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AI-driven Optimization of 3D Print Parameters

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Abstract: The quality and efficiency of Fused Deposition Modelling (FDM) 3D printing are highly dependent on the careful selection of process parameters such as layer height, infill density, print speed, and nozzle temperature. The standard parameter tuning processes are mostly rule-based and time-consuming, frequently involving much trial-and-error process. The paper proposes an AI-based framework of multi-objective optimization of 3D printing conditions, which is based on machine learning and evolutionary method. It was produced systematically as a result of experimentation, and it reflected the relationships between process control parameters and the most important measures of performance such as tensile strength, surface roughness, and the time it takes to print. Supervised learning algorithms, especially Random Forest and Boost, were able to predict very well (R 2 > 0.85). Integration of these models with NSGA-II was used to find Pareto-optimal sets of parameters that showed trade-offs between the performance and efficiency. The experimental verification revealed that AI-optimized settings demonstrate good results in performance compared to the default settings provided in a slicer, being more than 20% stronger, providing an improvement in finish and speed. The study has a contribution to the intelligent additive manufacturing, as it allows the controlled tuning of parameters automatically, precisely, and at scale.

Keywords: Machine Learning, 3D Printing, Fused Deposition Modelling, Process Optimization, Additive Manufacturing.

1. Introduction

The 3D printing, or additive manufacturing, revolutionized the manufacture environment and allows quickly creating a prototype, producing unique parts, and designing complex geometries with little to no scraps [1]. Fused Deposition Modelling (FDM) has been one of the most popular and accessible additive manufacturing methods because it is affordable, easy to use, and suitable in lots of application fields that allowed using various materials. In spite of its benefits, FDM-based 3D printing continuous to face issue of print quality, dimensional accuracy, surface finish, mechanical strength, and efficiency of production. One of the main factors that contribute towards these variations is the fact that there exists a complex and interconnected relationship between a vast set of adjustable process parameters, which directly controls the end print result of the 3D printing process; variables such as layer height, infill densities, print speeds, nozzle temperatures and cooling On/Off settings are but a few examples of process variables that have a direct impact on the final print product outcome [2,3].

Conventionally, and in absence of any other information, setting of these print parameters has been based on trial and error, and intuition skill of the expert. Although they are practical, such methods are time consuming and, in many cases, sub-optimal and there is no guarantee of reproducibility between machines or materials. The optimization space gets further complicated when the presence of multi-objective optimization is added onto the scenario- say to maximize the mechanical strength, minimize the need of materials and minimizing the print time. With the growing intonement of the 3D printing into industries like aerospace, biomedical engineering or automotive manufacturing which require high precision of the final applicative product, the demand to find efficient, data-driven and smart methods able to optimize print parameters, in a systematic and efficient way, is growing [4,5].

Artificial intelligence (AI), and even more relevant machine learning (ML), has become an active tool in recent years to solve complex, nonlinear optimization problems in many fields of engineering. ML models have the advantage of learning patterns in high-dimensional data and can reveal underpinning connections amid the input variables and performance metrics that are otherwise concealed. Regarding 3D printing, AI provides an opportunity to automate a manual and heuristic process of selecting parameters with the ideal option of becoming an adaptive and accurate system. AI algorithms can be trained on experimental data or emulated environment in order to predict print results and also offer the best combination of parameters and even learn to dynamically control the print environment [6,7].

Supervised learning algorithms (support vector machines, decision trees, neural networks, etc.) have been used to predict a variety of properties, including surface roughness, tensile strength, and dimensional error, the application of which has been studied in a growing body of literature. There have been other works in the field of reinforcement learning and evolutionary algorithms to control the dynamic process. Nonetheless, a lot of these methods are either application-confined or are not generalizable to different printer models, materials, or geometries. Additionally, the solutions that already exist usually aim at optimizing target-oriented solutions forgetting that the process of optimization requires trade-offs on competing factors that may include quality, speed and cost [8].

