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Review

A Review of Generative Design Using Machine Learning for Additive Manufacturing

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Abstract

This review explores how generative design is combined with machine learning (ML) to achieve additive manufacturing (AM) and its societal transformative effect. Generative design uses complex algorithms to automate the process of designing best-fit designs, mass customization, and customization to suit specific customer requirements with high efficiency and quality. The scalability and predictability of artificial intelligence (AI) models make handling huge data easy and enable scale-up of production without compromising quality. This paper also focuses on how generative design can help accelerate innovation and product creation because it empowers designers to play in a wider space of design and provide solutions that cannot be reached with traditional techniques. AI integration with existing production processes is also vital to real-time manufacturing optimization—further increasing overall operational effectiveness. Additionally, the emergence of sophisticated predictive models like gradient boosting regression shows how ML can enable better accuracy and robustness of 3D printing operations to achieve quality standards of the outputs. This paper ends with what generative design and ML hold for the future of AM and how designing continues to be improved and modified to match changing industry requirements.

Keywords: Generative Design, Machine Learning, Additive Manufacturing, Lightweight Design, Optimization

1. Introduction

Manufacturing has experienced major shifts due to the introduction of AM technologies. AM fabricates components layer by layer and, unlike subtractive manufacturing, creates complex geometries impossible using traditional techniques. These have stimulated the increasingly fashionable concept of combining ML to streamline the design process, resulting in the increasingly mainstream concept of generative design. Generative design makes use of algorithms utilizing ML to generate vast design possibilities that guarantee both high performance and optimization of materials and cost (Kumar et al., 2022).

Generative design is defined as an ability to model evolutionary mechanisms, enabling systems to evolve designs in response to performance demands and limitations. It uses AI and in particular ML to optimize the design stage, allowing engineers and designers to discover as many possible solutions as possible in a fraction of the time required by the conventional approach (Ng et al., 2024). The combination of generative design and ML further enhances the innovation of design, and it enables AM parts to be customized in order to further extend the capabilities of modern manufacturing (Lee et al., 2023).

Many recent studies have highlighted techniques and models that combine generative design and ML to develop AM materials and optimize AM processes (Jin et al., 2020; Wang et al., 2022). Both of these techniques rely on the increased predictive power of ML algorithms that are able to detect patterns in large datasets produced during AM, helping to guide design decisions that result in enhanced functional and structural properties of the parts (Wang et al., 2020). The application of ML methods to generative design will potentially change the way goods are designed, tested, and manufactured in the manufacturing industry.

Furthermore, the ML use in generative design goes beyond aesthetic or geometric developments to cover important operational parameters and constraints essential to AM, including material properties, process behavior, and environment (Ciccone et al., 2023). This deep dive of generative design methods employing ML for AM will shed light on the cutting-edge techniques, challenges, and future of this novel synthesis for the market (Johnson et al., 2020; Regenwetter et al., 2022).

In conclusion, the combination of generative design and ML marks a revolution in AM with an ability to innovate design creativity, efficacy, and effectiveness while also addressing AM's unique challenges. In our further parts of this retrospective, we'll be exploring the roles, trends, and disruptive potential of these developments in the context of today's manufacturing environments.

2. Methodologies to Implement ML in Generative Design for AM (DfAM)

When applying ML to generative DfAM, there are a number of techniques used for designing and manufacturing better. All of these approaches are beneficial and have their own uses to be efficient, cost-effective, and innovative.

