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Hybrid predictive maintenance model – study and implementation example

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Abstract
In this paper, the concept of hybrid predictive maintenance for a single industrial machine is presented. A review of the solutions in the area of machine maintenance (especially predictive maintenance) which have been described in the literature is provided. The assumptions of the hybrid predictive maintenance model for modules, machines, or systems are presented. The methods used within the developed methodology are described. This includes the use of diagnostic data, experience, and a mathematical model. A case study of an industrial machine on which a system for collecting diagnostic data has been pilot-implemented, using, among others, vibration sensors and drive system parameters for damage detection is presented. The registered data can be used to precisely determine the time of upcoming failure after detection of the characteristic symptoms resulting from component wear In addition, an analysis of the durations of correct operation and failure events was performed and indicators describing these values were determined. The values of the aforementioned indicators were determined based on empirical data and described using a gamma distribution. The objective of the research was to prepare, implement and draw conclusions on a hybrid predictive maintenance model. A real industrial machine was used in the research study. The hybrid predictive maintenance model presented in this paper enables the use of data of different types (diagnostic, historical and mathematical model-based) in scheduling machine downtime for maintenance actions. On the basis of the research conducted, it was determined which machine operating parameters are characterised by variability that enables the detection of upcoming failure. This allows for precise planning of maintenance activities and minimization of unplanned downtime.

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1. Introduction

Digitalised manufacturing machines are playing an increasingly important role in modern manufacturing enterprises. At the same time, companies are striving to optimise the costs of manufacturing processes and guarantee high reliability of the exploited equipment. Providing the suitable availability of machines is a key aspect for prompt order completion and ensuring the right quality of manufactured goods. Minimalization of equipment elements unplanned downtimes allows for the elimination of the need for maintenance resources in reactive mode. Depending on relation chains between the manufacturing machines (e.g. in a serial structure), the need for stopping other manufacturing entities is minimized as well. In order to achieve the goals described above, manufacturing facilities decide to implement preventive or predictive maintenance more frequently. It is a consequence of the growing market demands in terms of timely order deliveries, quality of the goods and the need to remain competitive. Additionally, an important factor influencing the need to administer the advanced maintenance methods is the growing automatization and level of complexity of the manufacturing processes. The chosen maintenance method is implemented for selected machines, manufacturing nests or entire manufacturing lines (Ahmed et al., 2021; Fossier and Robic, 2017). In comparison with the basic, reactive maintenance strategy, where maintenance actions are taken when a failure occurs, preventive and predictive strategies use historical failure data, as well as diagnostic data, allowing for assessing the technical condition.

They are used to define the intervals of the selected maintenance activities (preventive strategy) and to plan the maintenance activities when a failure of a used component is approaching (predictive strategy). Taking such actions aims to minimize or eliminate the unplanned downtimes of equipment or production lines.

The significant aspect of the preventive and predictive strategy is that modern machines are often connected to the company network, which creates the possibility of monitoring the operating parameters and saving them on company servers (Kumar and Iyer, 2019, Lampropoulos et al., 2018). This allows for easier integration of machines and the systems monitoring the parameters important for the users. As a consequence, collecting data regarding productivity, availability, operating times and downtimes (including failure duration and the time needed to remove the failure) is becoming more popular in the modern industry (Tran et al., 2021).

Considering the constant development and the increasing role of the predictive types of machine park tending in the Industry 4.0 manufacturing facilities, the conducted research concerns this scope of maintenance. The aim of the research and this article is to expand, implement and draw conclusions regarding the authorial proposal of a hybrid model of predictive machine maintenance. The direct result of the work performed is a pilot study – implementation of the predictive maintenance model for a selected machine. Additionally, during the pilot study, characteristic trends of certain machine parameters were identified, indicating wear and tear of components of specific modules.

2. Literature review

Manufacturing machines are operated mostly on the basis of one of three maintenance strategies: reactive, preventive or predictive, which are described in numerous literature sources (Yazdi, 2024 511; Molęda et al., 2024). Predictive maintenance strategies are used mainly for machines and production lines, where high reliability is required and the downtime costs are significant, and influence the client's satisfaction level (Shafiee et al., 2017; Carnero and Gomez, 2017). In addition, environment protection and sustainable development are playing an increasingly important role in the choice of the proper maintenance strategy (Scope et al., 2021; Zhao et al., 2022). The aim of this is to minimise the use of resources and negative environmental impact by providing durability and energy efficiency of utilised equipment (Ighravwe and Oke, 2019; Zwolińska and Wiercioch, 2022). The maximisation of the machine life cycle is a supplementary aspect, important from the manufacturing companies' point of view (Achouch et al., 2022). Predictive maintenance strategy is the most advanced approach to equipment maintenance; furthermore, it is being dynamically developed. Depending on the method of machine maintenance actions taken, literature specifies the following types of predictive maintenance: experience-based, model-based, physical-based, data-driven, knowledge-based, digital twins approach, and hybrid (Mallioris et al., 2024; Cao et al., 2022). Each of the specified types is characterized by a different way of defining the appropriate time for performing maintenance actions.

Hybrid types of predictive machine maintenance can utilize a combination of two or more predictive maintenance methods. This approach, although more complicated for implementation purposes, allows for a better fit for a given machine or production line (Luo et al., 2020). Due to numerous possibilities, hybrid types of predictive maintenance are subject of dynamic development (Zheng et al., 2022).

In order to identify whether the given machine, system or production line should be maintained according to the principles of predictive maintenance, it is crucial to define the criteria for the choice of the maintenance strategy. Literature sources propose selection possibilities depending on the cost efficiency, the impact of machine downtime on the production line and other production nests in the facility, as well as the impact on the client and the final manufactured goods quality (Ji et al., 2019; Tiddens et al., 2023).