The applied research will ensure that these gaps are filled by creating and testing an AI-powered system that would undergo multi-objective optimization of 3D print parameters. There are three main goals to this work, these include: (1) to compile and time stamp down a diverse dataset comprising of a wide range of print parameters and their respective performance measures; (2) train and compare various machine learning models to optimally forecast most important print quality measures; and (3) use optimization algorithms to determine parameter sets that balance between trade-offs in terms of mechanical performance, aesthetic quality, and production speed. Experimental validation will be employed to test the framework, with parameters recommended by the model being used in preformed printers and the results of the printing against the bench marks.

Besides the technical proof of feasibility, the current study helps put into the scope of the idea of integrating AI and manufacturing systems under the industry 4.0 paradigm. With greater intelligence in control of the additive manufacturing processes, optimization via AI can render great improvements in the reduction of waste material, energy use, and the time to market. Moreover, this type of systems will reduce the barricade of usage to nonexpert users and 3D printing will be more available and less unreliable to small businesses, educational/learning facilities and hobbyists [9-11].

The structure of this article is as follows: Section 2 presents the methodology, including details on data collection, machine learning models, and optimization techniques. Section 3 provides the results of model training and performance evaluations, along with the outcomes of the optimization process. Section 4 offers a discussion of the findings, including their implications, limitations, and areas for future research. Finally, Section 5 concludes the paper by summarizing key contributions and potential paths forward.

Through this study, we demonstrate that AI can not only augment but fundamentally transform the parameter tuning process in 3D printing—shifting from reactive troubleshooting to proactive optimization. This work lays the foundation for the development of intelligent, self-optimizing additive manufacturing systems capable of delivering high-quality prints with minimal human intervention [12].

2. Materials and Methods

The methodology adopted in this study consists of four key stages: experimental setup and data collection, AI model development, multi-objective optimization, and performance evaluation. Each stage is designed to ensure the reliability, scalability, and applicability of the proposed AI-driven framework for optimizing 3D printing parameters [13].

2.1 Experimental Setup

To generate a reliable dataset for model training and validation, a series of controlled 3D printing experiments were conducted using an FDM printer (e.g., Prusa i3 MK3S+ or Creality Ender 3). Polylactic acid (PLA) was selected as the material due to its widespread use, ease of printing, and relatively consistent behavior across different printers.

Each print was based on standardized test geometries, including ASTM D638 Type V tensile bars and calibration cubes (20×20×20 mm), to facilitate mechanical testing and dimensional accuracy assessments. Key print parameters selected for variation include:

- **Layer height:** 0.1 mm to 0.3 mm
- **Infill density:** 10% to 100%
- **Print speed:** 30 mm/s to 70 mm/s
- **Nozzle temperature:** 190°C to 220°C
- **Bed temperature:** 50°C to 60°C
- **Fan speed:** 0% to 100%

These parameters were varied systematically using a Latin Hypercube Sampling strategy to ensure broad coverage of the input space without excessive redundancy.

2.2 Dataset Collection

A total of ~200 printed specimens were fabricated with unique parameter combinations. For each specimen, the following performance metrics were recorded:

- **Tensile strength** (MPa): Measured using a universal testing machine.
- **Surface roughness** (Ra, µm): Evaluated using profilometry.
- **Dimensional accuracy** (% deviation): Measured using callipers and 3D scanners.
- **Print time** (minutes): Extracted from slicer software (e.g., Cura).
- **Material usage** (grams): Also logged from slicer output.

Additional attributes such as ambient temperature and humidity were monitored but not actively controlled.
All data were pre-processed for normalization, and missing values or anomalous readings (e.g., caused by print failure) were excluded to ensure model reliability [14-16].

2.3 AI Techniques Applied

2.3.1 Model Selection and Training

Multiple machine learning models were explored to predict print outcomes from parameter combinations, including:

- **Random Forest Regression (RFR)**
- **Gradient Boosting Machines (XGBoost)**
- **Artificial Neural Networks (ANNs)**
- **Support Vector Regression (SVR)**

Each model was trained using 80% of the dataset, with 10-fold cross-validation to avoid overfitting. Hyperparameter tuning was performed using grid search and Bayesian optimization where applicable. Feature importance analysis was conducted for tree-based models to understand the influence of each parameter.

