QPI 2021, volume 3, pp. 41-52

PREDICTIVE MANAGEMENT IN THE CONTEXT OF INDUSTRY 4.0

doi: 10.2478/cqpi-2021-0005

Date of submission of the article to the Editor: 09/07/2021
Date of acceptance of the article by the Editor: 17/09/2021

Marek Krynke[1] – *orcid id: 0000-0003-4417-1955*
[1]Czestochowa University of Technology, **Poland**

Abstract: The article presents information on the potential of Industry 4.0 in the field of maintenance. This work explores the potential and trends of predictive maintenance management in an industrial big data environment. The development of predictive maintenance, its technical challenges and in the context of Industry 4.0 was presented. In addition, a case study that illustrates how maintenance management and predictive maintenance can be applied to the maintenance of wind turbines is discussed.

Keywords: operation, maintenance management; predictive maintenance; Industry 4.0

1. INTRODUCTION

The objective of predictive maintenance to reduce downtime and maintenance costs within the production without failure by monitoring the status of equipment and predict when equipment failure may occur (Krynke et al., 2016; Mielczarek, Krynke, 2018).
Predicting future potential failures allows you to plan maintenance before failure. Ideally, the maintenance schedule can be optimized to minimize maintenance costs and achieve zero production failure (Knop, 2019; Li et al., 2016; Mazur, 2019). However, it is difficult to realize all the benefits of predictive maintenance without the foundation of correlation techniques such as big data and cloud computing (Jasiulewicz-Kaczmarek et al., 2020). Many production systems are not ready to manage large data sets due to high data access and data quality requirements, and use multiple data sources to extract relevant information (Ingaldi and Ulewicz, 2020; Knop, 2021).
Industry 4.0 refers to the fourth generation of industrial activities as a result of the fourth industrial revolution characterized by intelligent internet systems and solutions (Ślusarczyk, 2018). It combines the strengths of optimized industrial production with internet technologies and significantly changes the production process, maintenance strategies and maintenance management (Pietraszek et al., 2020). Therefore, many companies face the challenge of assessing the diversity of solutions and concepts summarized by the term Industry 4.0 and developing their own strategies (Mazur and Momeni, 2019; Ulewicz and Mazur, 2019). However, due to the lack of research on the potential use of Industry 4.0 and predictive maintenance prospects, many companies and organizations face the dilemma of waiting too long to implement Industry 4.0, or

starting too early and making fatal mistakes (Lasi et al., 2014; Pattanapairoj et al., 2021; Derenda et all. 2018).

Accordingly, this article aims to provide information on the potential of Industry 4.0 in the field of maintenance. It can help scientists and practitioners identify and prioritize towards predictive maintenance and state-based maintenance management in an Industry 4.0 environment. The rest of the article is organized as follows. Chapter 2 briefly presents the classification of maintenance strategies. Chapter 3 discusses related trends accelerated and promoted in the era of Industry 4.0. Chapter 4 discusses technologies for predictive maintenance systems. Chapter 5 discusses the analysis algorithms in predictive maintenance. Chapter 6 describes a case study that illustrates how maintenance management and predictive maintenance can be applied to the maintenance of wind turbines. The conclusions are summarized in the last section of this document.

2. REVIEW OF THE MAINTENANCE STRATEGY

Maintenance activities can include a range of maintenance activities: monitoring, condition analysis, routine maintenance, overhaul, repair and rebuild. According to the European standard, maintenance is defined as the combination of all technical, administrative and management activities during the life cycle of an object, aimed at keeping it in a condition in which it can perform the required function, or restoring it to such a state (Li i in., 2016; Zasadzień, 2017). Advances in the maintenance strategy benefit from a long historical development. As shown in Table 1, the classification of maintenance strategies can be divided into four classes (M1.0 ÷ M4.0) as corrective maintenance (CM), preventive maintenance (PM), condition-based maintenance (CBM), and predictive maintenance (PdM) (Jasiulewicz-Kaczmarek et al., 2020).

