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Optimization and Quality Control of Additives Manufacturing Based on Machine Learning: 3-year Research Review and Future Challenges

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Abstract

This paper aims to review the research progress in the optimization and quality control of additive manufacturing methods based on machine learning over the past three years. By systematically reviewing and analysing the relevant contributions, this paper discusses the application of machine learning in additive manufacturing, such as parameter optimization, material performance prediction, real-time process monitoring and data-driven quality evaluation. Machine learning technology significantly improves the stability and product quality of additive manufacturing, but it also faces challenges such as data standardization, multiscale modelling and interdisciplinary cooperation. Finally, this paper proposes the following: research directions and policy recommendations to promote the development of additive manufacturing technology.

Keywords

additive manufacturing, machine learning, optimization, quality control, data-driven

1. Introduction

In recent years, additive manufacturing (AM) technology has developed rapidly, has widely infiltrated key fields such as aerospace, medical, and automotive fields, and has become an important form of technical support for promoting high-end manufacturing upgrades. However, this technology still faces significant bottlenecks in practical applications: the complexity of the additive manufacturing process itself, the uncertainty of material properties, and the difficulty of product quality control. These problems together restrict its further large-scale and high-quality development. In this context, machine learning, as a tool with powerful data analysis and pattern recognition capabilities, provides an innovative solution to overcome the above bottlenecks. Through various machine learning algorithms, accurate optimization of additive manufacturing process parameters can be achieved, the accuracy of material performance prediction can be effectively improved, and real-time monitoring and dynamic quality control of the manufacturing process can be conducted, showing important application value and potential in this field.

Although many studies have focused on the application of machine learning in additive manufacturing, many challenges remain to be solved in how to use such methods systematically to effectively improve the efficiency and product quality of additive manufacturing, and a systematic summary of the research status in the field and an analysis of existing disputes are lacking. In view of this, this paper aims to review the research progress in additive manufacturing optimization and quality control based on machine learning over the past three years. On the one hand, it reveals the current research hotspots, core status and existing disputes. On the other hand, it deeply discusses the future development trends and potential challenges in this field to provide a valuable reference for researchers in related fields and then promotes the development of additive manufacturing technology based on machine learning in a more efficient and reliable direction.

2. Optimization of Additive Manufacturing via Machine Learning

The quality and efficiency of additive manufacturing (AM) are highly dependent on the control of process parameters and material properties. The traditional trial-and-error method has difficulty coping with the complex requirements of multiparameter coupling and multiobjective optimization. With the ability of data-driven pattern recognition and prediction, machine learning can achieve precise control of the whole process from process parameter optimization to material performance prediction and provide an effective way to solve the core problem of unclear 'process–structure-performance' correlations in additive manufacturing.

2.1 Optimization of Process Parameters

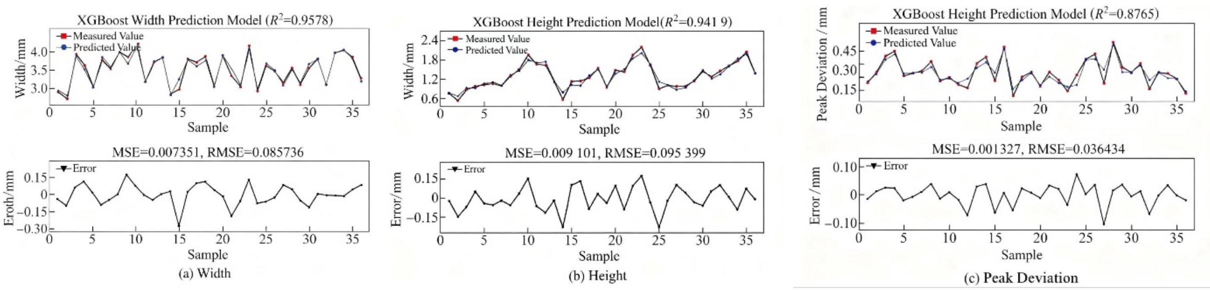
The process parameters are the key variables for determining the forming quality of additive manufacturing parts. The synergy between different parameters directly affects the molten pool behavior, interlayer bonding and final mechanical properties. Machine learning can efficiently screen the optimal parameter combination and reduce the test cost and number of cycles by constructing a mapping model of parameters and forming indices. The following two core variables are discussed from static parameters (layer thickness and laser power) and dynamic parameters (scanning speed and wire feeding speed).

2.1.1 Layer Thickness and Laser Power

Layer thickness and laser power are the basic parameters for regulating energy input and forming accuracy in additive manufacturing. The layer thickness directly affects the degree of interlayer fusion and surface roughness, whereas the laser power affects the temperature of the molten pool and the melting adequacy of materials. Both of these factors influence the density and mechanical properties of parts.

