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CONDITION MONITORING SYSTEM FOR ROTATING MACHINERY WITH IN SITU LEARNING

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Abstract

This article presents a system for monitoring the technical condition of rotating machines operating under variable operating conditions, i.e. variable load and temperature. The system can automatically determine sets of reference curves that describe the relationship between spectral component amplitudes and the load. Sets of reference curves are determined for different operating temperatures. These characteristics are determined in situ during fault-free operation of the machine. They are then used in the diagnostic process to determine new spectra of the rRMSD and rΔAmax parameters, which describe the deviation of the current curves from the reference curves. The new spectra are independent of changes in load and temperature.

The paper also describes the implementation of the method in an industrial controller with a real-time operating system (RTOS) and an FPGA. The developed monitoring system was tested on a laboratory test bench. The effectiveness of the method in diagnosing imbalance and misalignment of the gearbox output shaft was investigated. The system enabled the detection of subtle changes that had been made.

Keywords: vibroacoustic diagnostics, condition monitoring, real-time operating system, variable load

List of Symbols/Acronyms

ACQ – Acquisition;
DMA – Direct Memory Access;
FFT – Fast Fourier Transform;
FPGA – Field-Programmable Gate Array;
HMI – Human-Machine Interface;
rRMSD – The relative RMSD between the reference curve and the currently measured curve;
rΔAmax – The relative ΔAmax between the reference curve and the currently measured curve;
RT – Real Time;
RTOS – Real Time Operating System.

1. INTRODUCTION

Diagnosing rotating machinery operating under variable operating conditions requires the use of specialised diagnostic methods [1] [2] [3]. These methods are often tailored to the specific object being diagnosed [4]. This can be achieved using machine learning methods [5] [6] [7] [8], ranging from simple classifiers to highly complex models based on artificial neural networks [9] [10], or other machine learning methods [11] [12] [13]. Most methods, particularly those designed to identify faults, require data from faulty objects during the training process [14]. There are methods for detecting anomalies [15] [16] [17] that are trained exclusively on data from undamaged machines but can only detect damage. Interpretable models based on artificial neural networks are also being developed [18] [19]; however, in most cases, these require a lengthy training process and significant computational power. It is possible to conduct training in the cloud [20] [21] [22], but this is not always feasible in industrial settings, particularly in heavy industry, where internet access is limited. Due to these limitations, machine learning methods are not yet widely used in industry [23].

This article presents a method for diagnosing rotating machines operating under variable conditions. The method is an extension of the method presented in [24], incorporating parameters that describe changes in the amplitudes of all order spectrum components. Consequently, by interpreting changes in the order spectrum, the new method enables not only fault detection but also identification. The extension of the method also involves taking the influence of temperature into account by using sets of temperature-dependent reference curves. The method has been adapted for implementation in embedded systems in such a way that it can operate online. This has been confirmed by implementing the method in a CompactRIO device.

The method is suitable for implementation in industrial controllers, as it does not require

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significant computational resources for pre-processing and the diagnostic process. The method is also tailored to the machine being diagnosed, as the training process is carried out on the machine in situ during the initial phase of its operation, following the running-in period. During the training process, reference relationships between vibration amplitudes and machine operating conditions are recorded; as a result, the method is insensitive to changes in operating conditions. The reference curves are stored in non-volatile memory and compared with the curves obtained during the training process.

It should be noted that this method is not a classical machine learning method. It involves a stage of learning the machine's operating patterns, but does not utilise classical machine learning algorithms. The learning process involves recording reference characteristics that describe the machine's behaviour when in good working order under various operating conditions. The resulting reference curves are then used as a reference model in the diagnostic process by comparing them with current measurement data.

Chapter 2 presents a detailed description of the diagnostic method adapted for implementation in a CompactRIO industrial controller. The following chapter describes the implementation of the method in a controller running a real-time operating system (RTOS) and discusses the individual system modules and the communication between them. The method was then tested on a laboratory test bench for diagnosing cylindrical gearboxes. The process of training the algorithm in the cRIO industrial controller is presented, and the effectiveness of the implemented method in diagnosing imbalance and misalignment of shaft lines is examined.

