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Article

Artificial intelligence and machine learning for additive manufacturing composites toward enriching Metaverse technology

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Abstract: As a result of the growing significance and application of technology across a wide range of fields, digital environments such as Metaverse started to take shape over the span of the previous decade. This study aims to discover an area of engineering that could benefit from this new technology by developing an artificial intelligence (AI)—based approach to analyzing and predicting the mechanical properties of carbon fiber reinforced syntactic thermoset composites that are made through additive manufacturing (AM). These composites are intended to be utilized as a tool for metaverse technology in a variety of domains—as the presence of the limitations in the currently experimental methods. The metaverse allows for the generation of simulations through the application of artificial intelligence (AI) and machine learning (ML). Consequently, this paves the way for individuals to investigate various design possibilities and view the virtual manifestation of those possibilities. This is made possible by the use of machine learning algorithms, which allow for the monitoring and evaluation of user performance, as well as the provision of individualized feedback and suggestions for improvement. As a consequence of this, it is feasible that professionals will be able to get education and training that are both more efficient and effective. Consequently, this work aims to introduce an Adaptive Neuro-Fuzzy Inference System (ANFIS)—based model, which is able to effectively anticipate the behavior of mechanical systems in a variety of settings without the need for significant measurements. The validity of the ANFIS model was determined through the utilization of flexure and compression testing. The approach that was used to improve the technical assessment of the manufactured composites—is verified by the model's near-realistic predictions. Moreover, this method is superb for lowering weight, enhancing mechanical qualities, and minimizing product complexity.

Keywords: metaverse; composite materials; additive manufacturing; machine learning; adaptive neuro-fuzzy inference system (ANFIS)

1. Introduction

Starting with the introduction of the "metaverse" concept by Neal Stephenson in his book "Snow Crash" in 1992 [1], people are trying to immerse themselves in this environment in order to live a life that is similar to that of reality. The former term "meta" refers to a place that is beyond reality, also known as a realistic domain. The latter term, "verse" refers to the universe [2]. Examples include prospective online communities, the global web, and virtual worlds, all of which contribute to the overall air of ambiguity that surrounds it. The general view, on the other hand, is that users who are located in the real world connect to and control their avatars that are located in the metaverse by means of access terminals. This allows them to completely submerge themselves in a three-dimensional (3D) virtual environment. It is aided by the convergence of the Internet, the World Wide Web, and Extended Reality (XR), which encompasses Mixed Reality (MR), Augmented Reality (AR), and Virtual Reality (VR). The Metaverse is an immersive virtual environment that integrates the real world with the virtual world.

In point of fact, the metaverse may be summed up as an ecosystem that is based on the Internet and offers a hyper virtual reality experience. Virtual reality, augmented reality, mixed reality, artificial intelligence, machine learning, computer vision, speech recognition, blockchain, and the Internet of things are some of the technologies that are included in this ecosystem. These technologies encompass a wide range of fields. Mixed reality, augmented reality, and virtual reality are all examples of technologies that are virtualized and digitized. On the other hand, virtual reality is the definition of a technology. In addition, despite the fact that it is a fundamental component of the metaverse, it does not need a complete ecology, rules, or the Internet in order to be functioning [3].

The very definition of the term "ecosystem" implies that the various parts of the metaverse are interdependent and mutually limiting. In addition, they have achieved a state of dynamic equilibrium that is both stable and unified, leading to the creation of a virtual world that will last. However, the ecosystem would not be what it is today without a large user base regardless of its flawlessness, a 3D virtual vision system can only remain a concept if it remains unutilized. If a store sells a wide variety of things but doesn't have any paying customers, it's more accurately described as a warehouse than a mall. Users really drive demand, which propels metaverse growth and, in turn, draws more users, creating a virtuous cycle. To rephrase, there can be no successful metaverse without users, which raises the possibility that certain platforms may thrive while others fail [4,5].

The term "artificial intelligence" (AI) refers to a technology that is undergoing fast development and has a broad variety of applications. It is also causing a revolution in a number of different industries. It is possible that the ability of artificial intelligence to speed up processes, increase diagnostic accuracy, and enhance the quality of education might be useful to teaching, training, and research. This is a possibility that cannot be ruled out. It is essential to recognize that the incorporation of Artificial Intelligence (AI) and Machine Learning (ML) into the Metaverse has considerable implications for the ongoing evolution of the virtual environment. This is something that should be taken into consideration. As an example, take into account the development of the Metaverse; it provides designers and architects with new opportunities to build user interfaces that are not only dynamic but also captivating [6,7].

The Metaverse intends to achieve its ultimate objective of drastically changing the internet landscape in the workplace by developing a variety of three-dimensional virtual settings that are remarkably realistic and immersive. This will be accomplished via the establishment of these environments. On the other hand, artificial intelligence in the Metaverse plays a significant role in the management of the massive quantities of data that are built into the Metaverse itself. Devices and engines that are powered by artificial intelligence are very important to the Metaverse since they allow for efficient processing [8].

Because of the interplay of powerful artificial intelligence and data processing, including Machine Learning in Metaverse, it is possible to create virtual environments that are both scalable and finely detailed. This combination of technologies goes beyond artificial intelligence and includes blockchain, virtual reality, and augmented reality. As a consequence, it is possible to construct complex virtual worlds in a seamless manner [9,10].

