ISSN: 2583-9888
DOI: doi.org/10.51219/JAIMLD/praveen-haridasan/321

URF PUBLISHERS
connect with research world

Journal of Artificial Intelligence, Machine Learning and Data Science

https://urfpublishers.com/journal/artificial-intelligence

Vol: 2 & Iss: 2

Review

Generative AI in Manufacturing: A Review of Innovations, Challenges and Future Prospects

Praveen Kotholliparambil Haridasan* and Hemant Jawale

Citation: Haridasan PK, Jawale H. Generative AI in Manufacturing: A Review of Innovations, Challenges and Future Prospects. *J Artif Intell Mach Learn & Data Sci 2024*, 2(2), 1418-1424. DOI: doi.org/10.51219/JAIMLD/praveen-haridasan/321

Received: 03 June, 2024; **Accepted:** 28 June, 2024; **Published:** 30 June, 2024

***Corresponding author:** Praveen Kotholliparambil Haridasan, Independent Researcher, Frisco, USA, E-mail: PraveenKHari@gmail.com

ABSTRACT

Generative Artificial Intelligence (Gen AI) has emerged as a transformative technology in the manufacturing industry, enabling advanced design automation, process optimization, predictive maintenance and quality control capabilities. Using machine learning models like GANs and Variational Autoencoders (VAEs), Gen AI can create new data independently, improve decision-making across the entire manufacturing lifecycle and make workflows more efficient. Despite its potential, several challenges hinder its broader adoption, including data availability, computational demands, integration with legacy systems and ethical concerns. This paper provides a comprehensive review of the current applications of Gen AI in manufacturing, exploring its core concepts, practical use cases, challenges and future directions. It highlights the transformative impact of Gen AI, outlining the long-term benefits for manufacturing, such as enhanced sustainability, personalized production and autonomous systems. The findings suggest that while Gen AI offers immense promise, overcoming its limitations is critical for unlocking its full potential in reshaping the manufacturing landscape.

Keywords: Generative AI, manufacturing, design optimization, predictive maintenance, quality control, GANs, VAEs, process optimization, data challenges, sustainability, autonomous manufacturing.

1. Introduction

The advent of Industry 4.0 has revolutionized the manufacturing sector by incorporating advanced technologies such as the Internet of Things (IoT), robotics and artificial intelligence (AI). Within this transformation, Gen AI is emerging as a critical enabler of innovation, holding the potential to disrupt traditional manufacturing processes. Unlike traditional AI systems, which are largely deterministic and designed to optimize existing processes, Gen AI introduces a paradigm shift by autonomously generating new designs, optimizing workflows and fostering innovation. Leveraging advanced machine learning models, such as GANs, VAEs and other generative techniques, these systems have proven capable of performing complex tasks that were once restricted to human ingenuity, such as product design, process optimization and predictive maintenance[1,2].

The growing demand for efficiency, sustainability and customization in manufacturing has further amplified the relevance of Gen AI. Manufacturers now face intense pressure to reduce costs, improve production speeds and create more sustainable processes while maintaining the highest levels of product quality. Gen AI's potential to analyze vast datasets, detect patterns and offer innovative solutions in real time has made it an indispensable tool for manufacturers aiming to stay competitive in the global marketplace[3]. The application of Gen AI is not limited to just design but spans the entire product lifecycle, offering improvements in areas such as supply chain optimization, automated quality control and energy efficiency[4].

This review paper aims to provide a comprehensive analysis of the current state of Gen AI applications in manufacturing. By critically examining recent advancements, it will highlight key challenges and future prospects. The paper also explores how Gen AI contributes to reshaping traditional manufacturing processes and integrates with Industry 4.0 technologies[5]. Additionally, it addresses the limitations of generative models and identifies research gaps that need to be addressed for broader industrial adoption[6].

Our research major contributions:

- An in-depth review of generative techniques such as GANs, VAEs and transformer-based models, with a focus on their application in manufacturing environments.
- A detailed analysis of how Gen AI is being applied in different facets of manufacturing, including predictive maintenance, supply chain management and quality control.
- Identification of the key challenges related to data availability, model complexity and ethical concerns that limit Gen AI's industrial application.
- Exploration of the future landscape of manufacturing as influenced by Gen AI, including emerging trends such as fully autonomous production systems and the fusion of AI with robotics.