2. DIAGNOSTIC METHOD

The diagnostic method involves the simultaneous recording of vibration signals, rotational speed and machine operating conditions (e.g. current, temperature) that influence the vibration signals.

In the first stage of the method, the vibration signals are subjected to Series Analysis [25] [26] in order to obtain waveforms synchronised with the rotational speed of the machine under diagnosis. Such synchronisation allows for the acquisition of a power spectrum that is insensitive to changes in rotational speed. This allows observing changes in the amplitudes of the spectral components caused by load or other operating conditions (e.g., temperature). The relationships between the amplitudes of the spectral components and the rotational speed, whose changes are caused by variable load, are recorded, and polynomial curves are then fitted to the measurement points. The degree of the polynomial is selected such that the polynomial curve lies within the 95% confidence interval obtained from the analysis of the amplitudes of the spectral components. A detailed description of the selection of the polynomial degree is presented in [27]. The load on the machine affects the rotational speed. If the drive's set rotational speed is constant, the load torque will affect the rotational speed, and changes in load can be described by changes in rotational speed. In order for the curves to describe the full range of rotational speed variations, a sufficient number of measurements must be taken over a period during which the full range of load variations occurs. To this end, the speed profile must be recorded under the machine's nominal operating conditions. It is also possible to determine the load from a current measurement.

By recording such relationships for an undamaged machine, we can save them as polynomial curve parameters and use them as reference curves in the diagnostic process. Fig. 1 shows example reference curves (7th-order polynomials) obtained during the training process for a two-stage cylindrical gearbox.

In addition to the load, other operating conditions influence the shape of the resulting relationships, in particular the temperature of the machine under diagnosis [28]. Fig. 2 shows the reference curves determined for the same two-stage cylindrical gearbox with a housing temperature of 34.2°C. Significant differences can be observed in the shapes of the curves recorded under the same machine technical conditions but at different temperatures. A clearer picture of these differences can be seen in the speed-averaged spectra of the series shown in Fig. 3. In order to account for the effect of temperature, the proposed method involves determining sets of curves with a temperature resolution corresponding to the accuracy of the sensor used. These sets of calibration curves are stored in non-volatile memory.

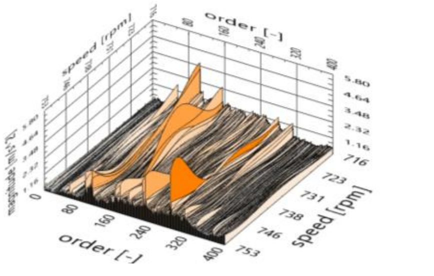

Fig. 1. Reference curves obtained during the training process for a two-stage cylindrical gearbox, gearbox housing temperature 31.6°C

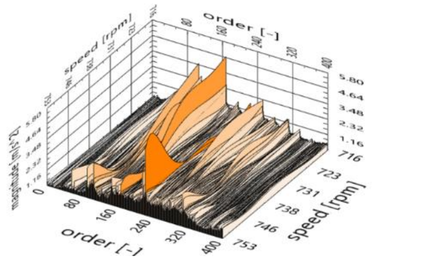

Fig. 2. Reference curves obtained during the training process for a two-stage cylindrical gearbox, gearbox housing temperature 34.2°C

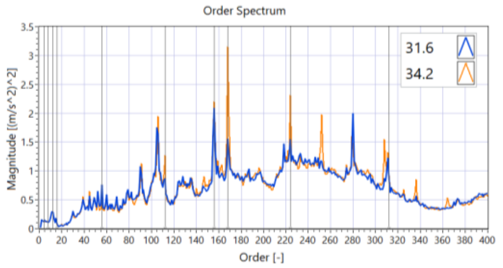

Fig. 3. Averaged spectrum of vibration acceleration series for a machine at 31.6°C (blue) and 34.2°C (orange)

The diagnostic process utilises reference curves obtained during the training process. First, a set of reference curves corresponding to the machine's current operating temperature is selected. If there is no set in the system corresponding to the current temperature, the set for the closest temperature recorded during the training process is selected. The curves are compared with one another, and parameters describing the distance between the curves are determined for each order individually:

$$rRMSD(r) = \sqrt{\frac{1}{N}\sum_{l=1}^{N}\left(\frac{A(r,l)-A_G(r,l)}{A_G(r,l)}\right)^2} \quad (1)$$

$$r\Delta Amax(r) = \left|\frac{A(r,l)-A_G(r,l)}{A_G(r,l)}\right|_{max} \quad (2)$$

where:

A(r,l) – amplitude of order r for load l,

AG(r,l) – amplitude of order r for the undamaged state for load l,

N – number of load cases.