In the study of laser cladding on inclined substrates, Yue (2022) used the laser power, layer thickness (indirectly related to cladding layer accumulation), scanning speed and powder feeding rate as input variables and constructed a prediction model of single-channel/multichannel coating morphology (width, height, peak offset) through an orthogonal test design. By comparing the three algorithms of support vector regression (SVR), particle swarm optimization back propagation neural network (PSO-BPNN) and extreme gradient boosting (XGBoost), the XGBoost model performs best, and the prediction determination coefficients (R^2) for the coating width, height and peak offset are 0.9578, 0.9419 and 0.8765, respectively, which can accurately capture the nonlinear relationship between the parameters and morphology (see the XGBoost prediction results in Figure 1). The study also verified that when the laser power is insufficient or the layer thickness is too large, the coating is prone to incomplete fusion defects; the high power leads to splashing of the molten pool, which provides a basis for the preliminary screening of the parameter interval.

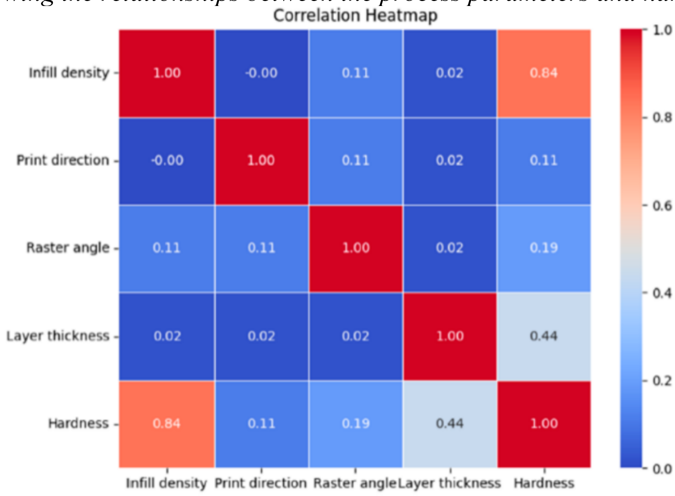
Figure 1: Prediction results of the XGBoost model (X. Li et al., 2025)



Yuan (2023) further incorporated the layer thickness, laser power, scanning distance and scanning speed in the study of laser powder bed melting (L-PBF) to form 316 L stainless steel and constructed a multiparameter-mechanical property prediction model. The results show that the random forest algorithm has the highest prediction accuracy for tensile strength (R^2 = 0.988), and the sensitivity analysis reveals that the laser power (contribution ratio of 35%) and layer thickness (contribution ratio of 28%) are the top 2 parameters affecting the tensile strength. When the layer thickness ranges from 0.1~0.15 mm and the laser power ranges from 180~220 W, the density of parts can reach more than 99.2%, and the tensile strength is stable at 580~620 MPa.

In addition, Mahmoud et al. (2024) quantified the influence of layer thickness and filling density on the hardness of polycarbonate (PC) parts through heatmap analysis (see Figure 2). The layer thickness was negatively correlated with hardness (correlation coefficient of −0.44), and the laser power indirectly affected hardness by regulating the fusion quality, which further confirmed the universal regulation value of these two parameters in different material systems.

Figure 2: Heatmap showing the relationships between the process parameters and hardness (Mahmoud et al., 2024)



2.1.2 Scanning Speed and Wire Feeding Speed

Compared with static parameters such as layer thickness and laser power, scanning speed (laser/print head moving speed) and wire feeding speed (for arc additive manufacturing and laser fuse deposition) are dynamic parameters that directly affect the forming efficiency and molten pool stability: excessively slow scanning speeds can easily lead to heat accumulation and overburning, and excessively fast speeds can cause insufficient melting of materials. The mismatch between the wire feeding speed and the scanning speed will lead to undermelting or overflow, and the collaborative optimization of the two is the key to improving the forming consistency.

In a study of laser cladding on the same inclined substrate, Yue (2022) synchronously analysed the influence of the scanning speed and powder feeding rate (similar to the wire feeding speed) and reported that the sensitivity coefficient of the XGBoost model to the scanning speed was 0.32, which was significantly greater than those of other algorithms (SVR: 0.21; PSO-BPNN: 0.27). When the scanning speed increases from 5 mm/s to 15 mm/s, the coating width decreases from 2.8 mm to 1.6 mm, and the matching interval of the 'scanning speed–powder feeding rate' can be found through model optimization (such as a scanning speed of 8--10 mm/s and a powder feeding rate of 1.2--1.5 g/min), such that the qualified rate of coating formation increases from 68% to 92%.

