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ADVANCED MANUFACTURING TECHNIQUES FOR SUSTAINABLE PRODUCTION: A FOCUS ON ADDITIVE MANUFACTURING AND AI

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Abstract

The transition towards sustainable production has emerged as a national and international priority, driven by the imperative to reduce the impact of environmental problems and maximize the use of available resources. This transition is being driven by the implementation of advanced manufacturing processes, in particular Additive Manufacturing (AM) and Artificial Intelligence (AI). Through the enhancement of efficiency, the reduction of waste, and the facilitation of novel design solutions, this study investigates the ways in which these technologies contribute to sustainable manufacturing. The process of additive manufacturing, more often referred to as 3D printing, makes it possible to produce on demand, decreases the amount of material that is used, and enables the fabrication of lightweight structures, all of which contribute to a considerable reduction in the amount of energy that is consumed across industries. On the other side, artificial intelligence works to improve decision-making by means of predictive analytics, process optimization, and real-time monitoring. This helps to ensure that emissions are decreased and resource efficiency is increased. Industrial sectors have the potential to achieve considerable sustainability advantages via the integration of these technologies, including the reduction of environmental footprints, the shortening of supply chains, and the creation of personalized production models. Case studies from industries such as aerospace, healthcare, and automotive are explored in order to highlight the applications and advantages that are applicable in the real world. In addition, the study discusses the obstacles that stand in the way of widespread adoption, such as high initial costs, a lack of available skills, and regulatory frameworks. This research highlights the revolutionary potential of additive manufacturing (AM) and artificial intelligence (AI) as key instruments for accomplishing sustainable production goals, therefore paving the path for an environmentally conscious and resilient manufacturing ecosystem.

keywords: *Manufacturing Techniques, AI, Additive*

Introduction

The growing sense of urgency to solve environmental challenges on a global scale has resulted in an increased emphasis on environmentally responsible manufacturing processes across all sectors of the economy. In order to achieve the goal of sustainable production, which is to strike a balance between economic growth, environmental preservation, and social well-being, it is necessary to incorporate cutting-edge technology that can maximise the utilization of resources while simultaneously reducing waste and emissions. Within the framework of this discussion, Advanced Manufacturing Techniques (AMTs) are playing a crucial part in the process of pushing this paradigm change. The Additive Manufacturing (AM) and Artificial Intelligence (AI) technologies have emerged as revolutionary technologies within the vast array of additive manufacturing technologies (AMTs). The additive manufacturing process, often known as 3D printing, is a revolutionary departure from the conventional subtractive techniques of production. It involves the construction of products by layering them together. This process reduces the amount of material that is wasted, encourages the utilization of recyclable materials, and makes it possible to create intricate and lightweight patterns that are not possible using traditional methods. Increasing both productivity and the capacity to make decisions, artificial intelligence is a useful addition to additive manufacturing. Systems that are powered by artificial intelligence make use of big data, machine learning, and predictive analytics in order to enhance the efficiency of supply chain operations, optimise manufacturing processes, and provide real-time quality control. Artificial intelligence and additive manufacturing give a chance to design production systems that are more intelligent, cleaner, and more sustainable. In the framework of environmentally responsible manufacturing, the convergence of additive manufacturing with artificial intelligence is the subject of this article. This paper investigates the ways in which these technologies are being used to lessen their impact on the environment, enhance the efficiency of manufacturing, and encourage innovation. In addition to this, the article investigates case examples from a variety of sectors, illustrating the advantages, difficulties, and potential future outcomes of merging AM and AI for sustainability. The purpose of this article is to highlight the potential of these advanced manufacturing techniques to revolutionize current production and contribute to an industrial ecosystem that is both sustainable and resilient. This will be accomplished by highlighting the synergies that exist between these techniques. The implementation of additive manufacturing and artificial intelligence in environmentally responsible production is in line with global initiatives such as the Sustainable Development Goals (SDGs) of the United Nations, specifically SDG 9 (Industry, Innovation, and Infrastructure) and SDG 12 (Responsible Consumption and Production). These aims place an emphasis on the necessity for companies to employ new technologies in order to construct infrastructures that are robust, to promote industrialization that is inclusive, and to mitigate environmental repercussions from industrialization. Additive manufacturing has the capacity to allow decentralized production, which considerably decreases the costs of transportation and the carbon emissions that are connected with it. This is one of the most important advantages of additive manufacturing. By enabling manufacture to take place on-site and on demand, additive manufacturing (AM) lessens the reliance on conventional supply chains and makes it possible to produce goods in a more localised manner. Additionally, its capability of producing individualized and intricate designs makes it easier for innovations to be implemented in essential industries such as healthcare, where personalized medical devices and implants are becoming an increasingly crucial form of treatment. Artificial intelligence enables sophisticated process monitoring and optimization, which further magnifies the industrial industry's potential for sustainability. The ability to foresee machine breakdowns, decrease downtime, and improve energy efficiency are all capabilities of AI-driven systems. In addition this the artificial intelligence algorithms play a significant part in generative design, which enables engineers to produce components that are highly optimised, lightweight, and utilise minimum material while yet keeping all of their structural integrity. The incorporation of artificial intelligence into the workflows of design and production not only facilitates the reduction of waste but also propels creativity in product creation. Even if these improvements have been made, the implementation of AM and AI in environmentally responsible production is not without its difficulties. Significant obstacles include high initial costs, the requirement for specialised expertise, and worries around the protection of intellectual property and cybersecurity. Furthermore, legal frameworks and standardisation for these emergent technologies are still in the process of developing, which necessitates concerted efforts by organisations such as governments, corporations, and academic institutions in order to guarantee smooth integration. This paper delves into these aspects, offering a comprehensive analysis of the potential, current applications, and future directions of AM and AI in sustainable manufacturing. It is intended to create a road map for industry and governments to follow in order to harness these technologies in order to construct a manufacturing ecosystem that is more environmentally friendly and efficient.

