Additive Manufacturing Process Control Using Machine Learning

Vishvesh Khanzode
BE.(Mechanical Engineering),
Datta Meghe College of Engineering,
Navi Mumbai, India

Dr. Koilakuntla Maddulety
Professor cum Deputy Director (Research),
SP Jain School of Global Management,
Mumbai, India

Abstract

Additive manufacturing attains supply chain resilience by enabling localized production, reducing prototyping time through swift design iterations, and achieving on-demand manufacturing by crafting customized products when required. These advantages stem from its interconnected layer-by-layer fabrication process, redefining traditional manufacturing approaches. Like other industries, AM exhibits intricate parameter interdependencies, necessitating novel predictive models. In this study we used a dataset obtained from PLA-based Additive manufacturing process and used data-driven methodologies on the dataset including measurements of input and output parameters.

The study aims to predict energy consumption, print duration, and object weight based on input variables - layer thickness, printing speed, and line infill pattern. We used advanced machine learning techniques including linear regression, decision trees and random forests to create a predictive model for data driven decision making.

We segregated the collected data into two distinct sets: a training set which was used to train the machine learning model, and a test set to assess the model's performance on unseen data. This approach ensures the model's robustness and ability to generalize, allowing it to make accurate predictions for real-world additive manufacturing scenarios.

Results highlight machine learning's efficacy in forecasting output parameters. The research emphasizes the potential of computational models for real-time process control. It enhances resource efficiency by minimizing material waste and energy consumption. Collectively, these outcomes empower companies to streamline processes, make informed choices, and ultimately deliver high-quality products efficiently and competitively echoing the trend of data-driven transformations in manufacturing.

Keywords
Additive Manufacturing, Machine Learning, Data Driven Modelling, Random Forest Algorithm, Quality Control

1. Introduction
Additive manufacturing (AM) represents a innovative digital manufacturing method for creating three-dimensional objects, typically by layering materials based on computer-aided design (CAD) models. In contrast to traditional manufacturing techniques, AM offers several benefits, including the ability to produce intricate components with intricate shapes and structures, distinct microstructural characteristics, and properties, all while reducing time and expenses. Consequently, AM has garnered substantial attention in both academic research and global industrial applications in recent times (Wang et al. 2020).

Machine learning is pivotal for additive manufacturing (AM) process control, offering numerous advantages. It optimizes printing parameters by analyzing data, ensuring efficient material usage and reduced waste. Machine learning aids in real-time defect detection, minimizing the production of faulty parts. Predictive models forecast part quality, allowing for early intervention if deviations occur. It enables predictive maintenance, ensuring AM machines operate smoothly and reducing unplanned downtime. Furthermore, machine learning streamlines material management, customizes designs, enhances energy efficiency, and facilitates closed-loop process control, making it an indispensable tool for improving AM precision, efficiency, and overall quality.

Persistent fluctuations in product quality remain a significant obstacle to the extensive adoption of additive manufacturing (AM) techniques in production settings. To overcome this challenge, the practice of monitoring AM processes and assessing AM materials and components has become more prevalent, marked by enhanced precision. Consequently, a fresh wave of data related to AM has emerged, offering a valuable asset for obtaining fresh perspectives on AM processes and informing decision-making (Razwi et al. 2019).

Machine learning-based process control models are essential for additive manufacturing (AM) due to the inherent complexity of AM processes. These models optimize printing parameters, such as temperature and layer thickness, enabling the production of high-quality parts while minimizing waste. Quality assurance is a top priority in industries like aerospace and healthcare, and machine learning can detect defects in real-time, reducing the likelihood of faulty components and the associated scrap rates. Furthermore, AM processes often face variability in materials, environmental conditions, and machine characteristics. Machine learning adapts to this variability, maintaining process stability and consistency.

Efficiency improvement is another crucial aspect of machine learning in AM. By optimizing parameters, machine learning reduces production times, energy consumption, and material waste, which is vital for cost-effectiveness and sustainability. Predictive maintenance ensures machine uptime by anticipating maintenance needs, reducing unplanned downtime and costly repairs. This proactive approach to maintenance is invaluable for continuous production. Moreover, machine learning supports customization and innovation, driving the design and manufacturing of customized products efficiently. It also provides data-driven decision-making capabilities, extracting valuable insights from the vast amounts of data generated during AM processes. In turn, this facilitates process optimization and quality control, granting companies a competitive advantage and enabling scalability across various AM machines and processes. Ultimately, machine learning-based process control models enhance the reliability, efficiency, and innovation potential of 3D printing.

