AI-Driven Optimisation of 3D Printing

Department of Mechanical and Materials Engineering

Bachelor's thesis

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Additive manufacturing has emerged as a key manufacturing method in industry due to the design freedom and material efficiency it offers. However, the wider adoption of additive manufacturing is slowed down by the complex and time-consuming optimisation of process parameters. The rapid development of artificial intelligence and machine learning offers solutions to this challenge, as data-driven optimisation methods can improve the quality of final products and reduce material waste and development time.

This thesis examines how artificial intelligence-based methods can be utilised in the optimisation of additive manufacturing. The study focuses in particular on extrusion-based 3D printing and powder bed fusion, and analyses the possibilities offered by artificial intelligence methods in the prediction and control of process parameters. Case studies illustrate how artificial intelligence-assisted optimisation can improve production efficiency and the mechanical properties of manufactured parts.

The study shows that artificial intelligence will play a significant role in the future of additive manufacturing, enabling smarter and more sustainable production processes. At the same time, the use of artificial intelligence must be critically evaluated from the perspective of its environmental impacts, and its effective application requires a high level of expertise. Nevertheless, artificial intelligence-driven methods offer substantial potential for advancing additive manufacturing.

Keywords: additive manufacturing, 3D printing, extrusion-based 3D printing, powder bed fusion, artificial intelligence, neural networks, machine learning, optimisation

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Lisäävä valmistus on noussut keskeiseksi valmistusmenetelmäksi teollisuudessa sen tarjoaman muotoiluvapauden ja materiaalitehokkuuden ansiosta. Lisäävän valmistuksen laajempaa käyttöönottoa hidastaa kuitenkin monimutkainen ja aikaa vievä prosessiparametrien optimointi. Tekoälyn ja koneoppimisen nopea kehitys tarjoaa tähän haasteeseen ratkaisuja, kun dataohjatuilla optimointimenetelmillä on mahdollista parantaa lopputuotteiden laatua sekä vähentää materiaalihukkaa ja kehitystyöhön kuluvaa aikaa.

Tässä tutkielmassa tarkastellaan, miten tekoälypohjaisia menetelmiä voidaan hyödyntää lisäävän valmistuksen optimoinnissa. Työssä keskitytään erityisesti pursotuspohjaiseen 3D-tulostamiseen ja jauhepetisulatukseen sekä analysoidaan tekoälymenetelmien tarjoamia mahdollisuuksia prosessiparametrien ennustamisessa ja hallinnassa. Esimerkkitutkimukset havainnollistavat, miten tekoälyavusteinen optimointi voi parantaa tuotantotehokkuutta sekä valmistettujen kappaleiden mekaanisia ominaisuuksia.

Tutkimus osoittaa, että tekoälyllä on merkittävä rooli lisäävän valmistuksen tulevaisuudessa mahdollistaen älykkäämmät ja kestävämmät tuotantoprosessit. Samalla kuitenkin on arvioitava tekoälyn käyttöä kriittisesti sen ympäristövaikutusten näkökulmasta. Samaan aikaan tekoälyn käyttöä on arvioitava kriittisesti, erityisesti sen ympäristövaikutusten osalta, ja sen tehokas soveltaminen vaatii korkeatasoista asiantuntemusta. Tekoälyyn perustuvat menetelmät tarjoavat kuitenkin huomattavaa potentiaalia lisäainevalmistuksen edistämiseksi.

Avainsanat: lisäävä valmistus, 3D-tulostus, pursotuspohjainen 3D-tulostus, jauhepetisulatus, tekoäly, neuroverkot, koneoppiminen, optimointi

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1 Introduction

The importance of additive manufacturing, or 3D printing, in modern industry has increased significantly over recent decades. Today, additive manufacturing has established itself as a versatile manufacturing approach that enables the production of parts with complex geometries by adding material layer by layer based on a digital model. In particular, extrusion-based 3D printing and powder bed fusion have become key technologies across various industrial sectors, such as aerospace, automotive, and medical industries. The advantages of additive manufacturing include material efficiency, design freedom, and the ability to produce customised and lightweight structures, making it a promising technology for future sustainable manufacturing.

Despite the advances in additive manufacturing, process optimisation remains a challenge. The print quality, mechanical properties, and dimensional accuracy of printed parts are influenced by numerous interrelated process parameters, including printing temperature, printing speed, layer height, and laser power. Traditionally, optimal printing settings have been determined through trial-and-error methods, which are not only time-consuming and costly, but also can consume lot of printing materials.

Using artificial intelligence to optimise additive manufacturing offers a solution to these challenges. Modern computers and improved data collection methods enable the understanding of complex relationships that traditional analysis methods cannot explain. Artificial intelligence-based approaches make it possible to move from experimental testing towards data-driven optimisation.

The objective of this thesis is to investigate how artificial intelligence-based methods can be utilised in the optimisation of additive manufacturing process. In particular, the thesis examines the benefits that artificial intelligence-driven optimisation offers in terms of the quality of additively manufactured parts and the efficiency of the production process. Furthermore, the impact of key process parameters, such as laser power and printing speed, on the prediction and optimisation of final part properties are analysed. This thesis used artificial intelligence-based Microsoft Copilot for improving text cohesion and language quality, and Anara AI to structure the source material.