For the selective laser melting (SLM) of Ti-6Al-4 V, Zou Miao (2023) further constructed the XGBoost model through hyperparameter optimization to realize the coupling prediction of the scanning speed, wire feeding speed (corresponding to the wire feed rate here), weld pool characteristics (weld pool depth, width) and relative density. The results show that the predicted root mean square error (RMSE) of the optimized model for relative density is only 0.87%, and when the ratio of the scanning speed to the wire feeding speed is 0.8–1.2, the molten pool flow is the most stable, and the porosity can be controlled below 0.5%.

Notably, Zhang et al. (2025) studied arc additive manufacturing (WAAM) found through heatmap analysis (similar to the parameter correlation analysis in Figure 2) that the interaction between the scanning speed and wire feeding speed contributed 42% to the weld bead height, which was much greater than the influence of a single parameter (scanning speed: 23%, wire feeding speed: 18%). This also explains why machine learning models (such as XGBoost and random forest) perform better in multiparameter collaborative optimization, as they can effectively capture the interaction effect between parameters.

2.2 Material Performance Prediction and Process Monitoring

Process parameter optimization provides a basis for the 'process control' of additive manufacturing, and material performance prediction and process monitoring are the core links of the 'result guarantee'. By integrating process data, thermal simulation information and sensing signals, machine learning can realize closed-loop control from performance prediction to real-time defect detection and compensate for the lag of traditional offline detection.

2.2.1 Prediction of Mechanical Properties

The mechanical properties of additive manufacturing materials (such as hardness, tensile strength, and fatigue life) are the core indicators for evaluating the service ability of parts. The traditional evaluation methods that rely on tests are costly and long-term. Machine learning can achieve rapid prediction and optimization of performance by constructing a 'process–structure–performance' correlation model.

For SLM-processed Ti-6Al-4 V, Zou (2023) compared XGBoost, random forest and support vector machine (SVM) models with laser power, scanning speed and layer thickness as inputs and relative density and tensile strength as outputs. The prediction R^2 of the XGBoost model for tensile strength was 0.96, and it was clear that the laser power (contribution ratio of 38%) was the key parameter for regulating strength through feature importance analysis. When the laser power increased from 150 W to 200 W, the tensile strength increased from 860 MPa to 920 MPa. The deviation from the model prediction is only 2.1%.

Cai (2023) further incorporated the printing temperature and layer thickness into a performance prediction model in the research of 3D-printed polypropylene (PP) matrix composites. Machine learning can effectively predict the dynamic mechanical properties of materials: at a lower printing layer thickness (0.1~0.15 mm) and printing temperature (190~200°C), the material interface is more closely combined, the storage modulus is 15%~20% greater than the traditional parameters, and the prediction error of the random forest model for the storage modulus is less than 5%.

Hu et al. (2024) noted that the advantages of machine learning in performance prediction are reflected not only in the improvement in accuracy (the average R2 is 0.15~0.25 higher than that of the traditional empirical model) but also in the reduction in test cost (40%~60% reduction in test volume) and accelerated evaluation cycle (from weeks to hours). However, it should be noted that data quality and dataset size significantly affect the generalization ability of the model. When the amount of data is insufficient (such as less than 50 groups), the model is prone to overfitting. At this time, data enhancement techniques (such as generative adversarial networks) or physical information neural networks (PINNs) need to be combined to improve robustness.

2.2.2 Thermal Simulation and Defect Detection

Thermal simulation can reveal the temperature field distribution and molten pool behavior in the additive manufacturing process, and defect detection directly guarantees the structural integrity of the parts. The combination of the two is the key to achieving 'defect-free forming'. Machine learning significantly improves monitoring efficiency and accuracy by replacing traditional time-consuming numerical simulations (such as finite element analysis) and automated defect recognition.

Ghansiyal, Ehmsen, et al. (2025) proposed a thermal simulation framework based on a graph neural network (GNN) (see Figure 3), which uses the laser power, scanning speed, and laser radius as inputs to predict the temperature distribution during laser powder bed melting (PBF-LB). The model shortens the simulation time from 9.61 s for the traditional numerical method to 3.31 s, and the mean square error (MSE) of the temperature distribution prediction is only 7.67 (see the temperature distribution comparison of t = 3 s, 20 s, and 40 s in Figure 4), which can quickly screen the optimal parameter combination of energy efficiency (such as a laser power of 3~5 W/mm2 and a scanning speed of 1~2 mm/s).