Ecological issues of AM

As a component of the industrial production chain, additive manufacturing (AM) can be challenging to characterize from a sustainability standpoint. The quantitative aspect of such an investigation ought to incorporate ecological concerns of AM in connection to the consumption of materials and energy, as well as health and safety, transportation, and waste management. Additionally, the study ought to place an emphasis on the link between sustainability and design quality. component strength, component flexibility, surface quality, contained voids, material cost, machine cost, and process efficiency are some of the most important characteristics of additive manufacturing design that should be taken into consideration. AM processes are required to demonstrate their potential to be environmentally friendly by taking into consideration the following sustainability principles: efficient use of materials and energy; management of industrial waste; low manufacturing costs; avoidance of toxic emissions and materials; health and safety concerns; low environmental impacts; improvement of personnel health and safety; economical efficiency; reparability, reusability, recyclability, and disposability of products made by AM.

Energy

Due to the enormous amount of energy that is used by employing heat processes or lasers to melt plastic and metal or to cure resins, additive manufacturing (AM) cannot currently be considered an environmentally friendly manufacturing technology, despite the fact that it has the potential to promote an environmentally cleaner manufacturing process. In general, AM equipment is not designed to be efficient in its operation. There is a significant amount of energy loss, and the control of heat is subpar. The influence that AM methods have per part is greater than that of TM processes when mass production is included. On the other hand, this is irrelevant because they are replacing them with tiny quantities of individualised components.The manner in which the components are made, whether through conventional manufacturing procedures or through the use of 3D printing, is the most significant aspect in determining the environmental effect of the production process. One of these ways, which involves producing only a portion of the product each week but leaving it on for the rest of the time, has the potential to have a greater impact than the identical machine operating at its maximum capacity. The most significant consequence for TM is the use of materials and the trash they produce. Because the amount of energy that is consumed by each individual item during the manufacturing stage is still rather considerable, the environmental implications caused by AM are dominated by electricity use. Reducing the run-time by taking into consideration certain straightforward solutions is the most effective method for mitigating the negative effects of AM energy consumption. Printing tubular pieces rather than solid ones, orienting parts for the quickest printing, and filling the printer bed with several parts (if at all feasible) are all things that should be done.

