International Journal of Scientific Research in Science, Engineering and Technology
Print ISSN - 2395-1990
Online ISSN : 2394-4099
Available Online at : www.ijsrset.com
doi : https://doi.org/10.32628/IJSRSET231052

Smart Manufacturing and its Impact on Production Processes A Review

[1]Adeleke Olorunnisola, [2]Awotundun Oluwagbenga Joshua, [3]Olukanri Riliwan Babatunde
[1]Federal University of Technology, Akure, Ondo State. Nigeria.
ORCID - https://orcid.org/0000-0003-4832-447X (Corresponding author)
[2]Kwara State University, Illorin, Mechanical Engineering department, Ilorin, Nigeria
[3]University of Lagos, Mechanical Engineering department, Lagos, Nigeria

ARTICLEINFO

Article History :

Accepted: 01 Sep 2023
Published: 08 Sep 2023

Publication Issue :
Volume 10, Issue 5
September-October-2023
Page Number :
57-65

ABSTRACT

This review paper aims to analyze the theoretical foundations of smart manufacturing and its impact on production processes, particularly in the domains of robotics and additive manufacturing, across past, present, and future time horizons. It also explores the potential of smart manufacturing to improve the precision of manufacturing processes, as well as the challenges it poses to the manufacturing sector. This overview will deepen our understanding of modern manufacturing practices. It's worth noting that some scientific developments and technological tools discussed here can be applied to a wider range of automated systems beyond the manufacturing sector. As such, this paper offers valuable insights for those involved in automated system design and implementation.
Keywords : Smart Manufacturing, Additive manufacturing, Robotics, Artificial Intelligence, Augmented Reality and Cyber Physical System

I. INTRODUCTION

1.1 Definition of smart manufacturing

Smart manufacturing is a term that encompasses a broad range of research domains, each with its own unique interpretation of the word smart [1]. However, at its core, Smart manufacturing is an advanced manufacturing paradigm that profoundly integrates the new generation of information technology such as Internet-of-Things, cloud computing and artificial intelligence, and cutting-edge manufacturing technology into the production process [2]. In the context of this review paper, we will define smart manufacturing as a multifaceted approach that involves three key elements.

Firstly, it involves maximizing physical resources in production to achieve more sustainable and cost-effective outcomes. Secondly, it is using data-driven decision-making essential for optimizing manufacturing processes and achieving greater efficiency. Thirdly, it entails the ability to adapt resources to dynamic and uncertain environments by changing system configuration [3].

1.2 Importance of Smart Manufacturing

Smart Manufacturing is a future growth engine that aims for sustainable growth by managing and improving existing major manufacturing factors such as productivity, quality, delivery, and flexibility based on technological convergence and various elements spanning societies, humans, and the environment. It enables effective and optimal

decision-making through faster and more accurate decision-making procedures [4].

A critical aspect of additive manufacturing is 3D printing, as it leverages computer-aided design (CAD), computer-aided manufacturing (CAM), machine vision, virtual reality (VR), and augmented reality (AR) techniques to revolutionize and recreate 3D models. By integrating these technologies, the design process is simplified and errors can be identified earlier in the development stage, leading to a reduction in the number of early-stage prototypes and ultimately cutting costs. AR can be immensely helpful in product inspection, maintenance, assembly, and repair tasks, as it provides technicians with a faster means of identifying and conducting repairs using AR applications, such as audio tracks for instructions and animated 3D models with task overlays. Additionally, the utilization of sensors, AR software, and displays enables the tracking of the task's orientation and position for the user, allowing for a comprehensive view of machinery without the need to physically open systems [5] [6] [7].

Over the years, carrying out maintenance activities has become increasingly challenging. To address this challenge while simultaneously reducing costs, the implementation of predictive maintenance utilizing Artificial Intelligence (AI) and various Information and Operational Technologies has become increasingly significant. This has enabled smart factories to predict and preempt issues, rather than solely reactive maintenance when failures occur. In the past, this was primarily referred to as e-maintenance. However, with the emergence of intelligent tools such as the Industrial Internet of Things (IIoT), intelligent sensors, and AI-based systems, it is now commonly referred to as maintenance engineering [6].

2.1 Intelligent Additive Manufacturing (IAM)

Additive manufacturing (AM), commonly known as 3D printing, is a manufacturing process helpful in product inspection, maintenance, assembly, and repair tasks, as it provides technicians with a faster means of identifying and conducting repairs using AR applications, such as audio tracks for instructions and animated 3D models with task overlays. Additionally, the utilization of sensors, AR software, and displays enables the tracking of the task's orientation and position for the user, allowing for a comprehensive view of machinery without the need to physically open systems [5] [6] [7].