Figure 3: GNN Architecture (Ghansiyal, Ehmsen, et al., 2025)

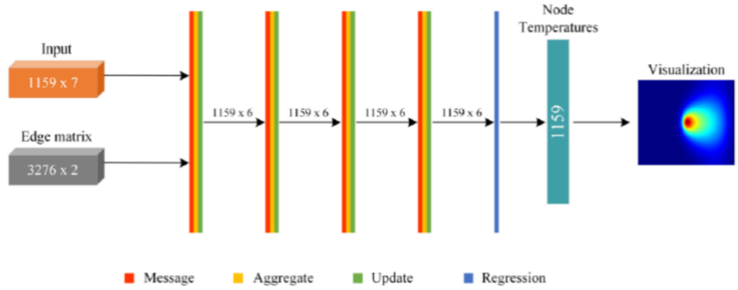
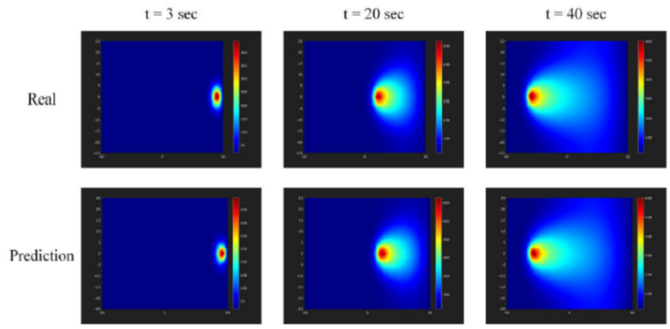
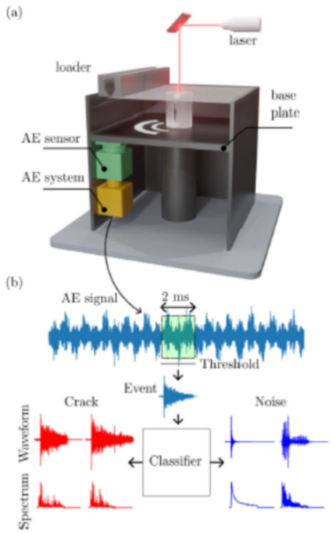


Figure 4: Visual comparison of the temperature predictions made for experiment 1 (Ghansiyal, Ehmsen, et al., 2025)



In terms of defect detection, Kononenko et al. (2023) proposed an in situ crack detection system based on acoustic emission (AE) and machine learning (see Figure 5). The crack signal and background noise were collected by an AE sensor, and the features were extracted via principal component analysis (PCA). K-nearest neighbor (KNN), SVM and other algorithms were used for classification. The KNN model had an accuracy of 99% for crack recognition, and the response time was less than 1 ms, which could realize real-time defect warning in the printing process.

Figure 5. Schematics of the in situ system for crack detection in the L-PBF process. (a) Experimental setup of the L-PBF machine accompanied by the AE monitoring system for specimen quality control. (b) Processing of the AE signal involves threshold-based detection of the event from the audio stream and performance of the binary classification procedure to reveal cracks (Kononenko et al., 2023)



In a study of additive manufacturing of nickel-based superalloys, Mu et al. (2024) further combined thermodynamic calculations and machine learning to construct a prediction model of hot cracking sensitivity: with the cooling rate and temperature gradient as inputs and the hot cracking sensitivity coefficient (CSC) as the output, the random forest model has R2 values of 0.96 and 0.81 in the training set and the verification set, respectively, which can accurately identify the process interval prone to cracking (for example, when the cooling rate is less than 100°C/s, the CSC is greater than 0.6, and the risk of cracking is significantly increased).

3. Quality Control and Monitoring

The quality fluctuation of additive manufacturing (AM) is the core bottleneck restricting its industrial application. Especially in metal and high-performance polymer additive manufacturing, small fluctuations in process parameters may lead to defects such as pores and cracks, which in turn deteriorate the mechanical properties. Machine learning technology provides a new way to solve this problem through data-driven real-time monitoring and predictive modelling. The following systematically reviews the application status, challenges and typical cases of machine learning in AM quality control from the two dimensions of real-time process monitoring and data-driven quality assessment.

3.1 Real-time Process Monitoring

Real-time process monitoring focuses on the state perception and defect warning of AM 'forming'. Through machine learning, real-time analysis of sensor data (such as acoustic emission, molten pool images, and temperature signals) is carried out to realize real-time identification of defects and dynamic adjustment of process parameters to reduce the cost of 'postdetection'. Its core technical branches include online defect detection and simulation prediction models.

3.1.1 Online Defect Detection

On-line defect detection technology based on machine learning constructs classification or regression models by extracting characteristic signals (such as acoustic emission and weld pool morphology) in the AM process to realize real-time identification of typical defects such as cracks and pores and incomplete fusion. At present, this technology has shown high accuracy in laser powder bed melting (LPBF), arc additive manufacturing (WAAM) and other processes, but it still faces two core challenges: data preparation and model generalization.

