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IMPROVING THE LEVEL OF PREDICTIVE MAINTENANCE MATURITY MATRIX IN INDUSTRIAL ENTERPRISE

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Abstract: Predictive maintenance is a maintenance strategy that applies advanced statistical methods and artificial intelligence to determine the appropriate maintenance time. The article focuses on future recommendations for industry and logistics to achieve a higher level of predictive maintenance maturity, which requires real-time monitoring of the state of the company's machinery and equipment. The article's main objective is to propose recommendations to increase effectiveness by improving the predictive maintenance maturity matrix from the current level to a higher level in the industrial enterprise. The current state of maturity has been indicated using the modified model of predictive maintenance and following recommendations from the document Manual for companies for the introduction of artificial intelligence. Simultaneously within the analysis, a predictive maintenance simulation was performed on a selected production line, including essential machines and equipment. The study also identified the individual assumptions (processes, data, infrastructure, personnel, applications, organization) necessary to implement predictive maintenance successfully. The presented case study results contribute to understanding how individual assumptions can be obtained for predictive maintenance improvement and how innovative solutions in the context of Industry 4.0 and Logistics 4.0 can be achieved in enterprises.

1 Introduction

One of the critical tasks in industrial production and logistics is to reduce costs and eliminate waste. One of the identified wastes are often downtimes, which are related to not optimal set maintenance cycles. Reasons are that two extreme cases might occur: either service interventions are too frequent, which increases maintenance costs or maintenance is neglected, which can lead to irreversible damage to the machine. The purpose of any machine or equipment maintenance is to reduce or eliminate losses caused by applying an unsuitable production method or often also as a result of a human factor. However, maintenance is to take care of machines and equipment and plan the costs associated with equipment operation and manage the range and number of spare parts [1,2]. According to [3], it is a matter of ensuring that machines can produce products in the required quality and quantity, at the lowest possible cost and in the shortest possible time. The types and methods of maintenance by which these goals are met have undergone significant changes. From the first corrective maintenance, which means the maintenance performed after a machine failure, which began to be applied in the distant past, we have gradually moved on to preventive strategies as presented in this article in the case study.

As part of the predictive maintenance approaches using machine condition diagnostics and prediction are dominated and desired.

2 Predictive maintenance

Predictive maintenance (PdM) seeks to determine the right moment for maintenance based on advanced statistical methods and artificial intelligence [4-7]. Unlike preventive maintenance, the maintenance of each device is assessed and planned based on the current state of the device while using various models to reveal the time and date of the failure. Subsequently, it is possible to extend or shorten maintenance cycles according to the actual state of the device. A well-functioning predictive maintenance system is closely linked to a well-designed diagnostics and prediction system that uses advanced statistical methods and artificial intelligence. With the help of predictive maintenance, it is possible to optimise operating conditions, improve the quality of products and services and thus make the most of the investment [8-10].

Predictive maintenance is one of the maintenance strategies, which may be understood as a set of rules based on which the maintenance schedule is prepared and the performance of individual maintenance activities. Usually, several strategies are applied together on the machinery. The choice of an appropriate strategy depends on several factors: state of the machines, the possibilities of implementing the chosen strategy, or the economic advantage of prevention [3]. Three terms are known within the maintenance strategy - corrective, preventive, and predictive maintenance (Figure 1). Corrective maintenance is the oldest maintenance strategy performed after a machine failure and can be found in the literature as reactive maintenance. The purpose of corrective maintenance is to put the machine into operation immediately after failures in the shortest possible time and with the lowest losses [3,11].

To reduce the inefficiency of corrective maintenance, manufacturing companies have switched to a preventive maintenance model. Preventive maintenance works on the principle of planning regular service of machines, whether it is repaired, replacement of parts, oil change, lubrication, and so on. The aim is to prevent machine failures before they occur, which eliminates the possibility of unexpected production downtime. Preventive maintenance is currently the dominant company maintenance strategy, but it is still far from optimal because machines often fail at the end of their service life. Companies must create maintenance plan based on actual information about the asset's condition to achieve optimal maintenance activity and not only on theoretical considerations. Predictive maintenance means that companies can plan maintenance activities based on accurate predictions of the device's life [12].