Over the years, carrying out maintenance activities has become increasingly challenging. To address this challenge while simultaneously reducing costs, the implementation of predictive maintenance utilizing Artificial Intelligence (AI) and various Information and Operational Technologies has become increasingly significant. This has enabled smart factories to predict and preempt issues, rather than solely reactive maintenance when failures occur. In the past, this was primarily referred to as e-maintenance. However, with the emergence of intelligent tools such as the Industrial Internet of Things (IIoT), intelligent sensors, and AI-based systems, it is now commonly referred to as maintenance engineering [6].

2.1 Intelligent Additive Manufacturing (IAM)

Additive manufacturing (AM), commonly known as 3D printing, is a manufacturing process that involves creating a product by adding material layer by layer based on a digital design. This stands in contrast to subtractive manufacturing (SM), which involves removing material from a larger piece to create the desired shape. With additive manufacturing, feedstock in the form of wire or powder can be fused, melted, or bonded layer by layer directly from a 3D computer-aided design (CAD) file with minimal human intervention [6].

Intelligent additive manufacturing and design can be broadly defined as a concept of manufacturing with the aim to maximize the value of AM by fully utilizing its design freedom in terms of materials, structures, and processes through interactions with cyber-physical systems based on both human and machine intelligence [7].

It's important to note that the different types of additive manufacturing technologies, such as fused deposition modeling, stereolithography, and selective laser sintering, each have their own unique processing mechanisms. This allows them to print different materials as feedstock, as detailed in Table 1 with varying degrees of geometrical accuracy. In general, additive manufacturing has the potential to revolutionize the way we produce goods, as it enables us to create complex shapes and structures that would be difficult or impossible to achieve with traditional manufacturing techniques [8].

Table 1.0. AM technologies

AM technologies	Type of machine	Printable material	Mechanism of printing	Application
Powder bed fusion	Selective laser sintering Electron beam melting	Metallic feedstocks, but can also be used to print ceramics, polymers, and composite	Uses electron or laser beams to selectively build 3D objects	Use to produce high-value customized biomedical and engineering products.
Directed energy deposition	Laser deposition laser engineered net shaping (LENS)	Used to print metallic feedstocks, but can be used to print ceramics, polymers	Using a laser beam to selectively build 3D objects.	Use to produce 3D objects for biomedical and engineering applications
Sheet lamination	Laminated object manufacturing (LOM) Ultrasound additive manufacturing (UAM)	Metals, plastic, papers	Sheets of materials are joined one after the other either by adhesive, welding or thermal bonding	Can be used to produce 3D objects at a lower cost compared to other 3D printing technology
Material extrusion	Fuse deposition modelling	Polymers, food, living cells	Material is drawn through a nozzle, heated, and deposited layer by layer.	It is commonly used to build inexpensive products for domestic and industrial applications.
Material jetting	Drop-On Demand (DOD) PolyJet technology NanoParticle Jetting (NPJ)	Polymers, ceramics, composite, biologicals and hybrid	Printhead dispenses droplets of photosensitive material that solidifies, layer-by-layer under ultraviolet (UV) light.	It is commonly used to build inexpensive products for domestic and industrial applications.
Binder jetting	Binder jetting	Metals, sands, polymers, ceramics and composites	A liquid binding agent is selectively deposited to join powder particles.	Production of casting patterns.
Photopolymer vat	Stereolithography (SLA) Digital light processing (DLP), Carbon® Digital Light Synthesis (DLS)	Polymers	Selectively curing of photo-reactive polymers by using a laser, light or ultraviolet (UV).	Production of 3D objects for biomedical and engineering applications.

2.2 Intelligent Robotics (IR)

An intelligent robot refers to a robot that can interact with its environment and perform tasks that require problem-solving skills, adaptability, and learning capabilities [27]. The development of human-robot interaction (HRI) technologies in the industrial environment has significantly improve the cognitive and intelligent level of robotic manufacturing systems.

Industrial robots have evolved from being simply capable of performing repetitive and simple tasks with minimal interaction with humans to working collaboratively with humans in the same workspace,

with a certain perception function, adaptability of offline programming, and the application of artificial intelligence [9].

The Hannover Messe of 2013 witnessed the Working Group of Industry 4.0 presenting their report, which served as the starting point for the Fourth Industrial Revolution in 2014. This revolution introduced the use of information technology in manufacturing, and its six intelligent technologies areas (as shown in Figure 1.0).

The first set of industrial robots manufactured at the General Motors factory in Ohio, marks the beginning of the modern industrial robotics revolution. Today, a broad variety of robots are utilized in manufacturing such as the industrial robotic manipulators offered by reputable vendors like ABB, KUKA, UR, FANUC, and YASKAWA, and as well as other types which includes AGVs and UAVs [28-31].

The introduction of robots in the manufacturing industry has proven to be beneficial, as it has liberated human workers from repetitive and overburdening tasks in the factory and led to a new generation of automation. However, this has not been without challenges, as the robots have not been able to exceed the original boundaries of robotics, which involve manipulating the physical world with computer-controlled movements. Issues such as dynamics, uncertainties, and flexibility have arisen. Thus, the desire for enhanced robotics has given birth to the concept of smart robotic manufacturing, where robots are designed to handle more complex tasks with a higher degree of intelligence [32-35].

