Development of an expert system to predict the mechanical properties of FDM manufactured specimen using artificial intelligence approach

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Abstract

The research focuses on developing an expert system to predict the mechanical properties of specimens manufactured using Fused Deposition Modeling (FDM), utilizing advanced artificial intelligence approaches. A comparative analysis was conducted between experimental data and predictions made by two different models: a Fuzzy Logic System and an Artificial Neural Network (ANN). The study involved 30 samples, with experimental measurements of tensile and flexural strengths serving as the benchmark. The Fuzzy Logic model provided estimates with a tendency to slightly underestimate the tensile and flexural strengths, particularly in lower-strength samples. In contrast, the ANN demonstrated a closer alignment with the experimental values, particularly in higher strength ranges. The findings suggest that both models can be useful in predicting the mechanical properties of FDM-manufactured specimens, with ANN showing greater accuracy. The results indicate that the Fuzzy Logic System generally underestimated tensile and flexural strengths compared to experimental values, with a notable discrepancy observed for lower strength samples. For instance, the experimental tensile and flexural strengths were 21.34 MPa and 25.56 MPa, respectively measured for respective samples, while the Fuzzy Logic System predicted 20.46 MPa and 24.99 MPa. In contrast, the ANN model demonstrated a higher accuracy in predicting these properties, as evidenced by its closer approximations to the experimental data. For the same sample, the ANN predicted tensile and flexural strengths of 20.58 MPa and 25.03 MPa, respectively, highlighting the superior predictive capabilities of the ANN model.

This research underscores the potential for AI-driven models to streamline material testing processes, providing a computationally efficient means of estimating material properties and highlighting areas for model refinement to enhance predictive accuracy across a broader spectrum of material strengths. The study's implications extend to the design and analysis of composite materials, where precise property prediction is critical for performance assessment and reliability.

Keywords: FDM; Fuzzy Logic; ANN; ANFIS; 3D Printing; AI; ML

1. Introduction

Additive Manufacturing (AM), commonly known as 3D printing, is a transformative technology that constructs objects layer by layer, directly from digital models. This approach contrasts sharply with traditional subtractive manufacturing techniques, which involve cutting away material to shape a final product. AM encompasses a variety of processes that offer unique benefits, such as material efficiency, design flexibility, and the ability to produce complex geometries [1-3]. The technology has found applications across numerous industries, including aerospace, automotive, healthcare, and consumer goods, where it has become a pivotal tool for rapid prototyping and manufacturing [4-6]. One of the most prevalent AM techniques is Fused Deposition Modeling (FDM). As shown in Fig. 1, FDM works by extruding thermoplastic materials through a heated nozzle, depositing the material layer by layer to form the desired object. This method is popular due to its relative simplicity, affordability, and the wide range of compatible materials, including ABS, PLA, and composites [7-9]. The versatility of FDM has made popular choice for prototyping, tooling, and even the production of functional end-use parts, enabling designers and engineers to create intricate and customized components efficiently [10-12].

