Composites Part C: Open Access 13 (2024) 100440

Contents lists available at ScienceDirect

Composites Part C: Open Access

journal homepage: www.sciencedirect.com/journal/composites-part-c-open-access

Crashworthiness optimization of composite hexagonal ring system using random forest classification and artificial neural network

Monzure-Khoda Kazi [a], E. Mahdi [b,*]

[a] Karen M. Swindler Department of Chemical and Biological Engineering, South Dakota School of Mines and Technology, 501 E. Saint Joseph St., Suite CBEC 3307

[b] Qatar University, Department of Chemical Engineering, College of Engineering, Doha, Qatar, PO. Box-2713

A R T I C L E I N F O

Keywords:
Crashworthiness
Hexagonal ring system
Composite design
Random forest classification
Artificial neural network

A B S T R A C T

This research aims to enhance the safety level and crash resiliency of targeted woven roving glass/epoxy composite material for various industry 4.0 applications. Advanced machine learning algorithms are used in this study to figure out the complicated relationship between the crashworthiness parameters of the hexagonal composite ring specimens under lateral compressive, energy absorption, and failure modes. These algorithms include random forest (RF) classification and artificial neural networks (ANN). The ultimate target is to develop a robust multi-modal machine learning method to predict the optimum geometry (i.e., hexagonal ring angle) and suitable in-plane crushing arrangements of the hexagonal ring system for targeted crashworthiness parameters. The results demonstrate that the suggested RF-ANN-based technique can predict the optimal composite design with high accuracy (precision, recall, and f1-score for test and train dataset were 1). Furthermore, the confusion matrix validates the random forest classification model's accuracy. At the same time, the mean square error value serves as the loss function for the ANN model (i.e., the loss function values were 2.84×10^{-7} and 6.40×10^{-7}, respectively, for X1 and X2 loading conditions at 45° angle). Furthermore, the developed models can predict crashworthiness parameters for any hexagonal ring angle within the range of the trained dataset, requiring no additional experimental effort.

1. Introduction

A composite material is created by combining two or more physically distinct parts, each preserving a significant portion of its original structure and identity. This advantage certainly encompasses natural materials (e.g., wood, bone, and teeth) and synthetic (e.g., plastic, reinforced concrete, fiberglass, paper). When they are combined, they make a specialized material for a specified purpose, such as increasing strength, weight, or resistance to electricity. Additionally, the composition and shape of composite materials can improve their crashworthiness [1]. Glass, carbon, and ceramic fibers are essential reinforcements for applications in mechanical engineering [2]. Glass fibers are used to reinforce polymers in various industries, including aerospace, automotive, marine, athletic, and recreational goods as construction and civil engineering. One of the primary benefits of employing glass fibers for polymer reinforcement is their excellent performance-to-cost ratio. The architectural membrane consisting of poly(tetrafluoroethylene) (PTFE)-coated glass fiber for stadium and airport ceilings is an example of how glass fibers may be used as membranes [3]. Furthermore, it is well-known that composites frequently exhibit superior resistance to environmental attacks. Therefore, glass-fiber composites are widely used in the chemical industry and marine applications [4]. Glass is by far the most commonly used fiber, owing to its low cost, corrosion resistance, and, in many cases, efficient manufacturing potential. In addition, it has low stiffness, high elongation, moderate strength, and weight, and a relatively low cost compared to other composites [4].

The advantages of fiber composites over more conventional materials such as metals are frequently attributed to their high stiffness and strength-to-weight ratios [5,6]. These characteristics make fiber-reinforced composites an attractive material for aerospace and sporting goods applications [6]. Crushing energy absorption studies are critical and expected from passenger vehicle safety design. The amount of energy absorbed by a vehicle during a collision is a concern to ensure that cars are safer and more reliable. Therefore, it is necessary to understand tubular structures' crushing behavior and energy-absorbing capacity to minimize occupant injury during a collision. In that effort, the crushing behavior of composite hexagonal ring systems has been

* Corresponding author.
E-mail addresses: Kazi.Khoda@sdsmt.edu (M.-K. Kazi), elsadigms@qu.edu.qa (E. Mahdi).

https://doi.org/10.1016/j.jcomc.2024.100440

Available online 3 February 2024

validated experimentally by several research groups. The effects of mandrel geometry on the crashworthiness and energy absorption capability of woven roving glass/epoxy hexagonal ring systems have been observed [7]. In addition, the cross-sectional geometry and loading circumstances were found to substantially affect the energy absorption capacity [7,8]. However, research on the crushing behavior of in-plane crushed composite hexagonal tubular structures is sparse and poorly understood [9].

Researchers employ particular mechanical criteria (such as load-carrying capacity and energy absorption capabilities) to determine a material's crashworthiness. The subject samples to a quasi-static axial crushing stress test in various studies and material testing. In addition, multiple random tests are conducted under varying stresses on the modular unit to ensure that the modular unit has the appropriate mechanical qualities for the purpose at hand. These investigations can be found in the composite materials literature [7,10]. However, because there isn't enough information about the mechanical parameters, it can be very time-consuming to find the best composite structure and geometry through experiments alone [1,11,12].

In comparison, machine learning algorithms can quickly and efficiently do this job if they have the correct data from experiments to build an accurate and reliable predictive model, leading to a possible configuration of alternative composite materials [1,12-14]. Designers employing experimental and artificial neural networks are called "computer-aided smart manufacturers." They can use this to help design experiments in the future.

Compiling natural fiber composites using computers can be easier using predictive data-driven models. It has long been accepted that nonlinear systems may be described using artificial neural networks (ANNs) [15–17]. While fuzzy systems and evolutionary algorithms can be used for system recognition when the industrial system model is complex but requires a less powerful computer method, ANNs outperform them [15]. For example, ANNs may be used to construct complex associations between nonlinear variables using machine learning adaptive algorithms [18,19]. The neural network recognition model (identifier) understands the unclear process [17]. Data-driven modeling eliminates the need for physical models by learning from examples (i.e., the data set). Because of this feature, ANN machines are particularly appealing in engineering applications when the underlying interrelations are not clearly understood or complete. Still, experimental measurements are readily available [10,20-34]. The use of ANN models for predicting the fiber structure of Glass reinforced composite is still in its early stages. The developed models thus far were used to predict certain features of composite materials, but not the overall structure of composite materials. Recently, Kazi and co-workers demonstrated that the ANN model could predict the optimal filling amount of cotton fiber while meeting the desired mechanical objectives [13]; and this type of technique may be used for varying materials and conditions as long as necessary experimental data are supplied. In material science, datasets might be modest or significant; and the dataset size can substantially impact the performance of ML models [35]. A model may be overfitted because of a scarcity of data, resulting in poor prediction accuracy or generalization [35,36]. Small datasets can have a detrimental influence on research; therefore, effective measures must be devised to address this challenge. For example, it is possible to get around dataset size limitations by employing ensemble approaches, which combine the strengths of numerous learners. Many ensemble algorithms have recently been demonstrated to be effective using on tree-based ensembles such as Random Forest, Gradient Boosting, eXtreme gradient boosting, etc. [24,35,37,38]. Random forest classifier is a subset of ensemble-based learning algorithms. They are easy to deploy, operate quickly, and have demonstrated exceptional performance in a range of fields [39]. The guiding idea in the random forest approach is to generate a large number of "simple" decision trees during the training stage and then classify them using the majority vote (mode). Among other benefits, this voting technique compensates for decision trees' bad tendency to overfit training data [40].

