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DEVELOPMENT OF A HYBRID PREDICTIVE MAINTENANCE MODEL

Opracowanie hybrydowego modelu predykcyjnego utrzymania ruchu

Abstract: *Progress in the field of technology and science enables the digitalization of manufacturing processes in the era of Industry 4.0. For this purpose, it uses tools which are referred to as the technological pillars of Industry 4.0. Simultaneously with the changes in the field of manufacturing, the interdisciplinary cooperation between production and machine maintenance planning is developing. Different types of predictive maintenance models are being developed in order to ensure the good condition of the machines, optimize maintenance costs and minimize machine downtime. The article presents the existing types of predictive maintenance and selected methods of machine diagnostics that can be used to analyze machines operating parameters. A hybrid model of predictive maintenance was developed and described. The proposed model is based on diagnostic data, historical data on failures and mathematical models. The use of complementary types of predictive maintenance in the hybrid model of predictive maintenance is particularly important in the case of high-performance production lines, where high quality of products and timeliness of orders are crucial.*
Keywords: maintenance, predictive maintenance, maintenance models, diagnostics, diagnostic methods, Industry 4.0, Maintenance 4.0, digitalization

Streszczenie: *Postęp w dziedzinie techniki i nauki umożliwia digitalizację procesów wytwórczych w erze Przemysłu 4.0. Wykorzystuje w tym celu narzędzia, które określane są jako filary technologiczne Przemysłu 4.0. Równocześnie ze zmianami w dziedzinie produkcji rozwija się interdyscyplinarna współpraca między produkcją a planowaniem obsługi maszyn. W celu utrzymania maszyn w należytej kondycji oraz optymalizacji kosztów obsługi i czasów przestojów, rozwijają się różne typy predykcyjnych modeli obsługi. W artykule przedstawione zostały istniejące typy predykcyjnej obsługi oraz wybrane metody diagnostyki maszyn, które mogą zostać wykorzystane do badania parametrów pracy maszyn. Opracowany oraz opisany został hybrydowy model predykcyjnej obsługi,* *wykorzystujący dane diagnostyczne, dane historyczne dotyczące awarii oraz modele matematyczne. Wykorzystanie w hybrydowym modelu predykcyjnej obsługi uzupełniających się typów predykcyjnej obsługi jest szczególnie istotne w przypadku wysokowydajnych linii produkcyjnych, gdzie kluczowe są wysoka jakość wyrobów oraz terminowość wykonywanych zleceń.*

Słowa kluczowe: obsługa maszyn, utrzymanie ruchu, predykcyjna obsługa maszyn, predykcyjne utrzymanie ruchu, modele utrzymania ruchu, diagnostyka, metody diagnostyczne, Przemysł 4.0, Utrzymanie ruchu 4.0, digitalizacja

1. Introduction

The fourth industrial revolution, unlike the previous ones, does not aim at mechanization and automation of manufacturing processes, but at their digitalization [1]. For this purpose, it uses achievements in the field of science and technology that enable the digitalization of manufacturing, as well as rapid development in the field of data processing and Internet technologies. The result of progressive digitalization is the transformation of manufacturing enterprises and the formation of Smart Factories, in which production systems are autonomously controlled by computer programs [1, 2].

In Industry 4.0, manufacturing is being revolutionized by increasing flexibility, greater customization possibilities than before, and improving quality and productivity [3]. An additional advantage, important from the point of view of enterprises, is also ensuring savings related to the production line operation by automating system monitoring, early detection of damage, reduction of machine downtime and predicting the functioning of equipment [4].

Technological pillars of Industry 4.0 have been described in numerous literature sources. Their use in the industry enables improvements in specific areas of production enterprises when implemented individually or in combination of a larger number of them [3, 5]. From the point of view of a modern production plant, all of the technological pillars may be important, but their selection must depend on the type of production structure, the size of production series or the industry in which they would be implemented [6]. Technological pillars of Industry 4.0:

- Industrial Internet of Things – the use of IoT technology in an industrial environment in order to fulfil tasks specific to industry [7]. Its goal is to integrate machines so that they can communicate without human participation,
- Big Data and Analytics – large and complex data sets, the processing and analysis of which influence decision-making processes in enterprises, can be used in very wide range, from the analysis of customer preferences to damage prediction in order to reduce the duration of failures [5],
- Horizontal & vertical system integration – integration of flexible and reconfigurable system inside the enterprise (referred to as vertical) with cooperants in the supply

chain (referred as horizontal layer), it is crucial from the point of enterprises agility [3, 5],

- Simulation – enable verification of designed or adopted solutions with the use of computer software before they are implemented in a real system [8],
- Cloud computing – a definition of utility calculations carried out in the cloud, in essence the use of computing, network and memory resources in real time [9]; it enables to share data from connected production machines to the cloud and store them in memory resources,
- Augmented Reality – a technology used for interaction between humans and machines, which enables the imposition of digital data on reality, which can be used, among others, in maintenance or other operating procedures [3, 10],
- Autonomous Robots – smart devices which are able to perform manufacturing tasks and cooperate with each other and with manufacturing operators [3, 10],
- Additive manufacturing – a manufacturing technique which enables fast and automated production of designed prototype components and small production series; moreover it enables manufacturing of complex shapes that are unattainable with other manufacturing techniques [11, 12],
- Cyber Security – ensuring reliable and secure communication, access control and security of company data and documents, as well as counteracting cyber threats [10].