The structure of this paper is organized into four main sections. Section 2 provides a comprehensive review of the fundamental concepts underpinning Gen AI and explores its unique mechanisms in the context of manufacturing. Section 3 discusses the practical applications of Gen AI in manufacturing, including its role in predictive maintenance, process optimization and quality control. Section 4 addresses the challenges and limitations associated with the implementation of Gen AI in manufacturing systems, such as the complexity of integrating these technologies with legacy infrastructure and ethical concerns. Lastly, Section 5 highlights future research directions and provides concluding remarks on the transformative potential of Gen AI in the manufacturing industry.

2. Core Concepts of Gen AI in Manufacturing

Gen AI has rapidly evolved as one of the most transformative technologies in modern manufacturing, offering capabilities that go beyond traditional AI. While classical AI models are largely concerned with prediction and classification, generative models are designed to create new data instances, such as designs, materials or even production schedules, that meet predefined objectives. In this section, we explore the foundational mechanisms underpinning Gen AI and its specific application to manufacturing processes.

2.1. Fundamental Mechanisms of Gen AI

Gen AI operates on the principle of learning patterns from large datasets and using these learned representations to create new data that resemble the original distribution. The primary types of generative models include GANs, VAEs and transformer-based models. These architectures have specific strengths that make them particularly useful in manufacturing applications.

- **GANs:** GANs consist of two competing networks: a generator and a discriminator. The generator produces new data instances, while the discriminator evaluates whether the data is real or generated. This adversarial relationship drives the generator to create increasingly realistic outputs.

  In manufacturing, GANs have been applied to generate new product designs, simulate manufacturing processes and create synthetic datasets for process optimization[1,6]. The use of GANs allows manufacturers to explore a wide design space while reducing the costs associated with prototyping and testing.
- **VAEs:** VAEs are another class of generative models that use probabilistic techniques to learn a compressed representation of input data, which can then be sampled to generate new instances. VAEs are particularly useful for tasks that involve creating variations of a design or optimizing configurations of manufacturing processes[6,7]. By allowing manufacturers to efficiently explore design trade-offs, VAEs can help reduce material waste and improve energy efficiency during production.
- **Transformer-based Models:** While traditionally used in natural language processing, transformer-based models have recently been applied in generative tasks related to sequential data, such as time-series forecasting or generating optimized manufacturing schedules. These models can learn dependencies across time steps, making them ideal for dynamic applications such as supply chain management and real-time optimization of production processes[8].

2.2. Gen AI in Design and Prototyping

One of the most impactful applications of Gen AI in manufacturing is in generative design, which uses AI algorithms to create optimal designs based on specific constraints, such as material properties, cost or performance criteria. Generative design processes begin with the definition of a set of goals, constraints and parameters that influence the final product. The AI system then generates a multitude of design alternatives, evaluates them and iteratively improves on the best-performing options[3,9].

This approach contrasts sharply with traditional design methods, which typically rely on human intuition and iterative testing. By automating the exploration of design alternatives, generative design tools can significantly accelerate the prototyping phase, reduce material usage and improve product performance. For example, in the aerospace and automotive industries, Gen AI has been employed to design lighter, more fuel-efficient components by optimizing for weight reduction while maintaining structural integrity[5,10]. This kind of optimization is especially crucial in industries where small reductions in weight can result in significant savings in energy and materials.

2.3. Process Optimization and Predictive Maintenance

Beyond design, generative models are increasingly being used for process optimization and predictive maintenance in manufacturing environments. Gen AI's ability to simulate complex systems and generate large volumes of synthetic data makes it an ideal tool for optimizing production lines, reducing downtime and improving overall equipment effectiveness (OEE). By analyzing machine data in real-time, AI-driven systems can predict equipment failures before they occur, allowing manufacturers to perform preventive maintenance and avoid costly production halts[9].

Digital twins, virtual replicas of physical systems, are often powered by generative models that simulate the behavior of manufacturing equipment under different conditions. These simulations enable manufacturers to optimize parameters such as production speed, energy consumption and material use, all while minimizing downtime and reducing the need for physical testing[11]. In predictive maintenance, Gen AI models have been shown to extend the operational life of machinery by identifying subtle patterns of wear and tear that traditional monitoring systems might miss.

