A Review of Machine Learning Methods for Process Parameter Optimization in Laser Powder Bed Fusion

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Abstract. Laser Powder Bed Fusion (LPBF) is an additive manufacturing technique that has gained significant attention due to its ability to produce complex geometries with high precision. However, the optimization of process parameters to achieve desired part quality remains a challenge. This paper presents a systematic review of machine learning (ML) methods applied to process parameter optimization in LPBF. The review covers key influential input parameters, in-situ sensors used in LPBF processes, and various ML approaches, including artificial neural networks (ANNs), and supervised, and unsupervised learning techniques. The paper discusses the strengths and weaknesses of different ML approaches, highlighting their potential to improve the efficiency and quality of LPBF processes. Additionally, the review identifies challenges and future directions in this field, emphasizing the need for further research to develop more accurate and robust optimization strategies.

Keywords: LPBF, Machine Learning, Process Parameter Optimization, In-situ Monitoring, Part Quality.

1 Introduction

Laser Powder Bed Fusion (LPBF) is an additive manufacturing (AM) technique that has gained significant attention in recent years due to its ability to produce complex geometries with high precision and accuracy[1]. The process involves selective melting and fusing metal powder layers using a high-energy laser beam, allowing for the fabrication of near-net-shape components[2]. One of the critical aspects of this technology is the optimization of process parameters, such as laser power, scan speed, hatch spacing, and layer thickness, to ensure the production of high-quality parts with desired mechanical properties and minimal defects. The use of machine learning (ML) methods has been explored as a means to streamline this optimization process, enabling faster and more efficient exploration of the parameter space[3].

Machine learning techniques, such as artificial neural networks, support vector machines, and Gaussian processes, have been employed to develop predictive models that can estimate the relationship between process parameters and part quality metrics, such as porosity, surface roughness, and mechanical properties[4-6]. These models can then be used to guide the selection of optimal process parameters, ultimately improving the productivity and cost-effectiveness of the laser powder bed fusion process. Other challenges in applying machine learning methods to laser powder bed fusion is the complex and nonlinear nature of the underlying physical phenomena. The laser-material interactions, powder behavior, and thermal history during the process are influenced by a multitude of factors, making it difficult to develop accurate and generalizable predictive models[5].

To address this challenge, researchers have explored various approaches, such as incorporating physics-based models into the machine learning framework, using advanced experimental techniques to generate high-quality training data, and leveraging transfer learning and domain adaptation to improve model performance across different materials and process

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conditions[7, 8]. Additionally, the use of multi-laser powder bed fusion systems has introduced new complexities in terms of process parameter optimization, as the interactions between multiple energy sources can significantly impact the final part quality[8]. Machine learning methods have been applied to this domain as well, enabling the development of optimized multi-laser scan strategies that can enhance productivity and part quality.

The application of machine learning methods to process parameter optimization in laser powder bed fusion has shown great potential in improving the efficiency and reliability of this additive manufacturing technique. By leveraging the power of machine learning, researchers and manufacturers can accelerate the development of high-performance metal components, ultimately driving the wider adoption of this transformative technology.

2 Key Process Input Parameters

The quality and performance of parts produced by laser powder bed fusion is heavily influenced by a range of process parameters, including laser power, scan speed, hatch spacing, and layer thickness[5, 9].

Laser power and scan speed are critical parameters that directly impact the energy input and melt pool characteristics. Higher laser power and lower scan speeds can result in deeper and wider melt pools, potentially leading to improved part density and mechanical properties. However, excessive laser power and low scan speeds can also cause issues such as balling, porosity, and thermal distortion[9, 10]. Hatch spacing, which determines the overlap between adjacent scan tracks, and layer thickness also play a significant role in part quality. Smaller hatch spacing and thinner layers can improve surface finish and part density, but may also increase manufacturing time and cost[9, 10]. In addition to these primary process parameters, other factors such as the scanning strategy, powder characteristics, and environmental conditions (e.g., chamber atmosphere, temperature) can also influence the laser-material interactions and the resulting part quality.