The use of artificial intelligence (AI) and machine learning (ML) in the Metaverse allows for the generation of simulations, which in turn enables humans to investigate various design options and see how they present themselves in the virtual world. Tracking and analyzing the performance of individual users is made feasible via the use of machine learning algorithms, which also allow for the provision of individualized feedback and suggestions for improvement. This has the potential to ensure that professionals get education and training that is both more efficient and effective. In research, this may be used to recognize trends and make predictions about the results [11].

In order to provide further support, one of the most important uses of artificial intelligence is in the investigation of the mechanical behavior of composite materials. These technologies, which are driven by artificial intelligence, may provide professionals with access to knowledge and resources, which can enhance the learning experience and make it more efficient and effective. A further advantage of artificial intelligence algorithms is that they can evaluate enormous volumes of data in a short amount of time and recognize patterns that may otherwise be missed. As an example, the performance of composites may be improved by predicting the behavior of mechanical components in situations where the construction of the composite requires a lot of manual effort.

As a consequence of this, it is difficult to make an accurate measurement of the mechanical behavior of composites over certain stages of reinforced content using experimental means [12,13]. In order to reduce the amount of work that has to be done in the laboratory, it is essential to investigate the methods that may be used to accurately assess the difficulty of forecasting mechanical characteristics. For the purpose of reducing the amount of time spent in the laboratory, this should be of assistance. When it comes to the adaptive network-based fuzzy inference system, also known as Adaptive Neuro-Fuzzy Inference System (ANFIS), it demonstrates a solid technique to forecast the mechanical characteristics of these composites in a variety of engineering subfields [14].

By using a hybrid learning technique, the ANFIS models that have been theorized may provide an algorithm that is input-output suitable by drawing on experimental information in a fuzzy if-then rule state. By using nonlinear regression, ANFIS is also able to analyze nonlinear functions and identify nonlinear components. They are all very accurate predictors, which allows for autonomous control, data classification, and decision analysis, in addition to the benefits already mentioned [15]. As previously, simulations may be developed in the Metaverse utilizing AI and ML to enable users to try out different layouts and see how they work in virtual reality. ML algorithms enable tracking and assessing the performance of such data and also provide customized comments and development recommendations.

Professional education and training may therefore become more efficient and productive.

As in decision making tools, stochastic models, and finite element analysis, there are indeed many approaches to handling these kinds of issues. To predict the result, these models do, however, need both complex computer processing and large data sets. In this article, the tendency to the Artificial intelligence approaches is due to the accuracy it has, even if it is used to little data set. In this sense, the ANFIS network design presented in this study is used as a basis to ascertain the basic mechanical characteristics of additively produced syntactic foam thermoset composites no experimental study was conducted. The established prediction models provide precise mechanical behavior predictions, to highly predict the mechanical performance in such situations.

2. Methodology

One type of substance that specialists have categorized is called syntactic foams, which include spherical particles that are interconnected by a matrix resin composed of ceramics, polymers, or metals [16]. Syntactic foams have been recently created to provide a straightforward and cost-efficient way to manufacture various intricately molded forms with great energy absorption and rigidity. Its decreased density, closely packed closed-cell structure, and considerable specific resistance are some of its distinguishing characteristics, making it widely favored and extensively used in many applications. This occurred because foam has the capacity to improve the structure by absorbing energy without increasing mass much, according to its low density. For instance, in the automotive sector, using foam to fill hollow structural components of vehicles enables the utilization of lighter building materials without compromising crash test performance, as it is crucial for creating and producing fuel-efficient automobiles while ensuring occupant safety. Moreover, several notable characteristics of this material include its commendable shock resistance, permeability to water, buoyancy, and robustness in withstanding high water pressure, making this material suitable for many applications [17,18].

The capacity of the foam to absorb energy without increasing the amount of stress or force that causes the material to deform is what is meant by the term efficiency. The foam was seen to acquire significantly greater peak efficiency and to sustain a higher efficiency throughout its deformation without compromising its effectiveness [19]. Consequently, studying the mechanical properties of syntactic foams plays a crucial role in optimizing their structural performance.

A thorough examination of syntactic foam materials indicates that the mechanical properties may be tailored by incorporating appropriate matrix elements with hollow microspheres [20,21]. The use of glass microspheres in conjunction coexisting with the matrix substance is pertinent to the additive manufacturing (AM) domain, specifically with reference to direct write methods and fused filament production [22]. 10 to 300 micron-diameter glass microspheres, are favored among researchers for their exceptional compressive stresses, which significantly exceed those seen by other classes of microspheres [23,24].

The manufacturing procedures often used for the manufacture of thermoplastic syntactic foam components are frequently identified as injection molding or compression molding. However, further investigation has shown the practical use of additive manufacturing techniques, including Fused Deposition Modeling (FDM) and direct writing procedures, in the production of thermoplastic syntactic foam composites with reinforcements. The achievement of this task included the use of the Fused Deposition Modeling (FDM) technique to fabricate the syntactic foams in a sequential layer-by-layer manner [25].

