Performance-Driven Optimization of Extrusion-Based Additive Manufacturing Using Hybrid AI Techniques for Sustainable Engineering Components

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Abstract

The potentials of additive manufacturing (AM) transformed the engineering field through innovative, customized, and rapid fabrication of complex geometries. This study investigates the capabilities of fused deposition modeling (FDM) additive manufacturing to attain the desired mechanical properties of parts for engineering applications. FDM gained popularity due to its low cost, ease of use, versatility and suitability for various engineering parts of different materials. The experiments are designed based on Taguchi methodology to fabricate the test specimens using Polylactic acid (PLA) material. The mechanical test was conducted and data collected for statistical analysis. An Artificial Intelligence (AI) based hybrid approach is used for the parametric optimization. The results show a significant improvement in tested mechanical strength corresponding to the optimum parameters settings. The optimized parameters are validated through experiments in conjunction with findings of former researchers. It resulted to saving of manufacturing time and material with 9.77% and 0.11% respectively with desired mechanical strength. The outcomes of this study are significant for the engineers, researchers and practitioners to understand the parametric role of AM for engineering applications.

Keywords: Additive manufacturing; Artificial Intelligence; Parametric Optimization; Mechanical Strength

1. INTRODUCTION

Additive manufacturing (AM), a revolutionary paradigm shift in engineering and manufacturing, has seen profound development, particularly in the area of extrusion-based methods. Extrusion-based AM, often referred to as fused filament fabrication (FFF) or fused deposition modeling (FDM), relies on the precise deposition of material, typically thermoplastic polymers or composite materials, through a heated nozzle onto a build platform (Dev and Srivastava, 2020; Yadav, *et al*, 2020; Dev and Srivastava, 2021; Yadav *et al.*, 2023). This process enables the layer-by-layer construction of three-dimensional objects with high precision. The extrusion-based approach offers several distinct advantages, including compatibility with a variety of materials, ease of use, and relatively low equipment cost, making it amenable to a wide range of engineering applications.

Recently, the use of extrusion-based manufacturing processes has increased significantly. This increase is driven by the desire to produce technical parts with better mechanical properties (Gupta, *et al*, 2019; Dev and Srivastava, 2021). Ensuring the desired strength in these parts is not just a choice; this is crucial for their effective use in various technical areas. These areas span a wide range of industries such as aerospace, automotive, consumer electronics, biomedical needs, snap fits, conceptual models for final manufacturing, casting, molding, and other plastic parts as shown in Figure 1 (Srivastava and Rathee, 2018a) where performance and reliability are of utmost importance. The FDM was also used to develop the security apparatus for defence application by many organizations such as RLM industries (US), Sheppard airbase firm, EOIR technology, Tiberius arms firm, etc. (Rathee *et al.*, 2017).

Figure 1 Engineering applications of EAM

Many former research studies evaluated the effects of EAM process parameters on the part characteristics. The structural integrity and mechanical properties of fused deposition modeling (FDM) components inherently depend on the effectiveness of filament bonding, as highlighted in previous research (Sun, 2008). The quality of filament bonding is primarily determined by the temperature parameters used during the extrusion process and the environmental conditions under which the structure is constructed. Inadequate temperature control during the printing process can result in uneven adhesion of successive layers within the geometric configuration, thereby affecting the mechanical properties of the components. However, if the temperature significantly exceeds the glass transition temperature of the material, this promotes accelerated bonding between filaments, as previous studies show (Bellehumeur and Li, 2004).

Samykano and colleagues (Samykano *et al.*, 2019) conducted a comprehensive experimental investigation to confirm the influence of key printing parameters on the mechanical properties of fused deposition modeling (FDM) components. Their results showed a direct relationship between layer thickness, fill fraction and screen angle with the improvement in tensile strength, but at the expense of reduced toughness. In addition, the research examined the influence of variables such as layer height, grid orientation and infill density on the mechanical properties of FDM parts. To achieve superior mechanical properties, it is recommended to use a minimum layer thickness and an intermediate build orientation as suggested in a study by a previous researcher. Panda et al. (Panda *et al.*, 2009) used design of experiments (DOE) to conduct a study to investigate the dependence of the strength of the manufactured part on FDM parameters. The strength increases because only the layer thickness increases based on selected parameters.