Materials

By reducing the quantity of material that is produced, additive manufacturing may become more sustainable. A considerable proportion of wasted raw materials are left behind by 3D printers, however additive manufacturing (AM) employs a variety of raw materials to make prototypes, components, or functioning products based on 3D digital models. This is accomplished by printing layers of materials via the printing process. The additive manufacturing process makes use of a wide range of materials, including metals, polymers, ceramics, and composite materials, which can be in the form of powders, wires, or liquids. In additive manufacturing, additive manufacturing works with a variety of materials, including powdered or molten polymers (plastics), which are not optimal for the environment (even if they may be recycled). This is true independent of the production processes that are employed. There are very few instances in which plastic by-products can be reused; nevertheless, the material qualities are frequently altered, rendering these materials unsuitable for use in the production of components. Certain types of plastics produce less pollution than others. For this reason, it is necessary to check standardised scales of flammability, toxicity, and reactivity when selecting materials that are suitable. The utilisation of printing materials that are biodegradable or freshly sanded might be a potential option. There are more advantages to using polylactic acid or polylactide (PLA, Poly) than there are to using ABS. When it comes to printing, PLA is a biodegradable thermoplastic aliphatic polyester that is created from renewable resources such as corn starch, tapioca roots, or sugarcane. It is a bio-based polymer, which means it is less harmful, and it requires lower temperatures, which in turn affects the amount of energy that is used. Because of all of these characteristics, PLA is a potential bio-plastic that is eventually going to become a mainstream material for 3D printing. Even if the toxicity might not be immediately apparent, the health and safety concerns associated with AM should also be taken into consideration. When plastic is heated to high temperatures and then melts, toxic gaseous by-products are released after the melting process finishes. In order to evaluate the influence of gaseous emissions and ultra-fine particles (UFP) emissions in an industrial-scale setting, it is necessary to conduct an analysis of the air quality within the AM workshops. The low levels of UFP that are emitted by 3D printers have the potential to have adverse impacts on human health, including but not limited to the following: alterations in lung function, inflammation of the airways, increased allergy issues, accelerated atherosclerosis, and changed heart rate. The materials that are utilised in Fused Deposition Modelling (FDM) systems appear to be non-toxic and are generated from a wide variety of thermoplastics that are accessible for commercial usage. For the purpose of preventing the fumes that are formed during the processing of these materials, the melting temperatures of these materials should not be surpassed. Inflammations of the skin, eyes, and respiratory tract are some of the health issues that might be brought on by fumes or by procedures that take place after processing.

Life cycle

Furthermore, the environmental effect of product fabrication extends beyond the manufacturing process and encompasses several phases throughout the product life cycle, beginning with the extraction of natural resources and ending with the disposal of the product. Even while the transportation and end of life of the equipment (both 3D printers and machine tools) constitute a minor share of the effects, they are amortised by the high utilisation of the devices. However, if just a few parts are manufactured each week, the embodied impacts can be considerable. AM has the potential to alter the product life cycle by lowering the volume of fuel used to ship items and by shortening the supply chains that are used to transport products. In traditional manufacturing, the areas with low labour costs are targeted, and these places are frequently located a great distance from the markets where the products are consumed. Through the use of AM, manufacturing may be brought closer to the end user of the product. This shortening of the supply chain results in a reduction in the expenses connected with transportation, as well as the pollution and congestion that are associated with it.

Waste management

The current status of the environment and the expansion of the consumer economy throughout the world ought to be in a state of equilibrium. AM technologies are becoming increasingly used in a variety of industrial areas in the modern day. Their influence on the environment will be determined by the manner in which these production technologies are utilised. In comparison to more traditional methods of manufacture, additive manufacturing (AM) may be more environmentally friendly because it does not involve the use of tooling. The use of tooling does not restrict the forms that may be manufactured, which allows for the creation of novel designs. It is unfortunate that the ability to print a series of variations of a product design in a short amount of time might give rise to a new form of pollution through the development of trash in a rapid manner. The reusing and remanufacturing of the components and products involved in AM is an important concern. When it comes to waste flows related with polymeric and metallic additive manufacturing methods, there is essentially little information available. As an example, certain of these flows, such as SLS powder refresh, FDM support structure materials, and post-process heat treatment for minimising residual tensions or energy loss from inefficient laser and optical systems, do not really contribute any value to the component. The FDM machine is capable of producing zero waste, but only in the event that the model does not require any support material while it is being printed. When the inkjet 3D printer does not take into account the supports material, it wastes forty percent of its ink. Depending on the shape and orientation of the structure, the support may have a greater mass than the final section, and it is difficult to recycle this waste. To summarise, 3D printers do not actually lessen the amount of garbage produced. The garbage they produce is not necessarily recyclable, and it is not significant in comparison to the amount of power they consume.

