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Harnessing Industry 4.0 Technologies: A Novel Predictive Maintenance Method for Advanced Production Systems

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Abstract
A novel approach has emerged to enhance the efficiency and reliability of predictive maintenance strategies, namely the taxonomy approach for defining types of production machines. This innovative method represents a significant departure from traditional categorisation methods, promising to improve how organisations manage and maintain their production equipment. Organisations can reduce overall maintenance costs and minimise unplanned downtime through proactive maintenance based on taxonomy-driven insights, increasing operational efficiency and profitability. The article explores how the taxonomy approach leverages data analytics and machine learning techniques to classify production machines into distinct categories based on their operational characteristics, usage patterns, and maintenance needs. Doing so offers several key advantages: improved precision, predictive maintenance customisation, data-driven insights, and scalability. The taxonomy approach is based on data-driven insights, allowing organisations to harness the power of big data and the Industrial Internet of Things (IIoT). Maintenance teams can detect anomalies and issues by analysing real-time data from production machines before they lead to breakdowns. In the discussion part, a brief overview highlights the integration of predictive maintenance with Industry 4.0, the uniqueness of the proposed method, and its potential implications for modern production systems.

Keywords
Industry 4.0; Predictive Maintenance; Production Systems; Data Analytics; IIoT.

Introduction

Objective and scope of the study

As organisations strive to enhance the efficiency and reliability of their predictive maintenance strategies, Authors propose a novel solution as a taxonomy approach for defining types of production machines. This innovative method, a significant departure from traditional categorisation methods, promises to revolutionise how organisations manage and maintain their production equipment. This approach enables proactive maintenance by providing taxonomy-driven insights, reducing overall maintenance costs and minimising unplanned downtime. The result is increased operational efficiency and profitability.

Predictive Maintenance in Industry 4.0

As one of the directions for developing maintenance processes, the predictive maintenance approach was the foundation of the Fourth Industrial Revolution. Social, industrial, and technological changes caused by the digital transformation of industry, forced by this revolution, create new opportunities for defining new formulas for ensuring the efficiency, operational readiness, and safety of automated technical systems. Using intelligent technologies enables the development of innovative maintenance management mechanisms supported by digital solutions. In this way, technological progress contributes to the dynamic changes in current paradigms in the field of maintenance. The growing role of digitalisation is also the reason for changes in this regard, as traditional planning methods against

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the background of the possibility of using big datasets assisted by intelligent algorithms make it possible to monitor maintenance processes in real mode and even ahead of potential adverse events. This creates innovative approaches to maximising this new potential. According to the EN 13306:2017 standard (CEN, 2017), "maintenance is a combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function".

Maintenance strategies are grouped into two subcategories (Fig. 1):

1. Preventive maintenance is one of the pillars of Total Productive Maintenance (TPM) (Bednarek & Santana Villagra, 2017). It is a method of improving production efficiency to achieve zero failures, losses, and defects. TPM includes improving the overall equipment effectiveness of machinery or production lines (OEE). In line with the EN 13306 standard, Condition-Based Maintenance (CBM) is a form of "preventive maintenance which includes assessment of physical conditions, analysis, and the possible ensuing maintenance actions."
2. Predictive maintenance (PdM), also known as condition monitoring, involves measuring the condition of a machine to predict and prevent failures. It is important to note that predictive maintenance should not be used as a replacement for traditional maintenance management methods. Instead, it should be considered a valuable supplement to a comprehensive maintenance programme. Data from a predictive maintenance programme can be used to schedule and plan plant outages; this lowers the operating costs of predictive maintenance methods so that any plant can implement this maintenance management programme cost-effectively. Predictive maintenance is a condition-driven preventive maintenance programme (Mobley, 2001).

Monitoring and analysing resource efficiency to identify trends, predict failures, and optimise maintenance schedules allow for achieving desired efficiency, minimising downtime, and aligning resource utilisation with broader business strategies and specific objectives. Resource conservation is also essential to ensure a safe working environment in the manufacturing industry.

Managing a company that develops in line with the paradigm of digital transformation to become an Industry 4.0 organisation is often referred to as intelligent management driven by the integration of business intelligence analytics, big data, artificial intelligence tools, and IIoT technologies for data acquisition in decision-making. The core aspects of a manufacturing company's intelligent management also include the integration of Enterprise Resource Planning (ERP) systems, Manufacturing Execution Systems (MES), and other digital tools, which enables better resource, process, and supply chain management.

Taking predictive maintenance into account in the implementation of TPM can be perceived, from the point of view of change management, as a pathway to reaching the highest, fifth level of digital transformation in the Advanced Manufacturing (ADMA) digital maturity assessment model in terms of the specific criterion for the area of advanced manufacturing technologies. The organisation then achieves a level of management of production technologies in the maintenance field by "monitoring key components in real time to focus intervention on moments of potential loss of productivity" ('ADMA scanner – Future Industry Platform', n.d.).

