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MAINTENANCE 4.0 TECHNOLOGIES – NEW OPPORTUNITIES FOR SUSTAINABILITY DRIVEN MAINTENANCE

Małgorzata Jasiulewicz-Kaczmarek[1], Stanisław Legutko[1], Piotr Kluk[2]

[1] *Poznan University of Technology, Poznan, Poland*
[2] *Zelka Sp. z o.o., Psary Małe, Poland*

Corresponding author:
Małgorzata Jasiulewicz-Kaczmarek
Poznan University of Technology
Faculty of Engineering Management
Prof. Jacka Rychlewskiego 2, 60-965 Poznan, Poland
phone: +48 61 6653364
e-mail: malgorzata.jasiulewicz-kaczmarek@put.poznan.pl

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Abstract
Digitalization and sustainability are important topics for manufacturing industries as they are affecting all parts of the production chain. Various initiatives and approaches are set up to help companies adopt the principles of the fourth industrial revolution with respect sustainability. Within these actions the use of modern maintenance approaches such as Maintenance 4.0 is highlighted as one of the prevailing smart & sustainable manufacturing topics. The goal of this paper is to describe the latest trends within the area of maintenance management from the perspective of the challenges of the fourth industrial revolution and the economic, environmental and social challenges of sustainable development. In this work, intelligent and sustainable maintenance was considered in three perspectives. The first perspective is the historical perspective, in relation to which evolution has been presented in the approach to maintenance in accordance with the development of production engineering. The next perspective is the development perspective, which presents historical perspectives on maintenance data and data-driven maintenance technology. The third perspective, presents maintenance in the context of the dimensions of sustainable development and potential opportunities for including data-driven maintenance technology in the implementation of the economic, environmental and social challenges of sustainable production.

Keywords
Maintenance 4.0, smart maintenance, data-driven maintenance, sustainable maintenance.

Introduction

Manufacturing companies and equipment manufacturers face two major changes affecting their business: digitalization and the sustainability. From the point of view of digitalization in the literature on production, the changes are referred to as the next (fourth) industrial revolution, which is often referred as 'Smart manufacturing', 'Industry 4.0' and 'Smart Factory' [1]. Only two years ago, Industry 4.0 was considered the future, today it is a widely accepted reality that changes the way companies operate and affects almost every industry around the world [2]. The term Industry 4.0 is defined in literature in many ways. Depending on the direction of the research conducted by the authors, various aspects are highlighted [3]. In general, Industry 4.0 can be defined as a term collectively describing changes in technological scope and organization of value chains [4]. This definition highlights two main aspects of digital transformation, namely the technological aspect and the business aspect. The technological aspect refers, among other things, to new possibilities of implementing and monitoring processes through the use of digital technologies [5, 6], while the business aspect includes primarily new business models [7]. In Industry 4.0 environment, manufacturing systems are able to monitor physical processes, create a so-called 'digital twin' of the physical system, and make smart decisions by real-time communication and cooperation with humans, machines, sensors, etc. [8, 9].

The second major change affecting manufacturers is the sustainable development (SD). Brundtland Commission (1987) defined SD as 'development that meets the needs of the present without compromising the ability of the future generation to meet their own needs'. In sustainable development environment, there has been an increased pressure on manufacturing companies to think beyond traditional economic measure and evaluate environmental and social effects of the business. As described by [10] sustainable manufacturing seeks to ensure that production will be performed economically, considering resources use, and securing social standards.

In the Industry 4.0 context, sustainable manufacturing definition and approach can be linked with production systems developed in order to be conscious, transparent, intelligent, efficient, flexible, agile, collaborative and responsive [11]. Digitalization and sustainability are important topics for manufacturing industries as they are affecting all parts of the production chain. According to [11] 'both approaches present practices' convergence, such as: design for disassembly, remanufacturing, and recycling applied in the life cycle management; reverse logistics for circular economy, 'lean and green management' for resource efficiency; sustainable design reducing safety risks for workers' and consumers' eliminating the use of toxics parts in the product and production processes'.

In such a context, various initiatives and approaches are set up to help companies adopt the principles of the fourth industrial revolution with respect sustainability. Within these actions the use of modern maintenance approaches such as Maintenance 4.0 (also called Smart Maintenance) is highlighted as one of the prevailing smart & sustainable manufacturing topics [12, 13].