In the era of Industry 4.0, one of the key issues is machine maintenance [13] and interdisciplinary cooperation between production and machine maintenance planning [3]. For this purpose, techniques such as IoT (Internet of Things), Big Data, integration of AI (Artificial Intelligence) and Cyber-Physical Systems (CPS) are used [14, 15]. The development of modern techniques allows for the evolution of diagnostics for continuous, automatic monitoring of the technical condition of machines [16]. Cyber-Physical Systems (CPS) can be defined as intelligent systems which consist of physical and computational components, very well integrated with each other, having a high degree of complexity in time and space scales [15]. The use of Cyber-Physical Systems in manufacturing systems is particularly important due to the need to have significant computing power to process numerous measurement data and achieve the goal of detecting defects [17].

The maintenance of the machine park in production enterprises is an integral part of resource management and one of the processes supporting production [16]. Maintenance can also have a significant impact on the costs of current operation of enterprises, affecting energy consumption, CO_2 emissions and the involvement of additional company resources [18]. It also affects the efficiency and productivity of manufacturing [16].

There are many factors that affect maintenance. These include selection of an appropriate maintenance strategy [16], staff qualifications, having factory standards, having a spare parts warehouse, having financial resources, legal regulations, care for the sustainable development [18, 19]. The area of diagnostics is directly related to the machines maintenance, in particular to predictive maintenance, which allows, among others, for determining the technical condition of machines and their components [20].

The aim of the article is to analyse the literature sources and characterize the basic maintenance strategies that are used in the industry: reactive, preventive and predictive, as well as selected techniques of machine diagnostics. The result of the literature review and own study is the development of a hybrid predictive maintenance model using machine diagnostics, historical data on failures and mathematical models prepared on their basis. The development of an author's concept of a hybrid predictive maintenance model aims to improve the effectiveness rate of machines. The use of complementary types of predictive maintenance enables an interdisciplinary approach to predictive maintenance, which is particularly important in high-performance production lines, where high quality of products and timeliness of orders are crucial (e.g. pharmaceutical and tobacco industries).

2. The use of diagnostics in the maintenance of machines

2.1. Predictive maintenance strategy

Machines maintenance strategies have evolved with advances in technology. Initially, maintenance actions were undertaken when a failure occurred (reactive maintenance strategy). Then the preventive maintenance strategy gained popularity, when repairs or replacements of components began to be planned. Along with technological development, the predictive maintenance model has gained popularity in recent years. According to literature sources, maintenance strategies can be divided into two main groups: reactive and preventive/predictive maintenance [21, 22]. In the second group, two main types of maintenance strategies can be distinguished: Time-Based Maintenance (TBM) and Condition Based Maintenance (CBM).

Time-Based Maintenance (TBM) uses the manufacturer recommendations, failure history, and the experience of maintenance personnel or operators to determine maintenance intervals. Due to the fact that this methodology do not use additional diagnostic devices and data, it is also easy to implement [22, 23]. On the other hand, Condition-Based Maintenance (CBM) is proactive and uses predictive models based on diagnostics to make decisions when it is necessary to perform specific maintenance activities to avoid unnecessary repairs or maintenance actions [22, 24]. Due to the presence of a monitoring system that monitors selected parameters, a machine Condition-Based Maintenance strategy (CBM) is more difficult to implement than a Time-Based Maintenance (TBM) strategy. However, due to numerous advantages, its use is becoming more and more popular [23]. A comparison of the three main machine maintenance strategies, based on selected criteria, is presented in Table 1.

Predictive maintenance is one of the concepts in which maintenance actions that maximize reliability of resources or systems are precisely matched to their technical condition. In this concept, maintenance determined by the condition of resources or systems (Condition-Based Maintenance) is supported by tools for monitoring their specific parameters and for predicting failures. Prediction based on diagnostic data makes it possible to predict trends and their correlation using statistical models or machine learning [4, 18, 25]. According to the concept, damage to the machine or its component should be detected by automatic monitoring system as soon as its degradation begins, and maintenance actions aimed at restoring the technical condition ensuring proper functioning should be planned and performed before complete damage and change the machine or its component into a state of inoperability, as shown in Figure 1.

Table 1

Comparison of the three main machine maintenance strategies, based on selected criteria

	Predictive maintenance	Preventive Maintenance	Reactive Maintenance
Main assumption	Avoiding unnecessary maintenance	Maintenance planning	Work until a failure occurs
Decision on when to perform the maintenance	Based on technical condition	Based on the specified interval	When repair or replacement is required
Failure data	Numerous data collected, processed and analysed	Data collected	Limited access to data and possibilities of its collection
Diagnostics	Diagnostics and prognosis is a priority	Diagnostics is a priority	No monitoring (and no monitoring costs)

