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Using Artificial Neural Network in Reverse Design of Fiber Reinforced Plastic Composite Materials

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Abstract

Composite materials are composed of two or more constituents, wherein the favorable properties of each material are contributed to improving the overall properties of the final composite material. Performing homogenized properties of composites is often challenging because it has a strong association with basic constituents at the micro-structure level. Therefore, the inverse approach for designing composite materials is a modern technique that can provide sophisticated theoretical support for composite materials.

In this study, an Artificial Neural Network (ANN) was employed to predict the parameters of the basic constituents on a micro-scale based on the final homogenized properties demanded by the designer. the necessary data was derived from Finite Element Method (FEM) model.

A micro-level structure was used to conduct the homogenization analysis, which consisted of the reinforcing phase (fiber) and supporting phase (matrix). While the required data for building the ANN model was obtained using the FEM model of the composite unit cell in conjunction with the Monte Carlo Simulation. Then, The input features were mapped to the output features by utilizing Backpropagation (BP) algorithm in the neural network.

The input variables were the homogenized properties of demanded composite material. While the output was the properties of the constituent's materials (i.e. fiber, fiber diameter, and matrix).

The outstanding performance of the reverse ANN model was revealed through a low value of mean square error (MSE) with a value of 0.00033, and also the coefficient of determination (R2) value which approached one. The contribution of this study is to produce an Artificial Neural Network (ANN) model, which offers a faster and highly accurate approach for obtaining the properties of composite constituents. This, in turn, provides significant practical engineering value in designing composite materials.

Keywords: artificial, neural network, fiber, reinforces plastic and composite materials

1. Introduction

Use Fiber Reinforced Plastic(FRP) composite materials for various industries has been steadily increasing recently, attributed to their high strength as well as low weight characteristics. Therefore, the properties of composite materials have gained more attention in modern research studies [1]. A matrix is defined as supporting phase component, while the reinforcing phase is fiber. The mutual reinforcement of both phase materials results in a new material characteristic that is superior to those of the individual original materials. Fiber Reinforced Plastic (FRP) materials are one of the more commonly used materials in the industry. For materials in which the fibers are aligned in the same direction, they are called unidirectional (UD) fiber-reinforced composites. An illustrative schematic of such unidirectional fiber composites is depicted in Figure 1. The stiffness and strength of are organized by fibers while the matrix plays main role in transferring load and provide required protection against environmental elements[2], [3].

Figure 1. Schematic of a unidirectional fiber reinforced composite.

The reliability of structures critically depends on the mechanical properties of the employed FRP composites. Researchers have investigated various models to perform the homogenization of composite materials. In the context of FRP, the homogenization approach assumes that the microstructure of composites consists of units of fiber-bound matrix that are periodically repeated. Therefore, many researchers have provided a reduced model, which is commonly referred to as a Representative Volume Element (RVE), that could be unit of cell for the unidirectional fiber reinforced composites [4]–[6].

An extensive survey of the literature reveals that homogenization techniques for Unidirectional Fiber Reinforced Plastic (UDFRP) have been reviewed. Babu et al.[7] developed four representative volume elements with different geometries involving hexagonal and square periodic structures with various orientations of fiber in considered composites. A Halpin-Tsai and Mori-Tanaka techniques are used to obtain effective property prediction. Kazimierczak [8]performed a computational simulation to determine the expected values, standard deviations, skewness, and kurtosis of the homogenized tensor for various composites containing metallic components. A square RVE was used to analyze the UDFRP composites. In another study, Gao et al. [9] proposed a framework the computational approach for engineering materials, they used the mixture rule to develop a unidirectional laminates of Carbon Fiber Reinforced Plastic (CFRP) structure. Three-point bending tests were conducted and compared with simulation results. Gruber et al. [10] focused on computational homogenization and micromechanics applied to composite materials to address the challenge of interfacial debonding. The authors explored two approaches to assess the collective behavior of composites with rigid-brittle interfaces. In their paper, Rohan and Ostachowicz[11], have conducted the computational modeling of delamination in composite shells under different temperature conditions. They have dedicated their efforts to studying the effects of delamination on laminated composite structures, particularly under purely bending loads. The study provided insight to delamination behavior and highlighted the importance of considering temperature effects in composite structures. Mishra and Chakraborty [12] investigated the utilization of a vibration-based inverse identification technique using a finite element model. The study was aimed to accurately determine the constituent elastic material parameters and boundary conditions of fiber-reinforced plastics (FRP). The authors demonstrated the effectiveness of their technique through a series of numerically simulated examples. In a study by Potrzeszcz-Sut and Pabisek [13], the authors addressed the inverse problem of predicting stress (σ) from strain (ε) using pseudo-empirical patterns. They employed neural networks as universal approximator for nonlinear functions to describe the material's constitutive equations. This approach was applied to model the

Ramberg-Osgood (RO) material behavior and analyze the shakedown of an aluminum truss. The proposed method successfully identified material parameters through ANN in solving the inverse problem. A reverse design of a composite sandwich structure has been studied by Sahib and Kovacs[14]. The study involved using ANN to predict the design parameters of the composite sandwich structure. The overall deflection of the sandwich structure was pre-assigned as input to the ANN model. A good agreement was noticed between the ANN predictions, analytical and numerical solutions. In a separate study, Lee et al. [15] conducted a Monte Carlo Simulation (MCS) to identify linear relationship for homogenized and material properties. In terms of Artificial Neural Network (ANN) and machine learning, Huang et al. [16] established ANN models based on experimental tests and Finite Element (FE) models data for learning constitutive laws. Le et al. [17]generated data to develop for nonlinear behavior at elastic limits depending on the model of constitutive. They developed an RVE analysis with periodic boundary conditions for this purpose. Sun et al. [18], [19]employed various models of ANN such as RNN and DRL to create surrogate models that enable the multiscale modeling of materials with porosities.

In addition to the above-mentioned studies, numerous investigations have utilized various models of artificial neural network for modeling a nonlinear material behaviors from Molecular Dynamics (MD) simulation data, particularly at smaller scales [20], [21]. Furthermore, ANN models have proven valuable in accelerating computationally expensive calculations in FE models [22], [23], thereby reducing the computational costs of numerous multiscale models relying on finite element analysis. Additionally, ANN models have been successfully applied to model physical phenomena, i.e. electrical conduction and thermal problems [19] [20].