2 Additive manufacturing

Additive manufacturing (AM), also known as 3D printing, refers to manufacturing methods in which an object is produced based on a digital 3D data [1]. Compared to other manufacturing methods, like infusion and milling, where the object is created by using a mould or by removing material, in AM the object is produced by adding the material layer by layer. Various stages of the AM process aim to ensure that the final product has adequate precision and quality. This is made possible through advanced software, materials, and printing technologies. [2]

Multiple different AM technologies exist; however, this study focuses on two of them, extrusion-based 3D printing and powder bed fusion. In extrusion-based 3D printing, the basic principle is that the equipment melts the supplied material and deposits it layer by layer to form a part according to a 3D model, which is created with a computer model. In powder bed fusion, powdered material (typically metal) is melted using a laser beam to produce the desired component. [2]

AM took its first steps in the early 1980s, when individual examples and developmental milestones began to emerge. By the early 1990s, three major 3D printing methods were developed. These were stereolithography (SLA), fused deposition modelling (FDM) and selective laser sintering (SLS), of which FDM is one of the extrusion-based 3D printing methods and SLS is included in powder bed fusion. The years 1990-2005 were significant time for the development of 3D printing companies. Additionally, polyjetting (liquid materials are hardened with UV-light) and direct ink writing (melted ink or paste is extruded through a small nozzle to a build platform) were founded as two new 3D printing methods. [3]

In terms of the development of 3D printing, the period between 2005 and the present day can be divided into two or three separate stages. By 2012, 3D printing technologies were well established, the number of patents increased, and 3D printing was already a widely known manufacturing method [3]. Since then, the development of 3D printing has continued, which is reflected in the increased use of bio-based and new functional materials and the growth of research and development funding in the field. Figure 1 shows these key events as well as their division into different stages.

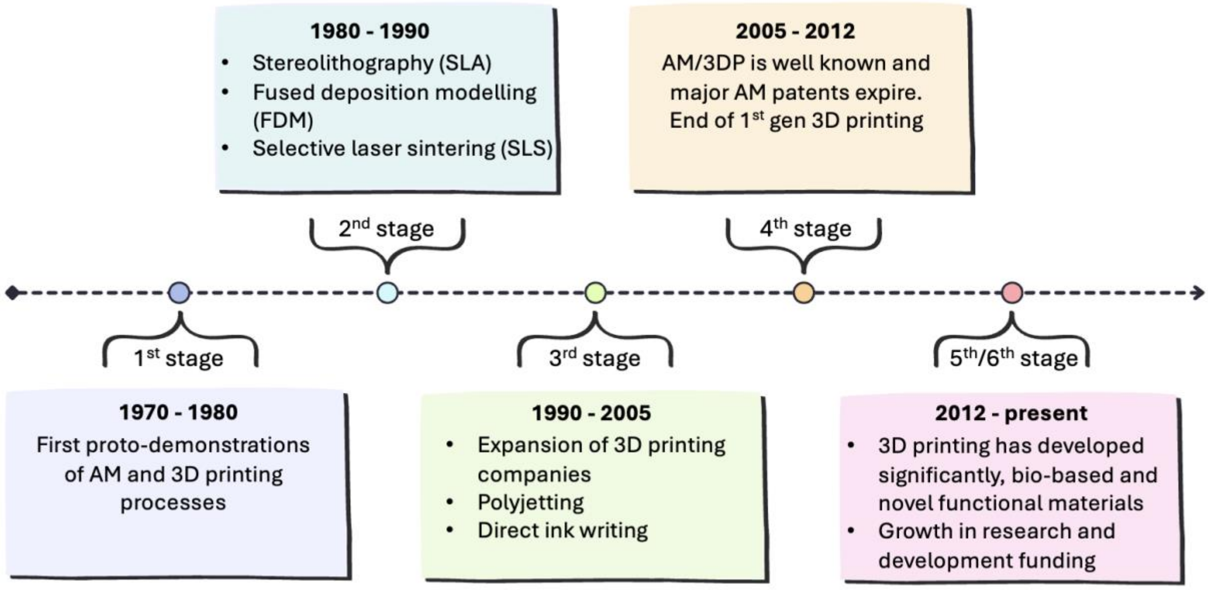

Figure 1. The development of additive manufacturing [3]

2.1 Extrusion-based 3D printing

Extrusion-based 3D printing is probably the best-known AM method [3]. The 3D model, by which an object is manufactured, is created with computer-aided design (CAD) software. After it is created, it is converted into an STL file and then sliced so that it is ready for 3D printing. Slicing means that the 3D model is sliced into layers, according to which the 3D printer can print the part. In extrusion-based 3D printing, the material passes through a heating chamber where it is melted. The molten material is extruded through a nozzle that moves above the build platform according to the sliced 3D model. The part is manufactured layer by layer, meaning the nozzle is raised upward after each completed layer. [4]

The structural properties of the printable material can be influenced by the process parameters [5]. These parameters are entered into the slicing software before printing begins. Possible parameters are e.g. printing temperature, printing speed, infill density, and the orientation of the printing pattern. By optimising these parameters, it is possible to affect layer adhesion, surface quality, dimensional accuracy, and the mechanical properties of the final part. [5]

There are several extrusion-based printing methods. In filament-based methods, the material is supplied in the form of a thin filament roll, and the filament is fed into the nozzle using drive wheels. The oldest and most used method is fused deposition modelling (FDM), followed by fused filament fabrication (FFF). The difference between them is that in FDM the printing chamber is closed and thermally insulated, allowing the temperature to remain constant. In FFF, printing takes place in an open environment, but the building platform is heated. During the process, the temperature may fluctuate. A part manufactured in an enclosed chamber develops a stronger interlayer bond, which enhances its mechanical strength, impact resistance, surface quality, and overall functional performance. [4]

The most used materials in FDM and FFF are polylactic acid (PLA), acrylonitrile butadiene styrene (ABS) and polypropylene (PP). PLA is a thermoplastic and biodegradable polymer which is widely used in the medical field and food packaging [2]. ABS is a type of plastic that contains acrylonitrile, styrene, and butadiene. The combination of these components makes ABS an amorphous, tough, and impact resistant material. PP is a semi-crystalline thermoplastic with low density used in household appliances and automotive and construction industries. [6]