Table 1 summarizes key input parameters in the Laser Powder Bed Fusion (LPBF) process, their descriptions, and how they impact part quality and performance. It highlights parameters like laser power, scan speed, and hatch spacing, and explains their influence on aspects such as melt pool dynamics, density, surface finish, and mechanical properties. Additionally, it provides references to relevant research for further information.

Table 1: Key-Influential input parameters for process parameter optimization in LPBF process

Process Parameter	Description	Effect on Part Quality and Performance	Reference
Laser Power	The power of the laser beam used to melt the powder.	Density and Porosity, Surface Roughness, Residual Stress and Defects	[5, 9-12]
Scan Speed	The speed at which the laser beam moves across the powder bed.	Improved density, mechanical properties (lower speed); balling, porosity, thermal distortion (very low speed)	[5, 9-12]
Hatch Spacing	The distance between adjacent laser scan lines.	Improved surface finish, density (smaller spacing); increased manufacturing time/cost (very small spacing)	[5, 11, 12]

Layer Thickness	The thickness of each layer of powder deposited and melted.	Improved surface finish, density (thinner layers); increased manufacturing time/cost (very thin layers)	[9, 10]
Scanning Strategy	Predefined path that the powder deposition head or laser beam follows during the additive manufacturing process	Influences heat distribution, melt pool dynamics, microstructure, residual stress	[5]
Sample thickness	The thickness of the fabricated part.	Sample thickness was found to have a statistically significant effect on tensile strength and relative elongation.	[12-14]
Meltpool depth	The depth of the molten pool created by the laser.	Melting pool depth is influenced by laser power, scanning speed, and hatch spacing and affects the microstructure and properties of the part.	[15, 16]
Volumetric energy density (VED)	The amount of energy delivered per unit volume of material.	VED is a critical parameter influencing melt pool characteristics, microstructure, and mechanical properties.	[17, 18]
Surface energy density	A measure of energy applied per unit area, relevant for specific part geometries.	Used as a parameter for parts in the form of thin walls and spatial structures.	[19]

3 In-Situ Sensors Used in the L-PBF Processes

To better understand and monitor the laser powder bed fusion process, in-situ sensors have been developed to measure various process parameters and part quality indicators. Table 2 presents common in-situ monitoring techniques in latest literatures used in the Laser Powder Bed Fusion process, along with the type of sensor/assessment used, the data collected, the insights gained from the data, and relevant sources for further information. These techniques, ranging from Melt Pool Monitoring to Qualitative Analysis, employ various sensors to capture data like temperature distribution, acoustic signatures, and gas composition. The insights gained from this data can help in understanding and controlling key aspects of the LPBF process, such as melt pool dynamics, defect formation, part quality, and overall process stability.

Table 2. Common in-situ monitoring techniques in Laser Powder Bed Fusion Process

In-Situ Monitoring Technique	Sensor/Assessment Type	Data Collected	Insights Gained	Source
Melt Pool Monitoring	Optical sensors (e.g., pyrometers, cameras)	Size, shape, temperature of melt pool	Local thermal history, solidification dynamics,	[16]

			potential defects	
Optical Imaging	High-speed cameras	Dynamic behavior of powder bed and melt pool	Defects, irregularities, powder bed uniformity, spatter patterns	[20, 21]
Acoustic Emission	Acoustic sensors (e.g., microphones)	Acoustic signatures of laser-material interaction	Defects, porosity, cracking, delamination	[22, 23]
Thermal Imaging	Infrared cameras	Temperature distribution across powder bed and part surface	Thermal anomalies, overheating, cooling rates, potential warping	[5, 20-23]
Gas Monitoring	Gas sensors (e.g., mass spectrometers, oxygen analyzers)	Gas composition, flow within the build chamber	Inert atmosphere maintenance, contamination detection, process stability	[24, 25]
Qualitative Analysis	Relative Density, Melting and Cooling Characteristics,	Temperature gradient (G), maximum temperature (Tmax), and solidification rate	Part Quality, Surface Roughness	[23, 26, 27]

4 Machine Learning Approaches for Process Parameter Optimization

Several studies have investigated the application of machine learning techniques to the optimization of laser powder bed fusion process parameters. These approaches typically involve the use of computational models, experimental data, or a combination of both to train predictive models that can estimate the relationships between process parameters and part quality metrics.