Real-time monitoring of production resources and managing proactive maintenance processes using artificial intelligence is becoming a core functionality of Enterprise Asset Management (EAM) systems. The EAM functionality allows for resource knowledge man-

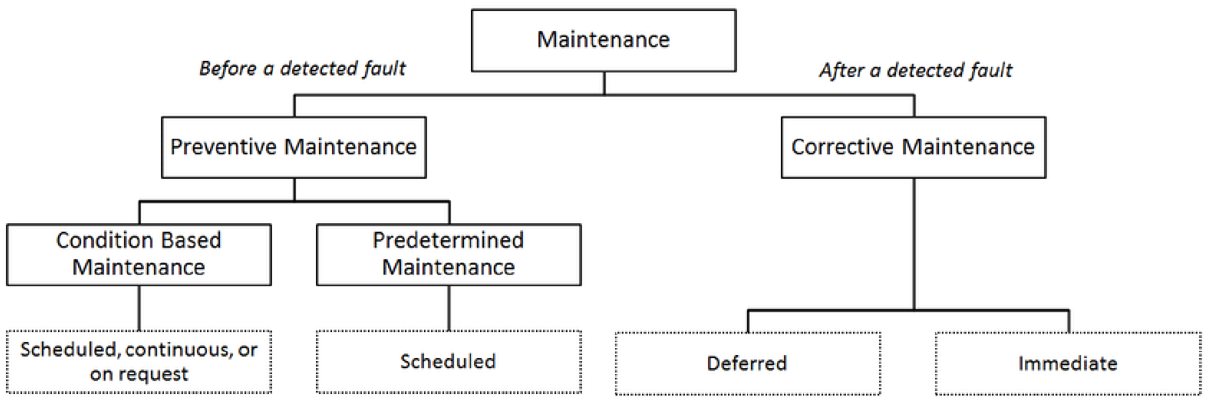

Fig. 1. Maintenance strategies, based on EN 13306

agement for the entire life cycle of the device, including the planning, performance monitoring, and recording of maintenance activities for all three types of maintenance strategies: preventive, predictive and reactive ('Predictive Maintenance – Maximo Application Suite |IBM', n.d.).

Structure of the study

The study is divided into three parts:

1. The structured literature review presents the rationale for a new approach to predictive maintenance.
2. The proposed authors' approach to determining the so-called predictive variables that characterise sets of machinery and equipment using group technology and a taxonomy approach to redundancy in the number of variables is presented.
3. The discussion part is a brief overview highlighting the integration of predictive maintenance with Industry 4.0, the uniqueness of the proposed method, and its potential implications for modern production systems.

These three defined key areas offer a comprehensive solution to the scientific problem and indicate the cognitive gap that is the concept of an innovative predictive maintenance method for advanced production systems.

Literature review

Evolution of maintenance strategies

In a broad sense, the strategy is a plan that considers future actions with a specific purpose and direction. In terms of time, the strategy generally refers to long-term actions. The modern approach to management involves dividing areas within the system into smaller components, including both subjects and objects of management. In this context, operational processes exemplify the latter. An approach based on separating areas under management means that assessing the efficiency and effectiveness of activities may cover not so much particular organisational units but, in particular, these processes, which are crucial for achieving ambitious values of high-performance organisation indicators. This type of management approach means that organisations that use this approach focus on maximising process efficiency to achieve ambitious goals in sales, costs, and individual operational processes, exemplified by maintenance processes in service and goods production companies. They are increasingly formulated as a strategic decision component in the company's corporate strategy and business model (Velmurugan & Dhingra, 2015).

Maintenance processes refer to technical facilities that require assurance that their reliability and operational readiness are at the expected level. Still, these levels depend at least on the type of facility, its application, construction, and functionality. For each technical facility, in the context of the conditions of the entire technical system it belongs to, it is necessary to develop an appropriate maintenance strategy. Approaches to implementing the maintenance strategy of technical facilities, especially in terms of the functioning of manufacturing companies, are evolving and depend on technical progress, information systems and the demand for the expected level of reliability. The choice of a specific maintenance strategy is usually determined by the assessment of additional investments, the scope of activity, the structure of costs and the possession of a set of maintenance skills. This should be considered when selecting these strategies (Sielaff & Lucke, 2021). The experience of recent years has proven the widespread use of solutions that fit into automation and robotisation strategies in the context of broad digital transformation. In this context, two core approaches emerge that trigger new solutions in the field of maintenance strategy, namely planning and predictive methods. The planning paradigm is broadly described and embedded in management theory and practice, as well as the work organisation and operation of technical systems, while the predictive approach is constantly evolving with the emergence of new solutions resulting from advances in the field of digital technologies. In this situation, the physical condition of the equipment is monitored, and maintenance work can be undertaken based on the expected or current condition of the object (Hernández et al., 2022).

The classic maintenance strategy typology includes at least four groups of defined maintenance strategies, namely (Özcan et al. 2021):

1. Corrective maintenance strategy based on action in the event of a failure. It is performed as a corrective action or when a probability of failure is detected. This maintenance aims to restore the system to a state where it can perform the required function in the shortest possible time.
2. Preventive (periodical) maintenance strategy performed according to predetermined periods or prescribed criteria.
3. The predictive maintenance strategy assumes reduced downtime and maintenance costs on the site. The goal is to achieve zero failures by monitoring the equipment's operating state and predicting when it may fail.
4. A revision maintenance strategy requires positive changes to the design, operating methods, operating conditions, installations, schedules, and

individual maintenance methods of a given machine/device to achieve its expected functions at the highest level.