The incorporation of a significant proportion of reinforcements, such as carbon fibers, into the matrix resin of syntactic foam has been seen to provide enhanced mechanical properties. However, it seems that there exists a threshold for the concentration of fibers used in composite fabrication, irrespective of the specific kind of fibers employed. Mechanical performance of composites over certain reinforced content levels is difficult to quantify experimentally. Hence, it is essential to prioritize research efforts towards the establishment of a pragmatic approach for assessing the complexity associated with predicting mechanical characteristics. The primary objective is to minimize the extent of labor-intensive tasks conducted in the laboratory. The ANFIS (Adaptive network-based fuzzy inference system) offers a viable approach for forecasting the mechanical properties of composite materials in many fields of engineering.

The present study introduces a unique ANFIS network design that serves as a basis for evaluating the basic mechanical characteristics of additively generated syntactic foam thermoset composites, eliminating the necessity for experimental analysis. This study demonstrates the ability to accurately predict mechanical performance in various scenarios through the utilization of developed prediction models. These models are capable of providing accurate predictions of mechanical behavior, irrespective of the concentration of fibers. The predictions are based on the analysis of sampled data collected under diverse conditions, eliminating the need for experimental investigation. The ANFIS model structure used in this investigation is shown in **Figure 1**. The portion of microspheres made of glass (M) and carbon fiber (Hi) are two variables that are included in the fuzzy inference approach utilized in each model, as the image shows. Conversely, the system just yields one output, including the modulus of flexural test (Ai), the stress of flexural test (Bi), the modulus of the compressive test (Ci), and the stress of the compressive test (Di).

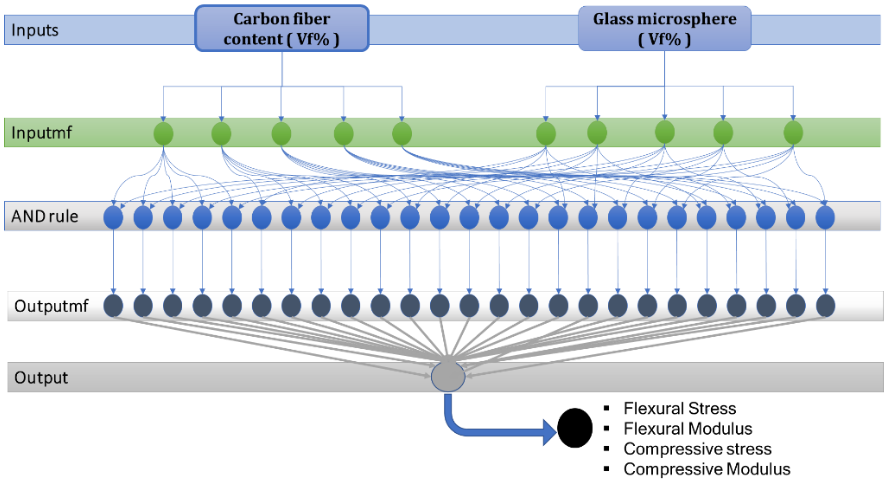


Figure 1. The framework of this study is based on the Adaptive Neuro-Fuzzy Inference System (ANFIS).

Following that, the implementation of Sugeno's fuzzy if-then rules is carried out, which is done by expanding upon the foundation of fuzzy if-then rules that have earlier been employed [26]. Using the pseudo-code, as seen in the following example, it is possible to demonstrate the representation of a Sugeno-Fuzzy rules system.

```
START
 Enter Hi, Mi
  IF Hi == "Xi" AND   Mi == "Yi" THEN
     Ai= n1i*Hi + n2i*Mi + n3i
     Bi= n4i*Hi + n5i*Mi + n6i
     Ci= n7i*Hi + n8i*Mi + n9i
     Di= n10i*Hi + n11i*Mi + n12i
     ENDIF
 Display Ai, Bi, Ci, Di
Stop
```

The volume of carbon fiber (Hi) and the volume of glass microspheres (M) are denoted as such in the equations that have been provided so far. The compressive modulus (Ci), the compressive stress (Di), the flexural stress (Bi), and the flexural modulus (Ai) are the sole outputs that these formulas produce. Contrarily, these formulas just offer one result. The values of the constant coefficients are shown by the variables n1i through n12i, which is the last but not the least important point.

The function's values ($\mu_x(Mi), \mu_y(Hi)$) are determined by:

$$\mu_x(Mi) = \frac{1}{1 + [\left(\frac{Mi - ci}{ai}\right)^2]^{bi}} \tag{1}$$

$$\mu_y(Hi) = \frac{1}{1 + [\left(\frac{Hi - ci}{ai}\right)^2]^{bi}} \tag{2}$$

Equations (1) and (2) demonstrate the output of the layer, which is characterized by a bell-shaped membership function. This function is defined by the premise parameters (a, b, c). The parameter "a" denotes the maximum height of the curve, while the value "b" represents the central position of the peak. The parameter "c" is connected to the standard deviation of the curve, which controls the width of the curve.