This study has been conducted for the additive manufacturing process of Fused Deposition Modeling (FDM), for the material Polylactic acid (PLA). From the literature we decided important parameters for process control and conducted trials on the sample piece for data collection. Based on the collected data we formulated machine learning models and tested them for prediction accuracy.

1.1 Objectives

This study has the following objectives: (i) to identify relevant process parameters in FDM process which can be considered for modeling, (ii) to identify suitable machine learning technique which can be used for developing predictive model, (iii) to decide the dimensional specifications for the sample test piece, (iv) to decide the values of process parameters to be set for the trials, (v) to conduct required number of trials and collect data, (vi) to develop a predictive model, based on machine learning algorithm, for effective process control in additive manufacturing, and (vii) to check the accuracy of the model. In the methodology section, the details are given in step-by-step manner.

2. Literature Review

In order to understand the current status of research in the subject area, we decided to carry out a literature review in the related domain. For this purpose, we searched for the literature on the following topics: additive manufacturing, process control, process parameters in FDM, machine learning techniques in additive manufacturing. We used these keywords as search strings in google scholar and other databases. From the search results, we excluded the results which were not published in peer reviewed reputed journals. Next, we reviewed the titles of the research papers to identify relevant papers for further study and reviewed the abstracts of the papers of interest. During our literature search we came across review papers discussing the applicability of machine learning algorithms for additive manufacturing process, and the papers presenting experimental results of application of machine learning algorithms. In the following paragraphs a brief review of the related papers is presented.

Baumann et al. (2018) present a comprehensive review of the impact and utilization of machine learning (ML) in the field of Additive Manufacturing (AM). The authors systematically identify the existing body of literature through a literature search and categorize it based on its practical applications within 3D printing. The research offers valuable insights into the current state of ML, deep learning, and related computational learning methods in the context of AM, including their potential implications for future developments such as cloud manufacturing and Industry 4.0 integration. The applications of ML within AM are explored in depth, encompassing areas such as process control, process monitoring, and the enhancement of product quality. Additionally, the study identifies key research questions and provides a comprehensive overview of the advantages and limitations associated with the convergence of AM and ML.

Baturynskaa et al. (2018) propose a conceptual framework for optimization of process parameters for powder bed fusion additive manufacturing (PBF AM) by combination of machine learning and finite element method. The authors present a review of application of statistical analysis to define significance of polymer powder bed fusion (PPBF) process parameters, application of mathematical modeling for analysis of PBF AM processes, application of Machine Learning for prediction of PBF process parameters and proposed conceptual framework on combination of Machine Learning and mathematical modeling.

To satisfy the rising consumer demand for top-notch personalized items, manufacturing firms must adopt innovative production methods like additive manufacturing. Yet, the widespread industrial and automated utilization of these technologies faces challenges due to inconsistent product quality and limited process stability. Sohnius et al. (2019) introduce an original method for forecasting product quality in Fused Deposition Modeling (FDM), relying on process parameters, real-time measurement data, and an apt machine learning algorithm. The objective is to lay the foundation for implementing process control and ensuring a steadfastly superior product quality.

Meng et al. (2020) discuss the most recent uses of machine learning (ML) within the additive manufacturing (AM) domain. These applications, spanning parameter refinement and anomaly identification, are categorized according to distinct ML functions, encompassing regression, classification, and clustering. The effectiveness of diverse ML algorithms in these specific AM functions is assessed and contrasted. Concluding the review, several prospective avenues for future research are proposed.

Additive manufacturing (AM) is a transformative technology, but its industrial adoption faces barriers like design challenges, limited materials, defects, and inconsistent quality. Machine learning (ML) has gained traction in AM for its data-driven capabilities. Wang et al. (2020) review ML applications in AM domains: ML enhances design by creating high-performance materials and topologies, optimizes processing parameters, analyzes powder spreading, and monitors defects during production. ML aids in pre-manufacturing planning and quality control. Concerns about data security in AM are addressed. This paper summarizes key findings and highlights ML's promising role in advancing AM research and development.

Li et al. (2021) used machine learning models for geometrical defect detection in additive manufacturing process. Five ML methods (Bagging of Trees, Gradient Boosting, Random Forest, K-nearest Neighbors and Linear Supported Vector Machine) were compared under various conditions and bagging and Random Forest were found the two best models regarding predictability.

In a comprehensive review, Qin et al. (2022) suggest that the adoption of additive manufacturing is hindered by complexities in manufacturing systems, rising demand for high-quality products, and challenges related to design, standardization, and quality control. To address these obstacles, machine learning (ML) technologies have emerged as crucial tools. This study employs a systematic literature review and clustering analysis to explore the state-of-the-art research at the intersection of ML and AM. Key areas include Design for AM (DfAM), material analytics, in-situ monitoring, defect detection, property prediction, and sustainability. Recognizing both challenges and opportunities, this research highlights ML's pivotal role in advancing AM.