Condition-based Maintenance (CBM) approach has been a significant trend in developing maintenance strategies since the 1950s of the XX century. CBM typically uses state detection systems to collect information from sensors built inside the production system. In this way, a system production degradation model is constructed to assess the condition of the equipment and adopt targeted maintenance strategies (Li et al., 2023a).

In addition, this approach may be based on data-driven CBM optimisation, which combines machine learning (ML) model prediction and reinforcement learning (RL) method based on reliability with the method for estimating the remaining useful life (RUL). This method minimises the average maintenance cost by maximising the system's RUL while maintaining low maintenance costs. In this approach, the system learns from the random forest (RF) predictive model introduced into RL (Mikhail et al., 2024). As system components and their interactions become more complex, problems with the reliability of the entire system under assessment arise. Therefore, individual components should be identified and ranked in terms of their significance and impact on the configuration and functionality of the maintained system (Chen et al., 2022). Thus, due to differences and interdependencies between components, various maintenance sequences can lead to significant differences in the effectiveness of system performance restoration (Zhang et al., 2022). It is also crucial to monitor the work state of the object in real time. The state depends on the function of time. Knowledge of the state of transition is used to describe the ageing and deterioration of the system. The transition probability and the ageing indicator are then estimated based on historical data (Chen, 2011).

The maintenance strategy currently being developed is Approximate Dynamic Programming (ADP), proposed by P. J. Werbos in 1968 (Werbos, 2007). The ADP approach uses selected simulations in conjunction with the implemented functions. The value function or policy function is updated with the states achieved in the simulation instead of analysing all states in the system operating space (Jin et al., 2023). An interesting trend in maintenance strategy development is strategy optimisation based on multi-agent deep reinforcement learning. This method uses a deep neural network to evaluate the state of devices in the operating space. Another approach is presented by Goal Programming (GP), which is aimed at defining the most cost-effective maintenance method. This approach is iterative and based on the search for the optimal solution using analytical methods. It can be supported by methods that support decision-making processes, such as the Analytic Hierarchy Process (AHP) or Failure Mode and Effects Analysis (FMEA). It is also worth paying attention to specific maintenance strategies appropriate for individual sectors of the economy. For example, separate, dedicated maintenance strategies are being developed for the rail transportation sector based on a deep understanding of the sector's specifics. A standard solution is to adopt a maintenance strategy based on time-dependent system reliability and life cycle cost analysis. During each maintenance, all critical failure modes and components are identified and repaired to reduce the probability of system failure below an acceptable level (Zhang et al., 2023). The possibility of using simulations for these models if they imitate real-world conditions is essential for their usefulness (H-Nia et al., 2023).

The presented maintenance strategies prove that this topic is very complex and includes concepts based on both an analogue approach, where planning and preventive approaches dominate, and a digital approach, where automation and robotisation make it possible to monitor the performance of maintenance objects through dedicated sensors and predict how these systems will behave in the future. These approaches include analytics supported by various iterative tools to uncover knowledge of the condition of the devices undergoing maintenance. All these approaches are fundamental to ensure business continuity, the expected reliability, operational readiness, and safety of the maintained technical facilities.

Systemic Approach to Maintenance

The object of maintenance is increasingly considered a complex system. It is created by building a network system. Then, it is subject to maintenance and is represented as a multi-agent of the network. Thus, maintenance strategies based on data generated by sensor systems are being widely developed. At the same time, the concept of predictive maintenance (PdM) based on machine learning (ML), now recognised as one of the most well-known data-driven solutions, begins to dominate. PdM aims to reduce equipment failure rates and minimise operating and investment costs by maximising the equipment's life. In this respect, a predictive maintenance strategy based on machine learning algorithms is economically viable compared to traditional repair maintenance (Arena et al., 2022).

In this context, increasingly widespread technologies such as cyber-physical systems (CPS), the Internet of Things (IoT) and big data are essential in developing intelligent and efficient manufacturing. The underlying strategy for achieving predictive efficiency is based on the data functions from a diagnostic system oriented on the rapid recognition of the health status of the equipment while influencing the time of starting maintenance activities. Some authors point out that the predictive maintenance strategy is based on risk because based on the online monitoring technique allows for the mitigation of the risk of loss of fitness of the device. Moreover, predictive maintenance employs techniques such as state-of-the-art signal processing based on pattern recognition and machine learning, neural networks, fuzzy logic, and other methods (Chinta et al., 2023). An interesting trend in modern maintenance strategies is presented by the concept of opportunistic maintenance, which is a widely accepted strategy for maintaining multi-unit systems and has gained many supporters. This leads to the development of a group maintenance concept, in which the units of a multi-unit system are grouped according to specific rules. When any unit in a group requires maintenance, all units in this group are maintained simultaneously. On the other hand, selective maintenance selects some units in a multi-system system for limited maintenance. Fewer resources are then employed to ensure the system's reliability and meet the expected maintenance requirements. Opportunistic maintenance means that while maintaining one unit in a multi-unit system, other units that require maintenance in the short term are maintained in advance. Therefore, opportunistic maintenance is more flexible than group and selective maintenance. It can make better use of the ability to support multiple units simultaneously and achieve the goal of saving maintenance costs (Li et al., 2023b).