This work aims to demonstrate machine learning algorithms such as RF and ANN to develop an intelligent system to optimize the composite materials system. The ultimate target is to develop robust multi-model machine learning algorithms to predict the optimum geometry and loading conditions of woven roving glass/epoxy hexagonal ring system for targeted crashworthiness parameters.

2. Experimental study: crashworthiness of composite hexagonal ring system

2.1. The material investigated and crushing test

Mahdi et al. (2012) previously manufactured and evaluated a woven roving glass/epoxy hexagonal ring structure [7]. The woven roving glass fiber is a reinforcing fiber, while the epoxy resin system acts as a thermoset matrix. Six layers of woven roving fiberglass were used to construct 18 prototypes. The woven roving glass/epoxy specimens of woven roving wound laminate (WRWL) hexagonal composite shells were constructed using the wet cloth winding procedure. The specifics of the fabrication process are available in the previous publication [7]. Researchers wanted to see whether a collapsible energy absorber might be used in automotive construction. It is supported at the distal end (i.e., attachment point) by a more robust structure and functions more like the quasi-static regular progressive mode. As a result, the quasi-static axial and lateral crushing tests on the produced specimens were conducted to determine the behavior of hexagonal composite tubes at various angles and configurations, utilizing an MTS servo-hydraulic testing equipment capable of sustaining a maximum force of 100 kN. Parallel arrays of composite thin-walled hexagonal rings were squeezed between parallel flat plates at a 2.5 mm/min crosshead speed. Two packing arrangements for hexagonal rings are used: side-based packing (X1) and angle-based packing (X2). The arrangement is intended to act as an energy absorber. Fig. 1(a) illustrates the hexagonal ring system's initial collapse behavior under various in-plane compression stress conditions (X1 and X2). The load and displacements were recorded using an automated data gathering system. The use of three similar

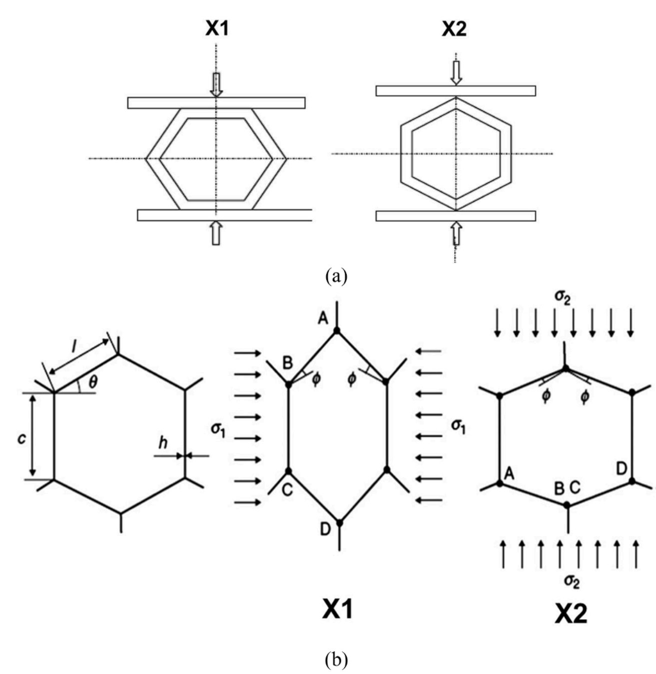


Fig. 1. (a) In-plane crushing of composite hexagonal ring systems; and (b) composite hexagonal ring failure due to cell wall collapse caused by localized elastic hinges.

specimens assured the reproducibility of the results. Two loading conditions were applied to test the rectangular tubes with five different hexagonal angles θ (see in Fig. 1(b)) ranging from 45° to 65° (e.g., 45°, 50°, 55°, 60°, 65°).

2.2. Experimental observation

For loading in the X1-direction, the top and bottom sides of the hexagonal ring (i.e., beams) are in complete contact with the top and bottom plates, respectively. On the other hand, the hexagonal inclined ring's walls (i.e., columns) do not directly contact the top and bottom plates. Therefore, the oblique ring walls significantly contribute to energy absorption capability than the top and bottom sides. One can notice that during the initial and post-crushing stage, the oblique wall experienced small shear deformation during the midpoint of the upper and lower move inward. Fracture lines are observed during the materials densification stage at the junction between the oblique sides and the top and bottom sides, as shown in Fig. 2. However, the load-carrying behavior curves of the hexagonal ring loaded in the X1-direction show an almost smooth gradual drop in their load-carrying capacity. All the rings experienced flattening deformation in the initial crushing stage, followed by hinges formed at the bottom, and top beams tend to lower the ring's load-carrying capacity. It can also be observed that crushing behavior is sensitive to the changes in the hexagonal interior angle.

For loading in the X2-direction, three main energy absorption mechanisms are observed during the crushing process of the hexagonal rings. These are brittle shear fracture, plastic deformation, and Euler buckling. During the initial crushing process, the oblique sides bend with small deflections. This stage is followed by one of two failure scenarios. These are Euler buckling and plastic collapses. The occurrence of these scenarios is based on the ratio of a thickness (h)/side, length (l)), which resulted from the changing of interior hexagonal angles. Accordingly, hexagonal ring oblique walls with small values of h/l experienced Euler buckling before brittle fracture.

On the other hand, hexagonal ring oblique walls with considerable h/l value experienced large deformation before brittle fracture. The brittle fracture occurs since glass fiber is a material with limited failure strain. Therefore, all the rings experienced brittle fracturing during the post-crushing stage, as shown in Fig. 2. The crushing load versus deformation is characterized by high fluctuations relative to the mean crushing load.

2.3. Experimental data

Experiments were conducted to determine the load-displacement curves and deformation history of composite hexagonal ring structures under uniaxial compression directions. Depending on the hexagonal angle, the hexagonally packed systems reacted differently to the crushing load. Therefore, the crashworthiness parameters shown in Table 1 were calculated based on the load-displacement curves, deformation history, and energy absorption capability and listed for a one-dimensional composite hexagonal array system. The detailed results and figures are available in a previous publication [7].

3. Problem statement

The experimental dataset for the crashworthiness characteristics of an in-plane crushed composite woven roving glass/epoxy hexagonal system with varying angles and arrangement is provided (see Table 1). The ring's behavior in terms of initial crushing load, post crushing load, energy absorbed, and crushing mode is understood. The experimental results indicated that ring shape and loading circumstances significantly affected the crush failure loads and energy adsorption capabilities. Without conducting more experiments, it is desired to construct a machine learning-based model to forecast the optimal loading condition and angle of the hexagonal sample for achieving various random targeted crashworthiness goals with minimal error. Later on, this model should be able to anticipate the crashworthiness characteristics for any given angle and loading situation, allowing users to construct their desired composite material using a computer-aided solution.