In terms of their physical makeup, robots are driven by motors, which are then powered by electric energy. These motors generate force and operate the mechanical body of the robot in accordance with robotic dynamics. By rotating the motors within the robot, the end effector or tool central point (TCP) can be moved to a position with a gesture in the Cartesian space, in accordance with the rules of robotics kinematics. Ultimately, these motions can be programmed for multiple manufacturing tasks, utilizing various tools attached to the TCP.

In manufacturing world, force control is a frequently employed technique for a range of applications, such as grasping, levering, and haptic human-robot collaboration [36]. This is accomplished through the utilization of torque sensors [37] or sensorless estimation [38]. Furthermore, in the context of customized robotic devices, it is commonplace for end-users to program the power of motors through the utilization of motor drivers and microcontrollers, typically achieved by employing pulse-width modulation.

Researchers have made significant progress in industrialization efforts, with ongoing research endeavors in this direction which will be discussed in other sections of this paper.

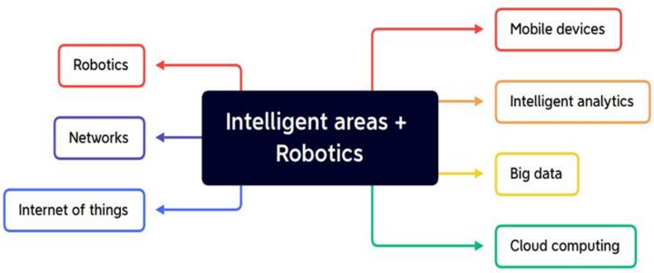

Fig 1. Six intelligence areas (CMIDAN) plus robotics

3.1 Key methods used in smart manufacturing, such as machine learning and computer vision

In a context of intense market competition, firms are adopting new strategies to differentiate themselves from their rivals. By leveraging cutting-edge technologies such as machine learning, computer vision, cloud computing, big data analytics, blockchain, the internet of things, and cyber-physical systems, companies aim to gain a competitive edge in the marketplace. These technological tools provide firms with the means to optimize their operations, increase efficiency, and enhance their offerings, all of which are essential for success in today's dynamic business environment. [10]

According to Choudhary et al., manual analysis of accumulated manufacturing data is not practical due to the vast amount of raw data involved. Thus, data mining techniques such as machine learning have been proposed as an effective means to obtain high-quality information. In a review conducted by Pham et al., five types of machine learning techniques were evaluated for their application in manufacturing, including quality control and scheduling problems. Wuest et al. classified machine learning into three types (supervised, unsupervised, reinforced) and focused on the usefulness of supervised machine learning algorithms for monitoring, fault diagnosis, and image recognition, among others. As a result, the integration of machine learning techniques into manufacturing can provide better insight into manufacturing processes and improve overall productivity [11].

It is worth noting that machine learning methods are not only limited to basic numeric or nominal data that are commonly generated by manufacturing systems. These techniques can also be effectively applied in the field of image processing, particularly in the context of industrial visual inspection systems. By employing sophisticated algorithms, machine learning can enable the extraction of essential rules and templates to facilitate more accurate image recognition and classification, thereby contributing to enhanced precision and reliability in industrial inspection processes. This highlights the potential of machine learning to enable advanced automation and optimization in manufacturing operations, ultimately driving improvements in productivity and quality control [12].

In the field of machine learning, the function that is fitted takes in raw data or handcrafted features as input and generates output by processing the information through itself. Prior to the advent of deep learning, feature engineering was the discipline used to manually extract features from data or to apply pre-defined rules to achieve this task. However, this process has been replaced by more complex models, such as deep neural networks, which possess a stronger representation. In addition to neural networks, linear models, quadratic models, probability distributions (such as Gaussian estimation or Gaussian mixture models), and even discrete tables are commonly employed as functions for machine learning. For deep learning, convolutional neural networks (CNN) [38], recurrent neural networks (RNN) [39], graph neural networks (GNN) [40], and dense neural networks (DNN) [41] are all viable alternatives. The choice of model is typically dependent on the complexity of the problem at hand. Neural networks are particularly well-suited for tackling difficult problems, as they are theoretically capable of representing any non-linear function [42]. However, the accessibility of a given model is often dependent on the dimensionality of the data, with larger datasets typically requiring more sophisticated models. During the learning phase of machine learning, the goal is to estimate the parameters of the chosen model based on the available data. These parameters include hyper-parameters, which are the inner settings of the model (such as the number of layers in a neural network or the combination of several Gaussian distributions). The input data can take many forms, including numerical arrays, paragraphs of text, audio recordings, or images. Similarly, the output can have a variety of dimensions, depending on the user's requirements and sometimes even the same input such as variational auto-encoder (VAE) [43] and generative adversarial network (GAN) [44].