Corrective maintenance is similar to the repair work that is performed when a device has an obvious malfunction. Therefore, CM is also referred to as failure-to-failure maintenance.

Preventive maintenance is performed at fixed intervals or according to previously described criteria, with the intention of reducing the probability of failure or degradation of certain functions. The PM is scheduled without any monitoring activities. The schedule can be based on the number of cycles or hours of operation. These two strategies are very well known in most industries (Jasiulewicz-Kaczmarek et al., 2020).

The commissioning of automation or more complex systems paved the way for maintenance to the next generation - condition based maintenance (CBM). The expectations of maintenance were of higher equipment availability and reliability, better product quality, long equipment life and great cost effectiveness. The development of automation gave the ideas for developing more maintenance models, which would contribute the production and profit. According to (Jardine et al., 2006) CBM is a maintenance program that recommends maintenance actions (decisions) based on the information collected through condition monitoring process.

The objective of predictive maintenance (PdM) is to reduce downtime and maintenance costs under the assumption of failure-free production by monitoring the operating status of equipment and predicting when equipment failure may occur.

Anticipating future potential failures allows maintenance to be planned before they occur. Ideally, the maintenance schedule can be optimized to minimize maintenance costs and achieve zero failure production.

Table 1. Classification of maintenance strategies (Jasiulewicz-Kaczmarek et al., 2020)

M1.0	**Machine**	**REACTIVE MAINTENANCE** Repair work done in reaction to an incident **Result:** Low routine maintenance costs but high costs in case of equipment failure and risk of long downtimes	**Development of industrial production**
M2.0	**Assembly line**	**PREVENTIVE MAINTENANCE** Maintenance done based on pre-defined service intervals and inspection. **Result:** Reduced likelihood of failure, but an ongoing-effort is necessary	
M3.0	**Automation**	**CONDITION-BASED MAINTENANCE** Condition Monitoring via sensors. Maintenance is performed, only when equipment problems have been registered **Result:** Anomalies are identified and resolved prior to functional failure	
M4.0	**Digital transformation**	**PRESCRIPTIVE MAINTENANCE** Prediction of failures based on the analysis of data and trends. Provision of specific recommendation. Support of the solution-finding process **Result:** Completely automated maintenance workflow	
		PREDICTIVE MAINTENANCE Condition Monitoring is enhanced by advanced statistics, stochastic, real-time analytics or even machine learning algorithms, which allow to make predictions on when equipment will fail **Result:** Equipment failure is predicted and preventative actions can be taken	

Predictive maintenance employs the use of sensors to precisely collect data describing manufacturing equipment's condition and overall operational state. The data can then be analysed to predict when failure events will occur (Jimenez-Cortadi et al., 2020). The key technologies involved in predictive maintenance are data collection and analysis technologies, such as Internet of Thinks (IoT), cloud computing, predictive analysis (such as fuzzy logic, neural networks, evolutionary algorithms, machine learning, probabilistic reasoning), and equipment repair technologies (Chen et al., 2018)

Compared to other maintenance strategies, predictive maintenance management has some advantages (Li et al., 2016):

- equipment that requires maintenance is only shut down before imminent failure,
- reduction of total time spent on equipment maintenance,
- reducing maintenance costs by avoiding catastrophic failures,
- increasing the availability and reliability of machines,
- extending the lifetime of devices and processes.

However, predictive maintenance faces several challenges, such as (Li et al., 2016; Aljumaili et al. 2015):

- High demands on data access, data quality and data fusion from multiple sources for data sharing and data publication. Since these sources of data often operate in a heterogeneous environment, integration between the systems is problematic.
- The capability to deal with industrial big data. To leverage big data, industrial businesses need the ability to support different types of information, the

infrastructure to store massive data sets, and the flexibility to leverage the information once it is collected and stored - enabling historical analysis of critical trends to enable real-time predictive analysis.

