Erzincan Üniversitesi
Fen Bilimleri Enstitüsü Dergisi
2023, 16(3), 869-887
ISSN: 1307-9085, e-ISSN: 2149-4584
Araştırma Makalesi

ErzincanUniversity
Journal of Science andTechnology
2023, 16(3), 869-887
DOI:10.18185/erzifbed.1253159
Research Article

Estimation of Critical Buckling Loads of Hybrid Composites in Different Environments Using Artificial Neural Networks

Ayla TEKİN[1],Ayşe ÖNDÜRÜCÜ[2*],Hüseyin Fırat KAYIRAN[3]

[1] Manisa Celal Bayar Üniversitesi, Soma Meslek Yüksek Okulu, Soma, Manisa, Türkiye.
[2]Isparta Süleyman Demirel Üniversitesi, Mühendislik Fakültesi, Makine Mühendisliği Bölümü, 32260, Isparta, Türkiye.
[3]TKDK Mersin İl Koordinatörlüğü, Mersin, Türkiye.

Received: 19/02/2023, **Revised**: 10/10/2023, **Accepted**: 20/10/2023**, Published**: 31/12/2023

Abstract

The primary objective of this work is to analyze the critical buckling load of the hybrid composite plate using test data on the effects of different environmental conditions. The artificial neural network (ANN) method was used for analysis. The MATLAB-based program was used to develop the ANN. The buckling data that emerged after being tested was trained on the ANN model. Inputs for ANN modeling; the holding times of the materials, ambient temperatures, environmental conditions, and material orientation angles, and the output parameter is the critical buckling load. In modeling, 80% of forty-two experimental data were taken for training and 20% for validation. The data obtained after training and testing the materials in Artificial Neural Networks were investigated by performing statistical analysis, which is frequently preferred in ANN models, it was seen that the resulting modeling was successfully applied and the results were very close to the real test results. While the average error rate was 1.82% in the training phase, it was 3.41% in the testing phase.

Keywords: Artificial neural networks, Critical buckling load estimation, Hybrid composite, Environmental conditions, Buckling behavior.

Yapay Sinir Ağları Kullanılarak Farklı Ortamlardaki Hibrit Kompozitlerin Kritik Burkulma Yüklerinin Tahmini

Öz

Bu çalışmanın birincil amacı, farklı çevre koşullarının etkilerine ilişkin test verilerini kullanarak hibrit kompozit levhanın kritik burkulma yükünü analiz etmektir. Analiz için yapay sinir ağı (YSA) yöntemi kullanılmıştır. YSA'nı geliştirmek için ise MATLAB tabanlı bir program kullanılmıştır. Deneye tabi tutulduktan sonra ortaya çıkan burkulma verileri, YSA modelinde eğitilmiştir. YSA modellemesi için girdiler; malzemelerin bekleme süreleri, ortam sıcaklıkları, çevre koşulları ve malzeme oryantasyon açıları, çıktı parametresi ise kritik burkulma yüküdür. Modellemede kırk iki deneysel verinin % 80'i eğitim için, % 20'si doğrulama için alınmıştır. Malzemelerin Yapay Sinir Ağlarında eğitilmesi ve test edilmesi sonrasında elde edilen veriler, YSA modellerinde sıkça tercih edilen istatistiksel analizler yapılarak araştırılmış ve elde edilen modellemenin başarıyla uygulandığı ve sonuçların gerçek test sonuçlarına oldukça yakınlık gösterdiği görülmüştür. Eğitim aşamasında ortalama hata oranı %1.82 iken, test aşamasında ise % 3.41 olduğu ortaya konmuştur.

Anahtar Kelimeler: Yapay sinir ağları, Kritik burkulma yükü tahmini, Hibrit kompozit, Çevre koşulları, Burkulma davranış

***Corresponding Author:** ayseondurucu@sdu.edu.tr
Ayla TEKİN, https://orcid.org/0000-0002-2547-0872
Ayşe ÖNDÜRÜCÜ, https://orcid.org/0000-0002-0319-456
Hüseyin Fırat KAYIRAN, https://orcid.org/0000-0003-3037-5279

1. Introduction

Composite materials, which have a very dynamic structure and are in constant change, are widely used in several areas such as transportation, construction materials, aviation, space, and defense industries, upon reduced costs and increased efficiency [1]. With the use of these high-strength materials, the buckling of the structural elements can occur much faster since the cross-sectional areas of the elements are reduced. In the literature, many studies are exploring the effects of hole size, shape and position, fiber orientation angles, and stacking sequences related to the buckling properties of laminate composites with different geometric shapes [2-6].

Examination of buckling behavior is quite challenging because it is affected by several parameters, a great number of samples is required and is time-consuming, demanding, and expensive. Researchers have tended to develop different methods because of these difficulties. The ANN can be considered an alternative method for determining critical buckling loads. ANN is an adaptive system that can adjust its structure according to external information provided to the network [7]. ANNs have been applied to model complex processes such as forecasting, classification, pattern recognition, diagnosis, interpretation, data filtering, and correlation in many engineering fields such as industry, finance, aviation, health, and electronics. It is important for many researchers to accurately estimate the stresses in structural components by analyzing the test data of composite materials, the use of which is increasing day by day, with appropriate models.

In the literature, it is seen that the ANN method is used in many study areas, and as a result of the analyses made with this method, realistic results are obtained. Xu et al. [8] in their study, have developed an ANN-based solution technique to advance the design of materials in nonlinear viscoelastic materials. Zhang and Friedrich [9] estimated certain properties of polymer composite materials using ANN. Kadi [10] evaluated the success of artificial neural networks in predicting important mechanical properties of fiber reinforced composites such as tensile strength, compressive strength, bending strength, and fatigue strength. In another study, the test results of fiber-reinforced polymer composites were compared with a new ANN model by Haj-Ali and Kim [11]. Albuquerque et al. [12] carried out damage assessment on composite plates with radioactive image analysis. They compared the obtained data with the results obtained from ANN. Tekin et al [13] have shown that the ANN model is quite successful in predicting the bearing strengths of pin-connected composite plates under different environments. Islak et al. [14] predicted the mechanical and characteristic properties of Cu-TiC composites by ANN. According to the values used in the training data, the authors obtained results close to the actual values in ANN and concluded that ANN could estimate successful results in this area.

Several researchers have explored the mechanical behavior of composite materials exposed to different environmental conditions. These studies in the literature show that different environmental conditions have different effects on the strength of composite materials. For example, while the cold environment affects the strength of composite materials positively [15-17] seawater negatively affects the strength of composite materials due to the corrosive effect [18-21]. In this present work, the influence of different environments and different hybrid configurations on buckling behavior was investigated. Since experimental studies require multiple experiments, this study, to save cost and time, considered ANN an alternative method and examined the estimation of these critical buckling loads obtained by long experimental studies using ANNs. For this purpose, the buckling loads obtained by the experimental study of hybrid composite samples that were kept in different ambient condition periods were trained through ANNs using a multilayer feedforward backpropagation modeling, and a network of models that best predict the experimental results has been created. A comparison of the results showed that the model showed high precision and had real-time recalculation feature. These highly accurate estimates would be of great help to the designer when choosing the geometrical parameters of the material.