There are several research gaps in the area of machine learning-based process control for additive manufacturing (AM) that offer opportunities for further investigation and advancement. Some of these research gaps include: (i) Variability: Many AM processes are susceptible to variations in material properties, environmental conditions, and machine characteristics. Research is needed to develop machine learning models that address variability, (ii) Limited Data: In some cases, obtaining sufficient labelled data for training machine learning models can be challenging. Research is needed to explore techniques for training models with limited data, (iii) Interpretable Models: Many machine learning algorithms, particularly deep learning models, are often considered "black boxes" with limited interpretability, (iv)

Transferability: Machine learning models developed for one AM process or material may not easily transfer to another, (v) Sustainability: Investigating how machine learning can be used to optimize AM processes for environmental sustainability, such as reducing energy consumption and material waste, is a critical research area.

Based on the literature review, we selected process parameters and designed the experiment in such a way to address the variability and sustainability issue for the FDM process. The details of the process parameters and the experiment are given in the next section.

3. Methods

In this study, the research method used can be divided in two parts: (i) method associated with AM process, and (ii) method associated with development of machine learning algorithms. These methods are elaborated in the following paragraphs.

3.1 AM Process

We conducted the study on the Fused Deposition Modelling (FDM) process, which is one of the commonly used 3D printing technologies. Fused Deposition Modeling (FDM) 3D printing is an accessible and versatile additive manufacturing process that constructs objects layer by layer using melted thermoplastic filaments. This technology is favored for its cost-effectiveness and applicability in producing functional prototypes and end-use parts. What sets FDM apart is its simplicity and broad utility, making it a widely adopted method across industries and educational settings, particularly for rapid prototyping and customization of objects. We used Prusa FDM 3D printer, which is a highly regarded and popular DIY 3D printing machine. It is known for its high-quality prints, durability, and ease of use. The Prusa FDM is a direct drive printer, which means the extruder is directly attached to the hot end, resulting in smoother and more accurate prints. Additionally, it has a heated bed and a fan-cooled hot end, making it suitable for printing with a wide range of materials. The 3D printer used for printing the test samples is shown in Figure-1.

To conduct the experiment we decided to use a standard I-shaped test piece made of PLA material. Polylactic Acid (PLA) is a commonly used material in Fused Deposition Modeling (FDM) 3D printing. It is a biodegradable thermoplastic derived from renewable resources such as cornstarch or sugarcane. PLA is known for its ease of use, low warping, and minimal odor during printing, making it a popular choice for both beginners and experienced users in the 3D printing community. The 3D Model of the test piece used is shown in Figure-2.

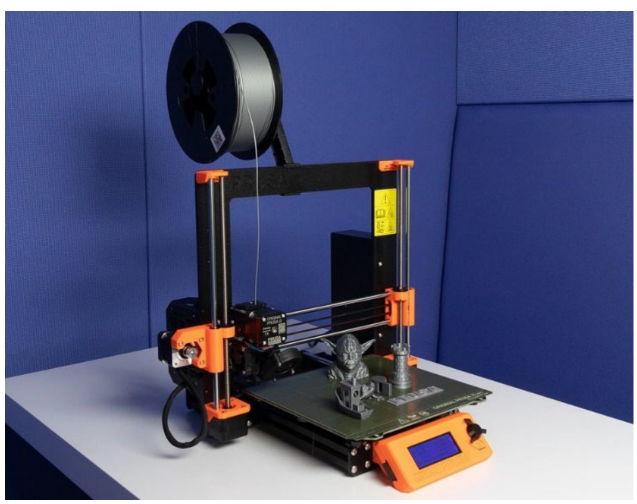


Figure 1. FDM 3D Printer

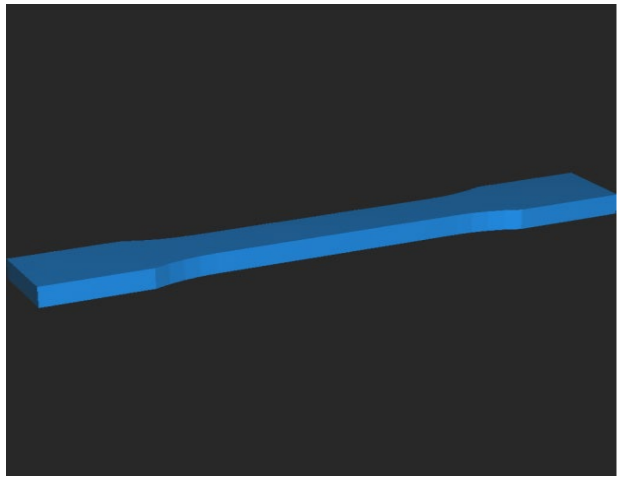


Figure 2. PLA test piece

Based on literature review we selected the following process parameters for conducting the experiment: (i) Layer Thickness (mm), (ii) Printing Speed (mm/s), (iii) Infill Percentage—as input parameters, and (iv) Energy Consumption (kWh), (v) Printing time (Hrs), (vi) Part weight (g)—as output parameters. Repeated trials were conducted for different values of input parameters and the output parameters were measured, which will be elaborated in section 4-Data Collection.