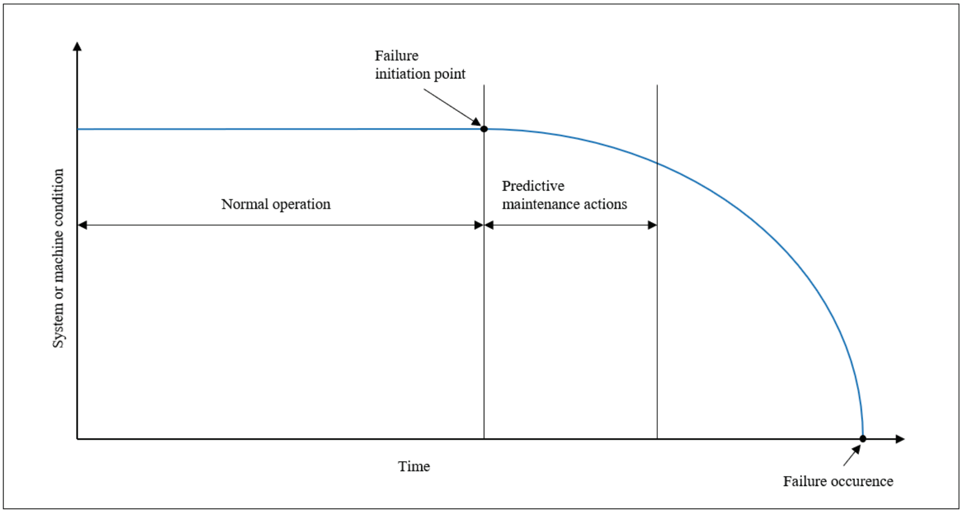

Fig. 1. Diagram presenting the time range in which maintenance actions should be undertaken to eliminate a developing damage, depending on the condition of the machine in the predictive maintenance model

The main goal of predictive maintenance is to undertake maintenance actions before damage develops and the components fails [14] to ensure continuous functioning of production lines and avoid unplanned downtime [9]. Important goals resulting from the implementation of predictive maintenance of manufacturing resources are: reduction of machines downtime, costs, control and improving the quality of products [26], improving reliability, availability and efficiency of production lines [2], increase in productivity by improving accessibility, quality, ensuring economically efficient automated processes for monitoring production systems, early detection of damage, reduction of machine downtime, prediction of the lifetime of the machines [13] and the associated ecological aspect, aimed at sustainable development [6, 27].

Predictive maintenance is a concept within which the different types of maintenance developed. On basis of numerous literature sources, it is possible to specify types of predictive maintenance that are used in practice: experience-based, model-based, physical-based, data-driven, knowledge-based, digital-twin approach and hybrid [2, 28, 29], which are presented in Figure 2. Due to the possibility of optimizing implementation time and costs, it is important to choose the proper technique for a given set of machines or the entire production line. Types of predictive maintenance:

- Experience-based predictive maintenance – model of predictive maintenance, based on experience, using specific principles and factors observed over the years of technical systems maintenance practice [28]; the knowledge possessed by specialists allows to identify failures, components wear and predict failures with the use of historical data; it is the most basic type of predictive maintenance [30];
- Model-based predictive maintenance – a technique based on mathematical models that can be used to describe the components or system wear; in this method, the failure prediction model is used to verify compliance between the values of measured parameters and the expected parameters of the process; some models use Markov chains, statistical models using Gauss and Weibull curves [31]; the linear and Wiener methods are used less frequently [28]; a feature of models of this type is high accuracy of prediction, but their implementation requires costly calculations, and its implementation is possible for a limited set of types of wear [32];
- Physical-based predictive maintenance – a model that uses physical and mathematical models to describe and evaluate component wear; in this method, it is possible to perform an accurate simulation of component degradation using physical models [28, 33, 34];
- Data-driven predictive maintenance – production machines are equipped with sensors monitoring their operating parameters; data obtained from sensors, e.g. vibration, noise, temperature or humidity are recorded and saved in a dedicated memory resources – usually in the cloud [35]; at the same time, they can be used to process and analyse component wear and predict the time to failure or to component wear [28, 33, 36]; The use of data-driven methods combined with machine learning enables the identification of complex relationships between data that are difficult

to detect using physical-based and knowledge-based models [37, 38]. However, this type of predictive maintenance requires the use of significant computational resources;

- Knowledge-based predictive maintenance – a model that is based on knowledge and experience in the system to reduce its complexity [29]; degradation modelling knowledge is based on data from previous failures [39];
- Digital twins approach to predictive maintenance – it consists in combining data and models creating a connection between the real and virtual environment [29];
- Hybrid predictive maintenance – an approach used in Industry 4.0 factories when production systems are complex; the level of complexity of devices and systems makes it impossible to evaluate all machines and components according to one model [28], so hybrid models are created that combine two or more types of predictive maintenance.

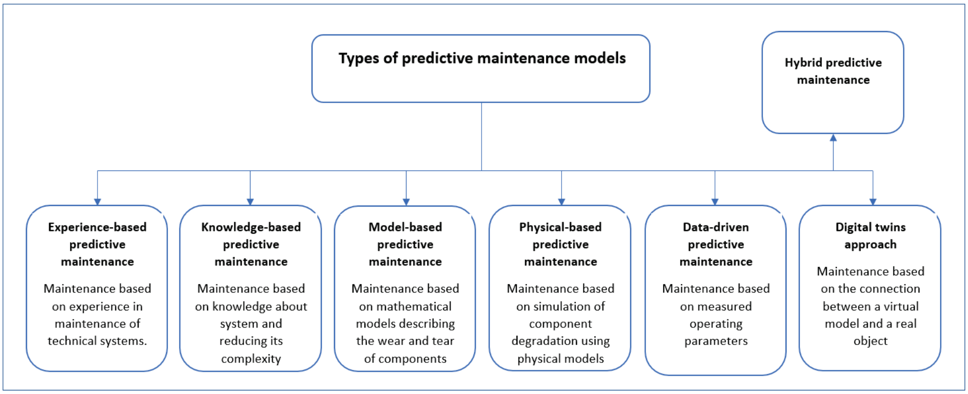

Fig. 2. Types of predictive maintenance models

One of the challenges for fault detection algorithms is the different input formats of data from different sensors. Simultaneous processing of information contained in the form of voltage response, photos, films, graphs and others may lead to the need to use a large number of devices for recording and processing data [40]. Another of the identified challenges in the changes taking place in the industry and the models of maintaining the production equipment is also the aspect of care for sustainable development [18]. In comparison to preventive maintenance, in the predictive maintenance model, components are not replaced at fixed, defined intervals, but depending on their condition. This enables better use of components and minimizes the frequency of replacing parts that remain in good condition. Another important issue from the point of view of sustainable development is energy management in Industry 4.0 [41].