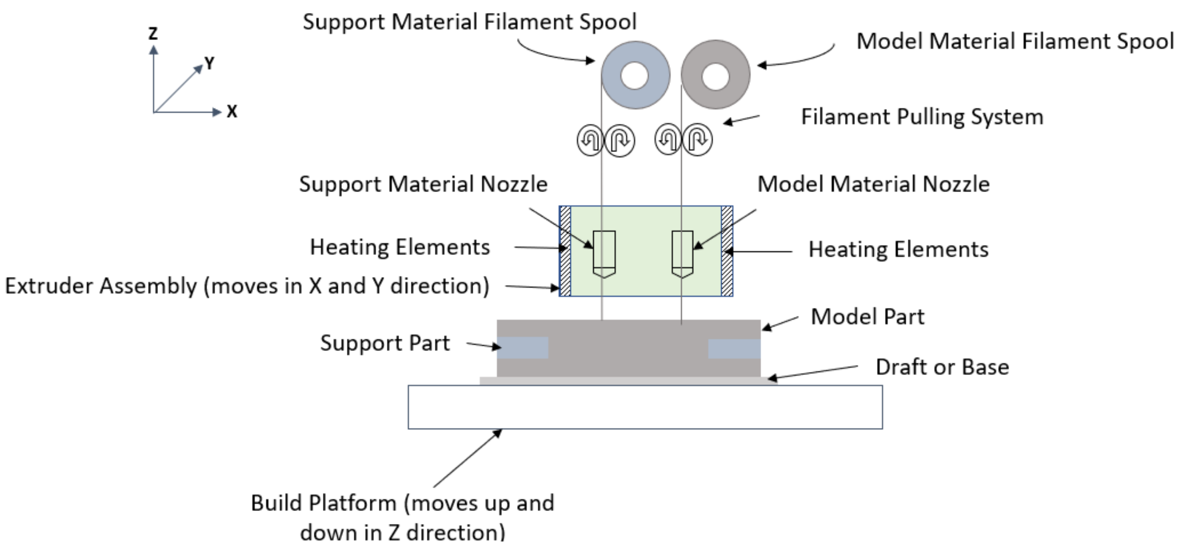


Fig. 1 Schematic diagram of Fused Deposition Modeling (FDM) Process

Fused Deposition Modeling (FDM) is one of the most widely used additive manufacturing techniques due to its versatility and cost-effectiveness. It involves the extrusion of thermoplastic materials to build parts layer by layer, offering significant advantages in prototyping and small-scale production. The mechanical properties of FDM-fabricated parts are influenced by a variety of process parameters, such as layer height, print speed, extrusion temperature, and infill density. Understanding the impact of these parameters is crucial for optimizing the mechanical performance and dimensional accuracy of FDM parts. Research on the influence of process parameters on FDM parts has been extensive. For instance, studies have shown that layer height significantly affects the surface roughness and mechanical strength of parts [12]. Smaller layer heights generally lead to improved surface finish and strength but at the cost of longer print times. Additionally, print speed and extrusion temperature are critical in determining the bond strength between layers, which directly impacts the overall mechanical integrity of the printed objects [13-15]. Infill density and pattern also play a vital role; higher infill densities usually result in stronger parts, though they require more material and longer printing durations [16-18]. Recent advancements in FDM technology have expanded the range of materials that can be used, including composites and high-performance polymers. This has led to further investigations into how varying process parameters affect the mechanical properties of these advanced materials. Studies have demonstrated that optimizing parameters such as nozzle temperature and cooling rate can significantly enhance the mechanical properties of parts made from materials like carbon fiber-reinforced polymers [19-22]. Moreover, the orientation of parts during printing has been found to influence the anisotropy in mechanical properties, highlighting the need for careful consideration of part orientation during the design phase [23-25]. In the context of composite materials, the dispersion and alignment of reinforcing fibers are additional factors that are influenced by process parameters. The nozzle temperature, print speed, and layer height can all affect the distribution of fibers within the matrix, which in turn impacts the mechanical properties of the final part [26-29]. Furthermore, post-processing treatments, such as annealing, have been explored to improve the mechanical properties of FDM parts, although these treatments introduce additional complexities and costs [30-32]. Despite these advancements, there remain challenges in fully understanding and optimizing the effects of process parameters on FDM parts. Variability in material properties, machine calibration, and environmental conditions can lead to inconsistencies in part quality. Therefore, ongoing research is focused on developing more robust models and control systems to predict and manage these variations [33-35]. The development of Additive Manufacturing (AM), particularly Fused Deposition Modeling (FDM), has revolutionized the production of complex and customized parts. FDM's layer-by-layer deposition process allows for the creation of intricate geometries and rapid prototyping, making it a preferred method in various industries, including aerospace, automotive, and biomedical engineering. The quality and mechanical properties of parts manufactured by FDM are significantly influenced by various process parameters, such as layer thickness, print speed, infill density, and nozzle temperature [36]. Understanding the relationship between these parameters and the resulting part properties is crucial for optimizing the FDM process. In recent years, machine learning (ML) methods have gained prominence in studying and predicting the effects of FDM process parameters. ML techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees have been employed to model the complex relationships between process parameters and part properties. These methods enable the analysis of large datasets and the identification of patterns that may not be evident through traditional statistical methods [37]. For instance, ANNs have been used to predict tensile strength and surface roughness of FDM-manufactured parts, demonstrating their potential to enhance process control and quality assurance [38]. The integration of ML techniques into the study of FDM processes offers several advantages, including improved accuracy in predictions and the ability to handle non-linear relationships between variables. Studies have shown that ML models can outperform traditional empirical models in predicting mechanical properties such as tensile strength, flexural strength, and impact resistance [39-40]. Additionally, the use of machine learning in FDM can facilitate the optimization of process parameters, leading to reduced material waste, shorter production times, and improved part quality [41-42]. Despite the advancements in this field, challenges remain in the widespread adoption of ML techniques in FDM research. These include the need for large, high-quality datasets and the complexity of model selection and training [43]. Furthermore, the generalizability of ML models across different materials and printer types is a critical area of ongoing research [44]. As the field continues to evolve, there is a growing interest in exploring hybrid approaches that combine machine learning with traditional simulation methods, such as finite element analysis (FEA), to achieve more comprehensive and accurate predictions [45]. To bridge the same, present work aims to developed an expert system using three artificial intelligence approaches i.e. fuzzy logic, artificial neural network and adaptive neuro fuzzy interface system.

2. Materials and Methodologies

2.1 Specimen fabrication using Design of Experiment (DoE) approach

To investigate the impact of FDM process parameters on the mechanical properties of the manufactured parts, a series of experiments were conducted. For Fabrication of specimens Tevo Tarantula 3D Printer is used with Bagasse natural filament. The parameters considered in this study included nozzle temperature, layer thickness, part orientation, and raster orientation. Each parameter was tested at three distinct levels to comprehensively understand their influence on the final properties of the parts. The details about the selected process parameters are as:

- Nozzle Temperature (°C)**:** The nozzle temperature was varied at three levels: 230°C, 240°C, and 250°C. This range was chosen to study the influence of different temperatures on the material's melting and flow properties, which can significantly affect the bonding between layers and overall mechanical strength.
- Layer Thickness (mm)**:** The layer thickness was set at 0.12 mm, 0.21 mm, and 0.30 mm. This parameter influences the surface finish and dimensional accuracy of the parts, as well as the mechanical properties, by altering the amount of material deposited in each layer.
- Part Orientation (°)**:** The orientation of the parts during printing was varied between 0°, 45°, and 90°. Part orientation affects the distribution of stresses and the overall mechanical behavior of the printed parts, as the layer bonding strength varies with orientation.

- Raster Orientation (°)**:** The raster orientation, or the angle at which the material is laid down, was set at 0°, 45°, and 90°. This parameter plays a crucial role in determining the internal structure and mechanical properties of the printed parts, particularly in relation to tensile and flexural strengths.

  Each experimental run involved printing test specimens with a unique combination of the specified parameters, adhering to the levels mentioned in Table 1. The specimens were then subjected to mechanical testing to evaluate the effects of the different settings on tensile strength, flexural strength, and other relevant properties. The results from these tests provided valuable insights into the optimal settings for achieving desired mechanical properties in FDM-manufactured parts and also helps to develop an expert system.

Table 1 FDM process parameters with their settings and levels

FDM Process parameters	**Units**	**Levels**		
		-1	**0**	**+1**
Nozzle Temperature	°C	230	240	250
Layer Thickness	mm	0.12	0.21	0.30
Part Orientation	°	0	45	90
Raster Orientation	°	0	45	90

In this study, a Face-Centered Central Composite Design (FCCCD) was employed to systematically investigate the effects of FDM process parameters on the mechanical properties of the manufactured parts. Using the settings outlined in Table 1, the FCCCD method allowed for a comprehensive analysis by incorporating the three levels of each parameter i.e. low, middle, and high. This approach facilitated the exploration of the interactions between nozzle temperature, layer thickness, part orientation, and raster orientation, providing a robust framework for optimizing the FDM process. The design enabled the assessment of both linear and nonlinear effects, offering a detailed understanding of how variations in these parameters impact the overall quality and performance of the printed parts. Table 2 mentioned the FCCCD schema for the present work to study effect of FDM process parameters on mechanical properties.

Table 2 FCCCD schema for mechanical properties measurement

Run	**Nozzle Temperature (°C)**	**Layer Thickness (mm)**	**Part Orientation (°)**	**Raster Orientation (°)**
1	250	0.3	90	90
2	230	0.12	90	45
3	230	0.3	90	0
4	240	0.21	90	0
5	240	0.21	45	0
6	250	0.3	0	90
7	250	0.12	0	90

8	240	0.21	45	0
9	250	0.21	45	0
10	230	0.12	0	45
11	250	0.12	0	45
12	240	0.21	45	45
13	230	0.12	0	45
14	230	0.12	90	0
15	230	0.21	45	90
16	240	0.21	45	0
17	240	0.21	45	90
18	240	0.12	45	90
19	250	0.3	90	45
20	230	0.3	0	45
21	240	0.3	45	45
22	250	0.12	90	0
23	230	0.3	90	45
24	250	0.12	90	90
25	230	0.3	0	90
26	240	0.21	45	45
27	240	0.21	0	45
28	250	0.3	0	0
29	240	0.21	45	45
30	240	0.21	0	90

2.2 Mechanical properties testing

In the present work, two types of mechanical testing are carried out during the present work i.e., tensile strength (as per ASTMD638) and flexural strength (as per ASTMD790).

