Selection and Optimization of Additive Manufacturing Process Parameters using Machine Learning: A Review

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Abstract. Process Parameters are crucial in controlling the properties of additive manufacturing (AM) products based on the complex nature of AM technologies. Traditional methods are being replaced by machine learning (ML) in the selection and optimization of AM process parameters due to the comprehensive features of ML. While several review studies have been conducted to search for different solutions in the field, most of these reviews are limited to a single AM technique. This paper aims to provide a comprehensive general overview of the latest developments in AM parameter selection and optimization using ML methods. By synthesizing review ML applications in various AM techniques, this paper offers valuable insights into advancements and trends in parameter selection and optimization using ML for a deep understanding and informed decision-making in the field.

Keywords: Additive Manufacturing (AM), 3D Printing, Parameter Optimization, Machine Learning, Artificial Intelligence.
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1 INTRODUCTION

Additive manufacturing (AM) has transcended its initial role in product prototyping for an integral part of the manufacturing process, which reshapes the production landscape with AM transformative capabilities. Through the additive process of building objects layer by layer from digital designs, AM stands in stark contrast to traditional subtractive manufacturing methods that rely on material removal from solid blocks [1]. This fundamental difference not only unlocks new possibilities for design complexity and customization but also introduces unparalleled efficiency and flexibility into the manufacturing workflow.

The versatility of AM extends across processing a wide range of materials, including composites, ceramics, and metals, further broadening its applicability in diverse industries. In sectors such as aerospace, automotive, healthcare, and consumer goods, AM has emerged as a game-changer, enabling the fabrication of intricate prototypes, customized medical implants, lightweight aerospace components, and more [2].

The ability to manipulate different materials at a microscale level and construct complex geometries with precision has revolutionized product development and manufacturing processes, driving innovation, and unlocking new opportunities for advancement across various industries [3]. In recent years, significant advancements in AM technologies have propelled the industry towards high levels of accuracy, reliability, and cost-effectiveness [1].

Innovations in material science, machine tools, and software algorithms have led to AM encompassing a broad spectrum of technologies and materials, each uniquely suited to different applications and research objectives. This diversity in AM technologies, ranging from Fused Deposition Modeling (FDM) and Stereolithography (SLA) to Selective Laser Sintering (SLS) and Direct Metal Laser Sintering (DMLS), stems from the need to accommodate varying design requirements, material properties, and end-use functionalities [1]. For instance, FDM is typically employed for rapid prototyping and plastic parts due to its cost-effectiveness and ease of use [12], while DMLS is preferred for producing high-strength, intricate metal components essential in aerospace and medical applications. Similarly, SLA is favored for its precision and surface finish, making it ideal for detailed prototypes and molds [32]. The broad range of materials used in AM, including polymers [33], metals [44], ceramics, and composites [2], further enhances its applicability across diverse industries, enabling the creation of products with specific mechanical, thermal, and chemical properties. This technological and material versatility is crucial in applications as it allows users to tailor their approaches to the unique demands of their projects, thereby advancing innovation and expanding the potential of AM in various fields. Table 1 outlines the key AM technologies, their working principles, types of materials they process, and their primary applications.

AM Technology	Working Principle	Materials	Applications
Fused Deposition Modeling (FDM)	Extrudes thermoplastic filaments layer by layer through a heated nozzle	Thermoplastics (e.g., PLA, ABS)	Rapid prototyping, plastic parts
Stereolithography (SLA)	Cures liquid photopolymer resin layer by layer using a UV laser	Photopolymers	Detailed prototypes, molds
Selective Laser Sintering (SLS)	Uses a laser to sinter powdered material, binding it together to create a solid structure	Polymers, composites	Functional prototypes, low-volume production
Direct Metal Laser Sintering (DMLS)	Melts metal powder layer by layer using a high-powered laser	Metals (e.g., titanium, aluminum)	High-strength components, aerospace, medical implants
Binder Jetting	Deposits a liquid binding agent onto a powder bed to create layers	Ceramics, metals, sand	Complex geometries, custom manufacturing
Electron Beam Melting (EBM)	Uses an electron beam to melt metal powder layer by layer	Metals (e.g., titanium alloys)	Aerospace, medical implants
Material Jetting	Jets droplets of photopolymer or wax material layer by layer, curing with UV light	Photopolymers, wax	High-detail models, casting patterns
Laminated Object Manufacturing (LOM)	Layers of adhesive-coated paper, plastic, or metal laminates are bonded together and cut to shape	Paper, plastics, metals	Low-cost prototypes, structural models
Digital Light Processing (DLP)	Uses a digital light projector screen to flash a single image of each layer across a resin surface	Photopolymers	High-resolution parts, dental applications

Table 1: Major AM technologies and their differences [1].

Differentiating AM technologies based on their working principles provides a clear understanding why various methods are employed across different applications. Each AM technique offers unique capabilities, material compatibilities, and application advantages, making it essential for users to select the appropriate technology for their specific objectives. This diversity in AM technologies underscores the broad applicability of AM in advancing innovation across multiple industries.