Machine learning can be used for a variety of tasks, including recognition, machine translation, machine generation (such as generating art or poetry), and dimension reduction. The method by which a machine learns is by finding the optimal values of its function's parameters. This process varies depending on the type of machine learning technology employed, including unsupervised learning, supervised learning, and reinforcement learning. The latter approach is particularly important for robotic learning, where agents can learn by maximizing rewards or minimizing costs. In summary, the field of artificial intelligence engineering encompasses a broad range of machine learning techniques that are used to train models to process data and generate useful outputs. The choice of model is typically driven by the complexity of the problem at hand, and the learning phase involves estimating the optimal values of the model's parameters [45-46].

3.2 Overview of the advantages and limitations of these methods

Understanding a material's structure, composition, process history, and characteristics is crucial for determining how and what parts are being manufactured. This is where microstructural characterization and analysis come into play. In the past, humans were in charge of choosing what to measure and how to measure it. However, further possibilities for information extraction from microstructural images have emerged as a result of recent developments in computer vision and machine learning. This entails encoding the visual data in microstructural images using computer methods, and then utilizing with machine learning approaches to find relationships and trends in the resulting high-dimensional image representation. With the aid of this technique, a variety of image analysis tasks can be completed, including picture classification, semantic segmentation, object detection, and instance segmentation. These tasks can produce new, rich visual metrics and reveal correlations between processing, microstructure, and property. Therefore, these technologies can be used in the aerospace, automotive, and part-producing industries to make decisions while developing mechanical components for manufacture [13].

In order to optimize the printing process and raise the caliber of printed parts, Jianyu Liang and his research group looked into the application of machine learning in additive manufacturing processes. The research team used robocasting, an AM technique that is frequently used to produce ceramic materials. In order to develop a closed-loop control with adaptive feedback in the robocasting process, they created an artificial neural network model employing a database of processing load, print width, and extrusion length. The research showed how machine learning can be used in additive manufacturing (AM) to create complex geometries and desirable features that are challenging to obtain with conventional production techniques [14].

Manufacturing productivity has increased significantly as a result of the application of computer vision and other machine learning techniques, benefiting both decision-makers and workers. This technology does have certain drawbacks, though. The requirement for specialized technical expertise to successfully setup a standard solution for optimal use is one of the main obstacles to its implementation. Furthermore, another problem with using sophisticated algorithms is that, despite their impressive efficiency, even specialists find it difficult to explain how these sophisticated algorithms work precisely. This difficulty brings about the significance of creating methods to interpret and explain these algorithms in a more understandable way, in other to improve our knowledge of and confidence in these systems. In fact, overcoming these obstacles is essential to the continued development and success of machine learning in the manufacturing sector.

4.1 Brief discussion of the practical applications of additive manufacturing:

AM has been promoted as a zero-waste manufacturing method as opposed to conventional SM which generate waste. It is particularly suitable for customized manufacturing of low volume products [15].

AM has emerged as a promising technology for various applications in recent years. Its flexibility for customization, rapid prototyping, and on-site manufacturing has made it a preferred choice for producing spare parts in a quick and cost-effective manner. Its capacity to facilitate reverse engineering of parts and products via 3D scanning has enabled the reconfiguration of designs for rapid reproduction, testing, and validation. One such industry where AM has already made significant strides is the medical sciences. Its use to produce implants in dentistry and orthopedics has revolutionized the replacement of injured body parts [16].

4.2 Brief discussion of the practical applications in Robotics:

In contemporary smart factories, the integration of robots and sensors facilitates human-robot collaboration within a secure workspace. These collaborative robots, commonly referred to as cobots, offer several advantages over traditional industrial robots. Primarily, they are designed to operate safely alongside humans and can function in the space typically required by traditional robots that mandate the use of guarding fences. Various safety mechanisms can be employed, such as proximity sensors that detect when humans approach and slow down the robot's movements accordingly, force limitations that minimize risks to humans and the environment, and the ability to sense human intent and adjust movements accordingly. Additionally, cobots allow for different levels of human-robot collaboration, where humans perform tasks requiring high levels of dexterity, while robots handle repetitive, heavy, and monotonous tasks. Essentially, the goal is to ensure the robot does not harm humans, and to achieve this, controlled force and speed, separation monitoring, hand-guiding, and safety-rated monitored stop mechanisms are employed.

Apart from safety, other aspects also distinguish how robots are utilized in smart factories. For instance, vision and computer-aided design (CAD) technologies can assist in robot planning and control, thereby eliminating the need for time-consuming manual programming. Moreover, learning by demonstration techniques can eliminate the need for manual programming by using dynamic motion primitives to parameterize robotic motions. This results in efficient production adjustments, particularly in the case of small batches of products with minor variations in shape and size [17].