The *rRMSD* parameter (1) describes the relative RMSD between the reference curve and the actual curve. This parameter is not always effective, particularly in the case of local differences between the curves. Consequently, *rΔAmax* (2) was used, which describes the relative maximum difference between the curves. Relative parameters were used to make it easier to define alarm thresholds, as they allow the magnitude of changes in a given parameter to be assessed.

Fig. 4 shows the vibration amplitudes determined using order analysis, along with the polynomial curves for the undamaged state (reference curve) and for the current diagnosed state. These are the amplitudes of the meshing order of the cylindrical gear, which, as can be seen, are sensitive to the introduced damage in the range of 710–730 RPM.

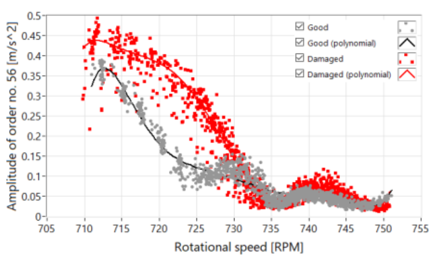

Fig. 4. Amplitude values of the 56th order of the vibration acceleration signal (transverse direction) as a function of rotational speed, determined by order analysis, and the fitted polynomial curves: reference curve (black), diagnosed condition (red)

The parameters *rRMSD* and *rΔAmax* are determined for each order separately; as a result, we obtain two new order spectra describing the values of the diagnostic parameters in the order domain. As these are normalised by the parameter, we obtain information on the relative change in the order amplitude value.

3. IMPLEMENTATION IN AN INDUSTRIAL CONTROLLER

The proposed diagnostic method was implemented in a CompactRIO controller [29] equipped with a real-time operating system and an FPGA. The programme consisted of three parts:

1. The part running on the FPGA.
2. A programme running on the real-time operating system (RTOS).
3. A programme running on a PC used for data visualisation and communication with the controller.

A block diagram of the entire monitoring system is shown in Fig. 5.

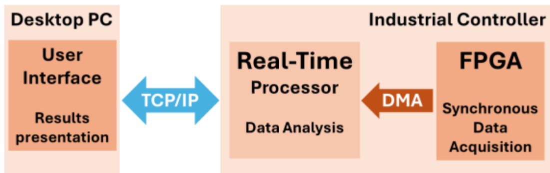

Fig. 5. Block diagram of the monitoring system

The part of the system operating within the FPGA enables the simultaneous measurement of vibration acceleration, rotational speed and temperature. The synchronisation of measurement channels to the sample is crucial when using series analysis to correctly resample vibration signals relative to shaft rotation.

The measurement signals are recorded using modules with Delta-Sigma converters. The raw recorded data is transferred via a high-speed DMA queue to a controller running a real-time operating system.

A multi-threaded programme consisting of three threads runs in the RT system.

The first of these is the *[RT] ACQ thread*, which receives raw data from the DMA queue, adds a timestamp and sends the recorded data to the *[RT] Analysis thread*. No data processing is performed in the *[RT] ACQ thread* to ensure data continuity and avoid sample loss in the event of computing power being occupied by analysis.

The *[RT] Analysis thread* implements the diagnostic method described in Section 2. The data is analysed in batches according to a step size determined in such a way as to ensure data continuity and make full use of the computational power. The results of the series analysis are collected into an array to obtain the minimum number of samples required to determine the polynomial curves. During the training process, sets of polynomial curves are saved as binary files in non-volatile memory. Separate sets of curves are determined for different temperature values in 0.5°C increments to account for the effect of temperature on vibration acceleration values.