The selection of the right set of parameters and their optimization governs the AM fabrication process [4]. Parameters such as layer thickness, build orientation, scanning speed, laser power, and material composition are significant in shaping the mechanical properties, surface finish, and dimensional accuracy of printed components. The careful selection and optimization of the parameters is significant for the quality, efficiency and economic feasibility of the AM process [5].

Traditionally, engineers and researchers relied on conventional methods such as the design of experiment (DOE) [22], Taguchi method [3], response surface methodology (RSM), trial-and-error method, and heuristic approach to determine optimal parameter settings for AM [47]. While effective to some extent, these conventional methods are time-consuming, resource-intensive, and often result in suboptimal outcomes due to the complex interdependencies among various parameters. As the demand for faster production cycles and higher quality standards intensifies, there arises a pressing need for more efficient approaches to the parameter selection and optimization in AM.

In recent years, Machine Learning (ML) has emerged as a powerful tool for addressing the challenges associated with the parameter optimization in AM. By leveraging large datasets, advanced algorithms, and computational modeling techniques, ML algorithms can analyze complex patterns, identify optimal parameter configurations, and iteratively refine process parameters to achieve desired performance objectives [9]. The integration of ML techniques into the AM workflow holds immense potential to revolutionize the way that researchers approach parameter optimization, leading to faster production cycles, improved part quality, and enhanced cost-effectiveness [10].

Several studies provide insights into correlations between processing parameters and mechanical properties in AM [12,15,25]. Additionally, research delves into laser powder bed fusion (L-PBF) and utilizes ML for anomaly detection, demonstrating ML potential to enhance the real-time control and optimization in metal AM processes [14]. Toprak et al. conducted a review of contemporary trends in optimizing process parameters in the metal powder bed fusion (M-PBF) to analyze their impact on part properties [44]. Wang et al. and Jin et al. reviewed ML roles in correlating process, structure, and property in AM, systematically analyzing data-driven modeling, including input features, outputs, data sources, models, limitations, and future research directions [8,16].

Different reviews have delved into the realm of parameter optimization in specific AM techniques, such as Powder Bed Fusion (PBF) [44] and Fused Deposition Modeling (FDM) [12]. These reviews provide insights into intricacies of the parameter selection and optimization tailored to nuances of individual AM processes. For instance, some studies have specifically explored the utilization of ML for the parameter optimization in Powder Bed Fusion AM [44], where the focus lies on optimizing parameters like the laser power, scanning speed, and powder bed temperature to enhance the part quality and build efficiency. Similarly, other reviews have concentrated on FDM, discussing methods to optimize parameters like the layer height, nozzle temperature, and infill density to achieve desired mechanical properties and surface finish in printed parts [12,39]. While these focused reviews offer valuable insights into the parameter optimization within specific AM domains, there remains a need for a more holistic perspective that transcends boundaries of the individual AM processes.

The aim of this paper is to provide a broader review of the parameter selection and optimization in AM, covering various AM techniques under a unified framework. By reviewing existing knowledge and drawing parallels across different AM processes, this paper seeks to explain common challenges, methodologies, and opportunities for leveraging ML techniques in the parameter optimization across AM. Rather than limiting into the specifics of any single AM technique, this review is to present a comprehensive overview of parameter optimization principles that are applicable across diverse AM techniques, thereby offering valuable insights for researchers in the realm of AM and ML.

The following parts of the paper are organized as follows. Section 2 introduces our review methods. AM parameters are introduced in Section 3. AM parameter selection methods are discussed in Section 4. Key challenges in ML-based parameter selection are explored including trade-offs, model selection, and data considerations in Section 5, followed by discussion and conclusion in Sections 6 and 7, respectively.

2 REVIEW METHOD

Literature is selected for review based on relevance, credibility and recency. The critical analysis and discussion are integrated to understand methodologies and implications of ML in AM parameter selection. This structured approach aims to offer valuable insights for researchers and practitioners in the field.

In compiling the review on the selection and optimization of process parameters in AM using ML, we carefully made a diverse selection of reviewed papers to ensure the relevance and quality. The collected papers stem from an initial pool of 160 papers, identified through keywords related to additive manufacturing, 3D printing, parameter optimization, machine learning, and artificial intelligence. Following rigorous screening based on the title relevance and abstract assessment, 100 papers are shortlisted. Ultimately, 50 reputable papers are carefully selected to form the core content of this review, ensuring a comprehensive exploration of the intersection between AM technologies and advancements in ML and AI.

As shown in Figure 1(a), the data collection yields contributions from various reputable databases and platforms. Notably, 20% of the collected papers are from the Web of Science, reflecting a comprehensive exploration of interdisciplinary research within the scientific community. 30% of the papers are sourced from Scopus for a broad representation of scholarly literature, emphasizing the significance of AM in engineering and technology disciplines. Additionally, 15% of papers are from IEEE Xplore, underscoring the importance of ML applications in advancing AM technologies. ScienceDirect provides another substantial portion, contributing 20% of the selected papers, demonstrating the platform wealth of research on AM and ML integration. Furthermore, 5% of papers are from PubMed, highlighting the emerging interest in biomedical applications of AM. Finally, 10% of the selected papers are from other databases and platforms, ensuring a comprehensive overview of the field. Through this careful selection process, we aim to provide readers with a comprehensive understanding of the intersection between AM process parameter optimization and ML.

