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

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Introduction:

Additive Manufacturing (AM) technologies can create complex parts using less energy and material [4]. However, a challenge in using AM is to decide the best parameter setting in the process. Factors such as the operation temperature, power, speed, and layer thickness are process parameters that affect the printing time, part quality, and energy usage [3]. The ideal combination of these parameters is determined by measures such as the printing quality, part geometry, and desired properties of the final product [2]. Machine Learning (ML) has been widely applied in the pre-processing, processing, and post-processing stages of AM [1]. In the design phase, ML can aid in tasks such as geometry prediction, design optimization, lattice design, and design classification. During the processing stage, ML is utilized to predict optimal process parameters and identify defective process states. In the post-processing stage, ML applications can assess various parameters related to product structure and properties of printed parts [8]. This paper reviews research and methods of the AM process parameter setting using ML. Development of the latest research is presented. The review covers different ML techniques used to decide the AM process parameters. Relevant literature is collected from scientific literature databases, including Web of Science, Scopus, Science Direct, and Research Gate. The review highlights the research problems, methods, trends, and limitations. Conclusions are made for recommendations for future research to fill gaps in the existing methods and solutions.

This review focuses on diverse ML techniques employed for parameter selections in AM. Rather than endorsing a single technique, the review aims to present an extensive overview of various ML methodologies, emphasizing their potential applications and influence in the field. The primary objective of this review is to furnish an updated and inclusive perspective on the state-of-the-art practices in parameter selections using ML in the realm of AM. By systematically exploring a range of ML techniques, the review seeks to provide researchers, practitioners, and stakeholders with a valuable resource that encapsulates the latest advancements and trends in this evolving domain. This collective insight is anticipated to serve as a foundation for informed decision-making, facilitating further research and advancements in the interdisciplinary intersection of ML and AM.

Main Idea:

Method: The review investigates applications of ML in selecting AM parameters. A framework is proposed to outline the review scope and objectives. The review finds important methods and tools for parameter selection and optimization in AM. Related databases are navigated with systematic search terms and selection criteria. Over 150 related publications were initially collected and categorized based on ML techniques used for the selection and optimization of AM parameters. The final review includes approximately 50 high-quality papers. Detail insights are synthesized and analyzed. The stage is set for explorations in this dynamic field. The discussion addresses implications of AM, emphasizing challenges and opportunities associated with the ML integration in the AM parameter selection and optimization. The conclusion underscores ML notable contributions in AM parameter setting, providing a valuable resource for the engineering community in the intersection of AM and ML.

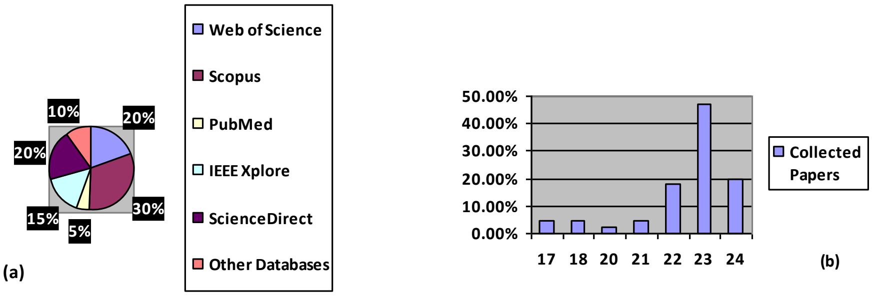

Fig. 1: (a) Contribution of databases, (b) Paper distribution by publication years.

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's 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.

Parameters are critical for the AM part quality, structural integrity, and functionality; they should be carefully selected in the AM process. They have significant impacts on the AM efficiency and overall quality of the manufactured part. 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, as shown in Tab. 1.

Tab. 2 highlights various ML techniques and their applications in both the design and manufacturing phases of AM processes. The left column shows techniques relevant to product design, while the right column outlines techniques applicable to the overall product manufacturing process [5]. Research has been undertaken to explore different methods in the selection and optimization of AM process parameters [3]. Process parameter selection, such as the nozzle temperature in FDM or the laser's power and scan speed in PBF, is not straightforward. Without an effective method, a skilled operator may choose non-optimal parameters, resulting in wasted time and material resources [1]. ML provides an effective tool to enhance the AM design and process control [7].

Different ML techniques, such as supervised, unsupervised, and reinforcement learning, are imperative to determine their appropriateness for addressing specific needs in the context of AM. Supervised ML algorithms, trained with labeled datasets, can predict properties of printed parts, like strength and porosity. For example, a random forest model was trained using historical data of laser powder bed fusion (LPBF), and a support vector machine (SVM) was trained using direct metal laser sintering (DMLS) data. Both achieved accurate predictions of the optimal parameters [6]. Unsupervised learning algorithms operate on unlabeled training datasets, extracting patterns from the unlabeled data. They are suitable for detecting anomalies and defects in printed parts. In contrast, reinforcement

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learning (RL) diverges from both supervised and unsupervised ML as it learns tasks through trial and error. In RL, the agent receives rewards for desired actions and penalties for undesired ones [7].