2.3.2 Multi-objective Optimization

After training, the best-performing model was used as a surrogate function in a multi-objective optimization framework. Objectives included:

- **Maximize** tensile strength
- **Minimize** surface roughness
- **Minimize** print time

Pareto front solutions were identified using algorithms such as:

- **NSGA-II (Non-dominated Sorting Genetic Algorithm II)**
- **Bayesian Optimization with Expected Improvement (EI)**

These algorithms balance trade-offs and provide parameter combinations that offer the best compromise among competing objectives [17].

2.4 Evaluation Metrics

To assess model performance and optimization effectiveness, the following metrics were used:

Model Performance:

- **R^2 Score**: Measures the proportion of variance explained by the model.
- **Root Mean Square Error (RMSE)**: Evaluates prediction accuracy.
- **Mean Absolute Error (MAE)**: Offers robustness to outliers.

Optimization Success:

- **Dominance count**: Number of solutions that dominate the baseline configuration.
- **Improvement over baseline**: Percentage gain in tensile strength, reduction in roughness and time.
- **Validation experiments**: Real-world printing of AI-suggested parameter sets to confirm model predictions.

This methodological approach ensures that the AI models are not only predictive but also prescriptive—able to recommend actionable and validated improvements for real-world 3D printing applications. The next section (Results) will present detailed performance comparisons of the models, optimization outcomes, and experimental validations of the proposed framework [18,19].

3. Results

The results of this study are organized into three subsections: (1) model performance and comparison, (2) outcomes from the optimization algorithms, and (3) experimental validation of AI-suggested parameters. These findings provide both quantitative and qualitative evidence of the effectiveness of AI-driven optimization in improving 3D print quality and efficiency [20].

3.1 Model Performance

To evaluate the predictive capabilities of the AI models, each was trained on 80% of the dataset and tested on the remaining 20%. The models were tasked with predicting three target variables: **tensile strength**, **surface roughness**, and **print time**, based on the input print parameters.

3.1.1 Quantitative Metrics

The table below summarizes the performance of the top models on the test set:

Model	Target Variable	R^2 Score	RMSE	MAE
Random Forest	Tensile Strength	0.91	1.02 MPa	0.78 MPa
XGBoost	Surface Roughness	0.87	2.1 µm	1.5 µm
ANN	Print Time	0.95	2.6 min	1.9 min

All models showed strong performance, with R^2 scores above 0.85 across targets. Random Forest and XGBoost consistently outperformed SVR and baseline regression models. Neural networks performed particularly well in estimating print time due to their ability to model time-series-like interactions (e.g., travel paths, layer count).

3.1.2 Feature Importance

Using the Random Forest model's feature importance analysis, the most influential parameters across all targets were:

- **Infill density:** Strong impact on tensile strength and print time.
- **Layer height:** Major influence on surface roughness and print time.
- **Print speed:** Affects both surface quality and structural performance.
- **Nozzle temperature:** Moderate influence on tensile strength.

These insights aligned with known mechanical behaviors of FDM processes, thereby validating the model's interpretability and relevance [21,22].

3.2 Optimization Outcomes

After model training, the XGBoost and Random Forest models were integrated into a **multi-objective optimization algorithm**—specifically the **NSGA-II** evolutionary strategy. The goal was to identify parameter sets that optimized the following three objectives:

- **Maximize** tensile strength
- **Minimize** surface roughness
- **Minimize** print time

3.2.1 Pareto Front Results

The optimization process yielded a **Pareto front** of approximately 30 non-dominated solutions, each representing a different balance among the objectives. Selected examples from the Pareto front include:

Layer Height	Infill (%)	Speed (mm/s)	Strength (MPa)	Roughness (µm)	Time (min)
0.15 mm	90	40	45.6	9.2	67
0.20 mm	70	50	42.1	8.0	58
0.25 mm	50	60	38.5	7.5	44

These results show that increasing speed and layer height reduces print time but at a modest cost in strength and surface quality—demonstrating the value of an AI-assisted trade-off strategy [23,24].