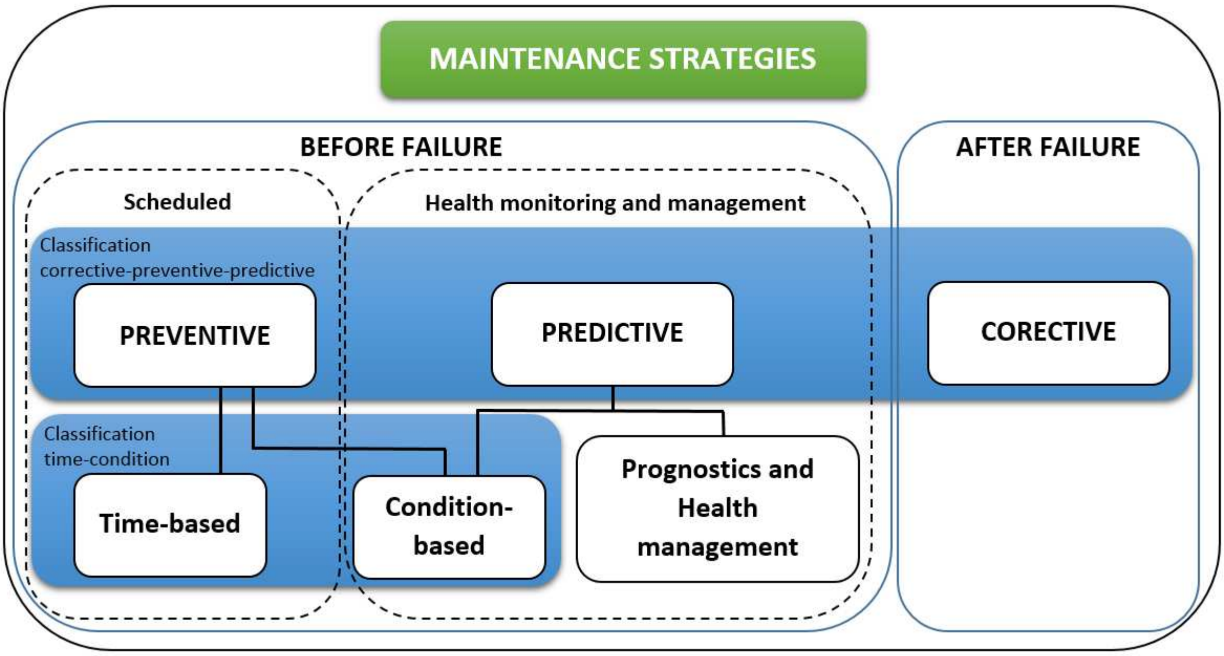

Figure 1 Maintenance strategy overview [11]

Predictive maintenance can solve the following problems: predict device failure in the future, identify unusual behaviour of the device, estimate the remaining life of the device, warn of incorrect setting of operating parameters [4]. Predictive maintenance thus brings innovations to the company, which improve the current maintenance system. For several years now, a set of OECD manuals has been used as a guide in science, research and innovation. The "Oslo Manual" [13] focuses on defining the concepts of innovation and innovation activity, and its definitions are currently used by 80 countries around the world. The Oslo manual defines an innovation as [13]: *"a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)"*. This definition uses the generic term "unit" to describe the actor responsible for innovations (companies, households or associations).

The latest edition of the Oslo manual reduces the previous list-based definition of four types of innovations (product, process, organisational and marketing), to two main types: product innovations and business process innovations. Predictive maintenance is key to optimizing internal processes, boosting service levels and ultimately increasing customer satisfaction. The benefits that PdM brings can be classified as business process innovation, which are defined as [13]: *"a new or improved business process for one or more business functions that differs significantly from the firm's previous business processes and that has been brought into use by the firm"*. Business process innovation include: production, distribution and logistics, information and communication systems [13].

Although PdM is a fundamental pillar of the Fourth Industrial Revolution - PdM 4.0 [5,14,15], very few companies can still predict the future failure of machines with sufficient accuracy and immediately apply the most effective preventive measures to the detected deviation. In most companies, predictions are made without smart sensors and artificial intelligence. They use diagnostic tools for measurement (vibration, temperature, or oil quality) to create short-term predictions. Predictive maintenance is at different levels in different companies and this influence significantly logistics and manufacturing processes. The authors Mulders and Haarma describe four levels of the company's Predictive Maintenance Maturity Matrix (Figure 2). The individual levels are defined as follows [16,17]:

Level 1 – Visual inspections: periodic physical inspections. The conclusions are based solely on inspector's expertise.

Level 2 – Instrument inspections: include expanding technical expertise and instrument inspections at periodic intervals, which provide more specific and objective information about machines. The conclusions are based on a combination of the 'inspector's expertise and instrument read-outs.

Level 3 – Real-time condition monitoring: continuous real-time monitoring of assets, with alerts based on pre-established rules or critical levels. The machines are constantly monitored by sensors that provide up-to-date data representing the state of the machine.

Level 4 – Predictive maintenance 4.0: continuous real-time monitoring of assets, alerts sent based on predictive techniques, such as regression analysis. It is about predicting future machine failures and the immediate application of the most effective preventive measures.