3.2 Machine Learning Algorithms

The machine learning algorithms are divided into two types, namely, supervised and unsupervised learning. In supervised learning, predictive models are developed based on both input and output data, while in unsupervised learning, data is grouped and interpreted based only on input data. Supervised learning models are further classified into classification and regression techniques, while unsupervised learning models are referred to as clustering techniques. The types of ML techniques are displayed in Figure-3.

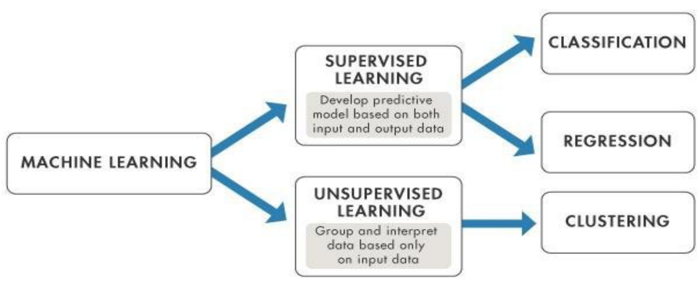


Figure 3. Types of ML Techniques

In the present study, both input and output parameters are continuous in nature, and it is required to develop a machine learning model to predict the output parameters from the given values of input parameters. Therefore, we chose to use regression techniques which helps us to build predictive models, based on supervised learning method. Particularly, we decided to use linear regression and random forest method to develop the predictive model.

Linear Regression is a fundamental predictive modeling technique that establishes a linear relationship between input variables and a target variable. It aims to predict continuous numeric outcomes by fitting a straight line to the data points. This widely used algorithm is simple, interpretable, and well-suited for tasks like price prediction, trend analysis, and correlation assessment. Random Forest Regression is a machine learning algorithm that combines the predictive power of multiple decision trees. It excels at making accurate predictions by averaging the outcomes of these decision trees, resulting in robust and reliable regression models. This ensemble technique is widely used for various applications, including prediction, forecasting, and data analysis.

As part of the research method, after selecting the applicable algorithms, we divided the collected dataset into two parts—training dataset (80%) and test dataset (20%). Python code was developed in latest version of python 3.10.3 and Jupyter notebook was used in open source Anaconda Navigator environment to run the code on a machine with Intel(R) Core(TM) i7-8650U CPU @ 1.90GHz 2.11 GHz processor and 8 GB memory. The code was used first to train the model, and then to predict the results.

4. Data Collection

The data was collected at of the additive manufacturing facilities—Arunoday Enterprises, in Kolhapur city. For collection of data, initially the parameters were classified as constant parameters, input parameters and output parameters. The following three parameters were treated as constant parameters: (i) Material—PLA, (ii) Infill pattern—line, (iii) Nozzle temperature—220°C. Next, for the input parameters, the full range was considered based on the machine specifications and several levels were decided with appropriate interval as shown in Table 1.

Table 1. Input Parameters and levels

Sr. No	Parameter (Input)	Range from	Rannge to	Increment	No of Levels
1	Layer Thickness (mm)	0.1	0.3	0.02	11
2	Printing Speed (mm/s)	50	90	5	9
3	Infill Percentage	60	100	5	9

Total of 100 trials were conducted by varying the levels of input parameters randomly. For each trial readings were collected for the output parameters. The snapshot of the data table is shown in the Figure-4.

