Artificial Neural Network-based fatigue behavior prediction of metals and composite materials

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Abstract: This article presents a study devoted to predicting the fatigue behavior of two different materials: aluminum alloy AL-2024-T6 and glass fiber composite samples. The approach used in the study involves the use of artificial neural networks (ANNs) to develop accurate models for predicting the fatigue life of these materials at various skewness ratios (R). For the first case study, the S-N curve of tensile-tested AL-2024-T6 was predicted for different values of R using a few sets of data for learning. The model was then tested on the same values of R as the learning set, as well as on a different value of R (-0.4), to demonstrate the ability of the model to predict fatigue data under varying conditions. The results showed that the model was capable of accurately predicting the fatigue life of AL-2024-T6 for different values of R. For the second case study, the stiffness degradation of bending-tested glass fiber woven composite samples was predicted for different values of R using ANN. Different layups of composite samples were considered in this study. The model was trained on a few sets of data and tested on the same and different values of R, demonstrating the ability of the model to accurately predict stiffness degradation of composite samples under varying coefficients of asymmetry. The results of both case studies showed that ANN-based models can be effective in predicting the fatigue behavior of different materials tested using different methods under varying coefficients of asymmetry. These findings have practical implications for industries involved in the design and manufacturing of materials, particularly in the aerospace and automotive sectors, where fatigue behavior is critical to the structural integrity of components.

1 Introduction

Fiber-resin composites are now widely used in many areas of engineering, especially in various means of transport such as aircrafts or automobiles. These materials have remarkable strength and low weight, making them the preferred choice for many applications. Despite fiber-reinforced composites having a good fatigue lifetime rating, the damage starts early due to their anisotropic and inhomogeneous nature. Therefore, fatigue must be considered when designing with composites, and procedures must be developed to predict the damage accumulation and expected lifetime of the material/component [1]. As the stiffness

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degradation starts early in composites, it imposes additional dangers when applied to civilian transportation. As a result, the structure loses efficiency when safety stands first in composite structures that are subjected to cycling loadings. This sometimes reduces the weight advantages of non-metallic materials greatly.

To safely use composite materials in structural elements, it is necessary to know precisely when the failure of material is occurred and how the properties are reduced during the structure life. There are several approaches developed for composites fatigue modelling such as classical S-N curves-based models [2, 3], residual strength [4-6] and stiffness [7-9] models, progressive damage models [10, 11]. In the topic reviews of the end of 20th century and the start of 21st century [12-14] and 2021st year review [15] scientists come to similar conclusions that there should be developed a model for realistic structures which accounts for a lot of different conditions and factors. The little difference in conclusions of reviews so widely separated in time means that there were no general inventions in the field of fatigue modelling of composites. However, recently a new approach started to get useful.

One of the innovative methods for the fatigue life prediction is the use of Artificial Intelligence. There are several methods that were used and tested for fracture mechanics analysis and mechanical fault detection: Fuzzy Logic, Case Based Reasoning, Genetic Algorithm, Bayesian Network, and Artificial Neural Network [16]. It could also be seen that there are many fields of engineering which used ANN for various applications [17-19] and for fatigue in particular [20-23]. In this work the ANN method is chosen for fatigue behavior prediction. It can provide high accuracy and great flexibility as it may be applied to any material which is also shown in this work. This modelling tool uses available data from experiments and predicts the material behavior based on what was “learned”.

This work shows that ANN can predict the material’s fatigue life based on some previously learned assets for different values of the coefficient of asymmetry. Moreover, it shows that the material is not important for this method as the prediction result are both accurate for the conventional alloy and the composite. With the successful application of ANNs to predict fatigue life, it becomes possible to reduce safety factors and fully exploit the potential weight advantages offered by non-metallic composite materials.

2 Computational method

2.1 ANN general description

An artificial neural network (ANN) is the name of computational approach. Among the many descriptions, the one common stands out first: ANNs are digital systems that are built to recognize patterns and make sense (for themselves) of complex sets of data. The inspiration for their creation was taken from nature as these systems aim to imitate the work of a living creature’s brain.

An artificial neural network consists nodes called artificial neurons which are organized in layers and interconnected between each-other. Three basic layer types in a typical ANN are called input, hidden and output. The total number of hidden layers may vary, it depends on the complexity of an ANN. Initial data comes to the input layer, then it gets processed in the hidden layer and then the final result of network calculations is obtained on the output layer (fig. 1-6).