2.2.1 Tensile Strength Testing

Tensile strength testing is a crucial method for evaluating the mechanical properties of materials, particularly plastics and composites. In the present work. This test measures the material's ability to withstand tension and provides important data regarding its strength and ductility. The ASTM D638 standard specifies the method for tensile testing of plastic materials, focusing on the Type I specimen, which is widely used for its representative characteristics. This methodology outlines the procedures and considerations for conducting tensile strength testing according to ASTM D638 Type I. Fig.2 illustrates into detail drawing mentioned as per ASTM D638.

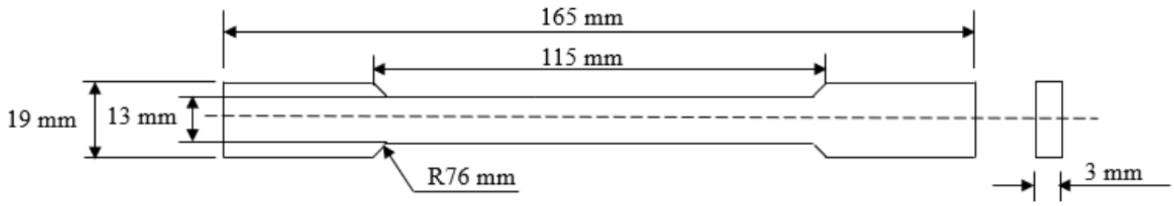


Fig. 2 Detail Drawing of Tensile Test Specimen as per ASTM D638 type-I

2.2.2 Flexural Strength Testing

In the present work, flexural strength specimens are fabricated as mentioned in Figure 9. Flexural Strength is a crucial mechanical property for materials used in structural applications. ASTM D790 is a standard test method for determining the flexural properties of unreinforced and reinforced plastics, including high-modulus composites. Fig.3 illustrates into detail drawing mentioned as per ASTM D790.

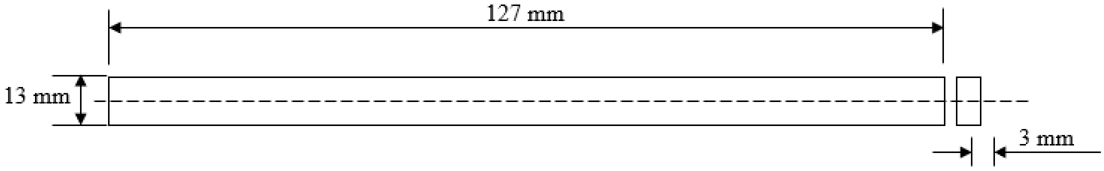


Fig. 3 Detail Drawing of Flexural Test Specimen as per ASTM D790

2.3 Designing an expert system using artificial intelligence approaches

In the present work. To predict the mechanical properties expert system is designed using machine learning approaches i.e. Fuzzy Logic System, Artificial Neural Network and Adaptive Neuro Fuzzy Interface System (ANFIS).

2.3.1 Fuzzy Logic base expert system

In this study, a fuzzy logic system was utilized to explore and examine the surface roughness of components produced through fused filament fabrication (FFF). Fuzzy logic serves as a computational framework that facilitates the representation and manipulation of imprecise or uncertain information. It provides a more adaptable and nuanced approach to decision-making and reasoning by incorporating degrees of membership and linguistic variables. The fuzzy logic system applied in this research comprised linguistic rules and membership functions. Linguistic rules delineate the relationships between the input variables (nozzle temperature, raster orientation, part orientation, and layer thickness) and the output variable (tensile strength and flexural strength). These rules were formulated based on expert knowledge and insights specific to the domain. Membership functions were employed to quantify the degree of membership of an input variable to a particular linguistic term (e.g., low, medium, high). These functions empowered the fuzzy logic system to manage imprecise or ambiguous information and make decisions grounded in fuzzy sets and fuzzy logic operations, such as fuzzy inference and fuzzy reasoning. By integrating the fuzzy logic system into the analysis of FFF surface roughness, the objective of this research was to capture the intricacies and uncertainties associated with the manufacturing process. The fuzzy logic system provided a robust framework to model and predict the surface roughness based on the input parameters, allowing for more accurate and comprehensive understanding of the relationship between process parameters and surface quality.

The utilization of a fuzzy logic system in this research paper enhances the predictive capabilities and decision-making process in relation to surface roughness optimization for FFF parts. It offers a valuable tool for process control and quality assurance, enabling manufacturers to improve product outcomes and customer satisfaction by effectively managing surface roughness in FFF manufacturing.

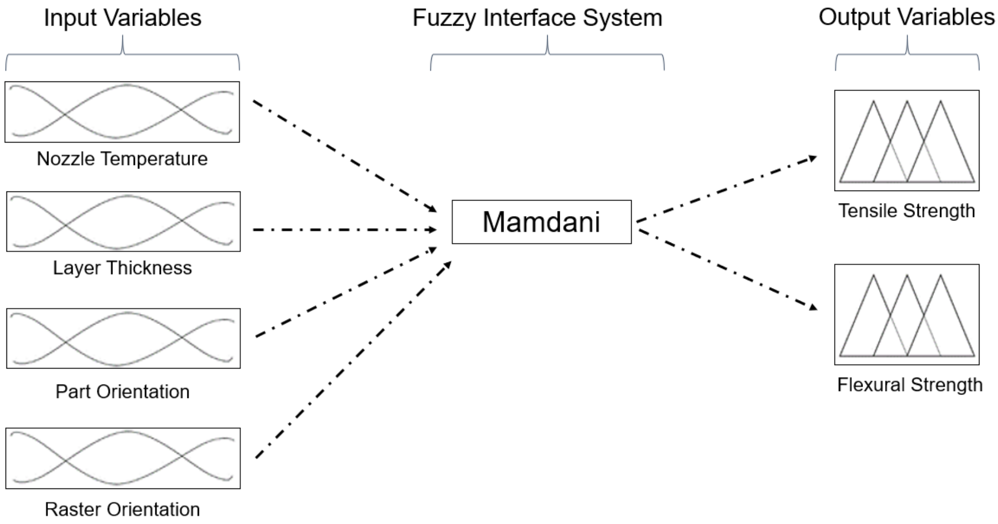


Fig. 4 Fuzzy interface system in MATLAB

The configuration of a three-input-one-output fuzzy logic unit is depicted in Fig.4. As illustrated in the figure, a fuzzy logic unit comprises a fuzzifier, knowledge base (consisting of membership functions and a fuzzy rule base), fuzzy inference system, and a defuzzifier. Each of these components is elaborated below:

