of machine faults. This type of wear is often accompanied by a reduction in oil film thickness, which leads to mixed lubrication. In such conditions the metallic surfaces often come into direct contact and microasperities are removed from them. Because of the cyclic loads the surface condition deteriorates and microcracks appear in the asperities on the contact surfaces. Subsequently the cracks propagate into the metal and pits appear on the interacting surfaces.

Surface fatigue in the form of pitting usually occurs on the tooth's flank around the pitch diameter. This is probably due to a reduction in oil film thickness on the pitch line where mixed lubrication usually occurs. Depending on their size, pits can be divided into (initial) micropits and macropits/spallings. Figure 4 show an example of fatigue pits on a gear wheel.

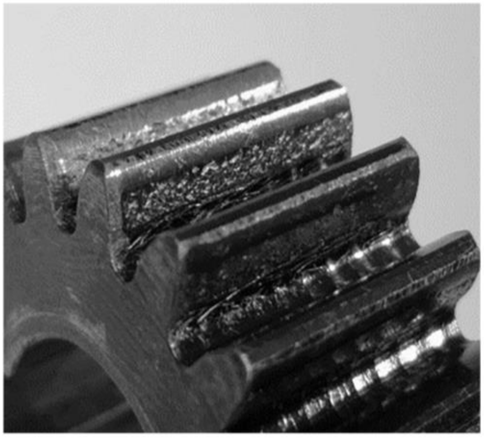

Fig. 4. Traces of fatigue wear in form of pitting and spalling on gear wheel surface [7]

2. 3. ADHESIVE WEAR

Adhesive wear is characterized by the transfer of surface materials within a tribological couple. Adhesion occurs when the lubrication is inadequate (i.e. when mixed or boundary lubrication conditions occur) and direct interaction between microasperities takes place. Under heavy loading or extreme temperatures the microasperities located in the place where contact occurs undergo microwelding, forming agglomerates which soon disintegrate due to the relative motion of the contact surfaces. During this process metal transfer takes place in each individual point of the contact [8].

At the running-in stage mild adhesive wear occurs in gear systems, but it is usually invisible to the naked eye. Adhesion intensifies to a moderate state when a noticeable amount of the original tool marks is removed. In cases when material is continuously removed from the tooth's surface, adhesive wear is classified as serious. It is known as scuffing and is usually observed at the contact between the addendum and the dedendum [5]. The cause of scuffing on the surface of teeth in gears is the abrupt interlocking of the microasperities of the interacting surfaces when the oil film is too thin relative to the height of the microasperities. Wear of this kind is intensified in the case of an insufficient inter-tooth clearance, an improper method of assembly, misalignment of the teeth or non-parallelism of the gear axles. This kind of wear can significantly change the involute tooth profile and worsen gear performance.

Therefore such measures as proper running in and the selection of a lubricant of proper viscosity are indispensable to prevent adhesive wear. Exemplary adhesive wear traces in the form of scuffing are shown in Fig. 5.

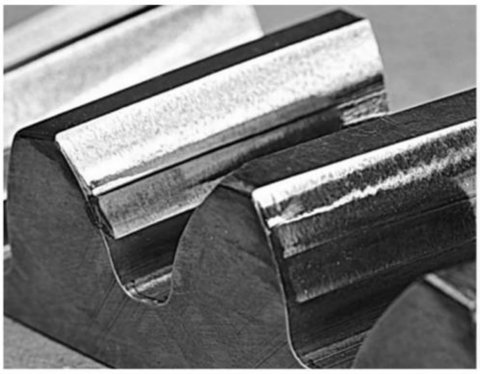

Fig. 5. Traces of adhesive wear in form of scuffing on surface of tooth roots and tips [7]

The occurrence of serious adhesive wear (scuffing) upsets the thermal and mechanical balance, whereby the wear process proceeds rapidly or its intensity is very high. In such conditions a large quantity of heat is generated, depending on the load value and the relative velocity of the surfaces of the interacting teeth. The amount of generated heat increases as the meshing frequency increases and the action of microasperities intensifies.

2. 4. OTHER TYPES OF WEAR

Corrosive wear occurs as a deterioration of the gear tooth surface, as shown in Fig. 6. It is caused primarily by chemical or electrochemical reactions with active ingredients in the lubricant. Mild corrosive wear in gears is usually induced by lubricant additives that are designed to prevent damage from scuffing. These are additives that protect against extreme contact pressures.

Fig. 6. Corrosive damage to tooth surfaces [3]

The wear phenomena discussed above comprise the major wear mechanisms of machinery, which are likely to be responsible individually or collectively for more than 95% of the wear occurring in today's machinery [3]. However, there are many other wear mechanisms that occur during the service life of gear units, such as erosion, impact chipping, polishing, fretting, scaling, cavitation, and electrical discharge. These mechanisms are different from the major wear mechanisms discussed above, but because of their lower incidence, they will not be discussed in detail.