From the perspective of technical application, Kononenko et al. (2023) proposed an in situ crack detection system based on acoustic emission (AE) and machine learning for LPBF-formed Al–Mn–Ce alloys (Figure 5). In this study, the acoustic signal in the forming process was collected by a high-sensitivity AE sensor, and a 2 V threshold was set to intercept a 2 ms-long signal fragment (a total of 379 events, including 196 crack signals and 183 noise signals). Principal component analysis (PCA) was used to reduce the dimension of the signal spectrum, and five classification models, such as logistic regression and random forest (RF), were constructed. The results show that the classification accuracy of the RF model based on the principal component of the spectrum is 99%, and single-event detection takes only 1 ms, which meets real-time requirements. In addition, Zhu (2023) used support vector regression (SVR), limit gradient boosting (XGBoost) and a back propagation neural network (BPNN) to predict the weld pool size for surface morphology detection during laser deposition additive manufacturing. The prediction error of the XGBoost model for the weld width is less than 0.1 mm, and a dataset expansion method based on transfer learning is proposed to solve the problem of the difficult preparation of profiled part morphology data.

However, the industrial application of this technology is still limited by two challenges: the difficulty of data preparation and the weak generalization ability of the model.

Data preparation challenge: High-quality labelled data are scarce, and the preparation cost is high. On the one hand, AM defect samples (such as cracks and keyhole pores) have a low incidence in normal processes (usually < 5%), resulting in an imbalanced dataset category. For example, in the study of Kononenko et al. (2023), the proportion of noise samples is 48.3%, which is significantly different from the scene of 'fewer defects and more normal samples' in actual production, which directly leads to an increase in the false detection rate of the model in the industrial field from 2% in the laboratory to 8%. On the other hand, defect labelling relies on professionals and high-precision detection equipment (such as X-ray CT). For example, Zhu (2023) combined an optical microscope and a three-dimensional profilometer to label weld pool morphology data. Single-sample labelling takes more than 30 minutes, which restricts the scale expansion of the dataset.

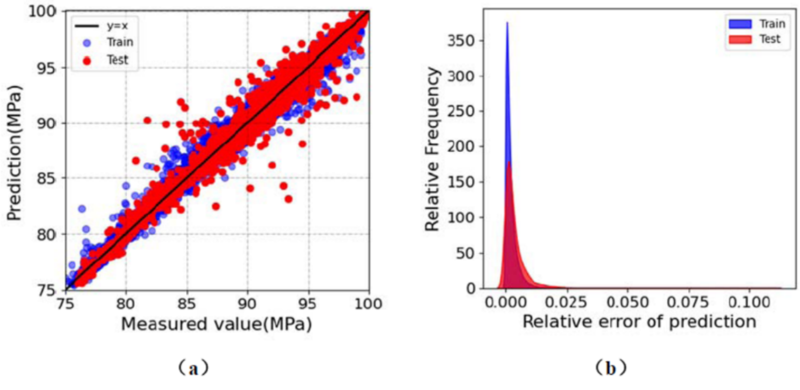
Model generalization challenge: The model is susceptible to differences in materials and equipment and has poor cross-scene adaptability. For example, Kononenko et al.'s (2023) crack detection model has an accuracy of 99% for an Al-Mn-Ce alloy, but when it migrates to a Ti-6Al-4 V alloy, the accuracy decreases sharply to 72% because of the significant difference in the acoustic emission signal characteristics (such as the frequency distribution and amplitude) between the two materials. Similarly, Zhu (2023) weld pool size prediction model performs well on 316 L stainless steel (RMSE = 0.12 mm). However, when Ti-6Al-4 V is applied, the dynamic characteristics of the weld pool change due to the difference in metal thermal conductivity, and the RMSE increases to 0.35 mm, which cannot meet the accuracy requirements.

3.1.2 Simulation and Prediction Models

The machine learning simulation and prediction model can predict the density, mechanical properties and defect risk of AM parts in advance by constructing a mapping relationship between process parameters and forming quality and reducing the cost of trial and error. At present, this kind of model has been used for parameter optimization in SLM, WAAM and other processes, but it still faces the problems of insufficient dataset integrity and insufficient integration of physical mechanisms.

