Title : Impact and scope of Artificial Intelligence on 3D printing

Author: Santhi Davedu, Data Scientist at Soothsayer Analytics

3-dimensional printing(denoted as 3DP henceforth) technology developed in 1980 has gained global interest and underwent significant development and innovation in the past few years. 3DP was initially used for rapid prototyping. At present, its scope and adoption by diverse industries has increased. The global 3D printing market size is expected to grow to USD 34.8 billion by 2026, at a CAGR of 22.5%. (Source: Global news wire)[1]

The manufacturing capability of 3DP processes has some technical and operational challenges that limit the transition of conventional manufacturing to 3DP and large scale utilization. Artificial Intelligence(denoted as AI henceforth) can be integrated into every stage of 3DP to address these issues and optimize the performance. AI can help improve 3DP processes such as process optimization, dimensional accuracy analysis, manufacturing defect detection, material property prediction etc.(Yu & Jiang, 2020).

In this document, some industry and research based case examples have been provided to showcase the possibilities of AI-3D integration. This will help to understand the role AI can play in bridging the gaps in 3DP, the scope of impact that AI can have on 3DP and the areas of focus. Some limitations and challenges have also been discussed towards the end of the document.

Introduction

Big data analytics, 3DP, advanced robotic systems, cloud computing, augmented and virtual reality and blockchain are examples of advanced digital technologies that are rapidly reshaping global value chains and impacting every industry and their businesses(Ahi et al., 2021).

Big data focuses on managing large volumes of data collected from a variety of sources. AI involves the development of computer systems to analyze the data from Big data systems, develop logic and reasoning and to make decisions in an efficient manner. AI is a broader superset of technologies such as Machine Learning(ML), Neural networks, Computer vision, Automation, Deep Learning etc. AI can help to automate repetitive tasks thus reducing human labor, identify patterns in past data, determine relationships, build models, and make decisions and predictions for the future scenarios. AI solutions have already been deployed in multiple sectors such as finance, healthcare, retail, manufacturing etc.

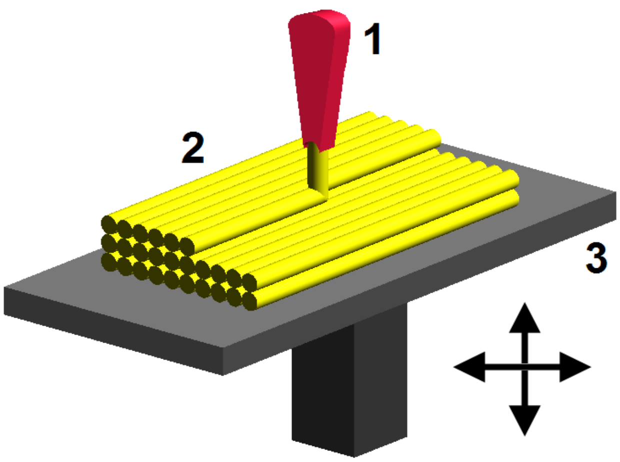
3DP, a subset of Additive Manufacturing(denoted as AM henceforth) is a rapid and flexible production process to build 3D parts in layers from digital designs. It can create parts from diverse materials like polymers, composites, ceramics, metals etc. It can create intricate designs and geometries.

[1] ReportLinker. (2021b, August 3). *The global 3D printing market size is expected to grow USD 12.6 billion in 2021 to USD 34.8 billion by 2026, at a CAGR of 22.5%*. GlobeNewswire News Room. https://www.globenewswire.com/news-release/2021/08/03/2273364/0/en/The-global-3D-printing-market-size-is-expected-to-grow-USD-12-6-billion-in-2021-to-USD-34-8-billion-by-2026-at-a-CAGR-of-22-5.html

Some of the capabilities of 3DP that have contributed to the increasing interest and adoption are:

- rapid production of on-demand products
- customization of each product for small production batches
- flexibility to add functionalities into the product
- ease of creating complex designs
- usage of wide range of materials with diverse material properties
- ability to evaluate the product and iterate on the design
- material optimization and waste reduction
- minimization of supply chain processes
- simplification of fabrication

3DP is done through various methods the popular ones being Fused deposition modeling (FDM) or Fused Filament Fabrication, Selective Laser Sintering (SLS), Direct Metal Laser Sintering (DMLS) and Stereolithography (SLA).