4.3 Overview of real-world manufacturing scenarios where smart manufacturing has been successfully implemented

Deloitte has collaborated with several renowned solution providers and technology innovators to establish The Smart Factory at Wichita experience, which aims to assist organizations in realizing the future of manufacturing. This immersive experience merges the digital, physical, and experimental domains, providing manufacturers with the opportunity to closely examine advanced manufacturing methods and technologies. The facility, which spans 60,000 square feet and is powered by a renewable energy smart grid, features a complete smart production line, as well as space for smart ecosystem sponsors and experiential labs. Additionally, the experience includes workshops that showcase the potential of smart factory applications, helping manufacturers create a tailored road map that aligns with their digital transformation goals [18].

The use of automated guided vehicles (AGVs) to move automobile bodies to the appropriate assembly facilities has been gradually adopted by the automotive industry. In this instance, 50 AGVs are put into service on the first factory level and moved via elevator to the assembly line on the second floor. The AGVs are wirelessly linked to a central control system that determines the AGVs' paths depending on a number of variables, including the car model, the model's unique configuration, and the use of various assembly stations. By using this strategy, the factory floor is successfully utilized without being bound to a particular car model.

IEEE 802.11 (also known as Wi-Fi) in the unlicensed 2.4-GHz frequency band is used to facilitate communication between the central control system and the AGVs. After more than a year of fruitful operation, unpredictably occurring communication problems began happening more regularly, leading to unscheduled stoppage of the AGVs. The issue was brought on by an increase in the number of Wi-Fi and Bluetooth-based applications using the 2.4-GHz frequency band, which temporarily produced coexistence problems. Unfortunately, due to high operating costs, the inability to operate the network themselves, lengthy service deployment times, and the inability to meet reliability, latency, and real-time requirements, switching to a licensed frequency band, such as a 4G/LTE or 5G cellular network, is not a practical option for many applications. Additionally, sensitive data is not sufficiently protected by current security procedures. Technology hasn't been able to totally solve the cohabitation issue yet, thus the only workable solution is containment.

A codesign of control and communication is the most promising approach to ensure the availability of the system [19].

4.3 Comparison of the benefits and drawbacks of different smart manufacturing application

Table 2. Benefits and drawbacks of different smart manufacturing application

Scenarios	Benefits	Drawbacks
Smart 3D scanning for automated quality inspection	**1.** Quality inspection can be automatically executed. **2.** Quality data can be visualized in real time for decision making	1. Data storage and processing may be an issue if the volume of real-time information is large.
Cloud-based numerical control	**1.** Highly sophisticated algorithms can be applied. **2.** Service is flexible and can be updated and upgraded easily. **3.** The process know-hows can be well protected	1. Concerns on cyber security and service availability may exist
CPS-based smart machine tools	**1.** Users can control the machine tool in real time by using cloud-based services. **2.** Real-time status can be reflected in the user interface.	**1.** Information confidentiality is an issue on the part of end users.

5.1 Discussion of the challenges that arise when implementing smart manufacturing, such as cybersecurity and data management

Although smart manufacturing systems have the potential to address various challenges and complexities faced by modern industries, there remain several obstacles during their implementation. These challenges may arise from different response variables, including security concerns, difficulties with system integration, insufficient return on investment in new technology, and financial issues encountered during the installation and upgrading of smart manufacturing systems within existing industries [20].

The emergence of smart manufacturing and interconnected companies has resulted in the availability of extensive manufacturing data for advanced analytics. However, this situation poses a significant threat to the core competencies of specialized manufacturers. By acquiring valuable data, competitors can potentially "reverse engineer" products and extract underlying knowledge and capabilities, which is an even greater concern. Conversely, companies that operate in different market segments but are competitors may collaborate within supply networks. For instance, the airline's service provider stores video data from aircraft surveillance, and sharing such information is advantageous for several reasons, including quality enhancements [21].

Essential features of a robust interoperability solution encompass a universal or open system that allows for the seamless integration of various types and brands of robots, a standardized interface for multiple functionalities like traffic control and navigation, an accessible task allocation management system, and data analytics for optimization purposes. Additionally, a leveled control of third-party robots is required to ensure efficient coordination within the fleet. Thankfully, the recent years have witnessed the development of interoperability standards in various countries such as the VDA 5050 in Germany and the MassRobotics Interoperability Standard Version 1.0 in the US. The VDA 5050 focuses mainly on AGV standards, whereas the MassRobotics Interoperability Standard concentrates on the transmission of basic robot-to-robot information [22].

Undoubtedly, these standards hold significant promise in advancing the course of robotics interoperability. However, the need for a comprehensive common interface that enables users to manage and regulate their entire fleet, regardless of robot type or brand, persists. It remains to be seen how this aspect will unfold in the future, and it is an exciting development to observe [22].