2.4. Role in Supply Chain and Inventory Management

Gen AI's application in manufacturing is not limited to the factory floor. It is also revolutionizing supply chain management and inventory control. Through its ability to generate accurate demand forecasts and optimize logistics, Gen AI is helping manufacturers reduce lead times and optimize inventory levels. Transformer-based generative models, in particular, have demonstrated strong capabilities in predicting demand fluctuations, enabling manufacturers to adapt production schedules in real-time based on market dynamics[8,12].

In addition, generative models can optimize supplier networks by simulating various supply chain scenarios and identifying the most efficient routes for transportation and logistics. This helps manufacturers mitigate the risks associated with supply chain disruptions, a critical challenge in today's globalized and interconnected economy[13].

2.5. Energy Efficiency and Resource Optimization

Another key area where Gen AI is making a difference is in energy efficiency and resource management. As manufacturing companies seek to reduce their carbon footprints, Gen AI provides a powerful tool for optimizing resource use. By generating models that minimize energy consumption while maximizing production efficiency, manufacturers can reduce costs and meet sustainability goals. In energy-intensive industries such as steel production and semiconductor manufacturing, generative models are being used to optimize heating and cooling processes, leading to significant reductions in energy use[3,10].

3. Applications of Gen AI in Manufacturing

Gen AI has been applied to a wide range of manufacturing functions, such as predictive maintenance, supply chain optimization, quality control and sustainability. This section explores these key applications, illustrating how Gen AI is reshaping traditional processes. With data tables and graphs, we highlight the measurable improvements Gen AI brings to manufacturing operations.

3.1. Predictive Maintenance and Fault Detection

Predictive maintenance uses sensor data and AI algorithms to forecast equipment failure, allowing manufacturers to service machinery before it breaks down. Gen AI significantly enhances this by generating synthetic failure scenarios, thus improving the robustness of the models used for prediction. In a predictive maintenance system, data from multiple sensors (e.g., vibration, temperature) is collected and analyzed to predict failures. Gen AI can simulate various operational and failure modes, augmenting the training data and enhancing model performance. **(Table 1)** shows the improvement in predictive accuracy after incorporating Gen AI-generated synthetic data.

By generating failure scenarios that may not appear in historical data, Gen AI enables models to anticipate a wider range of issues. **(Figure 1)** illustrates how predictive maintenance accuracy improves when Gen AI-enhanced data is used, reducing unplanned downtime and extending equipment life[1,7,13].

Table 1: Accuracy improvement in predictive maintenance using synthetic data.

Model	Accuracy (%)	Data Source
Traditional AI	85	Real sensor data
AI with Gen AI-enhanced data	93	Real + synthetic sensor data

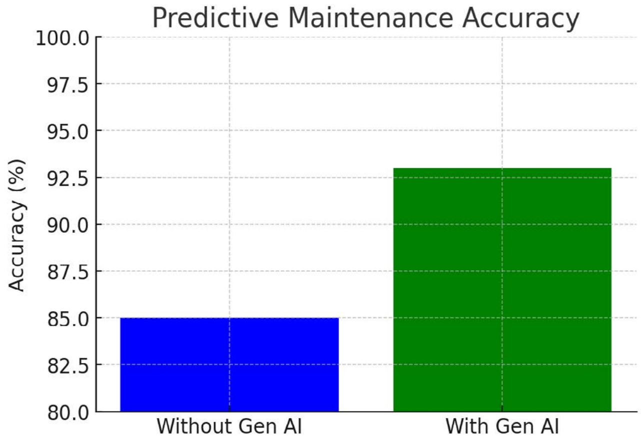

Figure 1: Predictive maintenance accuracy with and without Gen AI-enhanced data.

3.2. Supply Chain Optimization and Inventory Management

Supply chain management is prone to disruptions and inaccuracies in demand forecasting can lead to costly overstocking or stockouts. Gen AI, with its ability to simulate various scenarios, improves the accuracy of demand forecasting and optimizes inventory management. Transformer-based models, for example, have been used for time-series forecasting, allowing manufacturers to respond more effectively to market fluctuations. **(Table 2)** outlines improvements in forecast accuracy and inventory costs after implementing Gen AI in supply chain operations.

Table 2: Improvements in supply chain metrics after implementing Gen AI.