3. GEAR WEAR MONITORING TECHNIQUES

The aim of monitoring gear wear is to determine the current degree of wear in order to prevent failures of machine components [9]. In the operating conditions it is difficult to directly measure the wear of gears without stopping the operation of the machine. Furthermore, this could adversely affect the state of the contact and its lubrication. In industrial applications it is more advantageous to nondestructively monitor gear wear during machine operation.

Nondestructive methods of assessing wear are based on the interrelation between the physical phenomena accompanying wear and the degree of wear. These physical phenomena include the release of heat, the release of wear particles, vibrations and acoustic emission [10]. Hence the conventional nondestructive technologies of wear monitoring include thermal measurements, an analysis of wear particles [11] and techniques based on vibration signals and acoustic emission.

Various sensors can be used to monitor the condition of gears. Typical sensors for monitoring gear condition include accelerometers for measuring vibration, acoustic emission sensors, wear debris sensor for measuring the amount of material removed from the gear tooth surface, thermocouples for measuring oil temperature, microphone for measuring noise, torque sensor for measuring torque fluctuations, etc. [12]. The selection of the sensor depends on constraints such as accuracy, cost, location, size, frequency range, amplitude range, and operating and environmental conditions. However, the most important parameter in sensor selection is the ability of the sensor to effectively capture small changes in the condition of the gear teeth. According to the literature, vibration, acoustic emission and wear debris sensors are most effective in capturing changes in the gear teeth and are most commonly used for monitoring gear condition [12]. The following are the methods of analyzing the condition of the gear based on the above-mentioned sensors.

3. 1. THERMAL MEASUREMENTS

In mechanical systems during the friction and wear of their components heat is generated and the temperature changes. It is essential to measure and control the temperature to avoid the adverse effect of overheating on the tooth profile, leading to the intensification of gear wear. In the case of contact pairs one can measure the nominal temperature (the average volumetric temperature) and the flash temperature. The former refers to equilibrium temperature reflecting the average temperature of the interacting surfaces, while the latter is defined as a local rapid rise in temperature in the points of contact between the asperities of the meshing gear wheels during their operation.

The nominal temperature measurement is conducted on the macro level and comprises the heat generated by the tribological couple, the heat transferred by the flank surfaces of the teeth, the lubrication and the environment, and also the heat generated by other system components, such as bearings and the motor [13]. Conventionally this kind of temperature is measured by means of thermocouples brought into direct contact with the gear wheel immediately after the machine is stopped. Currently also noncontact methods using thermal imaging cameras [14] or pyrometers are available. Thanks to these methods the measurements can be conducted in real time. On the inter-tooth contact surfaces the nominal temperature is close to that at the tooth root and outside the meshing zone is uniform during gear operation.

The flash temperature refers to a rise in temperature on the tooth surface below the pitch circle during meshing [14]. It is difficult to measure the flash temperature directly and so most often analytical thermomechanical models are used to estimate it. A major limitation in the use of the method based on gear teeth temperature measurement for assessing the wear of gear wheels is the unclear (quantitative) relationship between temperature values and wear intensity. The temperature of a gear significantly increases when its wear is already serious, whereby the time for deciding on preventive maintenance procedures is considerably limited.

3. 2. WEAR DEBRIS ANALYSIS

Wear debris or particles are defined as a surface material which is torn off during the friction process and contains comprehensive information about the condition of the contact surfaces [15]. These particles are found in the lubricating medium and are direct evidence of the occurrence of wear. The aim of an analysis of wear debris is to determine the condition of the interacting surfaces by examining the features of the debris.

A wear debris analysis [16] consists of three stage: the collection of debris, the extraction of features and the interpretation of the wear mechanism. First debris are collected from the lubricating medium. This can be done using the conventional methods (e.g. filtering) for collecting physical debris. The advantage of these methods is that a larger number of physical features, such as the amount and density of wear particles and their size distribution, colour and chemical constituents can be extracted in the second stage [16]. However, this is quite a laborious task. Also advanced methods of acquiring information about wear debris during gear operation, are available. For example, one can use image processing techniques to acquire information about the shape of debris without the necessity of isolating them from the lubricating medium. Another example is the optical technique based on the principle of light extinction by impurities. Various sensors used to monitor wear debris in oil are shown in Fig. 7. The third stage of the analysis consists in classifying the wear types and identifying the degree of wear. In order to extract the features of the debris, one must have a comprehensive understanding of the various wear mechanisms and the tribological characteristics corresponding to them. For this purpose one can use the tribological standards for interpreting wear [17].