In extrusion-based 3D printing, there are other methods used when the material cannot be supplied in traditional filament form. These processes employ either a plunger or a screw mechanism, which are particularly suitable for metal- and ceramic-based materials. Plunger- or cylinder-based material extrusion is used for rods containing metal and ceramic powders. A motor-driven plunger or syringe feeds the material into the heating chamber to soften, after which it is extruded through the nozzle onto the build platform or on top of the previously printed layer [4]. Screw-based AM systems, in contrast, are designed for materials that cannot be processed into filament form. These systems are capable to process pellets, which first soften in the melting zone due to friction and heat and are then pressurised in the metering zone before being extruded through the nozzle. These different extrusion-based 3D printing methods are shown in Figure 2. [5]

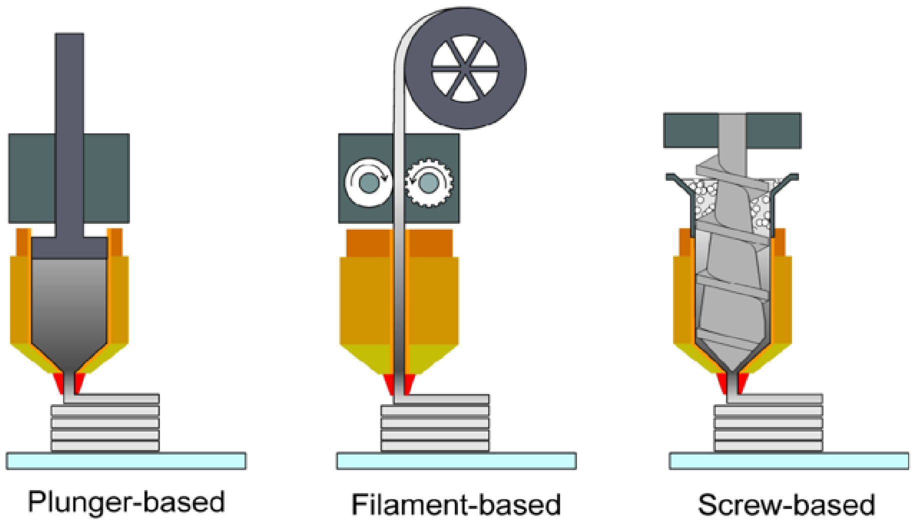

Figure 2. Extrusion-based 3D printing methods: plunger-, filament- and screw-based techniques. Reproduced from Gonzalez-Gutierrez et al. [5]. Copyright 2018 Gonzalez-Gutierrez, published by Materials.

In 1989, the FDM method was developed as the first 3D printing technology based on extrusion. After 2012, rapid improvements in hardware and software significantly expanded the range of printable materials [4]. In filament-based extrusion, the main advancements can be seen in optimised nozzle temperatures, layer thicknesses, and build orientations. These improvements result in printed parts with enhanced mechanical properties, such as higher tensile strength and reduced porosity. As screw-based 3D printing has evolved, it has become possible to print carbon fiber reinforced materials and biopolymers that cannot be manufactured into filament. These materials can achieve mechanical strength comparable to filament extrusion, while offering improved aesthetics and reduced warping. [7]

2.2 Powder bed fusion

Powder bed fusion (PBF) is a second widely used AM technology. In this method, the material is in the form of a fine powder that is melted into a 3D modelled shape using a heat source [2]. The powder is spread onto the build platform as a thin layer, forming a powder bed to which heat is applied precisely. After each layer is completed, the build platform lowers slightly, and a new layer of powder is deposited on top [8]. By melting the powder layer by layer, the final part is gradually formed.

The most common heat source is a laser, though thermal energy and electron beams can also be used to melt the material. A PBF printer consists of two main chambers: a powder chamber that contains the raw material, and a build chamber where the part is fabricated. The method enables the production of high-quality parts in a cost-effective manner. Because the powder itself acts as a support material, separate support structures are often unnecessary. This reduces the need for post-processing and allows the fabrication of complex geometries without extra support. Additionally, unused powder can be collected and recycled during the process, reducing material waste. A schematic figure of the PBF setup is presented in Figure 3. [8]