- Data Collection and Preprocessing: To make ML work in generative design, rigorous data collection and processing are the essential first steps. This is based on the collection of pertinent datasets that cover all sorts of parameters, such as material characteristics, geometry constraints, and performance parameters. It is such large datasets that help ML models to learn from various examples and predict more accurately. Preprocessing also denoises and normalizes the data, which removes noise and anomalies and improves the performance of the model (Chinchanikar & Shaikh, 2022).
- Feature Engineering: Feature engineering is used to transform inputs into ML models. With a bit of research and choosing the right features (such as dimensional parameters and material properties), the designers can significantly impact how the model performs. Well-done feature engineering makes the model generalizable so that it can correctly predict new designs based on the patterns learned from the training data (Wang et al., 2020).
- Model selection: The right ML model is also critical for the generative design. Algorithms like support vehicle machines (SVM), neural networks, decision trees, and others have strengths and weaknesses depending on the design problem difficulty. Model readability, computer speed, and the possibility of processing high-dimensional data are also aspects of selection. This phase makes sure that the model is correct for the application of the AM process (Jin et al., 2020).
- Training and validation: Then train the ML model that one chooses from collected and preprocessed data to train the model to learn the relationships between design parameters and results. At the time of training, the model must be checked against another dataset in order not to overfit the training data (and result in low performance on unseen data). Each validation session can refine the model parameters and make it work best, which ultimately makes it better to use for generative design (Johnson et al., 2020).
- Optimization algorithms: Optimization algorithms are essential to generative design by iteratively fine-tuning design solutions for specified goals. After the design space is determined, these algorithms check a number of parameters in parallel to find the best configurations that are at par with the required performance. Some of the commonly used optimization algorithms are genetic algorithms and gradient descent to direct the ML models to the best design solutions for increasing the efficiency of AM (Soori et al., 2024).
- Integration with Simulation Tools: Combining ML models with simulation tools enables designers to compare how the generated designs perform in various conditions before going to production. This combination enables the design to be tested and validated in virtual space without large-scale real-world prototypes. These simulations can be helpful in getting insights and running iterations and updates at speed that helps make generative design easier (Regenwetter et al., 2022).
- Continuous learning and adaptation: Implementing a continuous learning system is essential to keep the ML model up to date. It is a method where we regularly update the model with new information and results from AM. With more information—either from experiments or feedback from users—the model can scale changes in design, material properties, or produc-

tion process. This flexibility makes the model more efficient over time and adapts to industry changes (Williams, 2022).

- Postprocessing and analysis: The designs produced, and performance measures have to be processed after-the-fact to assess the effectiveness of imposed methodologies. This step will be looking at the outputs produced by the ML model to see which designs perform best under which conditions. Weight, strength and manufacturability are calculated to determine which design to proceed with. By analyzing outcomes closely, designers will have a better idea of how to improve their method and how to implement ML in generative design in the future (Vaneker et al., 2020).
- User Interface and Visualization: User interface and visualization tools are important for communicating between designers and generative designers. These interfaces let the user feel free to easily tweak design settings, view results, and learn more about the effects of variables. Powerful visualization is what makes complex data digestible and so can make the design decisions easier (Guo et al., 2022).
- Deployment and Feedback Mechanisms: The last phase is to use the ML solutions in real-world AM environments and build feedback loops for data gathering. This is the step where companies can measure the impact of the implemented methods and learn from production results. Feedback loops are the way to iteratively improve in order to keep advancing the ML models and the generative design processes they're backed by (Babu et al., 2022).

3. Benefits and Applications of ML in Generative DfAM

3.1. Benefits

The first advantage of applying ML to generative designs is better design optimization. It is also fast enough for ML algorithms to mine the large amount of data and detect the optimal design parameters that human minds cannot. With the help of historical performance data, ML can suggest weight and structure reduction designs that enhance the efficiency and performance of manufactured assemblies (Jin et al., 2020).

An additional benefit is the time savings on design. While ML algorithms can do most of the work, designers must spend time on it. They can, for example, quickly iterate on design variations and anticipate results, reducing product development time by hundreds of percentage points (Wang et al., 2020). This allows engineers and designers to work on things that matter instead of wasting so much time on tedious calculations and tinkering.

Save money—this is a key benefit of including ML into AM generative design. In designing to make the most of AM, ML helps avoid material waste and costs. Smart design algorithms, for instance, can propose building solutions that require less material while still performing—saving huge amounts in the manufacturing process (Westphal & Seitz, 2024). This efficiency can be used to lower the cost of AM for niche use cases that call for customized parts.

In addition, improved material performance is another big advantage of using ML in design. ML can anticipate how different materials will behave under different conditions, so we can make components lighter but more robust as well. With the right material selection and consumption optimized through predictive modeling, manufacturers can improve the overall quality and life of their products (Regenwetter et al., 2022).

Last but not least, ML allows for the integration of multidisciplinary expertise in design. Incorporating input from other areas of knowledge, including mechanical engineering and materials science, can help ML create novel design alternatives that demonstrate a more general understanding of the AM's needs and limitations. It is through this ambivalent methodology that we can see design innovation break the limitations of what is already possible with conventional means (Bendoly et al., 2023).

3.2. Applications

Topology optimization (TO) is one of the main use cases of ML in generative design. ML algorithms are used to calculate the optimal physical configuration of buildings according to performance constraints. The algorithms study the design and materials in use to identify the best practices for producing structures that are both usable and efficient, which are necessary for light and strong parts in aerospace and automotive designs (Jin et al., 2020).