As we delve into the complexities of automation project decisions, it is crucial to consider a multitude of factors. Deployment risk, operational risk, ongoing maintenance requirements, and worker anxiety all play a significant role in the decision-making process. At the same time, one must balance these concerns with the potential benefits of automation, such as increased flexibility, scalability, cost avoidance, and occupational health improvements. While traditional return on investment (ROI) tools are a valuable resource, they may fall short in capturing the full scope of such complex decisions. Such tools typically measure expected outcomes based on static, long-term assumptions about labor cost savings. However, in today's ever-evolving business landscape, relying solely on these metrics may lead decision-makers to an outcome that does not align with their strategic objectives or is predicated on unrealistic expectations of business stability [23]

5.2 Addressing Smart Manufacturing Security Concerns: Strategies for Resolution

Achieving the goal of limiting data usage solely to its intended purpose necessitates interdisciplinary research involving a diverse range of experts including policy makers, legal scholars, business leaders, computer scientists, and engineers. [21].

The ever-evolving robotics technology has profoundly influenced the functioning of warehouses, factories, and logistic centers. With the emergence of numerous technological innovations in the industry, the demand for interoperability has surged yet again. To this end, new technologies must exhibit the ability to connect effortlessly with any device or system, commonly known as universal connectivity. The Robot Operating Software (ROS) stands out as a remarkable instance of such technology, as it has facilitated the rapid development of mobile robots [22].

Business world is filled with much unprecedented evolution considering the advent of AI. However, with the aid of trends, business investors can be certain of long-term reward by investing in all these technologies.

6.1. Overview of how these emerging smart technologies will impact the future of manufacturing

The process of reengineering in the context of CPS and digitalization may be fueled by developments in artificial intelligence technology as well as business and human intelligence. Through physics-based analytics, prediction algorithms, automation, and in-depth subject knowledge, the strategic objective is to advance analytics. While augmented reality in maintenance will be implemented with an Industry4.0 management system, the personnel may be trained to achieve improved quality [24].

The evolution of machine learning algorithms will play a big role in the process of improving and advancing smart manufacturing and industry 4.0.

6.2. Suggestions for future research and development in smart manufacturing

Augmented Reality technology (and respective hardware) still needs to evolve, but as pace of innovation picks up, more and more promising use cases are implemented and evaluated for industry. Augmented Reality (AR) describes a technology that superimposes a computer-generated image on a user's view of the real world [25]. Understanding of the requirements and needs of the manufacturing in regards to AR-supported remote assistance still needs a deeper understanding [24]. We can see that current hardware still cannot completely fulfill industry requirements, especially when factors like rough weather conditions, noise, dirt and safety regulations (such as mandatory hard hats, work gloves and safety glasses) come into play.

Laser Metal Deposition (LMD) is an additive manufacturing method, which boasts of high flexibility and extensive performance. We think there are a lot of possible LMD applications which will lead to a further spread of the processing the next years. Nevertheless, we see the need for continuing process parameter of related material investigations to increase the variety of available metal powders for the LMD process that help to set up new use cases [24].

As regards Predictive Maintenance (PdM), it is evident that while machine learning algorithms have proven to be quite successful in data stream analysis, their implementation in real-world scenarios remains infrequent. Factors that are specific to each domain, such as the availability of labeled data and the tradeoff between breakdown prediction and reaction speed with confidence, are among the primary hindrances to the successful application of theoretical approaches in practical settings. Despite these challenges, the potential benefits of predictive maintenance in terms of time and material savings make it an area of continued interest for both researchers and practitioners. With the increasing digitization of industry, we can expect to see a growing number of real-world implementations soon [24]. Stochastic conditions are inevitable in unstructured environments, like complex industrial scenarios. How to estimate uncertainties and identify unknowns is still challenging [26].

II. REFERENCES

[1]. Bi, Z.; Xu, L.; Ouyang, P. Smart Manufacturing—Theories, Methods, and Applications. Machines 2022, 10, 742. [Crossref]

[2]. Wang, B., Tao, F., Fang, X., Liu, C., Liu, Y., Freiheit, T., 2021, Smart Manufacturing and Intelligent Manufacturing: A Comparative Review. Engineering, 7/6 [Crossref]

[3]. Cioffi, R.; Travaglioni, M.; Piscitelli, G.; Petrillo, A.; Parmentola, A. Smart Manufacturing Systems and Applied Industrial Technologies for a

Sustainable Industry: A Systematic Literature Review. Appl. Sci. 2020, 10, 2897. [Crossref]

[4]. Hyoung Seok Kang, Ju Yeon Lee, SangSu Choi, Hyun Kim, Jun Hee Park, Ji Yeon Son, Bo Hyun Kim, and Sang Do Noh. Smart Manufacturing: Past Research, Present Findings, and Future Directions: International Journal of Precision Engineering And Manufacturing-Green Technology Vol. 3, No. 1, pp. 111-128. [Crossref]

[5]. Mark Armstrong, Hamid Mehrabi, Nida Naveed. An overview of modern metal additive manufacturing technology. Journal of Manufacturing Processes Volume 84, 2022, Pages 1001-1029. [Crossref]

[6]. Janhavi Namjoshi, Manish Rawat, Role of smart manufacturing in industry 4.0, Materials Today: Proceedings, Volume 63, 2022, Pages 475-478, ISSN 2214-7853. [Crossref]