Based on a review of the existing literature, it is evident that an inverse design approach is essential for advancing the development of design theory and methods. In the context of FRP composite materials, inverse design involves the determination or specification of micro-structure (i.e. fibers and matrices) parameters based on the desired material response. Inverse approach of design has become progressively relevant in industrial applications, including the inverse approach in geometric designing of airfoils where distributed pressure were used as designing criteria [24].

The paper is organized into several sections. Section 2 provides an overview of the study's significance and key contributions, while Section 3 focuses on the modeling of the Representative Volume Element (RVE) and the process of generating data. Section 4 delves into the background of Artificial Neural Networks (ANN) and explains the methodology used to develop the ANN model for reverse design. The obtained results are discussed in Section 5, and finally, Section 6 summarizes the study's key findings and conclusions.

2. Study significance and key contributions

Composite materials have gained progressive attention in many industries due to their superior mechanical properties and lightweight nature. However, focusing most of the research on traditional methods for predicting the mechanical properties of composite materials (i.e., analytical and numerical approaches) makes obtaining specific mechanical properties not an easy task. This is due to the wide range of types of composite constituent materials (i.e., fibers and matrices) and their different configurations in the final composite materials. Although significant development has been achieved in theoretical methodologies and modeling tools, the design space for composite materials remains vast. A time-consuming and tedious trial-and-error process is the only conventional design method to obtain the desired properties that meet specific design criteria.

At this end, the necessity of composite reverse design is raised. In our research, the term "reverse design" refers to the final mechanical properties of composite materials, which are considered as outputs in conventional methods but become the inputs to Artificial Neural Networks (ANN). Conversely, the constituent properties (i.e., fiber and matrix properties), which are considered inputs in conventional methods, become outputs in the ANN reverse model.

Until this time, there have been no detailed studies on the reverse design of composite material properties for pre-selected homogenized mechanical properties. As a result, the elaborated method provides a novel and practical tool for designing Fiber-Reinforced Polymer (FRP) composites with sufficient accuracy while avoiding the trial-and-error repetition required by traditional design methods.

In this study, ANNs are proposed as an alternative tool for obtaining the composite constituent properties by preselecting the homogenized properties of the final composite, including longitudinal and transverse moduli of elasticity (E11, E22 , E33), shear moduli (G12, G13, G23), and respective Poisson's ratios (ν12, ν13, and ν23), as reverse inputs in a reverse design model. Meanwhile, constituent material properties, such as the moduli of elasticity of the matrix and fiber (i.e., Em , Ef), the Poisson's ratios of the matrix and fiber (nm , nf), and fiber diameter (df), are the results on the output side of ANN. Engineers can thus determine the required constituent data for the composite to meet design conditions at a preliminary design stage. As demonstrated in the results section, the design parameters (i.e., Em , Ef , nm , nf , and df) determined by ANNs based on the reverse design are verified by running them in a numerical model, proving the accuracy of the reverse design method and it can be suitable for utilizing in practical designs.

This study links Artificial Intelligence-based design and traditional design by addressing a problem that is important from a practical point of view. It contributes to a sophisticated approach that provides composite material designers with a useful, flexible, and time-saving tool to optimize and adapt the performance of composites for different types of applications. The main steps of ANN-based reverse design are illustrated in Figure 2.

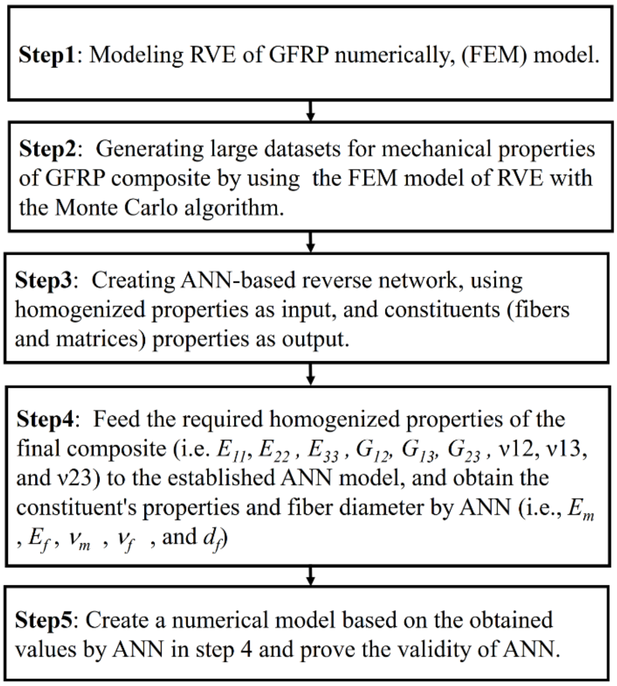


Figure 2. The main steps for creating ANN reverse design model.

3. FEM modeling and data generation of effective elastic properties

In order to develop a robust Artificial Neural Network (ANN) model, it is essential to acquire a substantial volume of data for both training and testing. Regardless of cost factors, experimental methods may fall short in meeting the demand for diverse data. Consequently, a finite element model is created to produce property data, utilizing a Representative Volume Element (RVE) under periodic boundary conditions for fiber-reinforced plastic composite materials. In this study, an integration between the i-sight and ABAQUS Softwares is conducted, where the i-sight employed for managing input data, and the ABAQUS, used to solve the RVE numerically to obtain the homogenized properties of the final composite material based on the input data. The following subsections provide detailed illustrations of the Finite Element Model (FEM) and the process of data generation.

3.1. Finite Element Model of RVE

I As previously mentioned, conducting experiments to predict the properties of FRP composites is associated with high cost and time consumption. Consequently, there is a need for a numerical method to predict the homogenized properties of composites. The homogenization technique in this study was conducted by selecting an RVE model. As illustrated in the Figure 3(a) , the RVE represents a unit cell of composite materials consisting of glass fiber and matrix repetitively arranged to produce the final composite structure [25], [26].