In general, these models are formulated within two main frameworks (Yang et al., 2018), namely, time-based maintenance (TBM) and condition-based maintenance (CBM).

This strategy allows for selecting system components to replace or undergo maintenance repairs based on the effect of importance measure concepts (IMC). IMC models are then based on determining each component's contribution. A component's significance is assessed regarding the degree of success or failure, considering the probability that the components will remain in operation under different conditions and the distribution of these components in the system structure (Rebaiaia & Ait-Kadi, 2022).

Datafication for Maintenance

Datafication is an information technology-driven sense-making process that involves transforming various aspects of the world into data for analysis and decision-making (Lycett, 2013). Modern analytics based on big data is integral to the Industry 4.0 concept. Digital transformation policies rapidly change industry and society (Greco et al., 2019). The so-called Industry 4.0 paradigm has shifted public interest towards technologies designed to deliver intelligence to industrial processes (Para et al., 2019). Monitoring events in a complex network-based system creates the conditions for making flexible returns to improve the efficiency of customer-oriented manufacturing processes. Data collection and analytical processes are used to implement a strategy for improving production processes. The subject of analysis of production processes within the framework of the concept of Industry 4.0 can be the processes themselves and their elements. These elements, as well as technical and operational resources, include human cognitive abilities, occupancy, and time of human processing of correct information, referred to as qualitative performance (Cavallo et al., 2021). The amount of data in production grows, providing process information and thus enabling autonomous monitoring, control, and optimisation for value-creation processes. Modern systems based on the assumptions of Industry 4.0 allow for the registration and detection of assessed parameters and the prediction of different wear conditions on the test bench with an accuracy exceeding 95%. Such systems can reliably detect wear states in the current profile and be used in an industrial environment. For example, the Lean Data approach enables the deployment of decentralised algorithms for pre-processing signals close to real-time. It also allows using machine learning methods in computational systems with limited resources (Küfner et al., 2021). An interesting application of analytics in production processes is predictive analytics in quality control based on the value of machine sensors during production. Therefore, it makes it possible to use specialised machine learning models in a controlled environment (Burggraef et al., 2023). Very often, dedicated analytical platforms supporting production and maintenance processes are used. Then, relevant data analytics is used, while big data processing tools and currently available industrial solutions within cloud computing platforms are applied (Kabugo et al., 2020). Better analytics is possible thanks to more easily accessible advanced techniques such as machine learning (ML) or artificial intelligence (AI) (Hammer et al., 2017). The application of relevant data analysis strategies to increase the intelligence of complex production systems is a condition for improving the efficiency of companies and achieving an even higher level of production excellence. Therefore, the broad application of the analytical tools creates new possibilities for analysing maintenance processes, focusing on predictive maintenance.

Proposed Methodology

Conceptual Description of the Novel Predictive Maintenance Method

Predictive operation is an essential pillar of Total Productive Maintenance (TPM), one of the most frequently implemented maintenance systems derived from KAIZEN, the philosophy of continuous improvement (Bednarek & Santana Villagra, 2017). In addition to the widely used autonomous service, predictive operation displaces scheduled operation due to lower costs (Kabugo et al., 2020). It is observed in the relevant literature that the authors of the presented prediction solutions focus on the one used in individual types of devices and machines. There is not found in the literature identified an approach to the prediction that seeks and attempts to create a universal model adapted to the production structure and, based on its codification and classification due to historical and measurement data, effectively infer the possibility of system failure from real-time data.

Quantitative and qualitative variables characterise predictive processes. To assess the impact of variables on processes, the authors propose using a taxonomy method (Florek et al., 1951), which also allows for selecting the most relevant variables for efficient prediction. For this purpose, the predictive operation process of the selected device is described as a function of the X_{ik} -variables forming a row of matrix (1).

$$X = \begin{bmatrix} x_{11} \dots\dots\dots\dots\dots\dots x_{1n} \\ x_{21} \dots\dots\dots\dots\dots\dots x_{2n} \\ \dots\dots\dots\dots\dots\dots \\ x_{w1} \dots\dots\dots\dots\dots\dots x_{wn} \end{bmatrix}. \qquad (1)$$

Each row of the matrix represents critical values of diagnostic parameters measured while the device is operational. Parameters are relevant for prediction based on Bednarek's classification and codification of machines using the Group Technology approach (Bednarek & Rybak, 2021). The proposed method was elucidated using the intricate structure of a group of machines, specifically machine tools utilised in the production system. A notable subset within this collection is a group of cutting machine tools for metal, distinguished by a variety of structural solutions stemming from their diverse purposes and applications. These machine tools are involved in shaping by altering the form or properties of the input material, thereby achieving the desired appearance, surface texture, and coarseness, among other mechanical properties (Fig. 2).