2. Material and Methods

Buckling Behaviors of Hybrid Composites

Experimental procedure

In the experimental study, hybrid composites were preferred because they have better properties than single fiber types. For the buckling test, 12-layer hybrid composite materials with different stacking arrangements were designed to meet the loading and stiffness requirements to be applied. As fiber orientation angles, different arrays with 0°, 30°, 45°, 60°, and 90° orientation angles were created. Using hybrid composite materials aims to obtain a more durable material than complete carbon or completely glass fiber reinforced materials by taking advantage of the positive properties of carbon fiber such as more durable and high rigidity, glass fiber cheaper, and having good mechanical properties. In addition to carbon and glass fibers, a hybrid configuration containing aramid was created to take advantage of the unique toughness and compression strength properties of aramid fiber. For this reason, a buckling test was performed for hybrid composites with different fiber combinations consisting of glass, carbon, and aramid fibers, and the effect of the fibers on the buckling behavior was investigated. To examine buckling behaviors, 12-layer hybrid composite plates with $[(0/90)_3]_s$, $[(30/-60)_3]_s$, $[(45/-45)_3]_s$ symmetric and $[(0/90)_6]_{as}$ antisymmetric orientation angles were produced. Three different fibers were used in producing the hybrid composite materials, namely carbon, E-glass, and aramid, and the resin system was used as the matrix material (Araldite LY1564 / Aradur 3486). The hot pressing method was used in the production of hybrid composite materials. The thickness of composite plates produced in 400 mm x 400 mm dimensions varies between 2.75 and 3.65 mm. Samples of 20 mm x 200 mm in size were cut from the produced composite plates with the help of a Rubi DS-300 1500 professional cutting machine. Hybrid composite configurations are indicated in Table 1 [22].

Table 1. Stacking Sequences of Hybrid Composites

Configurations number	Configurations	Stacking sequences	
1	C	$[(0/90)_3]_s$	$[0_C/90_C/0_C/90_C/0_C/90_C]_s$
2	CG	$[(0/90)_3]_s$	$[0_C/90_C/0_G/90_G/0_C/90_C)_s$
3	CAG	$[(0/90)_3]_s$	$[0_C/90_C/0_A/90_A/0_G/90_G)_s$
4	CAG30	$[(30/-60)_3]_s$	$[30_C/-60_C/30_A/-60_A/30_G/-60_G)_s$
5	CAG45	$[(45/-45)_3]_s$	$[45_C/-45_C/45_A/-45_A/45_G/-45_G)_s$
6	CAG*	$[(0/90)_6]_{as}$	$[0_C/90_C/0_A/90_A/0_G/90_G/0_C/90_C/0_A/90_A/0_G/90_G]$
7	GAC	$[(0/90)_3]_s$	$[0_G/90_G/0_A/90_A/0_C/90_C)_s$

C: Carbon fiber, G: Glass fiber, A: Aramid fiber, s: symmetric, as: antisymmetric, *: antisymmetric configuration, 30 means the $[(30/-60)_3]_s$ stacking sequences, 45 means the $[(45/-45)_3]_s$ stacking sequences.

As shown in Table 1, seven different configurations are available. Hybrid composites containing three different fibers are designed in different stacking arrangements. The hybrid composite materials were kept in the environments and times specified in Table 2 to investigate the effect of different environments on buckling behavior.

Table 2. Different Ambient Conditions and Waiting Times

Ambient conditions	Waiting times
Room temperature condition-I	90 days
Mediterranean water-I	90 days
Cold condition-I (-18 °C)	90 days
Black Sea water	90 days
Room temperature condition-II	150 days
Mediterranean water-II	150 days
Cold condition-II (-18 °C)	150 days

As seen in Table 2 below; the samples were left periods in four different environments: room conditions (normal environment), Black Sea water, Mediterranean water, and cooler. Two different waiting times, 90 and 150 days, were set. Hybrid composite specimens, whose waiting period has expired, were subjected to the buckling test at Dokuz Eylül University Mechanical Engineering Laboratory using a 100 kN Shimadzu AG-X universal tensile testing device. The buckling test was performed by applying a vertical load at one end of the test sample, which was supported at the other end to exhibit the behavior of a fixed beam. After three experiments were performed for the determined experimental groups, it was considered appropriate to average the results. Buckling load graphs were drawn using experimental data. Then, critical buckling loads (P_{cr})were determined from the buckling load curves for each hybrid composite configuration using the Southwell Plot. The effects of different environments and different stacking sequences on the buckling behavior of hybrid composites were examined by taking the samples kept at room conditions as the control group.

Theoretical approach

ANN is a nonlinear model that occurs in interconnected artificial neurons and includes an input set and a single output. Training the ANN to achieve the target outputs requires a greater number of inputs, as well as numerous output sets for the relevant inputs. These data sets, called "training" and "testing", are subjected to a learning process. After this process, a "test" process is performed using the inputs from the testing process. The mechanism that enables the arrangement of weights in the network to generate the desired outputs from ANN during training is called the learning algorithm. The training phase continues until the target output is reached. The error resulting from the difference between the expected output from the ANN and the values obtained from the data we have is minimized by changing the weights. Figure 1 shows the ANN flow chart in the chart in which the ANN is located. Moreover, we can see a few examples of ANN architecture in the literature [23-24]. Among these, the present study used a multilayer Feedforward back propagation learning mechanism for estimation purposes, which is suitable for engineering applications.

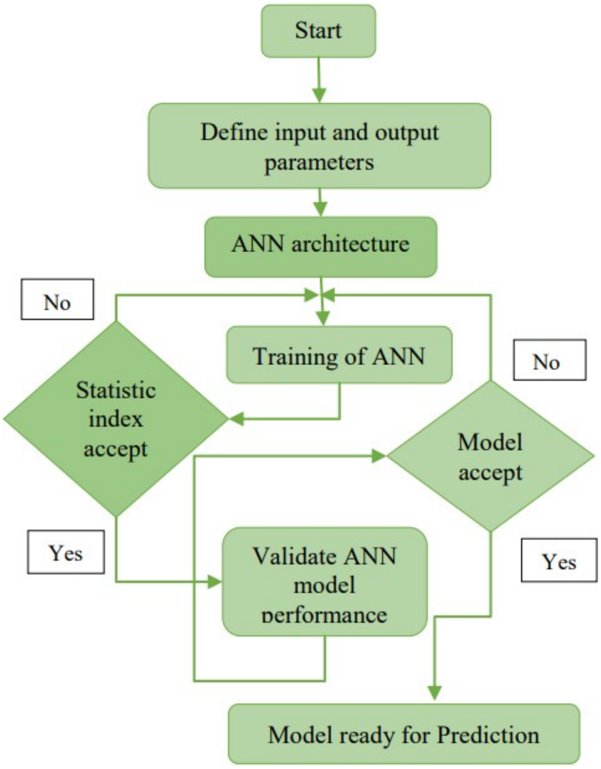


Figure 1. ANN Flow Chart [25]

A typical example of multi-layer ANN architecture is shown in Figure 2. In the Figure, the input layer is the first layer, the hidden layer is the middle layer, and the output layer is the last layer.