- The prediction accuracy for PdM. The inaccurate predictive information may result in either unnecessary maintenance, such as early replacement of components, or production downtime because of unexpected machine failures.

3. TECHNOLOGY OF PREDICTIVE MAINTENANCE SYSTEMS

3.1. Data-driven technology

Data is the basis of predictive maintenance processes. Data from networks, internet devices, monitoring, etc. are already in data-driven intelligent information - the Internet of Things. The Internet of Things (IoT) is an embedded technology that enables physical and connected objects to communicate (Al-Fuqaha et al., 2015). This technology enables the evaluation or interaction with the internal states or needs of the entire system. Managers and plant operators can switch selected production systems into predetermined predictive maintenance modes based on data and information provided by the Internet of Things. Predictive repairs can use many types of data to improve decision-making and proper operation, including equipment uptime, temperature, power consumption, and more. For example, in a consumer design, a device may run continuously and keep production constant, but energy consumption may increase before the device fails. This allows the operator to intervene when it detects an increase in energy consumption by monitoring machine energy data, avoiding downtime. If normal maintenance is used, the machine must be offline, which can result in unplanned downtime in the production cycle. By utilizing up-to-date machine performance data as well as historical data that have failed in the past, operators can reduce the adverse impact on system operation (Krynke i in., 2016).

3.2. Detection technology

The detection technology is divided into direct detection and indirect detection. Key issues include these two detection modes and strategies for placing sensors to obtain critical information on the health of devices (Ding, 2008).

The state of the device can be determined by a detection technology that can be used in both direct and indirect correlation detection modes depending on the remote sensing parameters and the mechanical state association. Direct detection technology measurements show the true number of mechanical events as defects tend to occur inside the machine. Direct inspection is usually performed by removing a mechanical fault and resuming normal operation. In the event of vibration (friction or heat) caused by mechanical defects, indirect sensing technology can measure various parameters of the mechanical state (e.g. force, vibration and noise etc.). Compared with direct detection, the cost of the indirect detection method is low. It can continuously detect all non-conformities (e.g. tool breakage or wear, etc.) without interrupting normal machine operation. The more intelligent sensors are used and the more sensors are placed on equipment and devices, the more complex the information these sensors provide and the more they reflect the state of the machine. However, the number of sensors is actually very limited by factors such as cost, installation, etc. Therefore, the type and location of the sensor must be considered in order to get as much information about the machine as possible (Doebling et al., 1998).

3.3. Machine Health Monitoring

Machine Health Monitoring is a predictive maintenance platform system for monitoring the health of key fault points through external transmission terminals. Monitoring technology has developed in various fields of engineering that have developed their own monitoring methods. Condition monitoring methods are divided into many types. Commonly used include: vibration monitoring method, noise monitoring method, temperature monitoring method, pressure measurement method, fluid analysis monitoring method, sound monitoring method. With the increase in the advancement of the monitoring system in the so-called In "smart" devices, they can provide their own condition monitoring data. Status information is generated from data ingestion and the collected data is used as input to calculate their condition (Ben Ali et al., 2015). The condition of the devices then depends on the actual condition consisting of historical data which is measured by direct or indirect discovery functions. A typical condition result is based on a status result that is compared to a given device's reference value. In addition, in order to evaluate the condition, the collected data may need to be pre-processed, such as: filtering, data correction, elimination of overlay trends, and so on. Depending on the application, various algorithms can be used for digital processing, from simple arithmetic functions, statistical functions, integrations, to transform functions such as fast Fourier transforms. As the computing power of microprocessors increases, these algorithms can be implemented directly into components at the sensor level. Data-driven analysis methods can also be used to monitor the condition and model the required system outputs from historical data, including algorithms such as linear regression or data filters, as well as algorithms typical of machine learning and data mining, such as neural networks and trees decision machines and Support Vector Machines (SVM) (Boyd, 2010). Due to the variety of functions, a uniform interpretation method is necessary to explain the calculated condition of the device. Here you should define the range of program values, represented by thresholds or reference values. However, computing the condition of a part may not be sufficient to examine the condition for the entire device or system. Therefore, it is necessary to combine the different status values for the parts of the device under test. The structure of this combination is called the functional structure of a device or system, which may include several logical levels.

