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DEEP LEARNING-BASED MECHANICAL PROPERTIES PREDICTION IN FUSED DEPOSITION MODELING: A DATA SCIENCE APPROACH APPLIED TO ADDITIVE MANUFACTURING

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ABSTRACT

Fused Deposition Modeling (FDM) has emerged as an additive manufacturing technology (AM) capable of creating parts with low production volume and high added value. One challenge observed in the FDM-AM process is to find the process parameters to each material that guarantee the repeatability and reproducibility in parts. This paper presents a data-driven predictive approach that estimates the mechanical properties of parts from the process parameters. A dataset with 50 experiments was used to train two models. These models have seven input parameters and one output parameter for each model. An exploratory data analysis was performed to understand the relation between the process parameters and the mechanical properties. Then Multilayer Perceptron (MLP) algorithm was used to estimate the roughness and tensile strength. The network architectures have four layers. The first layer has 20 neurons; the second layer has 25 neurons, and the third and fourth layers with 60 neurons, respectively. Root Mean Squared Error (RMSE) and coefficient of determination R2 score were used to evaluate the model precision. A comparison between the roughness and tensile strength allows observing that the roughness model obtained reliability for future forecasts with an R2 of 0.98 and a better fit with an RMSE = 1.73, in opposition to the Tensile strength obtained an RMSE of 2.69. and an R2 = 0.96

Keywords: Additive Manufacturing, Fused Deposition Modeling, Multilayer Perceptron, Roughness, Tensile Strength

1 Introduction

1.1 Additive Manufacturing

Additive Manufacturing (AM) has experienced different transformations to consolidate itself as one of the pillars that support the new concept of industry 4.0 [1]. One of the most popular techniques of AM is the Fused Deposition Modeling process (FDM), also known as Fused Filament Fabrication, Fused Layer Modeling, or Material Extrusion. This technique consists of depositing a filament from a nozzle at a high temperature while the nozzle system is moving. The material leaves the nozzle in a molten form, and due to the movement of the deposition system, it adheres to a printing heat bed. This process allows the creation of 3D models with a range of materials: metallic [2], ceramic [3], composite [4], and polymeric [5].

To create a part using the FDM process is necessary to follow a series of steps that start from preprocessing through production and post-processing [6]. In the pre-processing, the 3D part is used in the stereo-lithography format. When a new material is used, the process parameters must be adjusted considering the machine's capacity, the filament manufacturer's recommendations, and the worker's experience. A 3D printing slicing software is used to adjust the process parameters. Then the software transfers an STL file to a series of layers representing the machine path in G-code format [6].

Process parameters can be categorized into three groups: Temperature conditions: Nozzle temperature, bed heat temperature, and environment temperature; Building orientation: The main orientations are vertical, horizontal, or lateral. However, orientations can be modified based on the user experience. Slicing parameters: Nozzle diameter, layer thickness, deposition speed, flow rate, infill, raster orientation, raster pattern, air gaps, top thickness, bottom thickness, and number of contours [7].

1.2 Current State of the Knowledge

Data-driven approaches applied in the AM process have received attention in recent years due to their ability to offer accurate results from previously performed datasets. This approach allows us to improve the quality of parts obtained by this process. A source of information about this issue is explored in this paper.

Baturynska, (2018) developed a statistical study to measure the dimensional accuracy in additive manufacturing of the parameters of thickness, length, and width, based on linear regression, considering the properties of the model in STL format [8]. The mentioned work highlighted the impact of the number of mesh triangles on width and thickness (XZY orientation), length (in ZYX), and angle orientation. Baumann *et al.* (2018) analyzed the trends of the Machine Learning approach applied in the AM process, proposing five groups to improve the part quality in this process: process parameters, quality improvement, process monitoring and control, digital security, and additive manufacturing [9]. Also, emphasize using Artificial Neural Networks, genetic algorithms, and Support Vector Machine applied to AM. These aspects show an increment in the use of deep neural networks for component analysis and Particle Swarm Optimization.

Li et al. (2019) estimated the roughness surface in the FDM process using an ensemble of machine learning algorithms [10]. Features in time and frequency were extracted from two thermocouples and two accelerometers installed into the plate and the extruder system. They compared the accuracy between the ensemble model and individual algorithms obtaining a better accuracy of the model ensemble in terms of Root mean square error (RMSE) and relative error metrics.

Recently a comparative analysis between MLP and Convolutional Neural Networks (CNN) for predicting the scaling ratio for each part from the EOS P395 polymer-powder bed fusion was performed [11]. The mean square error (MSE) was used as a metric to compare the accuracy of each model. MLP outperformed the CNN and helped to reduce the dimensional precision. However, they highlighted the possibility of obtaining a better result using CNN if more experiments were performed.

A data drive predictive model to estimate the tensile strength using PLA as the printing material was developed [12]. Extruder temperature (ºC), printing speed (mm/s) and layer height (mm), were considered as the input parameters. One thermocouple and accelerometer were installed into the heat bed and included in the input dataset. Metrics obtained from the R2 allowed observing that the Long Short-Term Memory model has outperformed the random forest and supporting vector machine, with the respective improvement being 9.8% and 24.3%. They confirmed the effectiveness of the sequential layer by layer of the FDM process using the Long-Short Term Memory network.