The language variables associated with this node function are denoted by the symbols x and y. The values of x, representing glass microspheres (Mi), and y, representing the quantity of carbon fiber (Hi), show the degree to which the supplied inputs (Mi, Ci) satisfy the criteria of the linguistic variables. Each node receives an input signal, and the second layer is in charge of amplifying it and then transferring the output. (i.e., the output represents the firing intensity of a rule, denoted as E^i). For example, let us consider:

$$E^i = \mu_x(Mi)\,\mu_y(Hi) \tag{3}$$

In order to standardize the firing strength, the third layer calculates the aggregate firing strength of the i-th rule in relation to the total firing strength of all rules. Normalized firing strengths, which are the outputs of the layer (i.e., $\overline{E}i$), are computed in the following way:

$$\overline{E}i = \frac{Ei}{E1 + E2 + \cdots + En} \tag{4}$$

Layers four and five are responsible for receiving the normalized inputs and transmitting the defuzzified values to layer five. In turn, layer five produces the final output, represented by the variables U and U'. At each level, Equations (9) and (10) outline the mathematical procedures, with $K(i)$ being the estimated mechanical characteristic, which includes the flexural modulus, compressive modulus, compressive stress, and flexural stress.

$$U = \overline{E}i(K(i)) \tag{5}$$

$$U' = \frac{\sum_i \overline{E}i(K(i))}{\sum_i \overline{E}i} \tag{6}$$

3. Results and discussion

At the outset of data analysis, these statistics take into account the training data, which comprises 70% of the total, and the testing data, which comprises 30%. **Figures 2** and **3** provide a comparison between the observed experimental outcomes and the anticipated flexural and compressive stresses exhibited by syntactic foams. Keeping the track on the experimental findings; as the contour plot in **Figures 2** and **3**, the values expected for flexural strength and compressive strength are quite similar to those that were actually observed.

More specifically, this study's results clearly show that the ANFIS prediction model would accomplish a reasonably precisely estimate the stress levels of the flexural test during the experimental training phase. In spite of this, **Figures 4** and **5** highlight the accuracy of this model when applied to the prediction of the flexural and compressive moduli, respectively.

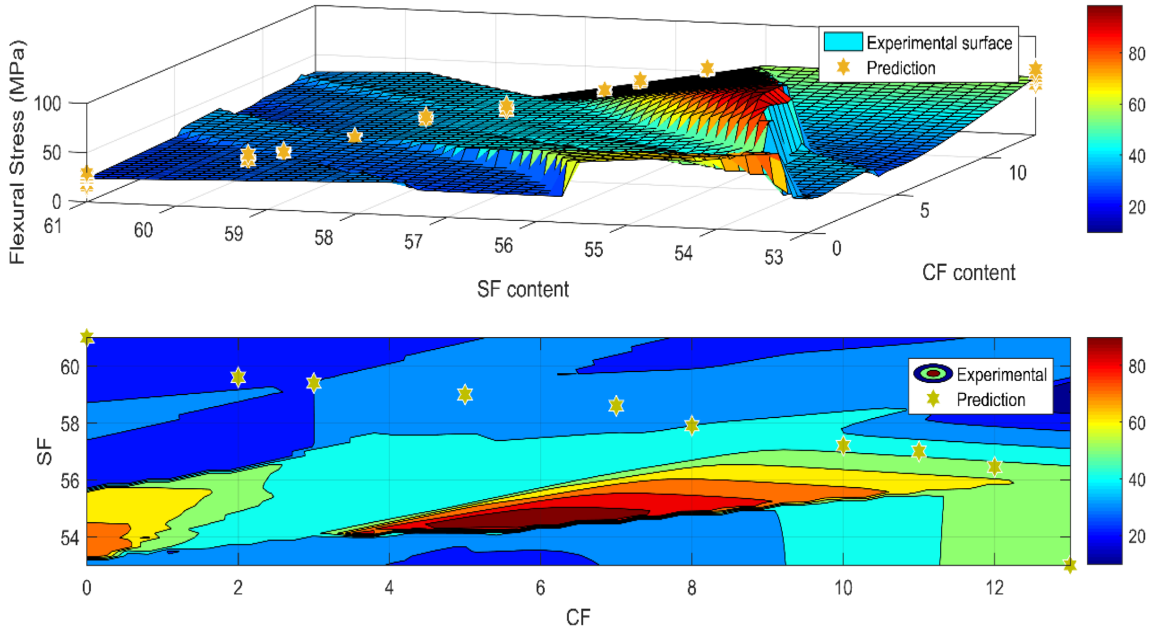


Figure 2. An analysis of the amounts of flexural stress expected and real.