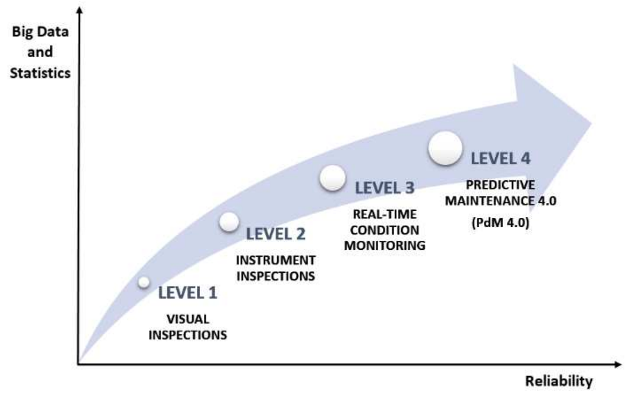

Figure 2 Predictive Maintenance Maturity Matrix [16]

When implementing predictive maintenance in the company, it is essential to know which individual types of failures can be identified from the available data and which parameters need to be collected. In the case of a large number of machines and devices in the company, it is not necessary to install sensors on all of them. First, it is required to focus on critical machines, the failure of which would directly affect production or stop it. Predictive maintenance research has a lot of attention in industry and academia due to its potential benefits in reliability, safety, and maintenance costs, among many other benefits. Predictive maintenance might [11]:

- reduce maintenance costs by 25%–35%,
- eliminate breakdowns by 70%–75%,
- reduce breakdown time by 35%–45%,
- and increase production from 25%–35%.

Predictive maintenance also requires less staffing of the maintenance department. Machine learning excels precisely in the tasks that consist of analysing a large amount of data. In practice, it is not realistic to accept a top expert for each machine, who will analyse hundreds of measurements a day. However, this is not a problem for artificial intelligence [4]. Despite the many benefits of PdM introduction, companies also have to deal with the risks during its implementation. The risks of PdM include [4]:

- *Early termination of the PdM project* – a longer time is needed to find hidden failures in the machine learning model.
- *It is impossible to predict the collected data* – at first, it is essential to analyse the types of failures (FMEA analysis) and then implement the Proof-of-Concept phase.
- *Overconfidence in the power of machine learning* - PdM cannot completely replace preventive

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maintenance and diagnostics. However, it can reduce its need and extend inspection intervals.

- *Risk of later return on investment* - data scientists can wait weeks or even months for the data they need to analyse and make suitable predictive models.
- *Reprogram of machine learning models* - sometimes machine learning models need to be reprogrammed, which is more time consuming.
- *Missing professional employees* – not enough specialists and data scientists.

3 Methodology

Following the goal of the presented paper, we focused on increasing the PdM maturity matrix to a higher level in a selected industrial enterprise. The modified preventive maintenance model was used to identify the current state of the level of maturity and perform the analysis following the recommendations of the strategic document Manual for companies for the introduction of artificial intelligence [4]. The conducted model of preventive maintenance contains six steps for the implementation of predictive maintenance in the company: identification of critical equipment and its parts; identification of degradable mechanisms and key parameters; implementation of equipment monitoring, montage of detectors, data analysis and trend identification, evaluation of results/project. In addition to implementing these six measures, companies must also ensure that they comply with the following six predictive maintenance assumptions: People, Applications, Infrastructure, Process, Data, and Organisation. We would like to emphasise that the implementation process fails if the company plans predictive maintenance but does not have enough specialists with specific comprehensive knowledge about the equipment and the technology. It is also necessary for success of project to create an infrastructure for collecting the specific data for prediction analysis. This innovation might include a transformation of the whole organisation, its corporate culture and thinking towards change from "traditional" to "digital" maintenance. The described model of preventive maintenance is presented in Figure 3 below.