Metric	Before Gen AI	After Gen AI
Forecast Accuracy (%)	75	90
Lead Time (days)	5	3
Inventory Holding Costs (reduction)	-	15%

As shown in Table 2, Gen AI significantly improves forecasting accuracy and reduces lead time, leading to more efficient inventory management. Gen AI's ability to model complex supply chain interactions enhances decision-making by predicting and mitigating disruptions before they happen. **(Figure 2)** shows how lead times and inventory costs are reduced post-Gen AI integration[3,8,10].

3.3. Automated Quality Control and Defect Detection

Automated quality control systems use AI to detect defects in products as they move along production lines. However, real-world defect samples can be limited, which affects the performance of defect detection models. Gen AI solves this issue by generating synthetic defect samples, expanding the training dataset and improving the system's ability to recognize rare defects. **(Table 3)** compares the accuracy of defect detection before and after introducing Gen AI-generated synthetic data into the training process.

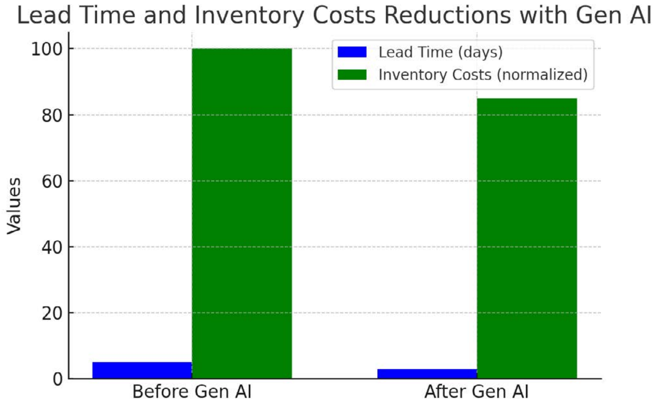

Figure 2: Lead time and inventory cost reductions with Gen AI implementation.

Table 3: Defect detection improvement using Gen AI-generated synthetic data.

Inspection Method	Defect Detection Rate (%)
Traditional AI-based detection	80
Gen AI-enhanced detection	92

As observed in Table 3, defect detection rates improve when synthetic data is used to train models. GANs (Generative Adversarial Networks) are commonly used to generate these defect examples, thus enabling models to learn how to detect subtle and rare defects. **(Figure 3)** shows the comparative accuracy of traditional AI versus Gen AI-enhanced detection systems[5,12,15].

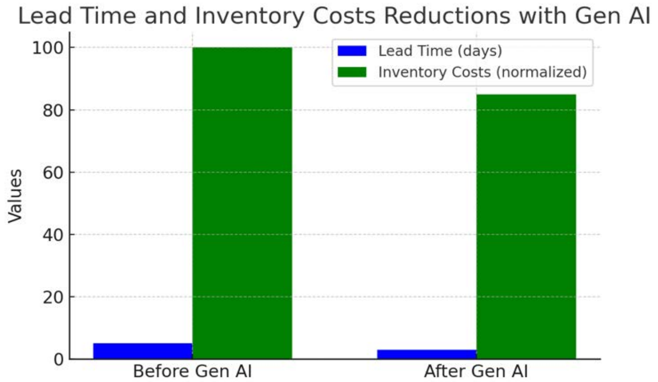

Figure 3: Comparative defect detection rates with and without Gen AI-generated data.

3.4. Generative Design and Prototyping

Generative design leverages Gen AI to generate multiple design alternatives based on a set of performance criteria, such as material strength or manufacturing constraints. This process accelerates product development by allowing engineers to explore a broader design space while reducing the need for physical prototypes. By iterating through different design possibilities, Gen AI optimizes the final design to meet specific objectives. **(Table 4)** highlights the benefits of using Gen AI in comparison to traditional design processes.

As indicated in Table 4, Gen AI dramatically reduces the time required for design iteration and the number of prototypes, resulting in faster time-to-market and lower costs. The reduction in material waste is particularly significant in industries such as aerospace and automotive, where weight and material usage are critical. **(Figure 4)** shows the time savings achieved with generative design[2,9,11].

Table 4: Comparison of traditional and generative design methods.