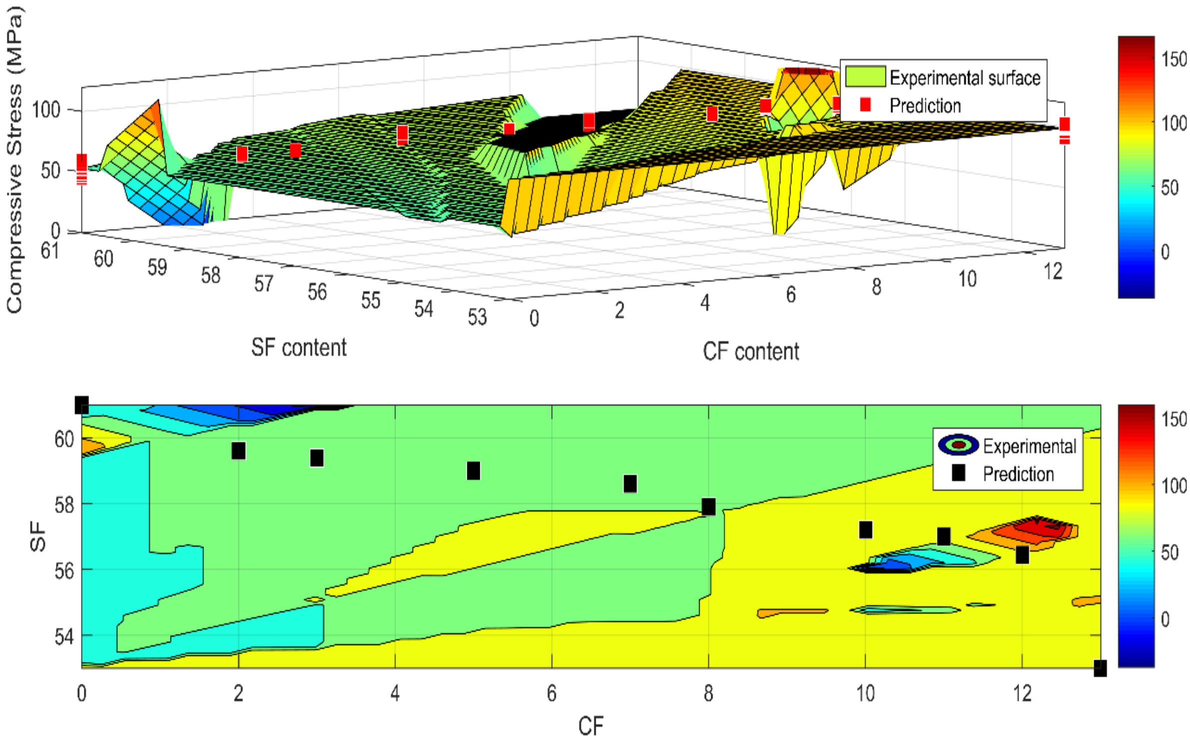


Figure 3. An analysis of the amounts of compressive stress expected and real.

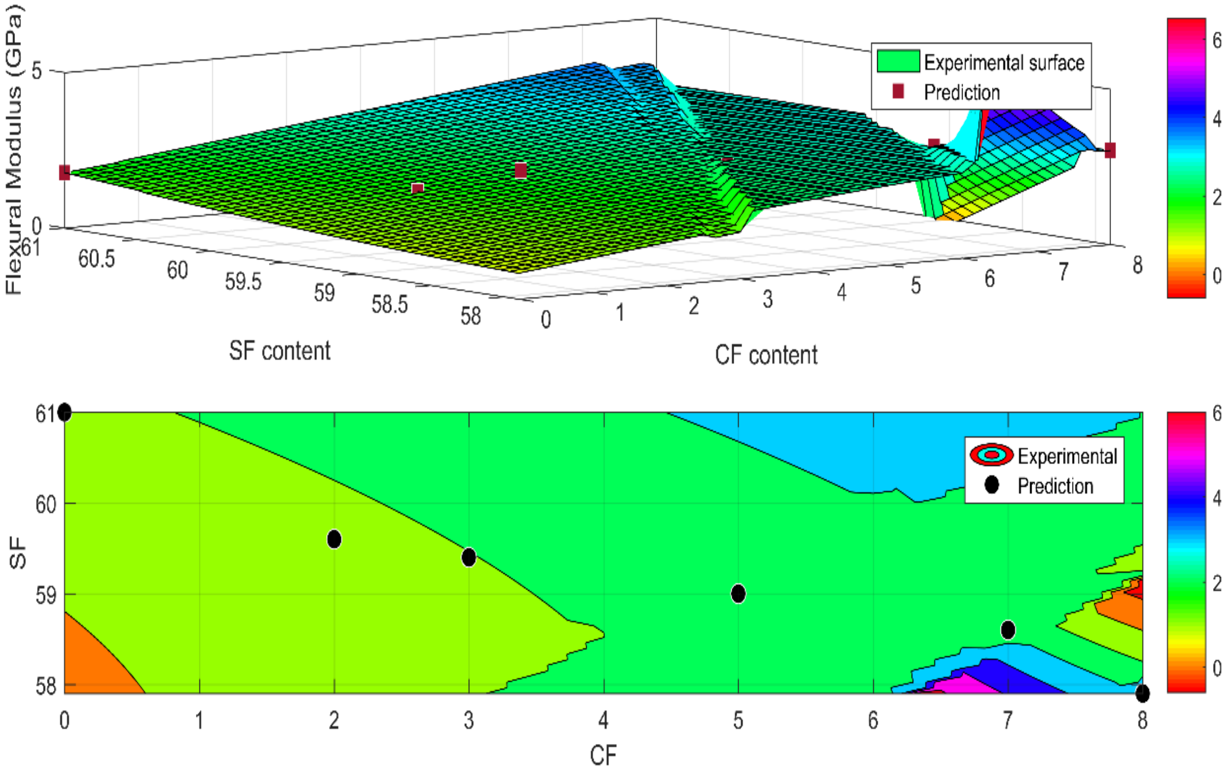


Figure 4. An analysis of the amounts of flexural modulus expected and real.