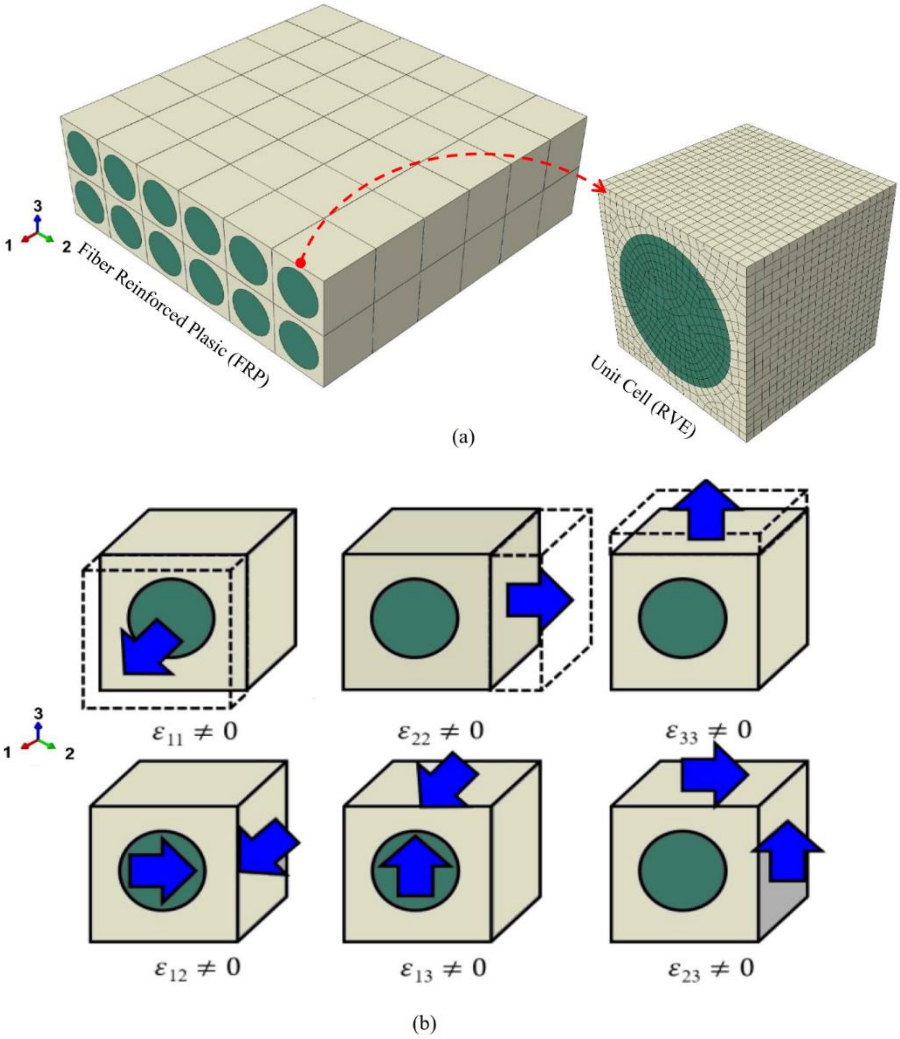


Figure 3. Schematic of GFRP and FEM model of RVE

A unit cell, as a micro-scale structure, has a significant effect on the final homogenized mechanical properties of composite materials at the macro-structure scale. In this study , The unit cells were modeled for a range of glass fiber diameters, and polymer matrices. Consequently, the mechanical properties of composites were predicted utilizing the ABAQUS software [27]. The right part of Figure 3(a). depicts the FE model of the RVE. The RVE was meshed with a solid (C3D8R) elements, each element has eight nodes and six degrees of freedom in this mesh type. The total number of elements and nodes was 9700 and 11046 respectively.

Figure 3(b) depicts the boundary conditions for the considered RVE of Unidirectional Glass Fiber Reinforced Plastic material (UDGFRP). The loads were applied in terms of directional deflections to obtain the mechanical properties based on the RVE response to the applied deflection in the consequences directions. ABAQUS software provides an effective tool to conduct the homogenization. The Micromechanics Plugin under ABAQUS was used to obtain the mechanical properties of the considered UDGFRP material. Additional elaboration on the Plugin and the method for obtaining homogenized properties can be found in [28]. In this study, a variety of glass fibers and polymer matrices were considered as the fundamental constituents of the final UDGFRP as it detailed in section 3.2.

3.2. Acquiring Data for reverse ANN

The predictive capability of an Artificial Neural Network model depends heavily on a large quantity of datasets. It is well-known that Finite Element Method simulations are computationally expensive, and thus acquiring individual samples can be time-consuming. To address this problem, the Monte Carlo method within the i-sight package is employed to map the inputs for the FEM model. The established FEM model is converted into a Python script, which is subsequently called by the Monte Carlo simulation under i-sight software environment for execution in non-GUI mode to reduce computational time. The mechanical properties of the glass fiber and their associated compatible polymer matrices are listed below:

Table 1. Fibers and matrix properties

	Parameter	Description	Value	Unit
Matrix	E_m	Matrix Modulus of elasticity	1600-5350	MPa
	ν_m	Matrix Poisson's ratio	0.34-0.4	-
Fiber	E_f	Fiber Modulus of elasticity	68900-86900	MPa
	ν_f	Fiber Poisson's ratio	0.14-0.276	-
	d_f	Fiber diameter	9-6	µm

The primary steps for data generation are summarized below:

Step 1: Establish the FEM model for the RVE, which consists of a fiber and matrix unit cell, as it illustrated in section 3.1.

Step 2: Abaqus software able to convert the FEM model to Python code, hence the main input parameters (i.e. Em , Ef , nm , nf , and df) were defined as variables in the Python code. Thus, when the code imported by i-sight, the parameters values varied within the range that specified pre-specified.

Step 3: Import the Python code into i-sight software.

Step 4: Identify the range of input variables, including elastic properties for fibers and matrices, as indicated in section 3.2.

Step 5: Select the number of Monte Carlo simulations to be conducted, which, in this study, is set at 500.

Step 6: Generate a set of uniformly distributed random numbers for each input variable within the specified range.

Step 7: Feed ABAQUS with new values of input parameters that provided by i-sight software through Paython code to obtain the mechanical properties (i.e. E11, E22 , E33, G12, G13, G23, n12 n13 and n23 for each set of input parameters.

Step 8: Repeat Steps 6 through 7 for the specified number of simulations, as determined in Step 5.

Step 9: Conduct post-processing by extracting the data from the linked component, which, in this study, is the i-sight and Python-FEM Model.

A total of 500 samples were specifically generated to train, test and validate the proposed ANN model. These samples were intentionally varied in terms of their matrix and fiber configurations to ensure that the proposed ANN model had a diverse range of input data for learning. This approach serves to enhance the accuracy of the ANN model in predicting outputs.