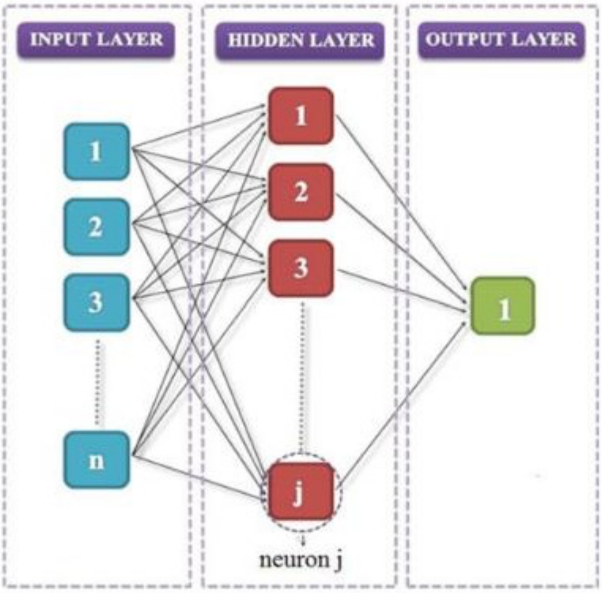


Figure 2. A Typical Multilayered ANN Architecture [26]

A four-input and one-output ANN network architecture was created to determine the applicability and potential of ANN in determining the actual critical buckling loads for hybrid composite beams. Within the scope of the study, the test times, ambient temperatures, ambient conditions (Table 2), and material arrangement angles (Table 1) were determined as input parameters and critical buckling loads as output parameters. The training set was created by assigning various values to the input elements of the network. Test data of actual critical buckling loads were used for hybrid composite beams. The MATLAB program was used to create and train the ANN model for critical buckling loads and displacements. In ANN models, it is preferred that 70% to 90% of the data is used for training and 10% to 30% for testing. In the present study, 80% of the 42 experimental data were used for training and the remaining 20% for testing. The training and test data were randomly selected to represent each input set.

After the training of the network was completed, it was tested using data sets that were not used previously during the training. The maximum and minimum values were identified for each input parameter and the values in between were normalized between 0 and 1. The purpose of the normalization is to maintain the steadiness of the input data that could be achieved by feature scaling. Many normalization techniques were tried for this study, and it was determined that the normalization between 0.1 and 0.9 using equation(1) produced more realistic results:

$$x_N = 0{,}8 * \left(\frac{x_i - x_{min}}{x_{max} - x_{min}}\right) + 0{,}1 \tag{1}$$

with X_N as the normalized data for the pattern, x_i being the actual value of a parameter, x_{min} being the minimum value of the training or test set, and x_{max} being the maximum value of the training or test set. Since the output data obtained after running the ANN will also be in the range of 0–1, normalization is reversed and the actual output data is obtained.

3. Results and Discussion

Experimental Study Results

Hybrid composite samples were subjected to the buckling test by keeping them in different environments for certain periods. Figure 3 shows the deformation that occurred in the composite sample under buckling load.

Figure 3. Deformation of the Hybrid Composite Sample After the Buckling Test

As a result of the experimental study, it was concluded that the stacking sequence, orientation angles, use of different fibers, and different environmental conditions affected the buckling behavior of hybrid composites. Hybrid composites cannot be produced in the same thickness because they have different fiber configurations. For this reason, to eliminate the thickness difference between the configurations, the Pcr/t values obtained by dividing the Pcr values of each hybrid configuration by the thickness were obtained and presented graphically in Figure 4. As a result of the experimental study showed that the critical buckling loads of the hybrid composites for ambient conditions were obtained as CAG-C-CG-CAG*-GAC-CAG30 and CAG45 in decreasing order (Figure 4). The highest critical buckling load occurred in the CAG configuration, and the lowest critical buckling load occurred in the CAG45 configuration.

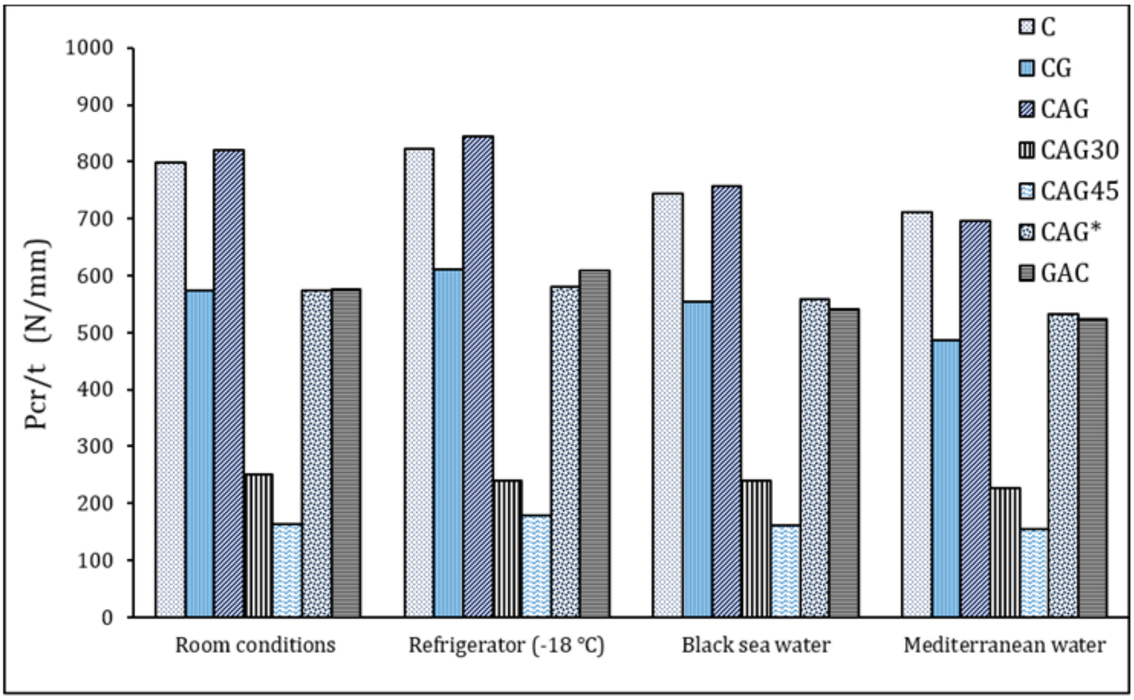
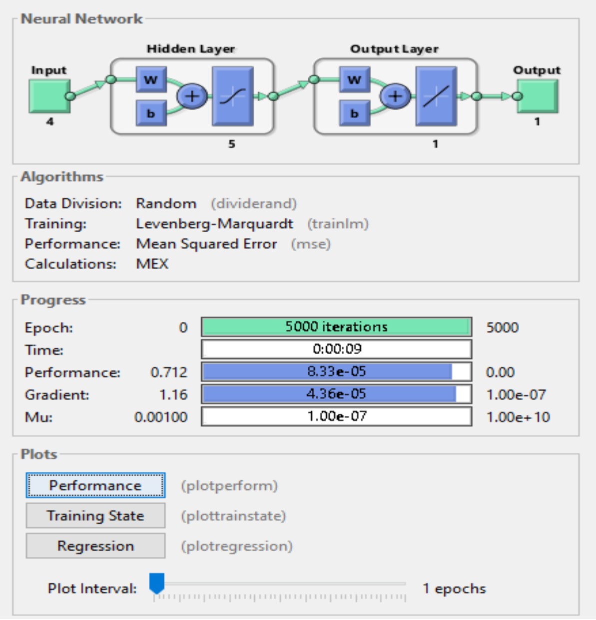