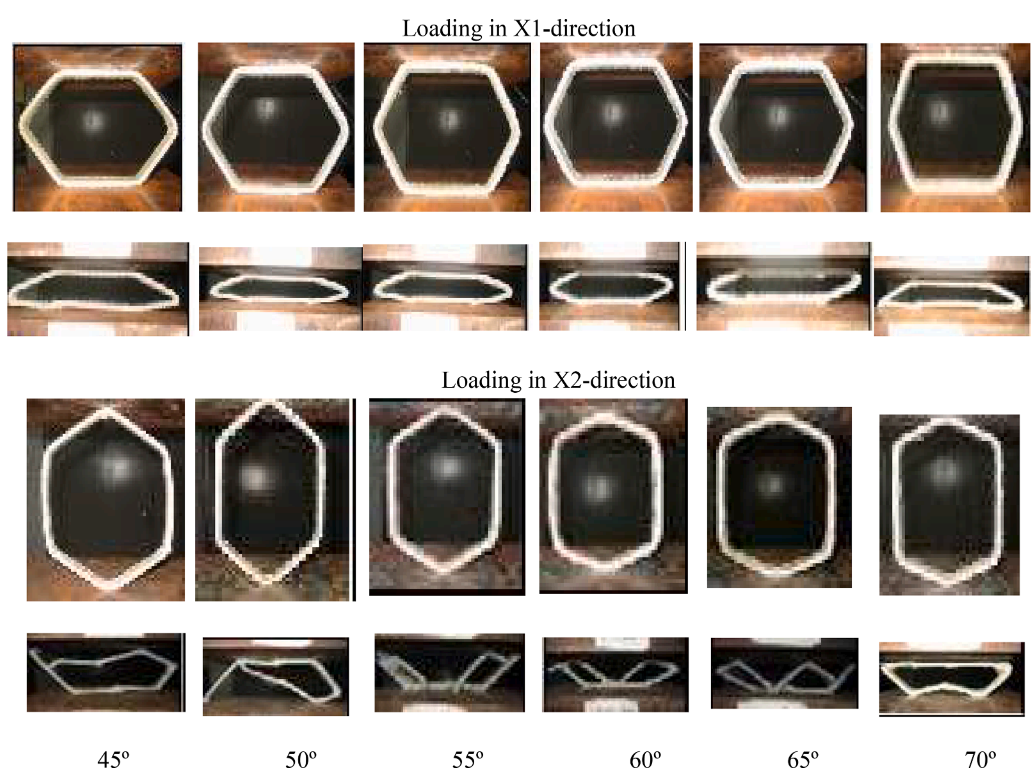


Fig. 2. Undeformed and deformed composite hexagonal ring systems.

Table 1
Crashworthiness parameters of in-plane crushed.

ID	Angle of hexagon (degree)	Loading condition	Initial crushing load (kN)	Average crush load (kN)	Maximum crush load (kN)	Crush force efficiency (kN/kN)	Initial failure indicator (kN/kN)	Specific energy absorption (kJ/kg m2)
45SX1	45	X1	0.45	0.29	0.64	0.45	1	2.11
50SX1	50	X1	0.5	0.41	0.82	0.51	0.98	2.72
55SX1	55	X1	0.52	0.49	0.94	0.44	1.18	3.13
60SX1	60	X1	0.57	0.35	0.62	0.58	0.98	3.48
65SX1	65	X1	0.65	0.39	0.59	0.67	0.97	3.57
45SX2	45	X2	0.14	0.769	0.18	0.39	0.36	2.81
50SX2	50	X2	0.16	0.895	0.18	0.45	0.36	3.24
55SX2	55	X2	0.17	1.18	0.14	0.64	0.27	4.56
60SX2	60	X2	0.15	1.255	0.12	0.89	0.17	4.79
65SX2	65	X2	0.17	1.306	0.13	1.2	0.14	5.45

4. Research methodology - ANN RF optimization

4.1. Machine learning approach

4.1.1. Why machine learning?

Product designers create materials for end-users to ensure that the materials meet specified crashworthiness requirements. The values for these crashworthiness characteristics vary according to the customer's needs and objectives. For example, in Table 1, it is evident that an increase in angle resulted in a significant rise in load-carrying capacity and crush force efficiency. In contrast, the initial failure indicator and maximum crush load showed the opposite. Also, the values of each crashworthiness parameter (e.g., crushing load, crush force efficiency, specific energy absorption, etc.) fluctuated considerably according to the loading conditions and hexagonal angle. The absence of correlations relating to key properties such as the hexagonal angle and loading condition of the composite material requires the repetition of laborious and time-consuming trials in search of the appropriate mechanical properties.

Supervised learning is a widely used machine learning technique taught using a known dataset containing inputs and outputs. The algorithm must determine how to get to those inputs and outputs by identifying patterns in the data, learning from observations, and making accurate observations predictions. This process is repeated until the algorithm reaches the desired level of accuracy/performance. Popular supervised machine learning algorithms include the Nave Bayes Classifier Algorithm, Logistic Regression, K-Nearest-Neighbour algorithm, Decision Trees, Random Forests, and Artificial Neural Networks, all popular supervised machine learning algorithms. Choosing the optimal machine learning algorithm is contingent on several criteria, including. Still, it is not limited to the volume, quality, and variety of the data and the kind of responses from that data. Additional factors to consider are accuracy, training duration, parameters, and data points. Thus, selecting the optimal method is a function of strategic requirement, specification, experimentation, and available time. Even the most seasoned data scientists cannot predict which algorithm would perform best without first trying with others.

4.1.2. Conceptual design - multi-modal approach

The loading conditions and hexagonal angle of the woven roving glass/epoxy hexagonal composite rings affect their load-bearing and energy absorption capacities. Thus, to attain the desired mechanical crashworthiness features, both the appropriate loading condition (X1 or X2) and the optimal hexagonal angle must be determined concurrently. This work combines a multi-modal approach combining Random Forest (RF) classification and artificial neural network (ANN) based regression methods to accomplish these tasks with minimal cost and effort. This technique overcomes nonlinearity, various loading circumstances, and issues with prediction when the experimental dataset is sparse. It should be emphasized that the choice of RF and ANN is not arbitrary; rather, our prior articles demonstrated that both ANN and RF have superior predictive performance when the experimental dataset is constrained. Because both RF and ANN can generate randomness through diverse combinations of features, they enable the resolution of overfitting difficulties when the dataset is sparse. [1,12-14,24]. The suggested multi-modal classification and regression approach for predicting the best hexagonal composite arrangement is conceptualized in Fig. 3. First, the experimental dataset will be collected following the methodology described in sections 3.1 and 3.2. Later, machine learning-based supervised multi-modal algorithms consisting of random forest classification and ANN regression will be used to achieve the targeted crashworthiness parameters set by the researcher by varying the hexagonal angle and loading condition. The final result will demonstrate the optimum configuration of the composite materials for the desired mechanical crashworthiness parameters.

4.2. Detailed procedures for developing an RF-ANN model

As shown in Fig. 3, the RF classification model will predict the suitable X1 or X2 loading conditions. The ANN regression model will predict the optimum angle of the selected loading condition to fulfill the targeted crashworthiness properties. The strategic steps for this RF-ANN model are outlined in Fig. 4. First, RF classification and ANN regression models need to gather experimental data summarized in Table 1, followed by data processing steps to format data and make those free of anomalies. The next expected step is the feature selection to identify the dependent and independent variables and split the test and training dataset. The whole model will be developed using Scikit-learn, the Python data science library, and TensorFlow's Keras-Dense layer. Finally, validation of the model will be done through the test dataset, where the confusion matrix and mean squared error loss function will determine the relative errors of the multi-modal system.