Figure 1(b) shows the distribution of the collected papers in years. It reflects a comprehensive exploration spanning the last seven years, highlighting the evolving landscape of AM research. With a notable surge in publications from 2022 onwards, comprising 17.78% of the total, followed by a dominant presence in 2023 and 2024, accounting for 46.67% and 20% respectively, it is evident that recent years have witnessed a substantial focus on AM advancements. The distribution underscores the significance of staying informed of the latest research developments in this rapidly evolving field, providing insights into emerging trends and areas of innovation.

3 AM PARAMETERS

AM parameters are critical for the part quality, structural integrity, and functionality, they should be carefully selected in the AM process. They have significant impacts on the 3D printing efficiency and overall quality of the manufactured part [4]. Meticulous control and optimization of these parameters are essential for advancing AM capabilities and applications, fostering continual evolution in quality assurance, design innovation, and manufacturing efficiency.

AM techniques represent a significant advancement in modern manufacturing, offering versatile capabilities across various industries. Parameter optimization is a crucial aspect of AM processes, regardless of the specific technique employed. Factors such as gas circulation, energy source characteristics (e.g., laser power or electron beam energy), scanning speed, and scanning strategy greatly influence the final properties and quality of printed parts. These parameters play a vital role in determining the structural integrity, surface finish, and dimensional accuracy of the manufactured components. Thus, meticulous adjustment and control of these parameters are essential for achieving optimal results and meeting the desired specifications in AM applications [19].

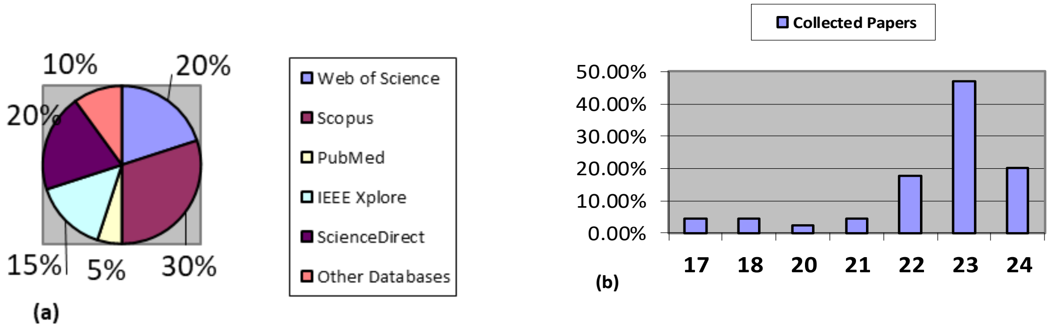

Figure 1: (a) Contribution of databases, (b) Paper distribution by publication years.

Table 2 outlines the key parameters in AM, their definitions, and properties they affect. In AM processes, these parameters play crucial roles in determining the quality, properties, and efficiency of the AM process. For instance, the layer thickness dictates the resolution and building time of the printed object, with thinner layers typically resulting in finer details but longer printing time [20]. Printing speed influences both building time and surface roughness, as higher speeds can lead to smoother surfaces but may compromise part integrity. Temperature control is vital for ensuring the proper material adhesion and minimizing warping or distortion during printing [9].

Parameter	Definition	Property Affected	Reference
Layer Thickness	Thickness of each layer deposited during printing	Surface finish, Resolution, Build Time	[2,51,25,11]
Printing Speed	Speed at which the printing head moves during deposition	Build Time, Surface Roughness, Warping	[51,25,11]
Temperature	Temperature of the printing environment or material during printing	Material Strength, Adhesion, Warping	[51,25,11,33]
Material Composition	Composition of the material used for printing	Mechanical Properties, Material Cost	
Infill Density	Density of infill material inside the printed object	Strength, Weight, Material Consumption	[2,25,11]
Cooling Rate	Rate at which the printed object is cooled after deposition	Warping, Cracking, Material Properties	[31]
Support Structure	Additional material added to support overhanging features during printing	Printability, Surface Finish, Time	[44]
Build Orientation	Orientation of the printed object relative to the build platform	Strength, Surface Finish, Warping	[31,10]
Nozzle Diameter	Diameter of the nozzle used for material deposition	Resolution, Extrusion Rate, Print Quality	[46]
Layer Adhesion	Adhesion strength between	Strength, Delamination,	[45]

	consecutive layers	Surface Quality

Table 2: Key AM parameters.

Material composition directly affects the mechanical properties and cost of the final product, making the material selection a critical decision. Infill density impacts the part strength and weight, with denser infill providing a greater structural integrity but consuming more material [20]. Cooling rate affects the rate of solidification and can impact part properties such as warping and cracking. Support structures are necessary for printing overhangs and complex geometries but can affect the surface finish and printability. Building orientation influences the part strength, surface finish, and warping tendencies, while the nozzle diameter determines printing resolution and extrusion rate [22]. The layer adhesion strength is crucial for ensuring part integrity and preventing delamination between printed layers. Understanding and optimizing these parameters are essential for achieving desired outcomes in terms of the part quality, strength, surface finish, and production efficiency in AM processes.