Figure 4. Experimental Critical Buckling Loads of Hybrid Composite Configurations for All Environmental Conditions (For a 90-Day Waiting Period)

When the graph is examined, it can be easily seen that the critical buckling loads of the configurations with (0/90) sequences are higher than the critical buckling loads of the configurations with 30 and 45 orientation angles. For example, the critical buckling load for the CAG configuration kept for 90 days at room conditions is 2663N, while the critical buckling load is 768N for the CAG30 configuration held for the same period and under the same conditions. For the CAG45 configuration, the critical buckling load was obtained as 492N. Accordingly, it was concluded that the fiber stacking sequence affected the buckling behavior for all ambient conditions. It was also concluded that the buckling behavior of hybrid composite materials is affected by environmental conditions. It was observed that the buckling strength of hybrid composite samples kept in a cold environment increased. The hybrid composites kept in seawater, in turn, were observed to decrease critical buckling loads compared to the composites kept in room conditions. In addition, it was seen that the composites kept in the Mediterranean Seawater with higher salinity had lower critical buckling loads than the composites kept in the Black Sea water. For example, it was observed that the critical buckling strength of CG, which was kept in the refrigerator for 90 days, increased by 2.92% compared to room conditions, while it decreased by 1.68% when left in Black Sea water for ninety days. When CG was kept in Mediterranean water for the same time, it was observed that the critical buckling strength decreased by 4.21% compared to room conditions. The fiber type and fiber arrangement affect the buckling behavior. When the CAG and CG configurations are compared, it is seen that the critical buckling load of the CAG configuration with aramid in the middle surface is higher. When the fiber arrangement is compared, it is seen that the buckling behavior of the CAG configuration containing carbon on the outer surface is better than that of the GAC.

ANN Results

Examination of buckling loads of materials involves experimental studies that are costly and require a long period. Modeling the strength with ANN is believed to be an application that can reduce testing costs and the required period. An ANN model has been developed to estimate the critical buckling loads of hybrid composite plates in different temperature environments and different waiting times. By changing the hidden layers, the training and testing process was repeated several times and the best architecture was determined. Therefore, a suitable back propagation ANN model was developed for neuron counts based on several trials. The architecture of the ANN model created for critical buckling load estimation, expressed as 4-5-1 obtained after many trials, consists of four input neurons, 5 hidden layers, and 1 output neuron. The waiting times, ambient temperatures, ambient conditions, and material arrangement angles of the samples were used as input data values, and critical buckling loads were estimated as output values. All data will be normalized to a range of 0.1-0.9. Many different models built on MATLAB were tried, and the training of the network was completed upon reaching acceptable values after 5000 epochs. The MATLAB ANN interface and training algorithm used are collectively presented in Figure 5.



Data Division: Random (dividerand)
Training: Levenberg-Marquardt (trainlm)
Performance: Mean Squared Error (mse)
Calculations: MEX

Epoch: 0 | 5000 iterations | 5000
Time: 0:00:09
Performance: 0.712 | 8.33e-05 | 0.00
Gradient: 1.16 | 4.36e-05 | 1.00e-07
Mu: 0.00100 | 1.00e-07 | 1.00e+10

(plotperform)
(plottrainstate)
(plotregression)

Plot Interval: 1 epochs

Figure 5. Used Matlab ANN Interface and Training Algorithm

The regression curves related to the training-test data were obtained by comparing the actual output and the ANN output to show the modeling performance as well as the results of all data presented in Figure 6.

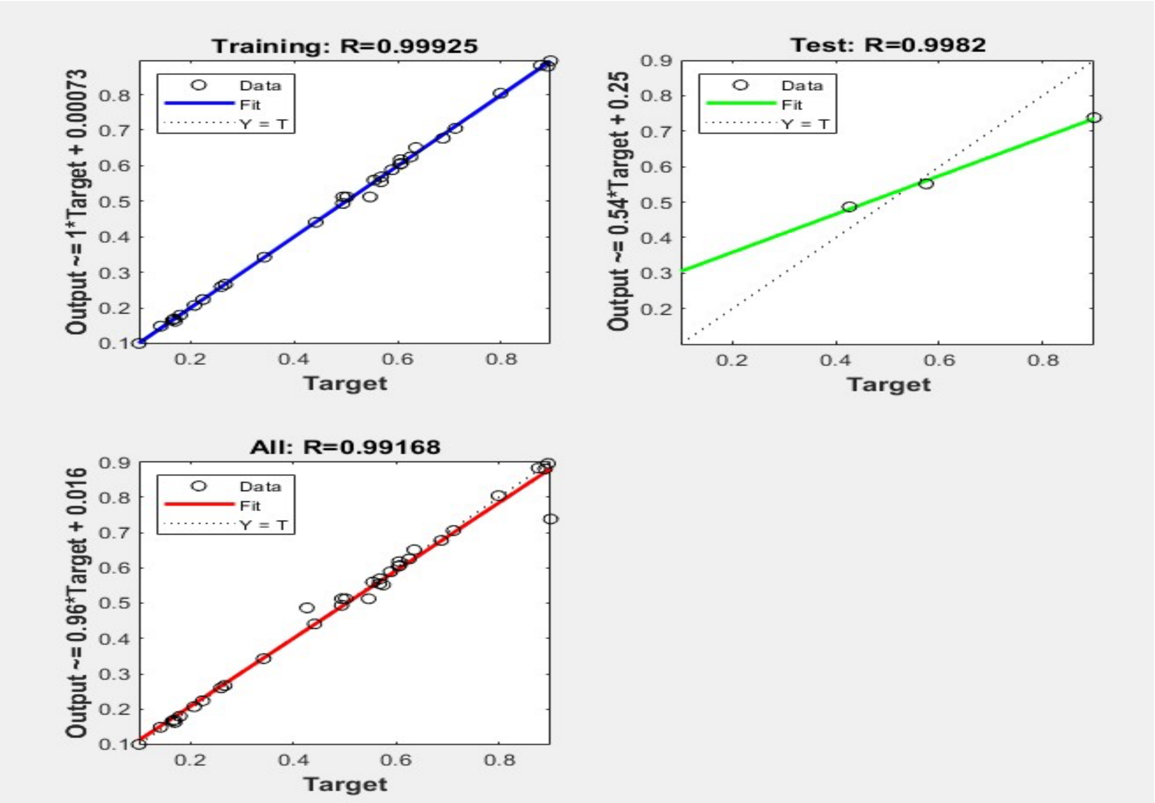


Figure 6. Regression Curves for the Results of Training-Test Data and All Data

As seen from the curves, the regression value was close to 1 for all data. In other words, the ANN model output yielded values very close to the real data. The overall ANN model simulation result is calculated as R = 0.99925. The average error rate in the critical buckling load results during the training phase was found to be 1.82%. Figures 7-9 show the experimental results of the critical buckling load and the results obtained from ANN for hybrid composite specimens kept in four different environments, namely room conditions (normal environment), Black Sea water, Mediterranean water, and cold environment, and at different waiting times. When the graphs in the figures are examined, it can seen that the experimental data and the results obtained from the ANN are very close to each other.