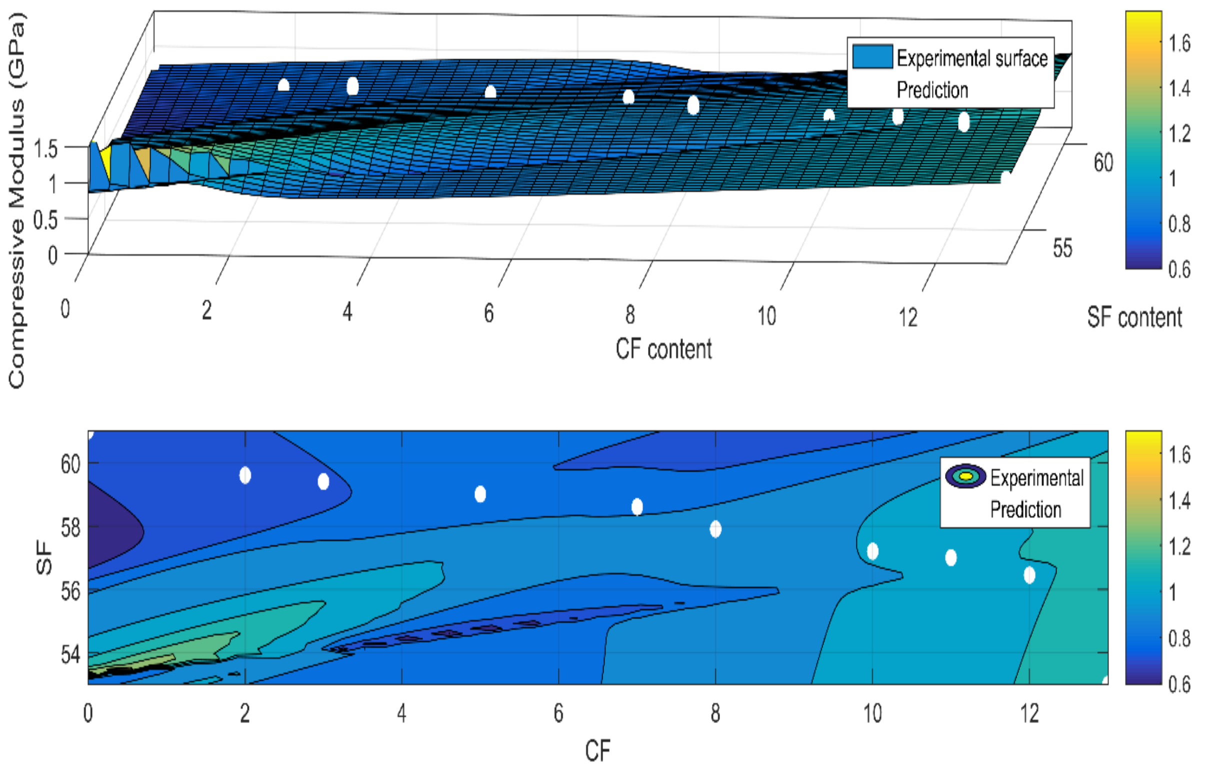


Figure 5. An analysis of the amounts of compressive modulus expected and real.

While it is worth noting that the anticipated values for the mechanical characteristics revealed some deviation from the actual experimental values, it is essential to emphasize the importance of thoroughly investigating all potential sources of inaccuracy. Upon closer examination of **Figures 6** and **7**, it becomes apparent that the estimated errors of the models developed by the Anfis Adaptive Neuro-Fuzzy Inference System are rather insignificant. The quantitative information on the estimated test values seen in the compressive and flexural tests is given in **Tables 1–4**.

Table 1. Study tests in figuring out the flexural stress results.

Carbon Fiber Content (Vf%)	2–4	4–8	9–13
Glass Microsphere Content (Vf%)	58–61	55–58	53–55
Research Findings (MPa)	23.12–35.2	35.2–50.8	50.8–66.26
Projected ANFIS (MPa)	20.9–31.8	31.8–43.3	43.3–56.2