Monitoring and registering the correct operation parameters, failure and diagnostic data is becoming more easily available with the use of the tools referred to as the technological pillars of Industry 4.0. This group includes industrial IoT, i.e. a virtual network connection of manufacturing machines, and Big Data, which can comprise of registering, retaining and processing machine exploitation data (Keleko et al., 2022; Rosati et al. 2022). Use of the tools mentioned above and addition of other components for monitoring the machine operation parameters allows for the collection of diagnostic and failure data, as well as its processing with the aim to create a mathematical model describing the failure duration times and the correct operation times. Diagnostic data can include the following areas depending on the analysed production line or a machine: vibration, electricity consumption, power or moment required for execution of the technological processes, noise and acoustics, thermovision, pressure, humidity, oil or chemical composition conditions, or even the communication and data transfer frequency (Randall, 2011; Nunes et al. 2022). The last parameter is especially significant in the case of robotic devices.

In order to utilize diagnostic data to predict an approaching failure and the need to plan a downtime allowing for replacement of the used components, a proper diagnostic data processing is required, as well as precisely defining the parameters reflecting on the component wear. To achieve this, it is needed to implement a system monitoring the selected parameters, important from the defects diagnostics point of view (Stodola and Stodola, 2020). It is an individual matter for various machine types.

3. Experimental

On the basis of literature in conjunction with defining a research gap related to the hybrid predictive machine maintenance types, the concept of using a hybrid predictive machine maintenance model, combining three data types (data-driven, experience based and model-based), was presented in an article (Wiercioch, 2023). The proposed authorial model integrates the use of an approach utilising diagnostic data with the approaches based on experience and mathematical models.

The proposed strategy of a hybrid predictive maintenance should in principle relate to highly-loaded machines, production lines or systems, for which a high reliability is required, and the unplanned downtimes have a significant impact on the client and generate high costs. The diagnostic part related to the developed method concerns constant monitoring of relevant machine parameters, such as electricity consumption, drive units moment, vibration characteristics, as well as other diagnostic data important for a given machine or system. The experience-based and model-based parts however, relate to owning historical failure data, defining the relevant indexes of correct operation times and failure duration times and describing them using the suitable probability density distribution. A diagram of the hybrid predictive maintenance type concept is shown in Figure 1.

The criteria for selection of a predictive maintenance strategy for the analysed machine were: the necessity of providing high reliability, high costs of each failure repair and unplanned downtimes. The need to define the time of ordering the replacement components and the direct impact on the client were significant aspects as well.

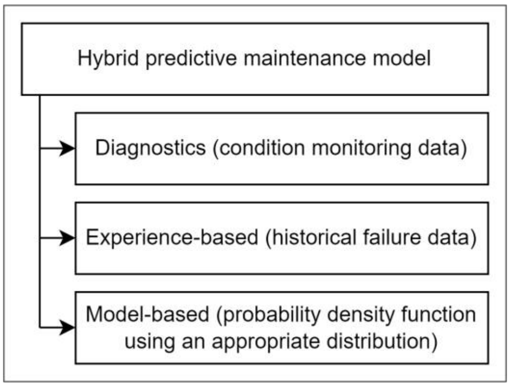

Fig. 1. Hybrid predictive maintenance concept

In order to implement and validate the proposed method of hybrid predictive maintenance, a machine characterised by the need for a very high reliability and availability was selected. It fulfils the criteria of high unplanned downtimes costs and significant client impact. The analysed machine is a four-axis robot used in the automotive industry. The purpose of the machine is to perform damage analysis on the bodies of vehicles using, among other things, vision modules placed on execution modules. The robot is fully automated and executes processes without human interaction. It is an individual machine that consists of the following modules of the kinematic chain: the support structure with slides, cable guides and power supply system (M0), the main axis (X), which consists of modules M1.1, M1.2, M2, the transverse axis (Y), which consists of module M3, the axis of rotation, on which one of the executive unit (M4) is located, and the vertical axis (Z), on which the second executive unit (M5) is located. A schematic diagram of the device is shown in Figure 2.

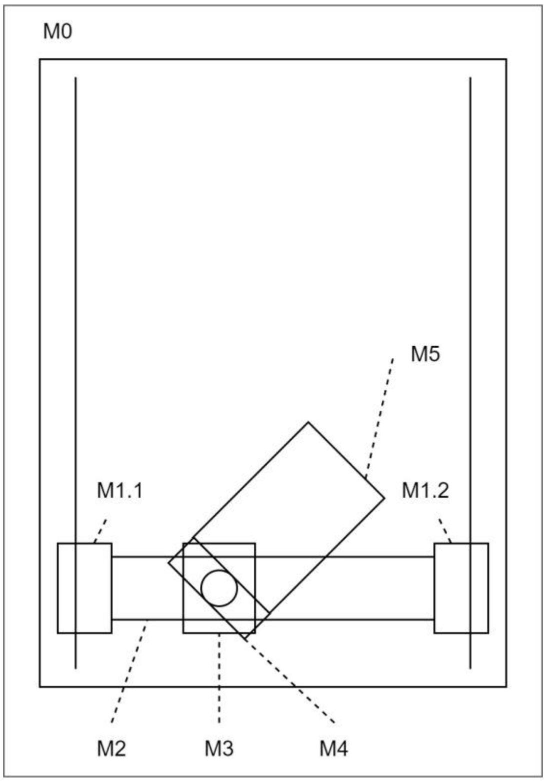

Fig. 2. Schematic diagram of the analysed machine

Considering the fact that the deployment sites have limited maintenance resources, it is necessary to implement a monitoring system for its selected parameters and to prevent the occurrence of unplanned failures. The pilot implementation of the predictive maintenance system also aims to define the values of characteristic symptoms reflecting on the approaching failures, as well as to define a timeframe designated for machine maintenance. The device subject to the analysis is characterised by cyclic, discontinuous operation. Depending on the performed process, a single operation cycle of the device lasts between 2,5 and 4 minutes.