4 SELECTION OF AM PARAMETERS

4.1 Traditional Methods

Traditionally, engineers and researchers have relied on various conventional methods to determine optimal parameter settings for AM. These methods include Design of Experiments (DOE), Taguchi method, Response Surface Methodology (RSM), trial-and-error, and heuristic approaches.

Design of Experiments (DOE) systematically varies parameters within predefined ranges to observe their effects on part quality and select optimal settings [22]. Taguchi method employs orthogonal arrays to efficiently explore parameter combinations and identify influential factors while minimizing experimental runs [32]. Response Surface Methodology (RSM) utilizes mathematical models to optimize parameters and predict part properties based on experimental data [47].

In the trial-and-error approach, engineers manually adjust parameters based on empirical knowledge and experience, iteratively refining settings until satisfactory results are achieved. Similarly, the heuristic approach relies on rule-based systems or heuristics to guide parameter adjustments according to predefined rules or expert judgment [5].

While these traditional methods have been valuable to some extent in optimization, they are often labor-intensive, time-consuming, and limited in their ability to account for complex interactions between variables [30]. As the demand for efficient and effective parameter optimization in AM continues to grow, there is increasing interest in leveraging advanced techniques such as machine learning to automate and enhance the optimization process, offering greater efficiency, accuracy, and adaptability to changing manufacturing conditions [10].

4.2 Machine Learning in AM Parameter Selection

Table 3 summarizes applications of ML in AM parameter selection and optimization. It shows that supervised ML predominates in ML applications due to its practicality despite the inherent complexities in AM processes hindering the full exploitation of ML potential. Other ML methods such as unsupervised ML and reinforcement learning (RL) have been explored. Unsupervised learning has been used for the defect detection [11], while RL has been employed for the toolpath optimization [31]. Furthermore, ML techniques have been applied to discern trends in high-dimensional datasets and identify patterns within manufacturing processes, demonstrating potential across diverse applications [10].

ML models, categorized as surrogate models, represent valuable tools for investigating non-linearities and can yield favorable outcomes with simulated or empirical datasets alike [29]. Training data can tune ML models. The AM process is quite complex involving multiple factors and parameters. To tackle this complexity, significant resources have been allocated to create databases filled with data that can be used in ML systems. These ML systems combine modern data driven techniques with traditional physics-based methods to make predictions [30]. For ML models to perform effectively, they rely heavily on receiving appropriate training data. In the context of AM, the process can typically be broken down into three main steps, process design, material design and part design. Each of these steps present unique considerations for selecting the most suitable ML methods and algorithms, but here we will only focus on applications of ML for the parameter selection and optimization [31].

Table 3 serves as a valuable reference for understanding the interaction between ML techniques, AM parameters, and resultant part qualities in the context of AM processes. It provides insights into how different ML algorithms can be leveraged to optimize AM processes and predict desirable part qualities, thereby contributing to advancements in AM technology.

Parameters Observed	**ML Technique**	**Target Property**	**Cons**	**Pros**	**Ref.**
Infill percentage, layer height, infill pattern, & wall thickness	KNN, SVM, DT, RF	Mechanical Strength	Linear relationship between the properties and parameter.	Performs well for linear relationship of parameter and properties	[2]
Powder size	KNN, RF	Fatigue life			[6]
Printing temperature, layer thickness, printing speed	EL	Strength, stiffness, ductility	A change in one parameter can trigger negative change in another property	Performs better within specific conditions	[51]
Fiber layers, concentric carbon-fiber rings, infill pattern	EL	Flexural strength	Only limited to the given parameters	The model is flexible to be adopted for predicting other properties	[50]
Nozzle temperature, printing speed, part cooling, part orientation	DCT, RFR, extra tree regressor, random boosting regressor	Young's modulus, tensile strength	Part orientation is dictated generally by part geometry	The model can be applied to other AM techniques like FLM	[33]
Infill Percentage, Layer Height, Print Speed, Extrusion Temperature	Logistic Classification, Gradient Boosting Classification, DT, KNN	Ultimate tensile strength	The study is limited to linear relationship between parameter and properties	The study demonstrated the use of classification models.	[30]

Location, orientation	KNN, SVM, RF, DT	Strain	Limited range of targeted properties	Better accuracy in prediction	[10]
Gas circulation, laser power, scan speed, scan angle	Multi-objective Bayesian optimization	Surface roughness, microhardness	Performance is highly dependent upon quality of initial dataset	It can be trained with smaller data	[9]
Laser power and scan speed	LR, DTR, RFR, MLP	Melt pool, density	MLP is limited to power and speed in specific ranges	MLP can predict the properties in the specific range of parameters	[23]
Laser power, scan speed, hatch spacing parameters	NN	Relative density, surface roughness, microhardness	Data quantity affects the performance of ML model	Reduces preprocessing time and cost	[43]
Scanning velocity, laser power, hatch distance, layer thickness	NN	Fatigue life	The study is limited to specific material	Not limited to specific optimization problems	[7]
Nozzle temperature, printing speed, layer height	LR, RF, LGBM, XGB, ANN	Tensile strength	Data variability due to data collection from different articles	Using data from existed articles	[11]
Nozzle temperature, layer thickness, printing speed, wall thickness	ANN, GA	Surface roughness	Ability to work with different ML techniques	Validated the use of hybrid models	[28]
Laser power, scanning speed, hatch spacing, layer thickness, sample direction	NN	Yield strength & ultimate tensile strength, Elongation	The study is based on data from literature and can be vulnerable to variance	Laser power, scanning speed, hatch spacing, Layer thickness and sample direction.	[27]
Wire feeding speed, travel speed	NN, GA	Tensile strength	High level of complexity	Additional parameters can be included in the observation	[45]