ML is also used for designing space exploration, where ML is used to automate the journey through different designs. Algorithms evaluate multiple parameters at once, and the most promising design solutions are found much more quickly than with any other means. It can bring out the design more imaginatively and more innovatively, making AM technologies more efficient (Chaudhari & Selva, 2023).

Predictive maintenance, another important ML use in generative design, is another one. Analyzing AM process data, ML algorithms will detect part failures or defects in advance of them occurring so that corrective action can be taken prior to them happening. This makes components created through generative design durable and secure, and it can drastically mitigate unexpected outages (Nyamekye et al., 2024).

In customizing and personalizing products, ML is also very helpful. ML in the healthcare sector can be used to design customized surgical implants or prostheses using patients' information. Automated design algorithms adjust the parameters based on one's needs to get the final result that is not just custom but also performance optimized (Westphal & Seitz, 2024).

Finally, ML helps in better simulation of some generative design cases. ML makes realistic simulations of the operation of parts at different temperatures that can help engineers verify designs before they're actually built. This is not only more time efficient for designing but also for checking that the end product is quality and functional—thus reducing the risk involved in launching new designs into the market (Regenwetter et al., 2022).

4. Past Projects in Manufacturing Companies Implementing ML for Generative Design in AM

The manufacturing environment has changed the build products with advanced technologies, especially ML and AM. Of all these developments, generative design is the one that has brought the capabilities of product design and manufacturing into the modern day. In this article, we want to share some of the earlier projects done by big-name manufacturing organizations that have implemented ML in AM for generative design. These efforts are proving both the promise of combining generative design and ML, and the impact these technologies can have across multiple industries. From aircraft to medical devices, Autodesk, General Motors (GM), Lockheed Martin, and NASA have all shown promising successes focused on designing parts more efficiently, automating production processes, and improving overall manufacturing efficiency. By explicating these projects, we can recognize how profoundly ML and generative design are still changing the way we build products.

4.1. Generative Design for 3D Printing at Autodesk (2018)

Autodesk introduced generative design for 3D printing, using an algorithm that reduces design repeats. Using this technology, engineers and designers can design any potential variety of solutions that fulfill some performance requirements, and it will help in reducing cost and being creative while designing products. Generic design tools allow one to generate thousands of designs at a moment's notice, creating lighter, stronger and more material-efficient parts than traditional ones. This ability comes in handy especially for applications like aerospace and automotive where optimal components are required. Autodesk's efforts in building complex scale 3D-printed building components with partners such as Acciona are just the beginning of applications of this technology (Toro, 2024). Introducing AI in the design flow is Autodesk's way to transform the creation process for products by going beyond traditional processes to build a more creative design world.

4.2. GM - Project Dreamcatcher (2018)

GM collaborated with Autodesk to use generative design to develop automotive parts, including low-slung seat brackets. In this collaboration, AI algorithms examined multiple design variants that maximize strength and lightness. Its generative design tools enable engineers to enter constraints and requirements that result in creative designs otherwise impossible by conventional methods (Beesley, 2020; Kvernvik, 2018).

4.3. Lockheed Martin – Spacecraft Components (2018)

Lockheed Martin also employed generative design in the design of components for spacecraft; AM is coupled with generative design for part optimization. The firm employed this technology, for instance, to build sophisticated brackets and other structures that are needed to run the satellite. Through the use of computer algorithms, to look at design options, Lockheed Martin developed high-fidelity aerospace-grade components that are also lightweight and affordable (Werner, 2018). This flexibility is important as the aviation industry becomes more advanced and efficient in designs that would otherwise be difficult to fabricate by conventional manufacturing.

4.4. NuVasive - Titanium Implants (2018)

NuVasive transformed spinal implant technology by ML-based generative design within AM. The Modulus titanium implants, created using proprietary optimization software, are organic and porous, mimicking natural bone in order to support osseointegration and minimize stress shielding (Mattias, 2024; Mazer, 2017). Hence, this process of generative design leads to the development of light and unsymmetric structures not possible with conventional approaches, leading to improved surgical performance and healing outcomes (Mattias, 2024). NuVasive highlights the ability of generative design to compare many designs rapidly, maximizing performance requirements while maintaining structural integrity (Christian, 2018). This same dedication to innovation can be found in these implants, which are a great advancement in introducing cutting-edge technology to medical devices (Mattias, 2024; Mazer, 2017). And thus, NuVasive is revolutionizing spine surgery through these new, patient-centric design techniques.