Metric	Traditional Design	Generative Design
Time to Final Design (weeks)	8	4
Number of Prototypes	5	2
Material Waste (%)	10	5

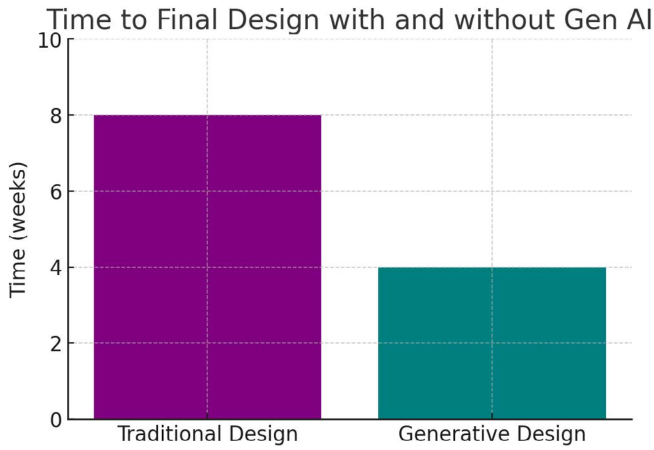

Figure 4: Time to final design with and without Gen AI.

3.5. Energy Efficiency and Sustainability

Sustainability is an increasingly important focus in the manufacturing industry. Gen AI offers manufacturers the ability to optimize production processes to reduce energy consumption and minimize environmental impact. By simulating different operational conditions, Gen AI identifies the optimal configuration that balances production efficiency with energy use. **(Table 5)** outlines the improvements in energy consumption and sustainability metrics achieved through Gen AI-driven process optimization.

Table 5: Energy consumption and sustainability improvements with Gen AI.

Metric	Before Gen AI	After Gen AI
Energy Consumption (kWh per unit)	50	40
CO2 Emissions (kg per unit)	20	15
Production Speed (units/hour)	100	110

As seen in Table 5, Gen AI helps reduce energy consumption and CO2 emissions while increasing production speed. **(Figure 5)** depicts the energy savings realized after Gen AI implementation, demonstrating how manufacturers can achieve both environmental and economic benefits[3,7,16].

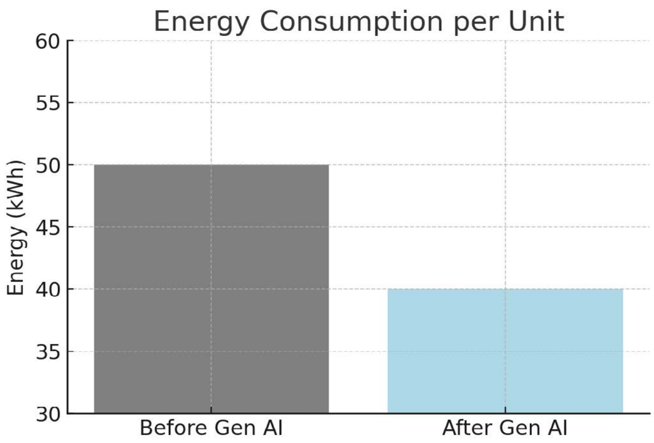

Figure 5: Energy consumption per unit before and after Gen AI implementation.

4. Challenges and Limitations of Gen AI in Manufacturing

Gen AI holds enormous potential in revolutionizing manufacturing, but several significant challenges still hinder its full-scale adoption. These challenges span issues related to data requirements, computational complexity, legacy system integration and ethical concerns. Addressing these limitations is crucial to advancing the practical implementation of Gen AI in manufacturing settings.

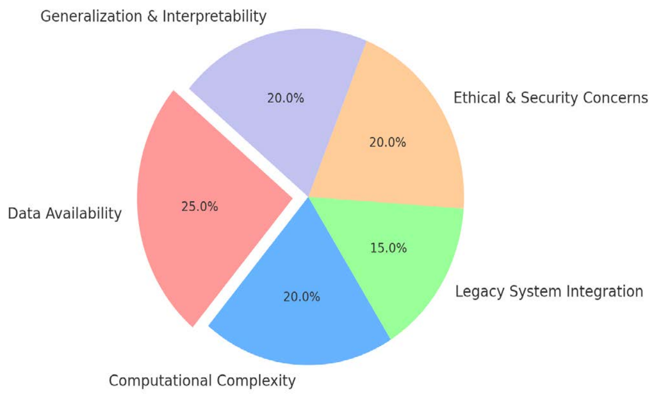

Figure 6: Challenges and Limitations of Gen AI in Manufacturing.