The first output of the RF-ANN model is based on the Random Forest classification model, which is a supervised learning technique that combines many decision trees to produce a more accurate and consistent forecast. Each internal node in a decision tree represents a 'test' of an attribute (e.g., whether an X1 or X2 loading condition). Each branch reflects the test result. Each leaf node provides a class label (decision taken after computing all attributes). A leaf is a node that has no offspring (see Fig. 5). Random Forest adds more randomization to the model while growing the trees. RF looks for the best feature from a random subset of available features, in this case, the different combinations of the crashworthiness parameters. This technique results in a high degree of variability, typically resulting in a more accurate model. Thus, in a random forest, the method for splitting a node considers just a random subset of the characteristics (in Fig. 5, the solid nodes reflect a different set of characteristics selected). In addition, the RF method makes it easy to determine the relative relevance of each feature in the prediction process. Sklearn in Python is a good tool for determining the significance of a feature by examining how much error is reduced across all trees in the forest by tree nodes that utilize that feature. After training, it automatically calculates this score for each feature and

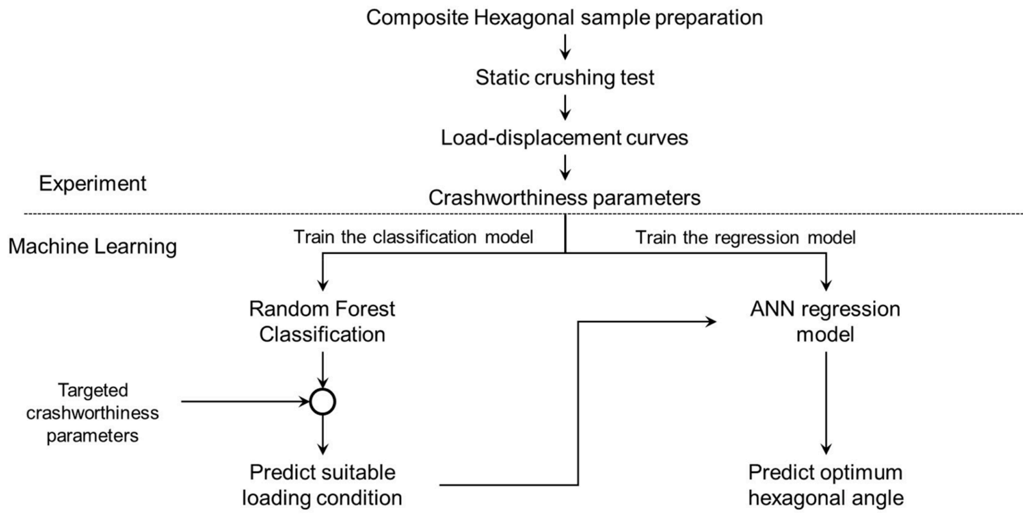


Fig. 3. Conceptual design of multi-modal classification and regression method to predict the optimal hexagonal configuration.

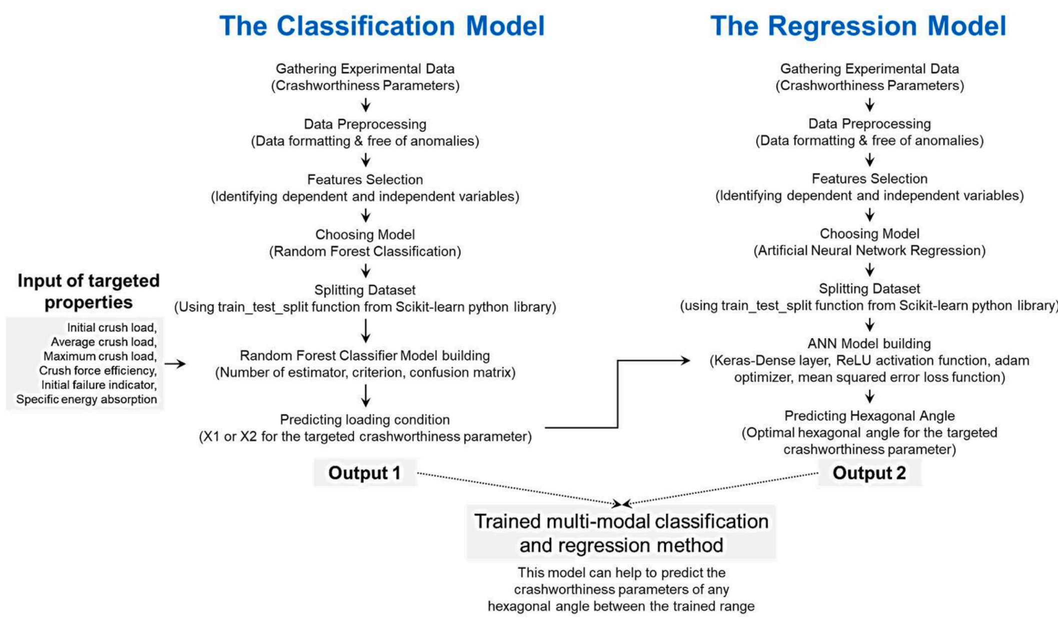


Fig. 4. Strategic steps for RF-ANN model development.

adjusts the findings such that the sum of all features' significance is equal to one. Depending on the final majority voting among the generated trees, the final class of loading conditions will be selected to feed into the ANN model regression.

After accomplishing the RF classification model, the selected loading condition will be given as the input in the ANN regression model. This is another supervised machine learning approach that will utilize appropriate hidden layers to forecast the hexagonal angle of the considered composite under X1 or X2 loading conditions to satisfy the desired crashworthiness parameter (see Fig. 6). In ANN, typically, neurons have a variable learning weight. Each link's weight either increases or decreases the signal's strength. Additionally, neurons may have a signaling threshold that is exceeded when the total signal exceeds the threshold. ANNs are designed to mimic how humans learn. Hence they operate as an adaptive data processing system that may change the architecture of their network or the internal information that flows throughout the training phase. The convergence theorem proves the neural network's ideal construction based on the selection criteria (the mean squared error loss function).

The most challenging part of the model is figuring out how to build the right architecture (i.e., the number of hidden layers, epoch, batch size, etc.). Forward and backpropagation methods will be used to identify the parameter values for the created models (such as node weights and bias). The input nodes will be the intended crashworthiness parameters, while the learning process will defer depending on the output of the preceding RF model. The same ANN architectural design does not validate the same model because the nodes' nonlinear interactions require a distinct mix of weights, bias values, transfer functions, and activation functions.

5. Results and discussion

While developing RF and ANN models, validation and accuracy of those developed models are crucial. In the following sections, the validation procedure along with the prediction accuracies will be reported to showcase the performance of the developed RF-ANN multi-modal system for identifying the suitable configuration of the examined woven roving glass/epoxy hexagonal composite material.