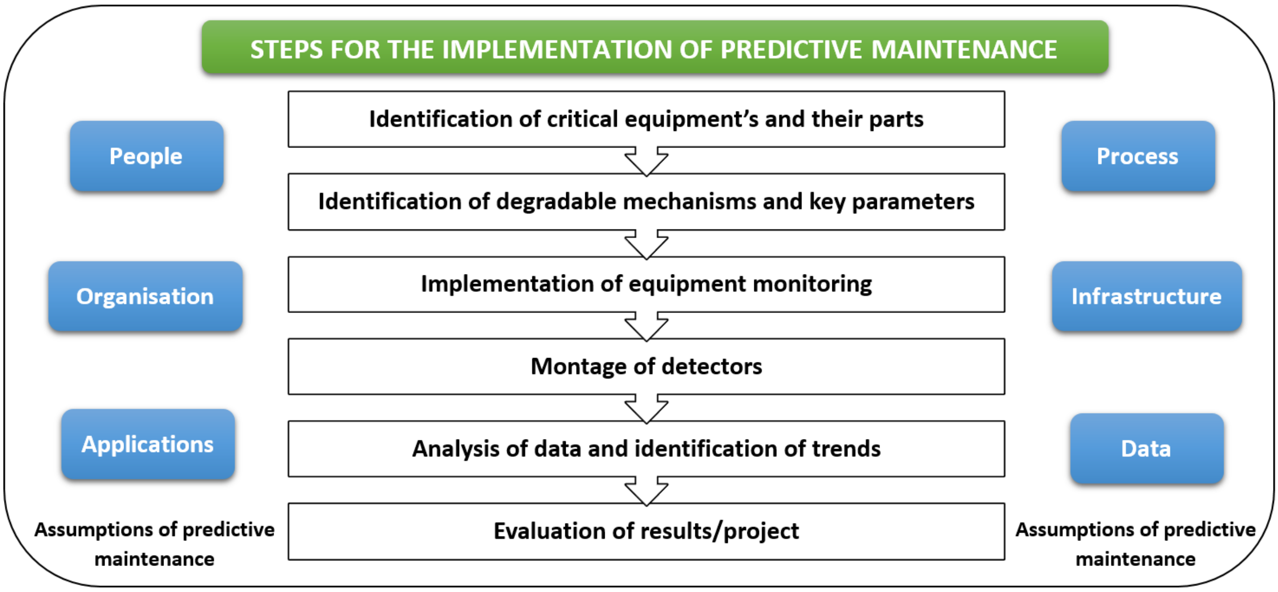

Figure 3 Modified model for implementation of predictive maintenance

The FMEA (Failure Mode and Effect Analysis) was used to identify the main causes of the failures. FMEA analysis was used to identify and assess the risk of potential mistakes, as well as their consequences [18-21]. Each threat was assessed according to its probability of occurrence (P), severity (S) and detection (D). The risk priority number (RPN) was calculated according to the formula

$$RPN = P \times S \times D \qquad (1)$$

Where [18]:

- P - probability coefficient, specifying the frequency of occurrence of the machine failure associated with a given risk, on a scale from one to ten, where one means no occurrence, and ten is for occurrence in each production cycle.
- S - severity coefficient, which determines how severe the given risk of the machine failure is, on a scale from one to ten, where one means negligible importance, and ten very high.
- D - detection coefficient, which determines the degree of difficulty in counteracting a given type of structural failure (early detection of the cause), is very difficult on a scale from one to ten, where one is an easy possibility to counteract, and ten is very difficult.

The risk priority number (RPN) may vary from one to 1000. The higher the RPN value is, the greater the risk associated with the threat is.

4 Results and discussion

This part of the paper focuses on applying the introduced modified model to implement predictive maintenance in the selected enterprise as a case study. The analysed industrial enterprise focuses on producing rubber-metal and plastic parts for the automotive industry, rail vehicles, ships, and aircraft. According to analysis, several types of maintenance are performed in the enterprise (autonomous, operative, preventive).

The technical diagnostics helps to avoid costly maintenance interventions, especially for critical machines. The enterprise has 354 machines and equipment, while technical diagnostics focuses on the following three areas: tribodiagnostics, thermodiagnostics and vibrodiagnostics.

- Tribodiagnostics is a method of diagnostics to detect, evaluate, and report foreign substances in the lubricant and its change from a quantitative and qualitative point of view. The oil level monitoring is performed on 130 machines in the analysed enterprise.
- Thermodiagnostics as a non-contact temperature measurement can be used wherever the diagnosed parameter is heat radiation. The aim of thermodiagnostics is to locate a possible problem on the machine caused by excessive overheating of its parts and to eliminate it in time. For measuring surface temperatures, such motors, heating coils and pumps are used by a handheld thermal imager. Thermodiagnostics determines whether the measured temperature exceeds the limit value (temperatures on the hydraulic circuit must not exceed 60 °C when the hydraulic oil loses its properties and degrades rapidly) or whether the measured temperature of the equipment during tempering does not deviate from reality. Another type of technical diagnostics that is performed in the enterprise on 120 machines is thermodiagnostics.
- The vibrodiagnostics aims at the smooth and reliable operation of the device. The service life of bearings can be affected by several factors, such as speed, dirt, working temperature, lubrication efficiency, bearing stress. Vibrodiagnostics locates the fault and determines the current state of the machine using a vibration sensor. It is non-disassembly diagnostics without the need to stop production. In the presented case study in the mentioned enterprise, there are 143 rotary machines on which vibrodiagnostics is performed. Competent employees who perform this type of technical diagnostics try to determine when the bearing is coming the end of its life.

The analysed enterprise is indicated on the second level PdM maturity matrix (Figure 2). Monitoring of the technical condition of machinery is performed at specified intervals, which are shortened and archived if necessary. Exceeded limit values are monitored. In the case of limit values, the evaluation is subjective, performed by technologists without sufficient theoretical knowledge about predictive maintenance and statistical data processing.

4.1 The procedure of introducing predictive maintenance on a production line in an industrial enterprise

The transition of an industrial enterprise to the third level of Predictive Maintenance Maturity Matrix requires real-time monitoring of machine condition, where sensors continuously collect data on the state of individual machines and equipment. Sensors send alerts based on predetermined rules or when critical levels are exceeded. According to the Manual for companies for introducing artificial intelligence [4], the introduction of Level 3 of the Predictive Maintenance Maturity Matrix was implemented online L in the following six steps.