i. Fuzzifier: The actual input to the fuzzy system is fed into the fuzzifier. In fuzzy literature, this input is termed as crisp input, as it provides precise information about a specific parameter. The fuzzifier transforms this precise quantity into an imprecise form, such as 'small,' 'medium,' 'large,' etc., along with a degree of membership, typically ranging from 0 to 1.
ii. Knowledge Base: The pivotal part of the fuzzy system is the knowledge base, encompassing both the rule base and the database. The database outlines the membership functions of the fuzzy sets used in the fuzzy rules, while the rule base contains several fuzzy if-then rules.
iii. Fuzzy Inference System: The fuzzy inference system, also known as the inference system or decision-making unit, executes inference operations on the rules. It governs how the rules are amalgamated.
iv. Defuzzifier: The output produced by the inference block is inherently fuzzy. A real-world system necessitates converting the fuzzy output into a crisp one. The role of the defuzzifier is to receive the fuzzy input and yield a real output. In operation, it functions in the opposite manner to the input block.

In this study, a Mamdani fuzzy system was utilized to evaluate a multi-response performance index by assessing multiple performance characteristics. The system, depicted in the accompanying figure, operates as a multi-input, single-output model to estimate complex performance indices even if some input conditions were not explicitly covered during model development. The model development involved several key steps:

i. Selection of Input and Output Variables: Inputs such as Layer Thickness, Nozzle Temperature, Raster Orientation, and Part Orientation were selected, with output variables being Tensile Strength and Flexural Strength. These variables were represented linguistically with categories like {small, medium, large} for inputs and outputs, allowing for fuzzy logic application.

ii. Selection of Membership Functions: Triangular membership functions were chosen due to their computational efficiency. These functions transform linguistic values into a normalized range between 0 and 1, facilitating simple and effective calculations.

iii. Formation of Linguistic Rule Base: A comprehensive rule base was developed to establish relationships between input variables and the desired output. This base, incorporating expert knowledge, used if-then rules to correlate input variables (each with three triangular membership functions) with the output variable. The system generated 15 rules using the max-min inference method.

iv. Defuzzification: The final step involved converting fuzzy outputs into a crisp result using the center of gravity method. This process computed the multi-response performance index (MRPI) by averaging the weighted outputs, providing a precise, actionable result from the fuzzy system.

2.3.2 Artificial Neural Network base expert system

An Artificial Neural Network (ANN) is a computational model inspired by the way biological neural networks in the human brain process information. ANNs consist of interconnected groups of artificial neurons that work together to solve specific problems. In the present work, Artificial Neural Networks (ANNs) implemented through MATLAB's specialized tools offer a powerful approach for creating expert systems aimed at predicting material properties. In this context, we delve into the methodology involved in utilizing MATLAB's ANN tools to construct a Backpropagation Neural Network (BPNN) based expert system tailored to predict Tensile Strength and Flexural Strength of materials, with input variables including Layer Thickness, Nozzle Temperature, Raster Orientation, and Part Orientation. The first crucial step in utilizing MATLAB's ANN tools for developing the BPNN-based expert system is data pre-processing. This involves acquiring a comprehensive dataset that includes a diverse range of values for each input variable along with corresponding Tensile Strength and Flexural Strength measurements. MATLAB provides various functions and toolboxes for efficient data pre-processing, including functions for data normalization or standardization to ensure that input variables are appropriately scaled. Proper pre-processing is essential for enhancing the convergence of the BPNN during training and improving the accuracy of material property predictions. Once the data pre-processing is completed, the next step is to design and implement the BPNN architecture using MATLAB's ANN tools. MATLAB offers a user-friendly environment with built-in functions and toolboxes specifically designed for creating, training, and evaluating neural networks. The BPNN architecture typically consists of an input layer, one or more hidden layers, and an output layer. MATLAB's ANN tools provide functions for defining the network structure, selecting activation functions, and initializing network parameters. Additionally, MATLAB's graphical user interface (GUI) facilitates the visualization of the network architecture, allowing for easy customization and optimization based on specific requirements. After designing the BPNN architecture, the next step is to train the network using the prepared dataset. MATLAB's ANN tools offer a variety of training algorithms, including backpropagation with different optimization techniques such as gradient descent or Levenberg-Marquardt. The dataset is typically partitioned into training, validation, and testing subsets to evaluate the network's performance and prevent overfitting. MATLAB's ANN tools provide functions for partitioning datasets and monitoring training progress through graphical representations such as training curves and performance metrics. Once the BPNN is trained and validated, it can be integrated into the expert system to predict Tensile Strength and Flexural Strength based on input variables, thereby providing valuable insights into material behavior and aiding in process optimization and product design.

The present research work investigates the potential of Artificial Neural Networks (ANNs) to enhance expert system design. To analyze the surface roughness pattern, an Artificial Neural Network (ANN) was implemented using MATLAB© 2021. The ANN utilized a supervised learning approach with three input variables: layer thickness, nozzle temperature, and part orientation, and one output variable representing the surface roughness as shown in Figure 5. Present work approach focuses on leveraging the strengths of both techniques to create a robust and adaptable intelligent system. Following steps are considered to design to design an expert system using ANN approach:

Step 1: Knowledge Acquisition and Pre-processing:

- Domain experts will be consulted to identify the key problem domain and the factors influencing the decision-making process.
- This knowledge will be translated into a structured format suitable for training the ANN. This may involve data collection from past cases, feature engineering to extract relevant information, and data cleaning to ensure quality.

Step 2: Neural Network Architecture and Training:

- Based on the problem domain and the characteristics of the data, a suitable ANN architecture will be selected. This could involve choosing the appropriate network type (e.g., Multi-Layer Perceptron, Convolutional Neural Network), determining the number of hidden layers and neurons, and selecting activation functions.
- A training dataset will be prepared, consisting of past cases with well-defined inputs (features) and corresponding desired outputs (expert decisions). The system will be trained using a suitable learning algorithm (e.g., Backpropagation) to identify complex patterns within the data.

Step 3: Integration and Evaluation:

- The trained ANN will be integrated into the expert system framework. This may involve developing a mechanism for the expert system to interact with the ANN, providing context and receiving its recommendations.
- The performance of the hybrid system will be evaluated using various metrics relevant to the specific application. This could include accuracy, precision, recall, and F1 score for classification tasks, or mean squared error for regression tasks. Additionally, expert feedback will be solicited to assess the system's reasoning capabilities and the alignment with domain knowledge.

Step 4: Iterative Refinement:

- Following evaluation, the system will undergo an iterative refinement process. Based on the results, the ANN architecture and training parameters might be adjusted. Additionally, the expert system's knowledge base could be enhanced with insights gained from the ANN's performance. This cyclical process aims to continuously improve the system's accuracy, robustness, and generalizability.