The machine subject to the analysis was divided into 6 modules, cooperating with each other. They were marked as M0, M1.1, M1.2, M2, M3, M4 and M5. The modules were singled out depending on the tasks they perform and the position they have in the kinematic chain of the robot. The simplified scheme of the cooperating modules is presented in Figure 3. In turn, a short characterization of the elements included in the individual functional modules can be found in Table 1.

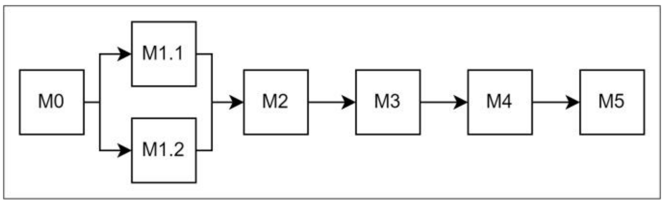

Fig.3. Diagram of the modules of the analysed machine

Table 1. Basic parameters of the machine modules

Machine module	Description
M0	Support structure, guides for modules M1. And M1.2, power supply system, network components, sensors, cable guide
M1.1	400W motor, planetary gearbox, 3 sets of wheels, sensors, support for M2 module
M1.2	400W motor, planetary gearbox, 3 sets of wheels, sensors, support for M2 module
M2	Guides for module M3, power supply, cable guides
M3	2x200W motor, 2xplanetary gearbox, 6 sets of wheels, sensors, support for M4 module, cable guide
M4	2x200W motor, executive device, cable guide, guides for module M5, power supply, sensors
M5	Executive device, sensors

The experiment was planned according to the schematic diagram shown in Figure 4. The first step was to identify failures and their durations in the functionally modularised machine. Next, monitoring of basic machine parameters was implemented, including torques generated by the drive units, power consumption and temperature in the individual drive units. The next step was to decide to extend the diagnostics of two modules (M1.1 and M1.2). By monitoring the basic operating parameters and the character of the vibrations occurring in modules M1.1 and M1.2, it became possible to predict the evolving failure.

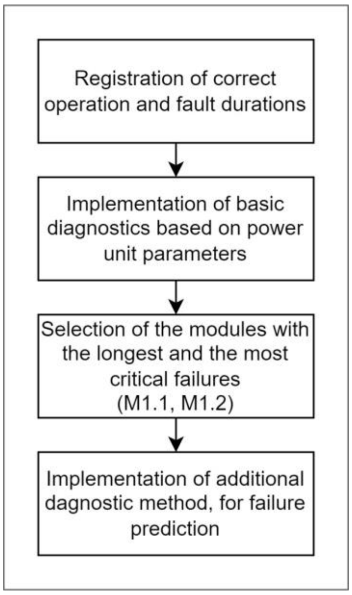

Fig.4. Diagram of the experimental plan

3.1. Data-driven part (diagnostics)

The machine subject to the pilot application of the hybrid maintenance model belongs to modern, digitalised devices. This means that the machine is connected to the company's IoT, which enables local and remote control of the processes executed by the machine. The connection to the company's server and dedicated software also makes it possible to set and record process-relevant parameters. This allowed for the implementation of selected operation parameters monitoring, with the use of the applicable software in the controllers and the preparation of the external monitoring system. The monitoring system consists of two main parts based on the device kinematics and the possibility of installing selected controllers: as internal system using the device controllers, connected to the data collection system located in the cloud server; and an external system consisting of acceleration sensors, connected to the data acquisition card (digital signal conditioner) and an external computer. The concept of a scheme is presented in Figure 5.

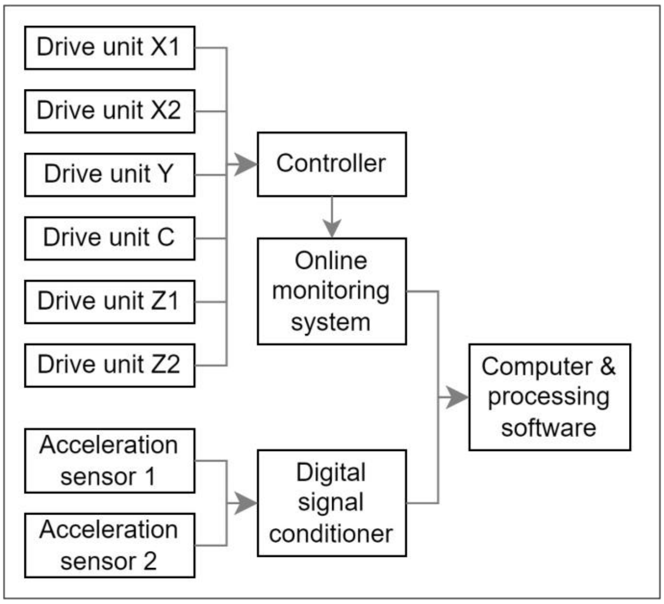

Fig. 5. Diagram of the monitoring system for the analysed machine

The research on the machine was conducted over nine months. In the first part, the basic parameters to be monitored were chosen. Their determination was crucial for predictive maintenance based on the state of a machine or a module. In the case of the proposed hybrid approach, it is one of three important parts, used for planning the replacement of the used components.