Although artificial intelligence approaches have stood out as an alternative that offers precision for linear and non-linear problems, the use of these approaches for ABS and PLA has not been developed before, as well as the use of parameters such as infill pattern and bed head. These parameters have significant importance in the quality of the part.

This paper presents a novel deep learning approach to predicting the surface roughness and tensile strength of parts from the FDM process. The remainder of the paper is organized as follows: Section 2 provides the materials and methods describing the dataset characterization, Pearson correlation, and the MLP algorithm, including the network architecture and the evaluation metrics. Section 3 presents the results and discussions, and section 4 provides conclusions.

2 Materials and Methods

The whole methodology of this study covers five main steps.

- Dataset characterization
- Pearson Correlation
- Multilayer perceptron
- Network Architecture
- Metrics Evaluation

2.1 Dataset Characterization

The dataset used in this study was made available by the Department of Mechanical Engineering at the University of Selcuk [13]. In this dataset, fifty experiments were analyzed. Nine process parameters were considered input parameters: Layer Height (mm), Wall Thickness (mm), Infill Density (%), Infill Pattern (honeycomb and raster), Nozzle Temperature (°C), Bed Temperature (°C), Print Speed (mm/s), Material (ABS and PLA), Fan Speed (%), and two outputs: Roughness and Tensile Strength.

The Nozzle temperature range used in this research for ABS is from 220 °C to 250 °C and PLA from 200 °C to 220 °C. The heat bed temperature for the ABS is between 60 °C and 80 °C. In addition, for PLA, between 60 °C and 90 °C. The basic statistics of the process parameters are. described in Table 1. The infill pattern and the material type were defined as discrete values. To the material type ABS = 1 and PLA = 0, and to infill pattern, honeycomb =1 and grid = 0.

2.2 Pearson Correlation

The Pearson correlation was calculated to understand the linear correlation between the input parameters and outputs. This metric allows us to observe if two study variables are proportional directly (positive values) or if these variables are proportional inversely (negative values). As well if the correlation is small (values between ±0.1 and ±0.3), medium (values between ±0.3 and ±0.5), or large (between ±0.5 and ±1). This equation is given for Eq. 1.

$$r = \frac{\sum_{i=1}^{n}(x-\bar{x})(y-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y-\bar{y})^2}} \tag{1}$$

In which x and y are variables samples, $\bar{x}$ is the mean of the values in x and $\bar{y}$ is the mean of the values in y.

2.3 Multilayer Perceptron (MLP)

An MLP can be defined as an algorithm able to learn and define complex nonlinear relationships between inputs and outputs [14]. This algorithm is composed of one input layer, one or more hidden layers, and one output layer, in which the outputs of every neuron are connected with the neuron inputs of the next layer. Consequently, the input signal propagates through the network. Rectified Linear Unit (ReLU) activation function is applied in all hidden layers except the last layer.

2.4 Network Architecture

MLP was used to estimate the roughness and tensile strength of two different models with the same architecture. The architecture used in these models has four layers: the first is composed of 20

Table 1: Basic statistics of process parameters and output variables.

	Layer Height	Wall Thickness	Nozzle Temp	Bed Temp	Fan Speed	Roughness	Tensile Strength
Mean	0.11	5.22	221.50	70.00	50.00	170.58	20.08
Std	0.06	2.92	14.82	7.14	35.71	99.03	8.93
Min	0.02	1.00	200.00	60.00	0.00	21.00	4.00
25%	0.06	3.00	210.00	65.00	25.00	92.00	12.00
50%	0.10	5.00	220.00	70.00	50.00	165.50	19.00
75%	0.15	7.00	230.00	75.00	75.00	239.25	27.00
Max	0.20	10.00	250.00	80.00	100.00	368.00	37.00

neurons, the second layer of 25, and the third and fourth layers of 60, respectively. It was considered 70% of the dataset for training and 30% for evaluation.
In the loss function used is the Mean Square Error, shown in Eq. 2. N represents the sample size, and the elements inside the parentheses represent the square of the difference between actual (y_i) and predicted values ($\hat{y}_i$)

$$MSE = \frac{1}{n}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{2}$$

This loss function value allows us to obtain positive values due to always squaring the errors. A Random state was used as a hyperparameter to control the randomness involved in the model.

2.5 Metric Evaluations

Evaluate the accuracy of predicted values obtained by the deep learning model in this study are discussed in terms of two metrics, Root Mean Square Error (RMSE) Eq.3, and the coefficient of determination, R^2 Eq. 4.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{3}$$

RMSE can be defined as the standard deviation of the residuals indicating the average model prediction error. RMSE is given for absolute values, and when its value is lower, it means a better fit for the model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

In which $\bar{y}$ is given for Eq. 5.

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{5}$$

The coefficient of determination is a measured value that indicates the spread between the actual and predicted values and is given in perceptual values. A Higher R^2 coefficient suggests a better fit for the model.