4.5. NASA's Utilization of ML-Driven Generative Design in AM for Aerospace Applications (2018)

NASA has implemented ML-based design into AM, which will transform aerospace component production. This is what enables AI to create optimized designs that meet given needs effectively. Since 2018, NASA has been using generative design to achieve remarkable improvements, such as cutting component weights by up to half and reducing development times from months to days (Rivera, 2024). The EXCITE mission highlighted new techniques where AI and AM have produced seemingly nonstandard structures that are structurally sound and functional in use (Rivera, 2024; Rosen, 2023). As Ryan McClelland explained, generative design makes it fast—creating 30-40 designs in an hour, maximizing mass and performance. This innovative technology can be used not only for better design but also to drastically reduce production costs, which was a revolutionary step in aerospace engineering (Rivera, 2024).

4.6. Airbus - Lightweight Aircraft Interior Components (2019)

Airbus is currently using generative design to create lightweight aircraft parts like the bionic partition for their A320 plane. The partition was created in Autodesk’s generative design software and was 45% lighter than conventional components without compromising structure. Airbus is able to can design parts that will lead to less fuel and better performance from the aircraft by adopting generative design techniques. This project fits into their aerospace sustainability agenda and strives to lower the ecological footprint of aviation (Deplazes, 2019).

4.7. GE Aviation - Aircraft Engine Components (2019)

GE Aviation uses generative design to optimize the internal parts of its aircraft engines, including fuel nozzles. The first 3D-printed fuel nozzle derived from generative design principles was launched by GE for weight reduction and performance enhancement. The algorithms let engineers test and prototype thousands of possible designs very quickly, making them lighter and more energy-efficient under load. These advancements underscored GE’s strategy of using cutting-edge manufacturing processes to optimize the aviation marketplace (Markovic, 2022).

4.8. Leveraging ML for AM in Boeing's Aircraft Design (2021)

Boeing also used ML to design AM process improvements for aircraft manufacturing (by much since 2021), optimizing component designs through the use of ML algorithms and making them to produce higher complexity geometries than traditional manufacturing processes could do (Warde, 2023). This option lowered the weight, enhanced performance, and improved production efficiency. Exhibits such as MEDAL, which used ML to improve AM characteristics of metal alloys, enabled

Boeing to accelerate the time and costs of production (Warde, 2023). Further, Boeing's partnerships with academia, including MIT, have spawned education initiatives that developed worker capabilities in AM and ML that reflected the rising use of AM and ML in aerospace. On the whole, Boeing's adoption of ML in AM was a major step in a journey towards new and efficient production in the aerospace sector.

Overall, ML for generative design in AM is something that has revolutionized the production possibilities of all sectors. In projects carried out by some of the largest firms—Autodesk, GM, Lockheed Martin, NuVasive, and Boeing—we could see the tremendous advantages of this technological co-design, such as higher efficiency, decreased material use, and structural optimization. Such previous projects provided a framework for future innovation and served as a model for other industries that seek to leverage technology for better products and manufacturing processes.

5. Overview of Past Research on Generative Design using ML for AM

The amount of research on generative DfAM using ML has grown dramatically in the past 10 years, with a peak in publications in 2020–2021. This trend is part of an increasing use of AI to innovate and improve AM design practices, which has remained consistent but at a somewhat lower rate ever since. Fig. 1 shows how the field has changed over the time from 2013 to 2024 (n = number of articles per year).

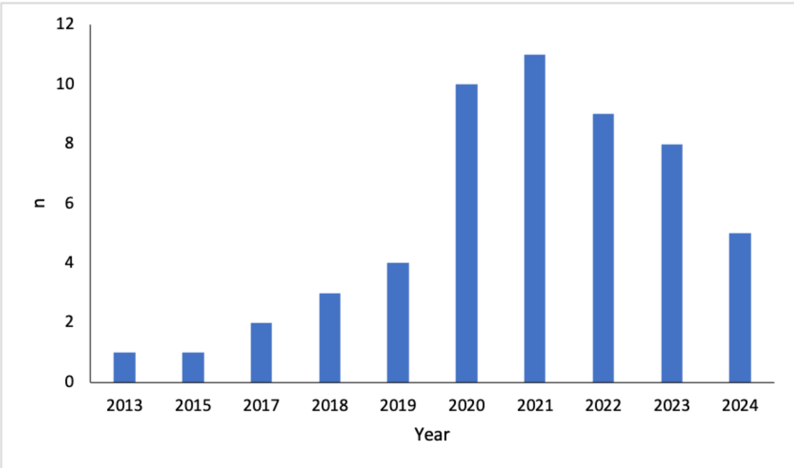

Fig. 1. Number of articles on Generative Design using ML for AM *vs.* year.