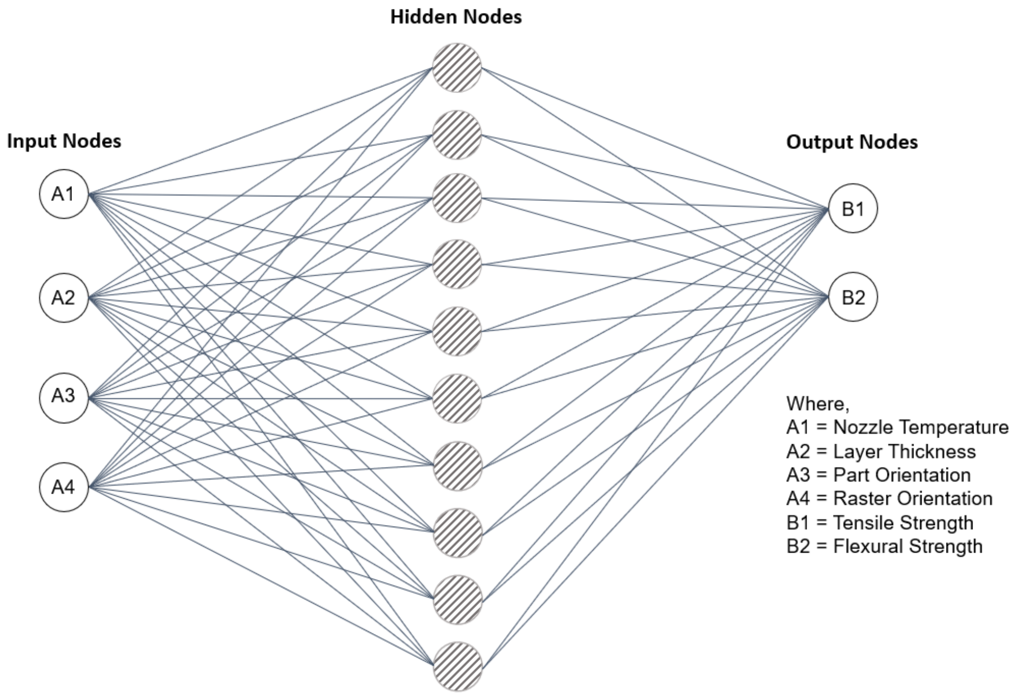


Fig. 5 ANN Architecture with 3 input nodes and 1 output nodes

In the present work, three input nodes i.e. layer thickness, nozzle temperature and part orientation and one input node i.e. surface roughness are considered. ANN emphasizes the collaborative nature of the approach. By combining human expertise with the learning power of ANNs, we aim to create an intelligent system that leverages the strengths of both paradigms.

2.3.3 Adaptive Neuro Fuzzy Interface base expert system

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid intelligent system that combines the learning capabilities of neural networks with the fuzzy logic reasoning of fuzzy inference systems. This integration leverages the strengths of both paradigms, allowing ANFIS to handle imprecise information and adaptively learn from data. Utilizing MATLAB's Adaptive Neuro-Fuzzy Inference System (ANFIS) tools presents a robust approach for constructing expert systems aimed at predicting material properties. In this context, we explore the methodology involved in leveraging MATLAB's ANFIS tools to develop an ANFIS-based expert system tailored to predict Tensile Strength and Flexural Strength of materials, with input variables including Layer Thickness, Nozzle Temperature, Raster Orientation, and Part Orientation. The initial step in employing MATLAB's ANFIS tools for building the expert system involves data pre-processing. This entails gathering a comprehensive dataset containing a diverse range of values for each input variable, alongside corresponding Tensile Strength and Flexural Strength measurements. MATLAB offers a suite of functions and toolboxes for efficient data pre-processing, facilitating tasks such as data normalization or standardization to ensure that input variables are appropriately scaled. Effective pre-processing enhances the convergence of the ANFIS during training and enhances the accuracy of material property predictions. Once data pre-processing is completed, the subsequent step is designing and implementing the ANFIS architecture using MATLAB's ANFIS tools. MATLAB provides a user-friendly environment equipped with built-in functions and toolboxes specifically tailored for creating, training, and evaluating ANFIS models. The ANFIS architecture typically comprises fuzzy inference systems combined with adaptive techniques, allowing for the modeling of complex relationships between inputs and outputs. MATLAB's ANFIS tools enable users to define the structure of the fuzzy inference system, select appropriate membership functions, and adjust parameters to optimize model performance. Additionally, MATLAB's graphical user interface simplifies the visualization of the ANFIS architecture, facilitating customization and optimization based on specific requirements. Following the design of the ANFIS architecture, the subsequent step is training the model using the prepared dataset. MATLAB's ANFIS tools offer various training algorithms, including hybrid optimization techniques that combine gradient-based methods with evolutionary algorithms. The dataset is partitioned into training, validation, and testing subsets to assess the model's performance and prevent overfitting. MATLAB's ANFIS tools provide functions for partitioning datasets and monitoring training progress through graphical representations such as learning curves and performance metrics. Once the ANFIS model is trained and validated, it can be integrated into the expert system to predict Tensile Strength and Flexural Strength based on input variables, thereby offering valuable insights into material behaviour and supporting process optimization and product design**.**

3. Results and Discussions

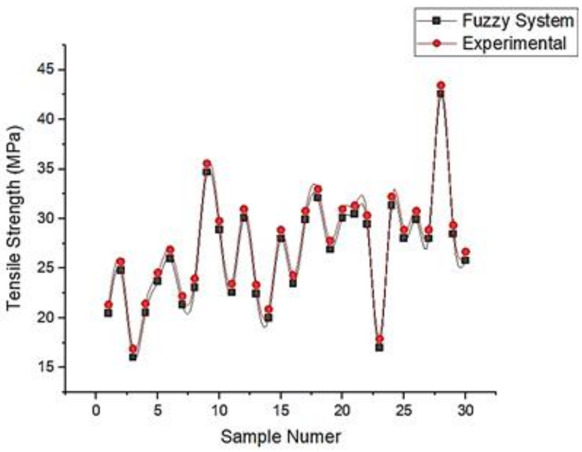
3.1 Discussions on fuzzy logic expert system results

The data in Table 17 compares experimental and Fuzzy Logic predictions of tensile and flexural strength for 30 composite material samples. The experimental values provide critical insights into material behavior under load, while the Fuzzy Logic predictions estimate these properties based on various inputs. For instance, Sample 1's experimental tensile strength is 21.34 MPa, with the Fuzzy Logic model predicting 20.4604 MPa. Similar trends are observed with flexural strength, where the model slightly underestimates the experimental results. As samples progress, the model's predictions show a closer alignment with experimental data for higher strength materials, such as in Sample 6, which has an experimental tensile strength of 26.89 MPa and a predicted strength of 26.0104 MPa. However, lower strength samples, like Sample 3, show more significant discrepancies, indicating the model's limitations in accurately predicting lower strength metrics. Overall, the Fuzzy Logic model tends to underestimate tensile strength in lower strength samples while providing closer approximations for higher strength samples, suggesting a need for refinement or additional parameters to better capture material behavior across a range of strengths.