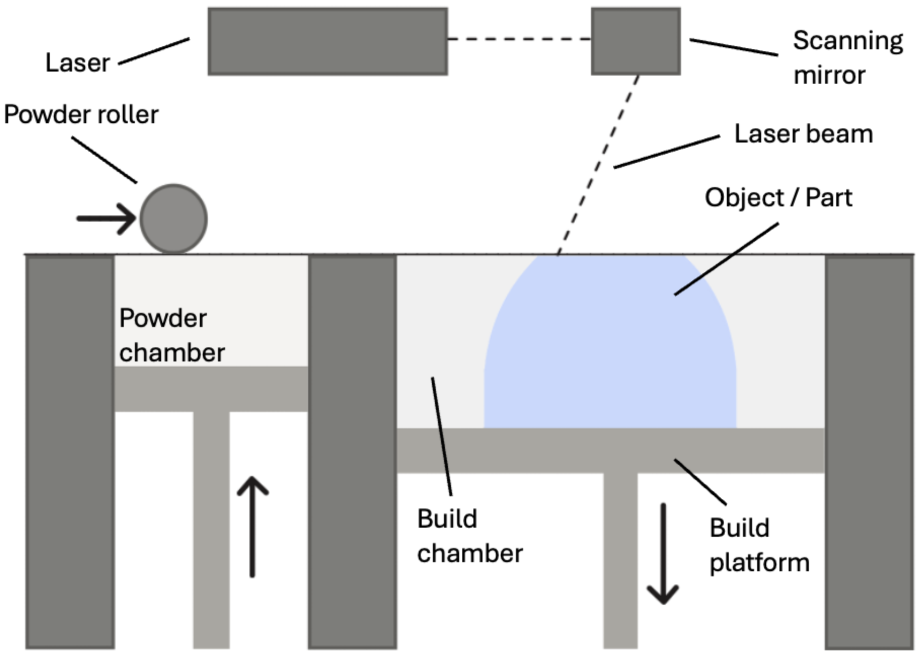

Figure 3. PBF principle

Similarly to extrusion-based 3D printing, the quality and build rate in PBF can also be controlled through process parameters. Studies have shown that the corrosion resistance of the produced parts can be improved by using coarser, water-atomised powders [8]. By optimising process parameters such as scanning speed, layer thickness, and laser power, it is possible to adjust the build rate while maintaining the quality of the final component. [2]

Selective laser melting (SLM) and selective laser sintering (SLS) are two types of PBF [8]. Both techniques use a laser beam to melt the powder material. Despite the similarity, the two processes differ in the extent to which the powder is melted. In SLM, the metal powder is fully melted and then solidified into a dense, solid component as it cools [2]. In contrast, SLS relies on partial melting, where the laser heats the powder particles just enough for them to partially melt and fuse together, forming a cohesive structure.

Due to the need for full melting and high mechanical performance in SLM, this technique is primarily used with metal powder. Common materials include titanium alloys, valued for their strength and biocompatibility, stainless steels for their good corrosion resistance and mechanical properties, and aluminium alloys, which are widely used in the automotive and aerospace industries due to their low weight and favourable thermal properties. In the SLS process, the materials are typically polymer powders such as nylon, as well as composites and ceramics. Both SLM and SLS technologies are widely used in the healthcare sector. SLM has been used in dentistry to manufacture tools related to orthodontic treatments, while SLS enables the production of patient-specific dosages of certain pharmaceuticals [2]. Both methods can produce components with highly complex geometries. [8]

3 Artificial intelligence

Artificial intelligence (AI) is a branch of science for which no universally accepted definition exists, even though the topic has been widely researched. According to Zhang et al. (2021), AI is a project in which knowledge is collected and analysed, and different methods of representing that knowledge are examined to simulate human intellectual activity. AI uses computers to imitate human intelligent behaviour and to teach computers human-like abilities, such as learning, reasoning, and making judgments. [9]

Kaplan et al. (2019) define artificial intelligence as a system with ability to interpret external data, learn from it, and flexibly apply what has been learned to achieve goals [10]. Similarly, Golec et al. (2025) describe AI as an interdisciplinary technology that imitates human intelligence through machine learning [11]. Although these definitions share similarities, such as learning capability and the simulation of human cognition, there is no single comprehensive, and universally accepted definition of AI.

The history of AI experienced a major turning point in the mid-1950s at the Dartmouth Conference, where John McCarthy introduced the concept of AI [9]. In the 1980s, AI began to spread into industry and healthcare, and advances in new neural networks and algorithms enabled significant progress in speech recognition and translation [11]. Since 2006, the field has grown explosively, driven especially by GPU technology that accelerates parallel computing, as well as substantial expansion of data storage capacity. [9]

Machine learning (ML) is a subfield of artificial intelligence in which computers learn from data and improve their performance without the need to be explicitly programmed for each task [1]. The goal of ML is to develop algorithms that identify patterns and structures in data and enhance model performance based on these insights [10]. Deep learning (DL) is a specialised subfield of ML, which uses multilayer neural networks to model complex and high-dimensional data. Neural networks are key computational tools that enable modern AI methods. They function as the central algorithmic structures that implement DL techniques and form a significant, data-driven component of contemporary artificial intelligence. [11]

3.1 Neural networks

Neural networks are mathematical or computational models whose structure simulates the brains of mammals [12]. Unlike biological neural networks, which contain billions of neurons, artificial neural networks (ANNs) are typically limited to only hundreds or thousands of processing units [13]. The basic units of an ANN are called artificial neurons, or nodes, which are connected to each other through edges. The edges model the synapses of biological neural networks. These connections join the artificial neurons into a multilayer neural network. [13]

A multilayer ANN consists of an input layer, one or more hidden layers, and an output layer [13]. The data fed into the ANN moves from the input layer through the hidden layer(s) to the output layer. Figure 4 shows the structure of a simple ANN. The neurons in the input layer receive the incoming data and forward it to the hidden layers, where each neuron processes the information passed on from the previous stage [12]. If the network contains multiple hidden layers, the information flows sequentially through them, with each layer refining the output further before sending it onward. After the final hidden layer has completed its processing, the result is delivered to the output layer, which then forwards the network's final output to an external system, process, or device. [12]