Different publishers have been responsible for publicizing this research. In Table 1 below, we have listed publishers and articles in this paper they have published.

5.1. Design and Performance Enhancement

Gu et al. (2018) used ML to build generative designs for hierarchical materials and showed that their ML-optimized designs improved mechanical properties to about 25 times tougher than traditional materials and were computationally fast, screening billions of designs in a matter of hours. A generative design optimization strategy by Strömberg (2019) combined TO and cellular lattices with massive increases in AM design efficiency using material layout optimization and support vector machines for prediction has been described. Goguelin (2019) focused on AM-specific generative design methods and showed how advanced computation enabled part geometries, performance, and better use of materials. In that research, it was shown that generative design resulted in enhanced strength-to-weight ratios and helped design difficult geometries previously unimaginable using classical techniques, making it applicable in fields from aerospace to automobile.

Hyunjin (2020) investigated how artificially generated generative design systems can radically alter the manufacturing process. This a study affirmed that AI and human designers work collaboratively to determine the best design choices and materials for an optimal product, implying an important paradigm shift to AI-based approaches in future product design. Ricotta et al. (2020) proposed a generative parametric model algorithm for elbow orthoses, which highlighted the role of 3D capture and modeling of structures in order to customize and predict orthopaedic device customization. They showed that it was feasible to use selective laser sintering (SLS) technology and found that generative algorithms could bypass the limitations of traditional CAD, making design easier.

Table 1. Number of articles on Generative Design using ML for AM by Publisher

Publisher	Number of articles reviewed
Springer	9
Elsevier	7
MDPI	7
arXiv (Cornell University)	4
IOP Publishing Ltd	4
ASME	3
Emerald	2
ACM	1
AIP Publishing	1
Cambridge University Press	1
CIMNE	1
eCAADe	1
IASDR	1
IEEE	1
IJECE	1
IJMRET	1
JETIR	1
Justia	1
MATEC	1
Royal Society of Chemistry	1
Taylor & Francis Group	1
Toronto Metropolitan University	1
UIKTEN	1
University of Bath	1
Wiley	1
Total	**54**

The same goes for Aman (2020), who studied the optimization and performance enhancement of bracket design using Autodesk Fusion 360; they differentiated generative design from optimization: iterative solutions verified via stress, heat and buckling simulation resulted in successful design implementation into workable assemblies.

Ntintakis and Stavroulakis (2020) talked about the latest developments in generative design, for instance, soft robot actuators. Their work demonstrated how generative design was able to generate complex forms in a way that conventional manufacturing wasn't able to produce, validating their models through finite element analysis (FEA) and exploring the effects of material choice on actuator behavior. Kumaran and Senthilkumar (2021) utilized generative design and optimization of topology to analyze industrial robot arms and showed that AM such as powder bed fusion and direct energy deposition (DED) can be used to solve structural complexity and weight and provide for efficient repair mechanisms. The generative design strategy of Yadav et al. (2021) was used to enhance Unmanned Aerial Vehicle (UAV) frame designs, showing the ability of AM to design complex geometries in response to performance needs by using FUSION 360 software.

Ricotta et al. (2021) specifically developed a generative algorithm for creating elastic shapes for orthopedic use and created an optimized elbow orthosis, better fitting and performing than previous designs based on Finite Element Method (FEM) simulations. Barbieri and Muzzupappa (2022) have examined generative design and TO to its full extent by redesigning mechanical parts of a Formula Student racing car and finding impressive performance gains. They showed that generative design outperformed TO for mass reduction and safety factors, showing that generative design could design light and strong structures. Watson et al. (2023) instead created a generative design approach for space-frame systems especially to optimize efficiency. They implemented formal TO techniques and generated high-performance designs by using a parameterization strategy that transformed voxel data into manageable models. In the paper, they claimed that six plausible topologies were generated while taking into account restrictions of certain input parameters.

5.2. Robust Material Design

Nordin et al. (2013) researched generative design systems that used nature-based algorithms to create sophisticated, mass-produced objects, showing the ability to combine form and function across a range of manufacturing processes, including CNC milling and AM. Jiang et al. (2020) developed a parallel trend by carrying out an ML-integrated design system that optimized design parameters of customized products (for example, a tunable mechanical performance ankle brace). Their example showed that ML made a big impact in design and gave us a detailed insight on how design decisions affect performance. Almasri et al. (2020) used a dual-discriminator generative adversarial network (GAN) to apply mechanical and geometrical constraints to AM design. That method effectively maximized topology, leading to mechanically reliable designs following sophisticated constraints.