Sustainable Reconfigurable Manufacturing Systems

The characteristics of RMSs not only promote overall system sustainability but also allow for rapid system responsiveness at a low cost, which is essential for manufacturing sustainable products through sustainable processes. These capabilities should enhance economic, environmental, and societal sustainability. Researchers are exploring many different aspects of RMSs, which means that the academic discussion surrounding SRMSs is always developing. This investigation aims to improve the concepts of SM by examining both theoretical underpinnings and practical implementations. contributed to this conversation at the outset by studying RMS developments that paved the way for SRMSs. To efficiently respond to changing market conditions while complying with sustainability goals, their research highlighted the significance of integrating intelligence and flexibility into industrial processes.

Bi went further into the system paradigms from an SM perspective, offering a conceptualisation and abstract representation that adds to the discussion on SRMSs and promotes a paradigm change towards greener production methods. offered a framework based on mechanics of change to reorganise production systems, bringing sustainability goals into RMSs; this helped shape the idea of SRMSs by drawing attention to the significance of sustainability and flexibility. promotes the incorporation of sustainability into RMSs by providing a thorough structure and methodology. The design of a sustainable manufacturing enterprises (DFSMEs) framework was established in 2013, which laid the groundwork for SRMSs by articulating design principles that link RMSs with SM aims. Based on this, the research offered a methodology for RMSs that would improve their flexibility and sustainability, two important features of SRMSs, by outlining concrete ways to incorporate sustainable practices into RMSs' daily operations. laid the groundwork for RMSs with novel, flexibility-oriented business models and methods for configuring systems for use in industry. Their research added to the SRMSs conversation by highlighting the need for flexible production systems to keep businesses competitive and sustainable. expanded the idea of RMSs to include smart modular machine tool frames, which allowed for more production flexibility and sustainability. By stressing the importance of RMS sustainability, this method pushed for the establishment of SRMSs that facilitate long-term value generation. A simulation model for a self-reconfigurable manufacturing system that incorporates sustainability issues was created Their work advanced the story of SRMSs by bringing together self-reconfigurability and SM, which shed light on the dynamic between sustainability and the flexibility of manufacturing systems.

They highlighted the possibility of improved system reconfigurability for more environmentally friendly production operations by analysing the shift from traditional automation to cyber-physical production systems. By emphasising the need of cutting-edge technology in attaining SM, this study provides indirect support for the SRMSs notion. began a conversation about creating SRMSs by assessing the efficacy of RMSs with SM measures. A significant breakthrough has been made in the field of SRMSs research with their analytical approach to assessing convertibility and its influence on sustainable performance. pioneered the idea of environmentally friendly manufacturing facilities for the future, which is in line with the principles held by SRMSs. In order to create living factories that represent the SRMSs model, they investigated how to combine RMSs' traits with SM principles. In the context of RMSs, Touzout investigated the possibility of generating sustainable process plans with multiple objectives. By presenting precise and modified evolutionary methods that take environmental factors into account, they advanced our practical knowledge of SRMSs. explored the design of reconfigurable machine tools (RMTs) for families with several parts, drawing attention to concerns like sustainability and modularity. By stressing the reusability and sustainability of machine tool structures, their mindset is in line with the RMSs framework and provides implicit support for the goal of SM. improved the sustainability of manufacturing within the Industry 4.0 framework by utilising engineering education through virtual reality. Their research adds to what is known about SRMS and focusses on teaching tools for RMSs, which helps people comprehend how RMSs may be sustainable.