The goal of this paper is to describe the latest trends within the area of maintenance management from the perspective of the challenges of the fourth industrial revolution and the economic, environmental and social challenges of sustainable development.

The rest of the paper is as follows. Firstly (chapter 2), a short literature review related to evolution on maintenance is introduced. In the next chapter, the evolvement history of maintenance data is reviewed and date driven maintenance technologies are presented. The fourth chapter is devoted to issues of sustainable maintenance. The fifth chapter presents the potential applications of Maintenance 4.0 technology in relation to the economic, social and environmental challenges of sustainable development. Finally, the main conclusion is presented.

From Maintenance 1.0 to Maintenance 4.0

In the last years, due to the evolution of technology, machines have become more and more complex and they also became more critical in terms of reliability and availability. To reduce the risk and minimize the consequences of unexpected stops and disruptions in digitalized manufacturing, maintenance must take a key role [13]. Over time, maintenance has evolved from reactive (Maintenance 1.0 – M1.0) to preventive (Maintenance 2.0 – M2.0) and then to condition based (Maintenance 3.0 – M3.0), to current predictive and prescriptive approach which is usually denoted as Maintenance 4.0 – M4.0 (Fig. 1).

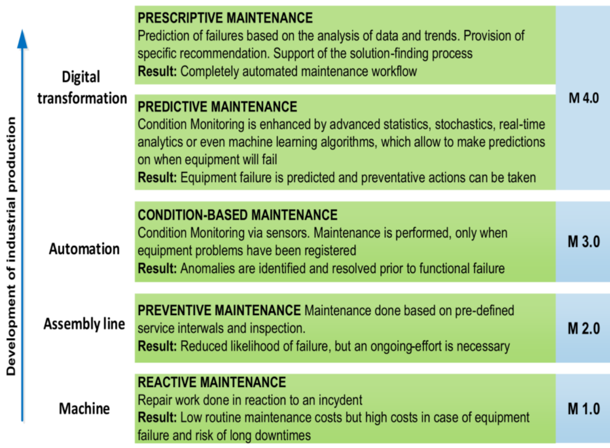

Fig. 1. Development of industrial maintenance.

During the first generation (Corrective maintenance or Maintenance 1.0), the machines were slow and simple to work and were simple in design and easy for repairing. Machine operators were responsible for equipment maintenance. Maintenance actions were based on solving the faults that have already happened. As the complexity of the machines grew and the maintenance operations increased, enterprises started to include maintenance departments in their structure. The objective of maintenance department was to reduce the number of corrective maintenance actions applied through periodic checks and replacement of worn parts. The concept of a system of planned preventive repairs has appeared (Maintenance 2.0). Its essence is servicing machines and devices at predetermined time intervals while often making use a checklist of original equipment manufacturers (OEM) recommendations.

The start of automation or more complex systems paved the way for maintenance to next generation – Maintenance 3.0 (also called 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 [14], CBM is a maintenance program that recommends maintenance actions (decisions) based on the information collected through condition monitoring process.

With the Industry 4.0, new maintenance paradigm, innovative methods and tools have to be developed. Maintenance has to change towards the requirements of Industry 4.0 to become an enabler for the smart factory [15]. In the context of Industry 4.0, the maintenance function is often denoted as Maintenance 4.0 or Smart Maintenance [16] and is defined as:

- 'a subset of the smart manufacturing system represented by self-learning and smart machines that predicts failure, makes diagnosis and triggers maintenance actions' [17];
- 'is the application of machine learning, automated processes and robotics/drones to reliability and maintenance activities' [18];
- 'is about predicting future failures in assets and ultimately prescribing the most effective preventive measure by applying advanced analytic techniques on big data about technical condition, usage, environment, maintenance history, similar equipment elsewhere and, in fact, anything possibly relating to the performance of an asset' [19].

According to [20], 'Smart Maintenance stands for an intelligent and learning maintenance management focusing on permanent improvement'. According to [21] 'Maintenance 4.0 does predictive analytics and suggests feasible solution, with major application in Industry 4.0 and especially on those maintenance aspects that deals with collection of data, its analysis and visualization and asset decision-making'. Recently [22] developed a conceptual definition of Smart Maintenance as 'an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies' and defined the four underlying dimensions: data-driven decision-making, human capital resource, internal integration, and external integration.

Given the above, Smart Maintenance or Maintenance 4.0 describes a set of techniques to monitor the current condition of machines with the goal to predict upcoming machine failure by using automated (near) real-time analytics and supervised or unsupervised machine learning, and to prescribe optimal course of action in real time, analyse potential decisions and interaction between them.