4. Artificial Neural Network background

The Artificial Neural Networks (ANN) utilization has become increasingly widespread across various fields due to their efficiency in modeling complex relationships based on historical data. ANNs are mimicked the principle of biological neurons. They are primarily composed of input, hidden, and output layers, with connections established through artificial neurons [29]. The neurons transmit weights and biases between layers. Activation functions process inputs to generate an output vector. During training, the ANN aims to minimize an objective function, like Mean Squared Error (MSE), by adjusting weights and biases through back-propagation. The process is repeated over many epochs until the desired accuracy is achieved. The number of epochs corresponds to the iterations during the ANN training process [30].

4.1. Data normalization used for ANN

Before training an artificial neural network, it is important to conduct preprocessing on the raw data. Specifically, data normalization is a critical step in improving the performance of ANNs. Normalization, in the context of ANNs, refers to the process of transforming the acquired data to a consistent scale, ensuring that all variables are standardized. Normalizing the data is particularly advantageous in preventing larger values from dominating data with smaller values. In this work, the acquired data from Section 2.2 was normalized to the interval [0.1, 0.9] using Equation 1 as prescribed by [31]:

$$x_i = \lambda_1 + (\lambda_2 - \lambda_1)\left(\frac{z_i - z_i^{min}}{z_i^{max} - z_i^{min}}\right) \dots (1)$$

The normalized value of a given parameter is denoted by xi, where as λ1and λ2 represent the upper and lower limits of normalized parameters, respectively. The variable zi refers to the original value of the corresponding normalized parameter, and z^{min} and z^{max} indicate the minimum value and maximum value for the data set.

4.2. Data normalization used for ANN

To assess the prediction ability for Artificial Neural Network model, the errors of model prediction must be evaluated. Typically, a portion of the training data is reserved as the testing set, and the performance of the training algorithm is evaluated based on different criteria. In this study, Determination Coefficient (R2) and Mean Square Error (MSE) are employed as standard metrics for ANN prediction performance. As MSE measures the discrepancy degree between the predicted and targeted values, where a lower value of MSE indicates an optimum prediction ability. On the other hand, when the R2 value is near unity, it signifies a well-trained ANN model. The performance parameters are calculated using the following equations [32]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(x_{act,i} - x_{pred,i}\right)^2 \dots (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(x_{act,i} - x_{pred,i}\right)^2}{\sum_{i=1}^{n}\left(x_{act,i} - x_{avg}\right)^2} \dots (3)$$

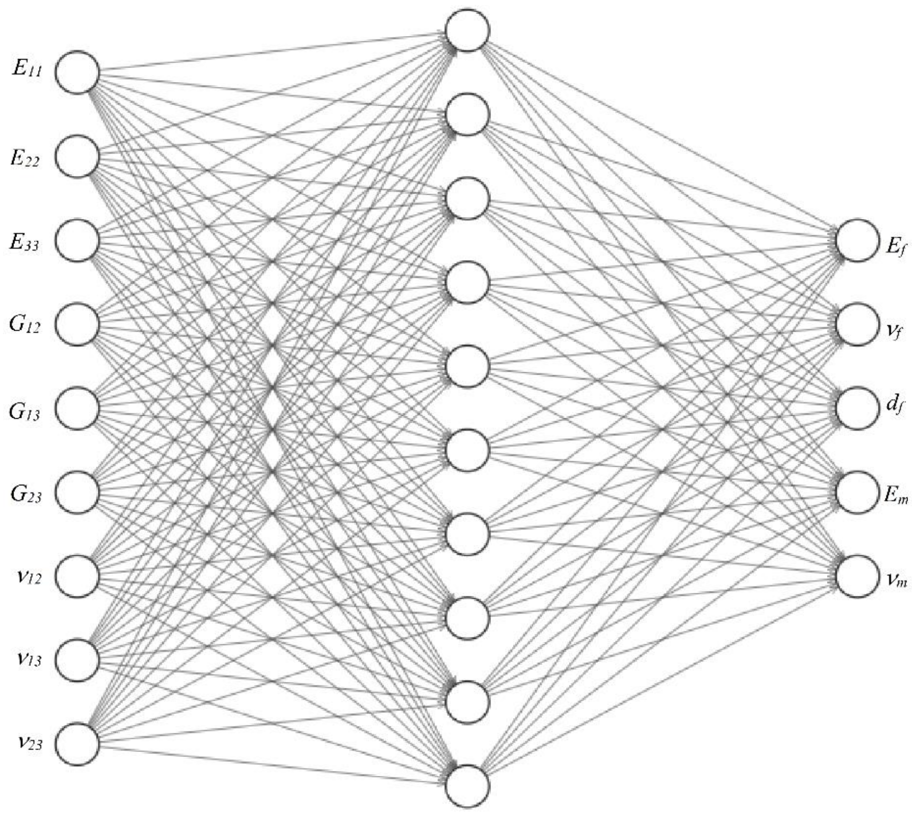
The n in above expression denotes total number of sampled data, xact represents the actual data point, xpred is the output value the established network, and xavg represents mean value of the xact.

4.3. Creating ANN Reverse Model

This study was selected the Feedforward Backpropagation Network (FFBN) due to its strong performance in solving a complex task [33]. Neurons in the input and output layers were configured to be the equal to the input and output parameters. It should be noted that the number of neurons and hidden layers were determined through trial-and-error experimentation. The optimal configuration of reverse ANN model was found to be using a single hidden layer consisted of 10 neurons and activated by (tansig) transfer function, while the output layer was activated by transfer function (purelin).

Three phases are typically conducted during the training process, namely Training, Validation, and Testing. The proposed ANN model was trained using the Levenberg-Marquardt (LM) training algorithm. The three groups were randomly divided into 70%, 15%, and 15% for training, testing, and validation, respectively. The ANN toolbox in the Matlab environment was utilized to construct the proposed ANN.

In the reverse design scenario, the input for the developed ANN consisted of the homogenized mechanical properties of GFRP. The model's output predictions included the mechanical characteristics for the constituents (matrices and fibers) in addition to the fibers diameter. Table 2 defines the input for the ANN reverse model and the corresponding output. Figure 4(a) is the representation of the developed ANN, while Figure 4(b) illustrates the number of inputs on the left side and the number of outputs on the right side of the proposed ANN.