One example is the use of artificial neural networks (ANNs) to predict clad characteristics, such as clad height and dilution, in metal additive manufacturing[8]. One such approach is the use of deep learning for quantitative structural characterization of additive manufactured parts[28]. By training neural networks on experimental data, researchers have been able to develop models that can accurately predict the microstructural properties of fabricated components, such as grain size and porosity, which are directly linked to the mechanical performance of the part.

Another technique is the use of hybrid modeling frameworks that combine machine learning models with physics-based simulations[8]. This approach allows for the leveraging of the predictive power of machine learning while also incorporating the underlying physics of laser-material interaction, leading to more accurate and robust models for process parameter optimization.

4.1 Artificial Neural Networks (ANNs) approaches

Artificial neural networks (ANNs) have been widely used in the optimization of laser powder bed fusion process parameters. These machine learning models can effectively capture the complex, nonlinear relationships between process inputs (e.g., laser power, scan speed, hatch spacing) and part quality outputs (e. g., part density, surface roughness, mechanical properties)[29]. By training neural networks on datasets of experimental or simulated process data, researchers have developed models that can accurately predict part properties, such as porosity, surface roughness, and mechanical strength, as functions of the laser power, scan speed, hatch spacing, and other process parameters[30, 31].

The trained neural network models can then be used in optimization frameworks to identify the optimal combination of process parameters that satisfy desired part quality requirements. This optimization can be performed using gradient-based methods or evolutionary algorithms, such as genetic algorithms or particle swarm optimization. The use of artificial neural networks for process parameter optimization has been shown to significantly reduce the computational cost and time required, compared to traditional trial-and-error or physics-based simulation approaches[31].

Table 3 demonstrates the potential of ANNs in enhancing LPBF process control and achieving desired part properties and summarizes the application of Artificial Neural Network (ANN) techniques for optimizing process parameters in Laser Powder Bed Fusion (LPBF) from recent literatures. It highlights three distinct ANN models, each employing different sensing mechanisms and input data to achieve specific outcomes. The first model utilizes optical microscopy and mechanical testing to optimize process parameters for desired surface roughness, density, and microhardness. The second model focuses on anomaly detection using image analysis. Lastly, the third model predicts surface roughness based on current, line offset, and scan speed.

Table 3: ANN techniques for process parameter optimization in LPBF process

ML Model	Sensing Mechanism	Input Data	Machine	Methodology	Outcome	Reference
ANN	Optical microscope, Vickers microhardness tester, micrometer	Laser power, scan speed, hatch spacing	SLM 125 HL	Supervised learning, ReLU activation function, Adam optimizer	Optimal process parameters for desired surface roughness, relative density, microhardness, and dimensional error	[26]
Levenberg-Marquardt algorithm, ANN	Image Analysis	Laser power, scan speed, hatch spacing, island size	n/a	Supervised Learning	Anomaly Detection	[32]

Bayesian Learning, ANN	n/a	Current, line offset, scan speed	n/a	Supervised classification	Surface roughness prediction	[33]

4.2 Supervised Machine Learning approaches

In addition to neural networks, other supervised machine learning techniques have also been explored for laser powder bed fusion process optimization. For example, researchers have used regression models, such as partial least squares regression, to identify the key process parameters that have the most significant impact on part quality[31].

By reducing the dimensionality of the problem, these techniques can enable more efficient optimization by focusing on the most important process variables. Table 4 provides a summary of how various in-situ monitoring and machine learning techniques are employed to enhance the Laser Powder Bed Fusion (LPBF) process. These techniques involve diverse sensing mechanisms, such as acoustic emissions, thermal imaging, and multi-sensor fusion, coupled with machine learning models like Bayesian Neural Networks and Convolutional Neural Networks. The collected data is used for real-time process monitoring, quality control, defect detection, and optimizing process parameters to achieve desired material properties in the final additively manufactured metal parts.