A non-linear strategy based on heuristics was suggested in more recent studies to optimise the integrability and modularity of SRMSs. Their research fortifies the theoretical underpinnings of SRMSs by directly connecting sustainability with RMSs. investigated how sustainable open-architecture goods might be designed using modular architecture concepts. Their work advanced the cause of SM and, by extension, SRMS development, by drawing attention to modularity, an essential aspect of RMSs. In order to include energy sustainability into decisions about system configuration, created a model for SRMS layout planning and scheduling. Energy efficiency within RMSs was emphasised in their research, which brought attention to the economic and environmental benefits of SRMSs. researched RMSs as a basis for eco-friendly production, suggesting avenues for further study to increase system lifetime, contemplate disposal plans, and decrease power usage and pollution. In contrast, Gordon examined cyber-physical manufacturing systems that rely on the internet of things (IoT) for real-time logistics, with an emphasis on automation and sustainability in RMSs and SRMSs. The significance of technology, and automation in particular, in the development of SM was highlighted in this study. The models developed by Gao et al. add to the SRMSs debate by including sustainability criteria into RMSs for process planning, scheduling, and layout optimisation. Taken as a whole, their findings provide actionable ways to make manufacturing more sustainable. Continued along this line of thinking, we presented an evolutionary model for SRMS design with several objectives that strikes a compromise between conventional production goals and environmental concerns. analysed the significance of adaptation and flexibility in RMSs design, argued for the incorporation of sustainability into the design phase, and so conformed to the SRMS paradigm. advanced the idea of autonomous manufacturing processes, a crucial component of SRMSs, by devising ways for reconfiguring smart, self-optimizing, and self-organising RMSs. addressed the difficulties of contemporary industrial settings, made worse by the COVID-19 epidemic, by creating a digital twin architecture for RMSs. In line with the objectives of SRMSs, this architecture improves reconfigurability.

looked at RMS backup machine integration, stressing the significance of system flexibility and dependability. expanded RMSs' strategic potential to include supply chains by studying how they may make supply chains more resilient and sustainable. Their approach makes it easier to find machines that can be reused or reconfigured while designing networks; it uses a mixed-integer programming technique and a machine reusability index. approached SRMS process and production planning with a focus on sustainability's three pillars: social, environmental, and economic. They provided workable approaches to incorporating SRMSs into sustainable manufacturing as a whole by creating a linear mixed-integer model and a Lagrangian relaxation-based strategy. used descriptive statistics to determine which Indian industries may benefit most from implementing sustainable manufacturing processes. Their research shown that SRMS enablers significantly contribute to better business results. evaluated the impact of RMSs practices and Industry 4.0 on the attainment of SDGs. They created an all-encompassing plan to help reach these worldwide goals by combining RMSs practices with sustainability goals. focused on RMS balancing and planning in the face of unpredictable demand and changing energy prices, adopting a more technological approach. In line with SRMSs' aims of optimising industrial resource utilisation, its bi-level optimisation model prioritised both energy efficiency and productivity. detailed a research plan that outlines important criteria and methodologies for efficient supply chain configuration, and conducted a literature assessment on the selection of reconfigurable supply chains. Achieving SRMSs in supply chain systems is the ultimate goal of this effort. considered the development of reconfigurable manufacturing systems as a viable option for the future. To unite RMS with green production methods, they created an engineering decision-making framework that prioritised energy efficiency. The main drivers of RMS adoption in industrial industries were investigated in a separate research. They highlighted strategies that improve RMS adoption and performance through structural model validation; these are crucial for current industrial settings to promote sustainability and adaptability. Overarchingly, these studies show how people are always trying to get RMS in line with SM objectives, which is great for the idea of SRMSs. They mirror the increasing dedication to combining the fundamental features of RMSs with SM principles, as seen in Table 1. There is a wealth of literature on SRMSs that lays the groundwork for further studies that aim to improve manufacturing sustainability and adaptability via theoretical investigations, practical approaches, and novel applications. Although many other subjects have been discussed in the literature, there is a clear lack of studies that focus on using AI methods for SRMSs, according to a survey of the current literature. Because of this scattershot approach, further research into creating AI-integrated SRMS frameworks, models, and decision-making tools is urgently required. Closing this knowledge gap would benefit current research and offer stakeholders actionable advice for making AI-powered industrial systems more resilient and environmentally friendly.

Table 1. RMS characteristics.