1 - nozzle ejecting molten material
2 - deposited material (modelled part)
3 - controlled movable table

Figure. Fuel Deposition model

3DP is used for a variety of applications such as electronics, medicine(medical equipment, surgical implants, dental structures, biomedical engineering parts), automotive, aerospace, construction, tool and fixtures, architectural models, toys, artistic sculptures, consumer products(footwear, furniture), reconstructing fossils etc.

Integration of AI and 3DP

AI can play an important role to improve and transform 3DP process. Some of the ways in which this can be done are :

- Design stage – optimize the design processes
- Printing stage – improve the optimal printing conditions, optimize the parameters that determine the printability, checking control, and monitor the printing processes , failure detection, failure compensation

- Post processing – predictive maintenance, workflow optimization
- Part evaluation – determine the mechanical properties
- Cloud service platform, service evaluation and security of attack detection.

Given below are some case examples to further outline these aspects

1. Development of new printing materials

The choice and development of the materials for 3DP/AM relies on domain knowledge of the materials, polymer chemistry and involves testing and experimental trails based on the requirement. This constrains the efficiency of material development. An optimization algorithm can be developed to find optimal 3D printing formulations (Erps et al., 2021). Thus, AI can be used to accelerate the development of new printing materials with optimized performance. There is also challenge of identifying and designing the optimal structure for any given application that must be addressed.

2. Design for 3DP

For 3DP, the designs must be created in CAD modeling software. These CAD designs are then converted to .stl files to determine the layers for printing. AI is being incorporated into modeling programs to create optimal 3D printable models. For example - SOLIDWORKS included AI in its 3D CAD modeling software to enable faster renderings and reproduction designs.

3. Identification of suitable printing conditions

3DP conditions or configurations especially for new materials affects the quality of the products being printed. However, identifying suitable printing conditions in extrusion based 3DP for biomaterials is resource intensive, requires extensive experimentation and is time consuming. AI has the potential to predict the quality of resulting printing by using the printing conditions, material composition as input parameters. A recommendation system consisting of Classification and Regression methods built on upon Random Forests can be built and trained using the past data which can then be used to make predictions on the current printing conditions. The classifier method is trained to distinguish between low- and high-quality prints and thus predict the print quality to be as “high” or “low”. The regression method can approximate the values of a printing quality metric. In order to build this recommendation system, the data collection has to be efficient to build this framework. (Conev et al., 2020)
ML has been used in various studies to predict and optimize printing parameters to maximize the structure's properties, optimize printability of the material and assess the quality of the prints.

4. Detection of geometric deviations

Since 3D printing process involves thermal processes, there are issues such as hot creep, bending and warping, deformed parts, cracks, bowing, melted parts, blurry layers etc. [2]
During the printing, distortions like material shrinkage or expansion occur. Mechanical problems with the models or printing belts, uneven or less-heated printing beds, and disorientation of the layers are also

---

[2] Emma Pollock, Powerblanket. “3D Printing: All about the Heat.” *Process Heating RSS*, Process Heating, 23 July 2019, https://www.process-heating.com/articles/93105-d-printing-all-about-the-heat.

possible. AI can help overcome these issues by ensuring pre-printing conditions and increasing the print accuracy. It can also monitor the entire process and prevent shape distortions by stopping the process midway if it detects the possibility of the occurrence of these issues. 3D printers in general are open-loop systems and do not receive feedback on the output and hence cannot correct errors. An MIT based startup called Inkbit has developed Inkbit Vista printers that use Computer vision and Machine learning to monitor the printing process and fix real time errors.