Print temperature, print speed, cooling fan speed	NN	Printable bridge length	The study is limited to FDM	The study claims to be the first study on PBL	[18]
Print speed, layer height, nozzle diameter, extrusion volume	NN	Material extrusion	The study needs to be validated to be used for other parameters	It can perform real-time print optimization on other materials systems	[38]

Table 3: ML techniques used for AM parameter selection and optimization.

Integration of ML holds promise to improve precision and efficiency of AM process through the optimization of critical parameters [16]. Recent research recognizes the potential of ML in optimizing process parameters for AM to predict the mechanical properties of AM parts. Based on the published research papers, the supervised machine learning method dominates ML applications in the AM parameter optimization [32].

Supervised ML can use Regression and classification models and Neural Networks for the AM parameters optimization. Regression models understand and quantify the relationship between one or more independent variables and a continuous dependent variable by analyzing historical data to predict future outcomes or understand changes in one variable to affect another [6], while the classification model categorizes data into predefined classes based on their features. The model is trained on labelled data sets, each of which is associated with a class label. The model identifies patterns and relationships within the data to accurately identify new unseen instances through the learning process [20].

Mechanical behavior analysis in AM searches solutions to improve the compressive strength and tensile strength of 3D printed components. Agarwal et al. investigated impact of the parameter optimization on the compressive strength of PLA-based surgical orthopedic cortical screws, utilizing parameters such as the infill percentage, layer height, infill pattern, and wall thickness [20]. The parameters were selected based on the targeted property to be predicted, for instance, the porosity of the printing structure is dictated by the infill density, and the height is defined by the layer thickness. Comparing K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree, and Random Forest, the study revealed that Random Forest outperformed others in the parameter prediction. It found that the infill pattern and infill percentage are the most influenced parameters while the layer height being the least influential. KNN and RF ML models were used because of their simplification and the ability to handle complex and non-linear data [50].

Mishra et al. also used KNN, DT, and logistic regression (LR) to predict the ultimate tensile strength of PLA [23]. They labelled the data with for the ultimate tensile strength less than 80%, and 1 for 80% and above. The study finds that KNN performs better. Another study also found KNN performing better in comparison to SVM, RF and DT in the prediction of strain in wire arc AM (WAAM) [43].

To find a relation between the powder size and fatigue life using ML, a study collected data from simulation models to train ML models and make predictions. Although the study claims accurate results, large experimental data are required to validate the hypothesis. RF and regression ML models are also applied in PLA and PLA-CF (carbon fiber) by observing parameters of the printing temperature, layer thickness, and printing speed to predict strength, stiffness, and ductility [9]. Ensemble ML models are applied for predictions, a combination of weak learners (random forest, boosting methods, and regression models) and meta learner (multiple linear regression models). The predictions from the weak learners were used as training data for the meta learner. Although the study claims the high accuracy of predictions, it is limited to a single material and a few parameters. Further research is needed to validate the effectiveness of the method.

The concept of ensemble learning (EL) is also utilized to study three design factors of the fiber layer, fiber rings, and polymer infill pattern to predict the flexural strength [50]. Multiple linear regression (MLR), lasso regression, multivariate adaptive regression splines (MARS), generalized additive model (GAM), K-Nearest neighbor (KNN), support vector machines (SVM), random trees and gradient boosting algorithms are used in ensemble learning model. The study found that the model has an acceptable level of accuracy for prediction of flexural strength. To investigate effects of the nozzle temperature, printing speed, part cooling and part orientation on the tensile strength and young's modulus of AM parts using ML models, decision tree regressor (DCT), random forest regressor (RFR), extra tree regressor, and random boosting regressor are also used [2]. The study found that orientation of the printed part has the greatest effect among all the parameters studied. However, it is pertinent to note that orientation of printing might be governed by the shape and design of the part to be printed.

Multi-objective Bayesian optimization showed promising results for parameter optimization, but it still needs to be tested with broader parameters and materials. Similarly, in another study, LPBF techniques were studied by investigating the influence of laser power and scan speed on the part density [38]. The ML models, i.e. linear regression (LR), decision tree regressor (DTR), random forest regressions (RFR), and a multilayer perceptron (MLP) are applied. The results were compared for accuracy and found that MLP reported the best results, while RFR reported the lowest accuracy. It can be attributed to the small dataset. The study suggests that overall, ML can be used for predictions but limitations of LR for only predicting the linear relationship. DTR can be vulnerable to overfitting, RFR is vulnerable to errors due to the lack of enough data. The study concluded that it is not advisable to solely rely on ML predictions. The findings of this study were based on limited data, which requires big data for improvement.