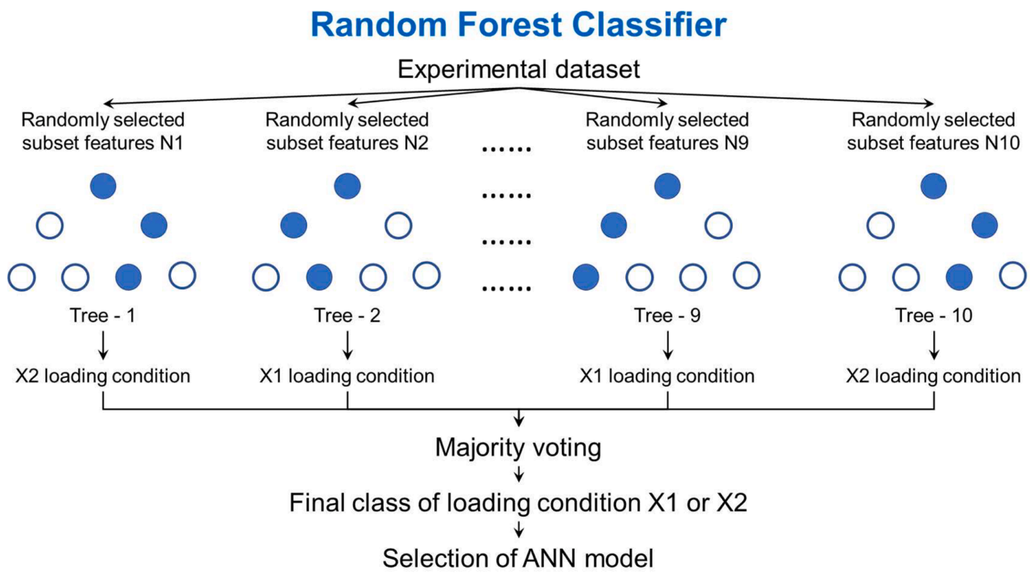


Fig. 5. RF model construction with trees for predicting the class of loading condition.

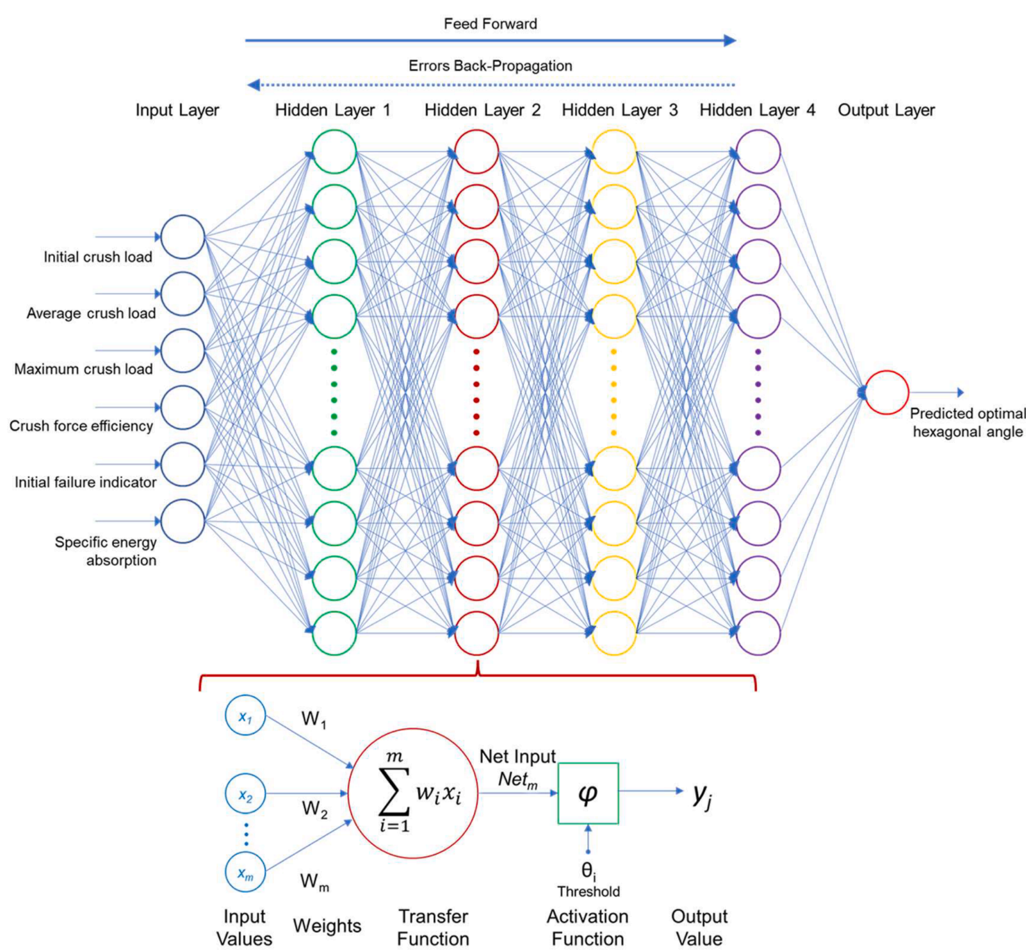


Fig. 6. The layered structure of the predictive ANN model to forecast the hexagonal angle (both for X1 and X2 loading conditions).

5.1. Model development and validation

The RF-ANN multi-modal algorithms were implemented in Scikit-Learn, Numpy, Pandas, and Keras, which used Tensorflow as the back-end. All scripts were written on a machine with an Intel® Xeon ® E-2176 M CPU (2.70 GHx) with 64 GB RAM.

The random forest was constructed using the RandomForestClassifier included in the Scikit-learn (sklearn) machine learning toolkit provided by Phyton. Additionally, the RandomForestClassifier's n_estimators option assisted in determining the number of trees to build, which was set to 100. While increasing the number of trees in the random forest improves accuracy, it also lengthens the average training time of the model. The bootstrap option was set to "True," indicating that only a few features will introduce variance into random forest subsets, avoiding overfitting. Entropy was chosen as the criterion for determining the optimal feature split.

Using True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP) values, the confusion matrix was utilized to provide the summary of the prediction result and performance measure for the RF classification (see Fig. 7). TP signifies the X1 loading condition, whereas TN denotes the X2 loading condition. The performance of the prediction system was assessed in terms of accuracy, precision, and recall. The developed RF classification model accurately predicted loading conditions for training and testing datasets. As illustrated in Fig. 7, the developed RF model can accurately predict all loading conditions. The findings indicate that the f1-score, calculated by combining the accuracy and recall of a classifier into a single measure by taking their harmonic mean, is equal to one, the maximum value that can be achieved.

The development of the RF classification model recognized the following important factors: (1) there is a limited experimental dataset, (2) the model prediction showed higher accuracy in the confusion matrix, and thus it is important to ensure that the RF classification model is not overfitted, and (3) it is important to check if the outcome is aligned with the experimental values. To address these main points in the developed RF model, five random sets of targeted crashworthiness parameters were fed into the model and the experimental points to see whether they could accurately predict the loading condition. The random points were chosen to get an intuitive idea of the suitable loading condition, and they were generated from Table 1 using the following approach.

- One set of crashworthiness parameters was derived by taking the minimum values of each parameter.
- The second set was the maximum values.
- The third was the average values.
- The fourth set was randomly generated between the minimum and average values.
- The last set of data was generated between average and maximum values.

In Table 3, the five considered points are listed and fed into the RF and ANN models to check and validate the performance (i.e., the predicted angles align with the experimental angles). The results of the ANN model show that the predicted angles are very much aligned with the experimental angles (see Table 2).

Table 2
Testing the accuracy of the developed ANN model.