1. *Identification of the critical equipment and its parts*

Simultaneously with the analysis, a simulation of predictive maintenance on a selected production line was carried out to identify problems and shortcomings that would not be revealed themselves. The selection of a specific production line was based on the ABC categorisation of machines as follows: Group A are strategic machines considered critical because a failure on the machines of this group causes partial or complete shutdown of production. Malfunctions on these machines result in high financial losses and the possible occurrence of a dangerous accident. Group B includes machinery with high priority, but in the case of failure, there will not be such severe consequences for the enterprise's production activity as for machines from the group A. The group C consists of other auxiliary devices that are not included in groups A and B. Based on the above classification of machines, machines from the group A have the highest priority, and it is essential to make predictions of possible failures. The mentioned group in the enterprise includes the production line with the working name Line L as the subject of the analysis. The L-line includes vulcanised parts for damping vibrations and vibrations in cars, the so-called silent blocks.

As already mentioned, the Line L belongs within the ABC categorisation among the equipment of the group A, the failure of which can cause a partial or complete shutdown of production. Based on the failure analysis (FMEA), two rivet heads in series were identified as critical for operating a given production line. The production and service of rivet heads are carried out exclusively in the country of the manufacturer, in the area outside the European Union. The logistical activities associated with the service take two weeks, and complications due to the customs procedure are several weeks longer. For this reason, it is essential to correctly predict the wear of the rivet heads, as their unexpected damage would cause undesirable production downtime.

2. *Identification of degradation mechanisms and key parameters*

First, the main parts of the rivet head were identified. The rivet head consists of the following functional elements: hydraulic, mechanical, pneumatic, and electrical. Based on FMEA analysis, critical parameters and degradation mechanisms were identified for individual components of the rivet head: the type of failure (error) that can occur on the component (equipment), the cause of the fault and the consequences of the fault. The FMEA analysis showed that all failures with the most significant impact on the functionality of the rivet head are indicated by an increased operating temperature, which is well measurable, distinguishable from the usual operating temperature. If the fault persists, the temperature usually rises. Early detection of disorders helps to prevent them easily because most disorders begin as an abnormality.

3. *Implementation of machine monitoring*

The implementation of condition monitoring for the critical equipment includes installing the necessary sensors, a system for collecting and storing this data and subsequent monitoring [16]. Based on the previous analysis and experience, it was found that the most failures on the rivet head are indicated before by an increase in operating temperature. For this reason, a temperature sensor was placed for condition monitoring.

4. *Installation of sensors*

In order to monitor the temperature of the machine, it was necessary to map the surface temperatures of the device during production. Surface temperatures were measured using a thermal camera applied in the enterprise for the thermodiagnostics. The highest temperatures were measured at the tip of the tool that forms the semi-finished product. A temperature sensor with a set alarm temperature of 60 °C, which is the upper limit of the operating temperature of the hydraulic oil, was then installed at the identified location. After several experiments, the sensing temperature period was set at ten minutes. The optimal time for measurement might be set so that the temperature is not sensed too often, causing an amount of unnecessary data, but sensing at long intervals is not recommended so as not to detect abnormalities in the operation of the rivet head.

5. *Data and trend analysis*

Data analysis is a necessary assumption for the correct implementation of predictive maintenance. A cloud application already provides the basic visualisation of data (temperatures over time). However, this data was exported to a spreadsheet processor Microsoft Excel to work with the measured data. The production was interrupted when it was necessary to wait for the parts to cool down after vulcanisation or a failure occurred and due to production interruption during the corona crisis (Figure 4a). Temperature values were excluded from the data set for further data analysis when the rivet heads were not in operation (Figure 4b). The next issue was the identification of the presumed temperature trends from the measured values. The values of the temperatures of the rivet heads during the production process are considerably fluctuating, and it is not easy to identify trends. The function of linear trendline in the Microsoft Excel program was used to indicate the possible trend of temperature values, ordering one-dimensional data in a straight line towards the future.

6. *Assuming the case study*

The assumed trend of the temperatures of both rivet heads indicates an increasing character of temperatures from the beginning of the measurement (Figure 5). The more reliable long-term prediction will require longer-term measurement and a more extensive data set. However, the presented procedure and scope of the conducted analysis, when diagnostic sensors were mounted on the rivet head, was sufficient for base recommendations to improve the level of Predictive Maintenance Maturity Matrix in an enterprise. A primary trend visualisation has been introduced into the enterprise, which is also well usable in processing scanned data in vibrodiagnostics and is easy to understand by workers responsible for technical diagnostics without special training. In this solution, the knowledge of employees trained at Six Sigma was used, representing a good base of statistical knowledge for future prediction needs. Implementing the *Manufacturing Execution Systems* (MES) system is planned to start in the enterprise.