Table 2. Study tests in figuring out the flexural modulus results

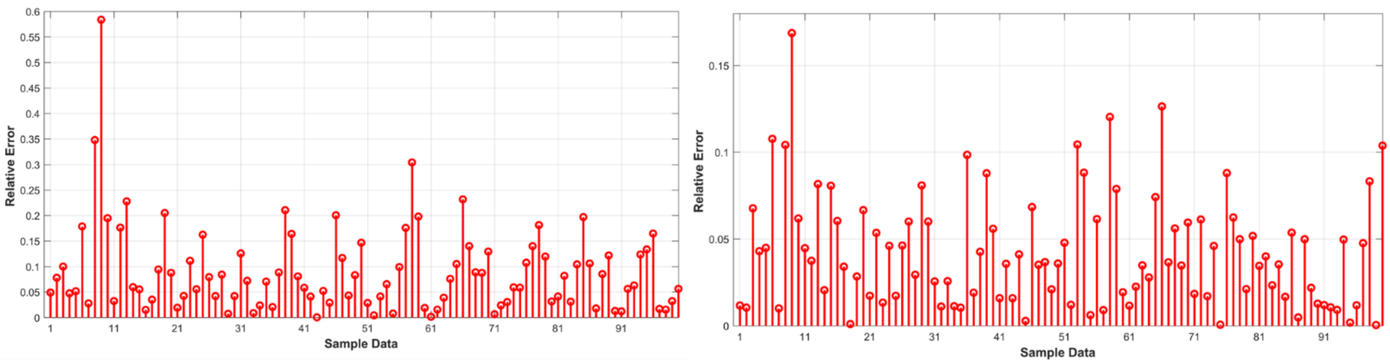
Carbon Fiber Content (Vf%)	2–4	4–8	9–13
Glass Microsphere Content (Vf%)	58–61	55–58	53–55
Research Findings (GPa)	1.4–2.9	2.9–3.7	3.7–4.5
Projected ANFIS (GPa)	1.8–2.6	2.6–3.8	3.8–4.1

Table 3. Study tests in figuring out the compressive stress results.

Carbon Fiber Content (Vf%)	2–4	4–8	9–13
Glass Microsphere Content (Vf%)	58–61	55–58	53–55
Research Findings (MPa)	50.7–73.2	73.2–86.1	86.1–100.9
Projected ANFIS (MPa)	49.8–74.6	74.6–83.2	83.2–99.2

Table 4. Study tests in figuring out the compressive modulus results.

Carbon Fiber Content (Vf%)	2–4	4–8	9–13
Glass Microsphere Content (Vf%)	58–61	55–58	53–55
Research Findings (GPa)	0.62–0.81	0.81–0.96	0.96–1.34
Projected ANFIS (GPa)	0.69–0.78	0.78–0.94	0.94–1.23



(a) **(b)**

Figure 6. Errors for ANFIS model types. **(a)** Flexural stress; **(b)** compressive stress.

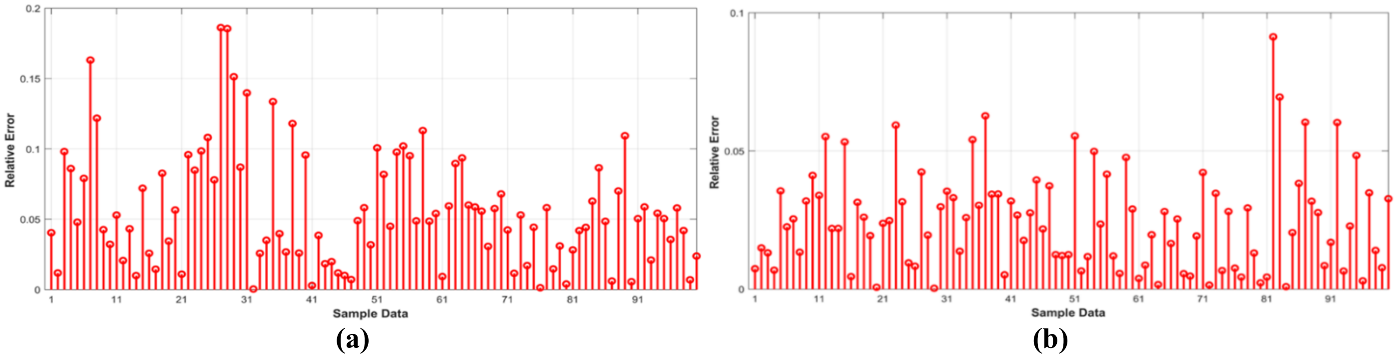


Figure 7. Errors for ANFIS Model types. **(a)** Flexural modulus; **(b)** compressive modulus.

Three performance measures—mean comparative rate of errors (MAPE), *R*-squared index of correlation, and mean square error (MSE)—are used to assess the mechanical testing. In **Table 5**, the anticipated outcomes for the ANFIS mechanical assessment are statistically summarized. The subsequent study of the observed statistical data provides insights into the accuracy of the constructed ANFIS model.

Table 5. Mechanical property prediction statistics.

	MSE	**MAPE**	R^2
Flexural Stress	0.93	7.01%	0.89
Flexural Modulus	1.05	2.85%	0.96
Compressive Strain	0.29	3.98%	0.94
Compressive Modulus	0.21	1.88%	0.95

Based on the R^2 values shown in the table, it can be inferred that the model exhibits a higher degree of accuracy in predicting the mechanical performance of the composites. Equations (7)–(10) display the correlations between the estimated equations for each Adaptive Neuro-Fuzzy Inference System (ANFIS) model, specifically focusing on the predicted measures of the composite generated.

$$X(H,M) = 4001 + 49.89H - 129.6M - 0.3154H^2 - 1.0235HM + 0.98M^2 \quad (7)$$

$$Y(H,M) = 2999 - 38.56H - 99.8M + 0.1002H^2 + 0.4656HM + 1.02M^2 \quad (8)$$

$$U(H,M) = -9.254 + 814.6H + 1998M - 1.8652H^2 - 14.96HM - 19.42M^2 \quad (9)$$

$$K(H,M) = 285.6 - 4.285H - 11.25M + 0.01H^2 + 0.0854HM + 0.12M^2 \quad (10)$$

where H is the carbon fiber content, M is the glass microsphere concentration, X is the flexural Stress, Y is the flexural modulus, U is the compressive Stress, and K is the compressive modulus.

