Machine Learning-Based Optimization of Temperature, Speed, and Layer Thickness in FDM 3D Printing

Zhuoran Zhou

{Zhouzhuoran400@gmail.com}

The Hong Kong Polytechnic University, Department of Electrical Engineering, 999077, Hong Kong, China

Abstract. Fused Deposition Modeling (FDM) is a widely used additive manufacturing technique due to its low cost and ease of operation; however, product quality strongly depends on process parameters such as extrusion temperature, printing speed, and layer thickness. Traditional trial-and-error optimization methods are time-consuming and lack generalizability. Recent advances in machine learning (ML) enable predictive and adaptive optimization of FDM parameters, offering improved control and reproducibility. This review summarizes the application of supervised learning, deep learning, and reinforcement learning for multi-objective optimization of key FDM parameters. It further highlights the positive effects of ML-based optimization on mechanical properties, dimensional accuracy, surface quality, and process sustainability. Finally, the integration of ML with IoT-enabled smart printers and digital twin technologies is discussed, demonstrating the potential for intelligent and autonomous FDM manufacturing systems.

Keywords: Computer vision, natural language process, reinforcement learning.

1 Introduction

Additive manufacturing systems have made a significant impact in the field of manufacturing with reduced material wastage [1]. In the list of additive manufacturing systems, the most feasible and economical process is Fused Deposition Modeling. FDM is based on the process of extruding thermoplastic material from a nozzle at high temperatures and building up the material layer by layer in order to develop three-dimensional models. Although this process is more versatile and economical, the quality variations tend to be high because of the complex interaction between process parameters [2].

The intrinsic limitations in FDM technology are due to the complicated thermodynamic and kinematic effects in the extrusion and deposition process [3]. The bonding of layers is not only affected by the melting properties of materials, but it is also affected by cooling rates, environment, and pressure [4]. The complicated effects contribute to an NP process with large nonlinearity.

ICMEEA 2026, April 24-26, Singapore, Singapore

DOI 10.4108/eai.24-4-2026.2364910

To deal with these issues, this review concentrates on machine learning-based optimizations regarding three most influential parameters in FDM technology, including extrusion temperature, print speed, and layer thickness. Later on in this review, analysis regarding individual as well as joint impacts of mentioned parameters on quality will be done. Following that, an overall description regarding different machine learning strategies involving Random Forest, Neural Network, Reinforcement Learning) used in prediction and optimization. Thereafter, real impact analysis based on ML optimization in terms of mechanical strength, surface quality, as well as sustainable practices, is done. Finally, future scopes in terms of real-time closed-loop systems based on AI integration are put forward.

Process variables including extrusion temperature, printing speed, and layer thickness are highly influential in affecting inter-layer adhesion, dimensional accuracy, and surface roughness, respectively. However, the existence of complex nonlinear interactions among these variables renders traditional optimization approaches inefficient and ineffective [3]. Machine learning, an art of learning from data, has recently shown promise in the field of process prediction and optimization. Unlike traditional optimization techniques, the ability of ML algorithms to optimize multiple conflicting objectives at the same time provides optimal results that can simultaneously optimize print time, mechanical performance, dimensional accuracy, and energy efficiency, among others [5].

2 Process Parameters and Their Effects

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2.1 Extrusion

The extrusion temperature is a direct parameter influencing the viscosity and interlayer adhesion of the polymer and thus forms an important process parameter for FDM printing. If the extrusion temperature is lower than the ideal value, there will be some voids and inadequate interlayer bonding and fusion, while higher temperatures might result in the degradation of polymer chains, forming stringing defects and discoloration of the polymer, as evident from Fig.1[6].