During the diagnostic process, polynomial curves are also determined and compared with reference curves appropriate for the current operating temperature. Parameters describing the distance between the curves, as described by equations (1) and (2), are then determined. As a result, two diagnostic spectra are generated, showing the values of the parameters *rRMSD* and *r*Δ*Amax* for each order of the vibration signal. The analysis results are passed to the next thread *[RT] Stream to PC*.

The *[RT] Stream to PC thread* receives the analysis results from the *[RT] Analysis thread* and transmits them via the TCP/IP protocol to the application running on the PC.

The structure of the programme running in the RT system is shown in Fig. 6.

The programme running on the cRIO industrial controller is designed in a modular fashion, allowing for the addition of further data analysis modules or communication threads without affecting the rest of the programme. Furthermore, the application runs on a real-time operating system (RTOS), which ensures the stability and continuity of data measurement and analysis.

The application running on a PC receives data from the industrial controller, displays it on the user interface and archives it on the hard drive. The use of the TCP/IP protocol ensures compatibility with any operating system.

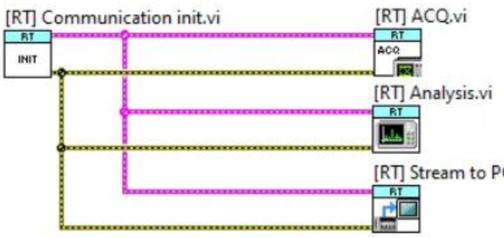

Fig. 6. Structure of a programme running on the RT operating system

4. SYSTEM TESTING ON A LABORATORY TEST BENCH

4.1. Laboratory workstation

To verify the method's correct operation on the CompactRIO industrial controller, an experiment was conducted on a laboratory test bench for helical gearbox testing (Fig. 7). The test bench consisted of a motor driving a two-stage RCV 162 P helical gearbox with a gear ratio of 3.7, and a second motor acting as a brake. The motors are powered by frequency converters, which allow any load function to be set. The braking motor was controlled in such a way that its rotational speed was equal to (in the absence of a load) or less than the speed of the gearbox output shaft (in order to load the system).

In the experiment, a variable load was applied, modelled on the load encountered under industrial conditions in the main gearbox of the KWK 1500s bucket excavator, scaled to the gearbox under test. The profile of the changes in the gearbox output shaft speed is shown in Fig. 8.

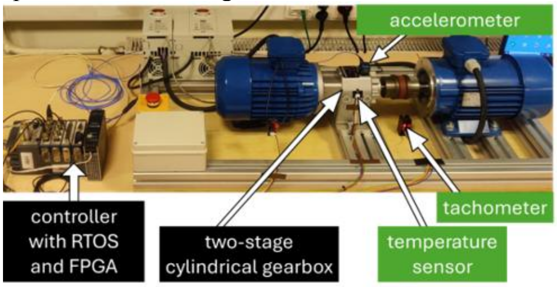

Fig. 7. Laboratory setup featuring the two-stage cylindrical gearbox under test, a controller with a real-time operating system, and measurement sensors

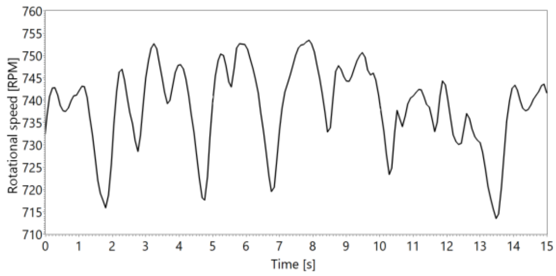

Fig. 8. Changes in the output shaft rotational speed of the gearbox caused by variable load

The vibration acceleration was measured using a triaxial piezoelectric sensor (PCB 356B08) mounted on the bearing housing of the gearbox output shaft, oriented in the X direction – along the shaft, Y – the horizontal direction perpendicular to the shaft, and Z – the vertical direction perpendicular to the shaft. A tachometer was mounted on the gearbox output shaft. Temperature measurements were carried out using an LM35 sensor mounted on the gearbox housing. The measurement sensors were connected to NI 9234 measurement cards, which were housed in a cRIO-9101 chassis integrated with a cRIO-9012 controller. All signals were recorded at a sampling rate of 12.5 kHz.