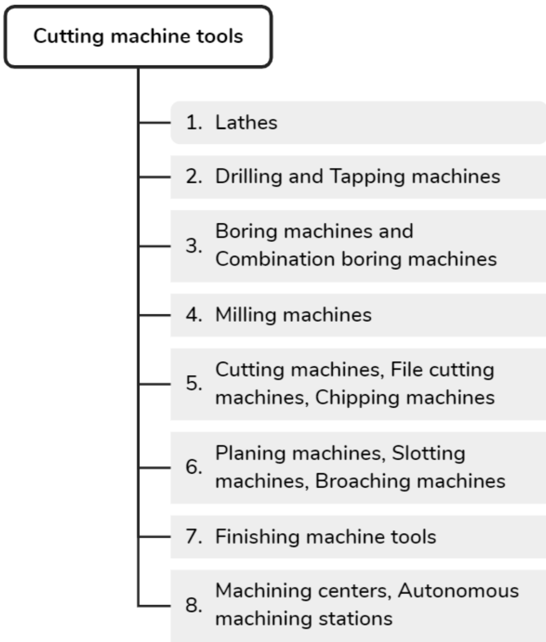

Fig. 2. Cutting machine tools

The variables in the matrix (1) are heterogeneous because they describe different properties of operation processes; hence, they occur in various units of measurement. Therefore, they should be standardised (2).

$$Z_{ik} = \frac{X_{ik} - \overline{X}_k}{S_k}, \qquad (2)$$

where:

- arithmetic mean of observation on variable X_k

$$\overline{X}_k = \frac{1}{w} \sum_{i=1}^{W} X_{ik}, \qquad (3)$$

- standard deviation

$$S_k = \sqrt{\frac{1}{w} \sum_{i=1}^{W} X_{ik} - x_k^2}. \qquad (4)$$

The next step involves identifying groups of machine tools that share similarities in their operational processes and relationships between variables. This step aims to determine the predictor variables for these groups, expressed by subsets of diagnostic variables. To achieve this, a detailed classification of the machine tools described in the different rows of the matrix (1) will be carried out. The ultimate goal of this activity is to use predictive actions to improve the performance of the machine tools. The bullet method will divide the objects into homogeneous groups, indicating the predictive variables.

We have a set of observations in the form of a matrix (1). To standardize this matrix, we use the formulas (2), (3), and (4). As a result, we obtain a new matrix of standardized observations called Z. Based on a standardised matrix of diagnostic variables Z, we calculate the distance matrix C, which we define as follows:

$$C = [C_{rs}] \qquad r, s = 1, 2, \ldots, w, \tag{5}$$

where:

$$C_{rs} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(Z_{rk} - Z_{sk})^2}, \tag{6}$$

- Z_{rk} is diagnostic variable for $r, k = 1, 2, \ldots, w$;
- Z_{sk} is explanatory variable for $r, s = 1, 2, \ldots, w$.

Appropriate transformations of the matrix (5) allow for the definition of such subgroups of objects (machine groups) that there are similar objects in each subgroup by diagnostic (correlated) variables, which define their **predictive operation processes.** The division of diagnostic variables into sets of correlated variables aims to determine so-called predictive variables for each set, i.e., reducing the number of these variables that will need to be observed and analysed during the predictive operation process. This is done using the centre of gravity method. Subsequently, we determine ranking coefficients for predictive variables. The higher the value of the ranking coefficient $\in 0 \le \lambda \le 1$, the more critical the variable for the correct operation of the predictive subgroup of machine tools. In this way, a predictive operation is performed only considering observations of fluctuations in the values of variables with the highest values of their ranking coefficients λ. To do this based on the observation matrix X (1), the matrix C (7) of correlation coefficients is calculated after its standardisation.

$$C = [C_{rs}] \qquad \text{for } r, s = 1, 2 \ldots, n, \tag{7}$$

where:

$$C_{rs} = 1 - |r_{rs}| \,. \tag{8}$$

In addition:

$$r_{rs} = \frac{\sum_{i=1}^{W}(x_{ir} - \overline{x}_r)(x_{is} - \overline{x}_s)}{W \cdot S_r \cdot S_s}. \tag{9}$$

Next, it is necessary to determine the values of the so-called ranking coefficients λ_i for individual predictive variables, which allow variables to be differentiated in their significance in the prediction process. Therefore, it is required to calculate the distance between variables according to the formula for observation matrix X (1) and after its standardisation according to formulas (2), (3) and (4), and then calculate the distance matrix C (10) between variables according to formula (11).

$$C = [C_{ij}] \quad i, j = 1, \ldots, N, \tag{10}$$

$$C_{ij} = \sqrt{\sum_{k=1}^{w}(z_{ki} - z_{kj})^2}, \tag{11}$$

where: N – number of predictive variables.

In matrix C (10) with calculated distances between predictive variables, their relationship in the form of a dendrite should be established (Florek et al., 1951). Completing the calculations, the found dendrite of the relationships between variables will be used to determine the numerical values of ranking coefficients, i.e. coefficients λ_i for each predictive variable. The ranking coefficients calculated in this way are standardised values (12)

$$0 \le \lambda_i \le 1. \tag{12}$$

The higher the value of the ranking coefficient λ_i, the more critical the ith predictive variable for the predictive operation process is. Matrix (1) can be created for each group of devices using Group Technologies and the basics of Technology, i.e. technological or geometric similarity. Taxonomy will allow for the development of universal standards of conduct when applying predictive operations for production structures.

Process of implementation

The sequence diagram (Fig. 3) pictures the taxonomy of variables based on the PDM implementation process. This will involve multiple entities and subprocesses, illustrating the flow of actions for implementing predictive maintenance based on the taxonomy method.