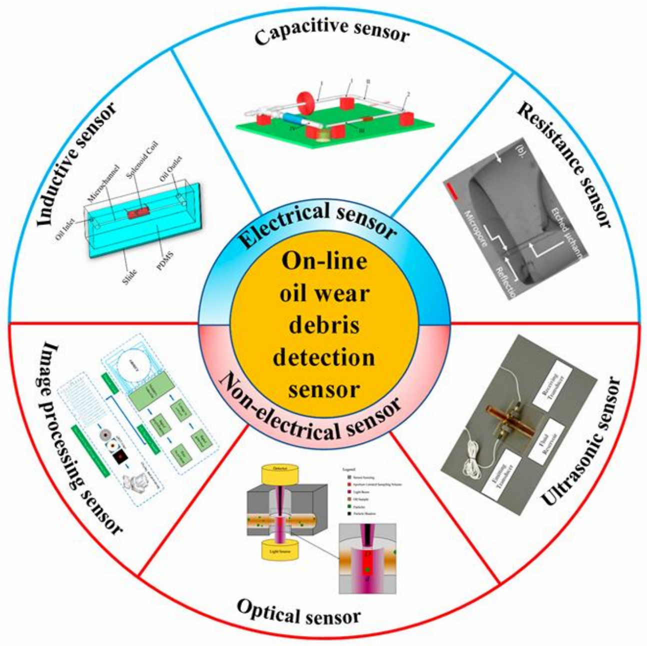

Fig. 7. Sensors used for monitoring wear debris in oil in maritime equipment [16]

A wear debris analysis can be performed as the machine is running or one can collect wear debris for analysis when the machine is at rest. The former analysis is more productive, but less precise because of the unstable motion of the impurities, which leads to unclear results, especially in the case of image analysis methods. The latter analysis is usually used in laboratory conditions and requires a wide range of experiments. In this way one can obtain more accurate results, but the task is more complex, time-consuming and labour-intensive.

3. 3. VIBRATION ANALYSIS

Vibration analysis is the most popular and most commonly used technique for monitoring the health of rotating machines. It is also called a feature extraction technique [18]. Vibration-based signal processing techniques can be divided into two main groups: time-statistical analyses and time-frequency analyses (Fig. 8). Each of the groups is divided into subgroups.

Vibration signals are widely used to diagnose gear faults [19–22]. The signals are generated mainly due a transmission error [23]. This error is defined as a difference in angular displacement between the meshing pairs of gear wheels and it is practically unavoidable, even in the case of perfect tooth profiles. Transmission errors can be induced by geometric errors, tooth deflection effects and dynamic effects. Gear wear contributes to changes in vibration signal characteristics because of the modification of the profiles of the teeth and a change in the geometric transmission error. Hence vibration analysis methods are often used to monitor the wear of gears. But first initial processing, consisting in filtering, order tracking, synchronous averaging over time, etc., must be carried out before the signal can be further processed using time-statistical methods or time-frequency methods [24].