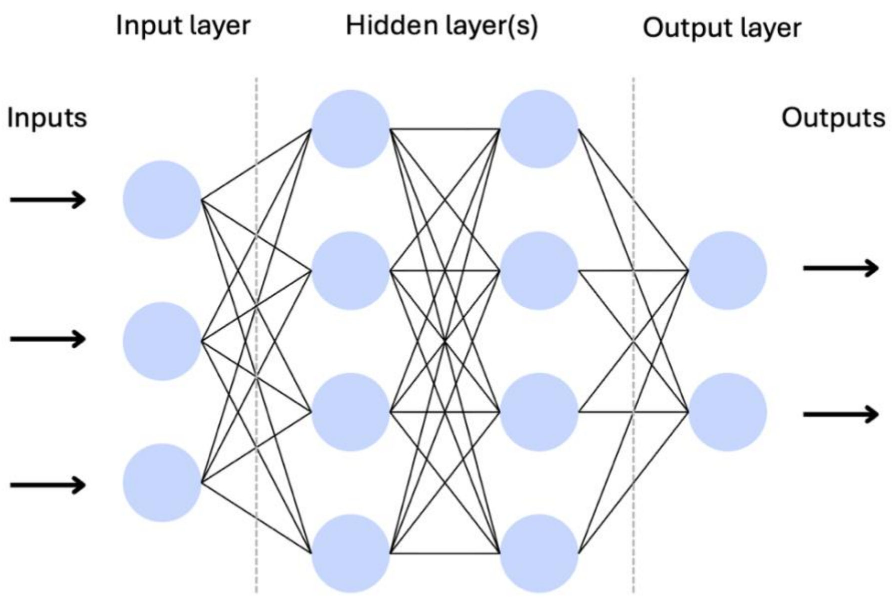

Figure 4. Artificial neural network: input, hidden, and output layers [13]

3.2 Machine learning

Machine learning (ML) is considered to have learned when its performance on assigned tasks improves as it gains more experience through repeated exposure to relevant examples [14]. In this way, ML enables computer models to continually refine their accuracy and adapt their behaviour over time. [15]

ML typically proceeds in stages, beginning with acquiring and preparing the data, then training the model using that data, and finally evaluating its performance with a separate test set [1]. The process begins with data collection, where information can be gathered with cameras or infrared sensors, for example in manufacturing environments. The raw data is then processed during preprocessing, where essential features are extracted, for instance using imaging methods [1]. During training, the model learns meaningful patterns through supervised or unsupervised methods, and neural networks are often central to this process due their ability to model complex phenomena such as feature recognition. After training, the model's accuracy is evaluated using separate test data, and once deployed, it can be used to predict structural deviations or material properties and further improved through continuous feedback. [16]

ML can be divided into four subfields based on their approaches: supervised learning, unsupervised learning, reinforcement learning, and semi-supervised learning. Supervised and unsupervised learning form the core of the field [15]. In supervised ML, a model is trained using labelled data, where observation consists of an input paired with its correct output [11]. This type of data allows the algorithm to learn by comparing its predictions with the actual result. As training progresses, the model gradually improves its ability to generate accurate predictions for new inputs and reduces the gap between predicted and true values. Supervised learning encompasses two main types of tasks: regression and classification. In regression, the aim is to predict continuous numerical values based on the input data [15]. In classification, the model is taught to assign observations to predefined categories according to their features. Both approaches rely on the model's ability to recognise relationships within the labelled data and apply this knowledge to previously unseen examples. These algorithms are used, among other things, to forecast prices in the stock and sales markets. [14]

Unsupervised learning is a ML method in which the model aims to identify and group input data based on their characteristics [15]. Unlike supervised learning, the available data does not contain predefined correct answers or classifications [14]. For this reason, unsupervised learning algorithms do not attempt to predict a specific output, but instead aim to detect structures, regularities, and similarities within the data [14]. One of the key techniques in unsupervised learning is clustering, where data is divided into groups so that the items within the same group are as similar to each other as possible [15]. Another important approach is association analysis, which seeks to discover connections and dependencies between different variables, for example by identifying features that frequently occur together in the same dataset [15]. One application of unsupervised learning is marketing, where data is analysed and used to personalise services for customers. [14]

In reinforcement learning, a model updates itself based on the feedback from the humans or from environment. Learning is driven by feedback: the agent receives rewards or penalties for its actions, gradually learning to make better decisions. The process can be described as earning through trial and error. Reinforcement learning is applied, for example, in autonomous vehicles, where it helps car identify roads and navigate turns. [14]

Semi-supervised learning lies between supervised and unsupervised learning. It uses of both labelled and unlabelled data, typically in such a way that only a small portion of the dataset is pre-labelled while the majority is not. This approach is particularly useful in many practical applications, such as speech recognition, where fully labelled datasets are often limited or costly to obtain. [14]

4 AI in extrusion-based 3D printing

Extrusion-based 3D printing, such as FFF and the printing of liquid bio-based materials, has become an established and versatile manufacturing method. However, a major challenge has traditionally been large number of process parameters and their complex interdependencies, which directly affect the quality, mechanical properties, and dimensional accuracy of the final product. Traditionally, optimal printing settings have been identified using a trial-and-error approach, which is not only time-consuming but also material-intensive and inefficient.

Using AI and ML in AM allows testing and optimising different processing parameters in large scale and more cost-effectively than traditional methods. Various algorithms, such as regression models, decision tree-based methods and AI-driven models like ChatGPT, offer new opportunities for process optimisation and troubleshooting. These developments demonstrate how AI enhance quality control, reduce development time, and support the adoption of new, sustainable materials in manufacturing industries.