4.2. Experimental procedure and data analysis

In the first phase of the experiment, the algorithm was trained to determine reference curves during the machine's warm-up process. The training process lasted 40 minutes, until the gearbox temperature had stabilised. As a result, 31 sets of curves were obtained within a temperature range of 30°C to 45°C during the machine's warm-up process. Each of the sets obtained corresponded to a different operating temperature; one of the sets is shown in Fig. 9.

In the second phase of the experiment, an imbalance was introduced by unbalancing the gearbox output shaft, with a mass of m = 12 g added. The second phase also lasted 40 minutes, in order to record the entire machine warm-up process.

When comparing the average order spectrum of vibration acceleration (transverse direction) shown in Fig. 11 for an unbalanced machine and a balanced one, no significant differences were observed. Differences in the shape of the curves compared with the reference curves can be seen by comparing Fig. 9 with Fig. 10.

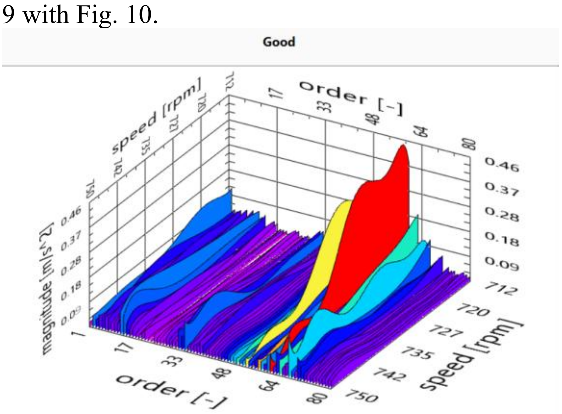

Fig. 9. Polynomial curves for the undamaged system, determined from the vibration acceleration in the transverse direction (gearbox housing temperature 45°C)

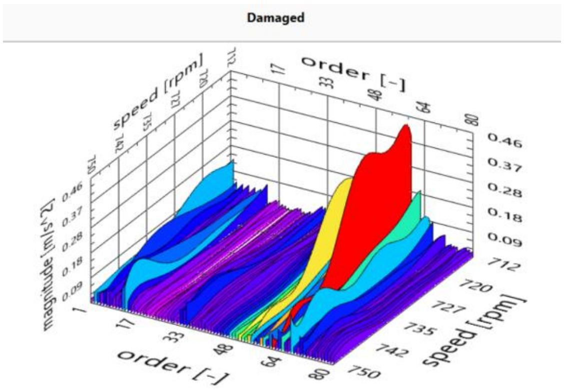

Fig. 10. Polynomial curves for the unbalanced system, determined from the vibration acceleration in the transverse direction (gearbox housing temperature 45°C)

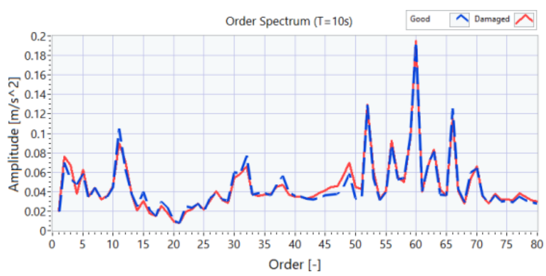

Fig. 11. Averaged order spectra for an undamaged system (blue) and an unbalanced system (red), gearbox housing temperature 45°C

When comparing the amplitude of the first order shown as a function of load in Fig. 12, an increase in vibration amplitude can be observed in the range of 730–740 rpm. This increase will be visible in the relative parameters describing the distance between the *rRMSD* and *r∆Amax* curves. These parameters were determined for all orders and presented as spectra. Fig. 13 shows the *rRMSD* values in spectral form, together with the 95% confidence interval for the mean values of this parameter. The *rRMSD* parameter is averaged over the entire measurement recorded during the machine's warm-up. The standard deviation of the mean value for the 40-minute measurement does not exceed 0.05, which demonstrates the stability of the method. The obtained spectrum shows the relative changes in vibration amplitude for each order individually. This spectrum is not sensitive to changes in load and temperature, provided that vibration values were recorded for the entire range of load and operating temperature of the machine under diagnosis during the training process.