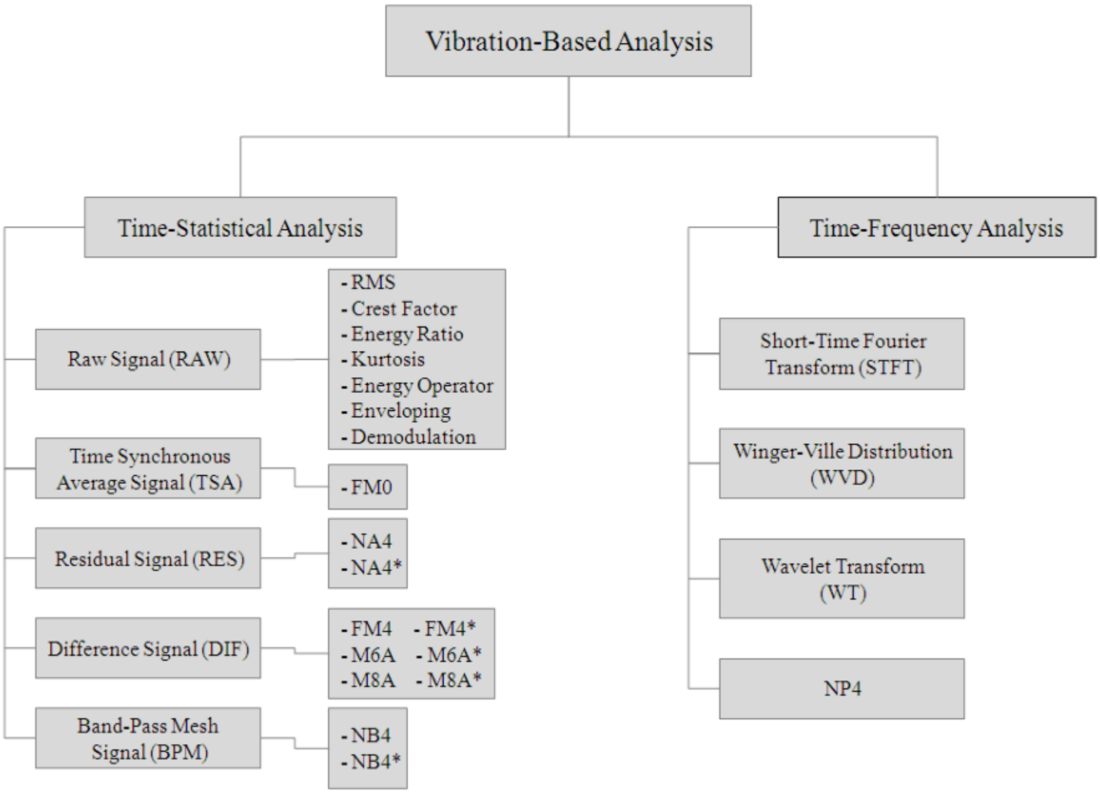

Fig. 8. Classification of techniques and indicators used in analysis of gear vibration [11]

3. 3.1. TIME METHODS

Statistical vibration signal parameters in the time domain are usually considered as reference points in gear wear monitoring studies. They are usually acquired directly from typical diagnostic investigations of machine faults, but they are not necessarily correlated with the gear wear phenomenon. For instance, the trend of raw vibration RMS values shows some fluctuations at the stage of moderate wear stage, whereas a large increase is observed only at a later period of operation when serious gear wear occurs.

Time-statistical analysis is one of the conventional methods used to detect failures of rotating machines and monitor their health. It is based on the statistical measurement of vibration energy. There are five different processing subgroups belonging to this category of analysis: raw signal, time synchronous average signal, residual signal, difference signal and band-pass mesh signal. The indicators used to assess gear condition are determined on the basis of these signals. Figure 8 shows the time signal processing flow for the techniques of extracting the particular condition indicators. The principles of determining the indicators can be found in, i.a., [18, 24].

It has been found that most failures of gears are caused by a several wear mechanisms, such as abrasive wear, pitting, micropitting, chipping, scratching, spalling, cracking and fracturing [25, 26]. The above mentioned indicators can be useful for monitoring gears and identifying various faults. This is presented in Table 1.

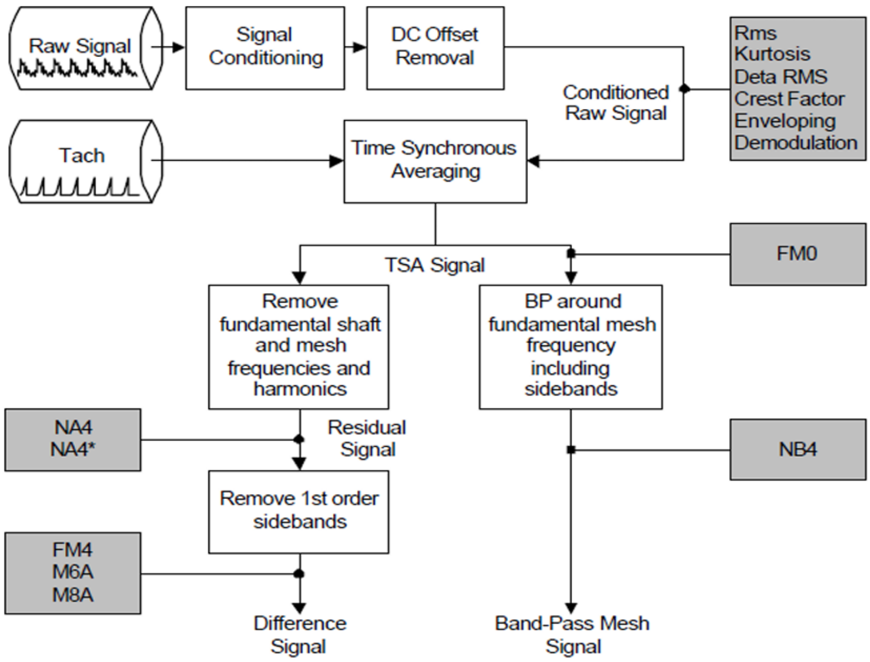

Fig. 9. Flow of processing time signals for techniques of extracting condition indicators [11]

Table 1. Condition indicators for monitoring gears in time domain and corresponding faults [27]