Table 4: Supervised ML techniques for process parameter optimization in the LPBF process

ML Model	Sensing Mechanism	Input Data	Machine	Methodology	Outcome	Reference
Bayesian Neural Network (BNN)	Airborne Acoustic Emission (supercardioid 0-150 kHz)	AE signatures	SISMA MySint 100	Self-supervised learning	Classification of LPBF process regimes (Lack of Fusion, conduction, keyhole)	[23]
CNN	Multi-sensor fusion (Digital Camera Manta G-917B, Microphone (G.R.A.S. 46AE 1/2’’ CCP, InGaAs photodiode C10439–11)	layer-wise images, acoustic emission signals & photodiode signals	FastForm-140	Supervised	In-situ quality monitoring	[22]
Surrogate Model (Random Forest, Support Vector	Temperature gradient (G), maximum temperature (Tmax), and solidification rate (R)	Laser power, scan speed, and scan strategy	Simulation Based Study (ABAQUS)	Supervised	design of process parameters for specific solidification structures	[27]

Regression (SVR) and Multi-Layer Perceptron (MLP))

4.3 Unsupervised Machine Leaning approaches

While most of the research has focused on supervised learning techniques, some studies have also investigated the use of unsupervised machine learning methods for laser powder bed fusion process optimization. For example, clustering algorithms can be used to identify distinct process regimes or defect signatures within the process data, which can then guide the selection of optimal process parameters[34].

Additionally, dimensionality reduction techniques, such as principal component analysis, can be employed to extract the most relevant features from high-dimensional process data, further enhancing the efficiency of the optimization process. Table 4 highlights the application of a hybrid machine learning approach, combining supervised regression and unsupervised K-means clustering, to optimize process parameters in Laser Powder Bed Fusion (LPBF). Specifically, it focuses on predicting the hardness of LPBF-built IN718 parts using a measure of energy density as the input. The model was initially trained using supervised regression, but then unsupervised K-means clustering was employed for further analysis or optimization, likely to group parameters with similar properties or identify optimal process parameter combinations.

Table 5: Unsupervised ML techniques for process parameter optimization in LPBF process

ML Model	Sensing Mechanism	Input Data	Machine	Methodology	Outcome	Reference
Extended and Weighted K-means (EWK-means)	n/a	A measure of energy applied per unit area, relevant for specific part geometries.	Concept Laser M2 Cusing	Supervised for Regression Unsupervised for K-Means	hardness of LPBF-built IN718 parts.	[35]

5 Challenges and Future Directions

While the application of machine learning in laser powder bed fusion has shown promising results, there are still several challenges that need to be addressed. One of the key challenges is the limited availability of experimental data, as the process of generating such data can be time-consuming and expensive[8]. To overcome this, researchers have explored the use of simulation-based data to augment the experimental dataset, as well as the development of hybrid modeling approaches that can effectively utilize both simulation and experimental data.

Additionally, the complexity of the laser powder bed fusion process, with its numerous interrelated parameters and their influence on part quality, presents a significant challenge for machine-learning models[28]. Researchers have emphasized the need for a better understanding of the underlying physics and the development of more sophisticated modeling techniques to capture these complex relationships. Ongoing research in this field is focused on addressing these challenges and expanding the capabilities of machine learning methods for process parameter optimization in laser powder bed fusion[36]. This includes the exploration of more advanced machine learning algorithms, the integration of physics-based modeling, and the development of standardized datasets and benchmarking frameworks to enable the systematic evaluation and comparison of different approaches.