In typical applications, Zou (2023) developed a mechanical property prediction model based on XGBoost, SVR and an ANN for SLM-formed Ti-6Al-4 V (Figure 6). Through hyperparameter optimization (such as when the tree depth of XGBoost is set to 8 and the learning rate is 0.1), the model's prediction R^2 for relative density is 0.94, and the prediction RMSE for the weld pool depth is only 0.02 mm. The optimized XGBoost model is three times more efficient than the ANN in calculation. In addition, Mu et al. (2023) combined thermodynamic calculations and machine learning to establish a crack sensitivity prediction model for nickel-based superalloys. The random forest regression (RFR) algorithm showed good prediction ability on both the training set (R^2 = 0.96) and the validation set (R^2 = 0.81) and could quickly evaluate hot crack sensitivity coefficients (such as FR and CSC). Hu et al. (2024) also reviewed the application of physical information neural networks (PINNs) in AM performance prediction. For example, after the PINN fuses the heat conduction equation, the prediction error of the Inconel 718 fatigue life is 40% lower than that of the traditional ANN.

Figure 6. The trained XGBoost model is used to perform regression analysis on the training dataset and the invisible test dataset. (a) Experimental and predicted values of the relative density; the solid line y = x is the reference line. (b) Training data. The relative error distributions between the set and the invisible test dataset (Zou, 2023)



The core challenges faced by such models include the following:

The integrity of the dataset is insufficient: the existing dataset covers a limited range of process parameters, and the prediction accuracy decreases after exceeding the range. For example, Zou's (2023) model focuses only on the parameter range of laser power 180--220 W and a scanning speed of 600--800 mm/s. When the laser power is reduced to 160 W, the relative density prediction RMSE increases from 0.5% to 2.5%, and the physical mechanism changes caused by the 'spheroidization effect' at low power are not covered by the dataset. In addition, differences in the raw materials (such as the powder particle size distribution and impurity content) also affect the accuracy of the model. Mu et al.'s (2023) study revealed that when the Al content in nickel-based alloy powder fluctuates by ± 0.1%, the prediction error of crack sensitivity increases by 15%.

Poor interpretability: Most machine learning models (such as ANN and XGBoost) are 'black box' models, which have difficulty correlating physical mechanisms and restrict process optimization guidance. For example, although the XGBoost model can accurately predict the size of the molten pool, it cannot explain the quantitative relationship between the laser power and the depth of the molten pool. Although the PINN improves interpretability by incorporating a physical equation, it requires more data (at least 500 sets of samples), and the computational complexity is 2--3 times greater than that of the traditional model.

3.2 Data-driven Quality Assessment

Real-time process monitoring focuses on 'in-process' defect identification, whereas data-driven quality assessment starts from the 'data life cycle'. Through systematic experimental design and data collection, combined with machine learning algorithms, a closed loop of 'ex ante' process optimization and 'ex post' performance evaluation is realized, which is the core support of AM quality control. Its technical system includes two links: data acquisition and preprocessing and machine learning algorithm application.

3.2.1 Data Acquisition and Preprocessing

High-quality data constitute the basis of data-driven quality assessment. It needs to be obtained through scientific experimental design and multisensor fusion and preprocessed to eliminate noise and deviation to provide reliable input for subsequent modelling. At present, mainstream data acquisition methods include flux experiments (such as Taguchi, Box–Behnken design) and multisensor synchronous acquisition, and preprocessing focuses on noise removal and data completion.

In terms of experimental design and data acquisition, the Box–Behnken design is widely used in AM data acquisition because it can effectively cover the interaction effect of parameters. For example, in the study of SLM forming Ti-6Al-4 V, Zou (2023) used a Box–Behnken design to construct a parameter matrix of 5 factors (laser power, scanning speed, powder layer thickness, scanning spacing, and substrate temperature) at 3–5 levels. A total of 120 groups of experiments were carried out, and 20 indices, such as relative density, molten pool morphology and tensile strength, were collected synchronously to form a structured dataset (Table 1), which provided sufficient samples for the subsequent XGBoost model. In addition, multisensor fusion has become a trend. X. Li et al. (2025) integrated an infrared pyrometer (sampling rate of 1 kHz, monitoring the temperature of the molten pool) and a high-speed camera (frame rate of 1000 fps, capturing the shape of the molten pool) in laser additive manufacturing. The amount of data collected per day is up to 5 GB, and the data are transmitted synchronously through Ethernet. The time deviation between the temperature data of the molten pool and the shape data is less than 1 ms.