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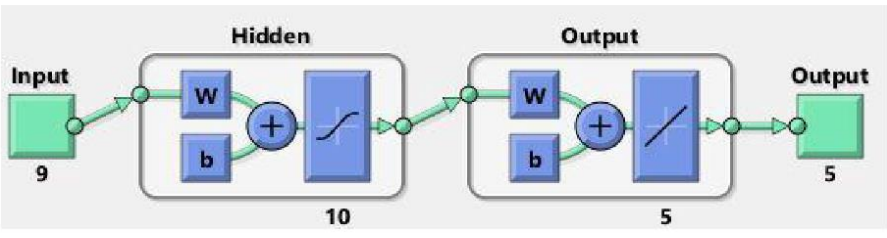

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Figure 4. Schematic of reverse ANN model

Table 2. Inputs and output for reverse ANN model

	Parameters	Definition
Input for reverse ANN	E_{11} (MPa)	Modulus of elasticity in longitudinal direction
	E_{22} (MPa)	Moduli of elasticity in transverse direction-2
	E_{33} (MPa)	Moduli of elasticity in transverse direction-3
	G_{12} (MPa)	Shear moduli in planes 1-2
	G_{13} (MPa)	Shear moduli in planes 1-3
	G_{23} (MPa)	Shear modulus in plane 2-3
	ν_{12}	1-2 plane Poisson ratios
	ν_{13}	1-3 plane Poisson ratios
	ν_{23}	Poisson ratio in the 2-3 plane
Output of reverse ANN	E_f (MPa)	Modulus elasticity of Fiber
	ν_f	Fiber Poisson ratio
	d_f (μm)	Diameter of Fiber
	E_m (MPa)	Elasticity modulus for Matrix
	ν_m	Poisson ratio of Matrix

Figure 5 depicts the flow chart of the main steps and software involved in creating the neural network for the reverse design model. The proposed approach can significantly reduce the design time of FRP composite materials.

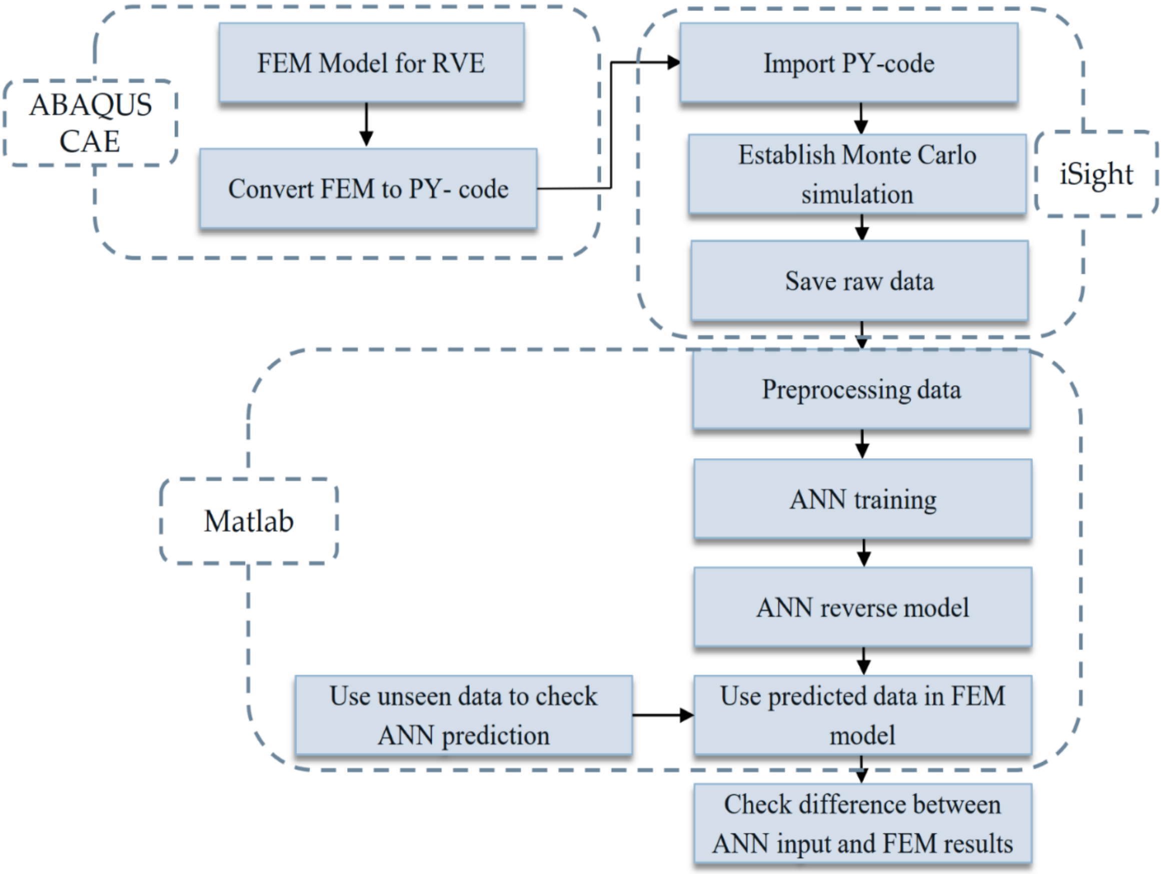

Figure 5. Flow chart of ANN reverse design model

5. Results of investigations

5.1. FEM model validation

The present study utilized the Finite Element Method to obtain the homogenized properties of the composite material. The responses of the Representative Volume Element (RVE) under the applied loads, as described in Section 3.2, are depicted in Figure 6. Figures 6a-f illustrate the deduced stresses and the deformed shape of the RVE under longitudinal, transverse, and shear loads, respectively. Additionally, to validate the employed FEM homogenization technique, the homogenized properties were compared with results from the literature [34]. The FEM model utilized the microstructure parameters of the composite material E-Glass/MY750. The detailed mechanical properties of the fibers and matrix are provided below:

Table 3. Mechanical properties for E-Glass/MY750 [34]

Matrix (MY750)		Fiber (E-Glass)		
E_m (MPa)	ν_m	E_f (MPa)	ν_f	d_f (μm)
3350	0.35	74000	0.2	0.7

