AL-Bahir
Journal for Engineering and Pure Sciences
BJEPS

Volume 1 | Issue 2 Article 3

RECENT TECHNICAL BREAKTHROUGHS ENABLE SMART MANUFACTURING: A REVIEW

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REVIEW

Recent Technical Breakthroughs Enable Smart Manufacturing: A Review

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Abstract

In human culture, machine learning has long been used to address complicated issues. Machine learning is successful because of the help provided by computational power and sensing technology. Data-driven strategies and the development of artificial intelligence will soon have a significant impact on the industry. Common examples include search engines, picture recognition, biometrics, speech and handwriting recognition, natural language processing, as well as medical diagnostics and credit scores. It is obvious that when artificial intelligence permeates our globe and, more precisely, our lives, numerous challenges will become public. According to predictions, Industry 4.0 or Smart Manufacturing will be the next Industrial Revolution. It all has to do with technology connectivity and improvements in the contextualization of data, as with many other advancements in recent years. Smart, however, cannot be realised without either the support of intelligent systems or the support of data science technologies.

Keywords: Smart manufacturing, Risk management, Sustainable energy, Green energy, Internet of things

1. Introduction

An Internet-connected piece of equipment is used in smart manufacturing (SM) to keep an eye on the production process. SM's objective is to find ways to automate processes and use data analytics to boost industrial efficiency. A particular use of the Industrial Internet of Things is SM (IoT). Sensors are embedded in manufacturing equipment during deployments in order to gather information about the machines' performance and operational state. Previously, the data was often stored locally on individual devices and only utilysed to determine the root cause of equipment problems after they had already happened.

A new phase of the industrial revolution is currently underway thanks to the development and widespread use of the new information technology generation. Many nations have developed and implemented their own manufacturing development initiatives in recent years, such as Germany's "Industry 4.0" initiative. Between these, SM has emerged as the primary path for the industrial revolution and development of the industrial sector. Furthermore, sustainable development has come to represent the majority in scientific progress. Special focus has been paid to sustainable innovation, the most significant subgroup of the sustainable development idea. T [16–18]. The environmental and social effects of SM, as a new era in production, are unclear and require special consideration [19].

A number of nations have introduced their national advanced manufacturing development strategies, such as Industry 4.0 in Germany, Industrial Internet

Received 11 October 2022; revised 10 November 2022; accepted 10 November 2022.
Available online 5 Decembar 2022

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https://doi.org/10.55810/2313-0083.1010

and manufacturing system based on CPS (Cyber-Physical Systems) in the USA, Made in China 2025, and Internet Plus Manufacturing, in response to the integration and widespread applications of the new generation of information technologies (such as cloud computing, IoT, big data, deep learning, and AVG) in the manufacturing industry. All information about the manufacturing process is made available when and where it is needed across whole manufacturing supply chains and product lifecycles thanks to smart manufacturing and the smart factory [2].

Manufacturing engineers and data analysts may now search for indications that certain components may break by evaluating the data coming off an entire factory's worth of equipment, or even across different sites. This enables preventative maintenance to eliminate unscheduled device downtime.

Manufacturers can also look for patterns in the data to see where in their operations manufacturing is slowing down or using resources inefficiently. Additionally, data scientists and other analysts can use the data to simulate several procedures in an effort to determine which ones are the most effective.

Machines will be better equipped to interact with one another as smart manufacturing spreads and more of them are networked through the Internet of Things, possibly allowing higher degrees of automation [1].

The proliferation of inexpensive sensors that can measure and digitize production processes, advances in data science that make it possible to use data, and the prospect of more effective and environmentally friendly manufacturing are what are driving the paradigm shift from traditional manufacturing to “smart”. Resilient and sustainable production are principles that are included in smart manufacturing [11–14]. Fig. 1 depicts a schematic of a typical SMS system with all of its required parts [15].