The diagram illustrates the generalised pattern of conduct consisting of fourteen key actions defining the scope, subject matter and core assumptions for a proposed solution as follows:

1. Using the taxonomy method, identify the technical object(s) that will be affected by implementing predictive maintenance.
2. Codify and classify production structure using historical data and real-time data metering on the possibility of failure in the system.
3. Collect historical and real-time data.
4. Describe predictive operation processes using quantitative and qualitative variables.

5. Select important quantitative and qualitative variables that are most important for efficient prediction.
6. Create matrices based on a set of critical (variable) diagnostic parameters measured during the operation of the device/devices relevant for prediction.
7. Standardise defined variables to unify the units which describe them.
8. Separate similar object groups in terms of the relationships between variables, which describe the processes of their operation and predictive operation, and indication of predictive variables.
9. Separate subgroups by the predictive operation of subgroups based on diagnostic (correlated) variables, which define the processes of their predictive operation.
10. Optimise by reducing the number of variables that must be observed and analysed during the predictive operation process.
11. Rank the importance of variables for the correct operation of the predictive subgroup of devices based on the observations of fluctuations in the values of variables with the highest values of their ranking coefficients.
12. Dendrite relationships between variables are determined using mathematical methods to determine the numerical values of ranking coefficients for each predictive variable. The greater the ranking coefficient's resulting value for a given variable, the more critical it is for the predictive operation process.
13. Implement universal standards of conduct for applying the predictive operation for production structures based on the described methodology.
14. Perform predictive maintenance.

The sequence of twelve tasks presented above comprehensively describes the proposed methodology of predictive maintenance, constituting the assumptions

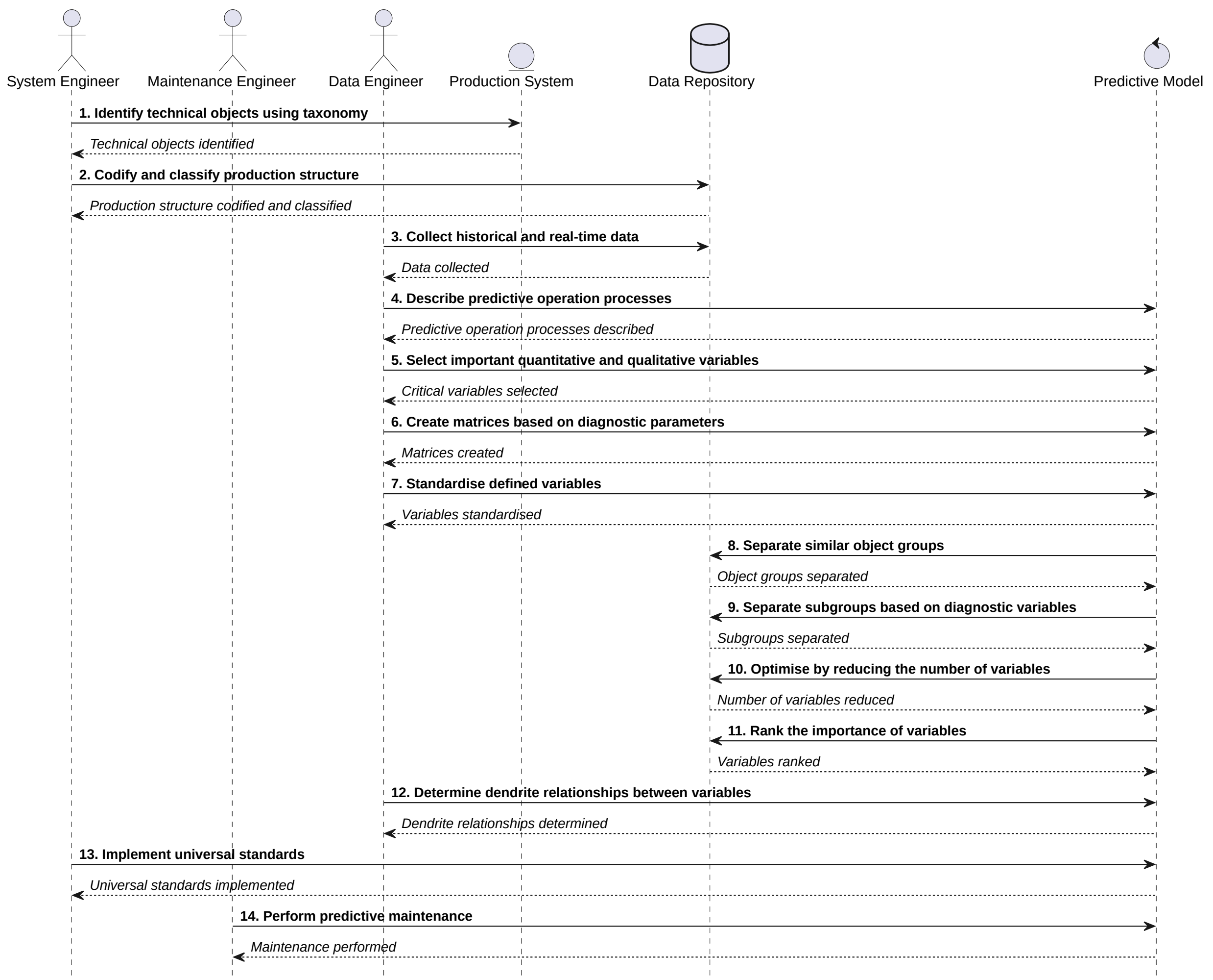

Fig. 3. Sequence diagram of taxonomy-based PDM implementation process

for a universal model of maintenance of groups of devices adapted to the production structure that meets the requirements of the Fourth Industrial Revolution. Due to its algorithmic nature, the proposed solution can be easily implemented by employing digital economy technologies and be included in the scope of intelligent automation and industrial robotics systems.