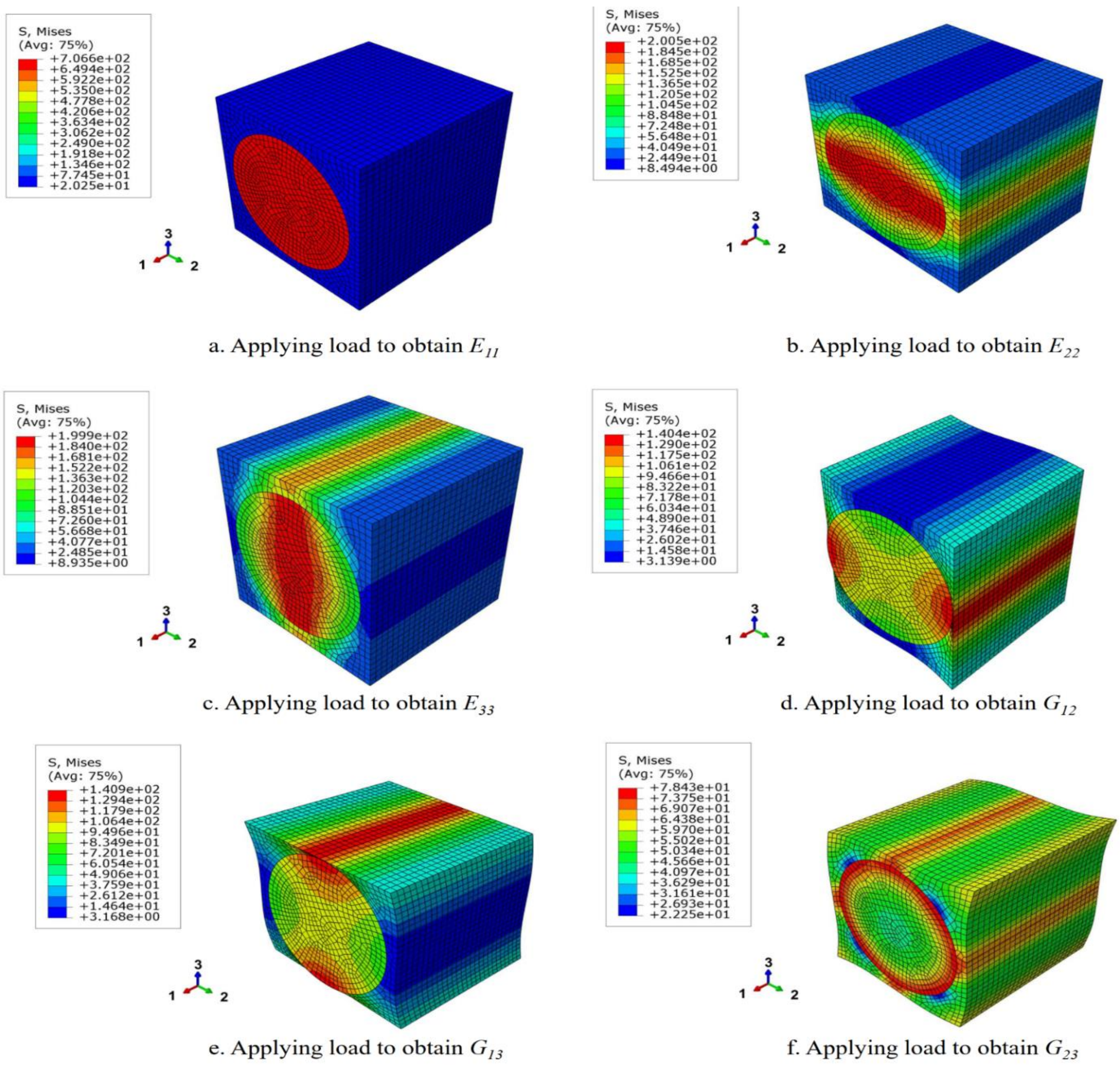

Figure 6. Stress distribution of the unit cell (RVE)

The corresponding homogenized results and the comparison are presented in Table 4. The current FEM outcomes align with the literature results, where a maximum deviation of 8%. Considering this, it can be concluded that the proposed model is reliable in homogenizing the properties of the considered FRP composite.

Table 4. Comparison between current model and literature [34]

Elastic property	Homogenized result		Difference %
	Proposed FEM model	Literature model [34]	
E_{11} (MPa)	45810.01	42110	8.08
E_{22} (MPa)	14951.52	14860	0.61
E_{33} (MPa)	14949.17	14870	0.53
G_{12} (MPa)	4583.322	4520	1.38
G_{13} (MPa)	4583.562	4520	1.39
G_{23} (MPa)	3256.467	3210	1.43
ν_{12}	0.25	0.24	4.0
ν_{13}	0.25	0.24	4.0
ν_{23}	0.26	0.25	3.85

5.2 ANN reverse model results

In this study, the back propagation neural network with feed forward layup was constructed using ANN toolbox in Matlab, as described in Section 4.3 ANN models were developed, modeled, and trained based on the RVE's generated dataset. The number of hidden layer neurons is a critical structural parameter associated with ANN performance [28]. Hence, the range of 3 to 10 neurons was considered for the number of neurons, and the search for the optimal ANN architecture in this study involved evaluating the Mean Square Error (MSE).

The impact of the hidden layer neurons on the predictive performance of the ANN is depicted in Figure 7a. The results indicated that when the number of neurons in ANN is three, the MSE value was higher at 0.01633. However, as neurons increases, MSE was rapidly decreased. It was observed that the MSE has tending to stabilize within the range of 6 to 10 neurons. Therefore, 10 neurons were adopted as final neurons in the hidden layer for the developed ANN structure, which provides a minimum MSE with a value of 0.000333.

The objective of the proposed neural network is to achieve a trained model capable of correlating the inputs with their corresponding outputs. To provide insights into the performance of the final ANN utilized for reverse composite design prediction, the performance parameters are illustrated graphically in Figure 7b. As shown, the MSE history started with a large value and rapidly decreased with further training iterations (epochs). The best MSE was reached after 643 epochs.