On the basis of the literature review it was concluded that the scientific publications to date refer to the use of one type of predictive maintenance, e.g. [29, 32, 42]. Hybrid predictive maintenance models are a new area of dynamic development in predictive maintenance, and models using two types of predictive maintenance are presented in the literature [2, 43]. Hybrid models can be applied in highly advanced manufacturing systems of the Industry 4.0 era, in which selected components require the use of more than one predictive maintenance type [13, 28]. The author's proposal of a hybrid predictive maintenance model, in contrast, takes into account a combination of three types of predictive maintenance and is dedicated to high-performance production lines.

2.2. Machine diagnostic methods used in predictive maintenance

An indispensable element of the predictive maintenance model is to ensure continuous and automated monitoring of specific parameters of machines and their components. Various diagnostic methods are used to assess the condition of machine components, allowing to examine specific operating parameters important form the point of view of wear. For selected machines or their components, it is possible to select one parameter which will be a subject of ongoing monitoring and analysis, or combination of more than one key parameters. The choice of the diagnostic method to be implemented will depend on the parameters whose change indicates wear and a developing defect. Their proper selection is crucial for the effectiveness of monitoring.

The most important parameters to diagnose in industrial machines are:

- Vibration – vibration sensors are one of the most popular for Condition-Based Maintenance (CBM), especially for machines with rotating components (bearings, shafts etc.); vibrations are tested directly in the machines and vibration diagnostics is one of the non-destructive diagnostic methods; popularly used acceleration sensors can be used for continuous monitoring, while in certain cases it is possible to use more specialized instrumentation [22, 44, 45];
- Visual inspections (based on various types of cameras) – visual inspections based on cameras are implemented in enterprises to detect dangerous situations od risk of failure; they are based on industrial cameras with a specific, usually high resolution, whose image is processed using, among others, neural networks; this makes is possible to perform visual inspections, e.g. on production line and detect dangerous situations or damage in automated manner [46, 47]; this allows e.g. for detecting damage in defected bearings or in damaged refractory coatings for liquids with high temperature (e.g. molten metal); the use of thermography cameras is particularly important in electrical switchboards to detect local hot spots in a non-contact manner [45];
- Power consumption – monitoring of changes in power consumption and in values related to electrical resistance, conductivity and insulation [48]; continuous diagnostics can use changes in power consumption to detect changes that indicate an impending failure; greater motion resistance between components, and thus a greater demand for energy, may indicate wear and the need to replace specific executive components;

- Noise and acoustic diagnostics – noise testing is a technique used in Condition-Based Maintenance (CBM); noise is directly related to vibration and similarly to vibration diagnostic, acoustic diagnostics is used for machines containing rotating components [22, 44]; however, the main difference is the lack of direct contact with the tested machine, which is not possible in the case of using numerous vibration sensors [49];
- Lubricant and oil analysis – in machines that use lubricants and oils, an examination of the lubricant can be a valuable source of knowledge about the wear and tear of cooperating components [22]; the presence of certain undesirable contaminants in the lubricant or oil can indicate the occurrence of failure or the imminent occurrence of failure; oil analysis can be divided into several categories: chip detectors, spectrographic oil analysis and ferrography [45];
- Thermodiagnostics – the most common diagnostic methods used in machines with rotating components (e.g. bearings) and in electrical and electronic modules and devices [22, 50];
- Infrared thermal imaging (IRT)-based diagnostics – a diagnostic method that is an alternative to vibration-based testing for condition monitoring of machines; it is a method based on non-contact measurements, which makes it safer than methods; moreover the method provides highly reliable results; this method has been implemented, among others, in the monitoring of machines with rotating components; the capabilities of the infrared-based method are extensive and make it suitable for electrical and mechanical fault diagnosis [19, 24];
- Pressure – one of the basic diagnostic values that can provide information on the occurrence of a fault (e.g. leakage) [29];
- Humidity – a diagnostic value that can verify, among others, the tightness of specific machine components [28];
- Chemical and environmental measurements – examination of the composition of e.g. exhaust gases, waste liquid, pollutants produced during the process by the machine, or the system may inform about the deteriorating technical condition and wear of specific components [27].

2.3. Cost-intensiveness of maintenance strategies - discussion

Choosing the proper machine maintenance strategy is crucial for companies primarily from an economic perspective. The choice of the right one will be influenced by a number of factors, including the production structure (series, parallel, series-parallel), the level of machine utilisation and having an operating reserve. A predictive maintenance model will work well for serial structures that do not have buffers or have significantly limited product storage between processes. Similarly, its application will be beneficial for machines with very high utilisation and no reserve, and which key spare parts are not or cannot be stored.

When implementing a predictive maintenance model, as important as the choice of the appropriate machine maintenance strategy is the choice of the type of predictive maintenance. During the first implementation of predictive maintenance for a production line, or using predictive maintenance for selected elements of the production system, it will be beneficial to use one of the existing commercial predictive maintenance system. For more specialised and complex production lines and the use of numerous monitoring data, a line-dedicated system may be beneficial.