With the increasing demand for customer needs, FDM processes face some challenges in producing parts of the desired quality without the need to develop new material. It is not easy to develop a new material to achieve the desired properties for each applied part. Some of these challenges require more research attention.

- It is critical for both manufacturers and consumers to gain a comprehensive understanding of how various factors affect the quality of FDM manufactured parts, including tensile strength, production time, and material consumption.
- The influence of process parameters on the properties of the final part highlights the importance of their selection, analysis, optimization and validation. These parameters can be specific to the material, modeling or production process.
- With the growing demand for multifunctional parts, there is a need for multi-objective optimization to meet different performance criteria simultaneously.
- The main focus of FDM technology should be to produce reliable products with the desired properties while minimizing material consumption and manufacturing time.

In recent years, more and more emphasis has been placed on finding the best process parameters in FDM process. Before starting production, it is essential to understand the relationships between process parameters, material properties and the desired quality characteristics of the desired part. However, it is important to note that there are no universally perfect process parameters that can achieve desired properties across all part types with minimal material input. Nevertheless, the relationship between process variables and part quality characteristics, especially when using combined artificial intelligence-based statistical methods, remains an under-researched area. Therefore, researchers and industry specialists are continually looking for new ways to improve the EAM process.

The main aim of the study is divided into two objectives;

- To study and experimental analysis of EAM process for mechanical properties.
- Optimization of EAM to achieve the desired mechanical properties of PLA material for engineering applications.

Taguchi methodology is used to design the experiments, and an AI-based integrated approach i.e. ANN-GA is used for multi-objective optimization of EAM process. Three process parameters such as layer thickness, feed rate and nozzle temperature are selected for the experimental observations concerning the response parameters.

Layer thickness (LT): The layer thickness is the layer size in the vertical direction. The value of layer thickness for most FDM machines is 0.254 mm. Generally, the value of slice height is affected by the type of material and nozzle size·(Tymrak, *et al*, 2014)(Rankouhi *et al.,* 2017)(Mohamed *et al*, 2015).

Feed rate (FR): The deposition rate indicates the extrusion rate of the semi-molten material through the die. A smaller layer thickness reduces the deposition rate and consumes more time and energy (Sood *et al*, 2012). By optimally selecting the process parameters, the desired product quality can be achieved with minimal use of resources.

Nozzle temperature (NT): The nozzle temperature is the temperature at which the filament melts and is released through the nozzle, forming the layer of the part to be manufactured. Nozzle temperature controls fluidity and fluidity, which further controls proper bonding of grids and layers. It affects part integrity and mechanical properties. The nozzle temperature also influences the surface properties of parts due to the annealing of the model.

2. METHODOLOGY

2.1. Material and Experiments

In this study, polylactic acid (PLA) is considered as a manufacturing material. PLA is a biodegradable and biocompatible thermoplastic polymer that is obtained from renewable raw materials such as corn starch or sugar cane. PLA is known for its environmental impact and ease of use, making it a popular choice in 3D printing and additive manufacturing. It is widely valued for its ability to produce parts with good mechanical properties and dimensional accuracy (Chacón *et al.*, 2017; Chalgham *et al,* 2021; Kumar *et al,* 2021).

The experiments are designed using the Taguchi approach in MINITAB-17 software. The Taguchi method is a powerful and widely used technique for experimental design and optimization (Sood, *et al*, 2009; Srivastava and Rathee, 2018b; Wankhede *et al.*, 2020). Three process variables are selected at three levels such as layer thickness (0.20 mm, 0.30 mm and 0.40 mm), nozzle temperature (220 °C, 230 °C, 240 °C) and feed speed (25.0 mm/s, 30.0 mm/s and 35.0 mm/s).

ASTM-D638 represents the reference standard for determining the appropriate dimensions of the tensile test specimen (Tontowi *et al.*, 2017). According to the chosen standard, the dimensions of the sample are: full length = 165 mm, distance between clamps = 115 m, parallel length = 57 mm, gauge length = 50 mm amd width of parallel section = 13 mm. Based on the designed experiments and standard dimensions sample parts fabricated using PLA thermoplastic filament. The setup of part fabrication is shown in Figure 2.