Condition indicator	Kind of fault
RMS, Delta RMS	General advancement of damage
Kurtosis K	Tooth breakage, wear
Crest factor CF	Impulse vibration caused by tooth breakage
Energy ratio ER	High wear (of more than one tooth in gear)
Energy operator EO	Seizing, serious pitting
Residual signal indicator FM0, Indicator FM4	Wear, seizing, pitting and tooth bending caused by crack at tooth root (serious faults)
Indicator NA4	Advancing damage
Indicator SLF	Noncoaxiality
Indicator SI	Gear rack quality
Indicators M6A, M8A	Surface damage
Indicator NB4	Local tooth damage

3.3.2. TIME-FREQUENCY METHODS

Time-frequency analysis is commonly used to detect gear faults. Gearbox vibration consists of three components: a sinusoidal component caused by cyclic loading changing over time, a wide-band impulse component caused by tooth impacts, and accidental disturbances. In a functional gearbox the sinusoidal component predominates. The trend indicated by sinusoidal components is more visible in the frequency domain, whereas the trends indicated by wide-band impulse components are more visible in the time domain. Time-frequency analysis techniques are used to capture both kinds of trends [26]. Among these techniques one can distinguish four different vibration signal processing subgroups: the short-time Fourier transform (STFT), the Winger-Ville distribution (WVD), the wavelet transform and the determination of the NP4 indicator [18].

The short-time Fourier transform is a tool for extracting information about how signal spectrum changes over time from an aperiodic signal, making it possible to simultaneously observe the signal's properties in both the time domain and the frequency domain. In this method a signal slice to be analysed is divided into segments, each of which is independently subjected to spectral analysis. This is a useful technique of detecting gear faults by examining the energy distribution signal in the time-frequency domain.

The Winger-Ville distribution is very useful for analysing, detecting and diagnosing gearbox faults [29]. It makes it possible to detect gearbox faults through the visual inspection of different patterns on WVD plots generated by various types of faults. In particular, it supplies information about the location of and degree of damage to gear teeth. An exemplary distribution plot for a helicopter's transmission with a broken gear wheel is shown in Fig. 10.

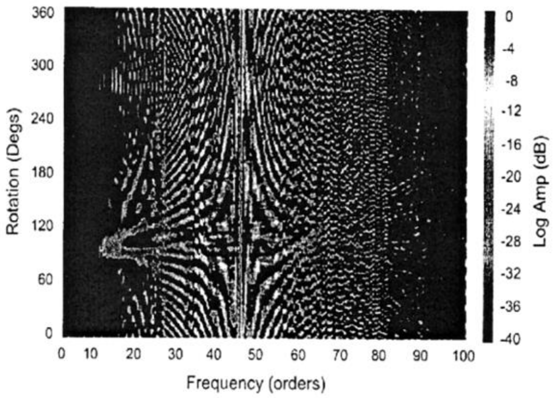

Fig. 10. Winger-Ville distribution plot for helicopter's transmission with broken gear wheel [28]

Moreover, the wavelet transform is used to analyse gearbox vibration signals. It uses a certain class of real and complex nonstationary basis functions (wavelets) which can be independently extended and shifted along the time axis. The advantage of this method is that it makes it possible to analyse the frequency without losing essential information about the time domain. The so-called smooth wavelets have been found to be particularly useful for detecting gear failures.

Also the NP4 parameter [30], determined through kurtosis and the Winger-Ville distribution, is used to detect gear faults. No signal of the faulty gear wheel and that of the functional gear wheel need to be compared to calculate NP4 [31]. This means that NP4 is a useful method of detecting faults without tracing the history of transmission vibration. NP4 can be defined as a normalized power signal kurtosis. Parameter NP4 is particularly useful for indicating a failure of a single gear tooth. Its usefulness for detecting faults deteriorates as the degree of damage to many gear teeth increases.

Vibration analysis is a good tool for detecting faults and inadmissible machine operating conditions at an early stage as it involves the use of spectral analysis and correlation analysis, which make the diagnosis of gear faults possible despite the high dynamics of the process taking place in gear transmissions. However, a fault in a machine cannot be detected using vibration analysis before the degree of damage affects the machine's vibration characteristic [32]. The classical vibration analysis can be used, especially for detecting cracks and their propagation in rotating shafts and gear wheels, only at relatively short pre-failure forecasting times. The early detection of cracks in shaft and gear wheels is possible owing to the acquisition and analysis of acoustic emissions. High-frequency vibrations caused by changes in the material structure provide the basis for the early detection of cracks and their propagation.