3. Hybrid predictive maintenance model

One of the basic assumptions of the predictive maintenance model using real-time diagnostic data, which is presented in the article, is to have integrated systems for monitoring, detection and prediction of damage formation and propagation in machine components. In general, in the process of machine maintenance planning with the use of diagnostic data (Big Data), the following stages should be included: data collection, data processing, detection, diagnosis, prediction and decision-making [14].

In order to successfully implement predictive maintenance, a strategy for implementing a hybrid type of maintenance of machines or their selected components has been proposed. It is presented in Figure 3. The algorithm of proceeding considers the following steps:

- Identification of machines and components that can be effectively maintained according to the assumptions for the predictive maintenance model, in essence, have the ability to implement monitoring of critical parameters (e.g. vibration),
- Determination of parameter values that indicate the onset and propagation of component damage – feasible using similar or identical machines (e.g. occurrence of aa certain dominant frequency in the spectrum, increased operating temperature),
- Recording data and detecting the occurrence of dangerous values and their nature or recurrence, addition of information on historical failures and historical failure rates of machines, allowing subsequent ex-post estimation of the operating time from the moment detecting the first signs of component wear until the failure occurs,
- Preparation of an automatic monitoring system with detection of dangerous changes in the parameters under monitoring (use of commercial or system-dedicated software for processing monitoring data, detection of dangerous parameter values and prediction of the moment of failure using historical data and mathematical model adequate to it),
- Launching a system of continuous, automatic monitoring, and in the case of detecting a developing defect, planning, using an ex-ante method, a machine or production line downtime in order to repair or replace the worn-out component.

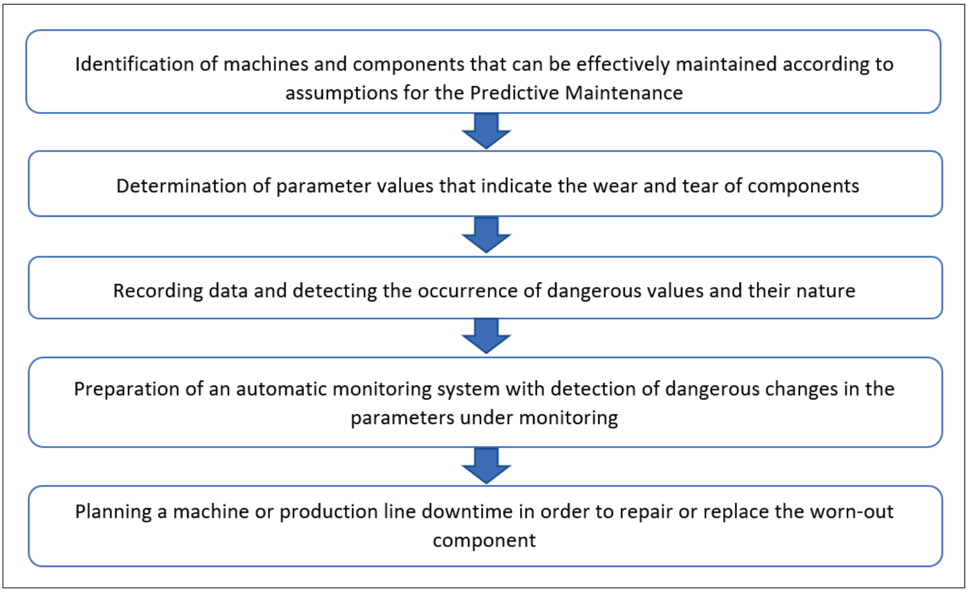

Fig. 3. Algorithm of implementation of a hybrid maintenance of machines or their selected components

The proposed predictive maintenance model can be categorised as a hybrid type of predictive maintenance. On the one hand, the model used diagnostic data coinciding with a data-driven approach, while on the other hand, the model uses historical failure data from the time of the first signs of wear during monitoring (experience-based approach). The model, in turn, is complemented by the determination of the predicted remaining correct operation time using statistical tools, so a type of predictive maintenance based on a mathematical model is also used (model-based approach). The use of this type of model allows a comprehensive approach to determining the appropriate moment when maintenance actions should be planned and undertaken, enabling maximum utilisation of components and, at the same time, minimising the duration of unplanned downtime as well as the funds allocated to stored spare parts. This approach, combined with the maintenance department's knowledge of parts delivery times and component replacement times, allows for the efficient maintenance of key machines.

The monitoring and prediction system in many cases can use specific, fixed parameter values, the exceeding of which will result in the recognition of an impending failure and the prediction of its occurrence time. It is also possible to use system-dedicated software to continuously monitor production system machines and predict failures. However, in certain cases, where the monitoring system is based on, for example, an image capture system, machine learning is a key part of preparing the software needed for an automated machine condition monitoring system [48]. In addition to the appropriately labelled dangerous values of the monitored parameters, which will be used to train the neural network, the system for predicting the remaining time to failure should also use historical failure data [48].

4. Conclusion

The article describes and compares the main maintenance concepts. Particular attention is given to predictive maintenance, which is gaining increasing popularity in industry. The subtypes of predictive maintenance and the diagnostic methods used in the industry were presented. The aim of the article, which included performing a literature analysis of predictive maintenance, its types and diagnostic methods, and developing a hybrid predictive maintenance model, was achieved.