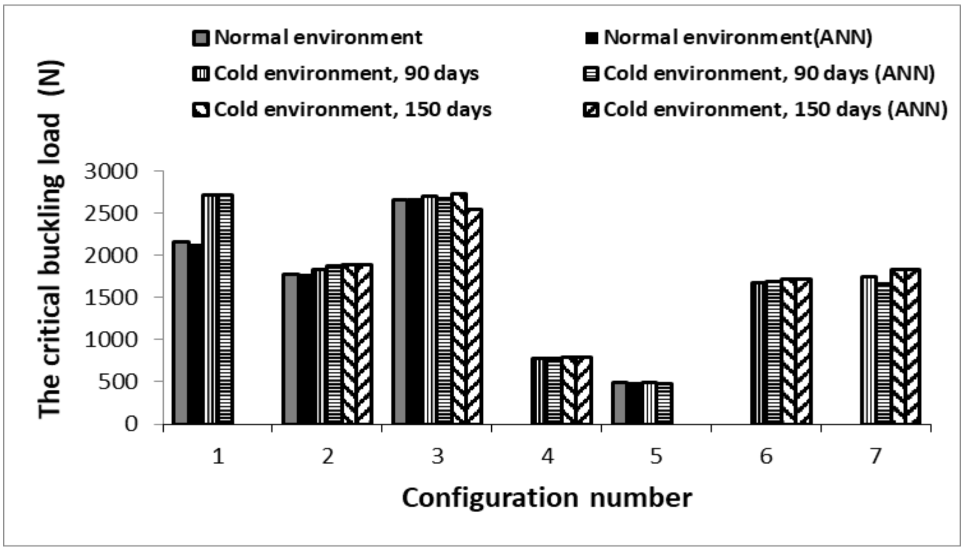


Figure 7. Comparison in the Critical Buckling Load Experimental Results for Samples Kept in Normal Condition and Cold Environments with the ANN Results in the Training Phase

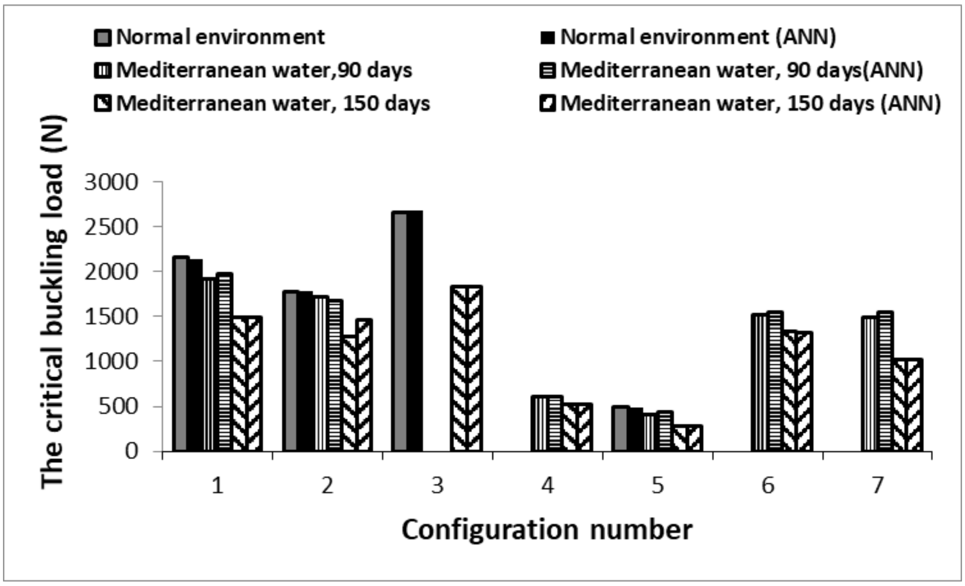


Figure 8. Comparison in the Critical Buckling Load Experimental Results for Samples Kept in Normal Condition and Mediterranean Seawater with the ANN Results in the Training Phase

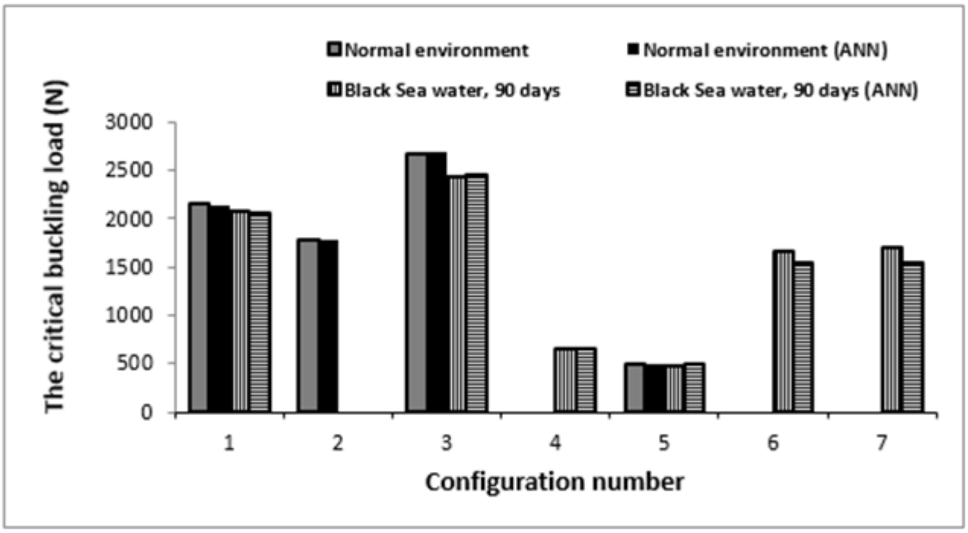


Figure 9. Comparison in the Critical Buckling Load Experimental Results for Samples Kept in Normal Condition and Black Seawater with the ANN Results in the Training Phase

After reaching the desired limit of error in the training of the ANN, testing of the ANN was initiated. Values not used in the training set were presented to the network during the testing phase. The test dataset is considered invisible data and is used to develop models. Therefore, the accuracy of the models developed on the test data set is shown in Figure 10 for the normal environment and cold environment, Figure 11 for the normal environment and Mediterranean water, and Figure 12 for the normal environment and black seawater. The results obtained from the ANN were compared with the experimental results. When the graphics were examined, it was observed that the prediction results of the ANN algorithm in the test phase were close to the results of the experimental study and were quite successful. The results obtained from the test set, when compared with the experimental results, show that the network produces results with sufficient precision. The average error rate during the testing phase is 3.41%. From this point of view, the ANN algorithm has revealed that results can be achieved with lower costs by conducting a small number of experimental studies.