4.1 Optimisation of compressive strength in 3D printed biocomposites

PLA is a renewable and biodegradable polymer commonly used in extrusion-based 3D printing, but it is brittle and not strong enough for high loads. To improve its performance, the material is often reinforced, for example, with natural fibres or ceramics. Jayaram et al. aimed to find an alternative raw material to reinforce PLA, and they used ML to determine the optimal 3D process parameters. [17]

In this study, almond shell particles were used as a reinforcing agent for PLA. These natural fiber fillers, which in addition being low-cost and environmentally friendly agricultural by-product, were found in previous studies to improve the mechanical properties of PLA. The compressive strength (CS) of almond shell-reinforced PLA (AmdPLA) components was optimised via FFF. The process parameters selected for optimisation were printing speed (PS), layer height (LH), and printing temperature (PT), as these directly affect interlayer bonding, defect formation, and material flow. All these factors play a crucial role in determining CS, while ML techniques were applied to model and optimise their values with respect to CS. [17]

Different ML methods were compared in terms of their ability to predict CS. Linear and polynomial regression (LR, PR) served as baseline models. In addition, more complex and nonlinear interactions were analysed using support vector regression (SVR), k-nearest neighbours regression (KNN), decision tree regression (DT) and random forest regression (RF) methods. The selected algorithms differ from one another in how they process data, such as in their approaches to dimensionality management, similarity assessment, or the integration of multiple models. These ML techniques and process parameters used in the study are presented in Table 1. [17]

Table 1. ML techniques and optimised process parameters in the study by Jayaram et al. [17]

Category	Method / Parameter	Abbreviation	Details / Range
ML Techniques	Linear Regression	LR	Baseline model
	Polynomial Regression	PR	2nd or 3rd order
	Support Vector Regression	SVR	Non-linear regression
	k-Nearest Neighbours Regression	KNN	Instance-based learning
	Decision Tree Regression	DT	Non-parametric model
	Random Forest Regression	RF	Ensemble method
Process Parameters	Print Speed	PS	10–40 $mm \cdot s^{-1}$
	Layer Height	LH	0.1–0.25 mm
	Printing Temperature	PT	190–220 °C

The results indicated that PR was the most effective model for predicting the CS of PLA and AmdPLA materials. The performance and predictive accuracy of the models were evaluated using the coefficient of determination (R^2), which represents the proportion of variance explained and describes the agreement between the predicted and experimental values [18]. The closer the R^2 value is to one (100%), the more accurately the model represents reality. The PR model achieved an R^2 value of 0.88, indicating excellent predictive performance. In addition, the results demonstrated the print speed was the most significant process parameter in optimising CS. [17]

4.2 ML analysis of parameter impacts on filament spreading in 3D food printing

Pectin is a biopolymer used as a bio-ink, and its concentration can be adjusted to modify its rheological properties, such as viscosity and complex modulus. In the study by

Outrequin et al., pectin ink mixtures were prepared using pectin and deionised water. The pectin inks were produced at concentrations ranging from 5 to 15 wt%. A low ink concentration results in low viscosity, and the weak rheological resistance of the material is insufficient to maintain the shape of the printed structure after extrusion. [18]

The aim of the study was to control the spreading of the printed pectin-based food ink by optimising process parameters during printing. In addition to the material properties, the spreading ratio, defined as the ratio between the printed line width and the nozzle diameter, is influenced by key process parameters such as nozzle diameter, extrusion pressure, and printing speed. By adjusting these parameters and using ML techniques, the goal was to develop a predictive model capable of identifying the optimal printing conditions for each concentration. The objective was to minimise unwanted deformation after extrusion and to ensure the geometric accuracy of the printed structure. [18]

By applying supervised learning, the dependence between the spreading ratio and the process parameters was modelled so that the algorithm learns from example data to predict filament behaviour under new parameter conditions. The modelling relies particularly on decision tree-based regression models. Through these models, it is possible to determine the key parameters governing ink spreading and building a reliable tool for selecting optimised printing conditions for different pectin concentrations. Table 2 presents these ML techniques and process parameters used in the study. [18]

Table 2. ML techniques and optimised process parameters in the study by Outrequin et al. [18]

Category	Method / Parameter	Abbreviation	Details / Range
ML Techniques	Decision Tree Regression	DT	Non-parametric model
	Random Forest Regression	RF	Ensemble method
	Extra Trees Regression	ET	Extremely randomized trees
	Gradient Boosting	GBR	Iterative ensemble method
	Extreme Gradient	XG	Scalable tree boosting
Process Parameters	Nozzle Diameter	D_0	0.4–0.8 mm
	Extrusion Pressure	P	0.5–1.5 bar
	Nozzle Movement Speed	V	10–40 mm·s^{-1}
Rheological Parameters	Complex Modulus	G_0^*	Angular frequency of 1 rad·s^{-1}
	Power-law Exponent	n	Frequency dependence of G_0^*

The results demonstrated that the ET model is a highly effective tool for predicting the filament spreading ratio in extrusion-based 3D printing. The model utilises four key input variables and achieved a high R^2 value (0.9775). Compared to traditional random forest models, the ET approach introduces more randomness by randomly selecting the split threshold values from the feature range and training each tree on the entire dataset. This reduces the variance of the model and improves its overall performance. The feature-importance analysis revealed that the rheological properties of the material dominate the outcome, accounting for more than 92% of the prediction, while the influence of the process parameters was approximately 8%. Thus, the four-variable ET model provides a highly reliable method for optimising both the printing process and ink formulation in order to achieve precise filament geometry. [18]

4.3 ChatGPT capabilities of improving AM troubleshooting

Badini et al. investigated the applicability of the ChatGPT, which is a large language model based on ANNs, for addressing challenges in AM, with particular focus on optimising G-code and process parameters for the FFF process. G-code is a fundamental control mechanism in FFF printing, as it defines the printer's movements and process parameters in detail on layer-by-layer basis and enables the communication between the slicing software and the printer. It is a set of instructions that tells a 3D printer exactly how to print an object. It is the code that is produced during the 3D object slicing. The objective of the study was to evaluate whether ChatGPT can identify FFF printing issues and optimise process parameters and G-code in a way that improves print quality while reducing time and material consumption. The optimisation was carried out using a question strategy, where ChatGPT was asked open-ended questions that focused on general FFF problems, problems with specific materials, and problems with specific boundary conditions (temperature, printing speed, etc.). [19]