Relevance to Industry 4.0-Driven Manufacturing Environments

Shaping the production environment is the fundamental condition of the process of improving the efficiency of the functioning of this type of complex organisational and technical system. Technological progress and the related scope of innovation implementation involve the search for solutions that will ensure a high level of automation and robotisation of intelligent manufacturing systems. In this way, the conditions for creating assumptions for production companies are developed using the following triple-element model: the technical system – operator – working environment system.

Industry 4.0 brings a paradigm shift in production through decentralisation and automation. It is based primarily on machines' collective intelligence. This enables smart manufacturing, which describes the ability of machines to change the layout of tasks and adjust operational parameters based on criteria such as cost, resource availability, and demand requirements. Industry 4.0 includes the concept of smart factories, cyber-physical systems, robotics, and cloud manufacturing systems (Rohini & Krishnan, 2017).

One of the objectives of Industry 4.0 is to improve management practices and build competitiveness by creating a functioning physical and digital environment. The Industry 4.0 environment employs driving technologies, such as Cyber-Physical Systems (CPS), Big Data, IIoT, Robots, Augmented Reality, and Additive Manufacturing (Silvestri et al., 2022). Industry 4.0, as part of industrial production, is evolving towards high flexibility, diversity, adaptation, and dynamics. It is an intelligent production system scenario that deals with planning complex production processes and multi-level products in a dynamic and flexible workshop environment (Zhang et al., 2021). The aim of Industry 4.0 is to combine production, information technology and the Internet. Thus, the latest information and communication technologies combine with the classic model of the functioning of industrial processes. This idea shows a fundamental paradigm shift – from centralised to decentralised control to ensure high flexibility in producing non-standard products and services (Pasetti Monizza et al., 2018). Therefore, with the advent of cyber-physical systems (CPS) and the Fourth Industrial Revolution, the focus is on identifying distributed architecture, coordination, and extensive communication between all system elements. Modern industrial production is based mainly on flexible production.

As part of the work environment, a combination of solutions and techniques for improving production processes, such as information and communication technologies, computing technology, operations technology, sensors and data acquisition technologies, and human-machine interaction, is used (Ghodsian et al., 2023). This approach enables technology development in Industry 4.0 to represent a qualitative change in production strategies, allowing companies to produce custom-made products (Partearroyo et al., 2023). What is essential is that Industry 4.0 transforms the manufacturing sector into dynamic, networked, and complex industrial environments, which generate vast amounts of data and employ intelligent manufacturing technologies and artificial intelligence (AI) to achieve efficient and sustainable manufacturing processes (Alenizi et al., 2023). Cyber-physical systems and data exchange in Industry 4.0 transcend traditional organisational boundaries, requiring an intelligent, interconnected, and flexible value chain (Caiado et al., 2021). However, the effectiveness and efficiency of implementing the Industry 4.0 concept depends on the company's digital maturity level (Senna et al., 2023). This affects the functioning of processes and the development of products and business models in the manufacturing industry and aims to design material and information flows efficiently along the value chain network (Dillinger et al., 2022). Such a work environment is conducive to improving the efficiency of a distributed operation system, which is closer to the work theory than system theory. Decentralisation and the role of communication technologies shape a new paradigm of planning and implementation of manufacturing processes, significantly increasing its capabilities.

Discussion

The article explores how the taxonomy approach leverages data analytics and machine learning techniques to classify production machines into distinct categories based on their operational characteristics, usage patterns, and maintenance needs. Doing so offers several key advantages: improved precision, predictive maintenance customisation, data-driven insights, and scalability. Unlike generic categorisations, the taxonomy approach provides a highly nuanced and accurate classification of production machines. This precision enables maintenance teams to tailor their strategies to the specific needs of each type of machine. With a more granular understanding of machine types, organisations can develop customised predictive maintenance plans considering machine age, usage intensity, and criticality. The taxonomy approach is based on data-driven insights, allowing organisations to harness the power of big data and the Industrial Internet of Things (IIoT). Maintenance teams can detect anomalies and issues by analysing real-time data from production machines before they lead to breakdowns. As companies expand their production facilities, the taxonomy approach easily scales to accommodate new machine types and evolving maintenance requirements. It can adapt to changing industry standards and technological advancements.

The taxonomy approach represents a paradigm shift in predictive maintenance, empowering organisations to optimise their production machine management strategies for a more sustainable and competitive future.

A widely recognised approach for PDM includes integrating sensors into equipment and utilising dashboards for real-time monitoring of conditions, which can offer a comprehensive view of asset health, enabling proactive maintenance actions and minimising unexpected failure. However effective, it is limited due to focusing separately on each production asset. Meanwhile, the proliferation of flexible manufacturing systems in the production industry brings a new perspective on condition-based maintenance: the dynamic nature of technological march routes and the variability of products leverage predictive maintenance from a sequence of machines' paradigm to a network of production assets.

