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Artificial Intelligence as Key Enabler for Sustainable Maintenance in the Manufacturing Industry: Scope & Challenges

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Abstract: Small and Medium-Enterprises (SMEs) in the manufacturing sector have developed a high level of dependability, accessibility, and viability in their frameworks as a result of rapid globalisation among the other industries. Maintenance management has a significant impact on the performance of the organization. Industries are looking to adopt sustainable maintenance practices to achieve the overall organizational performance. The use of Industry 4.0 technology increased the organization's productivity and improved the conventional maintenance plan. Due to technological advances, the era of Industry 4.0 with Artificial Intelligence (AI) and Machine Learning (ML), a subset of AI, has emerged as a tool for maintenance strategy. In this research, the role of AI as a enable technology for sustainable maintenance in manufacturing industries were examined through literature review process. The study concludes that the current trend in maintenance uses artificial intelligence and machine learning algorithms to detect equipment breakdowns for optimal efficiency of the plant. The future of predictive maintenance lies on AI and machine learning algorithms.

Keywords: SMEs; Sustainable Maintenance; Industry 4.0; Artificial Intelligence

1. Introduction

In the manufacturing organizations, product quality is the key aspect that presages a company's performance in the market. In addition, to achieve consumer satisfaction and value, businesses focus on the quality and reliability of their products and services[1)]. If the company's product is unreliable, it will assume that the product is of low quality, and vice versa. Environmental effects of industrial production include heavy metal contamination and greenhouse gas emissions[2, 3)]. The advancement of economics is one of the primary goals of modern society, and in order to accomplish this, a vast quantity of manufactured products have been produced and consumed[4,5,6)].

The foundation of smooth production in a factory lies in well-maintained equipment and production lines. To prevent failures, it is crucial to effectively monitor and maintain the equipment and production lines during operation[7, 8, 9)]. Traditionally, manual inspections and maintenance were performed after failures occurred[10,11)]. However, this approach fails to mitigate the negative impact of equipment downtime on quality and capacity, resulting in high costs[12, 13)]. Fortunately, the emergence of the Industrial Internet, powered by advancements in wireless sensor networks[14)], communication technologies [15-20)], big data [21-23)], artificial intelligence [24, 25)], and digital twins[26, 27)], has provided fresh impetus to the monitoring and maintenance of equipment and production lines.

The integration of machine learning and artificial intelligence (AI) into CNC machining operations has raised concerns about the future of manufacturing companies and how these concepts will impact the evolution of work processes[28, 29)]. The ability of machines to learn, adapt, and optimize output can be influenced by real-time data, analytics, and deep learning, with data sets playing a crucial role in operators' understanding of machine functionality and the coordination of multiple machines on a factory floor[30,31)]. The development of affordable, reliable, and resilient sensors, as well as acquisition and communication systems, has paved the way for novel implementations of machine learning approaches in tool condition monitoring[32, 33)]. Machine learning systems can comprehensively analyze data and identify areas for modification, with edge computing options being increasingly integrated into machine tools to record high-frequency internal drive signals, providing the vast amount of data needed for machine learning techniques in manufacturing[34, 35]. Artificial intelligence has the potential to enhance productivity and efficiency in CNC machine tools operations, leading to improved accuracy in CNC machining operations[36].

The maintenance of equipment in the production organization is an important operation because the reliable production system is regarded as a significant contributor to the efficacy and sufficiency of a manufacturing organisation[37].

The sustainable maintenance increases the efficiency of the organization by focusing on the reduction of wastes, negative environment and social impact. Sustainable maintenance can aid in reducing emissions, enhancing air quality, and decreasing waste. It can also improve the health and safety of your employees and lessen the negative effects of your business on the local community (noise and pollution). Sustainable maintenance has economic benefits, as it can help you raise compliance, improve utilization rates, eliminate needless maintenance, and decrease the expenses associated with fines, downtime, and breakdowns[38,39].

The globally competition of the market, along with the rise in automation spurred by the introduction of Industry 4.0, emphasizes the significance of sustainable maintenance inside businesses[40]. If the Industrial Internet of Things (IoT), cloud computing, and technologies like augmented reality (AR) and virtual reality (VR) are the main components of Industry 4.0, then Maintenance 4.0 is based on the implementation of these technologies in the company's maintenance practises[41,42]. Thus, Maintenance 4.0 is the application of intelligent technologies to enhance daily factory operations[43]. The objective is to maximize availability by eliminating unplanned, reactive maintenance. The Internet of Things takes machine-to-machine technology to the next level by incorporating a third component: data.

According to Cachada[44], all machine data will be accessible on a singular virtual network, allowing manufacturers to aggregate and analyses data in order to generate more accurate predictive analytic models. For additional information, the author suggests reading[45,46].