6 Conclusion

In conclusion, the application of machine learning methods for process parameter optimization in laser powder bed fusion has shown significant potential to improve the efficiency and quality of the manufacturing process. From supervised learning techniques, such as neural networks and regression models, to hybrid and data-driven approaches, researchers have demonstrated the ability of these methods to accelerate the optimization process and identify the most critical process parameters. As the field continues to evolve, further advancements in machine learning, coupled with a deeper understanding of the underlying physics of the laser powder bed fusion process, are expected to lead to even more accurate and robust optimization strategies.

References

1. 1. Wang, J., et al., Understanding melt pool characteristics in laser powder bed fusion: An overview of single-and multi-track melt pools for process optimization. Advanced Powder Materials, 2023. 2(4): p. 100137.
2. 2. Liu, M., et al., Additive manufacturing of pure niobium by laser powder bed fusion: Microstructure, mechanical behavior and oxygen assisted embrittlement. Materials Science and Engineering: A, 2023. 866: p. 144691.
3. 3. Grabowski, M., et al., Technological possibilities of the carbide tools application for precision machining of WCLV hardened steel. Advances in Science and Technology. Research Journal, 2022. 16(1): p. 141-148.
4. 4. Asnafi, N., Application of laser-based powder bed fusion for direct metal tooling. Metals, 2021. 11(3): p. 458.
5. 5. Jiménez, A., et al., Powder-based laser hybrid additive manufacturing of metals: a review. The International Journal of Advanced Manufacturing Technology, 2021. 114: p. 63-96.
6. 6. Masoomi, M., S.M. Thompson, and N. Shamsaei, Quality part production via multi-laser additive manufacturing. Manufacturing letters, 2017. 13: p. 15-20.
7. 7. Samantaray, M., D.N. Thatoi, and S. Sahoo, Finite element simulation of heat transfer in laser additive manufacturing of AlSi10Mg powders. Materials Today: Proceedings, 2020. 22: p. 3001-3008.
8. 8. Tayebati, S. and K.T. Cho, A hybrid machine learning framework for clad characteristics prediction in metal additive manufacturing. arXiv preprint arXiv:2307.01872, 2023.
9. 9. Wei, Q.S., et al., Effects of the processing parameters on the forming quality of stainless steel parts by Selective Laser Melting. Advanced Materials Research, 2011. 189: p. 3668-3671.
10. 10. Antony, K., N. Arivazhagan, and K. Senthilkumaran, Numerical and experimental investigations on laser melting of stainless steel 316L metal powders. Journal of Manufacturing Processes, 2014. 16(3): p. 345-355.
11. 11. Sahar, T., et al., Anomaly detection in laser powder bed fusion using machine learning: A review. Results in Engineering, 2023. 17: p. 100803.
12. 12. Khaimovich, A., et al., Optimization of process parameters for powder bed fusion additive manufacturing using a linear programming method: a conceptual framework. Metals, 2022. 12(11): p. 1976.
13. 13. Carrozza, A., et al., Investigating complex geometrical features in LPBF-produced parts: a material-based comparison between different titanium alloys. Metals and Materials International, 2023. 29(12): p. 3697-3714.
14. 14. Jiang, H., et al., Size effect on the microstructure, phase transformation behavior, and mechanical properties of NiTi shape memory alloys fabricated by laser powder bed fusion. Journal of Materials Science & Technology, 2023. 157: p. 200-212.