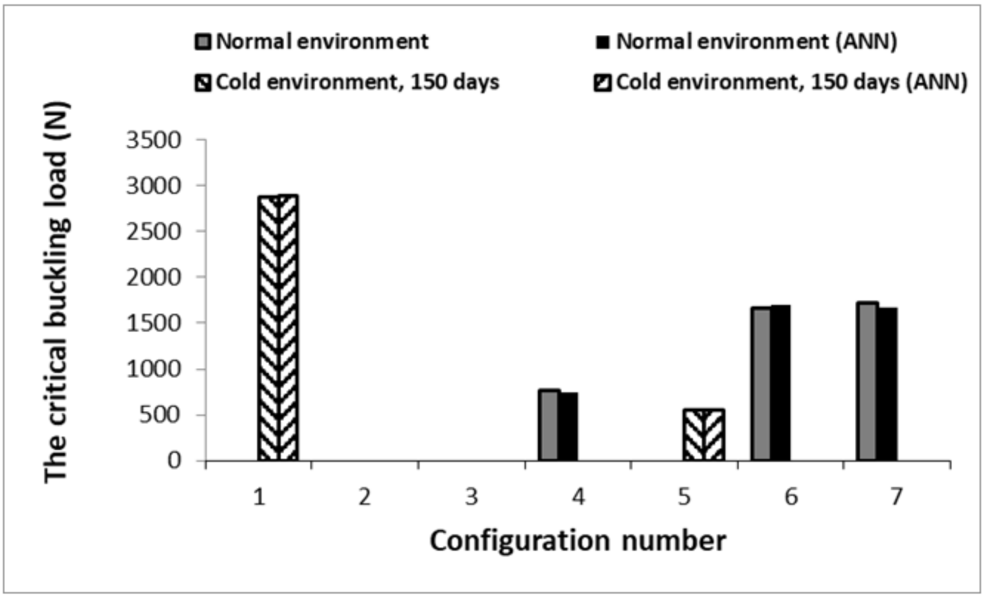


Figure 10. Comparison in the Critical Buckling Load Experimental Results for Samples Kept in Normal Condition and Cold Environments with the ANN Results in the Test Phase

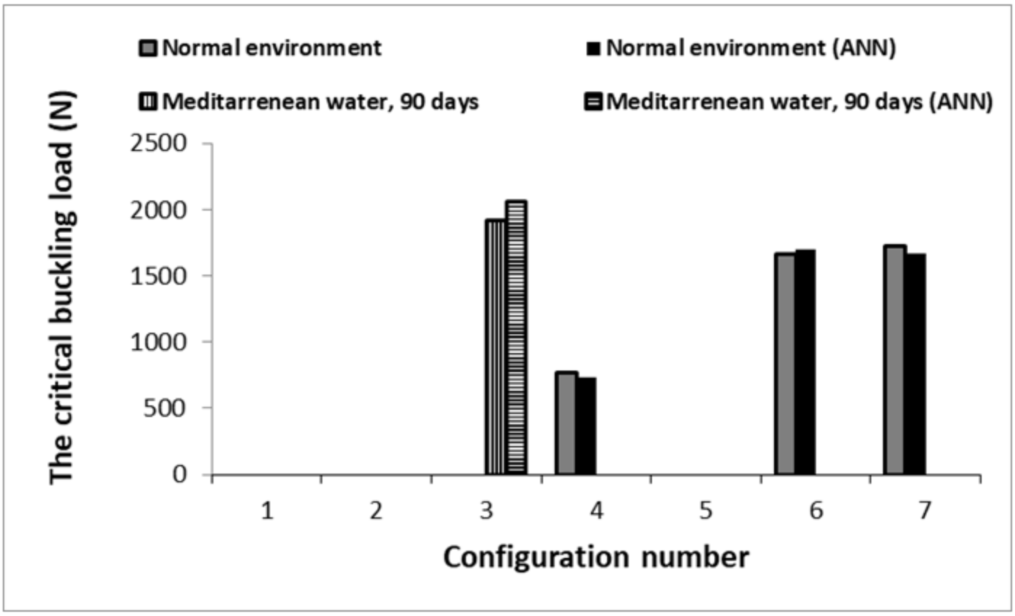


Figure 11. Comparison in the Critical Buckling Load Experimental Results for Samples Kept in Normal Condition and Mediterranean Seawater with the ANN Results in the Test Phase