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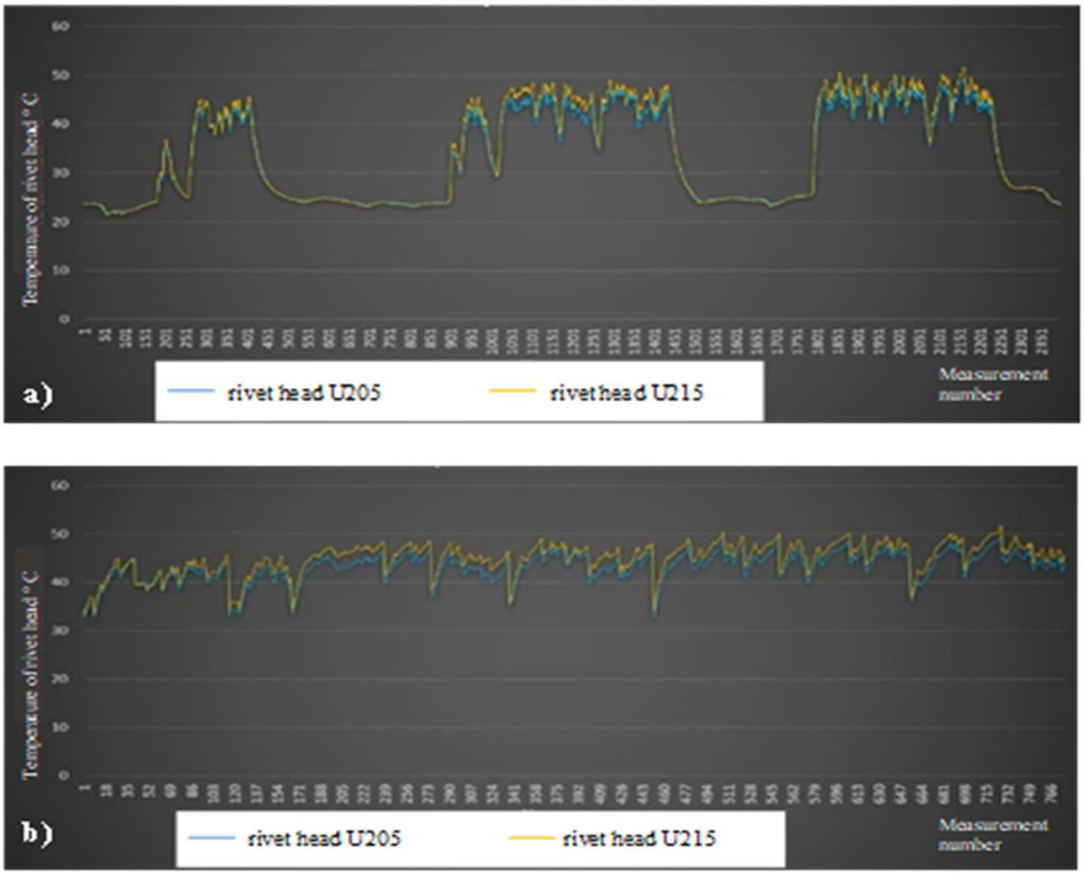

Figure 4 Temperature profile of rivet heads a) during production time and non-production time b) during production time

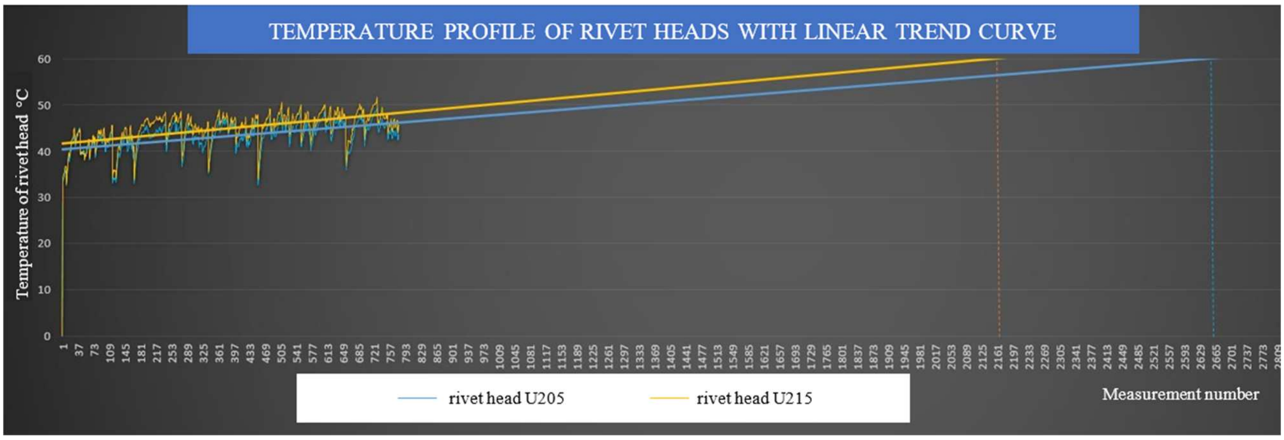

Figure 5 Temperature profile of rivet heads with linear trend curve

4.2 Prerequisites for improving the level of Predictive Maintenance Maturity Matrix in an industrial enterprise

The next part of the paper describes the key assumptions (Process, Infrastructure, Applications, Data, People and Organisation) that an industrial enterprise should analyse to improve the Predictive Maintenance Maturity Matrix [4]. The individual assumptions are closely related to the steps based on which the proposal to introduce predictive maintenance on Line L was implemented (Figure 3).