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 [23]. 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 [24–26]. Grubic [27] suggests that the use of predictive maintenance strategy is stimulated by servitization.

At the top level of Maintenance 4.0 (Fig 1), the use of advanced data analytics methods allows to not only predict when a failure occurs, but also by using libraries of standard maintenance tasks, prescribe recommendations to avoid such a failure and optimize maintenance schedulers and resources. Thus, the concept of prescriptive maintenance goes far beyond simply predicting failures [28]. Based on the analysis of historical data and real-time data on the state of the machine, required maintenance measures are predicted by a system and a course of action is prescribed. Prescriptive maintenance means changing the paradigm and moving from planned preventive maintenance to proactive and smart maintenance planning [29].

Data-driven maintenance

Maintenance data from time perspective

For any scientific maintenance practices, data are one of the most important requirements. In the Maintenance 1.0 age, because of manufacturing equipment was simply, maintenance activities were of low complexity. As a result, the data generated in the maintenance tasks was limited, as it existed mostly in the form of equipment operator experience. Machine operators and storage in operators' memory collected the maintenance data manually.

In the Maintenance 2.0 age, the way data was acquired and processed has changed. The increase in demand for products has led, among other things, to an increase in mechanization. Availability, durability and costs were recognized as important factors for achieving business goals. Enterprises began to establish specialized technical services (separate organizational units) to carry out maintenance and repair tasks, and machine and device operators in practice did not participate in these activities and had no impact on their scope. Maintenance data was increasingly handled by maintenance managers. Maintenance managers began to employ more systematic methods to document and analyse maintenance data. The raw data was recorded in written documents rather than stored in machine operator memory. Machine-related data was used to support decisions concerning machine maintenance, repair, and replacement. In particular, statistical models were introduced to analyse failure rate and spare parts consumption. Nevertheless, despite the fact that a larger quantity of maintenance data was analysed through scientific methods, data was still handled manually by maintainers. Therefore, the utilization rate of maintenance data remained relatively low.

With the introduction of the next industrial revolution (referred to in the literature as the information age), the role of information technologies and the scope of their application in production processes increased. Consequently, the companies gained the ability to obtain a large amount of data on both production processes and maintenance processes. Many factors influenced this ability. First, in order to facilitate maintenance management in production enterprises, IT systems, e.g. CMMS (Computer Maintenance Management System), have been used. Secondly, machine and device manufacturers have started to use computer systems such as computer-aided design (CAD) and computer aided manufacturing (CAM) to modify and optimize new machines. Thirdly, electronic devices and computers began to be used to automatically control production devices. Data from the processes of use and maintenance processes of machines and devices began to be stored in computer systems and managed by information systems. In addition, the effectiveness of data analysis has also increased due to the use of computational models. Still, in the decision-making process, the results of the analysis required interpretation by heads of maintenance. Due to implementation costs and competences necessary to maintain maintenance IT systems, many manufacturing companies (especially small and medium-sized enterprises) still found it difficult to benefit from the value of maintenance data.

In recent years, due to the significant increase in digitization and automation, as well as the complexity of production equipment, requirements for maintenance management have changed [15]. Today's maintenance managers face great challenges to increase output, to reduce equipment downtime, to lower costs, and to do it all with less risk to safety and the environment. Thanks to new technologies of Industry 4.0 (such as the Internet of Things and cloud computing), the possibility of collecting and storing as well as their processing and analysis has significantly increased. As a result, heads of maintenance departments, and consequently business managers, can start to benefit from the value of data. Effective analysis of data enables equipment manufacturers and machines users to deepen their understanding of equipment, processes, services, employees, suppliers, and regulators requirements. The comparison of maintenance data in different maintenance ages is shown in Table 1.

Table 1
Comparison of maintenance data in different maintenance ages.