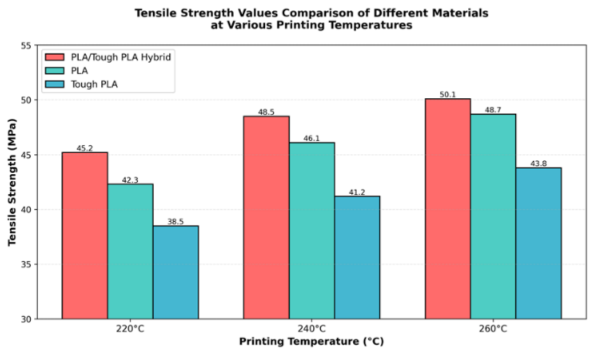

Fig. 1 Tensile Strength Values Comparison of Different Materials at Various Printing Temperatures

Research has proven that optimal temperature enhanced flowability and diffusion between layers, thus greatly enhancing tensile strength and layer integrity [4]. Hameed et al. agreed that using ASA [7] material, specimens undergoing Taguchi orthogonal design experiments obtained maximum values of tensile strength at optimal temperature variables. Analysis of experimental results indicates that when printing temperature was at 265°C and layer thickness was 0.08 mm, maximum tensile strength was 50.57 MPa, as seen in Table 1.

Table 1. L18 Orthogonal Array Experimental Design (Taguchi Method)

	Temperature (°C)	Speed (mm/s)	Layer Height(mm)	Tensile Strength (Mpa)	Surface Roughness(μm)
1	220	40	0.10	42.3	3.2
2	220	60	0.20	39.8	5.1
3	220	80	0.30	36.5	7.2
4	240	40	0.20	46.8	4.5
5	240	60	0.30	44.1	6.1

Also, the distribution of internal stresses and crystallinity of the polymer depend on the temperature. Quenching or annealing of the material, which depends on the cooling rates, can be rapid or slow depending on the thermal history experienced by the material during the printing process [8].

2.2 Printing Speed

This printing speed is an influencing factor of both the extrusion rate and the cooling rate of the layers of deposited filaments, thus creating a complex trade-off relationship with the desired part quality. For instance, high printing speeds exceed 80 mm/s. This high printing speed creates less time for the deposition of layers and the binding of the layers, thus increasing the likelihood of voids and weakness of the printed part. On the other hand, moderate printing speeds of 40-80 mm/s are an optimal value that provides an adequate binding of layers and relatively moderate printing time. Additionally, low printing speeds below 40mm/s provide an optimal binding of layers and surface finish, though the printing time is considerably long, thus increasing the likelihood of overheated materials.

Solouki et al. reported the decreasing trend of the tensile strength property with the increasing value of the printing speed when the temperature was held constant [4]. This is because a lower degree of fusion between the layers is achieved when the printing speed increases. Machine learning algorithms are able to incorporate all the complexities mentioned above and propose the best values for the printing speed according to the material, geometry, and application properties [3]. The outcome of the analysis is presented in Table 2.

Table 2. Experimental Design with Output Responses

Experiment	Temp	Speed(mm/s)	Layer H.[mm)	Tensile (MPa)	Elongation (%)	Hardness (shore D)

	(°c)					
Sample 1	220	40	0.15	41.2	3.5	78
Sample 2	240	50	0.20	46.5	5.2	81
Sample 3	260	60	0.25	48.1	4.8	82
Sample 4	250	45	0.18	47.3	5.0	80
Sample 5	265	40	0.08	50.57	6.1	79

2.3 Layer Thickness

Layer thickness is a dimension that is one of the most important factors that influence print resolution and mechanical anisotropy. In thin-layer printing, such as 0.1-0.15 mm, a small-scale detail and a smoother surface can be achieved, but the processing speed is much slower. In thick-layer printing, such as 0.3-0.4 mm, printing can be done much faster, and a "staircase effect" is observed, while the adhesion between layers is reduced owing to a shorter diffusion time. Fig 2 is the sketch of staircase effect.

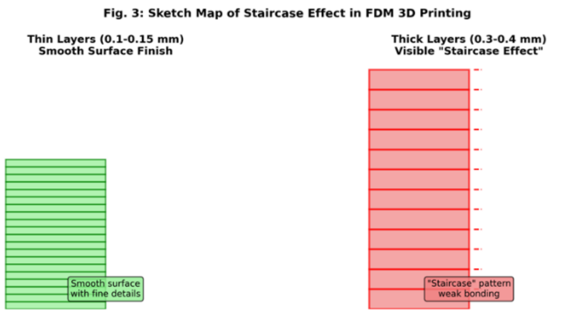

Fig. 2 Sketch Map of Staircase Effect in FDM 3D Printing

On analysis, it has been found that layer thickness is responsible for variation in tensile strength by 47.98%; thus, it is the most important parameter out of those analyzed [7]. Regression algorithms like Random Forest or Gaussian Processes have the capability to meet this trade-off based on data analysis obtained from various combinations of material parameters [9].