3. 4. ACOUSTIC EMISSION ANALYSIS

The measurement and analysis of acoustic emission (AE) are highly useful for the nondestructive testing of gears [34-37]. Through them one can track the buildup of cracks in the structure of the material under external strains or internal stresses. The method is based on the monitoring of mechanical energy released in the form of elastic waves accompanying the cracking of the structure of a material subjected to stresses. Using this method one can not only continuously monitor the propagation of cracks, but also predict macrofaults [37]. An AE signal is generated by the various parts of operating machines, including transmissions, bearings, electromagnetic brakes and motors. In order to limit interference and avoid signal damping on the boundaries of the meshing surfaces during acoustic emission transmission, AE sensors are installed possibly closest to the source (i.e. to the interacting gear meshing surfaces).

The most probable source of acoustic emission through the meshing surfaces is the stochastic inter-tooth contact between asperities. It has been found [38] that rolling contact generates transient AE components at the meshing frequency, whereas sliding contact generates a continuous wave form in the gear AE signals. Thanks to the AE signal, initial subsurface cracks can be detected earlier, i.e. before pitting occurs, than when the vibration signal is used. The AE signal and the vibration signal combined can be used to better distinguish uniform wear in the case of other types of gear faults (e.g. missing teeth, backlash and bearing defects). Artificial neural networks can be used for this purpose.

In order to detect gear wheel faults in transmissions through AE analysis, the signal path should be as short as possible [32]. This eliminates such interference as the impact of ball bearings and other machine parts and highlights useful information about the faults. On a gear test rig AE sensors were installed on the transmission housing and additionally on the ends of the rotating shafts to detect faults at an early stage as well as to locate them and determine which components have been affected (Fig. 11). As the acoustic emissions of the rolling bearings and those of other components are superimposed, it is not enough to take into account only the number and intensify of the emissions [32]. It is also necessary to evaluate the short-duration excitation in the frequency domain using wavelet analysis. In comparison with FFT, wavelet analysis offers a higher resolution in the time domain, especially for high-frequency events. The initiation and propagation of a crack at the tooth root are reflected in early changes in the wavelet diagram, which are periodic with rotational speed. Propagating pitting exhibits a different behaviour. The two different kinds of damage develop characteristically during the operation life of a gear wheel.

One should bear in mind that the difficulty in diagnosing transmission health on the basis of AE measurements consists in determining the characteristic AE parameters in such a way that the registered signals are correlated with a given destructive phenomenon. This makes it necessary to carry out time-consuming laboratory tests.

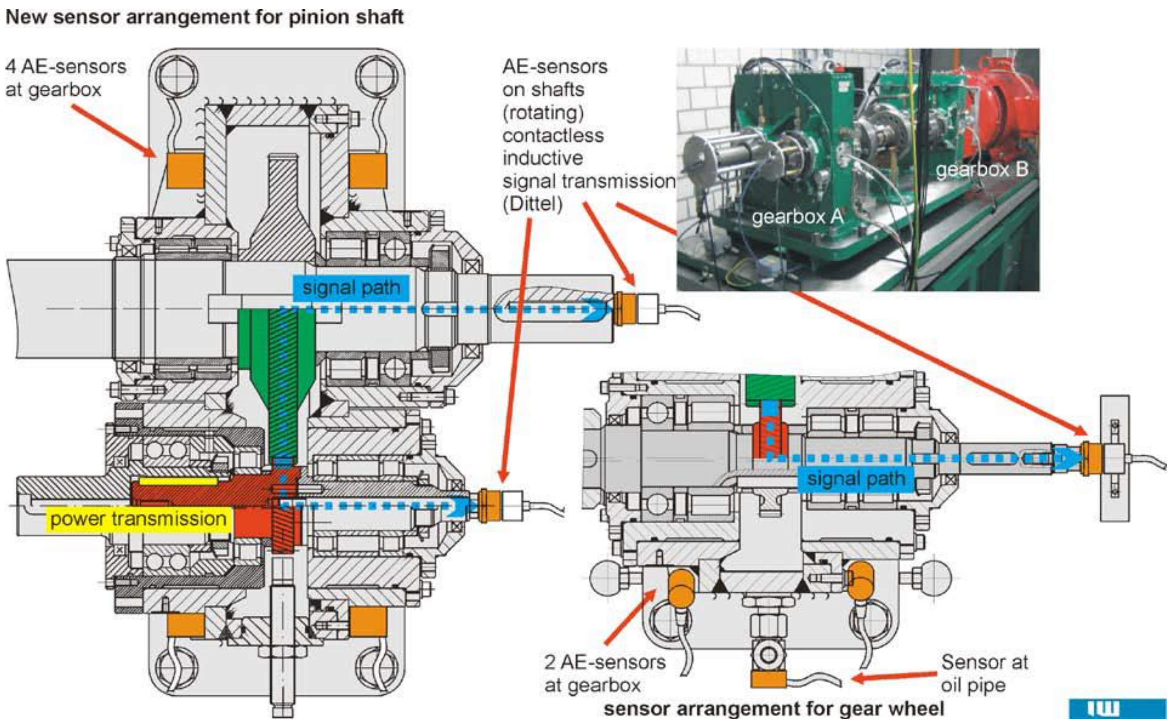

Fig. 11. Arrangement of AE sensors on gearbox [32]