The material examined in the study was thermoplastic polyurethane (TPU), which is flexible but prone to typical FFF-related defects such as warping, detachment from the build platform during fabrication, and stringing. Warping refers to curling, lifting, or distortion of a printed part away from the build platform, often visible as the edges or corners bending upward. This typically leads to reduced bed adhesion and geometric inaccuracies. Stringing means the formation of unwanted thin strands of material that accumulate between separate features of the printed part. This defect degrades surface quality and mechanical performance and often required post-processing to remove the excess strings. The objective of the optimisation was to eliminate these three major defect types by adjusting G-code-controlled process parameters using ChatGPT. [19]

The results demonstrated that ChatGPT is capable of correctly identifying key FFF printing issues and that it can present solutions in a hierarchical and logically structured manner, starting from the simplest and most effective corrective actions. To reduce warping, ChatGPT optimised the process parameters by, among other things, increasing the bed temperature and reducing the printing speed. Detachment of the part from the build platform was further mitigated by lowering the printing speed, adjusting the bed temperature, and increasing the thickness of the first layer. Stringing was mainly controlled by reducing the retraction and lowering the nozzle temperature. ChatGPT was able to optimise the process parameters in approximately one hour, whereas a comparable experimental optimisation would have required about three weeks. This resulted in significant time savings, a substantial reduction in material waste, and a more efficient product development process. Figure 5 shows how much optimised process parameters affect the quality of the final product. [19]

A B

Figure 5. 3D printed samples using (A) "not-optimised" and (B) "optimised" ChatGPT G-code. Reproduced from Badini et al. [19]. Copyright 2023, published by Advanced Industrial and Engineering Polymer Research.

5 AI in powder bed fusion

PBF is a widely applied AM technology for producing high-density, high-performance metal components with complex geometries. The quality of parts manufactured by the process are highly sensitive to process parameters such as laser power, scanning speed and hatch distance. These parameters exhibit strong and nonlinear interdependencies that directly influence e.g. relative density, microstructure, and mechanical properties. As a result, identifying optimal processing windows using conventional trial-and-error approaches is costly and time-consuming. The following sections present case studies in which different AI- and ML-driven approaches are applied to the optimisation of PBF processes for metallic alloys, highlighting their effectiveness in enhancing part quality and manufacturing efficiency.

5.1 ANN-driven optimisation of laser PBF of titanium alloy

Ti-5Al-5V-5Mo-3Cr titanium alloy (Ti-5553) is a standard alloy widely used in the aerospace industry. It is particularly suitable for structural applications that require high strength combined with good processability. The alloy is formable at elevated temperatures and exhibits good corrosion resistance. Shin et al. employed this alloy in their study to investigate how relative density of Ti-5553 parts fabricated by laser powder bed fusion (LPBF) can be predicted and maximised using AI based methods. Relative density describes how effectively the powder has melted and consolidated during laser processing. It also reflects the extent to which defects such as porosity, nonmelted powder particles, and lack-of-fusion interfaces are minimised during fabrication. Lack-of-fusion interfaces mean planar regions where two adjacent melt tracks or successive layers failed to fuse together, leaving a bond line rather than a continuous solid. The Ti-5553 powder used in the study consisted of spherical particles with a particle size distribution suitable for the LPBF process, enabling uniform layer formation and stable processing conditions. [20]

In the study, an ANN based model was developed to predict the relative density of Ti-5553 components produced via LPBF. The process parameters optimised in the ANN model were laser power (the amount of laser energy the LPBF laser emits per unit time), scan velocity (the speed of the laser beam across the powder bed chamber), and hatch distance (spacing between adjacent melt tracks). The ANN was trained via supervised learning, in which the model learns the relationships between input parameters and output responses to predict the relative density as accurately as possible. [20]

The ANN model developed in the study achieved very high predictive accuracy. The model performance was evaluated using the root-mean-square-error (RMSE) of the validation dataset, which was 0.1066%. Since RMSE is minimised for better model performance, this low value confirms the excellent agreement between the ANN model and experimental data. Statistical analysis conducted in the study demonstrated that laser power was clearly the dominant process parameter in the optimisation of relative density. The ANN-driven optimisation confirmed that increasing laser power is a key factor in achieving near-fully dense Ti-5553 components, while the developed simultaneously provided reliable and accurate predictions of relative density. [20]

5.2 ML-enhanced quality and productivity in LPBF of AISI 316L-2.5%Cu

The aim of the study conducted by Moradi et al. is to improve the quality of AISI 316L-2.5%Cu components manufactured by LPBF, while simultaneously increasing production efficiency. The investigated material is AISI 316L stainless steel, to which 2.5 wt% copper has been added in this work. Copper is alloyed with AISI361L for three main reasons: antibacterial activity, thermal-conductivity-driven microstructural refinement, and mechanical strengthening. These effects give the alloy better process control and higher hardness without compromising the corrosion resistance of the base stainless steel. [21]

One of the key material properties examined in the study is relative density, which is used directly as a measure of defect content in the manufacturing process. Relative density enables the evaluation of porosity in the manufactured components, which has a significant influence on the quality, mechanical properties and applicability of the manufactured components. In the study, seven supervised ML models were trained to predict and optimise relative density using different combinations of process parameters. The models were used to optimise three key LPBF process parameters: laser power, scanning speed, and hatch distance. The objective of the ML models was to identify a parameter window that enables the achievement of high relative density while simultaneously improving production efficiency, thereby allowing a balance between component quality and manufacturing speed. The ML methods and process parameters used in this study are presented in Table 3. [21]