Based on the analysis of the device, the monitored parameters were determined. The indexes of the components that are monitored are based on the names of the axes of the particular modules of the robot. These are the X-axis drive assemblies (X1, X2), Y-axis, and C-axis, as well as Z1 and Z2-axis. Therefore, the monitored parameters are the values of the power units' temperatures (Tx1, Tx2, Ty, Tc, Tz1, Tz2), the values of the torques generated by the power units (M_{X1}, M_{X2}, M_Y, M_C, M_{Z1}, M_{Z2}), the values of power consumed by the power unit (P_{X1}, P_{X2}, P_Y, P_C, P_{Z1}, P_{Z2}). The parameters additionally monitored were those concerning the communication frequency of the important modules of the device, the state of the device, as well as the state of the sensors that are used in the processes conducted with the use of the analysed machine. What's more, the values of the vibrations, which are registered in the form of voltage and later counted in the values of the acceleration, speed, and displacements used for the spectral analysis, were also monitored. During the research, the sensors of the accelerations were placed within the two opposite, symmetrically placed modules of the main axis of the device M1.1 and M1.2 in two different ways: parallelly to the direction of movement and perpendicularly to the direction of movement. The analysed modules are meant to drive the main axis of the device and to ensure the correct movement along the guides.

The data provided by the sensors in the measuring path is recorded using a program developed for this purpose in the Matlab environment. Here, they are saved as data files. Then, after loading the data into the program prepared for analysis, the value of the signal recorded in the form of voltage is converted into acceleration values, according to the sensitivity of the sensors, corrected by a coefficient determined during calibration of the measuring path with the use of a device emitting a reference signal. With data processed in this manner, it is possible to plot the acceleration values over time. In order to obtain the amplitude spectrum of the recorded vibrations, a Fourier transform of the processed acceleration values is performed. In turn, in order to determine the velocity and displacement values of the analysed vibrations, it is necessary to perform integration and double integration of the acceleration values.

For the conducted examination of the vibrations, two acceleration sensors ICP 603C01 were used, and they were attached using the cord in the BNC standard with a length of 20 meters, installed in the cable guide of the analysed device, with Digital ICP – Signal Conditioner, Model 485B39. The measurement card was connected to the computer and communicated with the use of a proprietary program registering and processing the measurement data.

The prepared measurement track should be calibrated after assembling. The necessity to calibrate and take into account the values determined during calibration, results from the possibility of different electrical parameters of the used cables and sensors. In addition to the periodic calibration of piezoelectric sensors recommended by the manufacturer, it is advisable to calibrate the measuring track after each assembly. For this purpose, the calibration exciter BruelandKjaer 4294 was used. It is used to generate the calibration vibrations with a frequency of 159.2 Hz and with the root mean square values of acceleration of 10 [m/s^2], speed of 10 [mm/s], and displacement of 10 [µm]. The calibration system in the spectral form is presented in Figure 6, whereas the form of a graph of the dependence of the accelerations in time for one sensor, is presented in Figure 7.

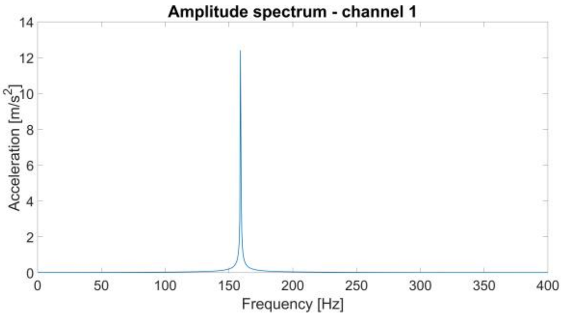

Fig. 6. Calibration vibrations signal processed in the form of an amplitude spectrum recorded for the measurement track connected to channel 1

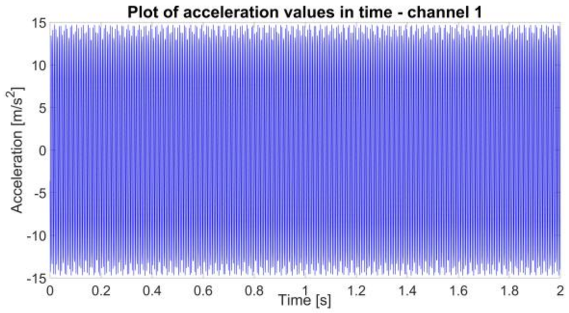

Fig. 7. Calibration vibrations signal processed in the form of acceleration values over time

As a result of the calibration process (triple registering of the signal of the calibration vibrations signal), the measurement track was corrected. In the case of the measurement track connected to channel 1 (with the SN LW456823 sensor), the average root mean square value was 10.384, whereas in the case of channel 2 (with the SN LW 456822 sensor), it was 10.145. The designated values were taken into account to correct the converting voltage signal magnitudes into acceleration, speed, and displacement values. For the measurement track connected to channel 1, the values measured during the tests were corrected by multiplying by the coefficient c_1 = 0.963, and for measurement track connected to channel 2 by the coefficient c_2 = 0.986, which were determined according to formula 1.

$$c_i = \frac{RMS_e}{RMS_m} \tag{1}$$

where: c_i – calibration coefficient of the i-th measurement track, RMS_e – root mean square value of acceleration generated by calibration exciter; RMS_m – root mean square value of acceleration registered by examined measurement track while registering the reference signal.

The purpose of the calibration process was to ensure that the correct values were analysed during the research. The calculated values of c1 and c2 coefficients were implemented when processing the values in software in the MATLAB environment. All values presented in the following sections of the article that were recorded using acceleration sensors were corrected utilising the values determined above.