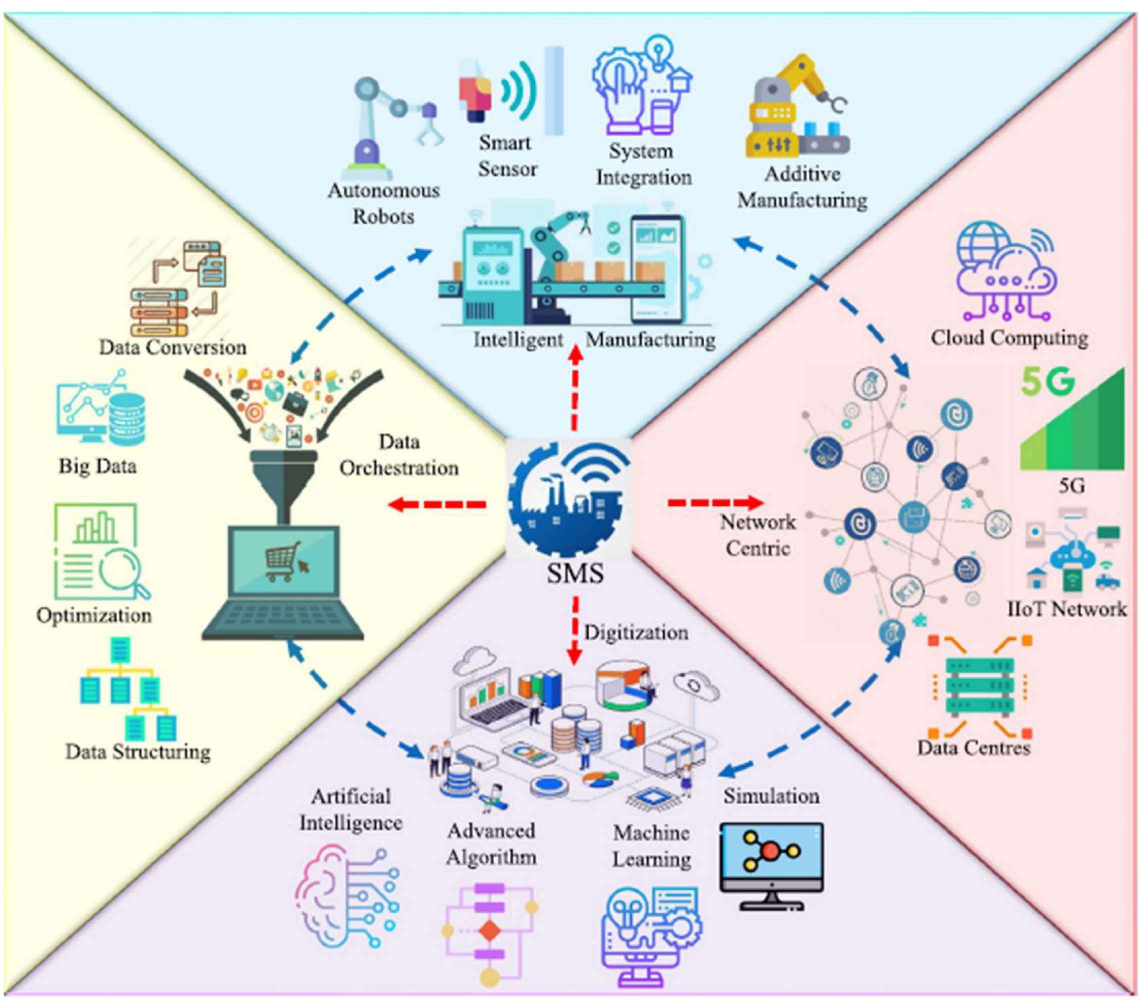

Fig. 1. Modern manufacturing techniques [15].

Manufacturing companies must consider, measure, and eventually enhance the environmental and social impact of their smart manufacturing activities because this is the core of the industry's development. This has emerged as a key research area [5,6].

Although SM is in theory environmentally friendly and sustainable, it must still overcome obstacles to sustainable production, transportation, public health, and risk management. Enterprises must analyse their viability from a green viewpoint in order to avoid the negative consequences of smart manufacturing in the future and to support its development in the direction of green smart manufacturing, and the quantitative assessment of green plays a crucial role in this process [20−22].

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2. History/background of SM

The first Industrial Revolution, which is believed to have begun about 1760, has been going on for over 260 years. The most recent version of this process, the fourth industrial revolution, is known as “smart manufacturing” in the United States and “Industry 4.0″ in Europe.

The assembly line and steam power dominated the first industrial revolution, the power loom and the assembly line dominated the second industrial revolution, and the advent of data-enhanced automation and automation in the 1970s ushered in the third industrial revolution. A variety of interconnected automated systems that combine the physical, digital, and biological worlds are what this fourth industrial revolution is known for.