By applying this model to additional validation sites, we can examine the equations presented above, which verifies the reliability of the work and makes investigation possible. **Figures 8** and **9** show that the investigation of these validation points shows a favorable relationship between the research investigation and the models of ANFIS. Nonetheless, the suggested ANFIS model's predictions are in line with these findings.

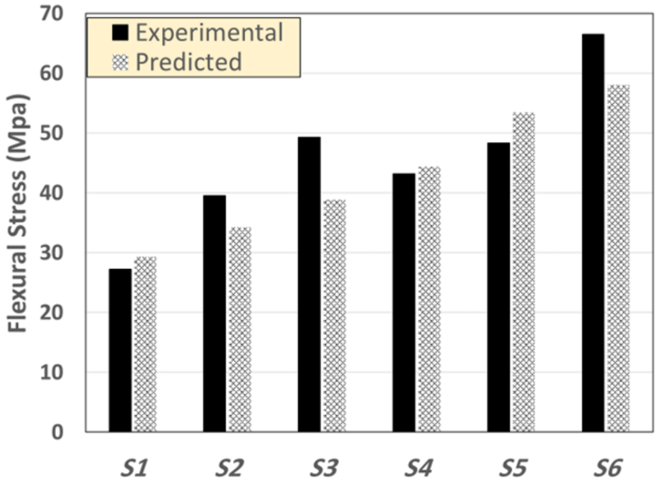


Figure 8. Verification of the ANFIS approach: flexure-type stress.

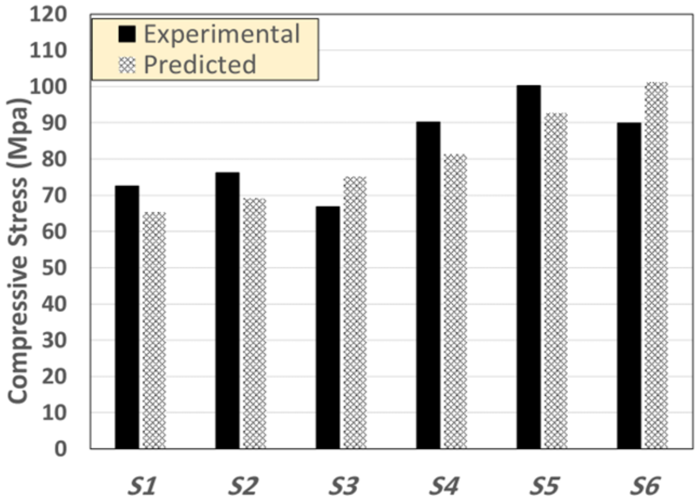


Figure 9. Verification of the ANFIS approach: compressive-type stress.

However, for the reference of **Figures 8** and **9**, **Table 6** provide a summary of each amount of carbon fiber and glass microspheres used- per each sample.

Table 6. A summary of each amount of carbon fiber and glass microspheres used- per each sample.

Validation samples	Carbon fiber content (vf%)	Glass Microsphere content (Vf%)
S1	3.1%	56.2
S2	5.2%	60.6
S3	8.5%	60.2
S4	12.3%	53.4
S5	18.1%	51.7
S6	22.4%	55.9

4. Conclusion

In conclusion, this study provides a comprehensive study of applying metaverse in engineering fields, specifically in the context of utilizing ANFIS prediction models to predict the mechanical behavior of syntactic–reinforced thermoset composites. Incredibly resistant to impact, lightweight, and with high specific strength, synthetic foams are a one-of-a-kind material system. Predicting mechanical performance is tough due to the difficulty of creating syntactic foam composites, particularly using additive manufacturing methods. In this work, the mechanical impacts of short carbon fiber support in syntactic foam thermoset composites were investigated with no laboratory assessment or carbon fiber amount, as a result of nozzle obstruction and fiber aggregation. Therefore, the mechanical performance may be reliably predicted by the prediction models presented in this study, independent of the fiber concentration. To be more specific, this prediction is made possible by the accuracy of ANFIS models, even when working with small data sets. The ANFIS models were validated, and mechanical performance was guaranteed by subjecting the produced samples to compression and flexure tests.

They reliably quantify the mechanical performance, according to the high degree of agreement between experimental findings and ANFIS predictions. In particular, there were small mean absolute percentage errors for compressive stress, flexural modulus, flexural stress, and compressive modulus, confirming the precision of the anticipated model. This means that innovative technological uses for additive manufacturing systems may be realized with the help of ANFIS models, which can make them more dependable without the need for exploratory tests.

Moreover, Metaverse applications of AI and ML allow for the generation of simulations. This opens up new opportunities for users to experiment with various designs and see them brought to life in virtual reality. Tracking and analyzing user performance, along with providing tailored feedback and improvement suggestions, is made possible by machine learning algorithms.

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Conflict of interest: The authors declare no conflict of interest.

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