Process: The first prerequisite for the correct operation of predictive maintenance is familiarity with the whole process. The company should map its technology well, identify diagnostic methods on its equipment, know the types of failures and, above all, the causes, and conditions under which the failure occurs. A thorough analysis of the maintenance department was performed in the analysed enterprise. Machines were divided according to the ABC categorisation, and individual types of technical diagnostics were identified. Realised technical diagnostics were performed on the machines using specialised diagnostic devices.

It is necessary to perform a comprehensive analysis of machinery and equipment throughout the enterprise for the analysed industrial enterprise to move to the third level of Predictive Maintenance Maturity Matrix. Consideration should be given to the use of Predictive Maintenance 4.0 tools in terms of return on investment and safety and health, property, environment, or legislation under the supervision of an entity with experience in implementing such projects. The analysis must include identifying critical and less critical parts of the equipment, understanding their function, and identifying safe operating conditions. The FMEA method [21] is suitable for determining degradation mechanisms and their detection, which has also proved successful in the analysis of Line L.

Proper mapping of the whole process is a key part of the individual assumptions. If the company correctly identifies individual processes, it can determine which need to be optimised or transformed.

Data: If a company plans to predict, a collected data database is needed - measured values from sensors just before the fault and under different operating conditions. However, it is not necessary to focus only on the negative data that arises in the case of a failure. It is needed to have a sufficient database from a standard operation, during which the failure did not occur. Data collection must be preceded by a correct definition of the individual processes, so the data is collected only from devices on which predictive maintenance makes sense [4].

The analysed enterprise collects data unsystematically. The amount of collected data is not suitable for possible prediction, and at the same time, the data collection is realised in long time intervals. In this case, it is important to analyse current data [22] and select just those data on which the actual state of the equipment can be determined as accurately as possible.

Applications: For each plant, it is possible to assume different equipment for machines, and information systems may also be different for predictive maintenance, MES (Manufacturing Execution System), PLM (Product Lifecycle Management), ERP (Enterprise Resource Planning) will most often be used. An industrial enterprise can have all applications available or only selected applications, even from different manufacturers. Data collection systems such as MES., SCADA (Supervisory Control and Data Acquisition) are often enriched with additional data from ERP, CMMS (Computerized Maintenance Management System), EAM (Enterprise Asset Management) systems. Many EAM, CMMS systems today provide predictive maintenance as a package (from data collection to maintenance scheduling) [4].

For the analysis of the L-line, a freely available mobile application (EasyLog Cloud) for smartphones with the Android operating system was used. The application offers a basic overview table of the device, which ich named "Mote1". The application provides graphical processing of measured data. The visual output of the measured data (Figure 6) shows the course of temperatures on the rivet heads over time. The blue curve represents the measured temperature on the rivet head U205 and the red curve on the rivet head U215. The measured data were exported to Microsoft Excel spreadsheet.

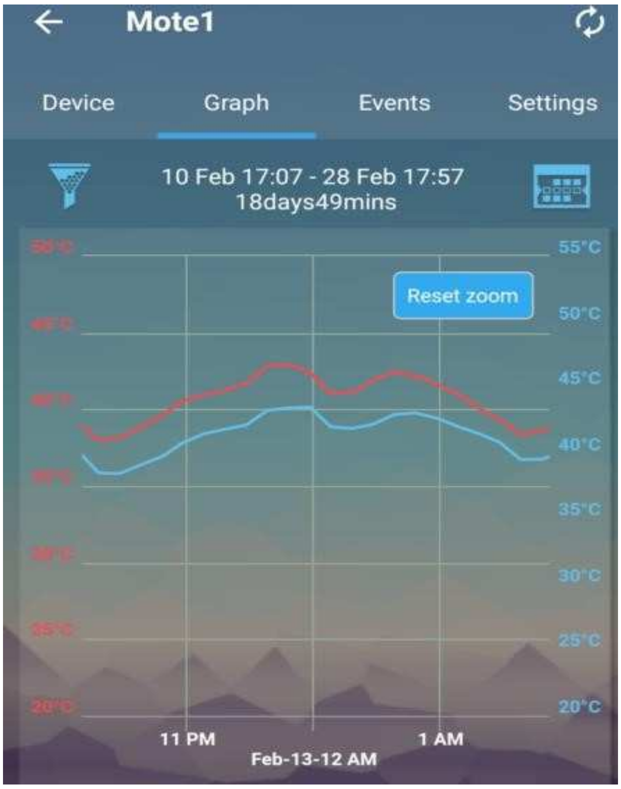

Figure 6 Display of measured operating temperatures of rivet heads over time

The selection of suitable applications for data collection, processing and display always depends on a specific enterprise, unique in its capabilities and current needs. However, the EasyLog Cloud application is used, and it is insufficient to implement enterprise-wide predictive maintenance. Currently, the analysed enterprise is working on introducing the MES approach [23], which is used to monitor production in real time. In this phase, the system is focused on production data from machines, which are then processed, evaluated, and visualised. According to the available information, the infrastructure is ready for data transmission for predictive maintenance.