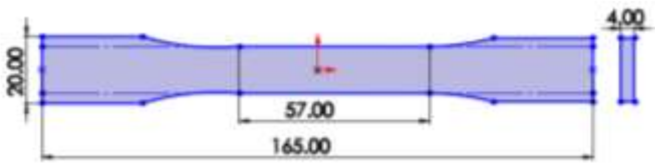

Figure 2 Dimensions of specimen

Further the specimens are subjected to the mechanical test through universal testing machine (UTM). The material weight measurements were carried out using a high-precision Shimadzu ATX224 analytical balance with a capacity of 220 g and an accuracy of 0.1 mg. the stop watch is used to record the manufacturing time of each sample.

2.2. Measurements

The mechanical tensile test is carried out on Tinius Olsen Universal Tensile Machine at a constant strain rate of 0.01 per second (Dev and Srivastava, 2022). The load-displacement curve obtained by loading the samples on the machine to determine the point of ultimate tensile strength. The average tensile strength value of three similar samples was taken into account for the analysis. The test setups for tensile strength is shown in Figures 3. The electronic balance with a capacity of 220 g, registered trademark of Shimadzu Corporation Japan, was used to measure the sample mass.

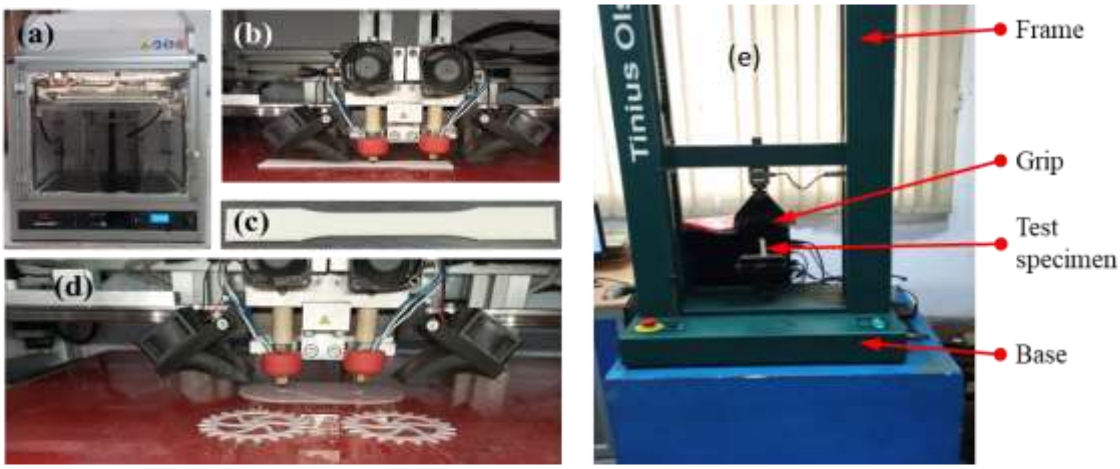

Figure 3 Setups (a) EAM machine (b) Extruder mechanism processing tensile sample (c) fabricated tensile sample (d) Mechanism processing gear train (e) UTM for tensile test

3. RESULTS

Table 1 presents the experimental results showing the average values of the response parameters corresponding to different input parameter combinations. The experimental data reveals that the maximum tensile strength achieved was 46.1 MPa (Run 4: layer thickness 0.2 mm, nozzle temperature 230°C, feed rate 25 mm/s), while the minimum material weight was 7.102 g and the minimum manufacturing time was 35.04 minutes (Run 25: layer thickness 0.4 mm, nozzle temperature 240°C, feed rate 35 mm/s). These results demonstrate that achieving optimal values for all response parameters simultaneously through a single parameter combination is challenging, necessitating multi-objective optimization..