	Maintenance 1.0	Maintenance 2/0	Maintenance 3.0	Maintenance 4.0
Data source	Operator experience	Maintainer and machines	Operator, maintainer, machines, information and computer systems	Operator, maintainer, information systems, OEM and suppliers data
Data collection	Manual collection	Manual collection	Semi-automated collection	Automated collection via sensors and IoT
Data storage	Operator memory	Written documents	Databases	Cloud services
Data analysis	Arbitrary	Reliability theory based on Bathtub curve assumption	Conventional algorithms	Fuzzy logic, neutral networks, evolutionary algorithms, machine learning
Data transfer	Verbal communication	Written documents	Digital files	Digital files
Data management	N/A	Human operators	Information systems	Cloud and artificial intelligence

Data-driven innovation in maintenance

The term 'data-driven' means the fact that implemented activities and processes are primarily stimulated by data, not by intuition or experience. Increasing easier access to data and awareness of the possibilities offered by data in the decision-making process drives enterprises to shift towards a new type of maintenance strategy called data-driven maintenance [30–33]. Research conducted by [34] show, that among 14 most important innovations in maintenance till 2020 five (smart sensor, big data, integrating asset management IT systems, mobile solution and 3D design/virtual reality) are primarily data-driven, where several of the process-driven innovations, such as CBM, are also strongly data-driven (Fig. 2).

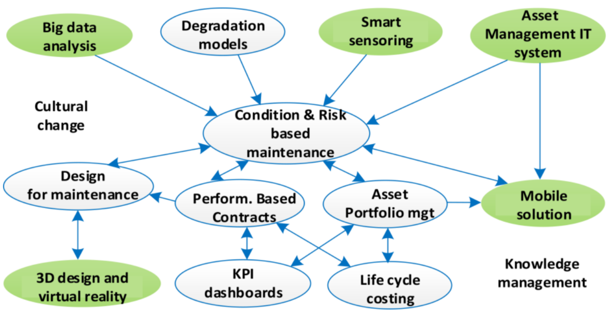

Fig. 2. Interdependencies between the 'Top 14' maintenance innovations [34].

Data is the key to intelligent maintenance. Until recently, the main problem for maintenance managers was the lack of information sources. Today the situation has changed. Over the past ten years, due to the intense development of information and communication technologies and their applications in production systems, and the development of sensor technology (e.g. smart sensors that allow, among others, digital signal processing and wireless data streaming) have caused that the maintenance system managers have gained a lot new data sources. These new data sources are rapidly generating large amounts of different types of data, known as big data. That data are available for maintenance decision makers and provide opportunities for enhancing the performance of maintenance processes [35, 36]. Big data has been often described as the next frontier for innovation, competition, and productivity. The use of data allows a better understanding of factors affecting the operation of individual machines and entire systems and provide more opportunity to predict upcoming issues in an equipment or system. Thanks to this, the implementation of maintenance activities will be able to be carried out in a more predictive way than before. However, due to a lack of knowledge and understanding, data from machine use and operation processes is often left unused because people simply do not know how to extract useful information and/or knowledge from data, or do not recognize the potential that is hidden in all collected data. To explore data, advanced data analysis is required. Runkler [37] defines data analytics as the use of mathematical methods to obtain information from data in order to optimize processes and support decision-makers in the decision-making process. Big data analysis (BDA) is the sub-area of big data concerned with adding structure to data to support decision-making as well as supporting specific usage scenarios. From the point of view of maintenance management, BDA can help maintenance departments in the company and OEM to better understand the open and hidden information contained within the data and enables identification of the data which from future decision-making perspective (e.g. on investments, changes of service strategy etc.) are the most important [38, 39]. Karim et al. [40] developed the concept for Maintenance Analytics. This concept based on four phases (Fig. 3): descriptive analytics, diagnostic analytics, predictive analytics and prescriptive analytics.

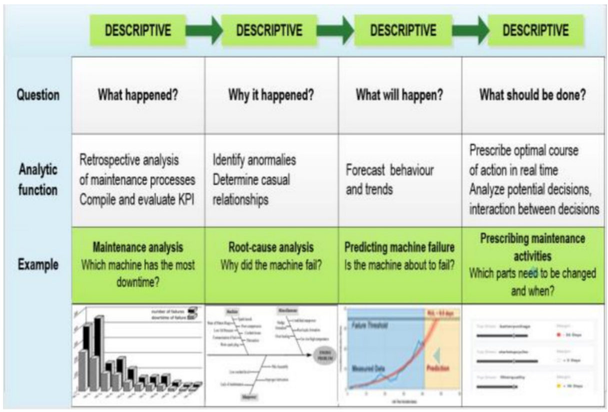

Fig. 3. Maintenance analytics phases.