3.5. ADVANTAGES AND DISADVANTAGES OF USING DIFFERENT PARAMETERS TO MONITOR THE CONDITION OF THE GEARBOX

Table 2 shows the advantages and disadvantages of using different parameters to monitor the gear condition. Their comparison shows that most of the information related to the gear dynamics contains the vibration signal. It is also quite sensitive to most types of gear tooth degradation. The vibration sensor is also cost-effective and convenient to use.

4. GEAR PREDICTIVE MAINTENANCE

Machinery Health Management is a comprehensive system which in real time supplies measurement data and performs analyses, whereby it becomes possible to monitor industrial machinery and maintain it in good condition. The predictive maintenance of machines has become a significant part of the life cycle of components in modern industries. It is implemented to identify types of faults, assess their effect on the functioning of machinery and predict the latter's health or residual life. Depending on the kind of machine or mechanism, this requires the use of different measuring and signal processing techniques. In the case of gears, the appropriate techniques require the classification of faults, the development of fault prediction models, the extraction of information about faults from the recorded raw signals and the selection of the best condition indicators for the different kinds of gear faults [39, 40].

Various techniques can be used in a comprehensive gear predictive maintenance programme (see Sect. 3). The key element of most of such programmes is vibration monitoring. However, it cannot supply all the information needed for effective predictive maintenance. This technique is limited to the monitoring of mechanical condition and it does not cover other critical parameters needed to maintain the reliability and productivity of machines [41]. Therefore a comprehensive predictive maintenance programme must include other monitoring and diagnostic techniques which cover not only vibration monitoring, but also thermography, tribology, process parameters, visual inspection, acoustic emission and other nondestructive testing methods [41, 42].

Table 2. Advantages and disadvantages of using different parameters for gear condition monitoring [12]

Monitored parameter	Advantages	Disadvantages
Temperature	Easy to use Expert knowledge is not essential for signal analysis Possible use of non-contact measurement techniques	Unclear relationship between temperature values and wear intensity Significant temperature increase only in the severe wear phase No possibility to measure flash temperature
Wear debris	Easy to use Expert knowledge is not essential for signal analysis Gives a strong correlation with physical damage on the gear tooth surface	Can't be useful to detect all kind of fault, for example, crack Hard to use in some gear applications where grease is used instead of oil for lubrication Sensor data may be affected by the degradation of other mechanical components inside a gearbox Expensive compared to vibration and acoustic emission sensor Unable to distinguish between different kinds of failure modes
Vibration	Vibration signal can be better correlated with gear dynamics Responsive to gear tooth degradation Possible to detect the type, location of the defect, and defective component in a gearbox Easily amenable to wireless capturing of the vibration signal Cost-effective compared to wear debris and acoustic emission sensor	Expert knowledge is required for extracting the health indicators from the signal The signal may be affected by structural resonance and mechanical background noise Direction dependent
Acoustic emission	Very good signal-to-noise ratio Not affected by the structural resonance and other kinds of noises Largely independent of direction Good sensitivity to incipient fault	Compared to the vibration sensor, acquisition hardware and associated accessories are very costly for acoustic emission sensor Need to acquire at a higher sampling rate Expert and domain knowledge is essential for better correlation of AE signal with gear dynamics The signal is significantly affected by electromagnetic interference Signal analysis needs high computational requirement compared to the vibration sensor

Gear predictive maintenance has several advantages [43]:

- reduces unplanned downtimes,
- helps to identify a gear fault or condition to avoid high repair costs,
- reduces planned downtimes by reducing the number of inspections and premature repairs.

In order to implement gear predictive maintenance procedures, one must define critical wear states and select assessment indicators most sensitive to changes in these states. For the identification and prediction of gear faults one can use artificial neural network and machine [44] and deep learning procedures [22]. In industrial conditions the acquisition of appropriate information about gears can be facilitated by dedicated measuring systems or Internet-of-Things (IoT) devices which thanks to the use of cloud data processing can be easily integrated with procedures which use artificial intelligence.

5. MACHINE LEARNING METHODS IN GEAR DIAGNOSIS

Machine learning methods, which thanks to appropriate algorithms are capable of data learning [45], are a great help in the analysis of large amounts of signal measurement data. In the field of diagnostics such methods constitute effective tools for identifying the technical condition of gears, classifying the types of faults and detecting anomalies in gear operation.