Table 1 Experimental conditions and corresponding responses

Exp. Run	Layer Thickness (mm)	Nozzle Temperature (°C)	Feed Rate (mm/s)	Tensile Strength (MPa)	Manuf. Time (min)	Material Weight (gm)
1	0.2	220	25	45.2	37.59	8.891
2	0.2	220	30	43.8	37.38	8.922
3	0.2	220	35	42.5	37.17	8.945
4	0.2	230	25	46.1	37.5	8.973
5	0.2	230	30	44.9	37.32	8.992
6	0.2	230	35	43.6	37.09	9.017
7	0.2	240	25	44.7	37.43	9.039
8	0.2	240	30	43.4	37.28	9.046
9	0.2	240	35	42.2	37.03	9.094
10	0.3	220	30	41.6	36.39	9.153
11	0.3	220	35	40.3	36.18	9.177
12	0.3	220	25	42.7	36.56	9.223
13	0.3	230	30	42.4	36.32	9.254
14	0.3	230	35	41.2	36.13	9.283
15	0.3	230	25	43.6	36.51	9.318
16	0.3	240	30	41.1	36.27	9.359
17	0.3	240	35	39.9	36.07	9.394
18	0.3	240	25	42.3	36.45	9.426
19	0.4	220	35	38.4	35.17	9.462
20	0.4	220	25	40.8	35.57	9.478
21	0.4	220	30	39.6	35.39	9.511
22	0.4	230	35	39.3	35.11	9.528
23	0.4	230	25	41.7	35.52	9.549
24	0.4	230	30	40.5	35.31	9.662
25	0.4	240	35	38.2	35.04	9.619
26	0.4	240	25	40.6	35.46	9.587
27	0.4	240	30	39.4	35.25	9.642

Table 1 also shows that increasing the layer thickness results in a noticeable reduction in tensile strength. The increased layer thickness leads to the formation of voids and a subsequent reduction in the number of bonds, which in turn leads to a reduction in the structural strength of the component (Nidagundi *et al*, 2015); (Tymrak *et al*, 2014);

(Rankouhi *et al.*, 2017). Conversely, a smaller layer thickness leads to a significant change in the physical morphology of the component. This promotes more effective void filling by improving both inter- and intra-layer bonding interactions.

Previous research studies, such as those conducted by Vicente and Leite in 2019, also examined analogous effects. Increasing the nozzle temperature results in a slight increase in the tensile strength (TS) of the printed object. This phenomenon is due to the critical role of nozzle temperature in influencing the bond quality between grids and layers, which ultimately determines the structural integrity and mechanical properties of the final component, as Sun noted in 2008 (Sun, 2008). The result is insufficient nozzle temperature in different regions. This leads to poor adhesion between the grids, resulting in reduced strength of the part. Conversely, a higher nozzle temperature coupled with a lower printhead speed improves the quality of the joints and thereby improves the mechanical properties of the part, as reported by Sun in 2008 and Dong et al. was confirmed (Sun, 2008); (Dong *et al.*, 2018). Conversely, the tensile strength decreases with increasing feed speed. This decrease in tensile strength at higher feed rates may be attributed to the reduced time available for the first layer to effectively adhere to the subsequent layer, which in turn hinders the establishment of a proper bond between layers and ultimately reduces the strength of the final part, as described by Dong et al. observed (Dong *et al.*, 2018).

3.1. Artificial neural network Models

The Artificial Neural Network (ANN) is a computational approach in the field of artificial intelligence that mimics the cognitive processes of the human brain for the purpose of information analysis and processing. Comprised of a complicated network of basic neural units, synapses and weight factors (Gupta *et al*, 2018); (Deshwal *et al*, 2020). The ANN has a remarkable self-learning ability that continuously refines its performance as it encounters ever larger amounts of data. To effectively use this capability, the first step is to construct the ANN model, which is created based on the input data and corresponding target values. The network is then trained and optimized. This training process is facilitated by applying the Levenberg-Marquardt algorithm, which fine-tunes the parameters of the network to produce a close match between input and target data. The degree of accuracy of this alignment is quantified by generating regression measures, often referred to as R-values. An R value close to 1 means a robust and precise correlation between the output of the network and the desired target, indicating a strong relationship.

The architecture of an artificial neural network (ANN) consists of three different layers, namely the input layer, the hidden layer and the output layer, as shown in Figure 4. The input layer serves as an initial repository for the input variables, where relevant data is initially entered. The information is then passed from the input layer to the hidden layer, which processes and transforms this information through a series of interconnected neurons. Finally, the output layer provides the response data and provides the final output or prediction of the neural network in response to the given inputs.