3.2. Experience-based and model-based part

To create an adequate database, which was to be used in the developed methodology of the approach based on the experience and on the mathematical models, in the analysed period, the data concerning the duration of the events of correct operation and failures was registered. With the objective of a precise definition of the values during the events mentioned before, they were divided into groups corresponding to the modules of the device. Based on that, the values of the parameters concerning the correct operation and the failures were designated for each module of the device in order: M0, M1.1, M1.2, M3, M4, and M5. For module M2, the indicators mentioned before were not designated for the reason of an absence of failure in this module in the analysed period of time. The indicator concerning the duration of the correct operation is MTTF - mean time to failure, whereas MTTR - mean time to repair - concerns the value of the average time until the failure is repaired. Both indicators are counted as an average value, according to the formulas (2) and (3) for the given modules of the device (Lysnianski et al., 2021; Daniewski et al., 2018).

$$MTTF_j = \frac{\sum_{i=1}^{N_{C(j)}} \boldsymbol{TTF}_{i(j)}}{N_{C(j)}} \tag{2}$$

where: $TTF_{i(j)}$ – duration of i-th correct operation event, $N_{C(j)}$ – quantity of correct operation events, j – machine identification number.

$$MTTR_j = \frac{\sum_{i=1}^{N_{R(j)}} \boldsymbol{TTR}_{i(j)}}{N_{R(j)}} \tag{3}$$

where: $TTR_{i(j)}$ – duration of i-th repair event, $N_{C(j)}$ – quantity of repair events, j – machine identification number.

Based on the designated values of the standard deviations of the indicators above, the corresponding probability-density distributions were assigned to them. They allow precision determination of the period during which, with a high probability, a failure of a module can be expected.

4. Results and discussion

While conducting a pilot implementation of the proposed hybrid predictive maintenance methodology, the data concerning the parameters of the functioning of the device (temperature, moments, power consumption of drive units) were registered, as well as the values of vibrations in the form of accelerations. Typical courses of the monitored values were registered during one shift (values of temperature), and also during the periods of singular cycles of the device's functioning. The graph showing the values of the temperature of the analysed drive units of the machine during one shift can be found in Figure 8. The following graphs, presented together in Figure 9 show the values of power consumption by specific drive units during a singular cycle of work in standard conditions. Figure 10 represents the values of the moments occurring on the drive units, also during the singular process.

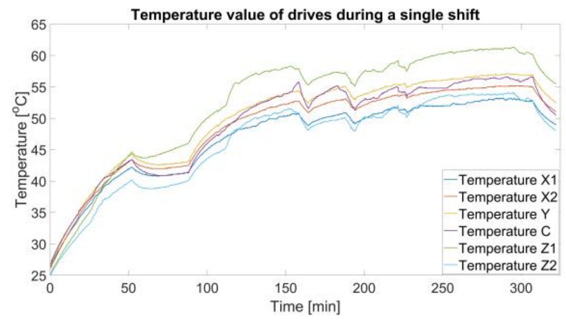

Fig. 8. Temperature values of the analysed machine drive units during single shift

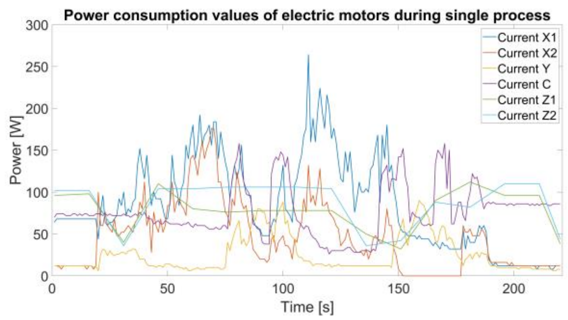

Fig. 9. Summary graph of power consumption values of the analysed machine drive units during a single working cycle

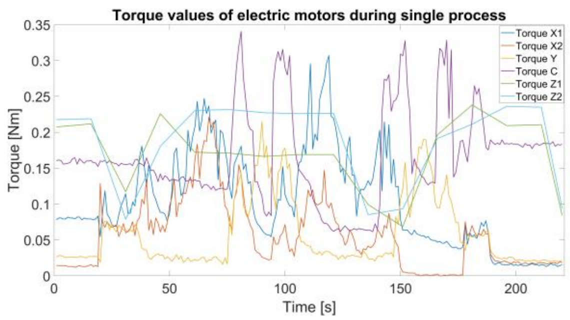

Fig. 10. Summary graph of the torque values generated by the analysed machine drive units during a single working cycle

Measurements with use of acceleration sensors were performed within modules M1.1 and M1.2 in two configurations. The positions of the sensors are shown in Figure 11. In the first configuration, the acceleration sensors were positioned along the direction of movement (sensors marked in green in Figure 11). In the second configuration, the sensors were placed within the same modules transverse to the direction of movement (sensors marked red in Figure 11).