Machine learning methods are most often divided into three groups:

- supervised learning,
- unsupervised learning,
- reinforcement learning.

The supervised learning methods are applicable in a situation when the training data on which the algorithm learns contain labels, i.e. information about the object state the training data relate to. The algorithms belonging to this group are used in regression and classification problems. Examples of the methods are: support vector machine [46–48], naive Bayes classifier [47, 49], decision trees [48, 50] and artificial neural networks [51-54].

The unsupervised learning methods use training data without labels, i.e. without information about the object state for which they were recorded. These methods usually need a greater amount of training data in order for the algorithm itself to recognize the interrelations and dependences existing in the data. The algorithms in this group are applicable to the clustering of cases and the recognition of anomalies in the recorded data. Examples here are: local density evaluation algorithms [55], the k-means cluster analysis algorithm [56, 57] and the autoencoder-based deep neural network [57-61].

In the case of the reinforcement learning methods (probably most seldom used) the algorithm is trained by awarding a reward or a penalty, depending on whether a right or wrong decision was taken. Machine learning consists in striving to maximize the award function. Examples of such solutions in gear diagnosis are provided in papers [62, 63].

The quality of obtainable results greatly depends on the quality of the input data, i.e. on the proper processing of raw measurement data. Although the choice of operations used in data preparation is an individual matter, several stages in data processing can be distinguished, such as: data precleaning, data segmentation, feature extraction, feature normalization and scaling, labelling and division depending on the intended use. Data precleaning entails incorrect data removal, noise filtration and the synchronization and smoothing of data coming from different sources. Segmentation can be required because of data division into time windows of specified width. Feature extraction is connected with the determination of characteristic (for a given signal) indicators, called time features, frequency features and transformation features, depending on the way of determining them. This can be followed by data normalization and scaling, as it is known that some methods perform better when the data are of similar scale. Labelling applies solely to supervised machine learning and its purpose is to assign labels (classification tasks) or numerical values (regression tasks). Finally, data are divided into sets for model training, testing and validation according to the defined proportions. Only data processed in this way can be effectively used.

6. SUMMARY

The large number of publications on gear condition assessment, of which only a fraction have been cited here, shows that the problem is still topical and is investigated in many research centres. The paper presents the most commonly used methods of gear condition analysis. They are characterized by varying degrees of usefulness and complexity. It seems that due to the relatively high simplicity of the measurement itself, the most commonly used methods are vibration analysis, which allow for the detection of various gear faults, but require the use of advanced mathematical tools. In turn, conducting an acoustic emission analysis requires extensive experience in setting the measurement threshold parameters, but provides the most sensitive diagnostic signal, allowing for the detection of gear faults in the early phase of wear development. However, using these methods for predictive maintenance of gears would require having reference values for specific indicators, which would be related to the permissible wear. In practice, it would be necessary to conduct experimental tests in specific operating conditions of the gear and in this way determine the critical reference values.

In the further part of the work, it was suggested to extend the diagnostics of gears with the use of machine learning methods. Their implementation, however, is associated with the process of teaching the diagnostic system and providing extensive readings of the gear states with permissible and limit wear. For this purpose, signals from vibration, acoustic emission, temperature and wear residue sensors installed on the gear could be used. The combination of a larger number of different types of sensors gives a greater probability of correct diagnosis of the gear state and detection of critical wear state.

Numerical models are becoming increasingly important in predicting the evolution of wear on gear tooth surfaces, most often using the basic or modified Archard abrasive wear model [64,65] that takes into account the normal force in tooth contact, the sliding length and the hardness of the softer surface of the contacting teeth. Newer approaches, included in the comprehensive contact fatigue wear model [44], take into account, in addition to the influence of load conditions and tooth surface hardness, also lubrication conditions, initial surface roughness and residual stresses. It is worth noting that the Archard wear model is the most widely used model for various materials, such as plastics and steel [66]. Modeling modern gears with tooth surfaces machined using special methods or covered with protective coatings requires the use of completely new wear models. These include multilayer and coating wear models. However, the available literature is very sparsely represented.

Modern measuring tools are also used in the studies of the mechanisms of the interaction of gear wear with fatigue, in which a scanning electron microscope was used to observe the tooth surface [66]. They showed that, under different lubrication conditions, the distribution of durability under the influence of the interaction of wear with fatigue follows a logarithmic-normal distribution. In the case of the study of the wear of gears with multilayer coatings, completely new parameters are introduced, for example permeability [67], which is determined on the basis of specific hardness measurements.

The benefits of using advanced gear diagnostics methods provide benefits in both preventive and predictive maintenance. In industrial conditions, this is of great importance for installations operating in continuous mode, whose failure or unplanned downtime is associated with large financial losses.

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