The present study configures a hidden layer consisting of six neurons denoted as X1, X2, and X3. In this architectural framework, X1, X2 and X3 serve as the input process variables. The hidden layer is associated with bias terms, specifically b1, b2, b3, b4, b5, and b6, corresponding to each of the six neurons. Furthermore, connections between these neurons and the output layer are established through weight parameters w1, w2 and w3. The activation of these neurons is computed using the logarithmic sigmoid transfer function. Notably, to mitigate issues related to computational complexity and resource-intensive calculations, a simplified linear transfer function is adopted for the output parameters, ensuring a more streamlined and efficient processing approach.

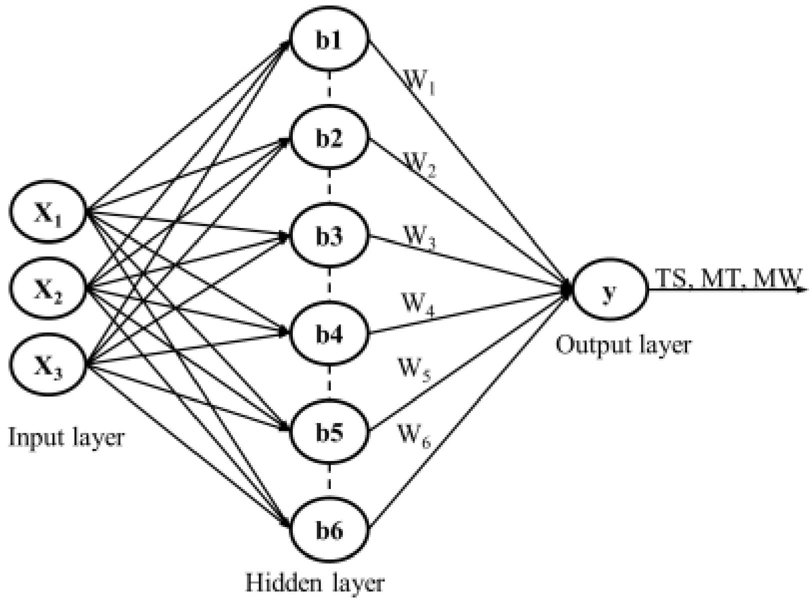

Figure 4 ANN architecture

The main steps to obtain the mathematical models based on weight and bias values are as follows: Step 1: Normalize experimental data between 0 and 1 to reduce variability before using it in an artificial neural network. Step 2: Calculate the output of each neuron within the ANN, where each neuron processes data based on its specific properties. Step 3: Determine the final output of the network by aggregating individual neuron outputs, a crucial step in extracting insights and predictions from the ANN (Gupta and Pandey, 2018).

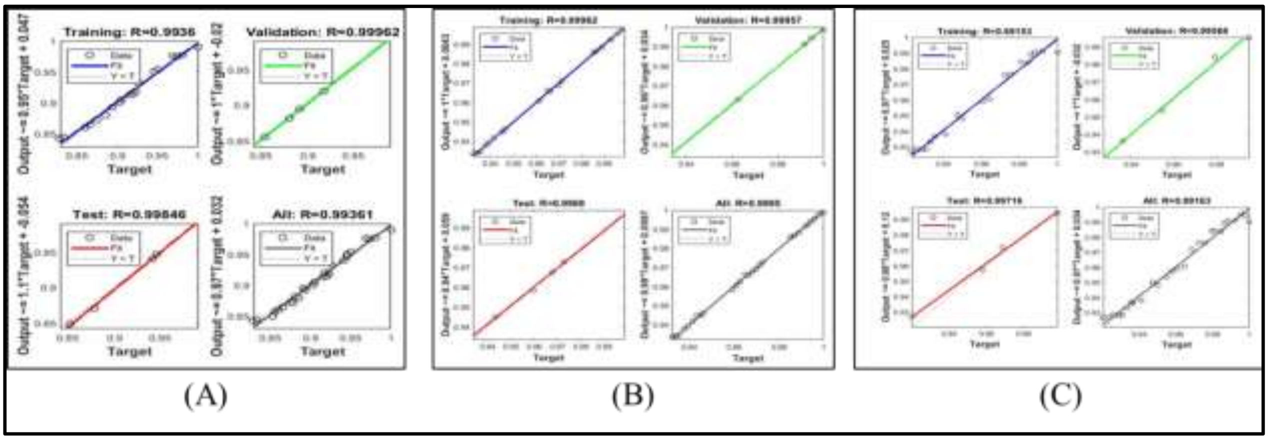

Figure 5 Regression plots corresponding to optimal training algorithm (A) TS (B) MT and (C) MW

Regression measures, represented by R values, are used to quantify the extent of the relationship between the output and the target variables. Figure 5, labeled as (a), (b) and (c), shows different R values corresponding to different facets such as training, validation and test results for TS, MT and MW. The R value close to unity shows the close relationship. The artificial neural network architecture includes three different layers: the input layer, the hidden layer and the output layer. The input layer is used to host the input variables, forming the basis for subsequent network operations.