5. Fatigue failure predictions

Composite materials(like fiber reinforced plastics, ceramic matrix materials etc.). enable the combination of different materials with diverse properties to cater to varied functionalities. Hence tuning composite designs is needed for material development. Traditional manufacturing methods for Composite materials production are constrained when manipulating complex microstructures of the materials and hence have limited tunable composite designs.[3]
3DP has the potential for production of composite materials with complex geometries.
Deep learning models can be employed to predict physical fields like complex strain and stress in composites based on image processing of the material microstructure geometry.
(Yang et al., 2021)

6. Prediction of dimensional features

3D printers available commercially cannot combine and offer together high speed, high precision and medical grade biomaterials limiting the applicability of 3DP in production of medical devices. Melt electrowriting 3D printer(MEW) has been developed that uses AI to improve precision and produce fibers with microscale resolutions. A Machine Vision system is used to monitor in real time and capture the images of the flight path of the extruded fiber from the electrohydrodynamically-stabilized molten jet. A ML system then analyses this data to identify relationships between significant parameters(such as jet angle, cone volume, electric fields etc.) and use these insights to correct fiber pulsing for accurate jet placement and predict the diameter of the produced part – all during the printing process. This helps in improving the quality and accuracy of the manufactured parts. (Mieszczanek et al., 2021)

7. Evaluating the performance of 3DP parts

Once the parts are printed, it is difficult to estimate their performance. The physical experiments as well as computational simulations are time and resource consuming. Deep learning and neural networks that incorporate both data and physics can be used to map relationships between 3DP process parameters and properties of the final product thus helping to predict the outcomes of the complex processes involved.[4]

---

[3] Mallick, P.K. (2007). Fiber-Reinforced Composites: Materials, Manufacturing, and Design, Third Edition (3rd ed.). CRC Press. https://doi.org/10.1201/9781420005981

[4] ScienceDaily. (2021, July 1). Using AI to predict 3D printing processes. ScienceDaily. Retrieved December 27, 2021,from https://www.sciencedaily.com/releases/2021/07/210701140913.html

8. Predicting the mechanical behavior of 3DP parts

The 3DP processing parameters (such as layer thickness, laser power, powder size, printing speed, raster orientation etc.) affect and determine the structural and mechanical properties of the 3DP products. Hence these parameters must be optimized to predict the mechanical behavior of the printed parts (Nasiri & Khosravani, 2021). AI can help with these parameters optimization.

9. Reducing waste in 3D printing using Neural networks

As the cost of materials increases, AI based optimization methods can help to improve the design, control the filament usage, operation of the injection system etc. thus reducing the wastage of the materials used in 3DP while maintaining the quality of the product. By integration with IoT, the entire production process can be monitored, optimized, sensor signals can be captured and used to predict and identify failures(Rojek et al., 2021). AI can help increase functionality, control, and streamline the 3DP processes. For example-analyzing the time required to print a part, predicting similarity to the parent object, fixing the printing schedule etc.

10. Fault diagnosis in 3D printing

As the complexity and adoption of large scale industrial production systems increase, faults/failure management becomes critical. Automatic fault diagnosis helps the operators in troubleshooting and taking necessary measures. Using sensors in 3D printing and a data acquisition system, datasets can be generated for the learning algorithms. This will help build Bayesian networks that give a probabilistic approach to diagnose and detect failures in industrial systems (Bacha et al., 2019).

11. Data generation

Given that 3DP-AI integration technologies are evolving there is a need to generate, capture and analyze data during the 3DP processes. This can help identify the problems in greater detail, create customizable algorithms, devise corrective actions, optimize design and thus increase the overall efficiency of the processes. Peregrine is an AI based software developed at the Manufacturing demonstration facility, Oak Ridge National Laboratory , collects, and analyzes data at every step of the 3D manufacturing process - from design to feedstock selection to the print build to material testing thus creating 'digital' clone for each part. The algorithms process pixel values of captured images while considering the edges, lines, textures etc. This data is then used to compare the parts and inform future builds for different materials and dimensions. Any anal molies detected by the software; alerts are issued to the operators so adjustments can be made. [5]

12. 3D printing of medicines

Personalized medicines instead of "one size fits all" is a critical need in healthcare but it involves the input of expert practitioners at every stage of the oral – formulations. AI can address this issue.

---

[5] AI software enables real-time 3D printing quality assessment. (2020, August 14). Retrieved from https://www.sciencedaily.com/releases/2020/08/200814163305.html

Intelligent IoT can also be built into the development of 3DP of medicines. This will enable acceleration of patient care to a personalized model.