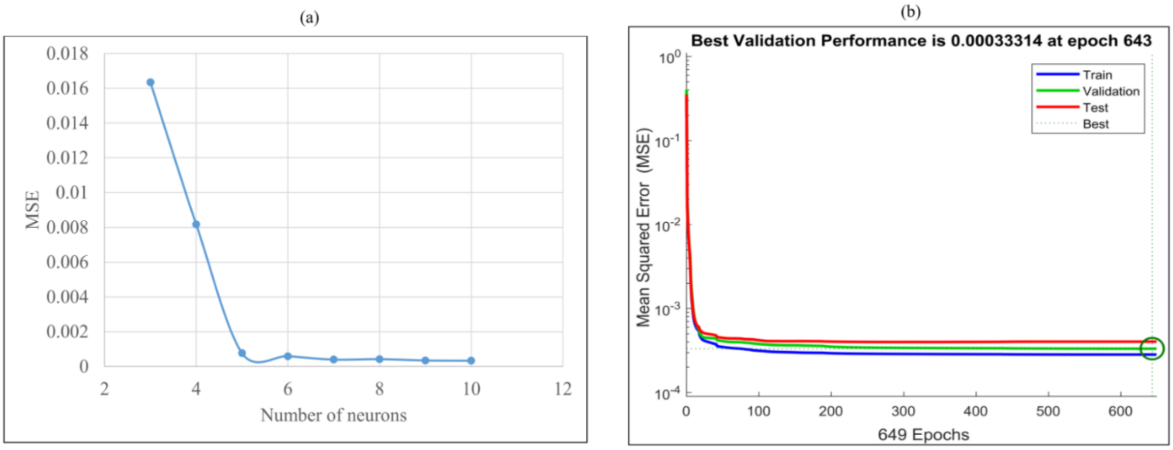

Figure 7. Effect of number of neurons on MSE error

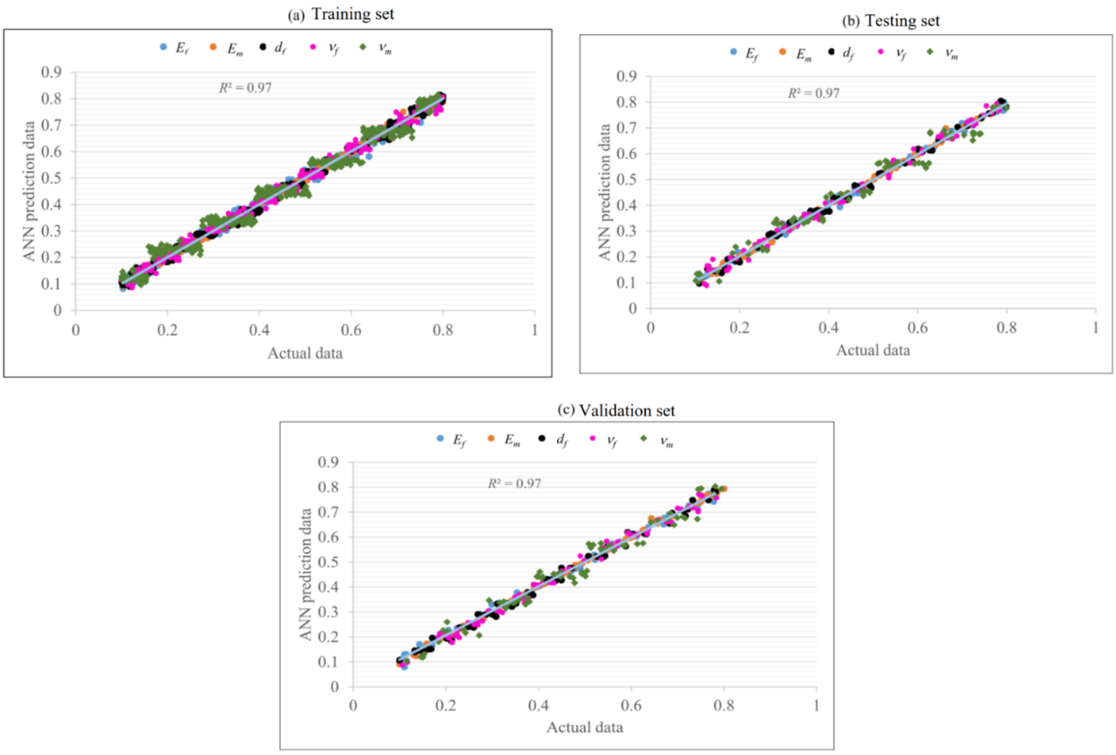

Figure 8 Neural network performance determination coefficient

From the other hand, Coefficient of Determination (R^2) for the three data groups (i.e., training group, testing group, and validation group) is showed a good correlation between the of normalized actual and ANN predicted data with a values closer to one as it shown in Figure 8(a) to 8(c). This in turn gives an indication that the proposed ANN provides good accuracy.

Figures 9(a) to 9(e) compared the values of E_f, d_f, v_f , E_m and v_m which used originally as an input parameters for the numerical model and organized as target values in the reverse ANN model with those predicted by the model ANN. For clarity, only the results of 20 data points (each representing a particular composite material design) are shown. The comparison showed that the reverse ANN model output agrees very well with the original values.