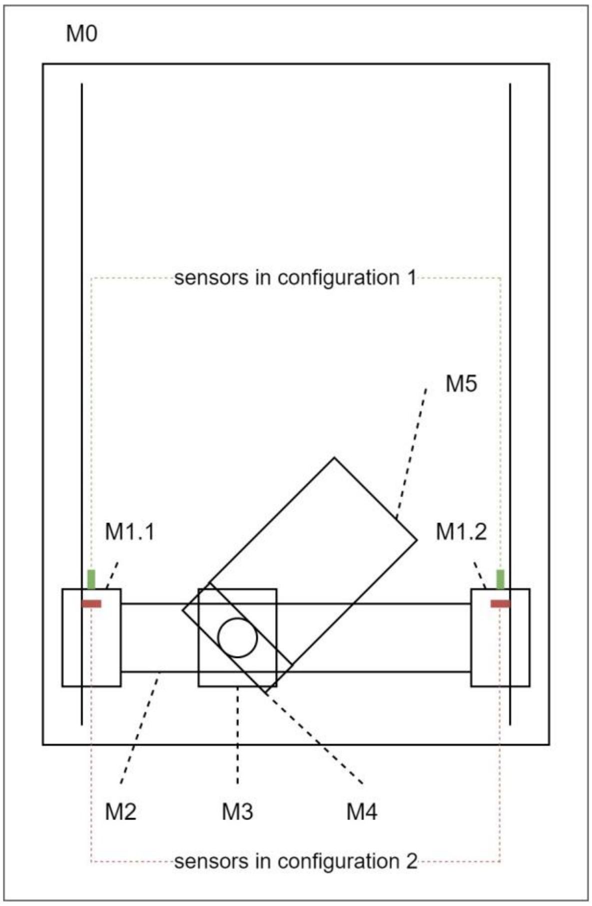

Fig. 11. Acceleration sensors positions in the machine schematic diagram

Registered and processed acceleration values registered from the acceleration sensors in the form of voltage, are presented in Figures 12 and 13. In Figure 12 example 1 is presented, where the values registered were the values of accelerations in the main axis of the device (X axis), parallel to the direction of movement. Figure 13 shows the values of the speed and accelerations perpendicularly to the direction of movement. Both of the presented cases concern the standard process, without observing any anomalies that could predict an upcoming failure.

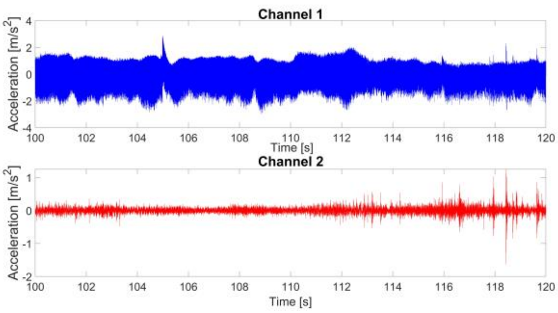

Fig. 12. Acceleration values recorded over time for the sensor mounted in module M1.1 (top) and module M1.2 (bottom) along the direction of movement

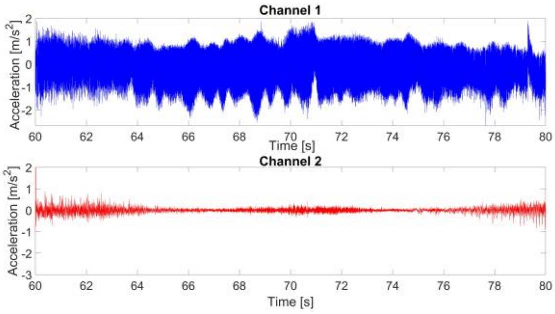

Fig. 13. Acceleration values recorded over time for the sensor mounted in module M1.1 (top) and in module M1.2 (bottom) transverse to the direction of movement

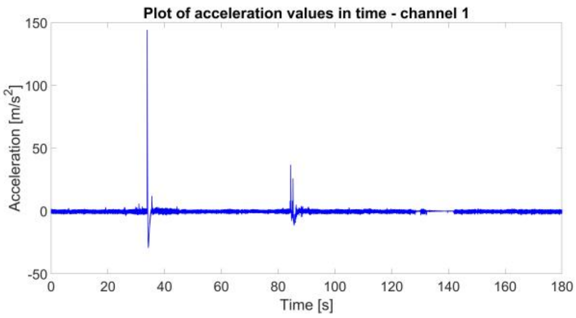

Fig. 14. Acceleration values recorded over time by the sensor mounted in module M1.1 along the direction of movement during a single process executed by the machine

Different diagnostics methods were used to detect different types of failures. An increase in power consumption, as well as in the moment generated by the drive units attests to the wear of the components of the modules responsible for the movement of the device. In the monitored period, a cycle of development of damages resulting in damage in the modules M1.1 and M1.2 was detected. This allowed the detection of the values, that if surpassed, can preview damage in a certain time perspective. Moreover, thanks to the use of acceleration sensors, it became possible to determine also different types of damage and to plan the service to prevent an unexpected downtime in the machine's work. Graphs that are characteristic of the propagation of damage are presented in Figure 14. This type of damage can occur in module M0, whereas detecting their propagation comes after converting the registered vibration values to accelerations values.

Spectral analysis may also prove useful during the research concerning early defects detection. The values registered throughout testing were calculated into a spectrum using the Fourier transform.

An example graph showing the spectral analysis is shown in Figure 15. The frequency values, for which the biggest acceleration occurs, were repeatable. The values were higher, especially in the moment of a sudden (emergency) stop of a process conducted by a machine. Selected levels and variability of the frequency for which the graph reaches the highest values could indicate the development and propagation of a failure. Nevertheless, no disturbing trend was registered during testing.