In AM, leveraging ML for parameter selection and optimization encounters several challenges. Firstly, striking a balance between various parameters is crucial, as enhancing one aspect may inadvertently detract from another, such as the trade-off between printing speed and surface finish quality. Secondly, the selection of an appropriate ML model depends on understanding the intricate relationship between parameters and desired outcomes; while linear regression suffices for linear relationships, more complex patterns necessitate advanced techniques like neural networks. Additionally, the scarcity and quality of data present significant obstacles with limited data risking overfitting and poor-quality data biasing predictions [8]. Hence, careful data preprocessing and feature engineering are critical to ensure the precision and reliability of ML models in optimizing AM processes.

Parameter	**Description**
Layer Thickness	Thickness of each layer deposited during the printing process.
Printing Speed	Speed at which the printing nozzle or laser moves during printing.
Extrusion/Deposition Temperature	Temperature at which the material is extruded or deposited.
Bed Temperature	Temperature of the build platform or bed where the object is printed.
Infill Density	Percentage of internal structure filling in the printed object.
Support Structures	Generation of support structures to assist overhanging features during printing.
Cooling Rate	Rate at which the printed material is cooled after deposition.
Material Flow Rate	Rate at which the material is extruded or deposited.
Build Orientation	The orientation of the object during printing.
Resolution	The level of detail and precision in the printed object.
Post-Processing	Additional processes or treatments are applied after printing.

Tab. 1: Additive Manufacturing Parameters [2].

ML Techniques for Design	**ML Techniques for Product Process**
Generative Design	Predictive Modeling
Topology Optimization	Quality Control & Defect Detection
Material Selection & Composition Optimization	Automated Parameter Tuning
Part Consolidation	Supply Chain Optimization
Simulation & Prototyping	Cost Prediction & Optimization
Machine Learning-Enhanced CAD Tools	Anomaly Detection & Error Prevention
Personalized Product Design	Process Monitoring & Feedback
Design Classification & Categorization	Market Trend Analysis
Energy Efficiency & Sustainability	
Design Collaboration Optimization	
Sustainable Design	

Tab. 2: ML techniques in AM Product Design and Process [5].

Comparison and Discussion

ML techniques employed in the selection and optimization of AM process parameters are compared. Various studies in the domain related to this subject are thoroughly reviewed and presented, as shown

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in Tab. 3. Using ML in AM has a significant promise for advancing the optimization of AM process parameters. The transformative impact of AM on manufacturing highlights the paradigm shift from traditional subtractive methods to a revolutionary approach where complex structures can be fabricated layer by layer, fostering unprecedented levels of design flexibility, rapid prototyping, and customization. It also shows challenges associated with AM process settings. AM parameters, including the operation temperature, power, speed, and layer thickness, influence the printing time, part quality, and energy consumption.

ML Tools/Techniques	Applications	Benefits	Examples
Regression Models: (e.g., Support Vector Regression)	Predict optimal process parameters based on desired material properties, build quality or efficiency.	Reduced trial and error, improved consistency, and faster build times.	Predicting laser power and scan speed for desired mechanical strength in metal AM.
Classification Models: (e.g., Random Forest)	Identify and classify defects based on in-process sensor data (e.g., thermal imaging, melt pool monitoring).	Real-time quality control, automatic adjustments to prevent defects, and reduced waste.	Classifying spatter formation during Laser Powder Bed Fusion based on melt pool dynamics.
Clustering Algorithms: (e.g., K-Means)	Group similar builds or materials based on process parameters and outcomes.	Identify trends and relationships and optimize parameter ranges for specific applications.	Clustering different polymer AM processes based on their mechanical properties and build parameters.
Reinforcement Learning:	Dynamically adjust process parameters during the build based on real-time feedback.	Highly adaptive control optimizes for unpredictable materials or complex geometries.	Learning optimal laser power profile for different sections of a build based on melt pool behavior.

Tab. 3: Summary of the ML techniques.

Findings and solutions:

- **ML Model Selection**: Advanced regression techniques and domain-specific insights are Incorporated to build robust ML models tailored to AM processes. Linear regression offers simplicity but may be limited by assumptions of linearity and vulnerability to overfitting. Decision trees provide interpretability yet are prone to overfitting and instability, especially with deep trees.
- **Data Quality and Quantity**: Collaborative efforts are essential for collecting, selecting, and preprocessing high-quality datasets. Investment in the data infrastructure can enhance data collection, storage, and analysis, which is crucial for improving ML model performance in AM. ML algorithms like random forests and support vector machines offer advantages in predictive accuracy but may suffer from limitations such as computational expense and vulnerability to overfitting.
- **Algorithm Consideration**: ML algorithms should be carefully selected based on suitability for the task. While algorithms like random forests and support vector machines offer predictive accuracy, they may have limitations such as computational expense and vulnerability to overfitting. Gradient boosting techniques demonstrate high predictive accuracy but require substantial computational resources and are sensitive to overfitting. Similarly, multilayer perceptron neural networks excel in capturing complex relationships but may suffer from overfitting and computational expense.

- **Neural Network Potential**: Despite challenges like overfitting and computational expense, neural network-based approaches hold promise for optimizing AM parameters due to their ability to learn from large datasets with many features.
- By leveraging advanced regression techniques, collaborative data efforts, and careful algorithm selection, researchers and practitioners can effectively utilize ML to improve AM processes and product quality.

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