3.4. Solving problems

Solving problems be divided into fault finding, fault locating, fault isolation and data recovery. The problem solving method may differ depending on the method or empirical knowledge of the analysis model. Among these methods, a qualitative and a quantitative method can be distinguished. The methods based on analytical models include forecasts and estimates. These methods need to describe an accurate mathematical model in the process, and modeling helps to gain a deep understanding of the process structure that aims to obtain an accurate model. However, there are often complex behavioral relationships that cannot be explicitly modeled. The expert system method is a typical method based on qualitative knowledge, which is widely used, for example, in electric motors (Ben Ali et al., 2015). Data-driven methods include statistical signal processing and quantitative artificial intelligence. These methods are widely used and flexible, especially for areas that are difficult to obtain precise models. Data-driven methods include gray theory (image and signal analysis), time series analysis, and multiple reporting methods. The Main Component Analysis (PCA) method is a representative multi-analysis method that maps dots and images to another space to reduce dimensions (Krzanowski, 2000). PCA methods are often used in processing industries such as chemical processes, but are not ideal for complex nonlinear systems. Signal processing based fault diagnosis is widely used in vibration-vibration signals, such as rotating machines, e.g. internal combustion engines. The tools used include wave transformation and filtering the signal according to the card pattern. It is worth noting that the analytical methods used are similar as there is an inbuilt relationship between condition monitoring, diagnosis and life expectancy.

3.5. Fault prediction

Failure prediction is based on monitoring and evaluation data. This forecasting focuses on predicting failures and the remaining life of a device or system. There are two research methods for remaining life: one is to estimate and predict the average remaining life, and the other is to find the probability distribution of the remaining life.
There are many factors that influence the service life of equipment, for example in the process of manufacturing, assembly, testing, transportation, installation, each link can affect the reliability of a part. The operation and maintenance environment, such as the production load of the equipment, the operating environment (temperature, humidity and dust), the level of maintenance of the equipment, and the responsibilities of the maintenance personnel affect the remaining life of the equipment.
Failure prediction is technically feasible. With the development of sensors, microprocessors, memory, battery technology and wireless communication network technology, it is possible to use sensor modules and automatic data logging to predict faults. As the core of the failure prediction system, signal information processing theory has also made great progress, especially the mathematical model of failure prediction has become more intelligent and practical. In addition, based on accurate prediction of the service life of key components, automatic identification technologies such as radio frequency identification (RFID) are combined to determine the position of parts in the supply chain. In this way, parts can be obtained quickly and delivered as required (Finkenzeller, 2010).

4. ALGORITHMS OF ANALYSIS IN PREDICTIVE MAINTENANCE

Predictive maintenance is about assessing the current state of components and predicting the future state based on the operational information of equipment and facilities. Commonly used methods include time series model forecasting method, gray model forecasting method and neural network forecasting method. There are basically three basic approaches in developing forecasting methods: physical models, knowledge systems and statistical models. In practical applications, these three approaches can be integrated to create a hybrid fault prediction technology that combines traditional physical models and intelligent analysis methods. The technology can process digital and symbolic information to make more effective maintenance predictions.
In the predictive maintenance process, not all forecasts will provide sufficient and effective data. Depending on the size and intensity of the data provided, an appropriate data observation model can be established.
For predictions where the amount of data is relatively small or the factors influencing the data are relatively single, simple methods of forecasting time series models such