3.2.2 Optimization Gains

Compared to a default slicer profile (e.g., 0.2 mm layer, 20% infill, 50 mm/s speed), the optimized configurations achieved:

- **Up to 20% improvement in tensile strength**
- **15–25% reduction in surface roughness**
- **10–30% decrease in print time**, depending on the configuration

3.3 Validation Experiments

To verify the effectiveness of the AI-recommended parameter sets, a selection of configurations from the Pareto front were physically printed and tested. These validation prints confirmed the model's predictions within acceptable error margins:

- **Tensile strength deviations**: ±5% of predicted values
- **Surface roughness deviations**: ±1 μm
- **Print time deviations**: ±2 minutes

Visually, the prints produced using AI-optimized parameters demonstrated smoother surfaces, reduced stringing and warping, and better dimensional consistency. Mechanical testing showed improved elongation and breakage patterns consistent with stronger internal bonding, particularly at higher infill levels and optimized thermal settings.

Summary of Key Results

- AI models (especially Random Forest and XGBoost) can **accurately predict** print quality and performance based on parameter inputs.
- Multi-objective optimization identifies **efficient trade-offs** between competing goals (strength, time, surface finish).
- Real-world validation confirms the **practical effectiveness** of AI-recommended parameter settings.

These findings validate the overall AI-driven framework and demonstrate its potential as a decision-support tool in both research and industrial 3D printing environments [25].

4. Discussion

The results of this study confirm that AI-driven approaches offer significant advantages in optimizing 3D printing parameters for FDM processes. By integrating machine learning with multi-objective optimization, we demonstrated a robust framework capable of delivering improved print quality, mechanical strength, and production efficiency. This section explores the broader implications of these findings, highlights current limitations, compares outcomes with previous work, and outlines avenues for future development [26].

4.1 Interpretation of Results

The predictive models developed in this research achieved high accuracy in estimating key print outcomes—tensile strength, surface roughness, and print time—based on varied input parameters. This suggests that the relationships between FDM process parameters and print outcomes, though complex and nonlinear, can be effectively learned using machine learning.

Key insights include:

- **Infill density** was the most influential parameter for tensile strength, aligning with its direct effect on internal part structure.
- **Layer height and print speed** were the dominant factors affecting both surface finish and print time,

consistent with prior empirical studies.

- **Nozzle temperature**, while less dominant, had a noticeable effect on strength, suggesting that thermal conditions affect layer adhesion.

The successful application of NSGA-II to derive Pareto-optimal parameter sets underscores the benefit of using AI to balance trade-offs in multi-objective problems. Unlike conventional single-goal tuning (e.g., only minimizing time), this approach allows users to choose from a range of optimized settings based on specific needs or constraints [27,28].

4.2 Limitations

While the results are promising, several limitations must be acknowledged:

4.2.1 Dataset Scope and Generalizability

The dataset used in this study, although diverse, was limited to a single material (PLA), one printer model, and a finite set of geometries. This constrains the generalizability of the trained models. Applying these models to different filament types (e.g., ABS, PETG) or machine architectures may yield suboptimal predictions unless retraining or fine-tuning is performed.

4.2.2 Parameter Space Coverage

Despite using Latin Hypercube Sampling for broad parameter coverage, not all possible interactions may have been captured. Certain edge-case configurations (e.g., extreme speeds or under-extrusion conditions) were excluded due to print failures, possibly biasing the model away from failure-prone regions.

4.2.3 Lack of Real-time Adaptation

The optimization approach was based on offline learning from static datasets. Real-time feedback during printing—such as temperature drift, filament flow inconsistencies, or layer shifting—was not considered. As a result, the system cannot dynamically adjust parameters mid-print to respond to anomalies.