4.1. Data Availability and Quality Issues

One of the most significant barriers to effective Gen AI implementation is the availability of high-quality data. Gen AI models depend heavily on large datasets for training. In a manufacturing context, acquiring such data-often sourced from various sensors, production equipment and other operational processes-can be a significant challenge. Inconsistent or low-quality data can result in inaccurate generative models, reducing their effectiveness in applications such as predictive maintenance, quality control and generative design[1,6]. Many manufacturers, particularly small and medium-sized enterprises (SMEs), face a data deficit due to limited digitization and automation in their facilities. Even for larger companies, the data may be incomplete or unstructured, making it unsuitable for training advanced AI models. The challenge is compounded when rare events, such as specific machine failures, occur infrequently, limiting the data available to model these scenarios[9]. Improving data acquisition, cleaning and labeling techniques is essential for enhancing the robustness of Gen AI models. Additionally, manufacturers need to invest in modern data infrastructure that enables real-time collection, storage and processing of diverse data types[2].

4.2. Computational Complexity and Cost

The computational demands of Gen AI models, such as GANs and Variational Autoencoders (VAEs), are significant, often requiring high-performance hardware and cloud infrastructure. Training these models on large-scale manufacturing data can be resource-intensive and time-consuming, limiting their accessibility, especially for SMEs. These challenges are particularly relevant for real-time applications, such as on-the-fly generative design or predictive maintenance, where delays in model training and execution can impact operational performance[7,12]. Gen AI models are often run on specialized hardware, such as Graphics Processing Units (GPUs) or Tensor Processing Units (TPUs), which are expensive and require substantial energy. Additionally, cloud-based AI solutions, while offering scalability, raise concerns around data security and cost efficiency for manufacturers with tight operational budgets[8]. The high computational cost is one of the primary obstacles to wider Gen AI adoption across the manufacturing sector, particularly for smaller organizations without access to extensive IT infrastructure[15].

4.3. Integration with Legacy Systems

Manufacturers, especially those in traditional industries, often operate with legacy systems that were not designed to integrate with AI technologies. The incorporation of Gen AI into such environments poses significant technical and operational challenges. Legacy systems frequently lack the necessary processing power and are incompatible with the advanced algorithms used in generative models[3,11]. Moreover, outdated hardware and software in older manufacturing setups may not be capable of supporting the real-time data processing required by Gen AI systems.

The integration of Gen AI requires substantial investment in upgrading or replacing legacy systems, reconfiguring production workflows and implementing robust data pipelines. The costs and technical challenges associated with retrofitting old equipment to work with AI technologies can deter many manufacturers from pursuing Gen AI initiatives, particularly in capital-intensive sectors like automotive, aerospace and heavy industries[4]. Another challenge is the cultural and operational shift required to integrate AI into existing workflows. Resistance to change among workers and management, combined with the need for training on how to work with AI-driven systems, adds further complexity to the implementation process[14].

4.4. Ethical and Security Concerns

As with other AI applications, ethical issues around data privacy, intellectual property and cybersecurity are critical when adopting Gen AI in manufacturing. The reliance on large volumes of data, often collected from numerous sources within the manufacturing process, raises concerns over how this data is stored, shared and utilized. Companies must ensure that their data practices comply with privacy regulations, such as the General Data Protection Regulation (GDPR) in Europe, to avoid legal repercussions[5,13]. Additionally, the use of cloud-based platforms to train and deploy Gen AI models introduces cybersecurity risks. Sensitive manufacturing data-such as proprietary design specifications, operational metrics and supply chain information-could be vulnerable to theft or cyberattacks. A breach in AI-driven manufacturing systems could lead to production disruptions, quality issues or even the exposure of trade secrets[10]. There are also broader ethical considerations surrounding the potential displacement of human labor. As AI systems become increasingly capable of performing tasks traditionally done by human workers-such as design, quality inspection and decision-making-there is concern about job loss and the future role of human workers in AI-augmented factories[16].