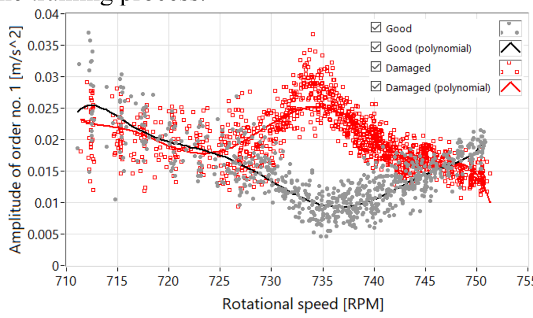

Fig. 12. The first order amplitude values plotted against rotational speed, obtained via order analysis, and the fitted polynomial curves: reference curve (black), diagnosed condition (red)

Fig. 13. The *rRMSD* spectrum for an unbalanced system: the green line represents the mean values, and the light green area represents the 95% confidence interval for the mean

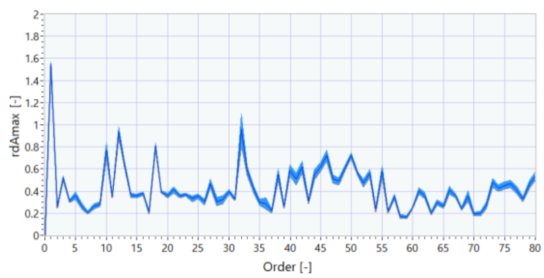

Fig. 14. The *r∆Amax* spectrum for an unbalanced system: the blue line represents the mean values, and the light blue area represents the 95% confidence interval for the mean

Fig. 13 shows the dominant *rRMSD* value for the first order, in accordance with the theory regarding the effect of the additional mass mounted on the machine shaft on the first order. The *rRMSD* parameter was found to be 0.75. This is the RMS value of the deviations relative to the values for the undamaged state, calculated for the entire range of rotational speed variation. In contrast, the *r∆Amax* parameter (Fig. 14) took the value of 1.55, indicating that the maximum deviation was more than double that of the undamaged state across the entire range of rotational speed variations. These variations are not visible in the averaged spectrum of the series in Fig. 11; thus, in this case, the method enabled the early detection of imbalance in rotors operating under variable conditions.

In the third phase of the experiment, the effectiveness of the system in diagnosing shaft misalignment was investigated. This phase also lasted 40 minutes, in order to record the entire machine warm-up process. Misalignment was introduced by placing 0.2 mm-thick shims under the rear feet of the drive motor. When comparing the two averaged order spectra for the same operating temperature, significant changes are visible for orders 2 to 14 (Fig. 15).

Fig. 16 shows the amplitude values of order No.2 as a function of rotational speed, which varied due to the changing load. Significant differences are observed at low rotational speeds, corresponding to the highest load on the system. If the machine were operating at a lower load corresponding to a rotational speed of 735–750 rpm, the misalignment would not be detectable.

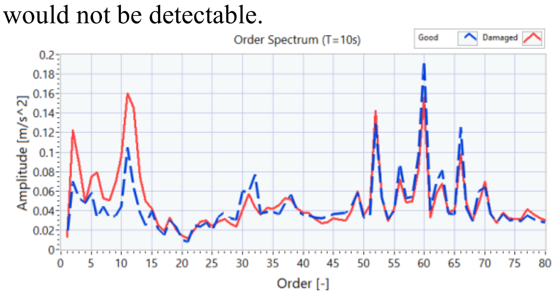

Fig. 15. Averaged order spectra for the undamaged system (blue) and the misaligned system (red), gearbox housing temperature 45°C

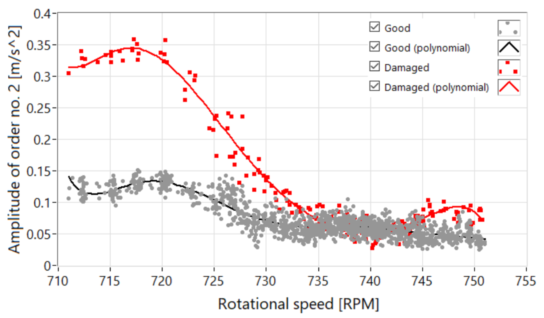

Fig. 16. The second order amplitude values plotted against rotational speed, obtained via series analysis, and the fitted polynomial curves: reference curve (black), misalignment (red)