3. Machine Learning Approaches for Parameter Optimization

3.1 Supervised Learning Models

Supervised Machine Learning techniques such as Random Forest, Support Vector Machines, and Artificial Neural Networks have already been used efficiently to predict surface roughness, tensile strength, and dimensional accuracy from the process parameter values [10].

Random Forest (RF). It performs well on non-linear data patterns and small to medium-sized datasets, and the results of feature importance are interpretable. The Random Forest model has shown that when estimating print quality with temperature, speed, and height, the R^2 value can exceed 0.92, reaching results far superior to those of linear regression models [3]. This is because the Random Forest algorithm is an ensemble method that is robust to outliers and overfitting, which can occur in data from a production process that may have some degree of noise. Fig 3 shows the Random Forest model.

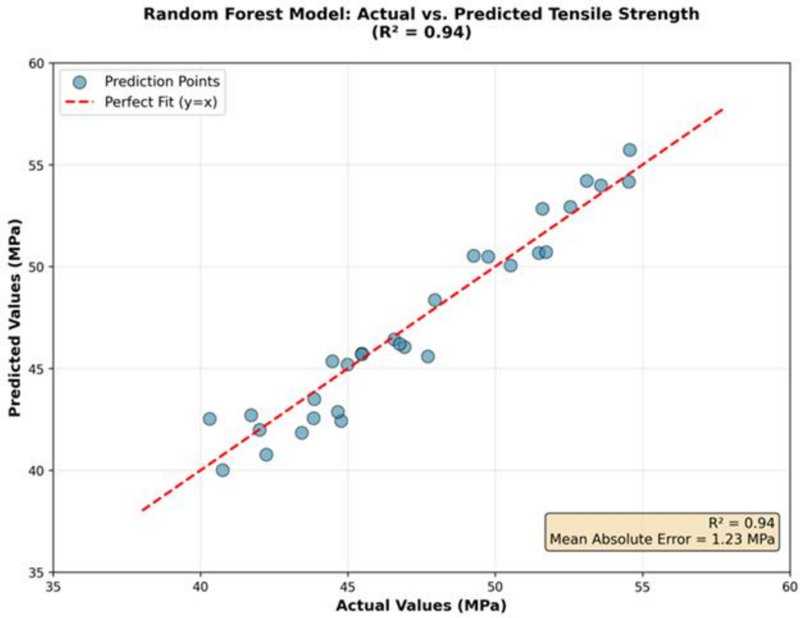

Fig. 3 Actual vs. Predicted Outcome Fitting from Random Forest Modeling

Support Vector Machines (SVM). This regression model provides outstanding outlier robustness and serves to be useful when estimating mechanical strength. This technique allows nonlinear relationships to be transformed into higher-dimensional spaces where linear separations with respect to variables might be achieved [6]. Research Works indicate that this model performs better than response surface methodology when treating nonlinear parameter interactions [11], as depicted in Fig.4 below.