as mixed linear regression, autoregressive and autoregressive moving average can be used.
The time series model is actually a regression model, that is, a quantitative forecast, based on the principle that, on the one hand, the continuity of the development of things is recognized and that data from past time series are used for statistical analysis. To predict the trend, the randomness caused by the influence of random factors is taken into account. In order to eliminate the influence of random fluctuations, the statistical analysis uses historical data, which is properly processed to predict the trend. The advantage of this method is its simplicity, easy use, it can take full advantage of the original time series data, high speed of calculations, dynamic determination of model parameters, good accuracy, possibility of combining with the time series of other models. The disadvantage of this method is that you cannot analyze the correlation between the two factors. Due to the lack of adequate data, this predictive model can be used for short-term forecasting for some relatively old devices and facilities (Mohanty and Listwan, 2021).
The gray model prediction method is an inaccurate systematic method. Prediction technology based on gray systems theory can predict a problem that may occur over a period of time and establish a prediction model for that problem when there is not much data available.
The basic idea of prediction in this model is to build a dynamic or non-dynamic white module from a known sequence of data according to a specific plan and then solve the future gray model according to the specified change and solution. Its main feature is that the model does not use the original data sequence, but the generated data sequence. Its basic system is the gray model (GM) that generates an approximate exponential solution by collecting the original data (or generated by other methods) (Nowak, 2016). The advantage of this method is that it does not require a large amount of data, which can solve the problems associated with less historical data. The disadvantage of this method is that it is only suitable for medium to long term forecasts and only for exponential growth forecasts. Forecast results for low volatility time series are weak.
In the case of neural networks, the most typical is the BP neural network (back propagation error method), which is the most representative and most used model among the current learning models with neural networks (Perzyńska, 2010). The BP neural network architecture consists of several layers of interconnected neurons, usually containing an input layer, an output layer, and several hidden layers, and each layer contains several neurons. The neural network, to achieve target convergence, adjusts the weight of the connection chain through training in accordance with the principles of learning. The transmission functions used by BP neural network are generally sigmoidal type (S-curved) differential functions, which are strictly increasing functions, showing a good balance between linearity and non-linearity, so that input and output can be realized. Linear mapping is suitable for medium to long term forecasting. The advantages of this method are: good approximation effect, fast calculation speed, no need to create a mathematical model, high accuracy, strong nonlinear adjustment possibilities. The disadvantage of this method is that the relationship between the input and output of the predicted system cannot be expressed and analyzed, the predictor cannot participate in the prediction process, the convergence speed is low, the obtained network fault tolerance is poor, the algorithm is incomplete, and it is easy to fall into local minimum.

6. WIND TURBINE MAINTENANCE - CASE STUDY

The standard lifetime of a wind turbine is approximately 20-25 years. However, the warranty of most wind turbines only covers the first two to five years of the turbine's lifetime. As the wind turbine system is aging, wind farm owners should be prepared to maintain them. The problem, however, is the lack of technical personnel required for maintenance work. Moreover, even if technicians are prepared to meet the daily maintenance requirements of wind farms, unscheduled maintenance will still have a significant impact on wind farm revenues. Wind turbine maintenance, from traditional fault maintenance to preventive maintenance in recent years, to the recent far-reaching predictive maintenance, is integrated with artificial intelligence.

6.1. Collecting data

Currently, data on the operation of wind turbines is mainly monitored and stored in real time by the SCADA (Supervisory Control and Data Acquisition) system (Gaushell and Darlington, 1987). SCADA is an important system for managing, monitoring and controlling wind farm devices. This system collects in real time environmental parameters and parameters of wind turbine operating conditions, condition parameters and control parameters. It enables wind farm managers to understand the operation and condition of wind energy resources in real time. A SCADA system generates a large amount of data on a daily basis, but most current systems are still limited to alarming when a failure occurs. These failures are often serious when they reach an alarm condition and wind turbines need to be shut down and repaired. This results in enormous power losses and maintenance costs. By observing and modeling the big data environment generated by the SCADA system, some serious failures can be predicted and diagnosed. As a result, existing traditional maintenance methods can be transformed into proactive and predictive maintenance methods that can effectively improve wind turbine performance, utilization, and operating and maintenance costs. (Wang and Liu, 2021).