In this environment, many programmers and techniques are established to assist businesses in adopting the sustainable principles of the fourth industrial revolution. Within these efforts, the application of current maintenance strategies, such as Maintenance 4.0 (also known as Smart Maintenance), is emphasized as one of the prevalent smart & sustainable manufacturing themes[47, 48]. The algorithm for anomaly detection compares the data to the prediction model. If the difference between the data and the prediction model exceeds the defined limits, we refer to the data as anomaly data[49, 50].

The potential of Artificial Intelligence systems to extract relevant information from massive data sets is considerable. The AI algorithm's benefits include equipment availability, improved operational performance, decreased maintenance expenses, and decision-making help[51,52].

The primary purpose of this work is to explore the role of Artificial Intelligence technologies in industries for sustainable maintenance and discussed the various challenges as the future research directions. For this, a review of the scientific literature was conducted, from which numerous findings can be drawn.

The remainder of the paper is structured as follows. Section 2 discusses the scope of industry 4.0 for sustainable manufacturing, while Section 3 focuses on the function of AI in industry. Section 4 concludes with a discussion of the study's key findings and the obstacles that stand in the way of AI deployment as a future direction for researchers.

2. Sustainable Maintenance with Industry 4.0

Sustainable Maintenance practices play a critical role in an organization and significantly affect the product quality of an organization. The basic model's maintenance plan is preventative maintenance (PM), with the block replacement policy as the parts replacement method[53,54]. Figure 1 shows the key sustainable maintenance practices used in manufacturing industries. Industries needs to be focus on optimized use of resources with proper maintenance strategy. Now a days use of advanced technologies in maintenance enhanced the performance of the organization.

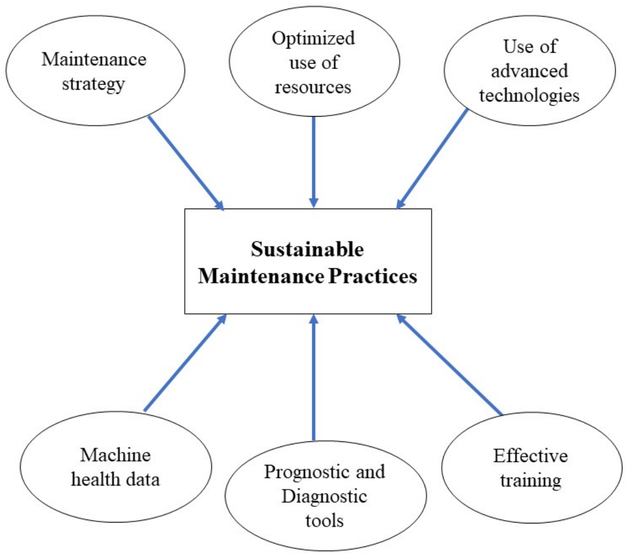

Fig. 1: Key Sustainable Maintenance practices in Manufacturing Industries

The increasing complexity of production equipment and industrial automation necessitates a modification of the maintenance plan. This advanced maintenance plan should raise the manufacturing industries' level of sustainable development[55, 56].

There are various classifications and categories of maintenance management strategies in the literature. The classification of maintenance proposed by some authors[57,58] are as follows:

Run-to-Failure (R2F) or Corrective maintenance: Run to failure is a maintenance technique in which equipment is only maintained when it fails. Run-to-failure maintenance, as opposed to unplanned and reactive maintenance, is a deliberate and calculated method intended to reduce total maintenance costs.

Preventive Maintenance (PvM): It emphasises routine maintenance of the equipment and to keep them in operating order and reduces unplanned downtime caused by unforeseen equipment failure. Early in the course of a problem, the maintenance department plans and schedules equipment repairs.

Predictive Maintenance (PdM): This is the proactive strategy technique that uses equipment's past data to create a predictive model and sophisticated analytics algorithm to predict the next equipment failure.

The maintenance schedule of various equipment may vary according to necessity. But human mistake, poor quality replacement parts, insufficient maintenance time, and other variables may impair the maintenance process to the point where the equipment cannot be restored to its original condition[59,60].

Numerous approaches have been proposed by researchers to express the effect of imperfect maintenance, including the virtual age method, the impact model method, and others[61]. Minor repair refers to the restoration of equipment to its pre-fault condition, without modification, following routine maintenance[62]. It is commonly believed that a simple repair will not affect the system's fault rate[63]. This revealed that industries need to have an optimum maintenance strategy with reduced resource use.