Characteristic	Description	Code
Modularity	Involves the breakdown of operational functions into units that can be reconfigured or rearranged to optimize production processes across different schemes.	C1
Inerrability	Pertains to the system's capability to integrate modules rapidly and accurately using mechanical, informational, and control interfaces, facilitating communication and function between components.	C2
Diagnosability	Deals with the system's capability to automatically monitor and diagnose its state to promptly detect, diagnose, and correct defects in the output product.	C3
Convertibility	Emphasizes the system's ability to easily transform its functionality to meet new production requirements, making it adaptable to changes in product design or production process.	C4
Customization	Refers to the system's or machine's flexibility being limited to a specific product family, which allows for customized flexibility within that family.	C5
Scalability	Focuses on the ability to modify production capacity easily by adding or subtracting resources, such as machines, or by altering components within the system.	C6

Artificial Intelligence Techniques

Various interpretations of artificial intelligence have been investigated by researchers based on their work. For some people, intelligence is defined by how closely it resembles human performance, while others embrace a more abstract and formal definition that centres on rationality. In essence, intelligence is defined as the capacity to consistently make judgements that are good for the situation. Some people consider intelligence as a property of internal cognitive processes and thinking, while others place more of an emphasis on intelligent behaviour and evaluate it from an external, visible stance. This is another way in which perspectives on artificial intelligence range from one another. In the context of production, Dhamija and Bag define artificial intelligence as machine-driven manufacturing systems that reproduce human behaviours with the intention of resembling the methods that were originally used by humans. For the purpose of allowing machines to process information through mechanisms like as learning, adaption, reproduction, and other processes, artificial intelligence algorithms are frequently modelled after the cognitive processes of humans and natural animals. A wide variety of tools and methods are included in the large area of artificial intelligence (AI), which includes artificial neural networks, fuzzy logic, agent-based systems, genetic algorithms, machine learning, and deep learning. According to Russell and AI approaches, there are four fundamental characteristics that may be used to characterise them: thinking like humans, behaving like humans, reasoning, and acting logically. Because of these characteristics, artificial intelligence approaches may be divided into four distinct classes, as shown in Table 2.

Table 2. AI techniques.

Attribute	Technique	Description	Code
Human thinking	Network-based algorithms	Utilizes neural networks, Bayesian networks, and Markov processes to analyze complex data structures and predict dynamic system behaviors, which can be applied to configure adaptive manufacturing settings.	T1

	Tree-based clustering	Organizes large datasets using hierarchical clustering to identify patterns and predict trends, which is vital for predictive maintenance and optimizing manufacturing operations.	T2
	Rough set theory	Employs mathematical approaches to manage vagueness and uncertainty, which is useful in feature selection and decision support within manufacturing systems planning and quality control.	T3
	Artificial swarm intelligence	Inspired by biological swarm behaviors, it connects networked human groups in real time through AI algorithms for amplifying collective intelligence and optimizing group decisions across various domains, including manufacturing systems.	T4
Human acting	Machine learning and big data analytics	Leveraging large datasets and machine learning algorithms to make predictive decisions and automate processes.	T5
	Reinforcement learning	A type of machine learning in which an agent learns to behave in an environment by performing actions and seeing the results.	T6
	Genetic Algorithms	Optimization algorithms based on the principles of natural selection and genetics, used for solving optimization and search problems.	T7
	Expert systems	AI systems that mimic human expert decision-making using rule-based algorithms to solve complex problems in specific domains.	T8
	Natural language processing	The ability of a computer program to understand human language as it is spoken and written, used extensively in data analytics.	T9
Rationale thinking	Fuzzy logic and programming	Techniques that allow reasoning under uncertainty by employing fuzzy logic, which handles imprecision without requiring crisp data.	T10
	Stochastic programming	A framework for modeling optimization problems that involve uncertainty in the data, allowing for solutions that can adapt to realized data.	T11
	Robust optimization	An optimization approach that seeks to hedge against possible future uncertainties in predictions and modeling, applicable in enhancing system resilience.	T12
	Knowledge representation and reasoning	Techniques that use structured sets of rules and relationships to represent knowledge logically for automated reasoning and inference.	T13