	INPUT PARAMETER									
Sr No	Layer thickness	Printing speed	Infill %	Energy Consumption			Time		Weight	
				Start reading	End reading	Consumption	Estimated time	Actual time	Estimated Weight	Actual Weight
1	0.1	50	100							
2	0.12	50	85	12	12.4	0.4	3h55min	3hr54min56sec	15	13
3	0.14	50	90	12.4	12.6	0.2	2h10min	2h12min11sec	13	12
4	0.16	50	60	12.6	12.8	0.2	1hr56min	1h57min2sec	13	12
5	0.18	50	65	12.8	13	0.2	1h26min	1h31min18sec	11	10
6	0.2	50	85	13	13.1	0.1	1h21min	1h22min10sec	11	10
7	0.22	50	80	13.1	13.2	0.1	1hr20min	1h23min45sec	13	12
8	0.24	50	75	13.2	13.3	0.1	1h10min	1h15min45sec	12	11
9	0.26	50	70	13.3	13.5	0.2	1h5min	1h10min7sec	12	11
10	0.28	50	60	13.5	13.6	0.1	1hr0min	1h4min2sec	12	11
11	0.3	50	65	13.6	13.7	0.1	55min	57min26sec	11	10

Figure 4. Snapshot of the data table

5. Results and Discussion

After the data was collected, it was divided into training and test dataset as explained earlier. Next, Python code was developed for the two selected algorithms, i.e. Linear Regression and Random Forest. The Pseudocodes of the two algorithms are provided in Annexure-1 and Annexure-2 respectively. The libraries used in the python codes are given in Table-2.

Table 2. Libraries used in Python Code

Serial No	**Name of Library**	**Description**
1	pandas (imported as pd)	Used for data manipulation and analysis, especially with structured data.
2	sklearn.model_selection	Module for splitting datasets into training and testing sets, part of scikit-learn.
3	sklearn.ensemble.RandomForestRegressor	Module for implementing Random Forest Regressor models, part of scikit-learn.

4	sklearn.metrics	Module for calculating evaluation metrics for regression models, part of scikit-learn.
5	joblib	Used for saving and loading machine learning models, like saving the Random Forest model.
6	matplotlib.pyplot (imported as plt)	Used for creating data visualizations, such as line plots to visualize model predictions.

After developing the codes for the two algorithms, they were tested on sample standard dataset for accuracy, and upon verification, the data collected from the trials was processed through the codes. The results obtained are presented in the following sections.

5.1 Numerical Results

The numerical results consisted of predicted output parameters, and were obtained for both the algorithms. A sample snapshot of displayed outcomes through the running of codes is provided in Figure-5 and Figure-6. For the Linear regression algorithm, the coefficients of the regression equation were obtained, which are displayed in Figure-4. Here, y indicates the output variable and in the RHS of the regression equation, the four row vectors correspond to the the coefficients of the three input variables and the constant term in the regression equation respectively. Further, each term in the row vector corresponds to one of the output variables, and as there are three output variables the row vector contains three terms.

Linear Regression Equation:
y = [-0.02448604 -0.01200359 0.00847143]*x1 + [-0.18528296 -0.19107423 0.00123896]*x2 + [-0.00299008 0.02390096 1.07799327]*x3 + [0.12375 1.171375 11.55]

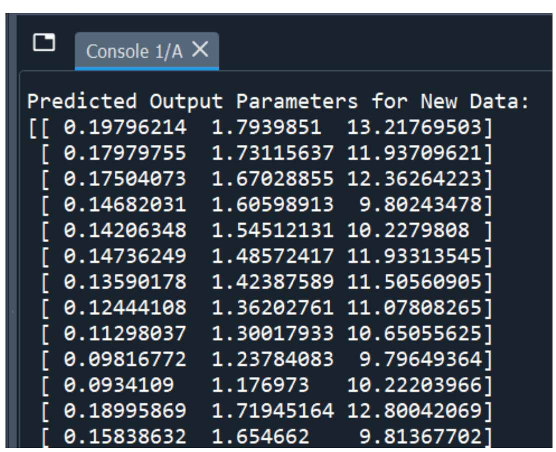
Figure 4. Coefficients of Linear Regression Equation

Thus, the regression equation for the third output variable, i.e. part weight can be written as follows.

Part weight = 0.008 * x1 + 0.001 * x2 + 1.077 * x3 + 11.55 **(Eq. 1)**

Where, x1, x2 and x3 represent the input variables.

Similar equations were derived for all the output variables and using the input values of the test dataset, the output values were predicted. A snapshot of the predicted values for the linear regression model is shown in Figure-5.



```
Console 1/A
Predicted Output Parameters for New Data:
[[ 0.19796214  1.7939851  13.21769503]
 [ 0.17979755  1.73115637 11.93709621]
 [ 0.17504073  1.67028855 12.36264223]
 [ 0.14682031  1.60598913  9.80243478]
 [ 0.14206348  1.54512131 10.2279808 ]
 [ 0.14736249  1.48572417 11.93313545]
 [ 0.13590178  1.42387589 11.50560905]
 [ 0.12444108  1.36202761 11.07808265]
 [ 0.11298037  1.30017933 10.65055625]
 [ 0.09816772  1.23784083  9.79649364]
 [ 0.0934109   1.176973   10.22203966]
 [ 0.18995869  1.71945164 12.80042069]
 [ 0.15838632  1.654662    9.81367702]
```

Figure 5. Snapshot of Sample Linear Regression prediction

Subsequently, we used Random Forest Regression algorithm to predict output variable values for the test dataset through a two-step process. First, during the training phase, an ensemble of data trees was constructed, each trained on a different random subset of the training data. These trees were trained independently to predict the output variable based on the input features.