These changes are also evident in the spectra of the relative parameters *rRMSD* (Fig. 17) and *r∆Amax* (Fig. 18), which show deviations from the reference spectrum. It should be emphasised that the spectra obtained using the proposed method are also insensitive to temperature changes. Values exceeding 1 on the *rRMSD* spectrum (Fig. 17) indicate a more than twofold increase in the RMS value describing the distance between the curves corresponding to individual orders. The confidence interval for the mean value of the 40-minute measurement reaches a maximum width of 0.2 for orders 67 and 68. A more than twofold increase in the maximum value *r∆Amax* (Fig. 18) is shown as values exceeding 2 for orders 2 to 14. The width of the confidence interval for this parameter reaches a maximum value of 0.5.

The diagnostic spectra obtained for individual orders provide the operator with valuable information about the machine's technical condition. By using relative parameters, it is possible to determine the extent to which (compared to the values for a machine in good working order) the amplitudes of individual spectral components have changed. These components can be attributed to faults in specific parts of the machine being diagnosed. The diagnostic process can also be automated by applying appropriate masking to the obtained spectra, using masks assigned to specific faults.

Fig. 17. The *rRMSD* spectrum for a system with misalignment: the green line represents the mean values, and the light green area represents the 95% confidence interval for the mean

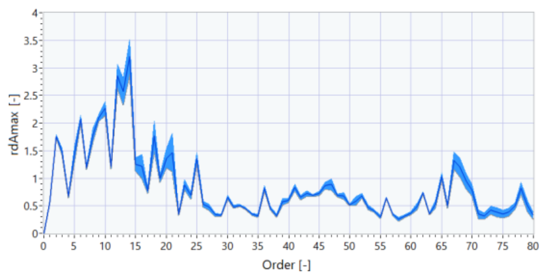

Fig. 18. The *r∆Amax* spectrum for a system with misalignment: the blue line represents the mean values, and the light blue area represents the 95% confidence interval for the mean

In the final phase of the experiment, the algorithm's performance was tested on a system without any faults introduced. The faults introduced into the test setup were removed, and the system was restarted in order to test the accuracy of the diagnosis in the absence of faults. The *rRMSD* values for all orders do not exceed 0.25, indicating that the relative RMS value between the curves has not changed by more than 25%. The maximum values generally remain at 0.3, except for orders 30 and 33, where the maximum value is 0.75. These maximum values stem from the fact that the differences are divided by the values corresponding to correct machine operation; consequently, the proposed parameters are highly sensitive to small changes in amplitude. However, by monitoring the *rRMSD* and *rΔAmax* spectra simultaneously, false alarms can be eliminated.

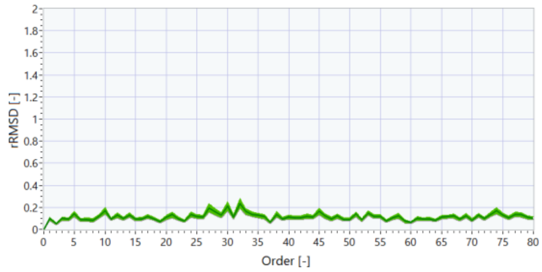

Fig. 19. The *rRMSD* spectrum for the undamaged system: the green line represents the mean values, and the light green area represents the 95% confidence interval for the mean

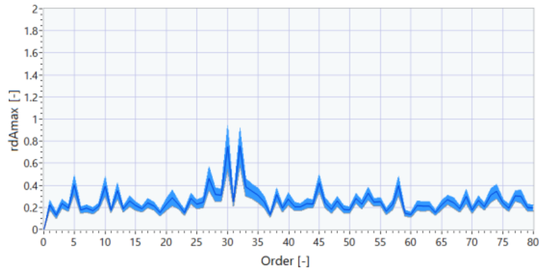

Fig. 20. The *rΔAmax* spectrum for the undamaged system: the blue line represents the mean values, and the light blue area represents the 95% confidence interval for the mean

Table 1 shows the values of the dominant spectral components *rRMSD* and *rΔAmax* for all the cases analysed. The maximum value of *rRMSD* for a machine in good working order is 0.24 for the order with index 32. As this is a relative parameter, this value represents a deviation of 24 % from the nominal value. Changes in amplitude within this range are acceptable and do not usually trigger alarm conditions in industrial measurement systems. The method is highly sensitive to changes in components with small amplitudes.