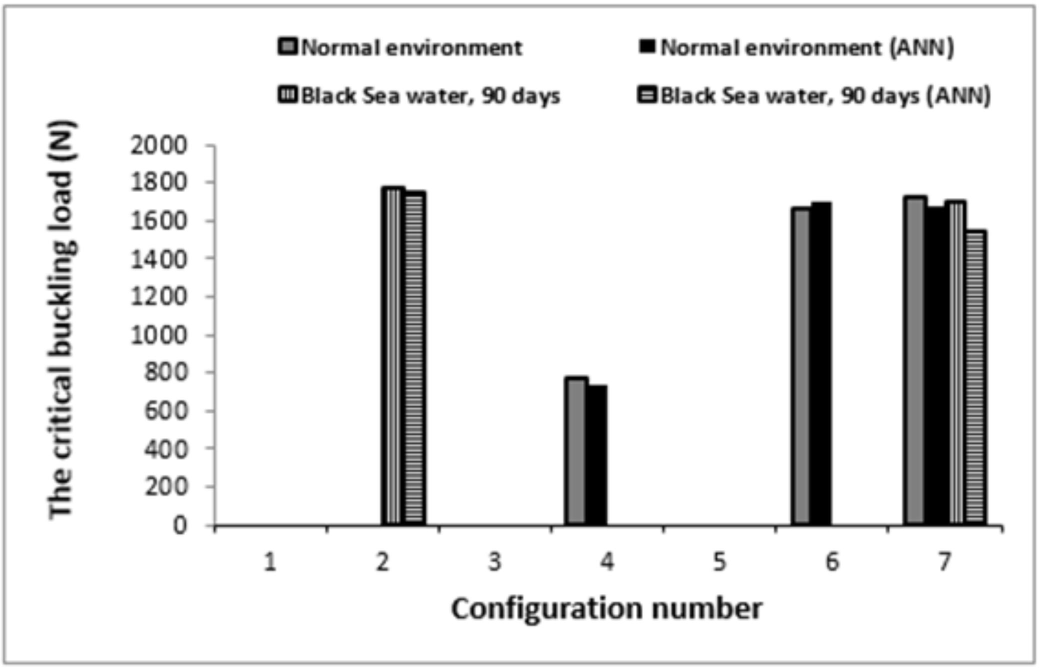
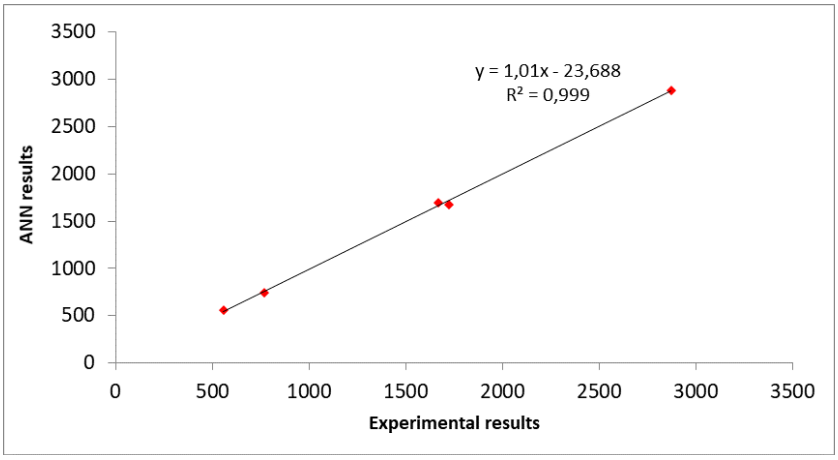
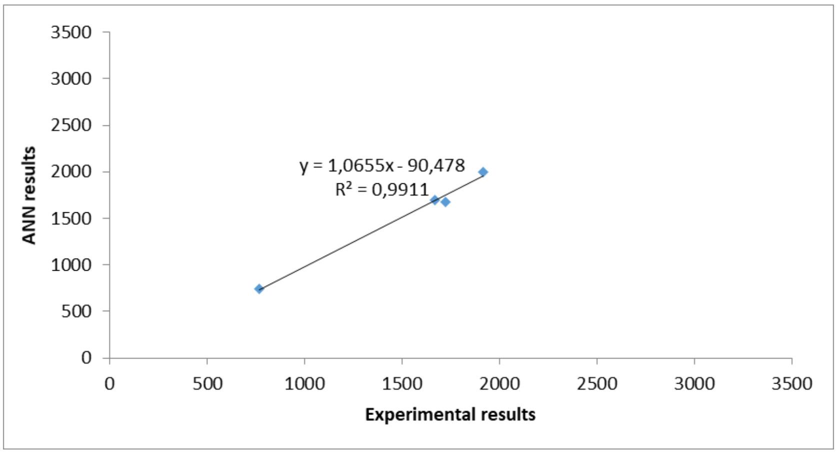


Figure 12. Comparison in the Critical Buckling Load Experimental Results for Samples Kept in Normal Condition and Black Seawater with the ANN Results in the Test Phase

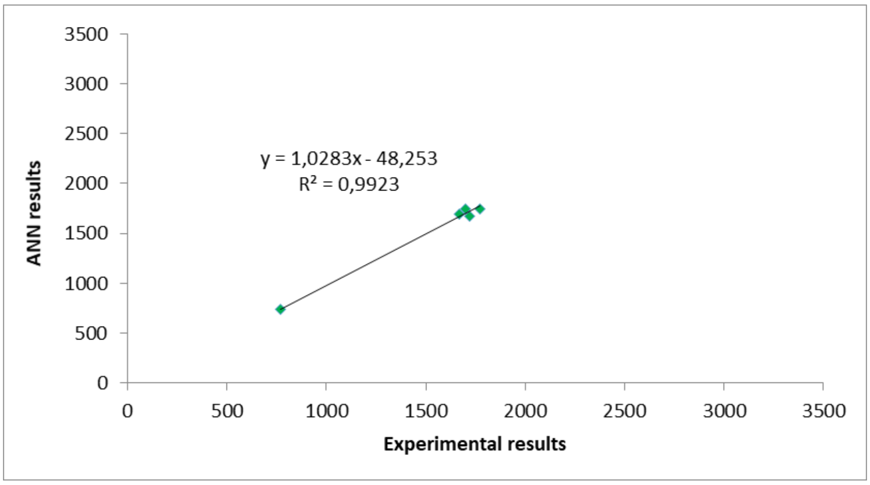
Figure 13 shows the correlations of experimental and predicted values on the test dataset. Figure 13-a shows the correlations of experimental and predicted values on the test dataset using the ANN method for the critical buckling load data of the samples kept in the normal environment - cold environment. In Figure 13-b, the distribution diagram for samples held in the normal environment- Mediterranean water is shown. Figure 13-c, on the other hand, shows the correlations of the experimental and estimated values on the test data set of the samples kept in the normal environment - Black Sea water. In all three scatter diagrams, the correlation coefficient for the critical buckling load was obtained as 0.99. As a result of the comparison of the critical buckling load values estimated by the ANN models, it is seen that the use of neural networks is appropriate in the calculation of the buckling loads of the bars subjected to axial load, without the need for classical methods.



(a) Scatter Diagram for Normal Conditions and Cold Environments



(b) Scatter Diagram for Normal Conditions and Mediterranean water



(c) Scatter Diagram for Normal Conditions and Black Sea water

Figure 13. The Correlation of Experimental and Predicted Values on the Testing Dataset of Critical Buckling Load (R^2: Correlation Coefficient)

The correlation coefficient for the critical buckling load was 0.99 in three-distribution charts. As a result of the comparison of the critical buckling load values estimated by the ANN models, it is seen that the use of neural networks is appropriate in the calculation of the buckling loads of the bars subjected to axial load, without the need for classical methods. From here, the ANN algorithm has revealed that results can be achieved at lower costs by performing a small number of experimental studies. The ANN algorithm has revealed that results can be achieved at lower costs by performing a small number of experimental studies. Factors such as the fact that experimental studies take a long time and require extra effort, and the complex structure of analytical expressions have made ANN advantageous in many studies. The present study also concluded that the applicability of the ANN was an effective and reliable method in determining the critical buckling loads of laminated hybrid composite plates since the data obtained with ANN were very close to the experimental results.

4. Conclusion

The effect of different environmental conditions on critical buckling loads of hybrid composite plates depending on exposure time has been investigated by a previous experimental study [22]. Experiments in multiple numbers are required to determine these characteristics. In this way, researchers have tried to overcome the challenges of cost and time by using genetic algorithms, artificial intelligence applications, fuzzy logic, artificial neural networks, and mathematical models. In this article, ANN is used to predict the results obtained from experimental data. It confirmed that the results obtained from the ANN training and testing are close to the real ones, confirming the possibility of using the ANN model to predict the buckling loads of hybrid composite plates, and the results are summarized below:

- In this study, it is seen that the values obtained from the training and testing phase are close to the real values. This result shows that it is possible to predict the critical buckling loads of hybrid composite plates with ANN.
- The network structure consisting of four inputs and one output gave high-accuracy predictions. Due to the low error rate of the training phase, the testing phase of the ANN was started and it was seen that the selected value was very close to the real test result.
- It has been concluded that a mathematical model can be created with ANN by reducing the number of experiments in the buckling load estimation of composite plates.
- Compared to experimental methods, it was possible to make predictions more quickly with ANN in the study.
- As a result of comparing the critical buckling load values predicted by ANN models, it can be concluded that the use of neural networks in calculating the buckling loads of rods subjected to axial load is appropriate, without the need for classical methods (experimental studies) that lead to a loss of time and cost, the use of ANN will be useful without a significant loss in terms of results.