15. 15. Criales, L.E., et al., Predictive modeling and optimization of multi-track processing for laser powder bed fusion of nickel alloy 625. Additive Manufacturing, 2017. 13: p. 14-36.
16. 16. Khorasani, M., et al., The effect of absorption ratio on meltpool features in laser-based powder bed fusion of IN718. Optics & Laser Technology, 2022. 153: p. 108263.
17. 17. Salandari-Rabori, A., et al., Enhancing as-built microstructural integrity and tensile properties in laser powder bed fusion of AlSi10Mg alloy using a comprehensive parameter optimization procedure. Materials Science and Engineering: A, 2021. 805: p. 140620.
18. 18. Ren, Y., Model Learning and Predictive Control of Laser Powder Bed Fusion. 2024.
19. 19. Ziri, S., A. Hor, and C. Mabru, Combined effect of powder properties and process parameters on the density of 316L stainless steel obtained by laser powder bed fusion. The International Journal of Advanced Manufacturing Technology, 2022. 120(9): p. 6187-6204.
20. 20. Balhara, H., et al., Imaging systems and techniques for fusion-based metal additive manufacturing: a review. Frontiers in Manufacturing Technology, 2023. 3: p. 1271190.
21. 21. Estalaki, S.M., et al., Predicting defects in laser powder bed fusion using in-situ thermal imaging data and machine learning. Additive Manufacturing, 2022. 58: p. 103008.
22. 22. Li, J., et al., A convolutional neural network-based multi-sensor fusion approach for in-situ quality monitoring of selective laser melting. Journal of Manufacturing Systems, 2022. 64: p. 429-442.
23. 23. Pandiyan, V., et al., Self-Supervised Bayesian representation learning of acoustic emissions from laser powder bed Fusion process for in-situ monitoring. Materials & Design, 2023. 235: p. 112458.
24. 24. Pesode, P. and S. Barve, Additive manufacturing of metallic biomaterials: sustainability aspect, opportunity, and challenges. Journal of Industrial and Production Engineering, 2023. 40(6): p. 464-505.
25. 25. Klingaa, C.G., et al., Towards a digital twin of laser powder bed fusion with a focus on gas flow variables. Journal of Manufacturing Processes, 2021. 65: p. 312-327.
26. 26. Theeda, S., et al., Optimization of process parameters in laser powder bed fusion of SS 316L parts using artificial neural networks. Metals, 2023. 13(5): p. 842.
27. 27. Vaghefi, E. and E. Mirkoohi. Artificial Intelligence-Based Design of Process Parameters in Laser Powder Bed Fusion of Ti-6Al-4V for Desired Solidification Structure. in International Manufacturing Science and Engineering Conference. 2023. American Society of Mechanical Engineers.
28. 28. Peles, A., V.C. Paquit, and R.R. Dehoff, Deep-learning quantitative structural characterization in additive manufacturing. arXiv preprint arXiv:2302.06389, 2023.
29. 29. Grierson, D., A.E. Rennie, and S.D. Quayle, Machine learning for additive manufacturing. Encyclopedia, 2021. 1(3): p. 576-588.
30. 30. Sibisi, T.H., et al., LAM additive manufacturing: A fundamental review on mechanical properties, common defects, dominant processing variables, and its applications. The International Journal of Advanced Manufacturing Technology, 2023. 128(7-8): p. 2847-2861.
31. 31. Subraveti, S.G., et al., Machine learning-based multiobjective optimization of pressure swing adsorption. Industrial & Engineering Chemistry Research, 2019. 58(44): p. 20412-20422.
32. 32. Babakan, A.M., et al., Predictive modeling of porosity in AlSi10Mg alloy fabricated by laser powder bed fusion: A comparative study with RSM, ANN, FL, and ANFIS. The International Journal of Advanced Manufacturing Technology, 2023. 129(3): p. 1097-1108.
33. 33. Arunadevi, M., et al., Enhancing surface quality of metal parts manufactured via LPBF: ANN classifier and bayesian learning approach. International Journal on Interactive Design and Manufacturing (IJIDeM), 2024: p. 1-9.
34. 34. Dutta, S. and R. Smith, Nonlinear optimization of turbine conjugate heat transfer with iterative machine learning and training sample replacement. Energies, 2020. 13(17): p. 4587.
35. 35. Baek, A.M.C., et al., Multi-objective robust parameter optimization using the extended and weighted k-means (EWK-means) clustering in laser powder bed fusion (LPBF). Expert Systems with Applications, 2024. 236: p. 121349.
36. 36. Zimbrod, P., M. Schreter, and J. Schilp. Efficient Simulation of Complex Capillary Effects in Advanced Manufacturing Processes using the Finite Volume Method. in 2022 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME). 2022. IEEE.