6.2. Wind turbine performance parameters

The performance parameters of wind turbines are mainly flow, pressure, power, efficiency and speed. In addition, the magnitude of noise and vibration is also a major design indicator for wind turbines. The flow rate is the volume of air, expressed as the volume of gas flowing through the turbine per unit time. Wind pressure refers to the increase in gas pressure in the turbine, which can be divided into static pressure, dynamic pressure and total pressure. The input power is the power at the turbine shaft. The ratio of the effective fan power to the shaft power is called efficiency. The total pressure efficiency of the wind turbine can reach 90%. Data on these parameters can be collected in real time via the SCADA system. However, in order to read the predicted condition of a wind turbine from this huge and disordered data, efficient intelligent data mining algorithms must be used. In this way, true predictive maintenance is achieved.

6.3. Prediction model

An example of algorithms for modeling and predicting failures is the Multivariate State Estimation Technique (MSET) method and methods based on neural networks.

The Multivariate State Estimation Technique (MSET) is a software system for real-time process monitoring. It provides system operators with timely and reliable information

regarding the conformance of process behavior, as inferred from sensor readings, with the expected behavior based on past observation (Cheng and Pecht, 2007).
The MSET method uses the data from the normal operating state of the device to create a process memory matrix, and then by modeling it obtains the estimated value of the temperature of the gear bearings, calculates the residual error between the estimated value and the actual value. By monitoring the trend of the mean value curve in real time, you can judge whether the change in temperature of the turbine gear bearing temperature is normal. If the mean temperature curve exceeds the threshold, it will thus predict the need for maintenance.
BP neural network time series method (back propagation error method) is to detect and estimate the temperature of the wind turbine gear bearing. When the wind turbine is operating normally, the BP neural network model can successfully cover all normal operating states of the equipment. The model estimation accuracy is very high. When the fan operates abnormally, its dynamic characteristics will change, and the relationship between several variables in the input layer is abnormal and deviates from the normal operating state space. During this time, the expected temperature and temperature distribution for the turbine gearbox bearing will be significantly different from normal operating conditions.
The above-mentioned methods of analyzing large amounts of data allow you to track the operating status of a wind turbine and predict its potential failure. Thus, the goal of predictive maintenance is achieved.

7. CONCLUSION

Maintenance is closely related to the activities of a production company whose goal is to produce high-quality products. The quality of maintenance activities determines the current quality of the means of production, i.e. devices and machines, which largely determines the quality of products.
Maintenance management is the primary task of implementing an equipment and facility maintenance plan. Industry 4.0 promotes predictive and intelligent production in the future. In Factory 4.0, machines are connected as a collaborative community that generates great potential for predictive maintenance. Predictive maintenance determines the expected reduction from the current state to a functional failure and provides an economical maintenance strategy. In addition, predictive maintenance must take into account the types of resources required for organizational maintenance, including workers, spare parts, tools, and time.
The amount of dynamically changing data generated throughout the life cycle of technical objects is growing. Data-driven manufacturing technologies inspire the use of data-driven maintenance. A number of benefits resulting from such an approach, such as improving the efficiency and availability of the company's technical resources, reducing costs or flexibility in approaching customer requirements, are an incentive to implement and apply new technologies, both by machine users and their manufacturers.
Predictive maintenance will play a very important role in future maintenance operations and will meet the demands of smart manufacturing, the so-called self-aware machine in the conditions of Industry 4.0.

REFERENCES

Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., Ayyash, M., 2015. *Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications*. IEEE Communications Surveys & Tutorials, 17(4), 2347-2376. DOI: 10.1109/COMST.2015.2444095.