Goudswaard et al. (2021) developed a neural network capability profile to improve filament deposition modeling (FDM) and showed that their generative design algorithm was capable of accurately predicting mechanical values such as ultimate tensile strength (UTS) and tensile modulus (E), with low prediction errors, and verifying the capability profile via successful load-bearing part designs. Siegkas (2022) used GANs to generate dense 3D porous architectures similar in nature to forms found in the natural world, showing how AM could benefit from biomimetic designs, despite observed differences in mechanical performance due to resolution variations in image generation. Felbrich et al. (2022) pioneered by integrating generative design software and deep reinforcement learning for robot autonomy in AM, establishing the critical role of geometric state representation and task-specific training approaches for complex structure construction.

Zhang et al. (2022) created a probabilistic ML-based prediction system for DED of about 1,150 tensile test specimens. Their findings showed that probabilistic modeling reduced the time and cost of validation of material systems to less than 0.5 for most properties with an R2 of over 0.5, and it also tackled dataset sparsity and aleatory uncertainty. Junk and Rothe (2022) focused on ultra-lightweight automobile parts using generative design and fiber-reinforced AM. Their findings showed dramatic decreases in cost and weight, with a safety factor of 1.44 in mechanical tests, though they do leave some room for improvements in fiber reinforcement design. Dheeradhada et al. (2022) expanded the domain of design of experiments (DoE)-informed design with ML that allowed higher manufacturing accuracy and a reduction of model uncertainty by 25%.

Milone et al. (2023) designed a shape optimization algorithm for hip replacement prostheses that increases volume and mass by 20% and maximum von Mises stress by 39%, indicating durability and performance. Awd et al. (2024) studied how manufacturing metadata can be integrated into ML models to predict fatigue properties in metamaterials, showing that mechanistic functions can quantify the influence of defects on fatigue lifetime to design better materials. Cao et al. (2024) used an image-based GAN algorithm to study microstructures in metal AM, which was able to produce high-resolution images very similar to actual microstructures and enable better material property measurements.

Headley et al. (2024) presented an augmented ML technique in AM of thermoelectric materials and reported over 99% density and shorter build times on bismuth telluride parts that allowed for improved process parameters without degradation in quality.

5.3. AM Process Automation and Optimization

Mostafavi et al. (2015) continued this by developing the Informed Design-to-Robotic-Production (D2RP) system for material deposition in robotic 3D printing. Their work forged a relationship between design and production, improving the performance of architecture with smart management of porosity. In contrast, Tutum et al. (2018) addressed functional generative design by using a variational autoencoder and surrogate modeling to optimize complex 3D-printed springs. They found both strength of the generated geometries and applicability of the method for other functional design challenges. Nguyen et al. (2018) developed a mixed generative-discriminative inverse materials design method that efficiently predicted design parameters with imperfect information, making the materials design process faster and more effective.

Ko et al. (2019), by comparison, introduced an ML-based system of continuous knowledge engineering in AM with the focus on design and manufacturing data-driven insights. The results they produced revealed that the algorithm could be used to automate the rule generation from AM data to significantly enhance part quality using intelligent decision-making. Jaisawal and Agrawal (2021) described many different techniques of generative design in detail, sorting by techniques and stressing the need to use computing power to come up with multiple design options during the multidimensional planning phase of product design. Their article emphasized the multidisciplinary-ness of generative design. Alternatively, Sotomayor et al. (2021) had an emphasis on reducing DfAM workflow with the help of advanced design tools and highlighted some optimization techniques such as topology and lattice infill optimization that complemented material efficiency and performance.

Ko et al. (2021) targeted establishing AM design rules with a data-driven approach leveraging ML and knowledge graphs to learn more about AM processes and consequences, resulting in LPBF-specific design rules. Grierson et al. (2021) also discussed the broad effects of ML on AM by noting its positive role in technological adoption but admitting to the limitations of existing applications, including the need for more powerful, field-tested ML packages and generalizable models for process parameter optimization. On the contrary, Hsu et al. (2022) had developed a novel approach that translated natural language input into 3D-designed material via a mixture of GANs and contrastive language-image pre-training. Their work demonstrated the effective design of materials of variable rigidity and showed potential to apply material science more broadly, but they were more concerned with the amputation of language to matter.