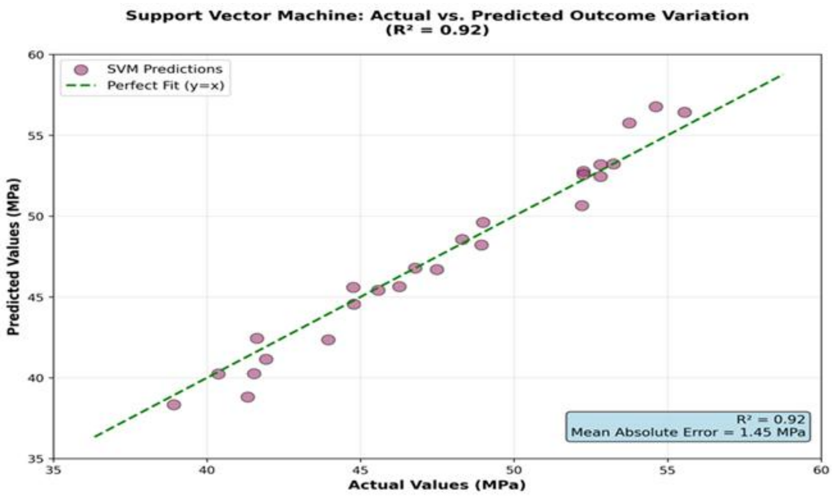

Fig. 4 Actual versus Predicted Outcome Variation from SVR

Artificial Neural Networks (ANN). When compared with RF and SVM, ANNs are able to learn nonlinear patterns and high-order interactions; however, they require significantly more samples (>500 samples) in their training dataset. Although the lack of interpretability in deep learning is still a problem, this is not such an issue with AI explainable methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) [5], as shown in Fig. 5.

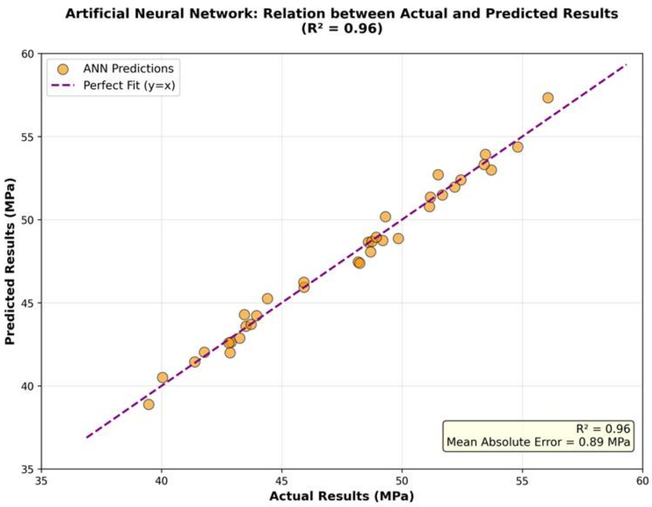

Fig. 5 Relation between Actual and Predicted Results from ANN [

Deep Learning and Computer Vision. Techniques for Deep Learning (DL), specifically Convolutional Neural Networks (CNNs), make it possible to process images directly to achieve real-time print monitoring and detection of defects. Thermal or optical images taken during the printing process can be input into CNNs to analyze potential layer defects, clogging of the nozzles, and geometry deviation during the process in a real-time manner [12].

Highly developed models, for instance, hybrid CNN-LSTM (Long Short-Term Memory) networks, forecast upcoming anomalies from previous image frames, thus allowing active modification of parameters before a material condition becomes irreversible. Models like these enable a printer to adapt control by autonomously varying temperature, print speed, and material flow rates based on observed thermal abnormalities or material deposition errors [13].

Studies have shown that the application of deep learning techniques is able to pick up signs of layer separation at an early stage, thus lowering the number of defects by up to 20% in comparison to monitoring systems that provide feedback in real time.

3.2 Reinforcement and Hybrid Learning Approaches

Reinforcement Learning (RL). RL has been applied to FDM control systems to adapt parameters based on reward functions optimized to maximize print quality, print speed, or multiple objectives. In these RL environments, sensors serve as feedback agents of the environmental inputs, and the algorithm learns optimal values of parameters through several million simulated or actual prints [14].

Recently, advancements in soft actor-critic learning, combined with digital twins, have shown rapid convergence for the policy and effective task completion in both simulation-based tasks, as well as real-world tasks, outperforming standard PID controllers by a considerable margin in real-time control tasks [14].

Hybrid ML Approaches. The best results have been observed with the combination of predictive models and optimization methods such as Genetic Algorithms, Bayesian Optimization, or Gray Wolf Optimization. These methods deal with multi-objective optimization such as maximizing strength and simultaneously optimizing printing time and energy [15].

4. Effects and Evaluation of ML Optimization

4.1 Improvements in Mechanical Performance

ML-based optimization always yields results that demonstrate an improvement in mechanical properties [4]. It has been shown that the combined effect of ML-based predictions of parameters enhanced the tension strength by 10-15%, which was not achievable when performing manual optimization of parameters on the basis of standard instructions from the manufacturer. This is because ML can point out unexpected settings of parameters that can counter the limitations of other parameters [4].