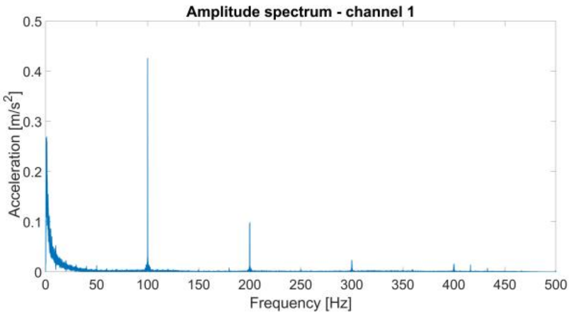

Fig. 15. Spectral analysis of the signal recorded by the sensor mounted in module M1.1 along the direction of movement during a single process executed by the machine

Data concerning the MTTF and MTTR values for selected modules of the analysed machine is presented in Table 2. The average values were supplemented with standard deviation, which is necessary for the selection of proper probability density distribution. The standard deviation was calculated according to formulas (4) and (5).

$$\sigma_{n<30} = \sqrt{\frac{\sum_{t=1}^{n}(t_i - \bar{t})^2}{n}} \tag{4}$$

$$\sigma = \sqrt{\frac{\sum_{t=1}^{n}(t_i - \bar{t})^2}{n-1}} \tag{5}$$

where: t_i – i-th element of the empirical sample for i = 1, 2, …, n; $\bar{\boldsymbol{t}}$ – arithmetic mean of the sample, n – number of empirical sample elements.

Table 2. MTTF and MTTR index values calculated for individual modules

Machine module	Parameter	Value [min]	Standard deviation [min]
M0	MTTF	4497.4	4603.7
	MTTR	42.4	45.5
M1.1	MTTF	8581.4	10949.8
	MTTR	154.6	122.6
M1.2	MTTF	5831.3	8515.6
	MTTR	106.1	111.6
M3	MTTF	3800.9	4070.5
	MTTR	32.6	20.8
M4	MTTF	1561.9	3183.3
	MTTR	11.0	15.3
M5	MTTF	5041.3	3424.7
	MTTR	14.8	20.6

The calculated values of MTTF and MTTR for individual modules of the device do not fulfil the relationship:
$MTTF_i \gg \sigma_{MTTFi}$ and $MTTR_i \gg \sigma_{MTTRi}$. Consequently, these parameters cannot be described using normal distribution. The empirical data characteristic is better suited for description using the two-parameter Gamma distribution (6).

$$X \sim Gamma(\alpha, \beta) \tag{6}$$

where: X – random variable, α – shape parameter, β – scale parameter.

The shape and scale (α and β) parameters are calculated using formulas (7) and (8) (Zwolińska 2019).

$$\alpha = \frac{4}{{A_S}^2} \tag{7}$$

where: A_S – skewness from empirical data calculated in accordance with the formula (9).

$$\beta = \frac{2}{s \cdot A_S} \tag{8}$$

where: s – standard deviation calculated according to formulas (4) and (5).

$$A_S = \frac{\frac{1}{n}\sum_{i=1}^{n}(t_i - \bar{t})^3}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - \bar{t})^2}^{\,3}} \tag{9}$$

The expected value (E) of Gamma distribution is calculated according to formula (10):

$$E(TTF_i, TTR_i) = \frac{\alpha}{\beta} \tag{10}$$

Table 3. Shape (α) and scale (β) parameter values for MTTR and MTTF parameters described by Gamma distribution

Machine module	Parameter	Shape parameter (α)	Scale parameter (β)
M0	MTTF	2.29842	0.00033
	MTTR	1.05118	0.02253
M1.1	MTTF	2.01195	0.00013
	MTTR	1.24852	0.00911
M1.2	MTTF	1.66027	0.00015
	MTTR	0.61665	0.00704
M3	MTTF	0.75764	0.00021
	MTTR	7.48201	0.13124
M4	MTTF	0.51056	0.00022
	MTTR	0.44590	0.04352
M5	MTTF	16.43728	0.00118
	MTTR	0.78111	0.04288

Table 3 contains the values of the shape and scale parameters determined for gamma distribution, which describe the MTTF and MTTR values of the individual modules of the machine under analysis. The full summary of the Gamma distribution parameters, including the skewness values and expected values of Gamma distribution for individual parameters is presented in Table 4 of Appendix A.

Based on calculated shape and scale parameter values, the example graphs showing the probability density were prepared – in Figure 16 for the correct operation time (MTTF) of the M1.1 machine module and in Figure 17 for the time until repair (MTTR) of the M1.1 module.

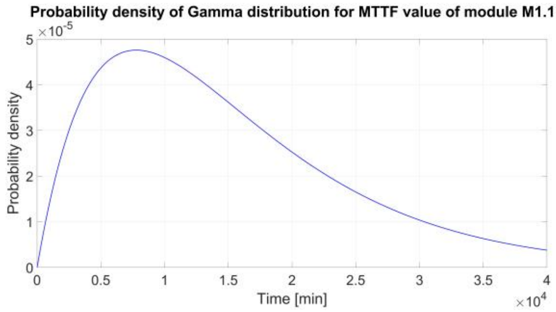

Fig. 16. The probability density graph of the correct operation time compliant with Gamma distribution for the M1.1 module

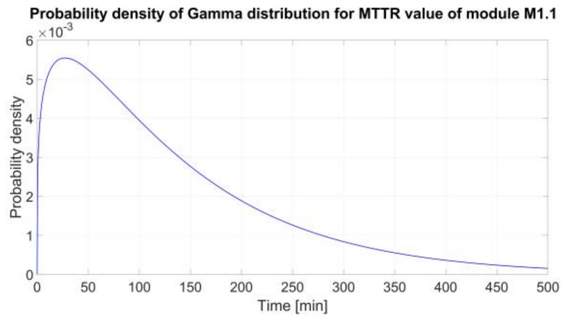

Fig. 17. The probability density graph of the time to repair compliant with Gamma distribution for the M4 module

The calculated expected values of correct operation time (MTTF) could be used to indicate when the machine downtime would be planned, necessary for replacing the components susceptible to wear. Their use is also recommended when deciding to order replacement components for the maintenance unit replacement component storage.