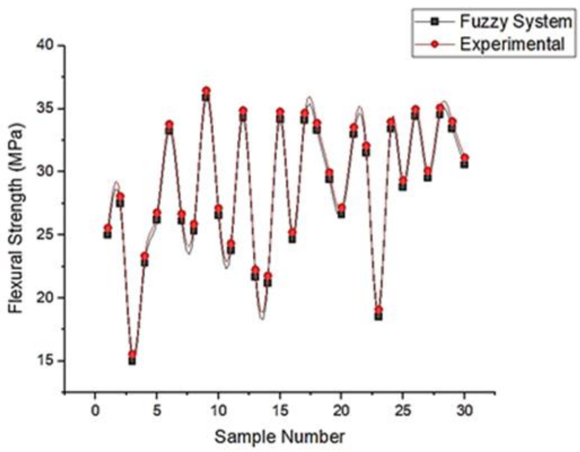
Table 3 Comparison between experimental and Fuzzy Logic system values

Sample No.	Experimental Tensile Strength (MPa)	Experimental Flexural Strength (MPa)	Fuzzy Logic based Tensile Strength (MPa)	Fuzzy Logic based Flexural Strength (MPa)
1	21.34	25.56	20.4604	24.9859
2	25.67	28.07	24.7904	27.4959
3	16.9	15.56	16.0204	14.9859
4	21.45	23.34	20.5704	22.7659

5	24.56	26.78	23.6804	26.2059
6	26.89	33.79	26.0104	33.2159
7	22.21	26.67	21.3304	26.0959
8	23.98	25.88	23.1004	25.3059
9	35.56	36.46	34.6804	35.8859
10	29.78	27.13	28.9004	26.5559
11	23.44	24.34	22.5604	23.7659
12	30.98	34.88	30.1004	34.3059
13	23.34	22.24	22.4604	21.6659
14	20.89	21.77	20.0104	21.1959
15	28.87	34.77	27.9904	34.1959
16	24.33	25.23	23.4504	24.6559
17	30.78	34.68	29.9004	34.1059
18	32.98	33.88	32.1004	33.3059
19	27.78	29.98	26.9004	29.4059
20	30.98	27.18	30.1004	26.6059
21	31.34	33.54	30.4604	32.9659
22	30.34	32.09	29.4604	31.5159
23	17.9	19.1	17.0204	18.5259
24	32.23	33.98	31.3504	33.4059
25	28.89	29.35	28.0104	28.7759
26	30.78	34.98	29.9004	34.4059
27	28.88	30.08	28.0004	29.5059
28	43.44	35.09	42.5604	34.5159
29	29.35	34.01	28.4704	33.4359
30	26.67	31.13	25.7904	30.5559



(a)



(B)

Fig. 6 Comparison between Fuzzy System and Experimental obtained (a) Tensile strength (b) Flexural Strength

Fig.6 shows a graph comparing tensile strength (in MPa) across different sample numbers using two different methods: a Fuzzy System and Experimental measurements. The x-axis of the graph represents the sample number, ranging from 0 to 30, while the y-axis represents tensile strength, measured in MPa, ranging from 15 to 45 MPa. This setup provides a clear view of how tensile strength varies with different samples. There are two sets of data points plotted on the graph. The Fuzzy System's results are represented by black squares (■), and the Experimental measurements are shown with red circles (●). This differentiation helps in distinguishing between the two methods at a glance. Both sets of data, from the Fuzzy System and the Experimental method, exhibit a similar trend and closely follow each other. The tensile strength values fluctuate across the samples for both methods. Despite these fluctuations, the data points generally increase and decrease together, indicating a high level of correlation between the Fuzzy System predictions and the Experimental measurements. The legend in the top right corner indicates the symbols used for each method, with a black square (■) representing the Fuzzy System and a red circle (●) for Experimental measurements. This legend helps in easily identifying which data points belong to which method. Overall, the graph demonstrates that the Fuzzy System's predictions closely match the Experimental tensile strength measurements across the range of samples.

3.2 Discussions on artificial neural network base expert system results

The table 18 provided compares the experimental values of tensile and flexural strengths of various composite samples with those predicted by an Artificial Neural Network (ANN) model. This comparison helps in assessing the accuracy and reliability of the ANN model in predicting the mechanical properties of composite materials. For Sample 1, the experimental tensile strength is 21.34 MPa, while the ANN predicted value is slightly lower at 20.5821 MPa. Similarly, the experimental flexural strength is 25.56 MPa, with the ANN prediction at 25.0264 MPa. The ANN model demonstrates effective prediction capabilities for both tensile and flexural strengths across various samples. For instance, Sample 2 shows experimental values of 25.67 MPa (tensile) and 28.07 MPa (flexural), with ANN predictions of 25.7027 MPa and 29.0739 MPa, respectively, indicating a close match. Sample 3 reveals a slight discrepancy in flexural strength, with experimental and predicted values of 15.56 MPa and 20.1326 MPa, respectively. Notably, Sample 9 exhibits the highest tensile strength of 35.56 MPa, closely matched by the ANN prediction of 35.5571 MPa. However, some samples, like Sample 13, show significant variations in predictions, suggesting areas for model refinement. Overall, the ANN model provides reasonably accurate predictions, evidenced by high R-values (0.99998 for tensile strength and 0.98847 for flexural strength), indicating strong linear relationships between predicted and actual values. This demonstrates the model's robustness and its potential as a valuable tool for predicting the mechanical properties of composite materials.