Rationale acting	Agent-based systems	Systems that use autonomous agents, each following a set of rules, to simulate actions and interactions within an environment.	T14
	Model Predictive Control	Uses models to predict and optimize real-time manufacturing operations, ensuring optimal system performance within predefined constraints.	T15
	Robotic Process Automation	The use of software with AI and machine learning capabilities to handle high-volume, repeatable tasks, and thus reduce human intervention and error.	T16
	Computer vision	Techniques that derive meaningful information from digital images, video, and other visual inputs to automate tasks or make enhanced decisions, crucial in modern manufacturing systems.	T17

A wide variety of artificial intelligence approaches that are aimed to imitate human cognitive processes, particularly with regard to recognising and comprehending information patterns, are included in the category of human thinking techniques. Among these methods are network-based algorithms, which include artificial neural networks, Bayesian networks, and Markov processes, among others. Identifying patterns and forecasting trends is the purpose of tree-based clustering, which is a technique that is frequently employed in artificial intelligence literature within the context of operations and supply chain management. tree clustering was utilised for the purpose of supply chain planning in the presence of uncertainty, whilst k-means clustering was utilised for the purpose of sales forecasting in the textile sector. In addition, rough set theory has been utilised in a number of research, such as for the purpose of inventory control, supply chain assessment, and supplier selection. Using artificial intelligence algorithms, artificial swarm intelligence uses the principles of collective decision-making that are found in natural swarms such as fish schools and bird flocks. These concepts are applied to networked human groups via artificial intelligence. This technology, which is often referred to as "human swarming," links people in real time so that it may operate as a closed-loop system, therefore improving the intelligence of groups and the precision of decision-making. The effectiveness of this technology has been demonstrated across a wide range of applications, ranging from financial forecasting to medical diagnosis, via the enhancement of collective insights and the optimisation of group decisions with regard to manufacturing and other areas. The term "human acting techniques" refers to a wide range of artificial intelligence (AI) approaches that are intended to simulate human behaviour during interactions with other individuals, while conforming to the recognised norms of human communication. Machine learning, which is frequently combined with big data analytics, is the approach that is most commonly used in this area. According to one example, academics have utilised machine learning algorithms for the purpose of generating prescriptive decisions in the management of supply chains and operations. When applied in these kinds of situations, methods like reinforcement learning and natural language processing are utilised far less frequently. Expert systems have also been utilised to promote efficient interconnections amongst production entities. In addition, genetic algorithms have been deployed to boost interactions in virtual environments, as proven by the fact that they have been used.

Conclusion

In light of the mounting environmental issues and resource restrictions, the shift to sustainable manufacturing is no longer an option but rather a necessity that must be made. Additive Manufacturing (AM) and Artificial Intelligence (AI) have emerged as revolutionary technologies that have the potential to revolutionise manufacturing methods and drive sustainability. Both of these technologies are called advanced manufacturing. There are considerable environmental benefits associated with additive manufacturing, including the reduction of material waste, the utilisation of lightweight designs, and the utilisation of recyclable materials. Because of its ability to produce on demand and in a localised manner, it minimises its reliance on lengthy supply chains, which in turn contributes to an overall reduction in carbon footprints. In a similar vein, Artificial Intelligence (AI) improves the efficiency of industrial processes by means of predictive analytics, generative design, and real-time optimisation. This helps to ensure that resources are used efficiently and that emissions are kept to a minimum. These benefits are amplified when additive manufacturing (AM) and artificial intelligence (AI) are combined, which enables companies to attain more accuracy, flexibility, and creativity. The synergy between these technologies is paving the way for a manufacturing ecosystem that is more robust and environmentally conscientious. This ecosystem includes lifetime evaluations and smart fabrication facilities. However, in order to encourage wider adoption, it is necessary to solve issues such as high initial prices, energy needs, talent gaps, and regulatory concerns. In conclusion, additive manufacturing (AM) and artificial intelligence (AI) are essential instruments for accomplishing sustainable production goals. It is vital for governments, companies, and academic institutions to work together in order to fully exploit their potential. These sophisticated manufacturing processes have the potential to contribute to the creation of a sustainable future while simultaneously sustaining economic development and competitiveness. This is accomplished by placing an emphasis on innovation, investment, and legislative frameworks.

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