Relationships between the nozzle temperature, printing speed, and layer height were observed for the tensile strength of PLA using different ML algorithms including LR, RF, light gradient Boost (LGBM), extreme gradient boosting (XGB), and ANNs [33]. It was found that the high infill density and low printing speed are effective parameters for the tensile strength. Among the ML algorithms, XGB presented the best results [33].

Neural Networks are computational models inspired by the structure and function of the human neurons [39]. They consist of interconnected nodes organized in layers, including input, hidden, and output layers. Each node (neuron) receives input signals, processes them using an activation function, and passes the result to the next layer. Neural networks learn from data through a process called training, where the model adjusts its weights and biases to minimize the difference between predicted and actual outputs. This optimization process is typically achieved using techniques like gradient descent and backpropagation [39].

A singular neural network can forecast the surface roughness, microhardness, and dimensional accuracy by optimizing the laser power, scan speed, and hatch spacing parameters [40]. The study observed that the predictions made by Artificial Neural Networks (ANNs) aligned with the testing data, however, it also shows the model sensitivity to the quantity of provided data. Despite reporting the commendable performance, a notable limitation of the study is its capacity to predict only one property at a time, lacking the capability to predict multiple parameters.

Neural networks can also be integrated with the physics knowledge to study effects of AM parameters like the scanning velocity, laser power, hatch distance and layer thickness on the fatigue life of printed parts [7]. A study observed the efficiency of AN against XGB, RF and LR, and XGB outperformed ANNs [33]. ANNs can also be used in a hybrid model with genetic algorithm (GA) to study effects of the nozzle temperature, layer thickness, printing speed, and wall thickness on surface roughness in FDM. The study found out that GA outperformed ANNs in parameter optimization [42]. Parameters like print speed, print temperature and fan speed also affect the printable bridge length (PBL). Using ANNs, a study found that lower print temperature and speed with high fan speed have positive impact on PBL [18].

ANNs have versatile applications in AM parameters optimization, such as optimizing parameters for LPBF laser power, scanning speed, hatch spacing, layer thickness and sample direction to observe their effects on yield strength, ultimate tensile strength, and elongation [27]. The study found that all parameters equally affected the targeted properties. Tensile strength was predicted by optimizing wire feeding speed and travel speed with high accuracy using ANNs with GA [45]. A study observed the printing speed, layer height, nozzle diameter, and extrusion volume against the optimal material use for FDM [38].

Table 4 presents a comprehensive overview of supervised ML techniques to predict AM part qualities by optimizing corresponding AM parameters. ML techniques are applied for specific AM parameters, along with the AM part qualities that can be predicted using these parameters. For instance, Linear Regression is associated with parameters like layer thickness, printing speed, temperature, and material composition that can influence qualities such as surface finish, strength, and build time [23]. Similarly, other ML techniques such as Decision Trees, Random Forest, Support Vector Machines (SVM), Logistic Regression, K-Nearest Neighbors (KNN), Gradient Boosting, Naive Bayes, MLP (Neural Network), and Neural Networks are aligned with relevant AM parameters and part qualities.

ML models can serve both predictive and optimization purposes, each addressing different aspects of problem-solving. Predictive ML models, such as regression [33] and classification algorithms [30], are trained on historical data to forecast future outcomes or classify new instances based on learned patterns. These models excel in identifying relationships between input features and output targets, enabling accurate predictions of properties or behaviors in various applications. On the other hand, optimization-focused ML models aim to determine the best set of input parameters that maximize or minimize a specific objective function. Techniques like GA [28] or Bayesian Optimization (BO) [9] systematically search the parameter space to find optimal configurations that yield the desired results.

Predictive models play a crucial role in the optimization and selection of parameters by acting as surrogates or guides in the optimization process. Initially, a predictive model is developed to understand how different input parameters influence the desired outcomes. Once this model is trained, it can be used to predict the performance of various parameter combinations without the need for exhaustive experimentation or simulation [10]. Optimization algorithms can then leverage these predictions to efficiently explore the parameter space, focusing on the most promising regions. For example, BO utilizes the predictive model to estimate the objective function and guides the selection of new parameter sets to evaluate, iteratively refining the search towards optimal solutions [9]. Thus, predictive models provide a foundational understanding for more efficient and effective optimization, leading to the identification of optimal parameters that achieve the desired performance outcomes.