Sandeep et al. (2022) assessed ML's role in AM, which highlighted the potential to maximize design, production, and defect detection and identified a lack of research about ML's repair and restoration applications. In a related article, Staub et al. (2022) proposed a ML-based technique for AM to detect problematic geometrical features with a success rate of 88% in detecting hard-to-manufacture geometries. This showed ML's ability to optimize manufacturability through custom scanning techniques. Ajayi et al. (2023) demonstrated a new 3D-VAE-SDFGAN method to create 3D forms from 2D pictures that scalably and visibly outperformed previous approaches, indicating that the use of ML for designing might be the future.

Pilagatti et al. (2023) analyzed GD and AM's integration in the space industry, recommending a process that automated the design selection cycle and reduced project duration. Trovato et al. (2023) identified other general trends of ML in AM design, separating use cases into geometrical design, process setup, and process monitoring. They highlighted the disadvantages of AM, such as cost and dimensional tolerances, and advocated ML as a way to improve the design process. Ng et al. (2024) also discussed ML applications in AM with detailed coverage of how ML has been used to identify pattern complexity and reverse-engineer design workflows to significantly improve production productivity and quality assurance.

5.4. New Use Cases

Oh et al. (2019) combined deep generative models with TO to build a system that produced performant designs through a case study that confirmed the effectiveness of the system over earlier generative approaches. Ghiasian and Lewis (2020) proposed a design recommender engine that used ML to convert legacy part inventories into AM. Their findings showed marked enhancements in design ease for AM, which also highlighted how ML could inform efficient design adjustments and improve manufacturing practices. Jin et al. (2020) turned to ML's capabilities to mitigate AM issues, including build deviations and material property differences. They detailed the use of ML algorithms for geometrical design, process parameter tuning, and in-place anomaly detection with a roadmap for enhancing manufacturing efficiency.

Pollák et al. (2020) demonstrated the use of generative design software for robotic 3D printing by showing the flexibility and speed of rapid prototyping with Rhinoceros and Grasshopper-based programs, allowing to go from design to simulation without friction. Junk and Burkart (2021) evaluated CAD software, Fusion 360, Solid Edge, and CogniCAD, in generative design terms: Fusion 360 and Solid Edge both produced the same design, but CogniCAD was far different, with user interfaces, calculation times, and design considerations varying across systems. Nebot et al. (2021) proposed a novel generative design approach that combines 3D morphing with genetic algorithms for breaking the cycle of traditional design obsession, but their conceptual process never got applied, setting a precedent for the coming years.

Yoo et al. (2021) examined how deep learning can be implemented within CAD/CAE for generative design and developed a formal model to automate 3D CAD model creation and analysis for a high-productivity conceptual design workflow using an example. Kanagalingam et al. (2023) were more interested in generative design as applied in medical implants—high tibial osteotomy fixation plates. Then, they presented an AM workflow that combined generative design and detailed design with significant enhancements in surface finish and geometric precision with the help of advanced post-processing. Marino (2023) analyzed drone frame optimization through generative design and AI algorithms and found that a square-type frame with load distribution was the most suitable one for PEEK 3D printing.

5.5. Challenges and Limitations

Yao et al. (2017) proposed a mixed ML solution that recommended AM design features, which could assist the novice designers by computing support for AM. Guerguis et al. (2017), in contrast, addressed the algorithmic design of massive AM architecture, which demonstrated that 3D printing was able to make architecture more energy efficient. In 2020, Cunningham et al. (2020) utilized a sparsity-preserving genetic algorithm paired with generative neural networks to create various useful 3D models. This strategy was successful in their discovery of latent space, and they could produce designs with a functional advantage while remaining close to the human models so as to allow for a transition from design innovation to experimental testing.

Peles et al. (2023) used GAN for structural analysis of additively made parts and showed that the technique could reliably predict melt pool boundaries and defects from optical photos. They found that melt pool geometries were positively skewed in their area probability distribution, indicating a strong use of deep learning for structural information in AM. Lastly, Peckham et al. (2024) in their paper also pointed out that generative design in AM has some randomness; performance varies as much as 592% from design to design, which warrants better user training and learning of generative design tooling to enhance the design results.