3 Results and Discussions

The Pearson correlation of the input parameters and tensile strength and roughness were calculated. Roughness showed a large proportional directly with the layer height. Other aspects, such as layer height, wall thickness, and infill pattern, showed a medium correlation with the tensile strength. The nozzle temperature showed a proportional inversely correlation with the tensile strength; depending on the material, when the nozzle temperature increases, the tensile strength decreases due to the solidification occurring during the process. The correlation observed with the infill density, and print speed with the output values presented a low correlation.
For this reason, it was excluded from the model. This decision allowed improve the performance. of the model. The results of this correlation are shown in Table 2.
The deep learning model was trained with 500 epochs. The loss function MSE of 100 in 100 epochs is shown in Table 3. The performance metrics were calculated and presented in Table 3, showing a decrease in the loss function value for each output. The tensile strength showed a coefficient of determination R^2 of 0.96, showing a reliable model for future forecasts. The RMSE to the tensile strength model was 2.96, which means the model can fit with the dataset.
The Roughness showed a coefficient of determination of 0.98, showing a reliable model for future forecasts and better fit concerning the tensile strength model (0.96). The RMSE to roughness showed a better performance (1.73) when com-

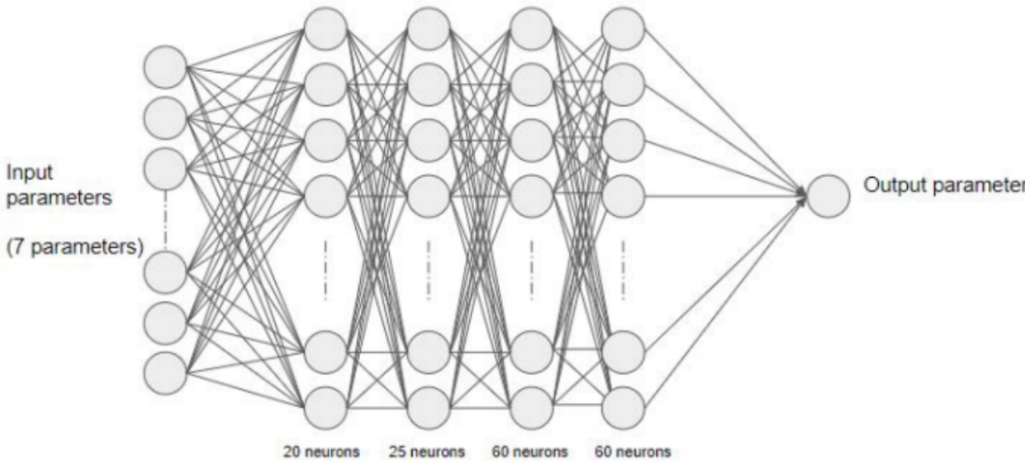

Figure 1: Network Architecture of four layers. To hidden layers was used The RELU activation function.

Table 2: Pearson correlation between input and outputs parameters.

	Layer height	Nozzle Temp.	Wall Thickness	Infill Pattern	Bed temp.	Material	Fan Speed	Infill Density	Print Speed
Tensile Strength	0.34	-0.41	0.4	0.36	-0.25	-0.30	-0.25	0.01	0.27
Roughness	0.80	0.35	-0.23	0.12	0.19	-0.40	0.19	0.05	0.12

Table 3: Loss Function to tensile strength and roughness of 100 in 100 epochs.

	Tensile Strength		Roughness	
Epoch	Loss	Loss Val	Loss	Loss Val
1	368.12	305.22	42339.35	43009.9
100	2.43	0.50	21.43	15.51
200	0.70	1.81	2.84	4.54
300	0.42	1.67	1.81	3.51
400	0.27	1.48	1.25	2.35
500	0.19	1.27	0.85	1.52

pared with the tensile strength (2.69). However, both indicators showed a good fit [15].

4 Conclusions

AM processes are highly interested in guaranteeing the repeatability and reproducibility of parts. The process parameters, the work material, and the environment control are important aspects of reducing the differences between printed parts. Adjusting the process parameters when new material is used is a priority to increasing the quality of components in terms of roughness and tensile strength.

This paper studied a dataset provided by the Department of Mechanical Engineering at the University of Selcuk. Fifty experiments were analyzed from a basic statistics approach. Then this dataset was used to train an Artificial Neural Network (ANN) based on the Multilayer perceptron algorithm. This approach creates a mechanism to estimate the roughness and tensile strength from process parameters provided by the dataset. One of the limitations found during this approach was using a dataset with a low number of experiments. This fact directly affects the model performance and evaluation metrics. On the other hand, using two materials in the dataset with different process parameters contributed to a longer learning process to understand new correlations depending on the material used. Comparing both models allowed us to observe that roughness outperformed the tensile strength model. Results for the MLP network show the possibility of using this method in future studies after more data is accumulated. A future Investigation that would help improve this line of research is using temperature sensors within the deposition area. It is due to the ABS being a sensitive material to the loss of temperature in front of airflow, increments so sudden that they cause cracking (layer delamination), and the total sentence of the print.

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