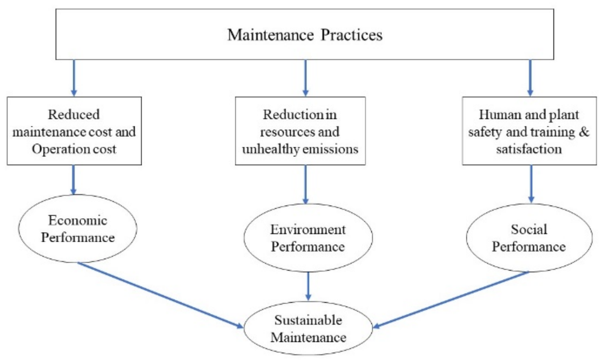

Fig. 2: Role of Maintenance practices to achieve Sustainability

Figure 2 depicts the contribution of various maintenance techniques to the manufacturing industry's pursuit of sustainability. The industry is currently experiencing what analysts have termed "The Fourth Industrial Revolution," often known as Industry 4.0. This fact is strongly related with the integration of physical and digital manufacturing systems. The integration of these environments enables the collection of a vast quantity of data generated by diverse equipment deployed in various factory sectors[64]. Rdseth et al.[65] highlight industry 4.0 as a mediator between production and maintenance planning to facilitate the implementation of a cost-effective production system. In order to get economic and technical benefits[66], industries are looking to industry 4.0 concepts as initial steps to improve maintenance strategies from traditional maintenance to predictive maintenance plans.

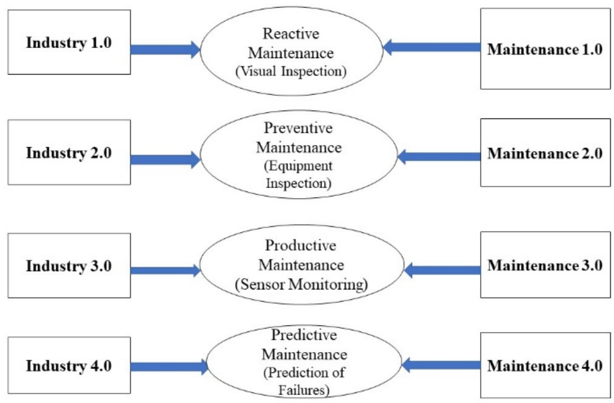

Fig. 3: Development of maintenance methodology with industrial revolutions

Figure 3 discussed the maintenance strategy developments in relation to industrial revolutions. During the first industrial revolution, maintenance 1.0 emphasised simple repair methods. Following a visual evaluation of the malfunction, the machine operators began maintenance. Through periodic inspections and replacement of worn parts, the maintenance department's primary purpose was to reduce the amount of corrective maintenance activities.

The second industrial revolution emphasised scheduled maintenance tasks called preventive maintenance. The maintenance crew performed routine machine inspections in accordance with OEM (original equipment manufacturer) standards.

In the third industrial revolution, automation has begun and there is increasingly complex machinery for manufacturing. The maintenance approach must be modernised with an emphasis on minimising downtime and improving product quality and dependability; hence, the notion of productive maintenance or condition monitoring has arisen. This technique utilised sensor data to check the health of equipment in real time.

The current age is the fourth industrial revolution, known as Industry 4.0, whose maintenance approach focuses on predicting equipment breakdowns in advance. In the context of Industry 4.0, the maintenance function is commonly referred to as Maintenance 4.0, where artificial intelligence plays a significant role in meeting industry requirements. Many domains, including artificial intelligence and control systems, can utilise fuzzy ideas[67].

3. Artificial Intelligence as key enabler for predictive maintenance

There are numerous major enabling technologies for Industry 4.0, but Artificial Intelligence will have a significant impact on future human life, economics, business, and even political institutions. Future predictive maintenance, an integral component of future sophisticated manufacturing systems, is positively impacted by artificial intelligence[68].

In 1956, a group of computer scientists at the Dartmouth Conferences coined the term artificial intelligence and gave birth to the discipline of AI. The goal is to create machines that can perform activities in a manner that humans would consider intelligent[69].

Artificial Intelligence (AI) is a major enabler technology for industry 4.0 and has numerous preventative maintenance applications. The use of AI in maintenance enables operators to improve operating and maintenance efficiency. This will raise customer satisfaction and reduce operational risk by increasing the dependability and availability of the rail vehicle system[70,71].

The several important components of Industry 4.0, including as sensing devices, the Internet of Things (IoT), and cyber physical systems, have a wide range of applications in the collecting and processing of massive amounts of data for maintenance purposes. These are necessary for deploying an AI based predictive maintenance model[72].

The Machine Learning (ML) techniques are capable of equipment failure prognostics and forecasting. It employs a vast volume of information to teach the model for calculating the machine's lifetime[73].