Optimization of both printing temperature and layer height led to improvements in dimensional accuracy with or without degradation in mechanical strength, whereas this is not achievable in single-parameter optimization methods [16].

4.2 Surface Quality and Dimensional Accuracy

Regression and ensemble ML algorithms effectively predict surface roughness and remove the influence of thermal warping distortions from printed parts. Surface roughness prediction helps to use process parameters optimal for either mechanical properties or aesthetics without manual trial and error process [5].

The deep learning network, which learns from sensor information while printing, recognizes delamination, bonding, and geometric defects early on, thus decreasing defects by at most 20% [12].

4.3 Multi-Objective Optimization and Sustainability

An important development in FDM technology is the optimization of competing goals by utilizing Pareto optimization, made possible by ML. Studies showed that there are optimization models that were able to optimize more goals simultaneously, including power consumption by 18%, dimensional accuracy by 12%, and reduction of waste by 15% more than single-goal optimization, as seen below Table 3.

Table 3. Predicted and Experimental Results with Error Percentage

Sample	Predicted Tensile (MPa)	Experimental Tensile (MPa)	Error (%)
1	42.5	42.3	0.47
2	46.3	46.8	1.07
3	48.5	48.1	0.83
4	47.2	47.3	0.21
Mean Error			0.62

Life-cycle assessment studies have shown that application of ML for parameter selection is an effective way to lower the ecological footprint in FDM. Optimized filling density, layer thickness, and printing speed enable a reduction in energy intensity by 15-25% with equivalent or improved material strength [17].

Sustainability Integration goes beyond energy efficiency. There is Emerging Research that highlights the need for integrating other aspects of eco-efficiency, including material recyclability and carbon footprint, into ML training objectives. Studies on recycled polymers and bio-based filaments show that ML algorithms training on alternative materials are capable of detecting sustainable processes without compromising component quality [18].

5. Future Prospects of Machine Learning-Driven FDM Manufacturing

5.1 Real-Time Closed-Loop Systems

"The next generation of manufacturing equipment will incorporate the use of machine learning algorithms and real-time sensing technologies such as thermal cameras, optics, accelerometers, and material flow sensors," according to Tarasankar Ghosh of the Indian Institute of Technology's Madras campus at the Indian Premier Technology Summit in Chennai on June 15, 2019 [19]. This will enable adaptive control by adjusting parameters during the printing process to enhance quality parameters and avoid digital twins, virtual copies of physical printers that work alongside the actual processes of manufacture, will be integrated with ML models aimed at printing predictions and recommendations of optimal parameters prior to printing, thereby decreasing trial and error associated with printing processes [20].

5.2 Data Standardization and Shared Repositories

However, the lack of available, standardized, and publicly accessible large datasets might pose a significant problem to the generalization capabilities of ML models over various printers and materials. It is imperative that future research efforts concentrate on the development of a centralized data repository for FDM process performance information [21]. This will enable the construction of ML models that can generalize from one material to another and one printer to another.

5.3 Explainable AI and Sustainable Manufacturing

Making ML models more interpretable with methods such as SHAP values and partial dependence plots will allow end-users to see how changes in parameters impact results, thus promoting acceptance in AI-driven manufacturing advice [19]. Incorporating sustainability factors like carbon footprint calculation, material use efficiency, and recyclability ratings into the objective function for the machine learning process will make machine learning for manufacturing more focused on green engineering [22].

6. Conclusion

Machine learning-based process optimization offers a strong and ever-growing paradigm for developing intelligent, autonomous FDM printing processes. The ability to understand complex, nonlinear processing relationships between various FDM parameters such as temperature, processing speed, and layer thickness, among others, with machine learning offers great prospects in high accuracy model prediction, minimizing wastage, and innovative advancements in additively manufactured products.

The interplay between smart machine learning approaches (such as supervised learning approaches, deep learning approaches, and reinforcement learning techniques), real-time sensing technologies, and developments in cloud infrastructure have brought unprecedented prospects in developing autonomous, adaptive printing processes for FDM printing. Coming developments in the fusion of machine learning approaches with IoT-based intelligent printing technology, digital twin design technologies, and overall sustainability concepts could bring innovative advancements in environmentally sustainable and economically viable additively manufactured processes to meet industry requirements under industry 4.0 and beyond developments.

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