6. Conclusions

As ML is already used in AM generative design, the production capability can grow across industries and scale. ML-driven generative design could provide new opportunities for production, allowing them to generate complex geometries that would not be achievable with conventional manufacturing. It allowed not only design accuracy but material consumption to be maximized for more effective manufacturing. Generative design helped to be sustainable by reducing material waste with algorithms and iterative optimization. This solution provides clear environmental benefits, for example, in the case of aerospace, where lightweight materials mean a reduction in fuel usage and associated environmental impacts. Optimization for a specific performance need (like strength, weight, etc.) leads to lightweight and economical designs. Not only does this lower production costs, but it also increased the overall performance of final products, which is what makes generative design such a powerful resource for manufacturers. Past innovations of the pioneers of a specific industry set the example for future innovation. The continuous adoption of ML in generative design should address underlying production efficiency and variability issues leading to reliable and innovative manufacturing technologies. The paper concludes that the convergence of generative design and ML isn't a mere technological solution but a force of change that can yield future more sustainable, efficient, and novel forms of manufacturing.

7. Future Scope

The potential for generative design coupled with ML in AM is huge for creativity and efficacy. The following are some of the most promising future directions:

- Advanced Predictive Models: Future research will have to focus on building better ML models capable of predicting the quality of 3D printed items with better precision. For example, gradient boosting regression (which achieved an R-2 score of 0.954) with improvement of models may enable one to better optimize construction orientation and component dispersion and deliver high-quality outputs during production.
- Integration with Production Management: It is essential to integrate AI models in the current manufacturing process. Moving forward, efforts need to focus on building flexible systems that support multiple data science tools and frameworks like TensorFlow and ONNX. This would also enable the telemetry between AI models and production sites in real time, enabling manufacturing automation in real-time.
- Sustainability Programs: With companies' awareness of sustainability, generating design could also be key to reducing waste and materials. The research needs to investigate even more advanced algorithms that further increase resource efficiency, along with environmentally friendly manufacturing processes in other sectors.
- Industry-Level Applications: Although current applications for aerospace and automotive are incredible, there is significant potential for generative design and ML to be applied in many

other fields, such as healthcare, consumer products, and construction. Analyzing these new areas could result in new products tailored to specific industrial issues.

- Academic Partnerships: Collaborations between leaders from industry and academic organizations could enable a skilled workforce capable of AM/ML. Such efforts as Boeing's and MIT's might help to lay the skills and knowledge base to drive further developments in the industry.

The future of generative design in AM through ML is truly endless and promises more predictive power, sustainability, and expanded domain application. This potential will require a sustained commitment to research and collaboration.

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Przegląd Projektowania Generatywnego z Wykorzystaniem Uczenia Maszynowego w Produkcji Przyrostowej

Streszczenie

W niniejszym artykule przeglądowym zbadano, w jaki sposób projektowanie generatywne jest łączone z uczeniem maszynowym w celu realizacji produkcji przyrostowej i jej transformacyjnego wpływu na społeczeństwo. Projektowanie generatywne wykorzystuje złożone algorytmy w celu automatyzacji procesu projektowania najlepiej dopasowanych struktur, masowej personalizacji i dostosowywania do konkretnych wymagań klienta przy zachowaniu wysokiej wydajności i jakości. Skalowalność i przewidywalność modeli sztucznej inteligencji (ang. Artificial Intelligence - AI) ułatwiają obsługę dużych ilości danych i umożliwiają skalowanie produkcji bez uszczerbku dla jakości. Niniejszy artykuł koncentruje się również na tym, w jaki sposób projektowanie generatywne może pomóc przyspieszyć innowacje i wytwarzanie wyrobów, ponieważ umożliwia projektantom działanie w szerszej przestrzeni projektowania i dostarczanie rozwiązań, których nie można osiągnąć za pomocą tradycyjnych technik. Integracja AI z istniejącymi procesami produkcyjnymi ma również kluczowe znaczenie dla optymalizacji produkcji w czasie rzeczywistym — co dodatkowo zwiększa ogólną skuteczność operacyjną. Ponadto pojawienie się zaawansowanych modeli predykcyjnych, takich jak regresja z pobudzeniem gradientowym (ang. gradient boosting regression), pokazuje, w jaki sposób uczenie maszynowe może zapewnić lepszą dokładność operacji drukowania 3D w celu zapewnienia standardów jakościowych wyrobów. Artykuł zakończono omówieniem projektowania generatywnego i uczenia maszynowego w aspekcie rozwoju przyszłościowego wytwarzania przyrostowego oraz sposobów, według których projektowanie może być udoskonalane i modyfikowane, tak aby dostosowywać się do zmieniających się wymagań przemysłu.

Słowa kluczowe: projektowanie generatywne, uczenie maszynowe, wytwarzanie przyrostowe, projektowanie struktur lekkich, optymalizacja