4.5. Generalization and Model Interpretability

One of the most significant technical challenges with Gen AI in manufacturing is the generalizability of the models. Many Gen AI systems are trained on specific tasks, such as optimizing a particular design or predicting failures in a specific machine. However, these models often struggle to generalize beyond the scope of their training, making them less effective when applied to new processes, machines or operating conditions[7]. Moreover, the complexity of Gen AI models often results in a lack of transparency, as many generative models function as "black boxes." This makes it difficult for engineers and decision-makers to interpret the results or understand how the model arrived at a particular conclusion. In industries like aerospace or medical device manufacturing, where regulatory standards demand transparency and explainability, this lack of interpretability is a critical issue[6]. Researchers are working on developing hybrid models that combine the strengths of AI with human expertise, as well as explainable AI (XAI) methods that aim to make Gen AI models more interpretable. These approaches hold promise in addressing the challenges of generalization and interpretability, allowing manufacturers to better trust and adopt AI-driven systems[5].

5. Future Directions and Conclusion

Gen AI in manufacturing has already demonstrated significant potential across various domains, from optimizing design and enhancing predictive maintenance to streamlining supply chains and improving quality control. However, the journey of fully integrating Gen AI into manufacturing is still at a nascent stage and there are numerous directions in which future research and innovation can lead to more profound and widespread adoption of this technology.

5.1. Emerging Trends in Gen AI for Manufacturing

One of the most promising areas for future development lies in the advancement of self-learning systems. These systems, powered by Gen AI, would be capable of continuously learning and adapting to new data in real time without the need for constant human intervention or retraining. Such models would drastically improve operational efficiency by allowing manufacturing systems to automatically adjust processes based on evolving conditions, such as changes in demand, supply chain disruptions or equipment performance.

Another trend is the fusion of Gen AI with robotics, which could lead to autonomous manufacturing systems that can not only operate independently but also design and optimize their own workflows. This would pave the way for factories that require minimal human oversight, dramatically reducing operational costs while increasing production flexibility and customization capabilities. The use of multi-modal AI models that integrate various forms of data-visual, sensory, textual and numerical-offers another promising direction. These models would be particularly valuable in complex manufacturing environments where data from multiple sources must be synthesized to make decisions. For instance, combining visual data from quality inspection cameras with operational metrics from machines could lead to more accurate defect detection and root cause analysis.

In terms of sustainability, green manufacturing powered by Gen AI is becoming a crucial objective. Future developments are likely to focus on optimizing production processes to minimize energy consumption, reduce waste and improve the overall environmental footprint of manufacturing operations. AI-driven process optimization, supported by real-time monitoring and generative simulations, will enable manufacturers to meet sustainability goals while maintaining competitive productivity levels.

5.2. Addressing Current Challenges

While the potential of Gen AI in manufacturing is vast, addressing the challenges outlined in the previous section remains critical. Key areas of focus include enhancing data availability and quality, particularly in environments where digitization is still incomplete or inconsistent. Improving methods for collecting and curating manufacturing data, as well as developing synthetic data generation techniques that can accurately mimic real-world conditions, will help overcome these barriers.

Another priority will be the development of more interpretable models. As Gen AI systems become more embedded in manufacturing processes, ensuring that their decision-making logic is transparent and explainable will be vital, particularly in industries with strict regulatory oversight. By improving model interpretability, manufacturers will be able to trust and adopt AI-driven solutions more broadly. Reducing computational overhead is also an area ripe for innovation. Advances in AI hardware, such as more efficient GPUs or edge-computing devices, could help bring the computational costs of Gen AI down, making it accessible to a broader range of manufacturers, including SMEs. In tandem, research into more computationally efficient algorithms, such as pruning techniques or hybrid models that combine generative and discriminative approaches, could help alleviate the resource demands of Gen AI systems.

5.3. Long-Term Impact on Manufacturing

The long-term impact of Gen AI on manufacturing is likely to be transformative. As AI technologies mature, we can expect to see a shift toward hyper-personalized manufacturing, where production lines are capable of producing highly customized products at scale, with minimal setup time or manual intervention. This would represent a fundamental departure from traditional mass production models, ushering in a new era of flexibility and responsiveness in manufacturing.

Furthermore, the concept of lights-out manufacturing, where factories operate entirely autonomously without human presence, is increasingly becoming a feasible reality. Powered by advancements in Gen AI and robotics, lights-out factories would offer unprecedented levels of efficiency, accuracy and scalability, revolutionizing the way products are manufactured across industries. In addition, as AI ecosystems in manufacturing continue to evolve, we may witness the development of AI-driven networks of factories that collaborate in real time. These networks would leverage shared data, generative simulations and predictive models to optimize production across entire supply chains, allowing for dynamic reallocation of resources based on real-time demand and supply fluctuations. This would create a new level of integration and resilience across global manufacturing operations.