- As a result of the experimental study, it was concluded that the stacking sequences of the composite and different ambient conditions affect the buckling behavior of hybrid composite materials.

- When the buckling behavior of hybrid composite specimens kept in four different ambient conditions was compared, it was observed that the critical buckling strengths of the specimens kept in cold ambient conditions were the highest. Based on this result, it was concluded that the cold environment had a positive effect on the buckling behavior of hybrid composite materials.

- It has been observed that the buckling strength of hybrid composite samples immersed in Seawater is lower than the buckling strength of samples kept in other ambient conditions. From this point of view, it was concluded that humidity and salt water negatively affect the strength of hybrid composite materials.

- It has been observed that the critical buckling load of hybrid composite samples increases as the waiting time in the cold environment increases.

- It has been observed that the critical buckling load decreases as the time of immersion of the hybrid composite samples in seawater increases.

Ethics in Publishing

There are no ethical issues regarding the publication of this study.

Author Contributions

The authors contributed equally. The first author: Concept, Data Collection &/or Processing, Software, Analysis of Results. The second author: Concept, Draft Preparation, Writing-Review &Editing. The third author: Literature Review, Experimental Data.

References

[1] Madenci, E, Shkarayev, S, Sergeev, B, Opliger, D.W., Shyprykevich, P. (1998). Analysis of composite laminates with multiple fasteners. *International Journal of Solids and Structures*, 35(15),1793-1811.

[2] Okutan, Baba B. (2007). Buckling behavior of laminated composite plates. *Journal of Reinforced Plastics & Composites*, 26(16),1637-1655.

[3] Davalos, J. E., Qiao, P., Salim, H. A.(1997). Flexural-torsional buckling of pultruded fiber reinforced plastic composite I - Beams: experimental and analytical evaluations. *Composite Structure*, 38(1-4), 241-250.

[4] Ray, C. (2004). An investigation on the effect of fiber weight fraction on buckling of laminated composite plates. *Journal of Reinforced Plastics & Composites*, 23(9),951–957.

[5] Erklig, A, Yeter, E. (2012). The effects of cutouts on buckling behavior of composite plates. *Science and Engineering of Composite Materials*, 19, 323–330.

[6] Hamani, N., Ouinasa, D., Taghezoutb, N., et al. (2013). Effect of fiber orientation on the critical buckling load of symmetric composite laminated plates. *Advanced Materials Research*, 629,95-99.

[7] Yang, B, Fu, K, Lee, J, Li, Y. (2021). Artificial Neural Network (ANN)-based residual strength prediction of carbon fiber reinforced composites after impact. *Applied Composite Materials*,1-25.

[8] Xu, X., Elgamal, M., Doddamani, M., Gupta, N. (2021). Tailoring composite materials for nonlinear viscoelastic properties using artificial neural networks. *Journal of Composite Materials*, 55(11),1547-1560.

[9] Zhang, Z., Friedrich, K. (2003). Artificial neural networks applied to polymer composites: A review. *Composites Science and Technology*, 63, 2029-2044.

[10] Kadi, H. (2006). Modeling the mechanical behavior of fiber-reinforced polymeric composite materials using artificial neural networks. *Composite Structures*, 73(1),1-23.

[11] Haj-Ali, R., Kim, H. (2007). Nonlinear constitutive models for FRP composites using artificial neural networks. *Mechanics of Materials*, 39(12), 1035-1042.

[12] Albuquerque, V.H.C., Tavares, J., Durao, L. (2009). Evaluation of delamination damage on composite plates using an artificial neural network for the radiographic image analysis. *Journal of Composite Materials*, 44(9), 1139-1159.

[13] Tekin, A., Öndürücü, A., Esendemir, Ü. (2017). ANN evaluation of bearing strength on pin-loaded composite plates in different environmental conditions. *Material Testing*, 59(7-8), 696-702.

[14] Islak, S., Akkaş, M., Kaya, Ü., Güleç, H. G. (2017). Estimation of mechanical and physical properties of Cu-Ti composites by artificial neural networks (ANN) model. Journal of Applied Science and Technology, 12(3),122–129.

[15] Kim, M., Kang, S., Kim, C., Kong, C. (2007). Tensile response of graphite-epoxy composites at low temperatures. *Composite Structures,* 79(1),84-89.

[16] Torabizadeh, M. A. (2013). Tensile, compressive, and shear properties of unidirectional glass epoxy composites subjected to mechanical loading and low-temperature services. *Indian Journal of Engineering and Materials Sciences*, 20,299-309.

[17] Jiangbo, B., Junjiang, X. (2014). Temperature effect on buckling properties of ultra-thin-walled lenticular collapsible composite tube subjected to axial compression. *Chinese Journal of Aeronautics*, 27(5),1312-1317.

[18] Gu, H. (2009). Behaviors of glass fiber-unsaturated polyester composites under seawater environment. *Materials & Design*, 30(4),1337–1340.

[19] Öndürücü, A. (2012). The Effects of seawater immersion on the bearing strength of woven glass-epoxy prepreg pin-loaded joints. *International Journal of Damage Mechanics*, 21, 153–170.

[20] Karakuzu, R., Kanlıoğlu, H., Deniz, M. E. (2018). Effect of seawater on pin-loaded laminated composites. *Material Testing*, 60(1), 85–92.

[21] Öndürücü, A., Kayıran, H. F. (2019). Effect of seawater on the buckling behavior of hybrid composite plates. *Journal of Composite Materials*, 53(9),1135-1144.

[22] Kayıran, H. F. (2018). Investigation of buckling behavior in hybrid composite plates subjected to different environmental conditions. Süleyman Demirel University, Graduate School of Natural and Applied Sciences, Ph.D. Thesis, Isparta.

[23] Karataş, Ç., Sözen, A., Dülek, E. (2009). Modeling of Residual stresses in shot-peened material C-1020 by artificial neural networks. *Expert Systems with Applications*, 36(2),3514-3521.

[24] Eker, A.M., Dikmen, M., Cambazoğlu, S., et al. (2012). Application of artificial neural networks and logistic regression methods to landslide susceptibility mapping and comparison of the results for the Ulus district, Bartın. *Journal of the Faculty of Engineering and Architecture of Gazi University*, 27(1),163-173.

[25] Sarali, D.S., V.A.I., Pandiyan, K. (2019). An improved design for neural-network-based model predictive control of three-phase inverters. *In Proceedings of the 2019 IEEE International Conference on Clean Energy and Energy Efficient Electronics Circuit for Sustainable Development (INCCES)*, Krishnankoil, India, 18-20 December, 1-5.

[26] Tiryaki, S., Bardak, S., Bardak, T. (2015). Experimental investigation and prediction of bonding strength of Oriental beech (Fagus orientalis Lipsky) bonded with polyvinyl acetate adhesive. *Journal of Adhesion Science and Technology*, 29 (23), 2521-2536.