What needs to be noted, throughout the time of the experiment, the significant number of unplanned machine downtimes stemmed from incorrect indications or the need for the calibration of the sensors, on the use of which the process is based. Consequently, in many cases, the unplanned downtime did not result in component replacement. Therefore, it is essential to provide an additional information source on the machine's condition, for example by monitoring the drive unit parameters and examining other important variables (such as vibrations). Information from the diagnostic part combined with experience and the developed mathematical model, describing events such as the correct operation time, allows for precise indication of the component that would need repair or replacement due to its wear.

The research performed used data recorded in two systems. One system consisted of a fully automatic recording of the machine’s operating parameters, while the second system included vibro-acoustic testing and was triggered manually at specific time periods. In the future, it would be worthwhile to fully automate the measurements and include the implementation of sensors for diagnostics into the machine’s permanent equipment. Data analysis was performed using a script prepared in Matlab environment. The recorded vibration values were processed sequentially. In future research, it would be beneficial to automate the data processing and to implement an information system for exceeding the permissible RMS values of vibrations. These should be determined in the course of further research. In addition, an individual machine approach is important when implementing a monitoring and diagnostic system for predictive maintenance. The diagnostic parameters selected and used on the analysed machine (power consumption, torque generated by drive units, temperature and vibration) may not be suitable for monitoring the condition of a different machine.

The implementation of the hybrid predictive maintenance model can contribute to a significant decrease in unplanned downtime and minimisation of spare component inventories. The economic assessment of the implemented solution is individual for each machine. It should take into account the costs associated with collecting failure data, implementing a monitoring system and determining the value to the production company of minimizing non-productive time, reducing the negative impact on the customer and the need for maintenance resources. However, it is important to correctly define the input parameters when implementing a hybrid predictive maintenance type. In the case of implementation of the model described in the article, it is necessary to have knowledge derived from monitoring the failure rates of selected components or modules. On this basis, it is necessary to define a suitable mathematic model that corresponds to the recorded data. The longer the period for collecting failure data for individual modules, the better, while the author’s recommendation is a minimum period of six months. In addition, a very important element of the described model is the monitoring of machine operating parameters. It is necessary to correctly define the machine operating parameters that indicate an upcoming failure. In the case of different machines, it will be necessary to monitor various parameters (e.g. power consumption, temperature, pressure, sound intensity).

5. Summary and conclusion

The research described in this article made it possible to identify the types of diagnostic methods that are beneficial for detecting specific types of failure. Monitoring selected machine parameters, such as power consumption and values of moments generated by drive units, enables the identification of an upcoming failure in the modules responsible for the movement of the robotic arms (modules M1.1 and M1.2). In turn, tests using accelerometers enable the early detection of faults within the M0 module, where the propagation of the fault is not visible on the trend line of changes in power demand and drive-generated torque. In addition, monitoring of communication frequencies, sensor status, and device states also allows diagnostics to be performed in this area. No correlation between changes in temperature values of the drive units and the occurrence of faults was found during the research. Therefore, the recommended parameters for future monitoring are the torque values generated by drive units, the power consumption of the drive units, and the vibration in the form of acceleration values. These parameters will allow an early prediction of potentially possible failures.

The parameters of the expected value of the gamma distribution determined in the model-based and experience-based sections are recommended for use in planning the need for spare parts to be in the maintenance stock during the period in which a failure is predicted to occur. Taking into account the analysed data on the duration of correct operation and failure events, the use of gamma distribution for the mathematical modelling is recommended.

The proposed hybrid predictive maintenance model, based on diagnostics, experience, and a mathematical model, fulfils its objectives. It was developed and tested over a period of nine months using an industrial machine. It enables data of different types to be used in scheduling machine downtime for maintenance activities. The proposed algorithm takes into account the use of historical failure data, which, combined with a mathematical model describing the time values of correct operation, specifies the requirements for having the necessary spare parts in the maintenance stock. Once the hybrid predictive maintenance model has been implemented, it is planned to continue the research in this area, also using the machine analysed in the paper. In addition, research will also be conducted on the development of precise criteria on the basis of which an appropriate machine or system maintenance strategy should be selected.

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Appendix

Appendix A

Table 4. MTTF and MTTR values, standard deviation, shape and scale parameters for gamma distribution, and the expected value of gamma distribution calculated for individual modules

Machine module	Parameter	Value [min]	Standard deviation [min]	Shape parameter (α)	Scale parameter (β)	Skewness (As)	Expected value (E)
M0	MTTF	4497.4	4603.7	2.29842	0.00033	1.31921	6979.5
	MTTR	42.4	45.5	1.05118	0.02253	1.95070	46.7
M1.1	MTTF	8581.4	10949.8	2.01195	0.00013	1.41001	15531.6
	MTTR	154.6	122.6	1.24852	0.00911	1.78992	137.0
M1.2	MTTF	5831.3	8515.6	1.66027	0.00015	1.55218	10972.4
	MTTR	106.1	111.6	0.61665	0.00704	2.54689	87.6
M3	MTTF	3800.9	4070.5	0.75764	0.00021	2.29771	3543.1
	MTTR	32.6	20.8	7.48201	0.13124	0.73117	57.0
M4	MTTF	1561.9	3183.3	0.51056	0.00022	2.79904	2274.6
	MTTR	11.0	15.3	0.44590	0.04352	2.99511	10.3
M5	MTTF	5041.3	3424.7	16.43728	0.00118	0.49330	13884.7
	MTTR	14.8	20.6	0.78111	0.04288	2.26295	18.2