Second, during the prediction phase, new datapoints were taken from the test dataset and individual predictions were collected from all the individual decision trees. The final prediction was obtained by averaging these individual predictions, which resulted in a more accurate and robust estimate of the output variable for that data point. The ensemble approach adopted reduced overfitting and improved predictive accuracy by leveraging the diversity of the constituent trees. A snapshot of the predicted values for the Random Forest model is shown in Figure-6.

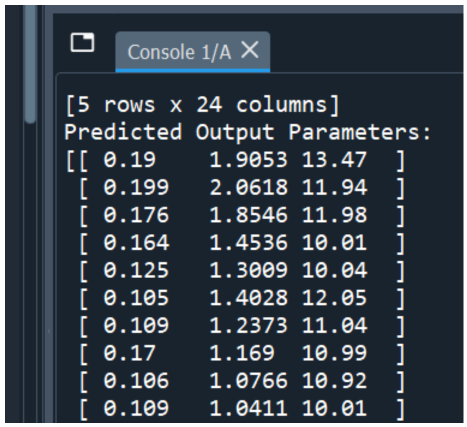


Figure 6. Snapshot of Sample Random Forest prediction

5.2 Graphical Results

The comparison of predicted vs actual values of the output variables are represented graphically in the following figures. Figures 7-9 respectively show the Predicted vs Actual values of Energy Consumed, The printing time and Part weight for Linear regression model. As observed from the graphs, the linear regression model makes conservative estimates of the predicted values, and is not able to accurately predict the extreme peaks in the dataset. However, if the data does not contain extreme values, linear regression fit is satisfactory.