[7]. Yi Xiong, Yunlong Tang, Qi Zhou, Yongsheng Ma, David W. Rosen, Intelligent additive manufacturing and design: state of the art and future perspectives, Additive Manufacturing, Volume 59, Part A, 2022, 103139, ISSN 2214-8604. [Crossref]

[8]. Thywill Cephas Dzogbewu, Samuel Koranteng Fianko, Nathaniel Amoah, Sampson Afrifa Jnr, Deon de Beer. Additive manufacturing in South Africa: critical success factors. Heliyon. Volume 8, Issue 11, 2022, e11852. [Crossref]

[9]. Yuyang Du, Jian Wang, Zhanxi Wang, Fei Yu, Chen Zheng, Robotic manufacturing systems: A survey on technologies to improve the cognitive level in HRI, Procedia CIRP, Volume 107, 2022, Pages 1497-1502, ISSN 2212-8271. [Crossref]

[10]. Bi, Z.; Zhang, W.-J.; Wu, C.; Luo, C.; Xu, L. Generic Design Methodology for Smart Manufacturing Systems from a Practical Perspective, Part I—Digital Triad Concept and Its Application as a System Reference Model. Machines 2021, 9, 207. [Crossref]

[11]. Yingxin Ye, Tianliang Hu, Aydin Nassehi, Shuai Ji, Hepeng Ni, Context-aware manufacturing system design using machine learning, Journal of Manufacturing Systems, Volume 65, 2022, Pages 59-69, ISSN 0278-6125. [Crossref]

[12]. Aksoy, M.S., Torkul, O. & Cedimoglu, I.H. An industrial visual inspection system that uses inductive learning. Journal of Intelligent Manufacturing 15, 569–574 (2004). [Crossref]

[13]. Holm, E.A., Cohn, R., Gao, N. et al. Overview: Computer Vision and Machine Learning for Microstructural Characterization and Analysis. Metall Mater Trans A 51, 5985–5999 (2020). [Crossref]

[14]. Zhang, Z., Yang, Z., Sisson, R. D., & Liang, J. (2022). Improving ceramic additive manufacturing via machine learning-enabled closed-loop control. International Journal of Applied Ceramic Technology, 19(2), 957–967. [Crossref]

[15]. Ramakrishna, S., Khong, T. C., & Leong, T. K. (2017). Smart Manufacturing. Procedia Manufacturing, 12, 128–131. [Crossref]

[16]. Phuyal, S., Bista, D., & Bista, R. (2020). Challenges, Opportunities and Future Directions of Smart Manufacturing: A State of Art Review. Sustainable Futures, 2, 100023. [Crossref]

[17]. Evjemo, L. D., Gjerstad, T., Grøtli, E. I., & Sziebig, G. (2020). Trends in Smart Manufacturing: Role of Humans and Industrial Robots in Smart Factories. Current Robotics Reports 2020 1:2, 1(2), 35–41. [Crossref]

[18]. Deolitte US. The Smart Factory @ Wichita: Deloitte's New Immersive Learning Center. YouTube, n.d. [Crossref]

[19]. D. Baumann, F. Mager, U. Wetzker, L. Thiele, M. Zimmerling and S. Trimpe, "Wireless Control for Smart Manufacturing: Recent Approaches and Open Challenges," in Proceedings of the IEEE, vol. 109, no. 4, pp. 441-467, April 2021. [Crossref]

[20]. Phuyal, S., Bista, D., & Bista, R. (2020). Challenges, Opportunities and Future Directions