To build an intelligent manufacturing prediction system to analyse massive data and diagnose the manufacturing process, a decision tree algorithm and linear regression are suggested in 2019 [3]. A model for an intelligent medical diagnostic assistance based on the Multilayer Perceptron (MLP) is presented in 2019 and Support Vector Machine techniques [4]. The production shop scheduling problem is constructed using the particle swarm optimization (PSO) and genetic algorithm (GA), as discussed in 2019 [5]. The suggested approach also offers advantages for bioinspired computing that are dependable, compatible, and scalable. The ant colony optimization algorithm (ACO) in 2020, to create the material requirement planning (MRP) in the manufacturing process, which is a bioinspired computer technique is described [6]. According to the results, the ACO algorithm may effectively shorten the MRP deployment time and increase system implementation effectiveness. In order to increase production efficiency and identify the optimal product portfolio for intelligent manufacturing firms in 2020 [7], employed artificial neural networks. The results demonstrated that big data analysis could be advantageous for businesses operating in an integrated and complex information environment.

Generative Adversarial Network (GAN), Info-GAN (Information GAN), deep convolutional GAN (DC-GAN), f-divergence GAN (f-GAN), and category-aware GAN (Cat-GAN) models were compared by [8] in 2019 and machine vision systems based on these deep learning techniques were built in. For the system and process of intelligent manufacturing, the proposed model may be helpful. Text classification in product production to use four well-known deep learning models in 2020 by [9], including convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM), and bi-directional long short-term memory (BiLSTM). The experimental findings showed that CNN performed the best. Additionally, LSTM and BiLSTM's single-layer architecture can perform better than multiple-layer architecture [10]. also used the CNN algorithm in 2020 to create a recognition model for the function diagram of an oil well.

3. Durability of SM enterprises via information combination

Resilient and sustainable manufacturing are concepts that are included in SM [23]. The emergence of inexpensive detectors that can assess as well as digitise manufacturing processes, advances in data science that make it possible to use data, and the prospect of more effective and environmentally friendly manufacturing are what are driving the paradigm shift from traditional manufacturing to “smart.” The discipline of industrial information integration engineering (IIIE) includes these developments. As a result, the Internet of Things (IoT) and IIIE have been integrated to create SM [24−27]. Risks must be acknowledged in the context of SM, taking into account both their source and the influence they have on the larger organisation. Beyond manufacturing procedures, supply chains, and cybersecurity, an enterprise-level resilience is taken into account in [28]. The urgent demand for production organization durability is further driven by the rising frequency of global events having an impact on businesses.

In the publications mentioned above, it can be seen that some of them have a focus on the supply chain, a cross-sector evaluation that focuses on the risk to occupational safety, and business resilience for SM systems. Their conclusion is that risks are more difficult for users to understand in the context of smart manufacturing, resilience strategies can be complicated and must therefore be tailored for the context of SM, and the emphasis is on risk and the function of information integration in reducing those risks. Although risks were only briefly discussed in the majority of studies, there was a wide range in the suggested levels of risk mitigation. For instance, studies investigating production system failures targeted reduction through scientific [29–31], structural [32] and manufacturing and logistics system-specific [33] solutions.

A. Sheth and A. Kusiak [28] provides an illustration of the holistic context of smart manufacturing, as well as the variety of risks and effects of individual solutions. The production system and supply chain disruption are just two separate examples of the manufacturing enterprise that must be considered as part of a broader set of risk foci for smart manufacturing to be resilient. We anticipate future research to concentrate on business level hazards that transcend conventional manufacturing or supply chain operations, as well as research on their integrated multi-level consequences. The multi-level and integrated risk mitigation of corporate risks is fundamental for the resilience of smart manufacturing, in general.

Some of literature work in tabular form is shown in Table 1.

4. Related technologies

Smart manufacturing will be made possible by a number of technologies in addition to the Internet of Things [1], such as:

1. Machine learning and artificial intelligence (AI) allow for autonomous decision-making based on the vast amounts of data that manufacturing businesses gather. All of this data may be analysed by AI/machine learning, which can then use the inputted data to make wise judgments.
2. By lowering the number of personnel required to do routine activities, including driving cars around a facility, drones and autonomous vehicles can enhance production.
3. Blockchain can offer a quick and effective means to collect and retain data because of its advantages, such as immutability, traceability, and disintermediation.
4. Edge computing - edge computing aids manufacturers in transforming enormous volumes of machine-generated data into usable information so they may get insights and make better decisions. This is achieved by using network-connected resources, such as temperature sensors or alarms, to enable data analytics at the data source.
5. Using predictive analytics, businesses may examine the vast volumes of data they get from all of their data sources to foresee issues and enhance predictions.
6. Digital twins are virtual representations of a company's processes, networks, and equipment that may be used to predict issues before they arise and increase productivity and efficiency.