Opportunities

- Prototyping applications, automotive industries are accelerating the growth of 3DP technologies with North America and Europe regions being the major key players.
- Numerous research projects and startups globally continue to work on developing products and services involving 3DP and AI
- Government investments in 3D-AI projects are also increasing the recent years.

Limitations

- Availability of data on materials, composition, properties, limited availability of materials and their high costs, lack of standard process control, limited production size etc. are some factors that are limiting the growth of the 3DP market (Ramakrishna et al., 2019).
- Need for data sharing culture among materials community
- The ethical issues related to AI and 3DP

Conclusion

Material informatics is a field of science that employs the tools, theories drawn from AI and computer science to material science, engineering to accelerate material, product, and manufacturing innovations. (Ramakrishna et al., 2019). AI and its concepts are rapidly infusing chemical engineering research especially molecular data science. Areas in AI such as Deep learning, computer vision , neural networks etc, are also being continuously worked upon. As these areas continue to develop and advance, this will further accelerate the innovations in products and services for the integration of AI in 3DP. This integration will help build efficiency, increase value add to the existing industrial processes and improve the success rate of 3DP.AI can help detect issues in early stages to inform decision making in real time. The speed of operations of 3DP can be improved without additional costs, thus expanding the possibilities of Additive manufacturing. This will also accelerate the large scale adoption of 3DP for efficient production.

References

Ahi, A. A., Sinkovics, N., Shildibekov, Y., Sinkovics, R. R., & Mehandjiev, N. (2021). *International Business Review xxx (xxxx) xxx Advanced technologies and international business: A multidisciplinary analysis of the literature*. https://doi.org/10.1016/j.ibusrev.2021.101967

Bacha, A., Sabry, A. H., & Benhra, J. (2019). Fault diagnosis in the field of additive manufacturing (3D printing) using Bayesian Networks. *International Journal of Online and Biomedical Engineering*, *15*(3), 110–123. https://doi.org/10.3991/ijoe.v15i03.9375

Conev, A., Litsa, E. E., Perez, M. R., Diba, M., Mikos, A. G., & Kavraki, L. E. (2020). Machine learning-guided three-dimensional printing of tissue engineering scaffolds. *Tissue Engineering - Part A*, *26*(23–24), 1359–1368. https://doi.org/10.1089/TEN.TEA.2020.0191/FORMAT/EPUB

Erps, T., Foshey, M., Lukovic, M. K., Shou, W., Goetzke, H. H., Dietsch, H., Stoll, K., Von Vacano, B., & Matusik, W. (2021). Accelerated discovery of 3D printing materials using data-driven multiobjective optimization. *Science Advances*, *7*(42), 7435–7450. https://doi.org/10.1126/SCIADV.ABF7435

Mieszczanek, P., Robinson, T. M., Dalton, P. D., Hutmacher, D. W., Mieszczanek, P., Robinson, T. M., Hutmacher, D. W., & Dalton, P. D. (2021). *2100519 (1 of 7) Convergence of Machine Vision and Melt Electrowriting*. https://doi.org/10.1002/adma.202100519

Nasiri, S., & Khosravani, M. R. (2021). Machine learning in predicting mechanical behavior of additively manufactured parts. *Journal of Materials Research and Technology*, *14*, 1137–1153. https://doi.org/10.1016/j.jmrt.2021.07.004

Ramakrishna, S., Tong, ·, Zhang, Y., Lu, W.-C., Quan Qian, ·, Sze, J., Low, C., Heiarii, J., Yune, R., Daren, ·, Loong Tan, Z., Bressan, S., Sanvito, S., Surya, ·, & Kalidindi, R. (2019). Materials informatics. *Journal of Intelligent Manufacturing*, *30*, 2307–2326. https://doi.org/10.1007/s10845-018-1392-0

Rojek, I., Mikołajewski, D., Kopowski, J., Kotlarz, P., Piechowiak, M., Dostatni, E., & Weber, F. E. (2021). *materials Reducing Waste in 3D Printing Using a Neural Network Based on an Own Elbow Exoskeleton*. https://doi.org/10.3390/ma14175074

Yang, Z., Yu, C. H., & Buehler, M. J. (2021). Deep learning model to predict complex stress and strain fields in hierarchical composites. *Science Advances*, *7*(15). https://doi.org/10.1126/SCIADV.ABD7416