Table 1: SLM process parameters and their ranges for generating data (Zou, 2023)

Process Parameters	Unit	Value
Laser scanning speed	mm/s	800, 900, 1000, 1200, 1300, 1400, 1500, 1600, 1700, 1800, 1900, 2000, 2100, 2200, 2300, 2400, 2500
Laser power	W	80, 90, 95, 100, 105, 110, 115, 120, 130, 135, 140, 145, 150, 155, 160, 165, 170, 175, 180
Hatch distance	μm	30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 10
Power layer thickness	μm	20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80

Data preprocessing is a key step in improving the accuracy of modelling. It mainly solves three major problems:

Noise removal: Interference signals in the AM process (such as spatter and arc light) can cause data distortion. For example, X. Li et al. (2025) used Gaussian filtering ($\sigma = 1.5$) to remove the splash noise in the weld pool image, which improved the accuracy of subsequent CNN defect recognition by 8%. Kononenko et al. (2023) used 50–600 kHz bandpass filtering for AE signals to filter out the background noise (600 kHz) of an air pump, and the signal–to–noise ratio was increased from 20 dB to 35 dB.

Missing value completion: Sensor failure or equipment interruption leads to data loss, which needs to be repaired via interpolation. For example, H. Wang et al. (2025) used the K-nearest neighbor interpolation method to fill the missing values in the tensile strength data (missing rate < 5%) in the performance evaluation of AM materials. The standard deviation of the repaired data and the original data is less than 3%.

Data standardization: Dimensional differences in different parameters (e.g., the laser power unit is W and the scanning speed is mm/s) affect the convergence of the model. Zou (2023) used the Z score to standardize the processing parameters so that the mean value of each feature was 0, the standard deviation was 1, and the training convergence speed of the XGBoost model was increased by 40%.

3.2.2 Application of Machine Learning Algorithms in Quality Assessment

Different machine learning algorithms have different advantages in AM quality assessment because of their different structural characteristics: tree-based algorithms (such as XGBoost and RF) are good at addressing nonlinear parameter interactions; deep learning algorithms (such as CNN and LSTM) are suitable for image and time series data; and physical information models (such as the PINN) can balance data requirements and physical consistency. The following, combined with typical cases and data comparisons, explains its application characteristics:

1) Tree-based algorithm: parameter optimization and performance prediction

The tree-based algorithm has become the mainstream choice for AM quality assessment because of its strong anti-overfitting ability and good interpretability. Zou (2023) compared the prediction performance of XGBoost, RF and SVR on the relative density of Ti-6Al-4 V (Table 2). The results show that the XGBoost model with optimized hyperparameters has an R^2 of 0.94 and an RMSE of only 0.5%, which is significantly better than those of the RF (R^2 = 0.91, RMSE = 0.7%) and SVR (R^2 = 0.87, RMSE = 1.2%) models. The advantage of this approach is that it can capture the coupling effect of the laser power-scanning speed when the laser power increases from 180 W to 220 W. The optimal range of scanning speeds that XGBoost can identify is from 600–700 mm/s to 700–800 mm/s. In addition, Huang et al. (2025) used the RF algorithm to predict the fatigue life of Al-Si-Mg alloys. On the basis of eight characteristics, such as porosity and grain size, the average error of the model is less than 5%, and the efficiency is 10 times greater than that of the traditional finite element method (24 h/sample), which can quickly screen the combination of process parameters with excellent fatigue performance.

Table 2: Comparison of the prediction results of the SVR, ANN and optimized XGBoost models on unseen test sets (Zou, 2023)

Test	SVR	ANN	Optimized XGBoost
MAE	1.3344	0.8576	0.8011
RMSE	4.8646	1.7316	1.7171
R^2	0.7687	0.7849	0.9184

2) Deep learning: image and time series data processing

Deep learning is especially suitable for unstructured data in AMs (such as molten pool images and temperature time series). X. Li et al. (2025) used a CNN to process LPBF weld pool images (resolution 224 × 224), and the recognition accuracy of three types of defects, 'unfused', 'keyhole pores' and 'spheroidization', reached 97%. The confusion matrix revealed that the recall rate of 'unfused' defects was 95%, which was better than that of the traditional threshold segmentation method (82%).

3) Physical information model: Balancing data and physical mechanism

To address the "strong data dependence" problem of traditional machine learning, a physical information neural network (PINN) reduces the data requirements and improves the generalization ability by incorporating AM's physical equations (such as the heat conduction equation and fluid flow equation). Hu et al. (2024) reported that in the fatigue life prediction of Inconel 718, only 100 groups of samples were required to achieve the accuracy of the traditional ANN (500 groups of samples) (R^2 = 0.92). In the cross-material prediction (migration from Inconel 718 to Hastelloy X), the RMSE increased by only 0.8%, which was significantly better than that of the traditional model (which increased by 2.5%).