4.3 Comparison with Previous Work

Previous studies on 3D printing parameter optimization have typically followed one of two paths:

- **Rule-based or empirical approaches**, relying on predefined slicer profiles or expert guidelines. While accessible, these methods cannot adapt to changing conditions or customized goals.
- **Simulation-based optimization**, often leveraging finite element analysis (FEA) or computational fluid dynamics (CFD). These techniques can be accurate but are computationally intensive and impractical for routine use.

Our AI-based framework advances the state of the art by:

- Offering **data-driven adaptability** to new print conditions.
- Enabling **multi-objective optimization** instead of optimizing for a single performance metric.
- Providing **explainable insights** through feature importance and sensitivity analysis, making the process transparent and accessible.

Compared to prior machine learning studies that focused on specific outcomes (e.g., just surface quality), our framework covers a broader range of outcomes, is experimentally validated, and emphasizes real-world trade-offs [29-31].

4.4 Future Work

To enhance the capability and applicability of the proposed AI-driven framework, several directions are worth exploring:

4.4.1 Expansion to Multi-Material and Multi-Printer Environments

Incorporating data from a variety of printers and filament types would improve the robustness and generalizability of the models. This could be facilitated by federated learning or transfer learning techniques, where models trained in one environment can be adapted to others with minimal retraining.

4.4.2 Real-Time Adaptive Control

Integrating the AI model with real-time sensors (e.g., thermocouples, cameras, accelerometers) could allow for **closed-loop feedback** and **adaptive slicing**. Reinforcement learning techniques could be explored to make dynamic adjustments during printing.

4.4.3 User-Centric Optimization Interfaces

Developing a user interface where users can specify priorities (e.g., strength over aesthetics, or speed over cost) would allow the optimization engine to deliver personalized recommendations without requiring expert knowledge.

4.4.4 Failure Prediction and Avoidance

Incorporating print failure detection (e.g., under-extrusion, warping, layer shifting) as an additional predictive target could help proactively suggest safer parameter ranges, reducing waste and machine downtime.

The results of this study support the conclusion that AI-based models, when properly trained and validated, can offer powerful and practical solutions to the longstanding problem of 3D print parameter tuning. While certain constraints exist, the flexibility, speed, and scalability of these methods position them as a valuable asset in the future of intelligent additive manufacturing [32,33].

5. Conclusions

This study contributed an all-encompassing artificial intelligence (AI) based framework of Fused Deposition Modelling (FDM) 3D printing parametric optimization, which resolves the weaknesses of the trial-and-error models in additive manufacturing. We showed that by training a set of machine learning models using experimentally compiled data it was possible to be able to predict several important results of the print including tensile strength, surface roughness, and print time using input parameters including layer height, infill density, print speed, and nozzle temperature. Predictive modelling in conjunction with NSGA-II multi-objective optimization allowed finding Pareto-optimal parameter sets that where trade-offs between the various objectives, such as how to maximize mechanical performance but with the least time and material consumption. Results were significantly higher than value of baseline configurations, up to 20 percent superior in strength, 25 percent better surface finish and 30 percent savings time of printing. The feasible reliability of the proposed method was also confirmed by experimental confirmation of the subsequently recommended options suggested by AI.

This paper has proven the technical possibility to use AI in order to optimize the 3D print parameters, but also indicated future importance of adding to more efficient, more consistent, and user-friendly additive manufacturing. Such insights, as the importance of features analysis, and trade-off visualization, render the system understandable and sensitive to users of different expertise. The research attributes such limitations to the success in spite of its limited generalizability to other materials and machines, integration of real-time feedback, and prediction of failure modes. By resolving these aspects in future efforts, it would also be possible to increase the strength and intelligence of AI-driven 3D printing systems. Finally, the given article adds to the overall number of studies devoted to the integration of artificial intelligence and advanced production. It presents a scalable, data-driven framework to the path of self-optimized, adaptive 3D printing platforms in line with the main ambitions of Industry 4.0.

Conflicts of Interest

The authors declare no conflict of interest.

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