Based on the neuron weight and bias values, the mathematical models are developed for selected responses as mentioned in Eq. 1, 2 and 3.

$$\text{Tensile stregth} = 3.0037*N_{(1)} - 0.15346*N_{(2)} - 0.87704*N_{(3)} - 2.5502*N_{(4)} - 0.36295*N_{(5)} - 0.26836*N_{(6)} - 0.55494 \quad [1]$$

$$\text{Manufacturing time} = 0.056924*N_{(1)} - 0.94578*N_{(2)} - 1.2931*N_{(3)} + 0.14657*N_{(4)} + 0.76399*N_{(5)} - 2.1098*N_{(6)} + 2.1753 \quad [2]$$

$$\text{Material} = 0.066765*N_{(1)} + 0.73868*N_{(2)} + 0.59319*N_{(3)} - 1.289*N_{(4)} - 0.16728*N_{(5)} + 0.39071*N_{(6)} + 0.23181 \quad [3]$$

In the mathematical models, N is representing the neuron. These models are further considered as objective functions in Matlab for optimization and getting the desired outputs.

3.2. Multi-objective Optimization

Achieving the desired performance with minimal resource conservation depends on the precise configuration of the process parameters. Achieving an optimized parameter set for one response variable may not necessarily match the optimization requirements of another, mainly due to the inherent conflicts between response variables. Therefore, to circumvent these challenges, the use of the multi-objective genetic algorithm within the MATLAB software environment was considered essential for the optimization of artificial neural network based mathematical models. This algorithm, which acts as a search heuristic, is based on the principles of natural inheritance and offers an effective means of tackling such complex optimization tasks.

The genetic algorithm (GA) was first conceptualized by Holland and colleagues around the 1960s-1970s (Konak, Coit and Smith, 2006). The main steps of the algorithm are shown in Figure 6. The strength should be maximized and at the same time the material weight and manufacturing time should be minimized. The minimum and maximum ranges of the process parameters are considered constraints, e.g. $0.2 \leq LT \geq 0.4$, $220 \leq \mathrm{NT} \geq 240$, $25 \leq FR \geq 35$.

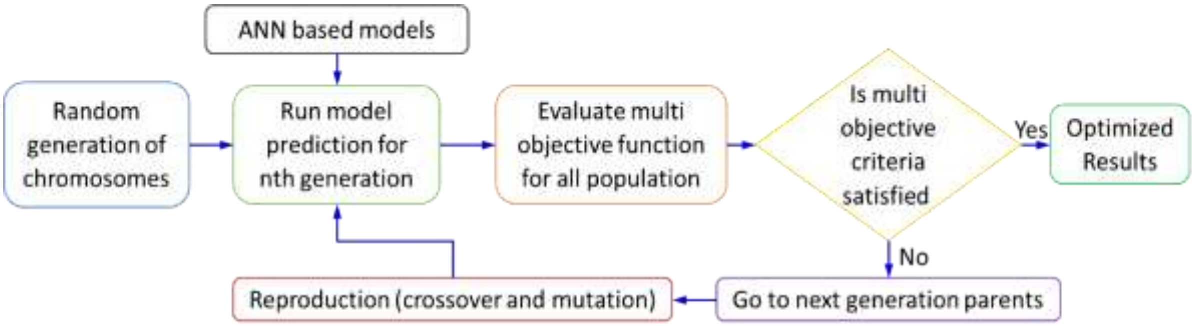

Figure 6 Multi Objective Genetic Algorithm

After implementing the multi-objective genetic algorithm, many optimal solutions obtained corresponding to different parametric settings. The parameters providing the fabrication with minimum time are considered for the further validation. The optimized values of parameters are layer thickness= 0.25 nozzle temperature= 226.66 ℃ and feed rate is 28.18 mm/s with tensile strength 45.21 MPa, manufacturing time 9.02 and material 36.02 gram. The same parameters are used to fabricate the part to validate the optimized results. The fabricated specimen subjected to tensile strength test. The result represented graphically in Figure 7 and Table 2. The experimental results shows the tensile 44.71 MPa, manufacturing time 35 minutes and material is 9.15 gram.