The network operates by assigning weights to inputs received by each neuron. These inputs are multiplied by their corresponding weights, and the resulting products are aggregated. Subsequently, the sum undergoes a non-linear transformation through an activation function. The output from each neuron serves as input for the neurons in the subsequent layer, establishing a continuous flow of information within the network. The structure of a typical ANN could be seen on Fig. 2

In the training phase, the Artificial Neural Network (ANN) undergoes training utilizing a dataset comprising input-output pairs. The neurons' weights and biases undergo iterative adjustments through a process known as backpropagation. This technique involves propagating the error between the network output and the desired output back through the network. Consequently, the network progressively refines its internal parameters, enhancing its capacity to make precise predictions or classifications.

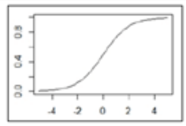
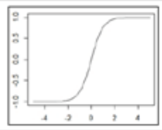
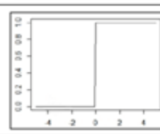
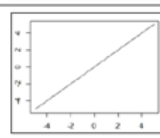
Function	Equation	Chart
Sigmoid	$f(x) = \frac{1}{1+e^{-x}}$	
Hyperbolic tangent	$f(x) = \frac{1-e^{-x}}{1+e^{-x}}$	
Hard limiting threshold	$f(x) = \begin{cases} 0 & if\ x < 0 \\ 1 & if\ x \geq 1 \end{cases}$	
Linear	$f(x) = x$	

Fig. 1. Activation functions equations and shapes.

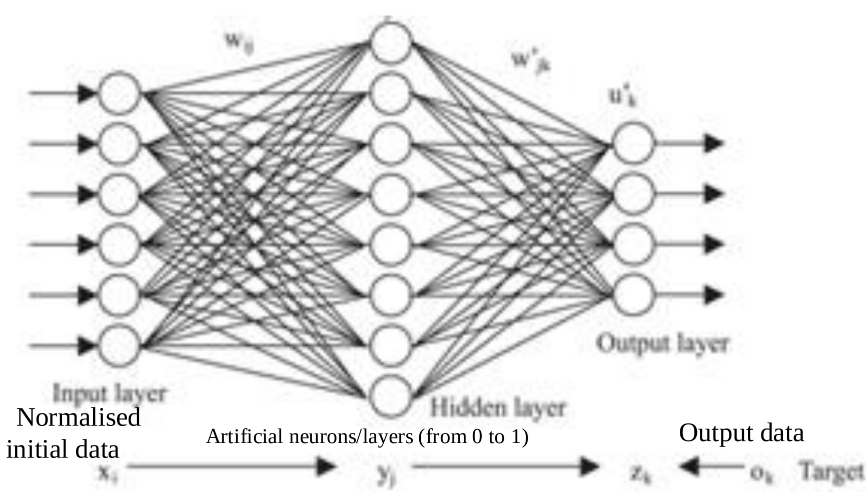


Fig. 2. Artificial Neural Network scheme.

3 Method validation

A method to validate the accuracy of an ANN in predicting fatigue behavior is to run it through test problems for various materials.

3.1 First validation task

The first task is to obtain the S-N curve for the aluminum 2024-T6

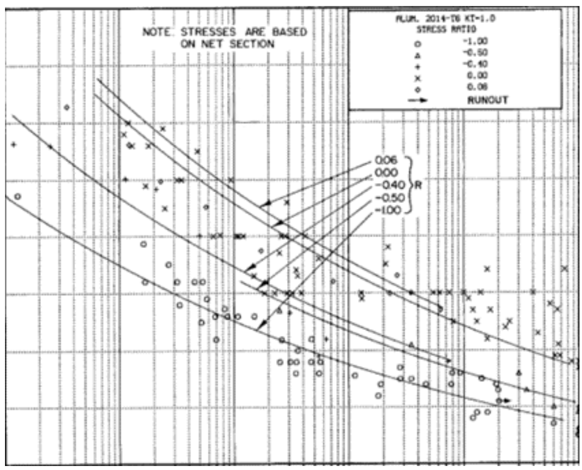
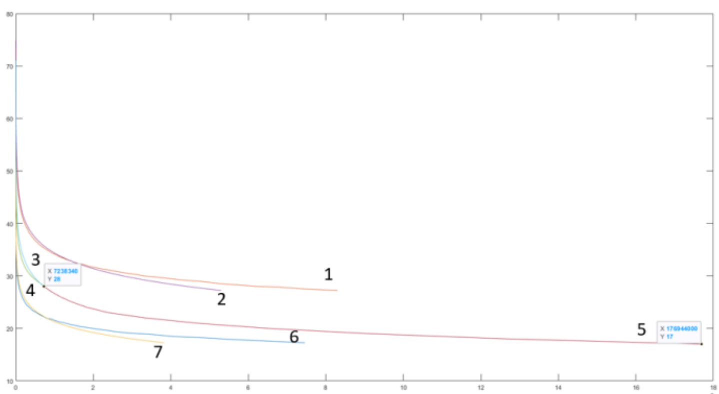


Fig. 3. Reference SN curves for AL 2024-T6 [24].