4. Future Challenges and Development Directions

4.1 Data Standardization and Sharing

This section discusses the importance of data standardization and sharing in the optimization and quality control of additive manufacturing based on machine learning. Su et al. (2022) noted that machine learning requires a large amount of database as the training support of the model, so the construction and development of the database is the premise of machine learning. They emphasized that with the development of data mining technology for material experiments, a rich database would be conducive to promoting the development of new materials in the field of additive manufacturing. In addition, Yuan et al. (2025) mentioned that there are still some shortcomings in the current machine learning methods in AM. For example, in data processing, the dual constraints of massive data demand and difficulty in obtaining high-quality annotation data and an uneven distribution of data weakens the generalization energy of the model, resulting in a significant decrease in accuracy of the model for new data scenarios. In summary, data standardization and sharing are important for improving the prediction accuracy and generalizability of machine learning models in additive manufacturing. Therefore, it is necessary to strengthen the construction of data standardization and sharing mechanisms.

4.2 Multiscale Modelling and Simulation

This section discusses the application of multiscale modelling and simulation in additive manufacturing and how to improve the prediction accuracy through machine learning technology. Combined with machine learning technology and multiscale modelling methods, H. Wang et al. (2025) carried out multiscale analysis and optimized the design for the fracture toughness of materials and improved their fracture toughness. By evaluating the fracture toughness of a material, damage to the material under different working conditions can be predicted, which provides an important reference for the design and practical application of the process. In addition, Hu et al. (2024) summarized a multiscale modelling method for the performance prediction of composite materials in additive manufacturing and noted that machine learning technology can be combined with a multiscale modelling method to effectively couple information at different scales to realize the full prediction of the fatigue and creep properties of materials. Through deep learning technology, the correlation between different scales is learned, and the prediction accuracy of the model is improved. In summary, multiscale modelling and simulation combined with machine learning technology provide an effective and accurate solution for the performance prediction of additive manufacturing materials. Future research should further explore how to optimize these models to better serve actual applications.

4.3 Interdisciplinary Cooperation and Technological Innovation

This section discusses how interdisciplinary cooperation and technological innovation can promote the progress of the optimization and quality control of additive manufacturing. Su et al. (2022) reviewed the optimization of additive manufacturing processes on the basis of machine learning and the research and development progress of new materials and emphasized the application of machine learning in additive manufacturing, including forming process monitoring and quality control, window prediction and deposition path optimization. In addition, they noted that the development of machine learning technology relies on a reliable dataset, which provides a solid foundation for the development of new materials in the field of additive manufacturing. Cao et al. (2024) further discussed the application of machine learning in additive manufacturing, including model parameter selection, defect and performance prediction, in situ monitoring and composition optimization, process optimization and structure optimization, with the aim of providing guidance for process control and performance optimization of additive manufacturing. Hu et al. (2024) focused on the application of machine learning in the mechanical property prediction of alloy materials for additive manufacturing and mentioned physics-informed machine learning methods. This method can better handle the complex nonlinear relationships between high-dimensional physical quantities, providing a new perspective for the mechanical property prediction of additive manufacturing materials and components. Huang et al. (2025) studied the application of machine learning in the fatigue life prediction of additive manufacturing and proposed that by combining physical mechanism knowledge with machine learning, the internal prediction mechanism of the model can be clarified, and the profit rate and calculation efficiency of the data can be improved. In summary, interdisciplinary cooperation and technological innovation have played important roles in the field of additive manufacturing. The application of machine learning technology not only improves the efficiency of art optimization and quality control but also provides new ideas for the research and development of new materials.

5. Conclusion

This paper reviews the research progress of additive manufacturing optimization and quality control based on machine learning over the past three years and analyses three core dimensions in detail: process parameter optimization, material performance prediction, quality control and process monitoring. Machine learning technology has significant application potential in the field of additive manufacturing, especially in the accurate optimization of process parameters and real-time monitoring of manufacturing processes, which can effectively improve the production efficiency and product quality stability of additive manufacturing. However, current related research still faces urgent challenges, which are reflected mainly in the lack of unified standards, the efficient sharing mechanism of data, and the immaturity of multiscale modelling and simulation technology. Although the existing research has achieved certain results in local applications, a systematic solution has not yet been developed, and it is difficult to fully meet the needs of large-scale and high-precision development of additive manufacturing. Therefore, future research should prioritize the establishment of unified additive manufacturing data standards and the improvement of cross-institutional data sharing mechanisms while strengthening the deep cross-integration of materials science, computer algorithms, mechanical engineering and other disciplines and breaking through technical bottlenecks with interdisciplinary innovation. Through the above path, the overall improvement in additive manufacturing optimization and quality control ability is finally realized, which provides strong support for the wide application of additive manufacturing technology in key fields, such as aerospace, medical, and automobile.

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Conflicts of Interest

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