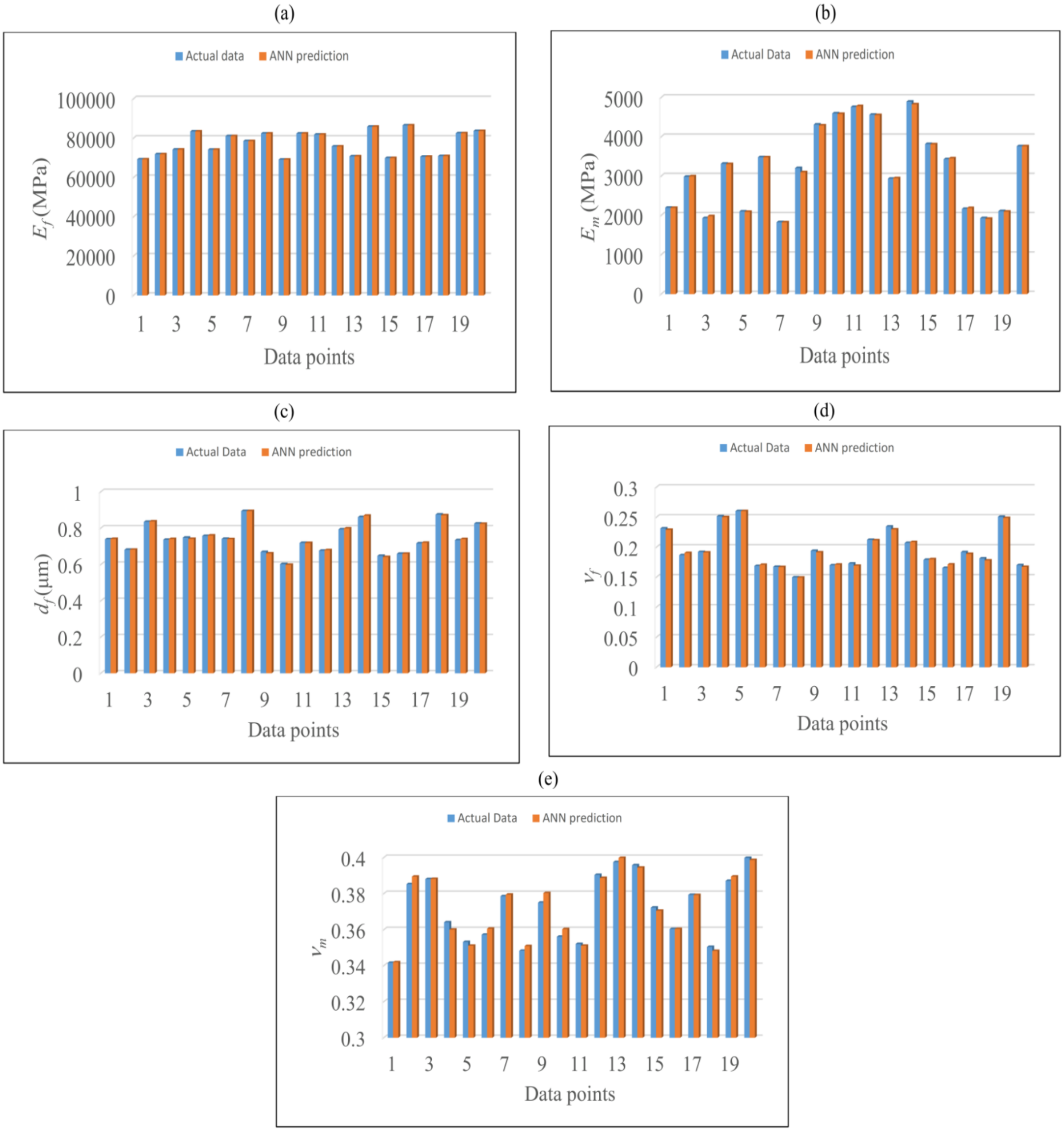

Figure 9. ANN prediction for the composite constituent's properties

Finally, to assess the accuracy of the developed ANN, unseen homogenized parameters are used as input. Consequently, the ANN predicts micro-parameters representing the fiber and matrix properties, which are then incorporated into the FEM model to evaluate the final properties of the unidirectional composite lamina at the macroscale level. The resulting elastic properties obtained from the FEM approach are presented in Table 4 (third column). A comparison is made between these properties and the originally pre-assigned values. The results demonstrate a good agreement between the effective elastic properties and the FEM results, with a maximum difference of approximately 8.5%. This indicates the reliability of the reverse neural network model, showcasing strong predictive capabilities and high accuracy. Consequently, it inspires confidence in utilizing the model for further analysis in composite material optimization.

Table 4. Numerical solution depending on ANN prediction

Required homogenized properties (ANN-input)		Reverse ANN prediction (Micro-structure parameter)		Homogenized mechanical properties (FEM result)		Difference required and FEM results (%)
E_{11} (MPa)	45000	E_f (MPa)	84418.97	E_{11} (MPa)	43489.13	3.4
E_{22} (MPa)	9000	E_m (MPa)	2365.00	E_{22} (MPa)	8511.78	5.7
E_{33} (MPa)	9000	d_f (μm)	0.799	E_{33} (MPa)	8507.76	5.7
G_{12} (MPa)	2600	ν_f (-)	0.171	G_{12} (MPa)	2504.45	3.8
G_{13} (MPa)	2600	ν_m (-)	0.364	G_{13} (MPa)	2503.23	3.8
G_{23} (MPa)	1900			G_{23} (MPa)	1848.4	2.7
ν_{12} (-)	0.25			ν_{12} (-)	0.26	3.8
ν_{13} (-)	0.25			ν_{13} (-)	0.26	3.8
ν_{23} (-)	0.32			ν_{23} (-)	0.35	8.5

6. Conclusions

This study presents an efficient approach for estimating the mechanical properties of constituent materials, specifically the elastic properties of fibers and matrices in Unidirectional Glass Fiber Reinforced Plastic (UGFRP) composite materials. The methodology involves integrating Finite Element Modeling (FEM) of Representative Volume Element (RVE) with the Monte Carlo Algorithm to obtain data. Subsequently, an Artificial Neural Network (ANN) model is developed using this data.

While substantial efforts have been made to estimate the 'homogenized' material parameters of FRP composites, the utilization of ANN models for estimating constituent-level parameters remains rare in the current literature. This study addressed this gap by establishing an ANN model for reverse predicting purpose.

The process initiated with the establishment of an FEM model for the material RVE to obtain homogenized mechanical properties. The FEM model validation confirms the reliability of the employed homogenization technique, as the homogenized properties obtained align well with results from the literature [34], with a maximum deviation of 8%. Subsequently, the validated FEM model is employed with the Monte Carlo Algorithm to generate the necessary dataset for creating a reverse ANN model. This dataset includes various designs of UGFRP, involving different types of matrices and compatible glass fibers.

The trained ANN model, utilizing one hidden layer, the Levenberg-Marquardt (LM) training algorithm, transfer function (tansig), and ten neurons in the hidden layer, exhibits strong predictive performance, as evidenced by high R2 and low MSE. Results indicated that the constructed ANN model effectively predicts reverse elastic material parameters at the constituent level (i.e., Em, Ef, νm, νf, and df) for the investigated materials. The obtained constituents' properties were then modeled into the FEM model to evaluate the final properties of the composite lamina. The resulting elastic properties obtained from the FEM approach align well with the originally pre-assigned values, with a maximum difference of approximately 8.5%.

For designers faced with the challenge of identifying suitable constituent materials during the preliminary design phase, this study provides an advanced and efficient approach. Utilizing the proposed intelligent model, designers can seamlessly select the desired homogenized properties of the composite material (reverse inputs) and accurately predict the mechanical properties of the constituents (reverse output).

The emphasized significance of this research lies in providing designers with a streamlined, convenient, and readily applicable tool for practical composite material designs. This approach offers the advantage of lower computational costs while maintaining a reasonable level of accuracy. Thus, designers can save valuable time and resources by employing this simplified and expedient method in their composite material selection and design processes. Finally, the developed ANN model introduced a strong predictive capabilities and high accuracy, inspiring confidence in its utilization for further analysis and optimization of composite materials.

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