Aljumaili, M., Wandt, K., Karim, R., Tretten, P., 2015. *eMaintenance ontologies for data quality support*. Journal of Quality in Maintenance Engineering, 21(3), 358-374. DOI: 10.1108/JQME-09-2014-0048.

Ben Ali, J., Fnaiech, N., Saidi, L., Chebel-Morello, B., Fnaiech, F., 2015. *Application of empirical mode decomposition and artificial neural network for automatic bearing fault diagnosis based on vibration signals*. Applied Acoustics, 89, 16-27. DOI: 10.1016/j.apacoust.2014.08.016.

Boyd, S., 2010. *Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers*. Foundations and Trends® in Machine Learning, 3(1), 1-122. DOI: 10.1561/2200000016.

Chen, J., Zhang, R., Di Wu., 2018. *Equipment Maintenance Business Model Innovation for Sustainable Competitive Advantage in the Digitalization Context: Connotation, Types, and Measuring*. Sustainability, 10(11), 3970. DOI: 10.3390/su10113970.

Cheng, S., Pecht, M., 2007. *Multivariate state estimation technique for remaining useful life prediction of electronic products*. Downloaded from: https://www.aaai.org/papers/symposia/fall/2007/fs-07-02/fs07-02-004.pdf.

Ding, S.X., 2008. *Model-based fault diagnosis techniques: Design schemes, algorithms, and tools*. New York: Springer.

Doebling, S.W., Farrar, C.R., Prime, M.B., 1998. *A Summary Review of Vibration-Based Damage Identification Methods*. The Shock and Vibration Digest, 30(2), 91-105. DOI: 10.1177/058310249803000201.

Finkenzeller, K., 2010. *RFID handbook: Fundamentals and applications in contactless smart cards, radio frequency identification and near-field communication* (3rd edition). [Hoboken (N.J.)]: Wiley; IEEE Press.

Gaushell, D.J., Darlington, H.T., 1987. *Supervisory control and data acquisition*. Proceedings of the IEEE, 75(12), 1645-1658. DOI: 10.1109/PROC.1987.13932.

Ingaldi, M., Ulewicz, R., 2020. *Problems with the Implementation of Industry 4.0 in Enterprises from the SME Sector*. Sustainability, 12(1), 217. DOI: 10.3390/su12010217.

Jardine, A.K., Lin, D., Banjevic, D., 2006. *A review on machinery diagnostics and prognostics implementing condition-based maintenance*. Mechanical Systems and Signal Processing, 20(7), 1483-1510. DOI: 10.1016/j.ymssp.2005.09.012.

Jasiulewicz-Kaczmarek, M., Legutko, S., Kluk, P., 2020. *Maintenance 4.0 technologies – new opportunities for sustainability driven maintenance*. Management and Production Engineering Review, 11(2), 74-87. DOI: 10.24425/MPER.2020.133730.

Jimenez-Cortadi, A., Irigoien, I., Boto, F., Sierra, B., Rodriguez, G., 2020. *Predictive Maintenance on the Machining Process and Machine Tool*. Applied Sciences, 10(1), 224. DOI: 10.3390/app10010224.

Knop, K., 2019. *Analysis and Improvement of the Galvanized Wire Production Process with the use of DMAIC Cycle*. Quality Production Improvement - QPI, 1(1), 551-558. DOI: 10.2478/cqpi-2019-0074.

Knop, K., 2021. *Management of Packaging Labeling Technology in the Context of Improving the Final Product Quality and Work Safety*. System Safety: Human - Technical Facility - Environment, 3(1), 116-128. DOI: 10.2478/czoto-2021-0013.

Krynke, M., Czaja, P., Zasadzień, M., 2016. *Systemy techniczne: Technologia, jakość, eksploatacja*. Częstochowa: Oficyna Wydawnicza Stowarzyszenia Menedżerów Jakości i Produkcji.

Krzanowski, W.J., 2000. *Principles of multivariate analysis: A user's perspective* (Revised ed.). *Oxford statistical science series: nr. 22*. Oxford: Oxford University Press.