Descriptive analytics answers the question 'What happened?' by providing information about previous maintenance operations. Diagnostic data analysis can respond to 'Why it happened?' by identifying causes. Predictive analytics estimates future events (what will happen, when?) by learning from historical maintenance data (possibly in real-time). Prescriptive analytics can respond to 'What should be done?' by providing actionable recommendations for decision making and improving and/or optimizing forthcoming maintenance processes. Both descriptive and diagnostic analytics methods are reactive while predictive and prescriptive analytics approaches are proactive.

Analysing the literature, it can be stated that Big Data analytics in maintenance has opened new opportunities to support maintenance managers in the decision-making process, while for scientists it has opened new research areas. For example, [41] developed an industrial big data pipeline architecture, which is designed to meet the needs of data-driven industrial analytics applications focused on equipment maintenance in large-scale manufacturing. Solution presented in the paper is based on real-world requirements obtained from manufacturing facility. Cortadi et al. [42] proposed solution for the predictive maintenance problem in a real machining process. The authors developed a decision-making application to provide a visual analysis of the Remaining Useful Life (RUL) of the machining tool. Truong [43] used Big Data Cloud and IoT to provide a predictive analytics approach for maintenance. On the other hand, many new challenges have been raised. One of the gaps in the existing literature on the analysis of large data sets in maintenance is that the proposed concepts and solutions are either only useful for some types of maintenance problems, or are not detailed enough and do not describe the procedures for analysing data and components needed to develop specific data analysis solutions in maintenance systems. Therefore, in order to effectively apply the analysis of large data sets in maintenance systems and support decision-makers in the decision-making process, it is necessary to integrate skills and knowledge in the field of information and communication technologies with engineering knowledge and expert knowledge.

An important aspect of using large data sets is the visualization of analysis results, including the presentation of trends and other forecasts using appropriate visualization tools [44]. Due to the complexity of large data sets, conventional data visualization tools and techniques such as tables, bars or line charts are insufficient. Visualizing big data requires some innovative approaches. The main purpose of modern methods of data representation is to improve the forms of images, diagrams or animations so that they are useful for decision-makers without forgetting that human perception is, however, limited.

According to [45], the trend recognized in visualization of big data sets is implementation of augmented reality (AR). AR visualization is a popular visualization technique that combines the real world and virtual objects. The literature on AR identifies maintenance service as one of the growing application areas [46–50]. A set of possible applications and benefits that AR could provide to maintenance, repair and assembly tasks have been analysed by [51, 52]. Webel et al. [53] developed a method for multimodal AR-based training of maintenance skills. According to [54], AR technology in maintenance, visualizing digital instruction in real time on the real working area, can potentially lead to many advantages, such as: ‘employ less-skilled operators; data are up to date; time and cost saving; error rate reduction; knowledge is retained in the system and not in people; the information level can be adapted to the user skills’. Masoni et al. [55] present a solution for remote maintenance based on off-the-shelf mobile and AR technologies. Manuri et al. [56] proposed a system for supporting maintenance procedures through AR. The system consists a computer vision algorithm, which is able to evaluate, at each step of a maintenance procedure, if the user has correctly completed his task, or not. The areas with a great number of applications of AR in maintenance processes are: aerospace [57–59], automotive [60–62] and industrial plants [4, 63]. Due to the increasing complexity of maintenance processes, various assistants (e.g., tablets with smart software, smartphones, and virtual assistants) increasingly support employees of technical departments. Using an AR application on smartphones or tablets supports maintenance technicians in making informed decisions about maintenance and repair activities and their safe implementation.

In the context of Industry 4.0, a digital machine is not only the material result of the production process. The digital machine is also an intelligent source of data obtained from the process of its use. These data allow physical machines to gain a new virtual dimension by building their digital equivalent called ‘digital twin’ [64–66]. According to [67], ‘A digital twin is a virtual representation of a physical object called a Physical Twin. The physical and the digital twin may be connected to each other. A digital twin can provide more information about its physical twin than the physical twin itself can provide’. By using cloud-connected sensors embedded in machines, it is possible to send data from the operational level in real time, and this allows you to create current virtual simulations of real machines (real-world machines). One of the areas of application of digital twin technology is and will be in the near future to monitor the operational status and functionality of complex and critical machines, especially in industries where an emergency event can have catastrophic consequences for people and the environment. According to [65] and [68] digital twin can be used to predict of the remaining useful life (RUL) of the physical machine by using a combination of physics-based models and data-driven analytics. Wang et al. [69] presents a digital twin reference model for rotating machinery fault diagnosis. Cattaneo and Macchi [70] developed a maintenance digital twin solution for a drilling machine with low availability of run-to-failure data. Research conducted among others by [64, 66, 71] indicate that the use of digital twin technology gives a number of possibilities in the field of simulation and optimization of maintenance processes, including but not limited to: evaluation of machine conditions based on descriptive methods and machine learning algorithms, identification and evaluation of potentially applicable maintenance methods as well as integration, analysis and management of data from machines and production processes and their processing at equal stages of the machine / technical system life cycle. In general, the far-reaching goal of research is to launch a digital twin for any real technical system. One of the important factors enabling the implementation of this goal is the completeness of the database necessary to build such models and then supply them with operational data that would allow updating the status of the digital twin. The challenge, therefore, is the integration of real-time data streams into simulation-based and digital models of machines for real-time (re) configuration and online directing of machines.