Table 1. Dominant values in the *rRMSD* and *rΔAmax* spectra for all cases

Machine condition	*rRMSD*	*Order index*	*rΔAmax*	*Order index*
Good	0.24	32	0.75	32
Unbalance	0.75	1	1.55	1
Misalignment	1.80	14	3.20	14

For imbalance, the maximum *rRMSD* amplitude is 0.75 for order index 1, which is close to the alarm threshold typically set for 100% changes. In the case of de-centring, the maximum *rRMSD* value is 1.80, representing an almost twofold increase in order no. 14. This marks the boundary of the band comprising orders 2–14 with values above 1. In the case of de-centring, the symptoms will be observed in orders 2, 3, 4, 8 and 12 due to the use of a claw coupling. High values of the *rRMSD* parameter were also recorded for these components. The *rΔAmax* parameter reached relatively higher values because it is based on the maximum deviation rather than the average across the entire range of load variation.

5. SUMMARY

This paper presents a system for monitoring the technical condition of rotating machines, incorporating a training process under industrial conditions. The training process is carried out in situ due to the specific nature of the objects being diagnosed and the individual impact of operating conditions on the machine.

The system does not require training data from faulty objects to diagnose and identify faults. Identification involves analysing changes in the spectral components of the series whilst compensating for the influence of operating conditions. The identification of spectral components can also be automated using masks appropriate for specific faults [19]. This is a very important aspect, particularly when used in industrial conditions, where data on faults is unavailable or scarce.

It should be emphasised that the system does not require additional computing power that necessitates a constant connection to the network. This is often a prerequisite when using complex diagnostic methods or those based on deep machine learning.

All calculations relating to both the training and diagnostic processes are implemented within an industrial controller. Data analysis has been implemented in a real-time operating system due to the stability of this system. Part of the user interface has been implemented on a PC, which communicates with the controller via the TCP/IP protocol. The use of this protocol also allows for communication and data visualisation via an HMI device.

The system's performance was tested on a laboratory test bench. The system correctly detected the imbalance and misalignment of the shaft lines. It should be emphasised that the system unambiguously detected a relatively small imbalance of 12 g, whereas analysis of the averaged spectrum of the orders did not allow for such identification.

The spread of the analysis results was also examined and presented using 95% confidence intervals. The maximum width of the confidence interval for the *rRMSD* parameter is 0.2 for several series, whilst it is 0.5 for the *rΔAmax* parameter.

The method is based on relative parameters, i.e. values normalised to the values corresponding to the machine's correct operation; this allows for the detection of low-energy but relative changes. This also makes the method highly sensitive to changes in small amplitude values, and in some cases this may result in false alarms being generated.

The use of relative parameters—that is, values divided by the value corresponding to the machine's normal operation—makes it easier to set alarm thresholds. Setting the threshold for the *rRMSD* parameter to 1 indicates a 100% change in the RMS of the differences; for example, in ISO 20816 [30], the limits of the machine vibration zones differ by a factor of 2.

Determining the *rRMSD* and *r*Δ*Amax* parameters for all spectral components allows for interpretation in the same way as for a machine operating under steady-state conditions. Furthermore, the method can be used to identify other types of faults whose symptoms are visible in the vibration spectrum. An example of applying these parameters to diagnose a planetary gearbox using acoustic signals is presented in [31]. The aim of further work will be to test the system's ability to diagnose other faults in rotating machinery.

It should be noted that the method also has limitations which must be taken into account during implementation. During the training process, signals must be recorded across the full range of variable conditions; otherwise, the method may generate false alarms due to missing reference values. The training process must also be repeated if the measurement points are changed or following a machine overhaul, as the relationship between vibrations and conditions may change.

Due to the modular design of the application running on the RT system, it can be expanded to include other concurrently running analyses and measurement signals.

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