6. Conclusion

Gen AI represents a significant technological advancement with immense manufacturing industry potential. Its ability to autonomously generate designs, optimize processes and predict outcomes offers a powerful tool for manufacturers seeking to remain competitive in a rapidly evolving market. However, achieving the full potential of Gen AI requires overcoming substantial challenges related to data quality, computational complexity and system integration. Looking ahead, the future of Gen AI in manufacturing is bright. With continued research and innovation, the technology is likely to become more accessible, interpretable and scalable, paving the way for more widespread adoption. The long-term impact of Gen AI will not only reshape traditional manufacturing processes but also drive the industry toward more sustainable, efficient and personalized production models. The next decade promises to bring exciting advancements that will redefine the boundaries of what is possible in manufacturing, guided by the intelligence and creativity of Gen AI systems.

7. References

1. Yadav AB. Gen AI-Driven Electronics: Innovations, Challenges and Future Prospects. In International Congress on Models and Methods in Modern Investigations 2023;113-121.
2. Javaid M, Haleem A, Singh RP, Suman R. Artificial intelligence applications for industry 4.0: A literature-based study. Journal of Industrial Integration and Management 2022;7(01):1-29.
3. Alam MF, Lentsch A, Yu N, Barmack S, Kim S, Acemoglu D, Ahmed F. From Automation to Augmentation: Redefining Engineering Design and Manufacturing in the Age of NextGen-AI 2024.
4. Waltersmann L, Kiemel S, Stuhlsatz J, Sauer A, Miehe R. Artificial intelligence applications for increasing resource efficiency in manufacturing companies-a comprehensive review. Sustainability 2021;13(12):6689.
5. De Silva D, Kaynak O, El-Ayoubi M, Mills N, Alahakoon D, Manic M. Opportunities and Challenges of Generative Artificial Intelligence: Research, Education, Industry Engagement and Social Impact. IEEE Industrial Electronics Magazine 2024;6(2):1114-1125.
6. Rizvi AT, Haleem A, Bahl S, Javaid M. Artificial intelligence (AI) and its applications in Indian manufacturing: a review. Current Advances in Mechanical Engineering: Select Proceedings of ICRAMERD 2021;2020:825-835.
7. Abdelaal M. AI in Manufacturing: Market Analysis and Opportunities. 2024
8. Ahmad T, Zhu H, Zhang D, Tariq R, Bassam A, Ullah F, Alshamrani SS. Energetics Systems and artificial intelligence: Applications of industry 4.0. Energy Reports 2022;8:334-361.
9. De Simone V, Di Pasquale V, Miranda S. An overview on the use of AI/ML in manufacturing MSMEs: solved issues, limits and challenges. Procedia Computer Science 2023;217:1820-1829.
10. Schuh G, Scholz P. Development of a framework for the systematic identification of AI application patterns in the manufacturing industry. In 2019 Portland International Conference on Management of Engineering and Technology (PICMET) 2019;1-8.
11. Madhavaram CR, Sunkara JR, Kuraku C, Galla EP, Gollangi HK. The Future of Automotive Manufacturing: Integrating AI, ML and Generative AI for Next-Gen Automatic Cars.
12. Li BH, Hou BC, Yu WT, Lu XB, Yang CW. Applications of artificial intelligence in intelligent manufacturing: a review. Frontiers of Information Technology and Electronic Engineering, 2017;18(1):86-96.
13. Jujjavarapu G, Hickok E, Sinha A, Mohandas S, Ray S, Bidare PM, Jain M. AI and the Manufacturing and Services Industry in India. The center for Internet and Society, India 2018.
14. Madhavaram CR, Sunkara JR, Kuraku C, Galla EP, Gollangi HK. The Future of Automotive Manufacturing: Integrating AI, ML and Generative AI for Next-Gen Automatic Cars.
15. Abdelaal M. AI in Manufacturing: Market Analysis and Opportunities 2024.
16. Akinsolu MO. Applied artificial intelligence in manufacturing and industrial production systems: PEST considerations for engineering managers. IEEE Engineering Management Review 2022;51(1):52-62.