The hybrid predictive maintenance model presented in the article provides a comprehensive approach to determining the remaining correct operation time of components or machines. The implementation of a system using system-dedicated or commercial software to process and analyze data of monitored parameters and the use of predictive algorithms will enable minimization of the occurrence of unplanned machine downtime due to failures in comparison with other maintenance strategies. The main advantages will therefore be to maximize production line efficiency, minimize non-working line time and reduce line stops for maintenance tasks. In addition, the implementation of a predictive maintenance model for production lines using a preventive strategy so far, taking into account the costs incurred to implement a diagnostic and predictive system, can bring financial benefits in the long term, due to performing maintenance only when it is necessary. Another advantage is the environmental benefit, due to the use of fewer spare parts.

The author's concept of a hybrid predictive maintenance model aims to improve the effectiveness of machine operation in production systems. The predictive maintenance methodology proposed in this article, as well as selected diagnostic techniques, will be subjected to further development. The next stage of the research will be the implementation of the developed hybrid predictive maintenance model in a real production system, which is characterized by short production series. According to the assumptions related with the development of the hybrid model, highly repeatable processes will be investigated.

Due to the numerous advantages of a predictive machine maintenance strategy, it will become increasingly popular in manufacturing enterprises. In particular, it is recommended for implementation for machines or systems when high availability is required and when they are strategically important to ensure the continuity of system operation. Despite the need to invest significant funds in implementing a hybrid type of predictive maintenance, for high-performance production lines which operate at near maximum capacity, this type of maintenance can bring benefits in the areas of on-time order execution and ensuring high product quality.

5. References

1. E. Michlowicz, "Logistics engineering and Industry 4.0 and digital factory". Archives of Transport, Vol. 57, Iss. 1, 2021. DOI: 10.5604/01.3001.0014.7484.
2. Q. Cao, C. Zanni-Merk, A. Samet, C Reich., F.B. Beuvron, A. Beckmann and C. Gianetti, "KSPMI: A Knowledge-based System for Predictive Maintenance in Industry 4.0". Robotics and Computer-Integrated Manufacturing, Vol. 74, 2022. DOI 10.1016/j.rcim.2021.102281.
3. L. Silvestri, A. Forcina, V. Introna and A. Santolamazza, "Maintenance transformation through Industry 4.0 technologies: A systematic literature review". Computers in Industry, Vol. 123, 2020. Available: https://www.sciencedirect.com/science/article/pii/S0166361520305698?via%3Dihub
4. Y. Wen, M. F. Rahman, H. Xu and T.L.B. Tseng, "Recent advances and trends of predictive maintenance from data-driven machine prognostics perspective". Measurement, Vol. 187, 2022. Available: https://www.sciencedirect.com/science/article/pii/S0263224121011805
5. G. Erboz, "How to Define Industry 4.0: The Main Pillars Of Industry 4.0. Managerial trends in the development of enterprises in globalization era", presented at Conference: Managerial trends in the development of enterprises in globalization era. Slovak University of Agriculture in Nitra, Slovakia, 2017.
6. E.O.B. Nara, M.B. Costa, I.C. Baierle, J.L. Schaefer, G.B. Benitez, L.M.A.L. Santos and L.B. Benitez, "Expected impact of industry 4.0 technologies on sustainable development: A study in the context of Brazil's plastic industry". Sustainable Production and Consumption, Vol. 25, 2021. Available: https://www.sciencedirect.com/science/article/pii/S2352550920305212?via%3Dihub
7. H. Boyes, B. Hallaq, J. Cunningham and T. Watson, "The industrial internet of things (IIoT): An analysis framework". Computers in Industry, Vol. 101, 2018. Available: https://1library.net/document/y4we065q-industrial-internet-things-iiot-analysis-framework.html.
8. S. Jiang, Cao J., H. Wu and Y. Yang, "Fairness-based Packing of Industrial IoT Data in Permissioned Blockchains". IEEE Transactions on Industrial Informatics, Vol. 17, Iss. 11, 2021. DOI 10.1109/TII.2020.3046129.
9. G. Aceto, V. Persico and A. Pescape, "Industry 4.0 and Health: Internet of Things, Big Data, and Cloud Computing for Healthcare 4.0". Journal of Industrial Information Integration, Vol. 18, 2020. Available: https://www.sciencedirect.com/science/article/pii/S2452414X19300135.
10. N.Z.N. Hasnan and Y.M. Yusoff, "Short review: Application Areas of Industry 4.0 Technologies in Food Processing Sector. In Proceedings of 16th Conference on Research and Development, Bangi, 2018. DOI 10.1109/SCORED.2018.8711184.
11. B. Motyl and S. Filippi, "Trends in engineering education for additive manufacturing in the industry 4.0 era: a systematic literature review". International Journal on