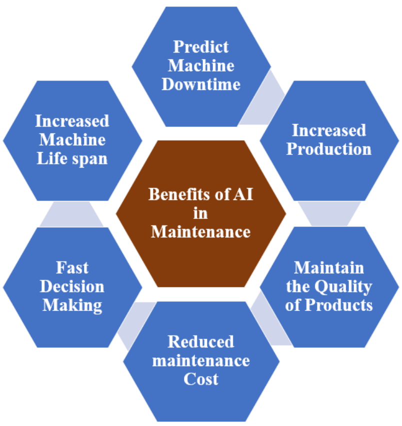

Fig. 4: Benefits of AI supported maintenance in manufacturing industries

Figure 4 illustrates the several advantages realised by industries that adopt AI algorithms for predictive maintenance. It decreases machine downtime, hence increasing equipment availability. Increased machine longevity decreases total maintenance expenses and increases output. A swift decision-making procedure enables managers to alter a flawed procedure and so continue to maintain product quality.

TABLE I. Different modelling approaches with sub model adopted by the authors[74,75,76]

S. No.	Modelling Approaches	Sub models/algorithms
1.	Physics-based modeling	Kalman Filters Probability Distribution Markov models Fault trees Monitor-based
2.	Knowledge-based modeling	Binary Trees Bayesian Decision Fuzzy System Expert Systems Machine degradation model
3.	Data-driven modeling	Genetic algorithms Data mining Convolutional Neural Network Random Forest Deep learning Support Vector Machine Back Propagation Neural Network (BPNN)
4.	Hybrid modeling	Sparse Autoencoder (SAE) and SVM Redio Frequency and Long Short-Term Memory (LSTM) SVM and Naive Bayes Digital Twin

One study combined neural networks and fuzzy logic to solve the challenge of on-board electric vehicle fault diagnostics. It was discovered that the inadequate processing capability and limited storage capacity of electric vehicles hinder onboard and real-time problem identification[77]. Digitalization or digital technology in the modern era not only alters the business unit's paradigm or structure, additionally it makes the service accessible to the greatest potential of customers[78].

Figure 5 depicts the operation of a predictive maintenance framework in which the state of industrial equipment is monitored via various sensors. An array of smart sensors connected to the equipment and a centralised or decentralised network of hardware and software collect the historical data. The data is pre-processed, the proper AI or machine learning technique is utilised to train and evaluate the model. Now, using real-time data monitoring, the trained model is utilised to predict impending equipment failures and to schedule maintenance accordingly.

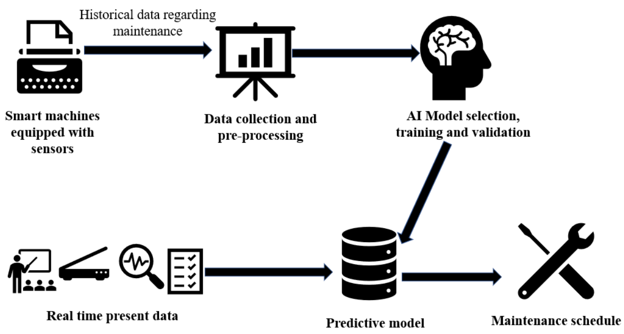

Fig. 5: AI enabled predictive maintenance framework in manufacturing industries

4. Conclusion and Future Scope

In industries, efficient and appropriate maintenance operations are necessary for the operation of industrial equipment since they can considerably increase the equipment's reliability, availability, and safety while minimising equipment failures. This research focuses on the advanced maintenance technique, predictive maintenance, which allows for the prediction of future problems and the prompt implementation of repair procedures to minimise downtime.

Numerous sensors are available to collect real-time data of physical characteristics of machines, according to the findings of a study concluding that sensor and network technology has undergone rapid development in recent years. Artificial intelligence (AI) approaches have been widely utilised in condition monitoring systems due to the wide availability of past and real-time equipment data. AI has emerged as a facilitator of predictive maintenance. It offers numerous benefits for sustainability. The study demonstrates how artificial intelligence can effectively detect faults or anomalies in a variety of applications and has become a valuable predictive maintenance tool.

However, AI has significant advantages in maintenance. Yet, there are numerous obstacles to adopting AI algorithms in industries with enormous data sets. Following are some challenges, researchers may pursue research to overcome them.

- Reliability of the model in AI is big challenge, while developing a machine learning model, one must ensure both the quality of model reliability in production and the reliability of the model training process.
- It takes a significant amount of time to practical implementation of the model in industries. Slow systems, data overload, and high demands typically demand a great deal of time to produce precise results.
- The function of digital twins in predictive maintenance. A digital twin indicates the real asset condition and incorporates pertinent asset-specific historical data.
- Security of data to preserve intellectual property rights and sensitive consumer data, an improved cybersecurity system must be implemented.
- For effective predictive maintenance, large quantities of historical data are required. Collecting historical data needs significant time and effort.
- The absence of a centralised platform for integrating data from environmental sources and other systems will impede execution efficiency.

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