Loading condition X1 Experimental angles	Predicted angles	Loading condition X2 Experimental angles	Predicted angles
45	45.000885	45	45.164
50	50.000515	50	50.177
55	55.00057	55	55.276
60	60.00908	60	60.289
65	65.00047	65	65.326

TensorFlow's Keras-Dense layer was used to build the ANN regression model. In developing the neural network, it is challenging to find the proper mix of hidden layers and their neurons with the least error and the most accuracy. To ensure the optimal ANN model structure for the presented case here: six input neurons were used to make up the input layer, followed by four hidden layers, one output layer, and 200 neurons in each hidden layer. Scikit-python Learn's data science library's 'train_test_split' function divided data arrays into training data (80%) and testing data (20%). A rectified linear activation unit (ReLU) function was used for layer development. While compiling the model, the 'adam' and 'rmsprop' TensorFlow optimizers were tested for updating the weights to reduce errors by backpropagation and 'mean squared error' (MSE), the loss function was used to evaluate the developed ANN model. The dropout method was used to prevent overfitting during training. The ANN model demonstrated higher accuracy than the benchmark experimental data (see Table 2). Test and train scores and loss function values were low for all considered sample experimental points (i.e., the loss function values were 2.84 × 10–7 and 6.40 × 10–7, respectively, for X1 and X2 loading conditions at 45° angle). And the variation of loss-function values became small over 20,000 epochs (see sample loss function curves for both loading conditions at 45° angle Fig. 8).

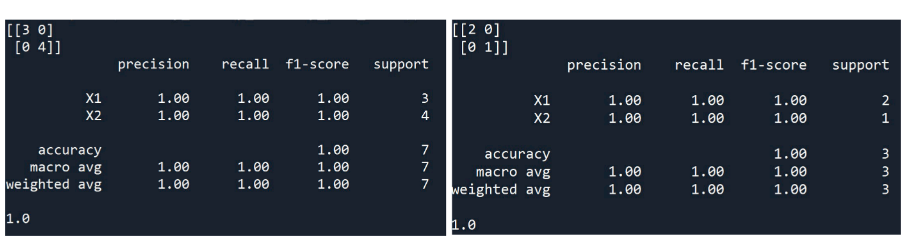
5.2. Prediction of optimal hexagonal composite configuration

The specified multi-modal RF-ANN model is used to predict the optimal configuration of the hexagonal ring system for the woven roving glass/epoxy composite. The five random sets of targeted crashworthiness parameters used as input to the model and the model's predicted loading condition for each are shown in Table 3. It is observed that while targeting minimum values of the considered crashworthiness parameters, the X2 loading condition is suitable. In contrast, the X1 loading condition is suitable for higher target crashworthiness parameters.

Upon selecting the suitable loading condition through RF classification, the ANN regression model was used to predict the optimum hexagonal angles. The identified angles were between 30° and 89° for

Training dataset		Predicted P (X1)	Predicted N (X2)
Actual	P (X1)	(TP) 3	(FP) 0
Actual	N (X2)	(FN) 0	(TN) 4

Test dataset		Predicted P (X1)	Predicted N (X2)
Actual	P (X1)	(TP) 2	(FP) 0
Actual	N (X2)	(FN) 0	(TN) 1



```
[[3 0]
 [0 4]]
              precision    recall  f1-score   support

          X1       1.00      1.00      1.00         3
          X2       1.00      1.00      1.00         4

    accuracy                           1.00         7
   macro avg       1.00      1.00      1.00         7
weighted avg       1.00      1.00      1.00         7

1.0
```

```
[[2 0]
 [0 1]]
              precision    recall  f1-score   support

          X1       1.00      1.00      1.00         2
          X2       1.00      1.00      1.00         1

    accuracy                           1.00         3
   macro avg       1.00      1.00      1.00         3
weighted avg       1.00      1.00      1.00         3

1.0
```

Fig. 7. Performance evaluation through confusion matrix for random forest classification both for training and test dataset.

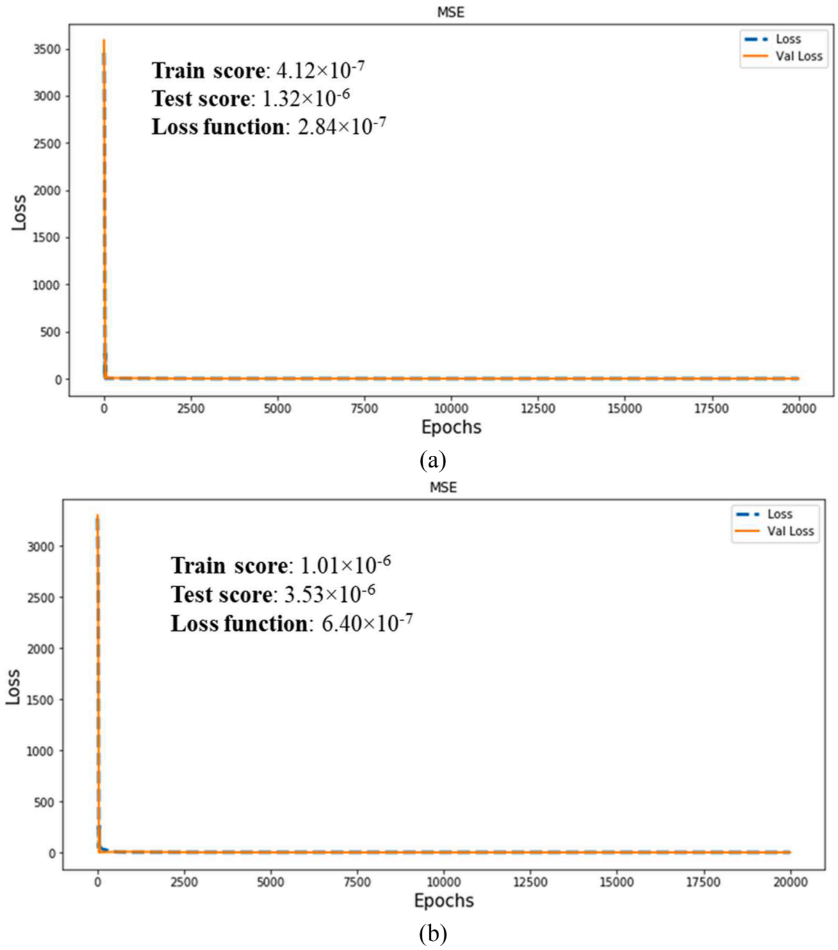


Fig. 8. Enhanced values of loss functions over the epochs for (a) X1 loading condition and (b) X2 loading condition at 45° hexagonal angle.

Table 3
Prediction of loading condition and hexagonal angle using multi-modal RF-ANN.

Targeted crashworthiness parameters	Targeted values Min	Random 1	Avg	Random 2	Max
Initial Crush Load (kN)	0.14	0.18	0.348	0.5	0.65
Average Crush Load (kN)	0.29	0.51	0.734	1	1.306
Maximum crush load (kN)	0.12	0.28	0.436	0.7	0.94
Crush force efficiency (kN/kN)	0.39	0.5	0.622	0.90	1.2
Initial failure indicator (kN/kN)	0.14	0.39	0.641	0.91	1.18
Specific energy absorption (kJ/kg m2)	2.11	2.85	3.586	4.50	5.45
	Predicted values				
Predicted Loading condition (X1 or X2)	X2	X2	X2	X1	X1
Predicted Hexagonal Angle (degree)	30.10	42.23	56.01	73.66	89.10

the five random sets of targeted parameters. Note that in the experiment, the specimens were prepared at only five different angles ranging from 45° to 65° Hence, the trained model can successfully predict the optimum angle outside the range of their training dataset (outside the experimental angles). It indicates that the training data did not overfit the model; in fact, it was able to gain insights into the complex relationship among the six crashworthiness parameters. Furthermore, even if the loading condition and the angles were observed closely, it could be seen that the predicted values were aligned with the experimental data. For example, if the average point of Table 3 is compared with the 55SX2 and 60SX2 samples of Table 1. The values are very much aligned, and the identified loading condition X2 and hexagonal angle 56.01° are in between the value of 55° and 60°. Also, the angles changed while changing the set of targeted crashworthiness parameters from minimum to maximum. Therefore, the developed models were not overfitted as different loading conditions and angles were obtained for different attributes (besides the experimental points).