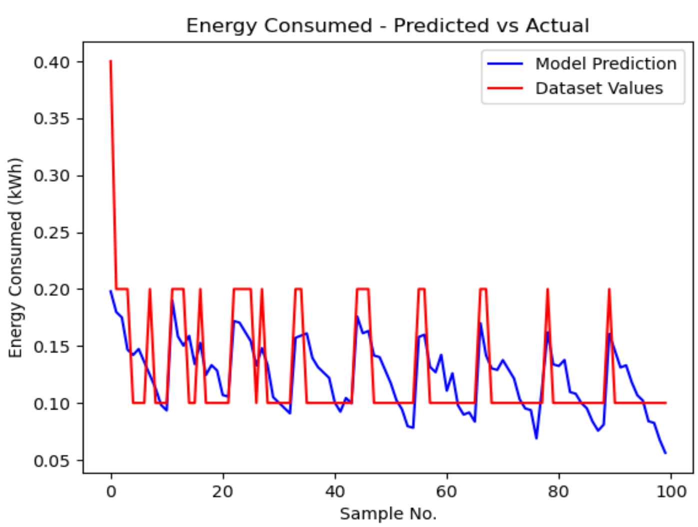


Figure 7. Energy Consumed Predicted vs Actual for Linear Regression

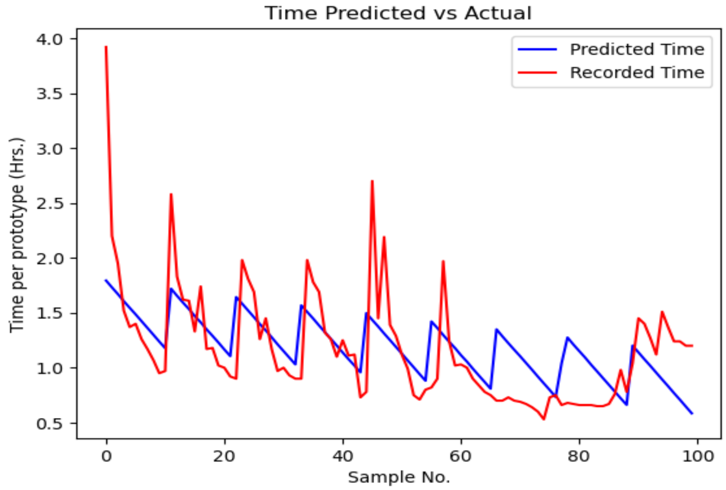


Figure 8. Printing Time Predicted vs Actual for Linear Regression

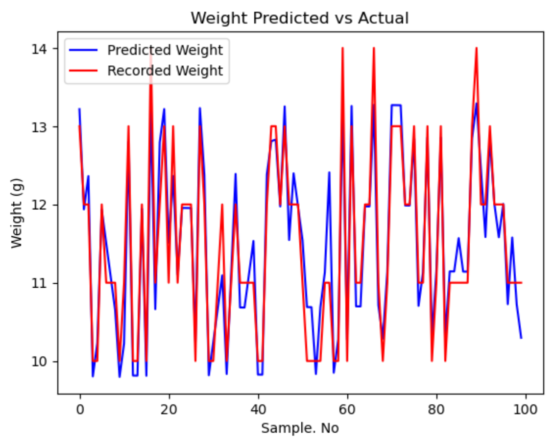


Figure 9. Part Weight Predicted vs Actual for Linear Regression

Figure 10-12 display the predicted vs actual values of output parameters, respectively Energy Consumed, The printing time and Part weight for Random Forest model. It is observed that the random forest model is able to predict with higher accuracy and also the predictions follow the extreme values in the dataset closely. This phenomenon is observed for all three output variables.

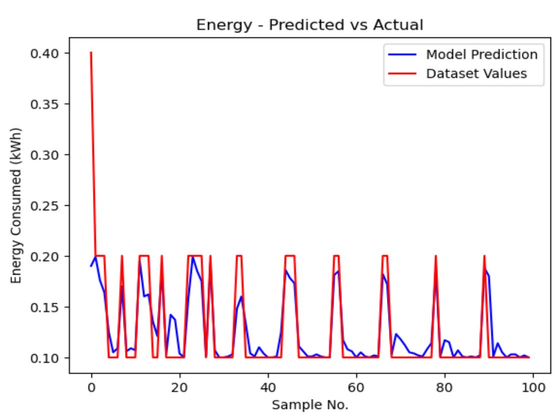


Figure 10. Energy Consumed Predicted vs Actual for Random Forest

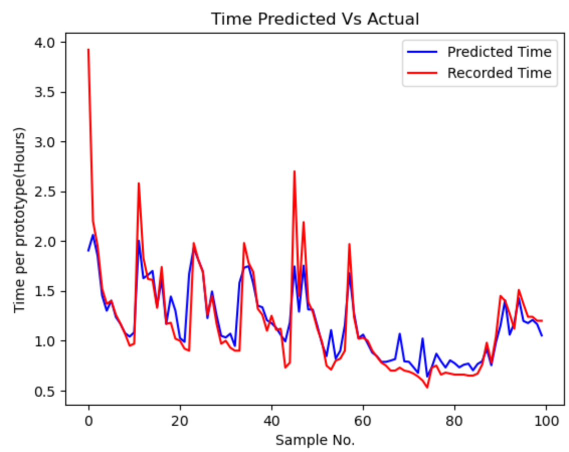


Figure 11. Printing Time Predicted vs Actual for Random Forest

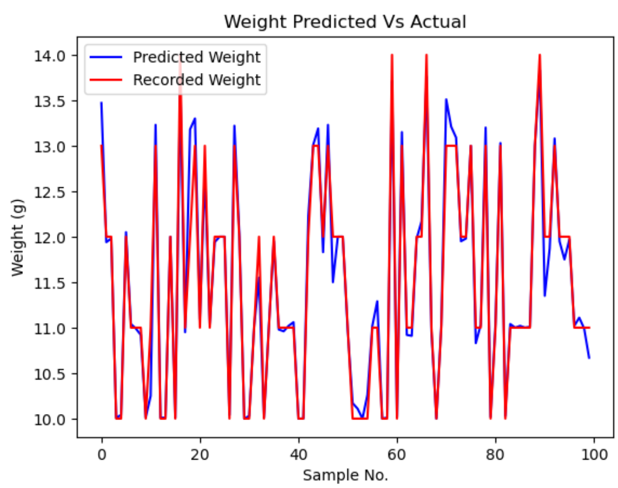


Figure 12. Part Weight Predicted vs Actual for Random Forest

5.3 Validation

We used the standard statistical parameters—Mean Absolute Error, Mean Squared Error, and Coefficient of determination (R-squared)—for validation of the regression models. These values were calculated on the test dataset using the parameters obtained from the model and are shown in Table-3. It was observed that random forest model was able to make better predictions as compared to linear regression model.