Interactive Design and Manufacturing, Vol. 15, 2021. Available: https://link.springer.com/article/10.1007/s12008-020-00733-1.
12. V. Madhavadas, D. Srivastava, U. Chadha, S.A. Raj, M.T.H. Sultan, F.S. Shahar and A.U.M. Shah, "A review on metal additive manufacturing for intricately shaped aerospace components". CIRP Journal of Manufacturing Science and Technology, Vol. 39, 2022. Available: https://www.sciencedirect.com/science/article/pii/S1755581722001304.
13. A.T. Keleko, B. Kamsu-Foguem, R.H. Ngouna and A. Tongne, "Artificial intelligence and real-time predictive maintenance in industry 4.0: a bibliometric analysis". AI and Ethics, 2022. Available: https://link.springer.com/content/pdf/10.1007/s43681-021-00132-6.pdf.
14. M. Achouch, M. Dimitrova, K. Ziane, S. Sattarpanah Karganroudi, R. Dhouib, H. Ibrahim, M. Adda, "On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges". Applied Sciences, Vol. 12, Iss. 16, 2022. Available: https://www.mdpi.com/2076-3417/12/16/8081.
15. Lamban M.P., Morella P., Royo J., Sanchez J.C.: Using industry 4.0 to face the challenges of predictive maintenance: A key performance indicators development in a cyber physical system. Computers and Industrial Engineering, Vol. 171, 2022. Available: https://www.sciencedirect.com/science/article/pii/S0360835222004417?via%3Dihub
16. A. Turygin, A. Mosyurchak, M. Zhalo and M. Hammer, "Maintenance and technical diagnostics of machine tools". MM Science Journal, 2016. DOI 10.17973/MMSJ.2016_11_2016167.
17. H. Webert, T. Döß, L. Kaupp and S. Simons, "Fault Handling in Industry 4.0: Definition, Process and Applications". Sensors, Vol. 22, Iss. 6, 2022. Available: https://www.mdpi.com/1424-8220/22/6/2205.
18. B. Zwolinska and J. Wiercioch, "Selection of Maintenance Strategies for Machines in a Series-Parallel System". Sustainability, Vol. 14, Iss. 19, 2022. Available: https://www.mdpi.com/2071-1050/14/19/11953.
19. J.S. Kim, K.N. Choi and S.W. Kang, "Infrared Thermal Image-Based Sustainable Fault Detection for Electrical Facilities". Sustainability, Vol. 13, Iss. 2, 2021. Available: https://www.mdpi.com/2071-1050/13/2/557.
20. A. Jablonski, "Condition Monitoring Algorithms in MATLAB". Springer, 2021.
21. P. Poor, D. Zenisek and J. Basl, "Historical Overview of Maintenance Management Strategies: Development from Breakdown Maintenance to Predictive Maintenance in Accordance with Four Industrial Revolutions". In Proceedings of the International Conference on Industrial Engineering and Operations Management, Pilsen, 2019.
22. E. Garcia, N. Montés, J. Llopis and A. Lacasa, "Miniterm, a Novel Virtual Sensor for Predictive Maintenance for the Industry 4.0 Era". Sensors, Vol. 22, Iss. 16, 2022. Available: https://www.mdpi.com/1424-8220/22/16/6222.
23. B. Jonge, R. Teunter, T. Tinga, "The influence of practical factors on the benefits of condition-based maintenance over time-based maintenance". Reliability Engineering

and System Safety, Vol. 158. 2017. Available: https://www.sciencedirect.com/science/article/pii/S0951832016306238?via%3Dihub.

24. G.K. Balakrishnan, C.T. Yaw, S.P. Koh, T. Abedin, A.A. Raj, S.K. Tiong and C.P. Chen, "A Review of Infrared Thermography for Condition-Based Monitoring in Electrical Energy: Applications and Recommendations". Energies, Vol. 15, Iss. 16, 2022. Available: https://www.mdpi.com/1996-1073/15/16/6000.
25. S. Arena, E. Florian, I. Zennaro, P.F. Orru and F. Sgarbossa, "A novel decision support system for managing predictive maintenance strategies based on machine learning approaches". Safety Science, Vol. 146, 2022. Available: https://www.sciencedirect.com/science/article/pii/S0925753521003726.
26. T. Zonta, A.C. Costa, R.R. Righi, M.J. Lima, E.S. Trindade and G.P. Li, "Predictive Maintenance in the Industry 4.0: A systematic literature review". Computers and Industrial Engineering, Vol. 150, 2020. Available: https://www.sciencedirect.com/science/article/pii/S0360835220305787?via%3Dihub.
27. W.C. Satyro, J.C. Contador, S.F.d.P. Monken et al., "Industry 4.0 Implementation Projects: The Cleaner Production Strategy — A Literature Review". Sustainability, Vol. 15, Iss. 3, 2023. Available: https://www.mdpi.com/2071-1050/15/3/2161.
28. J. Li, D. Schaefer and J. Milisavljevic-Syed, "A Decision-Based Framework for Predictive Maintenance Technique Selection in Industry 4.0". Proceedings of the 55th CIRP Conference on Manufacturing Systems, 2022. Available: https://www.sciencedirect.com/science/article/pii/S2212827122002293.
29. F. Arena, M. Collotta, L. Luca, M. Ruggieri and F.G. Termine, "Predictive Maintenance in the Automotive Sector: A Literature Review". Mathematical and Computational Applications, Vol. 27, Iss. 1, 2022. Available: https://www.mdpi.com/2297-8747/27/1/2.
30. W. Tiddens, J. Braaksma, T. Tinga, "Decision Framework for Predictive Maintenance Method Selection". Applied Sciences, Vol. 13, Iss. 3, 2023. Available: https://www.mdpi.com/2076-3417/13/3/2021.
31. H. Meriem, H. Nora, O. Samir, "Predictive Maintenance for Smart Industrial Systems: A Roadmap". The 6th International Conference on Emerging Data and Industry (EDI40), Leuven, 2023.
32. J. Gama, R.P. Ribeiro, B. Veloso, Data-Driven Predictive Maintenance. IEEE Intelligent Systems, Vol. 37, No. 4, 2022. DOI 10.1109/MIS.2022.3167561.
33. J.J.M. Jimenez, S. Schwartz, R. Vingerhoeds, B. Grabot, M. Salaun, "Towards multi-model approaches to predictive maintenance: A systematic literature survey on diagnostics and prognostics". Journal of Manufacturing Systems, Vol. 56, 2020. Available: https://www.sciencedirect.com/science/article/pii/S0278612520301187.
34. P. Aivaliotis, Z. Arkouli, K. Georgoulias, S. Makris, "Degradation curves integration in physics-based models: Towards the predictive maintenance of industrial robots", Robotics and Computer-Integrated Manufacturing, Vol. 71, 2021. Available: https://www.sciencedirect.com/science/article/pii/S0736584521000600.