The next of the most frequently mentioned technologies supporting Maintenance 4.0 are a group of technologies referred to as a common name Additive Manufacturing. According to ISO/ASTM 52900:2015, Additive Manufacturing (AM) is 'the process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive and formative manufacturing methodologies'. From the point of view of maintenance, the aim is to utilize 3D printing technology to reduce stock levels and optimize all of the logistics, which surround maintenance activities. According to [72], 3D printing 'will have a significant impact on the spare parts business. 3D printing will enable suppliers to increase the availability of spare parts, reduce lead time, and decrease costs'.

In summary, data-driven technologies of Industry 4.0 provide a set of main directions and suggestions for implementing data-driven maintenance strategies. The incentive for the implementation and application of new technologies by both machine users and their manufacturers is a set of benefits, among which the most frequently mentioned are [73]: improving the efficiency and availability of production equipment, reducing costs, flexibility in approaching customer requirements. In addition, in the case of OEMs it is possible to reduce the total cost of ownership and reduce the risk to customers [74].

Sustainability-driven maintenance

In the last few years, research has focused on a sustainable manufacturing paradigm, which aims to develop sustainable production processes, innovative technologies, and new tools for evaluating economic, environmental, and social impacts of industrial assets. According to [75], 'The maintenance activity is by nature an important lever for action on the sustainability of production systems'. As described by [76], 'maintenance as part of the circular economy can be considered, first, as an enabling system to sustain the artefact throughout its life cycle, then as a key tool to keep the regeneration potential of this artefact, and finally, as a target system that must be sustainable'. In this context 'maintenance function, necessary to ensure the availability, reliability, and safety of industrial assets, could become one of the main pillars for sustainable manufacturing' [12]. As such, sustainability goals must be included in conventional maintenance processes. Jasiulewicz-Kaczmarek and Żywica [77] defined Sustainable Maintenance as 'a set of proactive technical, economic and management activities implemented throughout the whole life-cycle of a technical facility aimed at realizing functions of a technical facility, ensuring at the same time the achievement of goals and the ability to create the economic, environmental and social value for all stakeholders in the long-term horizon'.

In the last years, the role of maintenance as contributing to the sustainable manufacturing has attracted more attention [12, 78, 79]. Hennequin and Restrepo [80] proposed a fuzzy system to estimate the hedging point and preventive maintenance period values taken into account the economic cost, an environmental impact corresponding to greenhouse gas emissions and a social impact corresponding to machine ergonomics and incidents. Afrinaldi et al. [81] developed a mathematical model optimizing the preventive replacement schedule to minimize the total economic and environmental impacts of an asset. Hoang et al. [82] proposed the Residual Energy Efficiency Life concept, to estimate the time left before the object loses its energy efficiency property. Ighravwe and Oke [83] based on four of the sustainability criteria (economic, environmental, social and technical) proposed the structure of maintenance system sustainability for manufacturing concerns. The authors developed the idea of selecting the proper maintenance strategy based on integrated fuzzy axiomatic design (FAD) principle and fuzzy-TOPSIS. Boral et al. [84] proposed a hybrid artificial intelligence based conceptual decision-making model to solve sustainable maintenance strategy selection problems. Singh and Gupta [85] identified fourteen maintenance factors for sustainable performance improvement. By using ISM (Interpretive structural modelling) and fuzzy MICMAC (Matriced' Impacts Croisés Appliquée á un Classement) the authors developed a framework for sustainable performance improvement and ranking the major driving factors by TOPSIS approach. According to the authors top management support and commitment, strategic planning and implementation, continuous upgradation of maintenance system to reduce manufacturing lead-time and cost are major factors to ensure the sustainable competitive advantage.