Table 3. Model performance measures

Model	**Mean Absolute Error (MAE)**	**Mean Squared Error (MSE)**	**R-squared (R^2)**
Linear Regression	0.2525	0.1851	0.5547
Random Forest	0.2086	0.1645	0.582

6. Conclusion

In this study, we have shown the applicability of machine learning techniques for prediction of process parameters in the additive manufacturing process. We used two fundamental algorithms, for the purpose of developing prediction model, based on experimental data. A case of FDM process using PLA material was selected for the experimentation purpose. It was ensured that the full range of input parameters was used for experimental settings to obtain better results. We found that random forest algorithm produces more accurate predictions as compared to linear regression. The practitioners can use similar approach to build and test the model, and the validated model can be used for online predictions, of output variables based on live process data. The current study uses only two algorithms and the number of samples used for training and testing purpose are limited due to overall costs constraints of the experiment. However, we can achieve better predictions by increasing the sample size. Also, more complex algorithm like Support Vector Machine, X-G Boost and Deep learning-based methods can be deployed for building more accurate prediction models. Furthermore, hyper-parameter tuning and optimization can be done to improve the overall prediction accuracy. Finally, a live decision support system can be developed which can take inputs from the process, and predict outputs dynamically.

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Biography / Biographies

Vishvesh Khanzode is a Mechanical Engineering Graduate with research interests in areas of Operation research and supply chain. He has worked with steel valve industry and also with E Commerce startup as operations executive. He has presented his work he did with Numer8(A data analytics company), in the area of humanitarian logistics, in International Conference on Industrial Engineering and Management (2022) and won the best paper award. He has also conducted study in area of foundry quality control, which has been selected for International Conference on Business Analytics and Intelligence by ORSI at IISC, Bangalore.

Dr. Koilakuntla Maddulety is Professor cum Deputy Director (Research) at SP Jain school of Global Management, Mumbai. He holds B.Tech. Degree from Acharya Nagarjuna University, DIM (Diploma in Management) and PGDIM from IGNOU(Indira Gandhi National Open University), M.Phil and Ph.D from Shivaji University. He has 15 industrial experience, and 12 years of academic experience at NITIE and SP Jain School of management Combined. He has conducted several training programs in Taguchi Robust Engineering for Process Design Optimization, Design of Experiments and ANOVA for Process Optimization, Six Sigma for Business Excellence, Lean Six Sigma for

Business Breakthrough, Process Improvement through QC 7 Tools, ISO-9001: 2000, ISO 9001:2008, Five S, Lean Manufacturing, SQC/SPC for Process Variation Control, and Total Quality Management.

Annexure 1: Pseudocode for Linear Regression Algorithm

```
# Load the dataset from a file
Load the dataset from "path_to_dataset.csv"

# Separate the dataset into input features (X) and target variables (y)
Extract "layer_thickness," "printing_speed," and "infill_percentage" as X
Extract "energy_consumption," "time," and "weight" as y

# Split the data into two parts: one for training and the other for testing
Split the data into training and testing sets (80% for training, 20% for testing)
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Normalize the feature values to have a consistent scale
Normalize the training and testing features

Create a model to predict target variables
Create a linear regression model

Train the model using the training data
Train the model using the training features and target variables

Use the trained model to predict target variables for the test data
Predict target variable values using the testing features

Evaluate the model's performance
Calculate the Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R2)

Print the evaluation metrics
Display the MAE, MSE, and R2 values

Prepare new data for prediction
Create a new dataset with different input feature values

Normalize the new data using the same scaler used for training
Normalize the new data

Use the trained model to predict target variable values for the new data
Predict target variable values for the new dataset

Print the predicted output values for the new data
Display the predicted output values

Visualize the data (optional)
Create plots to visualize energy consumption, time, and weight data

Annexure 2: Pseudocode for Random forest Algorithm.

Import necessary libraries
Import the required libraries for data manipulation and machine learning.

Load the dataset
Load a dataset from a specified file location.

Prepare data
- Select specific columns from the dataset as input features (X) and target variables (y).
- Print the first few rows of the dataset to inspect its contents.

Split the data
Divide the dataset into a training set and a testing set, typically with an 80/20 split.

Create and train a Random Forest Regression model
- Initialize a Random Forest model with specific parameters.
- Train the model using the training data.

Make predictions
Use the trained model to predict target variables on the test data.

Evaluate the model's performance
Calculate various performance metrics such as Mean Absolute Error, Mean Squared Error, and R-squared.

Print the evaluation metrics
Display the calculated performance metrics.

Save the trained model
Save the trained model to a file for future use.

Generate new data for prediction
Create a new dataset with different input values.

Predict using the trained model
Apply the trained model to predict target variables for the new data.

Display predicted output parameters
Print the predicted output parameters for the new data.

Visualize time data
Create a plot comparing predicted and recorded time values.

Visualize weight data
Create a plot comparing predicted and recorded weight values.

Visualize energy consumption data
Create a plot comparing predicted and actual energy consumption values.