35. M. Uppal, D. Gupta, N. Goyal et al., “A Real-Time Data Monitoring Framework for Predictive Maintenance Based on the Internet of Things”. Complexity, 2023. Available: https://www.hindawi.com/journals/complexity/2023/9991029.
36. J. Lee, M. Mitici, H. Blom, P. Bieber and F., “Freemen Analyzing Emerging Challenges for Data-Driven Predictive Aircraft Maintenance Using Agent-Based Modeling and Hazard Identification”. Aerospace, Vol. 10, Iss. 2, 2023. Available: https://www.mdpi.com/2226-4310/10/2/186.
37. E.C. Ozkat, O. Bektas, M.J. Nielsen and A. Cour-Harbo, “A data-driven predictive maintenance model to estimate RUL in a multi-rotor UAS”. International Journal of Micro Air Vehicles, 2023. Available: https://journals.sagepub.com/doi/10.1177/17568293221150171.
38. M. Mitici, I. Pater, A. Barros and Z. Zeng, “Dynamic predictive maintenance for multiple components using data-driven probabilistic RUL prognostics: The case of turbofan engines”. Reliability Engineering and System Safety, Vol. 234, 2023. Available: https://www.sciencedirect.com/science/article/pii/S095183202300114X.
39. E.G. Popkova, Y.V. Ragulina, A.V. Bogoviz, “Fundamental Differences of Transition to Industry 4.0 from Previous Industrial Revolutions”. In: Industry 4.0: Industrial Revolution of the 21st Century, Springer, 2019.
40. T. Mezair, Y. Djenouri, A. Belhadi, G. Srivastava and J.C. Lin, “A sustainable deep learning framework for fault detection in 6G Industry 4.0 heterogeneous data environments”. Computer Communications, Vol. 187, 2022. Available: https://www.sciencedirect.com/science/article/pii/S014036642200055X?via%3Dihub
41. C. Sassanelli, T. Arriga, S. Zanin, I. D’Adamo and S. Terzi, “Industry 4.0 Driven Result-oriented PSS: An Assessment in the Energy Management”. International Journal of Energy Economics and Policy, Vol. 12(4), 2022. Available: https://econjournals.com/index.php/ijeep/article/view/13313/6834.
42. K. Classens, S. Verbeek, M. Heemels and T. Oomen, “Joint Estimation of Additive and parametric Faults: A Model-Based Fault Diagnosis Approach towards Predictive Maintenance”. IFAC PapersOnLine, Vol. 55, Iss. 6, 2022. Available: https://www.sciencedirect.com/science/article/pii/S2405896322005316?via%3Dihub.
43. M. Zhang, N. Amaitik, Z. Wang, Y Xu., A. Maisuradze, M. Peschl, D. Tzovaras, “Predictive Maintenance for Remanufacturing Based on Hybrid-Driven Remaining Useful Life Prediction”. Applied Sciences, Vol. 12, Iss. 7, 2022. Available: https://www.mdpi.com/2076-3417/12/7/3218.
44. S. Kumar, D. Goyal, R.K. Dang, S.S. Dhami and B.S. Pabla, “Condition based maintenance of bearings and gears for fault detection - A review”. Materials Today: Proceedings, 2018. DOI 10.1016/j.matpr.2017.12.219.
45. R.B. Randall, “Vibration-based condition monitoring : industrial, aerospace and automotive applications”. John Wiley & Sons Ltd, 2011.
46. A. Galdelli, M. D’Imperio, G. Marchello et al., “A Novel Remote Visual Inspection System for Bridge Predictive Maintenance”. Remote Sensing, Vol. 14, Iss. 10, 2022. Available: https://www.mdpi.com/2072-4292/14/9/2248.

47. A. Dogru, S. Bouarfa, R. Arizar and R. Aydogan, “Using Convolutional Neural Networks to Automate Aircraft Maintenance Visual Inspection”. Aerospace, Vol. 7, Iss. 12, 2020. Available: https://www.mdpi.com/2226-4310/7/12/171.
48. R. Rosati, L Romeo., G. Cecchini, F. Tonetto, P. Viti, A. Mancini and E. Frontoni, “From knowledge-based to big data analytic model: a novel IoT and machine learning based decision support system for predictive maintenance in Industry 4.0”. Journal of Intelligent Manufacturing, Vol. 34, 2022. Available: https://link.springer.com/article/10.1007/s10845-022-01960-x.
49. A.K.S. Jardine, D. Lin and D. Banjevic, “A Review on Machinery Diagnostics and Prognostics Implementing Condition-Based Maintenance”. Mechanical Systems and Signal Processing, Vol. 20, Iss. 7, 2006. Available: https://www.sciencedirect.com/science/article/pii/S0888327005001512.
50. B. Jakubek, K. Grochalski, W. Rukat and H. Sokol, “Thermovision measurements of rolling bearings”. Measurement, Vol. 189, 2022. Available: https://www.sciencedirect.com/science/article/pii/S0263224121013932.