Table 3. ML techniques and optimised process parameters in the study by Moradi et al. [21]

Category	Method / Parameter	Abbreviation	Details / Range
ML Techniques	Bayesian Regression	BR	Probabilistic linear regression
	Decision Trees Regression	DTR	Non-parametric model
	Gradient Boosting Regression	GBR	Iterative ensemble model
	Gaussian Process Regression	GPR	Probabilistic, kernel-based
	k-Nearest Neighbours Regression	KNN	Instance-based learning
	Random Forest Regression	RFR	Ensemble method
	Support Vector Regression	SVR	Kernel-based regression
Process Parameters	Laser Power	P	100–340 W
	Scanning Speed	v	400–1000 $mm \cdot s^{-1}$
	Hatch Distance	h	0.10–0.20 mm

The study demonstrated that among the trained ML models, SVR clearly outperformed the others in predicting and optimising the material's relative density. Using the SVR model, it was possible to identify a process parameter combination that resulted in very high component quality and low defect content. The optimised process parameters were also found to influence the material's hardness, and the addition of copper was shown to significantly enhance the hardness of AISI 316L. According to the study results, laser power was the most dominant individual process parameter governing relative density and reducing defect formation. Scanning speed and hatch distance functioned alongside laser power as adjustment parameters, enabling fine control of energy input and melting conditions. Furthermore, analyses related to scanning speed indicated that the highest relative densities were achieved only when the laser power was within an optimal range, emphasising the primary role of laser power in process optimisation. [21]

6 Conclusions

The integration of AI-based methods into AM represents a significant step forward compared to traditional manufacturing methods in industry. The shift towards data-driven optimisation enables the control of complex manufacturing processes in a way that traditional experimental methods cannot match. AI not only provides the means to precisely adjust individual process parameters but also enables more comprehensive quality assurance and improved resource efficiency, which is essential for modern sustainable production.

Research shows that by utilising AI methods, such as ML and neural networks, significant advantages can be achieved in the speed of product development. When critical variables of the AM process, such as temperature, print speed and energy input, are optimised based on AI-based models, material waste and expensive trial-and-error experiments can be reduced at the same time. The more efficient use of materials is directly reflected in cost savings and reduced environmental impacts for companies. In addition to saving resources, the acceleration of product development in AM enabled by AI supports the production of individualised and customer-specific products.

The ability of AI-based methods to find nonlinear dependencies in input data is a key factor in the optimisation, prediction, and quality management of complex processes in additive manufacturing. Studies showed that AI models were able to predict key material and process properties and identify the most critical process parameters that affect the quality of the final product. It was also found that AI can be effectively utilised in identifying and correcting process errors. These capabilities make it possible to increase efficiency and improve production and reduce errors. Predictive analytics enables the detection of deviations at an early stage, which reduces the number of failed parts and supports quality management.

Despite these opportunities, there are also challenges in exploiting nonlinear dependencies, especially from the perspective of their interpretability. Although AI models are able to identify complex connections between input parameters and outcomes, the underlying cause-and-effect relationships of these dependencies can remain unclear. It is difficult to distinguish or explain the impact of individual variables on the outcome in an unambiguous way. This reduces the transparency of the models and can limit their reliable application, especially in medical applications, where precise quality assurance and compliance with standards are key.

AI models need a lot of high-quality data to function reliably, as their performance is directly dependent on the amount and quality of data available. If the data is incomplete or contains errors, the predictions of the models may be inaccurate or misleading. Furthermore, in AM, the variability of different devices, materials, and process conditions can limit the generalisability of the models, so that a model trained on one dataset may not work reliably in all cases. This can mean that models have to be adapted or retrained on a device or process-specific basis, which is time-consuming and resource-intensive. These challenges highlight the importance of careful data pre-processing and analysis, as well as the need for in-depth process understanding. Effective use of AI therefore requires strong expertise in manufacturing processes.

Although it is already possible to 3D print a wide range of different materials today, in the future, AI-based optimisation methods could significantly accelerate the introduction of new and sustainable materials in AM by reducing the need for extensive experimental tests. In the future, it could also be possible for new materials to be developed using AI directly for use in 3D printing, rather than in traditional manufacturing methods. In addition, in the future, it could be possible to integrate AI methods into the control systems of 3D printers. Since AI models learn from the data fed to them, 3D printers could be able to learn from each print and thus adjust parameters in real time and identify potential errors proactively. This would further improve the stability of the process and the quality of the final products.

Although the use of AI could make production processes more efficient in the future, its use is associated with environmental challenges. The training and use of AI require significant amounts of resources, such as energy and clean water. On the other hand, AI-based optimisation can reduce material waste and thus reduce the environmental impact of manufacturing processes that consume a lot of water, in particular. Therefore, the overall sustainability impacts of AI must be examined holistically, considering both the savings achieved and the environmental impacts of its use.

If AM processes were to become self-learning in the future, this would inevitably affect the nature and amount of work done by humans. Although the operation of AI systems will continue to be light and their development and use require expert knowledge, the role of humans would shift even more from manual process control to monitoring, interpreting and developing systems. Such a change highlights the importance of multidisciplinary expertise. On the other hand, this can also be considered a major concern, as advanced and self-learning AI systems could replace a significant part of the work done by humans in AM processes in the future.

In summary, AI can help AM field use fewer resources and create new possibilities. Studies have shown that data-driven optimisation can enhance process controllability, predictability, and quality in ways that traditional experimental approaches cannot achieve. However, large-scale implementation requires careful consideration, particularly regarding data quality, system reliability, and environmental impacts. AI is therefore not a universal solution, but its effective use depends on informed application and collaboration between humans and intelligent systems.

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