of Smart Manufacturing: A State of Art Review. Sustainable Futures, 2. [Crossref]
[21]. Thoben, K., Wiesner, S., & Wuest, T. (2017). "Industrie 4.0" and Smart Manufacturing - A Review of Research Issues and Application Examples. Int. J. Autom. Technol., 11, 4-16. [Crossref]
[22]. Michelle Schlechtriem. Interoperability: A Key Challenge for the Robotics Industry | #HowToRobot. [Crossref]
[23]. Austin Weber. Justifying Investment in Automation. AssemblyMag. [Crossref]
[24]. Gayen, D. K., Hameedur, S., & Zaini, R. (2022). Future of Factory Through the Techniques of Smart Manufacturing, Process and Business Excellence for World Class Production. " 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 422-427 [Crossref]
[25]. Amo, I.F., Erkoyuncu, J.A., Roy, R., Wilding", S., 2018. Augmented reality in maintenance: An information-centered design framework. Procedia Manufacturing 19, 148 – 155. Proceedings of the 6th International Conference in Through-life Engineering Services, University of Bremen. [Crossref]
[26]. N. Sünderhauf, O. Brock, W. Scheirer, R. Hadsell, D. Fox, J. Leitner, et al., The limits and potentials of deep learning for robotics, Int. J. Robot. Res. 37 (2018) 405–420. [Crosref]
[27]. Z. Liu, Q. Liu, W. Xu, L. Wang, and Z. Zhou, "Robot learning towards smart robotic manufacturing: A review," vol. 77, p. 102360, 2022, doi: 10.1016/j.rcim.2022.102360. [Crossref]
[28]. V. Digani, L. Sabattini, C. Secchi, C. Fantuzzi, Ensemble coordination approach in multi-agv systems applied to industrial warehouses, IEEE Trans. Autom. Sci. Eng. 12 (2015) 922–934. [Crossref]
[29]. F. Gu´erin, F. Guinand, J.F. Breth´e, H. Pelvillain, UAV-UGV cooperation for objects transportation in an industrial area, in: 2015 IEEE International Conference on Industrial Technology (ICIT), 2015. [15]J. Nikolic, M. Burri, J. Rehder, S. Leutenegger, C. Huerzeler, R. Siegwart, A UAV system for inspection of industrial facilities, 2013 IEEE Aerospace Conference, 2013. [Crossref]
[30]. Q. Liu, Z. Liu, W. Xu, Q. Tang, Z. Zhou, D.T. Pham, Human-robot collaboration in disassembly for sustainable manufacturing, Int. J. Prod. Res. 57 (2019) 4027–4044. [Crossref]
[31]. Y. Lu, X. Xu, L. Wang, Smart manufacturing process and system automation–a critical review of the standards and envisioned scenarios, J. Manuf. Syst. 56 (2020) 312–325. [Crossref]
[32]. Y. Qu, X. Ming, Z. Liu, X. Zhang, Z. Hou, Smart manufacturing systems: state of the art and future trends, Int. J. Adv. Manuf. Technol. 103 (2019) 3751–3768. [Crossref]
[33]. L. Wang, R. Gao, J. V´ancza, J. Krüger, X.V. Wang, S. Makris, et al., Symbiotic human-robot collaborative assembly, CIRP Ann. Manuf. Technol. 68 (2019) 701–726. [Crossref]
[34]. Wang, Y. Chen, Y. Jia, Evaluation and optimization of dual-arm robot path planning for human–robot collaborative tasks in smart manufacturing contexts, ASME Lett. Dyn. Syst. Control 1 (2021), 011012. [Crossref]
[35]. S. Liu, L. Wang, X.V. Wang, Sensorless haptic control for human-robot collaborative assembly, CIRP J. Manuf. Sci. Technol. 32 (2021) 132–144. [Crosref]
[36]. A. Al-Yacoub, Y. Zhao, W. Eaton, Y. Goh, N. Lohse, Improving human robot collaboration through force/torque based learning for object manipulation, Rob. Comput. Integr. Manuf. 69 (2021), 102111. [Crossref]
[37]. S. Liu, L. Wang, X.V. Wang, Sensorless force estimation for industrial robots using disturbance observer and neural learning of friction approximation, Rob. Comput. Integr. Manuf. 71 (2021), 102168. [Crossref]

[38]. Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, Gradient-based learning applied to document recognition, Proc. IEEE 86 (1998) 2278–2324. [Crossref]

[39]. D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning Internal Representations by Error Propagation, California University San Diego La Jolla Institute for Cognitive Science, 1985. [Crossref]

[40]. F. Scarselli, M. Gori, A.C. Tsoi, M. Hagenbuchner, G. Monfardini, The graph neural network model, IEEE Trans. Neural Networks 20 (2008) 61–80. [Crossref]

[41]. Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436–444. [Crossref]

[42]. K. Hornik, M. Stinchcombe, H. White, Multilayer feedforward networks are universal approximators, Neural Netw. 2 (1989) 359–366. [Crossref]

[43]. Y. Pu, Z. Gan, R. Henao, X. Yuan, C. Li, A. Stevens, et al., Variational autoencoder for deep learning of images, labels and captions, in: 30th Annual Conference on Neural Information Processing Systems (NeurIPS), 2016 [Crossref]

[44]. I.J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, et al., Generative adversarial nets, in: 28th Annual Conference on Neural Information Processing Systems (NeurIPS), 2014. [Crossref]

[45]. D. Silver, S. Singh, D. Precup, R.S. Sutton, Reward is enough, Artif. Intell. 299 (2021), 103535. [Crossref]

Acknowledgements

We acknowledge the efforts of the authors Data availability: This work does not contain any data
Funding: No funding was required to do the review
Conflict of interest: The authors declare that there are no conflicts of interests nor competing interest for this work
Author contributions: All authors contributed to this work
Ethics approval: Not applicable
Consent to participate: Not applicable
Consent to publication: Not applicable

Cite this article as :

Adeleke Olorunnisola Oyeyemi, Awotundun Oluwagbenga Joshua, Olukanri Riliwan Babatunde, "Smart Manufacturing and its Impact on Production Processes : A Review", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Online ISSN : 2394-4099, Print ISSN : 2395-1990, Volume 10 Issue 5, pp. 57-65, September-October 2023. Available at doi : https://doi.org/10.32628/IJSRSET231052
Journal URL : https://ijsrset.com/IJSRSET231052