5.3. *Application of developed multi-modal system*

The RF model was saved with the help of the pickle module, which defines a technique for converting any Python object to a sequence of bytes. This is often referred to as "serializing" the item. The object's byte stream may be transferred or saved and rebuilt to generate a new object with the same properties. The ANN model's features (obtained structure, weight, and bias values) were recorded using the save function on the model and giving a filename, which resulted in the model's information being saved as a JSON file. The JSON file will allow the designer to use the stepwise algorithm to predict the crashworthiness parameters. This step can be done by simulating all possible combinations of crashworthiness parameters and averaging down the corresponding results (see Fig. 9). For instance, testing was done at 60° and 65° hexagonal angles; however, the generated models can estimate the crashworthiness characteristics for a 63° hexagonal angle using the trained model (see Table 4).

The created RF-ANN multi-modal system derived the anticipated crashworthiness parameter values (Table 4). As observed, the expected values are aligned with the experimental ones. Therefore, further experimental runs can be conducted to further physically validate the

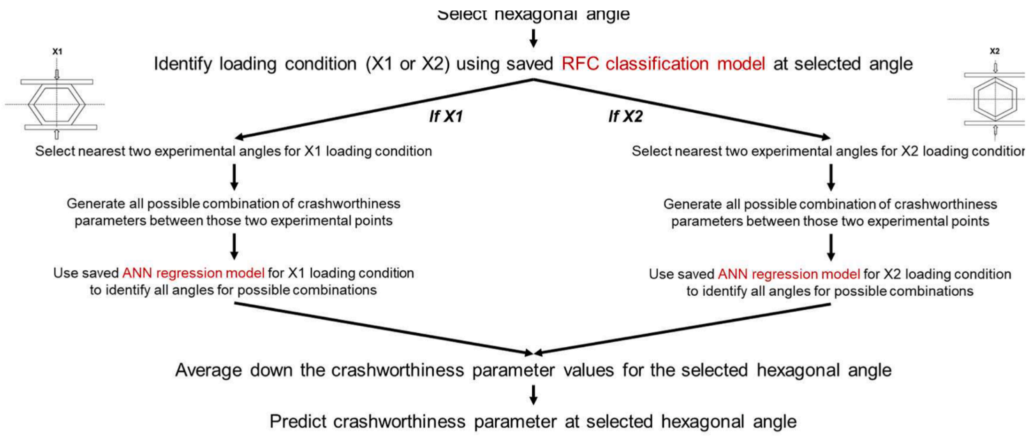


Fig. 9. Architecture for predicting crashworthiness parameters using developed RFC and ANN models.

Table 4
Predicted crashworthiness parameters for given hexagonal angle and loading condition.

	Initial crush load (kN)	Average crush load (kN)	Maximum crush load (kN)	Crush force efficiency (kN/kN)	Initial failure indicator (kN/kN)	Specific energy absorption (kJ/kg m2)
Experimental values for 60°	0.57	0.35	0.62	0.58	0.98	3.48
Predicted values for 63°	0.59	0.36	0.61	0.65	0.98	3.53
Experimental values for 65°	0.65	0.39	0.59	0.67	0.97	3.57

predicted parameters from the model.

6. Conclusion

This study constructed a multi-modal system utilizing the Keras Python library that combines random forest (RF) classification and artificial neural network (ANN) regression models in the TensorFlow backend. The RF-ANN model was trained on experimental data for six distinct crashworthiness characteristics to forecast the optimal hexagonal angle for a woven roving glass/epoxy composite material ring system and the loading conditions required to attain the necessary mechanical strength. The created RF-ANN model successfully forecasted the optimal configuration of the composite for different random sets of crashworthiness characteristics. The RF model's accuracy, precision, and recall were evaluated using a confusion matrix. Accordingly, in this model, 3 true positives and 4 true negatives were obtained without any false positive or negative for training data, whereas 2 true positives and 1 true negative were obtained without any false positive or negative for the test dataset. The ANN model obtained low loss function values (i.e., the loss function values were $2.84 \times 10{-}7$ and $6.40 \times 10{-}7$ respectively for X1 and X2 loading conditions at an angle of 45°) and showed greater accuracy in predicting the experimental dataset and in-between values (error less than 5%). The projected loading condition and hexagonal angle values are consistent with the experimental data pattern in terms of nonlinearity. The developed RFF-ANN multi-modal system predicted the angles between the experimental data points and outside the experimental data point range, indicating the developed model's robustness. The RFF-ANN will pave the way to allow the designer to assess any additional crashworthiness parameter values inside the training range. It generates the necessary composite configurations while leveraging the established complex relationship among the six crashworthiness parameters. The generated models can also estimate the crashworthiness characteristics for any specific composite sample with known hexagonal angle and loading condition. This predictive model may help smart manufacturing and industry 4.0 applications by using a hexagonal ring system of woven roving glass/epoxy composite, lowering manufacturing costs and speeding up production.

CRediT authorship contribution statement

Monzure-Khoda Kazi: Concept, methodology, software, data curation, validation, writing.
E. Mahdi: Concept, experimental work, writing, supervision, resources, validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

This paper was made possible by NPRP grant 5 - 1298 - 2 - 560 from the Qatar National Research Fund (a member of the Qatar Foundation). The statements made herein are solely the author's responsibility [s].

References

[1] M.-K. Kazi, F. Eljack, E. Mahdi, Design of composite rectangular tubes for optimum crashworthiness performance via experimental and ANN techniques, Compos. Struct. 279 (2022) 114858.
[2] M.C. Tanzi, S. Farè, G. Candiani, Chapter 1 - organization, structure, and properties of materials, in: MC Tanzi, S Farè, G Candiani (Eds.), Foundations of Biomaterials Engineering, Academic Press, 2019, pp. 3–103.
[3] M. Shioya, T Kikutani, Chapter 7 - synthetic textile fibres: non-polymer fibres, editor, in: R Sinclair (Ed.), Textiles and Fashion, Woodhead Publishing, 2015, pp. 139–155.