Based on literature review maintenance contribution to business competitive priorities and more sustainable manufacturing processes has two main dimensions: sustainability dimension (represented by the three sustainability aspects: economic, environmental and social) and life-cycle dimension (represented by three life-cycle phases: beginning of life (BOL), middle of life (MOL) and end of life (EOL)). Regarding the economic aspect of maintenance contribution, there are four relevant economic factors affected by the maintenance function: quality and productivity, delivery on time, innovation and cost [86]. With reference to the social aspects, according to [87], in maintenance management, 'social implications' should be made 'mandatory' instead of 'if applicable'. Social sustainability of maintenance processes involves wider social benefits that can be derived from delivering high quality maintenance services. This means investing to maximize contributions to people's health and safety, development of their competences, satisfaction from work, etc. Finally, environmental sustainability can be achieved by resource efficiency (water, air, energy, spare parts and materials), prevention of environmental damage, emission reductions and land conservation [22, 88, 89].

The perspective of the life cycle of manufacturing equipment has prompted the redefinition of the maintenance role as being 'a prime method for life cycle management whose objective is to provide society with the required functions while minimizing material and energy consumption' [90]. In Sustainable Maintenance, the perspective of life cycle management focuses on the management of information along the equipment life cycle. Effective and efficient maintenance processes depend upon companies' ability to leverage their data assets for decision making, planning, and executing maintenance activities.

From the point of view of sustainable production, it is also important to note that none of the company's organizational functions and no process add value on its own (independently). Maintenance serves several different stakeholders, each with their own focus. Generally, these are production, business, and society. The challenge for the maintenance manager is to balance the interests of production (uptime, overall equipment effectiveness), business (spent as a percentage of the total asset value), and society (environment, health & safety). The typical trade-off choices in maintenance arise from trying to provide the maximum value to stakeholders. From the one hand companies want to maximize quality (e.g., repair quality, doing it right the first time), service level (e.g., prevention of failures), output (e.g., reliability and uptime) and at the same time, they want to minimize time (e.g., time and mean time to repair – MTTR), costs (e.g., cost per unit output) and risk (e.g., predictability of unavoidable failures) [91].

Smart & sustainable maintenance

According to [92], the enabling technologies of the Maintenance 4.0 could become key-drivers in pursuit of sustainable maintenance and asset life-cycle management. Digital technologies integrated within the Maintenance 4.0 concept enable real-time access to detailed information on the status, availability and current location of the technical facility. From the point of view of managing the life cycle of technical facilities and meeting the challenges of sustainable maintenance, this is very important. It increases the transparency of information about the real condition of a technical object throughout its life cycle and enables appropriate actions to be taken to extend the life cycle by the OEM or service provider [93]. In addition, making decisions regarding maintenance based on data instead of relying on people's experience can increase the credibility of decisions, and thus increase the effectiveness of ongoing maintenance activities and the efficiency of related human and material resources (spare parts and auxiliary materials).

The literature analysis shows that deploying data-driven maintenance approach creates many new opportunities for improving maintenance processes. The improvements concern all dimension of sustainability (Table 2).

Table 2
Benefits from implementation of new technologies in Maintenance confronted with SD dimensions – examples.