1,3,6 – Initial data for (R = 0, -0.4, -1)

2,4,7 – Predicted data for (R = 0, -0.4, -1) based on (R = 0, -1)

5 – Predicted extrapolation for curve №4 (R = -0.4)

Fig. 4. Initial and obtained curves for AL 2024-T6.

3.2 Second validation task

The second test task is to obtain predicted force-cycle curve for composite sample bending.

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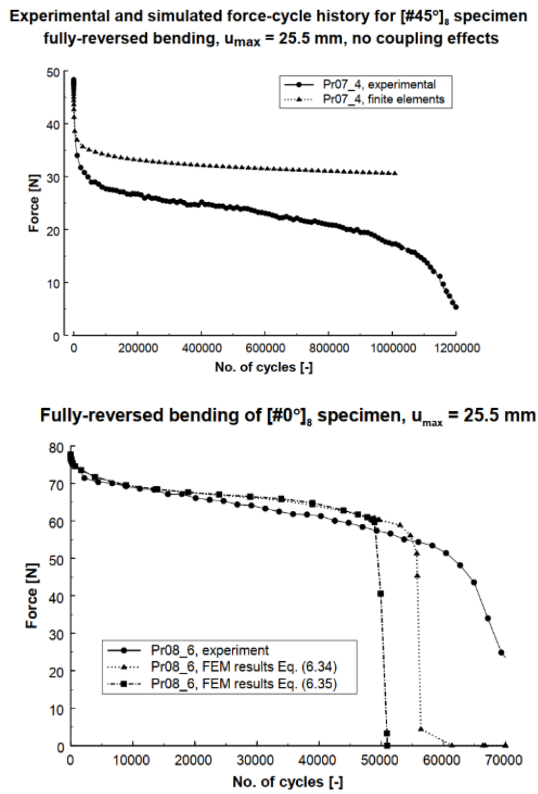
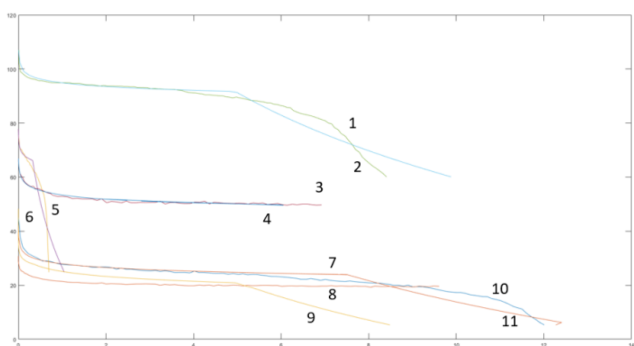


Fig. 5. Reference stiffness degradation curves for e-glass/epoxy composite [25].



1,3,5,10 – Initial data for different layups and asymmetry coefficients R
2,4,6,7,9,11 – Predicted data
9 – Predicted curve without initial data

Fig. 6. Initial and obtained curves for r e-glass/epoxy composite.

4 Results discussion

Taking into account the dispersion of the initial data, ANN predicted curves turned out to be of relatively good accuracy. There was found a relation between the initial data given for the ANN learning and the output predictions. So, if ANN learned on two sets of the data with the coefficients of asymmetry R = 0,4 and R = 1 it could be said that it will give good prediction for R lying within the interval of 0,4 and 1. The prediction will lose accuracy when R is taken out of the interval, the further from the initial borders the worse the accuracy is.

5 Conclusion

Novel computational tool such as ANN proves to be a reliable modeling tool for capturing the nonlinear characteristics of CFRP laminates under constant amplitude loading. This method exhibits effectiveness in representing fatigue life characteristics for various material systems, displaying comparable or superior modeling capabilities when compared to alternative methods. To this day, ANN have been used as nonlinear regression tool stochastic in its nature. The advantages of this approach can be summarized like: Computational methods, like ANN, function as stochastic tools for nonlinear regression, enabling the modeling of fatigue behavior in any material, provided sufficient training data is available. The stochastic nature of these methods is crucial, generating distinct outputs for identical input data with each model run. This property facilitates the creation of new datasets based on specific inputs to enhance limited databases. The modeling process avoids reliance on assumptions, such as adherence to a specific statistical distribution for the data or the use of a power curve equation to represent the S-N curve. Additionally, the method does not account for the mechanics inherent in each material system. In short, this computational approach is a data-driven and material-independent method that correlates input and output values to establish a model describing their relationship. Consequently, the proposed method readily lends itself to application across various materials, contingent upon the availability of sufficient data. The S-N curves derived through this data-driven modeling technique do not adhere to any predetermined mathematical form; rather, they conform to the trend observed in the available data, providing the best estimate of material behavior in each instance. While previous studies have demonstrated the ease with which output data can be fitted with simple second to fourth-order polynomial equations, caution is warranted in cases involving limited datasets, as artificial intelligence methods may risk overfitting in such instances.