Table 4 Comparison between experimental and ANN values				
Sample No.	Experimental Tensile Strength (MPa)	Experimental Flexural Strength (MPa)	ANN based Tensile Strength (MPa)	ANN based Flexural Strength (MPa)
1	21.34	25.56	20.5821	25.0264
2	25.67	28.07	25.7027	29.0739
3	16.9	15.56	16.9014	20.1326
4	21.45	23.34	21.454	24.9898
5	24.56	26.78	24.0274	25.7619
6	26.89	33.79	26.8855	33.9508
7	22.21	26.67	23.0651	26.879
8	23.98	25.88	24.0274	25.7619
9	35.56	36.46	35.5571	35.249
10	29.78	27.13	29.7625	25.575
11	23.44	24.34	23.4347	24.9908
12	30.98	34.88	27.1603	34.1208
13	23.34	22.24	29.7625	25.575
14	20.89	21.77	21.64	29.041
15	28.87	34.77	28.8408	34.0543
16	24.33	25.23	24.0274	25.7619
17	30.78	34.68	29.8308	35.4393
18	32.98	33.88	32.9583	35.4633
19	27.78	29.98	27.8508	30.8156
20	30.98	27.18	30.9566	24.7188
21	31.34	33.54	31.3422	33.0129
22	30.34	32.09	30.27	31.7927
23	17.9	19.1	17.897	22.3519
24	32.23	33.98	32.2142	33.6758
25	28.89	29.35	28.8801	29.3917
26	30.78	34.98	30.12	35.21
27	28.88	30.08	28.54	30.01
28	43.44	35.09	43.21	34.99
29	29.35	34.01	29.54	34.51
30	26.67	31.13	26.21	31.35

Table 5 outlines the ANN training parameters for predicting tensile strength. The showWindow parameter is set to true, enabling a graphical display of training progress. The showCommandLine parameter is false, so details are not shown in the command line. The show parameter updates the training status every 25 epochs, aiding in performance tracking. The training runs for up to 1000 epochs (epochs), with no time limit (time set to Inf). The goal parameter is 0, indicating no specific error target. Training stops if the performance gradient falls below 1e-07 (min_grad), or if there are 100 consecutive validation failures (max_fail).

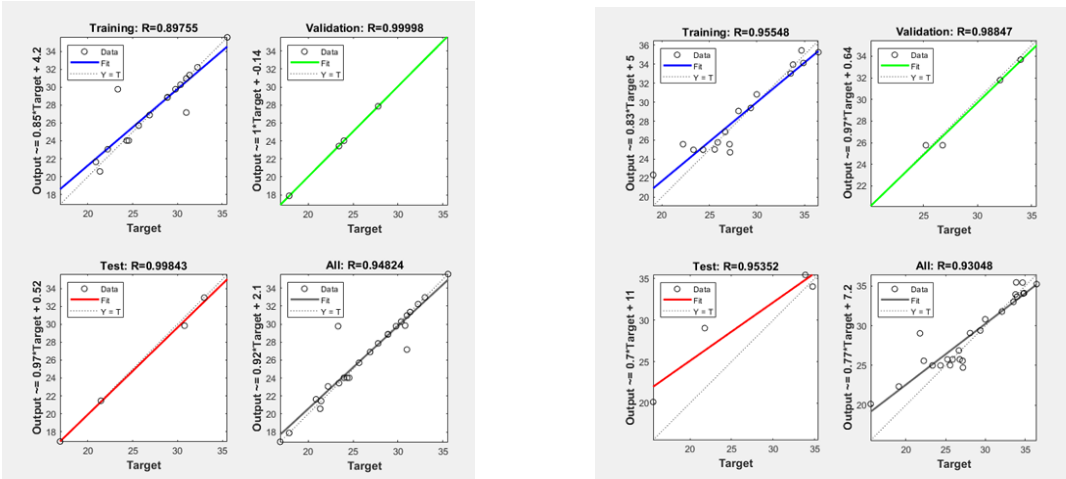
The Levenberg-Marquardt optimization uses mu parameters: mu starts at 0.001, decreases by 0.1 (mu_dec) when performance improves, increases by 10 (mu_inc) when performance worsens, and can reach a maximum of 10^10 (mu_max). These settings balance gradient descent and Gauss-Newton methods, optimizing training stability and efficiency.

Table 6 outlines the training parameters for predicting flexural strength using an Artificial Neural Network (ANN). The showWindow parameter is set to true, enabling a graphical interface to display training progress. The showCommandLine is false, limiting detailed outputs and focusing on essential updates. The show parameter, set at 25, controls the frequency of progress updates, occurring every 25 epochs. Training is capped at 1000 epochs (epochs), ensuring the process does not run indefinitely.

Table 5 Training Parameters settings for tensile strength prediction in ANN			
showWindow	true	min_grad	1e-07
showCommandLine	false	max_fail	100
show	25	mu	0.001
epochs	1000	mu_dec	0.1
time	Inf	mu_inc	10
goal	0	mu_max	10000000000

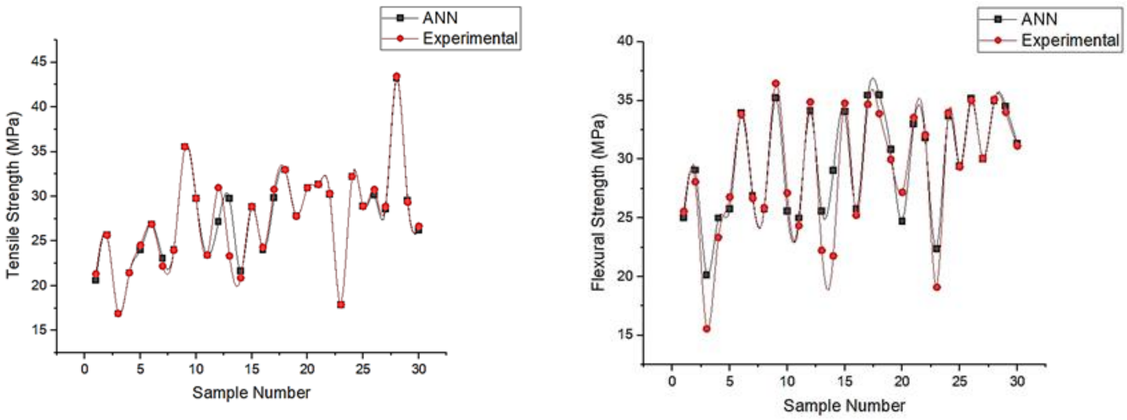
Table 6 Training Parameters settings for flexural strength prediction in ANN			
showWindow	true	min_grad	1e-07
showCommandLine	false	max_fail	100
show	25	mu	0.001
epochs	1000	mu_dec	0.1
time	Inf	mu_inc	10
goal	0	mu_max	10000000000

The time parameter is set to Inf, allowing training to continue until other criteria, such as the goal of zero training error, are met. The min_grad is set at 1e-07, stopping training if the gradient falls below this, indicating a learning plateau. The max_fail parameter is 100, halting training if validation does not improve after 100 epochs, preventing overfitting. The mu parameter, starting at 0.001, controls the learning rate, with mu_dec at 0.1 decreasing it after successful error reductions, and mu_inc at 10 increasing it after unsuccessful steps. The mu_max is capped at 10 billion to prevent destabilization from excessively large learning rates. Fig.8 demonstrates the statistical stability of the proposed ANN model, designed to enhance the accuracy of tensile test predictions. The model utilizes a 4:10:2 architecture, consisting of an input layer with four neurons, a hidden layer with ten neurons, and an output layer with two neurons. This configuration balances complexity and computational efficiency, enabling the network to capture intricate data relationships without becoming overly complex. The model's robustness and predictive power were evaluated using the R-value (correlation coefficient), a statistical measure indicating how well the ANN's predicted values align with the experimental data. The R-value quantifies the strength and direction of the linear relationship between predicted and actual values, showcasing the ANN model's effectiveness.