	Potential benefits	Description	References
Economic dimension	Improves economic efficiency.	Predictive maintenance can reduce machine downtime and the cost of unplanned downtime. Regular maintenance of machines and systems can increase their service life.	[1, 15, 25, 34, 42, 70, 84, 85, 94, 95]
	Reduces maintenance time	Continuously evaluation of the captured data makes it possible to determine the best time for an upcoming maintenance. Automatic reports for maintenance scheduling and proactive repairs reduce maintenance time and decreases overall maintenance costs.	
	Improves machine performance	The permanent analysis of the collected data makes it possible to improve the performance of the machine and achieve higher productivity in the long run.	
	Decreases spare parts inventories	3D printing can provide benefits in spare parts creating, particularly it is good solution when parts that are discontinued are needed.	
Environmental dimension	Decreases spare parts and lubricant utilization.	With condition-based, predictive and mainly prescriptive maintenance worn equipment parts are replaced only when necessary, lubricants are changed only as needed, rather than on a fixed schedule for planned or preventive maintenance.	[1, 13, 15, 18, 34, 38, 42, 84, 94, 96]
	Improves environmental safety	Breakdowns of machinery can lead to catastrophic events. By predicting issues before they escalate, it will be able to reduce environmental impact.	
	Minimizes end of life waste	Predictive maintenance promoted by big data analytics extends the lifespan of machinery.	
	Optimizes energy consumption	Enhancing ecological footprint by better gauging and controlling energy consumption and environmental conditions for energy conservation.	
Social dimension	Implements new educational model.	Through virtual reality, it is possible to educate operators, by teaching the right operations to do for maintenance or machine setup. The augmented reality system aims to replace old paper manuals that are difficult to understand.	[12, 72, 73, 75, 78, 97, 98]
	Improves worker safety	Breakdowns of machinery can lead to catastrophic events and harm workers. By predicting issues before they escalate, it will be able to reduce accidents and boost team morale.	
	Improves working condition	Through the application of virtual reality it is possible to obtain additional information and to proactively assess different variants of maintenance processes realization to optimize the key factors of the given operation of manual work, visibility, accessibility, usability of equipment, comfort and risk factors.	
	Improves workers satisfaction	Work performed in safe and healthy conditions improves the efficiency of the maintenance staff and increases their motivation and efficiency.	

Some studies have described servitization as a useful business model to address environmental and social demands [99]. Rodseth et al. [94] presented a structured approach for data-driven predictive maintenance in terms of profit loss indicator. The outcomes of this study suggested that a data-driven maintenance strategy had a positive effect on profit loss indicator values, which can be analysed for long-term sustainability. Zhang et al. [100] proposed BDA architecture for maintenance processes of complex products to make better cleaner production decisions based on lifecycle data. According to [101] usage of BDA can significantly enhance the ability to predict failures for key spare parts. By applying predictive maintenance service, the reliability of machines can be increased and empty load energy consumption due to stopping and restarting of equipment and downtime can be reduced. Furthermore, by using the spare part prediction service, the inventory cost and material consumption can also be reduced. Bevilacqua et al. [102] proposed a data analytic model for IoT, in order to integrate the data collected from different sources (e.g., workstations energy consumption, material delivery date from suppliers, working time and manufacturing cycle) and to improve energy-aware decision-making. Macchi et al. [64] suggested digital twin modelling as full of promises about the lifecycle management of assets. Bevilacqua et al. [66] proposed a reference model for the implementation of Digital Twin models with the purpose of enhancing the safety level of employees in the workplace. According to the authors, the developed Digital Twin model will enable virtual modelling of maintenance processes, thus preventing high-risk events for operators.

In summary, maintenance management today is experiencing a real change in both human and technological organizational level. Maintenance function taking on ever-increasing importance within corporate functions. Now, it is not only simple production index with an unavoidable cost generation. Today maintenance is a competitive tool and is considered a profit centre in all respects.

Conclusions

For many years, maintenance was considered as nonvalue-adding activity with a low level of automation and digitization. However, the last decade of development in the area of intelligent technologies and models for analysing large data sets has created new opportunities not only in the scope of increasing the reliability, availability and efficiency of using technical objects, but also in the scope of challenges of environmental and social implementation of sustainable development. Today, maintenance is closely related to the activity of a production company aiming to produce high quality products. The quality of maintenance operations determines the current quality of production means, i.e. devices and machines, which largely determines the quality of products.

In this work, intelligent and sustainable maintenance was considered in three perspectives. The first perspective is the historical perspective, in relation to which evolution has been presented in the approach to maintenance in accordance with the development of production engineering. The next perspective is the development perspective, which presents historical perspectives on maintenance data and data-driven maintenance technology. The third perspective, on the other hand, presents maintenance in the context of the dimensions of sustainable development and potential opportunities for including data-driven maintenance technology in the implementation of the economic, environmental and social challenges of sustainable production.

The amount of dynamically changing data generated over the entire life cycle of technical objects is growing. Data-based production technologies are an inspiration for using data-based maintenance. A set 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 clients' requirements is an incentive for the implementation and application of new technologies, by both machine users and their manufacturers. The collected data can be used not only to increase the efficiency of production machinery and equipment, and thus to achieve economic goals, but also to more efficient use of resources (technological media, consumables and spare parts), and thus support the enterprise in achieving environmental and social. Maintenance of machinery and equipment is therefore considered in an increasingly broader context.

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