The proposed solution is characterised by versatility, scalability, and relatively low implementation costs due to the method architecture, which enables the following: defining any production system for predictive maintenance using a generalised description method, modularity, integration with the company's IT infrastructure, and the possibility of integration with the cloud in the software as a service (SaS) model.

Attention should be paid to the limitations of the proposed model, which result from the following conditions: first, the number of typological groups is usually unknown, which may give rise to problems resulting from the identification of the range of analysed variables. Secondly, since objects in the same group should be as similar as possible, this raises issues of reliable determination of the similarity criteria and subjective assessment. The dendrite method, named the Wrocław taxonomy, was used to develop this model by constructing the dendrite as a multi-stage procedure. The dendrite is completed when all the interconnected clusters form a coherent graph. This complex process is exposed to calculation deviations depending on the number of iterations used. The problem is the separation of subsets of homogeneous objects in terms of studied characteristics to reliably specify the factors that determine the reliability of the analysed phenomena.

Due to the above limitations, some possible challenges should be mentioned as follows:

- The taxonomy approach may introduce unnecessary complexity and rigidity into maintenance strategies for production machines. By focusing on highly nuanced categorisations, maintenance teams may struggle to adapt quickly to changing operational needs and find managing many distinct machine categories challenging.
- The reliance on data-driven insights and real-time analytics may not always guarantee accurate predictions or early detection of issues, as anomalies in machine behaviour can still go undetected or misinterpreted.
- While innovative, the Wrocław taxonomy method may introduce computational complexities and uncertainties due to the iterative nature of the dendrite construction process.

These challenges could hinder the taxonomy approach's practical application and scalability in real-world production environments, limiting its effectiveness in optimising maintenance strategies and machine management.

To address these challenges, researchers are exploring the integration of machine learning algorithms and artificial intelligence techniques to enhance the accuracy and efficiency of anomaly detection and predictive maintenance in industrial settings. The integration concept is based on developing domain-specific language (DSL) and an appropriate execution engine to simplify mirroring and monitoring the production system with the proposed novel method. A Domain-Specific Language is a specialised programming language finely tuned for addressing a particular set of problems. This type of language leverages the principles and regulations inherent to a specific field or domain. DSLs are designed to simplify the coding process by providing specialised syntax and semantics tailored to the particular requirements of the targeted domain, allowing developers to express solutions more concisely and effectively. The domain-specific language and a transformation engine can be customised to accommodate specific industry requirements and production system complexities, ensuring a tailored solution for each unique operational environment. Moreover, the low-code nature of DSL and interoperability of the execution engine by design would allow for seamless integration with existing MES and SCADA systems through UPC

UA servers to maintain bidirectional data and control signals exchange. As a result, it would be possible to implement a digital twin-based solution enabling proactive decision-making and timely interventions to prevent costly downtime. Furthermore, integrating advanced analytics capabilities within the digital twin framework can provide predictive maintenance insights, optimise asset performance, and maximise operational efficiency.

Conclusions and future avenues

An attempt was made to create a universal model for the predictive maintenance of complex production systems. The model is adapted to the production structure, subject to the codification and classification of predictive variables, and is intended to neutralise adverse events in the production system. Maintenance objects are now considered complex systems developed by building a network system. From this perspective, the taxonomy method is becoming a productive way to identify all predictive variables of the maintenance system and create a consistent measurement model. In this way, the shaped work environment is conducive to improving the efficiency of a distributed operation system, which is closer to network theory than system theory. Decentralisation and the role of communication technologies shape a new paradigm for planning and implementing manufacturing processes, significantly increasing their capabilities.

Against this background, the presented model of predictive maintenance of complex production systems is based on the taxonomy method. The concept comprises fourteen implementation tasks and comprehensively describes the predictive maintenance methodology. It constitutes the assumptions for a universal model of maintenance of groups of devices adapted to the production structure, meeting the requirements of the Fourth Industrial Revolution. Due to its algorithmic nature, the proposed solution can be easily implemented by employing digital technologies and included in the scope of intelligent automation and industrial robotics systems.

Future research and challenges arising from the developed concept should relate to empirical testing of the model using the experimental method in an actual production environment. The future research plan includes:

- collecting and preparing data from real production systems,
- choosing the software framework suitable for the rapid development of a prototype computational model,
- using developed procedures and mathematical models to implement the proposed method.
- computational experiments to validate the applicability of the proposed method sourced from data from the actual production system.

Furthermore, the research will also focus on developing domain-specific language employing both a taxonomy approach and an ontology of production machines aimed at condition-based maintenance purposes to make possible future cost-effective and scalable implementation of the proposed method across different industrial sectors to assess its broader impact and potential for widespread adoption.

In conclusion, developing a universal model for predictive maintenance in complex production systems is crucial for enhancing efficiency and productivity in the Fourth Industrial Revolution era. The taxonomy method identifies predictive variables and creates a consistent measurement model for maintenance systems. This model presents a new paradigm for planning and implementing manufacturing processes by leveraging communication technologies and decentralised operations. Future research should focus on empirically testing the model in real production environments and developing a digital twin-like software framework to implement presented concepts fully.

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