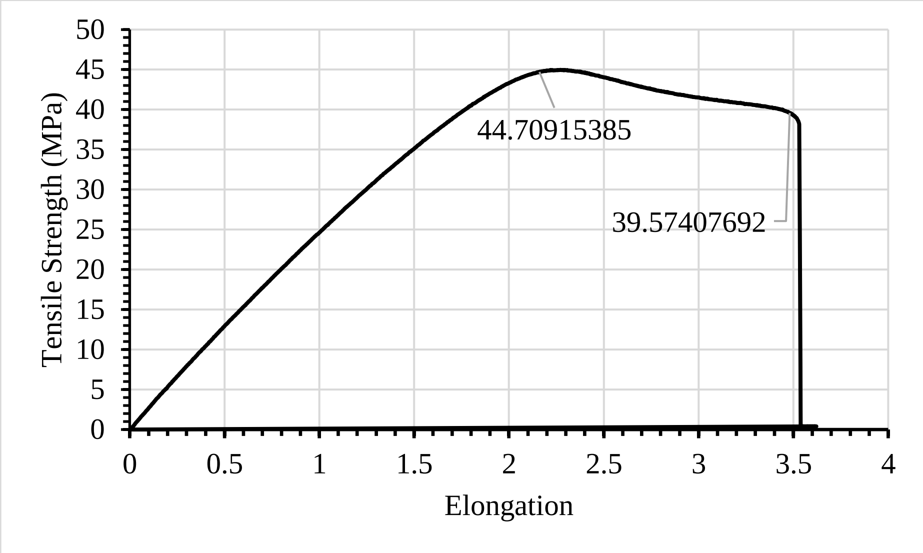

Figure 7 Tensile strength corresponding to optimized parameters

Table 2 Result confirmation

Particulars	**Input Parameters**			**Responses parameters**		
Parameters	LT (mm)	NT (°C)	FR mm/s	TS (MPa)	MT (mins)	MW (gm)
Optimized	0.25	226.66	28.18	45.21	36.02	9.02
Experimental	0.25	226	28	44.71	32.50	9.01
Error (%)				1.10	-9.77	-0.11

4. CONCLUSIONS

This study focused on the potential of extrusion-based additive manufacturing for engineering applications. Using Taguchi methodology, authors designed experiments to produce test samples from polylactic acid (PLA) material. The subsequent tests provided us with valuable data for detailed statistical analysis. In addition, we have integrated an artificial intelligence (AI)-based hybrid approach to optimize the process parameters. The results of the study were very promising as achieved significant improvement in the mechanical strength of the components and further verified the optimized parameters through additional experiments in line with previous research results. Importantly, these optimizations translated into real benefits, with a significant reduction in manufacturing time (9.77%) and material consumption (0.11%) while achieving the desired mechanical strength. These results have far-reaching implications and provide valuable insights for engineers, researchers, and practitioners in the field. They shed light on the crucial role of parameter optimization in achieving the desired mechanical properties for technical components and contribute to the continuous development of additive manufacturing in technical applications, which ultimately improves resource efficiency and cost efficiency in the technical industry.

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Figure legends

Figure 1 Engineering applications of EAM
Figure 2 Dimensions of specimen
Figure 3 Setups (a) EAM machine (b) Extruder mechanism processing tensile sample (c) fabricated tensile sample (d) Mechanism processing gear train (e) UTM for tensile test
Figure 4 ANN architecture

Figure 5 Regression plots corresponding to optimal training algorithm (a) TS (b) MT and (c) MW
Figure 6 Multi Objective Genetic Algorithm
Figure 7 Tensile strength corresponding to optimized parameters

<u>Table Captions</u>

Table 1 Experimental conditions and corresponding responses
Table 2 Result confirmation