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., Hoffmann, M., 2014. *Industry 4.0*. Business & Information Systems Engineering, 6(4), 239-242. DOI: 10.1007/s12599-014-0334-4.

Li, Z., Wang, K., He, Y., 2016. *Industry 4.0 - Potentials for Predictive Maintenance*. Atlantis Press. Downloaded from: https://ntnuopen.ntnu.no/ntnu-xmlui/handle/11250/2599772.

Mazur, M., 2019. *Quality Assurance Processes in Series Production of Car Elements*. Quality Production Improvement - QPI, 1(1), 610-617. DOI: 10.2478/cqpi-2019-0082.

Mazur, M., Momeni, H., 2019. *LEAN Production issues in the organization of the company - results*. Production Engineering Archives, 22(22), 50-53. DOI: 10.30657/pea.2019.22.10.

Mielczarek, K., Krynke, M., 2018. *Plastic production machinery – the evaluation of effectiveness*. Production Engineering Archives, 18(18), 42-45. DOI: 10.30657/pea.2018.18.07.

Mohanty, S., Listwan, J., 2021. *An Artificial Intelligence/Machine Learning Based Regression-Clustering-Sensor-Fusion Framework for Predicting Unmeasurable Time-Series Strain From Other Sensor Measurements*. Journal of Nondestructive Evaluation, Diagnostics and Prognostics of Engineering Systems, 5(1). DOI: 10.1115/1.4050592.

Nowak, M., 2016. *Zastosowanie szarego modelu GM (1,1) w predykcji krótkich szeregów finansowych na przykładzie przedsiębiorstw sektora produkcji materiałów budowlanych*. Zeszyty Naukowe Politechniki Poznańskiej Organizacja i Zarządzanie, 155-164. DOI: 10.21008/j.0239-9415.2016.070.11.

Pattanapairoj, S., Nitisiri, K., Sethanan, K., 2021. *A Gap Study between Employers' Expectations in Thailand and Current Competence of Master's Degree Students in Industrial Engineering under Industry 4.0*. Production Engineering Archives, 27(1), 50-57. DOI: 10.30657/pea.2021.27.7.

Perzyńska, J., 2010. *Budowa prognoz kombinowanych z wykorzystaniem sztucznych sieci neuronowych* (nr. 103). PRACE NAUKOWE UNIWERSYTETU EKONOMICZNEGO WE WROCŁAWIU nr 103. Downloaded from: https://dbc.wroc.pl/content/74165/perzynska_budowa_prognoz_kombinowanych.pdf.

Pietraszek, J., Radek, N., Goroshko, A.V., 2020. *Challenges for the DOE methodology related to the introduction of Industry 4.0*. Production Engineering Archives, 26(4), 190-194. DOI: 10.30657/pea.2020.26.33.

Ślusarczyk, B., 2018. *INDUSTRY 4.0 – ARE WE READY?* Polish Journal of Management Studies, 17(1), 232-248. DOI: 10.17512/pjms.2018.17.1.19.

Ulewicz, R., Mazur, M., 2019. *Economic Aspects of Robotization of Production Processes by Example of a Car Semi-trailers Manufacturer*. Manufacturing Technology, 19(6), 1054-1059. DOI: 10.21062/ujep/417.2019/a/1213-2489/MT/19/6/1054.

Wang, Z., Liu, C., 2021. *Wind turbine condition monitoring based on a novel multivariate state estimation technique*. Measurement, 168, 108388. DOI: 10.1016/j.measurement.2020.108388.

Zasadzień, M., 2017. *Six Sigma methodology as a road to intelligent maintenance*. Production Engineering Archives, 15(15), 45-48. DOI: 10.30657/pea.2017.15.11.

Derenda T., Zanne M., Zoldy M., Torok A., 2018. Automatization in road transport: a review. Production Engineering Archives vol. 20, pp 3-7.