Supervised ML Technique	**AM Parameters Optimized**	**AM Part Qualities to Predict**	**Ref.**
Linear Regression	Layer Thickness, Printing Speed, Temperature, Material Composition	Surface Finish, Strength, Build Time	[23]
Decision Trees	Layer Thickness, Infill Density, Support Structure, Build Orientation	Strength, Surface Finish, Printability	[10]
Random Forest	Printing Speed, Material Composition, Cooling Rate, Nozzle Diameter	Material Properties, Surface Finish, Warping	[2]
Support Vector Machines (SVM)	Temperature, Layer Adhesion, Support Structure, Build Orientation	Material Strength, Surface Finish, Printability	[20]

Logistic Regression	Material Composition, Support Structure, Build Orientation	Printability, Material Properties, Surface Finish	[11]
K-Nearest Neighbors (KNN)	Layer Thickness, Printing Speed, Temperature, Cooling Rate	Build Time, Surface Finish, Material Strength	[30,10]
Gradient Boosting	Layer Thickness, Material Composition, Printing Speed, Cooling Rate	Material Properties, Surface Finish, Warping	[11]
Naive Bayes	Material Composition, Layer Adhesion, Support Structure, Build Orientation	Material Properties, Printability, Surface Finish	[9]
MLP (Neural Network)	Layer Thickness, Printing Speed, Material Composition, Infill Density	Strength, Surface Finish, Material Properties	[23]
Neural Networks	Layer Thickness, Printing Speed, Material Composition, Infill Density	Strength, Surface Finish, Material Properties	[7,18,27,28,38, 45]

Table 4: Supervised ML techniques for AM parameter selection and optimization.

5 CHALLENGES IN THE PARAMETER SELECTION USING ML

5.1 Trade-Offs in the Parameters Selection

Selecting an appropriate set of parameters is crucial for optimizing the AM performance using ML models. Each AM parameter can have a distinct impact on specific properties of the printed part. For example, increasing the layer thickness and printing speed will reduce the printing time but could compromise the surface finish [20,9]. Additionally, refining porosity in Powder Bed Fusion (PBF) processes can influence surface roughness. It is essential to carefully select parameters for desired properties while considering potential trade-offs between different aspects of the part quality [19].

5.2 ML Model Selection

The relationship between parameters and the target property is indeed pivotal in selecting an appropriate ML model for AM applications. Understanding the nature of this relationship is essential for achieving accurate predictions and optimizing part properties effectively. Linear regression models, such as the simple linear regression, are suitable when the relationship between parameters and the target property is linear and can adequately capture the trend in the data [20]. However, in cases where the relationship is nonlinear or complex, more sophisticated regression models, such as the polynomial regression, spline regression, or neural networks, may be necessary to accurately model the underlying patterns and variations in the data [40].

Moreover, it is important to consider the inherent complexity of AM processes and the multidimensional nature of the parameter space. AM parameters often interact in nonlinear ways, leading to complex and sometimes unpredictable effects on part properties [9]. Therefore, employing advanced regression models to capture nonlinear relationships and interactions among parameters can be beneficial for achieving more accurate predictions in AM. Additionally, feature engineering, which involves transforming and selecting relevant features from the input data, plays a crucial role in the ML model selection and optimization. By carefully engineering features and considering the domain-specific knowledge, we can enhance the performance of ML models and improve their ability to capture nuances of AM processes.

5.3 Data Quantity and Quality

ML models heavily rely on data to learn patterns and make accurate predictions. However, the quantity of data available for training ML models in AM can often be limited due to factors such as the high cost and time associated with experimentation, especially in research and development settings [43]. Insufficient data can lead to overfitting, where the model learns the noise and variations in the training data rather than the underlying patterns, resulting in poor generalization to new data. Moreover, the quality of the data is equally important as the quantity. Inaccurate, incomplete, or poorly preprocessed data can introduce biases and errors into the ML model, negatively impacting its performance. When the precision and reliability are paramount in AM, ensuring the accuracy and integrity of the data is crucial for producing reliable predictions and optimizing process parameters effectively [19,20]. Data preprocessing techniques, such as outlier detection, normalization, and feature scaling, are essential for cleaning and preparing the data before training ML models. Additionally, domain-specific knowledge and expertise are invaluable for identifying relevant features and eliminating irrelevant noise from the data.

To further address the issue of limited and high-quality data, modern data-processing techniques such as data augmentation, transfer learning, and data-physics combinations can be employed [30]. Data augmentation techniques which involve generating synthetic data or modifying existing data can help increase the dataset size and diversity, thereby reducing overfitting and improving model robustness. Transfer learning allows for leveraging pre-trained models on large datasets from related domains, which can be fine-tuned for specific AM tasks, effectively mitigating the need for extensive labeled datasets. Combining data-driven approaches [48] with physics-based models also enhances data quality and model accuracy by incorporating fundamental principles governing AM processes, ensuring that predictions align with physical realities.

6 DISCUSSION

The selection of an appropriate ML model depends on relationships between parameters and target properties in AM. Understanding this relationship, leveraging advanced regression techniques, and incorporating domain-specific insights are essential for building robust and accurate ML models for the AM parameter selection and optimization.

Addressing challenges of the data quantity and quality in AM requires a considerable effort to collect, curate, and preprocess data systematically. Collaborative efforts between researchers, engineers, and domain experts are essential for acquiring high-quality data sets that accurately represent the intricacies of AM processes. Furthermore, investing in data infrastructure and technologies, such as data management systems and data analytics tools, can facilitate efficient data collection, storage, and analysis, ultimately enhancing the performance and reliability of ML models in AM applications.

The efficacy of ML lies in the quality of the data utilized for training the ML model. ML models can only perform as effectively as the data quality [47]. The selection and optimization of parameters for AM using ML techniques offers a promising avenue for improving manufacturing processes and product quality. Based on the comprehensive overview of the advantages and disadvantages associated with various ML techniques commonly employed in AM [49], main features of ML techniques for the AM parameter selection and optimization are identified in Table 5 as follows.