(a) (b)

Fig. 7 Statistical stability and relationship in proposed ANN for (a) Tensile Strength (b) Flexural Strength



(a) (b)

Fig. 8 Statistical stability and relationship in proposed ANN for (a) Tensile Strength (b) Flexural Strength

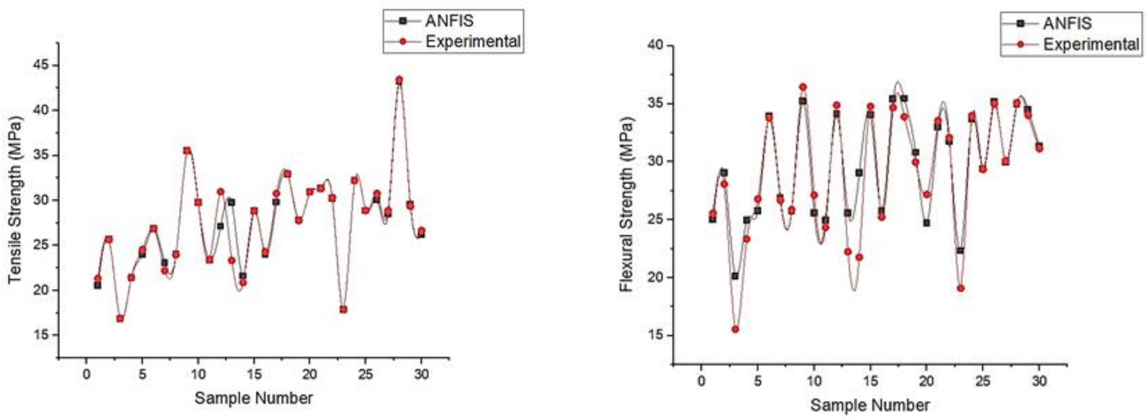
3.3 Discussions on adaptive neuro fuzzy interface base expert system results

The comparison between experimental and ANFIS (Adaptive Neuro-Fuzzy Inference System) values for tensile and flexural strengths across various samples provides insights into the accuracy and reliability of the ANFIS model in predicting mechanical properties. Table 7 illustrates the ANFIS outputs. In general, the ANFIS model closely approximates the experimental tensile and flexural strengths, with slight deviations observed in certain instances. For tensile strength, the ANFIS predictions are generally in good agreement with the experimental results as shown in Fig.9. Most samples show minor differences between the experimental tensile strengths and those predicted by the ANFIS model. For instance, samples such as 1, 2, 4, and 5 exhibit close alignment between the experimental and ANFIS-based tensile strengths, indicating that the model can effectively predict tensile properties within a reasonable range. However, some samples, like 3 and 13, show more considerable variations, suggesting areas where the model's predictive capability could be improved. In terms of flexural strength, the ANFIS model also demonstrates a high degree of accuracy in predicting values. Similar to tensile strength, the majority of samples show ANFIS predictions that are very close to the experimental measurements. Samples such as 2, 6, 9, and 18 exhibit minimal differences between the experimental and predicted flexural strengths, underscoring the model's reliability. Nevertheless, a few samples, including 3 and 14, show more significant deviations, indicating potential areas for refinement in the model. Overall, the comparison highlights that while the ANFIS model generally provides accurate predictions for both tensile and flexural strengths, there are specific instances where the model's predictions deviate from the experimental values.

Table 7 Comparison between experimental and ANFIS values

Sample No.	Experimental Tensile Strength (MPa)	Experimental Flexural Strength (MPa)	ANFIS based Tensile Strength (MPa)	ANFIS based Flexural Strength (MPa)
1	21.34	25.56	20.5621	25.005
2	25.67	28.07	25.6827	29.0525
3	16.9	15.56	16.8814	20.1112
4	21.45	23.34	21.434	24.9684
5	24.56	26.78	24.0074	25.7405
6	26.89	33.79	26.8655	33.9294
7	22.21	26.67	23.0451	26.8576
8	23.98	25.88	24.0074	25.7405
9	35.56	36.46	35.5371	35.2276
10	29.78	27.13	29.7425	25.5536
11	23.44	24.34	23.4147	24.9694
12	30.98	34.88	27.1403	34.0994
13	23.34	22.24	29.7425	25.5536
14	20.89	21.77	21.62	29.0196
15	28.87	34.77	28.8208	34.0329
16	24.33	25.23	24.0074	25.7405
17	30.78	34.68	29.8108	35.4179
18	32.98	33.88	32.9383	35.4419
19	27.78	29.98	27.8308	30.7942
20	30.98	27.18	30.9366	24.6974
21	31.34	33.54	31.3222	32.9915
22	30.34	32.09	30.25	31.7713
23	17.9	19.1	17.877	22.3305
24	32.23	33.98	32.1942	33.6544
25	28.89	29.35	28.8601	29.3703

26	30.78	34.98	30.1	35.1886
27	28.88	30.08	28.52	29.9886
28	43.44	35.09	43.19	34.9686
29	29.35	34.01	29.52	34.4886
30	26.67	31.13	26.19	31.3286



(a) (b)

Fig. 9 Statistical stability and relationship in proposed ANFIS for (a) Tensile Strength (b) Flexural Strength

4. Conclusion

The application of artificial intelligence, particularly neural networks and fuzzy systems, has proven to be an effective approach in optimizing FDM (Fused Deposition Modeling) process parameters. This study utilized the Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict tensile and flexural strengths of materials with high accuracy. The results indicate that neural networks and fuzzy systems can model complex relationships between process parameters and mechanical properties, offering reliable predictions and optimization strategies. The ANFIS model, in particular, demonstrated strong predictive capabilities, closely aligning with experimental values. Continuous refinement and incorporation of additional data can enhance the model's accuracy and reliability. Furthermore, the study successfully developed an expert system designed to predict the tensile strength of composite FDM parts. This expert system integrates knowledge from experimental data and AI models, providing accurate predictions based on input parameters such as fiber orientation, weight, and FDM process settings. The practical application of this expert system is significant, as it can be utilized by manufacturers and researchers to optimize FDM processes, enhance composite material properties, and reduce experimental costs by minimizing the need for extensive physical testing. This approach not only improves efficiency but also contributes to the advancement of FDM technology.

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