[4] F. Rubino, A. Nisticò, F. Tucci, P. Carlone, Marine application of fiber reinforced composites: a review, J. Mar. Sci. Eng. 8 (2020).
[5] S. Hesseler, S.E. Stapleton, L. Appel, S. Schöfer, B. Manin, 11 - Modeling of reinforcement fibers and textiles, in: NT Akankwasa, D Veit (Eds.), Advances in Modeling and Simulation in Textile Engineering, Woodhead Publishing, 2021, pp. 267–299.
[6] M. Sreejith, R.S Rajeev, 25 - Fiber reinforced composites for aerospace and sports applications, editors, in: K Joseph, K Oksman, G George, R Wilson, S Appukuttan (Eds.), Fiber Reinforced Composites, Woodhead Publishing, 2021, pp. 821–859.
[7] E. Mahdi, A.M.S. Hamouda, Energy absorption capability of composite hexagonal ring systems, Mater. Des. 34 (2012) 201–210.
[8] E. Mahdi, O.M.S. Alkoles, A.M.S. Hamouda, B.B. Sahari, Ellipticity ratio effects in the energy absorption of laterally crushed composite tubes, Adv. Compos. Mater. 15 (2006) 95–113.
[9] L.-q. An, X.-c. Zhang, H.-x. Wu, W.-q. Jiang, In-plane dynamic crushing and energy absorption capacity of self-similar hierarchical honeycombs, Adv. Mech. Eng. 9 (2017) 1687814017703896.
[10] E.-S. Mahdi, H El Kadi, Crushing behavior of laterally compressed composite elliptical tubes: experiments and predictions using artificial neural networks, Compos. Struct. 83 (2008) 399–412.
[11] A.A.S. Abosbaia, E. Mahdi, A.M.S. Hamouda, B.B. Sahari, Quasi-static axial crushing of segmented and non-segmented composite tubes, Compos. Struct. 60 (2003) 327–343.
[12] M.-K. Kazi, F. Eljack, E. Mahdi, Data-driven modeling to predict the load vs. displacement curves of targeted composite materials for industry 4.0 and smart manufacturing, Compos. Struct. (2020) 113207.
[13] M.-K. Kazi, F. Eljack, E. Mahdi, Optimal filler content for cotton fiber/PP composite based on mechanical properties using artificial neural network, Compos. Struct. (2020) 112654.
[14] M.-K. Kazi, F. Eljack, E Mahdi, Predictive ANN models for varying filler content for cotton fiber/PVC composites based on experimental load displacement curves, Compos. Struct. (2020) 112885.
[15] R. Kumar, S. Srivastava, J.R.P. Gupta, A. Mohindru, Comparative study of neural networks for dynamic nonlinear systems identification, Soft. comput. 23 (2019) 101–114.
[16] R. Kumar, S. Srivastava, J.R.P. Gupta, Modeling and adaptive control of nonlinear dynamical systems using radial basis function network, Soft. comput. 21 (2017) 4447–4463.
[17] M. Gupta, L. Jin, N. Homma, Static and Dynamic Neural Networks: From Fundamentals to Advanced Theory, Wiley, 2004.
[18] H. Rahmanpanah, S. Mouloodi, C. Burvill, S. Gohari, H.M.S. Davies, Prediction of load-displacement curve in a complex structure using artificial neural networks: a study on a long bone, Int. J. Eng. Sci. (2020) 154.
[19] Sivanandam S.N., Sumathi S., Deepa S.N. Introduction to neural networks using MATLAB 6.0. 2010.
[20] A. Afram, F. Janabi-Sharifi, A.S. Fung, K. Raahemifar, Artificial neural network (ANN) based model predictive control (MPC) and optimization of HVAC systems: a state of the art review and case study of a residential HVAC system, Energy Build. 141 (2017) 96–113.
[21] Y. Al-Assaf, H.E. Kadi, Fatigue life prediction of composite materials using polynomial classifiers and recurrent neural networks, Compos. Struct. 77 (2007) 561–569.
[22] S. Gowid, E. Mahdi, F. Alabtah, Modeling and optimization of the crushing behavior and energy absorption of plain weave composite hexagonal quadruple ring systems using artificial neural network, Compos. Struct. (2019) 229.
[23] M.I. Khan, Predicting properties of High Performance Concrete containing composite cementitious materials using Artificial Neural Networks, Autom. Constr. 22 (2012) 516–524.
[24] A. Khandakar, M.E.H. Chowdhury, M.-K. Kazi, K. Benhmed, F. Touati, M. Al-Hitmi, et al., Machine learning based photovoltaics (PV) power prediction using different environmental parameters of Qatar, Energ. (Basel) 12 (2019) 1–19.
[25] X. Li, Z. Liu, S. Cui, C. Luo, C. Li, Z. Zhuang, Predicting the effective mechanical property of heterogeneous materials by image-based modeling and deep learning, Comput. Methods Appl. Mech. Eng. 347 (2019) 735–753.
[26] T. Mareš, E. Janouchová, A. Kučerová, Artificial neural networks in the calibration of nonlinear mechanical models, Adv. Eng. Softw. 95 (2016) 68–81.
[27] B. Medi, K. Monzure-Khoda, M. Amanullah, Experimental implementation of optimal control of an improved single-column chromatographic process for the separation of enantiomers, Ind. Eng. Chem. Res. 54 (2015) 6527–6539.
[28] T. Sabiston, K. Inal, P. Lee-Sullivan, Application of artificial neural networks to predict fibre orientation in long fibre compression moulded composite materials, Compos. Sci. Technol. (2020) 190.
[29] A. Vassilopoulos, E. Georgopoulos, V. Dionysopoulos, Artificial neural networks in spectrum fatigue life prediction of composite materials, Int. J. Fatigue 29 (2007) 20–29.
[30] S. Yan, X. Zou, M. Ilkhani, A. Jones, An efficient multiscale surrogate modelling framework for composite materials considering progressive damage based on artificial neural networks, Composit. Part B: Eng. (2020) 194.
[31] M. Zakaulla, F. Parveen, Harish Amreen, N Ahmad, Artificial neural network based prediction on tribological properties of polycarbonate composites reinforced with graphene and boron carbide particle, in: Materials Today: Proceedings, 2020.
[32] T. Zarra, M.G. Galang, F. Ballesteros Jr., V. Belgiorno, V Naddeo, Environmental odour management by artificial neural network - A review, Environ. Int. 133 (2019) 105189.
[33] G.B. Veeresh Kumar, R. Pramod, C.S.P. Rao, P.S.S Gouda, Artificial neural network prediction on wear of Al6061 alloy metal matrix composites reinforced with -Al_2O_3, in: Materials Today: Proceedings 5, 2018, pp. 11268–11276.
[34] O. Laban, S. Gowid, E. Mahdi, Experimental investigation and uncertainty prediction of the load-carrying capacity of composite double hat for lattice core sandwich panels using artificial neural network, in: 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT), 2020, pp. 67–72.
[35] Y. Zhang, C. Ling, A strategy to apply machine learning to small datasets in materials science, NPJ. Comput. Mater. 4 (2018) 25.
[36] M.W. Ahmad, M. Mourshed, Y. Rezgui, Tree-based ensemble methods for predicting PV power generation and their comparison with support vector regression, Energy 164 (2018) 465–474.
[37] A. Marani, M.L. Nehdi, Machine-learning prediction of compressive strength for phase change materials integrated cementitious composites, Constr. Build. Mater. 265 (2020) 120286.
[38] A. Torres-Barrán, Á. Alonso, J.R. Dorronsoro, Regression tree ensembles for wind energy and solar radiation prediction, Neurocomputing. 326-327 (2019) 151–160.
[39] P.D. Caie, N. Dimitriou, O. Arandjelović, Chapter 8 - Precision medicine in digital pathology via image analysis and machine learning, editor, in: S Cohen (Ed.), Artificial Intelligence and Deep Learning in Pathology, Elsevier, 2021, pp. 149–173.
[40] L. Breiman, Random forests, Mach. Learn. 45 (2001) 5–32.