5. Smart manufacturing's benefits and drawbacks

1. A variety of advantages come with smart manufacturing, such as greater production, enhanced efficiency, and long-term cost savings. Productivity is continually improved in a smart factory. The data will indicate any issues, such as a machine that is causing production to lag, and the artificial intelligence algorithms will try to fix them. Greater flexibility is possible thanks to these highly flexible systems.
2. The decrease in production downtime results in one of the biggest cost benefits in terms of efficiency. Modern machines frequently have remote sensors and diagnostics installed to notify operators of issues as they develop. The use of predictive AI technology can identify issues before they arise and take action to reduce the associated expenses. Automation and human-machine collaboration are elements of a well-designed smart factory that promote operational effectiveness.
3. The initial cost of deployment is a significant drawback to smart manufacturing. As a result, many small to medium businesses won't be able to afford the technology's high cost, especially if they adopt a short-term mindset.
4. However, even if enterprises can't instantly integrate smart factories, they must prepare for the future since long-term benefits will surpass the starting expenditures.
5. Due to the complexity of the technology, it is also a drawback that systems that are inadequate for a certain activity or poorly built might reduce earnings.

Table 1

S.No.	Author	Work	Outcome	Suggestion
1.	Lianhui Li et al. [22]	The green performance evaluation technique and smart manufacturing application research	A quantitative assessment of smart manufacturing's environmental impact is the contemporary manufacturing sector's primary direction.	Can be detailed study on social impact evaluation.
2.	Ananya Sheth et al. [28]	Resiliency of smart manufacturing businesses with the help of Information integration.	by transcending the conventional perception of manufacturing resilience single domains to concentrate on, such the supply chain or cyber resilience company-wide dangers.	New generation technology can be used in order to minimize the risk.
3.	Ravi Sharma et al. [15]	a method for analysing and describing research to recognise and rate functional and technological, economic, social, and performance evaluation elements that are not functional are crucial to the assessment of SMS.	the prospect of self-driving SMS is required for production flexibility and customisation, as well as for foundations that are user-friendly and reasonably priced.	Additional specifications addressing different SMS components may be used.
4.	Julio C. Serrano-Ruiz et al. [34]	A job shop smart manufacturing multidimensional conceptual model	DT enabling technology and the ZDM management model intersect in the work shop scheduling to favour automation, autonomy, real-time action capability, and robustness to probable disturbances and disruptions. This aggregate conceptual SMS model is described.	Feasibility of more physical setting of the job shop is crucial for SMS viability and for the support of virtual job shop simulation selection of the DES system can be included.
5.	Xianyu Zhang et al. [35]	the flexible production planning issue of sales orders based on client personalization, as well as the flexible layout and resource optimization for flexible smart manufacturing system in mass personalization manufacturing model.	It is possible to reduce overall production costs and increase the usage of the equipment and production plan area.	A number of model algorithms must be created.

6. What sets SM apart from conventional production techniques

Traditional manufacturing techniques, which were created during the mass production era, emphasis equipment usage and economies of scale. Companies kept machines running continually because it was believed that if a machine was not in use, it was losing money [1].

Traditional manufacturing businesses maintain sizable inventories so they can meet prospective orders and maintain customer satisfaction. In order to lower the cost of producing the components, these businesses must operate their machines with specified settings for as long as possible [1].

Batch-and-queue processing is a method of mass manufacturing where parts are processed, passed on to the next step, and then queued up regardless of whether they are required (queue) [1].

This strategy, however, is ineffective for a number of reasons, including:

- Since nothing is generated while a machine is offline, a longer machine setup time results in greater lost production time.
- Because faulty pieces in a batch are likely not discovered until the subsequent operation, the quality of the final product diminishes. This necessitates repeating the task, which costs money and uses up important resources.

7. Conclusion

Smart manufacturing is a technology-driven approach to manufacturing that uses Internet-connected gear to monitor the production process in order to optimise the manufacturing process. Organizations may utilise data analytics to enhance production performance and find potential for automation of processes. These studies can increase the accuracy of the manufacturing process and plan, decrease the demand on human resources and computing power, and produce better informed judgments based on big data during routine business operations.

The practical issues faced by the current smart manufacturing firms serve as the foundation for the green performance evaluation methodology and application study of smart manufacturing presented in this paper. It intends to conduct a quantitative green evaluation of smart manufacturing, which is the present manufacturing industry's key direction. This exploratory study combines the requirements for green development with the distinctions between existing industrial paradigms in terms of their effects on the environment and society.

The Covid-19 epidemic revealed manufacturing companies' weaknesses. However, this is not the first time that the scientific community has become aware of industrial problems. A manufacturing company's resilience is impacted by a number of variables, some of which are outside of its direct control, including its external operating environment, business limitations, technical advancements, and both long-term and short-term societal trends.

Conflict of interest

Authors declare that there is no conflict of interest.

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