Infrastructure: At present, traditional informational technologies (IT) in enterprises is replaced by cloud solutions, where the customer buys the service of a software solution and does not deal with the technical infrastructure on which this solution runs. As part of data transmission, basic processing, visualisation, and availability, the analysed enterprise was proposed to use the IoT sensor infrastructure (Figure 7), in which sensors mounted in machines send data directly to the cloud via a wireless Internet connection [24]. The main benefits when changing from traditional systems are the raise of flexibility, robustness, efficiency and also the chance for mastering the actual complexity [25].

The acquired data as part of logistics information flow can be monitored using a mobile application, and, if necessary, it can be exported to a corporate spreadsheet.

Figure 7 Diagram of IoT sensor infrastructure [24]

People: Although the gradual transition to predictive maintenance in the context of Industry 4.0 and Logistics 4.0 presupposes more maintenance staff, experts are required to analyse the moments in which artificial intelligence fails. According to Bronislav Balga [26], a specialist in business performance improvement, maintenance has been struggling for several years with the scarcity and quality of maintenance workers, which in recent years has shown very little or no progress towards Industry 4.0.

The analyzed enterprise has 41 employees in the maintenance department (from total of 850 employees). The main factor for implementing the proposed measures is the targeted training of maintenance department staff in prediction. Even under the influence of new modern technologies beyond the current understanding of predictive maintenance, the enterprise must continue to educate its employees. Predictive maintenance workers at Level 2 are experts in their field with extensive practical experience, but training in predictive maintenance is still necessary. Top employees should also understand the creation of predictions of failures and residual life of the equipment or its critical part. They should not passively rely on ready-made solutions provided by the technology supplier but also actively engage in improving predictions.

The enterprise must focus on improving the qualifications of employees in this area and, if necessary, cover some positions with representatives of third parties - external consultants. These are mainly professional functions, namely [4]:

- Data engineers who manage the data and the relevant data platform to make it fully functional for analysis;
- Data scientists who prepare, study, visualise, and model data on a data science platform;
- IT architects manage the basic infrastructure needed to support data science;
- Application developers deploy models to applications to create data-based products;
- Experts for data visualisation and interpretation.

Organisation: As in the presented case study, managers in the companies are often not fully aware of predictive maintenance benefits. The transition of an enterprise to predictive maintenance in the context of Industry 4.0 is more than just IT issue. It requires the transformation of the whole organisation, its corporate culture, which will change from "traditional" to "digital". It is a culture that prioritises employee engagement, stimulates experimentation with new technologies, and new ways of working. The culture will need to stimulate cross-functional cooperation and is comfortable with data-driven decision-making, even if decision-making goes against managerial and employee experiences and introduces a new way of thinking [10,27].

A prerequisite for successfully implementing maintenance using Industry 4.0 and Logistics 4.0 tools is support from the enterprise's top management, which will provide resources (finance, people, infrastructure, software, time, training) for its implementation, maintenance, and further development. When implementing the solution, it is appropriate to create expert working groups, within which there will be cooperation between maintenance technicians and data analysts who know the predictive model and its possibilities. The process of implementation requires a considerable amount of documented information [28,29]. In this step it is important to raise awareness of the various benefits of prediction across the enterprise [30,31].

5 Conclusions

Maintenance is necessary for the proper functioning of logistics in any industrial enterprise. Choosing the right strategy of maintenance can be saved a lot of work, time, and money. Predictive maintenance can manage maintenance more efficiently. Industry 4.0 and Logistics 4.0 concept opened a new horizon of possibilities using the most modern intelligent technologies streamlining maintenance in their company. Predictive maintenance is a key activator and impetus for Industry 4.0 and Logistics 4.0, while still facing several challenges in practical implementation from a technical and commercial point of view. Managers need to be aware of the main challenges to prepare for the digital transformation of production and the transition to the Industry 4.0 revolution.

The aim of this paper was to present and describe the steps and assumptions needed to improve the current state of the Predictive Maintenance Maturity Matrix in an industrial enterprise. Based on the analysis results, the enterprise can move to the third Level of PdM maturity matrix. Then following benefits will be achieved: reduced failure rates, reduced unplanned downtime and extended maintenance cycles, increased production, reduced spare parts, extended equipment life, increasing safety and reducing maintenance costs. Quality improvement in predictive maintenance will influence positive return on investment in approximately 3-5 years. Several studies confirm that predictive maintenance management benefits overall operations in both manufacturing and process plants [32]. However, with all the benefits of predictive maintenance, the risks and obstacles to its implementation should not be forgotten [33]. The real challenge is not in sensor technology, data processing, condition monitoring or correct diagnostics. These solutions are highly advanced and their implementation requires extensive knowledge and understanding. Thus, the implementation of contemporary solutions in the field of Industry 4.0 and Logistics 4.0 requires that the organization first improve the absorption of knowledge [34]. This concept, introducing revolutionary changes in manufacturing and logistics, will fundamentally change society and economy [35]. Businesses now need to focus on the predictive skills of their employees and support processes and opportunities that will support the creation of a new predictive-oriented business model.

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