References

1. K. L. Reifsnider, *Life prediction analysis: directions and divagations.* Sixth International Conference on Composite Materials and Second European Conference on Composite Materials(ICCM & ECCM) **4** (1987)
2. K.L. Reifsnider, Zh. Gao. Int. J. of Fatigue **13.2** (1991): 149-156. doi: 10.1016/0142-1123(91)90007-L
3. T.P. Philippidis, A. P. Vassilopoulos, Journal of Composite Materials **33.17** (1999): 1578-1599. doi: 10.1177/002199839903301701
4. J. R., Schaff, B. D. Davidson. Journal of composite materials **31.2** (1997): 128-157. doi: 10.1177/0021998397031002
5. W.X. Yao, N. Himmel. Composites science and technology **60.1** (2000): 59-64. doi: 10.1016/S0266-3538(99)00100-1
6. H. A. Whitworth, Composite structures **48.4** (2000): 261-264. doi: 10.1016/S0263-8223(99)00113-0
7. J. Gao, et al. Engineering Failure Analysis **137** (2022): 106290. doi: 10.1016/j.engfailanal.2022.106290
8. Samareh-Mousavi, Seyed Sina, and Fathollah Taheri-Behrooz. Composite Structures **237** (2020): 111955. doi: 10.1016/j.compstruct.2020.111955

9. L. Herrmann, et al. Composites Science and Technology **230** (2022): doi: 109729. 10.1016/j.compscitech.2022.109729
10. J. Sun, et al. International Journal of Mechanical Sciences **259** (2023): 108604.
11. M.M., Shokrieh, L.B. Lessard. Journal of composite materials **34.13** (2000): 1056-1080. doi: 10.1177/002199830003401301
12. B. Harris, *Fatigue behaviour of polymer-based composites and life prediction methods.* AIB-Vinçotte Leerstoel 2 (1996)
13. R. Talreja, *Fatigue damage evolution in composites-A new way forward in modeling.* Proceedings of the second international conference on fatigue of composites. (2000)
14. J. Degrieck, W. Van Paepegem. Appl. Mech. Rev. **54.4** (2001): 279-300. doi: 10.1115/1.1381395
15. C, Ganesan, P. S. Joanna, D. Singh. Materials Today: Proceedings **46** (2021): 555-561. doi: 10.1016/j.matpr.2020.11.119
16. S. Nasiri, M. Reza Khosravani, K. Weinberg. Engineering Failure Analysis **81** (2017): 270-293. doi: 10.1016/j.engfailanal.2017.07.011
17. T. Cong, et al. Progress in Nuclear Energy **62** (2013): 54-71. doi: 10.1016/j.pnucene.2012.09.003
18. X. Wang, Ch. Miao, R. Chen. Structures. **42**. (2022). doi: 10.1016/j.istruc.2022.06.020
19. A.Y. Alanis, et.al., eds. Artificial neural networks for engineering applications. (Academic Press, 2019). doi: 10.1016/C2018-0-01649-7
20. J.A. Lee, et.al., Composites Part A: Applied Science and Manufacturing **30.10** (1999): 1159-1169. doi: 10.1016/S1359-835X(99)00027-5
21. A.P., Vassilopoulos, et.al., International Journal of Fatigue **29.1** (2007): 20-29. doi: 10.1016/j.ijfatigue.2006.03.004
22. G. A. B. Oliveira, et al. International Journal of Fatigue **162** (2022): 107011. doi: 10.1016/j.ijfatigue.2022.107011
23. G. A. B. Oliveira, et al. Tribology International **180** (2023): 108250. doi: 10.1016/j.triboint.2023.108250
24. United States. Dept. of Defense. Military Handbook: Metallic Materials and Elements for Aerospace Vehicle Structures. Vol. 1. US Department of Defense (1990)
25. Van Paepegem, Wim. Development and finite element implementation of a damage model for fatigue of fibre-reinforced polymers (GUAP, 2002)