- Linear Regression emerges as a straightforward method capable of capturing both linear and nonlinear relationships between parameters. However, its limitations include assumptions of linearity and vulnerability to overfitting, particularly with small datasets. Decision Trees offer interpretability and flexibility but are prone to overfitting and instability, especially with deep trees.

- Random Forest, a popular ensemble method, mitigates overfitting by averaging multiple trees but is computationally expensive and lacks transparency due to its ensemble nature. Support Vector Machines exhibit effectiveness in high-dimensional spaces but may suffer from overfitting and slow training times with large datasets.
- Logistic Regression provides simplicity and interpretability but is constrained by linear decision boundaries and susceptibility to overfitting. K-Nearest Neighbors offers simplicity but requires careful selection of parameters and suffers from computational expense during the prediction phase.
- Gradient Boosting demonstrates high predictive accuracy but requires extensive computational resources and is sensitive to overfitting. Naive Bayes is simple and fast but assumes independence between features, which may not hold true in practice.
- MLP (Multilayer Perceptron) Neural Networks and traditional Neural Networks excel in capturing complex nonlinear relationships but are prone to overfitting and computational expense, particularly with large datasets and complex architectures. Despite their challenges, these neural networks-based approaches hold promise for optimizing AM parameters due to their ability to learn from large datasets with many features.

	Advantages	Disadvantages
Linear Regression	• Capture linear and nonlinear relationships between parameters. • Suitable for optimizing continuous AM parameters such as layer thickness or printing speed. • Can provide insights into the impact of individual parameters on AM outcomes	• Assumes linear relationship between parameters. • Sensitive to outliers and multicollinearity. • May not capture complex nonlinear relationships well. • Vulnerable to overfitting, especially with small datasets
Decision Trees	• Can handle both numerical and categorical data. • No need for data normalization. • Easy to interpret and visualize decision boundaries	• Prone to overfitting, especially with deep trees. Instability due to small variations in data. • High variance, leading to overfitting. • Can create biased trees if features with more levels are favored.
Random Forest	• High accuracy and robustness. • Reduces overfitting by averaging multiple trees. • Low risk of overfitting due to ensemble approach. • Handles high-dimensional data well	• Complexity and computational cost. • Lack of transparency due to ensemble approach. • Computationally expensive, especially with large datasets and many trees. • Not suitable for interpretability
Support Vector Machines	• Effective in high-dimensional spaces. • Effective in high-dimensional spaces. • Works well with small and medium-sized datasets	• Prone to overfitting if the kernel parameters are not properly selected. • Slow training time with large datasets. • Limited effectiveness with noisy datasets

Logistic Regression	• Simple and interpretable model. • Suitable for binary classification tasks. • Easy to implement and understand	• May not perform well with nonlinear relationships. • Limited to linear decision boundaries. • Vulnerable to overfitting, especially with small datasets
K-Nearest Neighbors (KNN)	• Simple and intuitive algorithm. • No training phase required. • Suitable for small to medium-sized datasets	• Computationally expensive prediction phase. • Sensitive to irrelevant features and noise in the data. • Requires careful selection of distance metric and k value
Gradient Boosting	• High predictive accuracy. • Handles missing data and outliers effectively. • Suitable for large datasets with high dimensionality	• Computationally expensive and time-consuming training. • Prone to overfitting, especially with deep trees. • Sensitive to hyperparameter tuning
Naive Bayes	• Simple and fast algorithm. • Handles high-dimensional data well. • Performs well with small datasets	• Assumes independence between features, which may not hold true in practice. • May not perform well with highly correlated features. • Cannot capture complex relationships between variables
MLP (Neural Network)	• Ability to capture complex nonlinear relationships between parameters. • Suitable for both regression and classification tasks. • High flexibility in model architecture	• Prone to overfitting, especially with small datasets. • May not perform well with highly imbalanced datasets. • Computationally expensive, especially with large datasets and complex architectures. • Difficult to interpret and understand the learned representations.
Neural Networks	• Capture complex nonlinear relationships between parameters. • Suitable for complex optimization tasks involving multiple AM parameters. • Ability to learn from large datasets with many features	• Prone to overfitting, especially with small datasets. May not perform well with highly imbalanced datasets. • Computationally expensive, especially with large datasets and complex architectures. • Difficult to interpret and understand the learned representations.

Table 5: ML techniques and their pros and cons

7 CONCLUSIONS

In conclusion, while each ML technique presents unique advantages and disadvantages, the selection of the most suitable algorithm for AM parameter optimization hinges on factors such as the dataset size, process complexity, and interpretability. Future research should focus on the hybrid approaches, combining strengths of multiple ML techniques to overcome individual limitations and enhance the parameter selection and optimization in AM. As AM continues to evolve, there is a need for tailored ML algorithms to address emerging challenges, fostering innovation and efficiency in manufacturing. Collaborative efforts between academia and industry are vital for advancing ML-based approaches, ultimately shaping a more efficient and sustainable future for additive manufacturing.

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