Prediction of the mechanical properties of Polypropylene reinforced with Snail Shell Powder with a Deep Neural Network Model and the Finite Element Method

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Abstract. Neural networks have led to the evolution of the processing methodology of computational sciences. The problems like bio composites modeling and prediction are difficult to model with classical mathematical and statistical tools because of the data inherent noise. NN’s processing capability in the forecasting, recognition, modeling, system analysis and control can give fast characterization, modeling and prediction of bio composites properties, provided as long as datasets are available. Using Matlab®, a neural network model was evaluated to characterize the optimal properties of the ANS reinforced the Polypropylene. The feed forward multilayer model provided best results in comparison with the finite element method and the experimental tensile tests. The trained neural network is able to provide a best prediction of such bio composite based on natural particles having more advantages to the environment, economy and the sustainable development.

Key words: Bio composites, Natural Particles, Neural network, Feed forward multilayer, Finite Element Method.

1. Introduction

Neural network approach can be trained to give intelligent decisions by using its knowledge base[1]–[4]. Researchers confirmed that particles reinforced polymers properties are non-homogeneous, inconsistent and varying [5]–[10]. Based on learning and adaptation, the neural structure and the problem definition can serve in prototype development of novel bio composites and generate several decisions reserved to human expert.

NN have shown good results towards modeling composites property. Research results illustrate that with an appropriate NN aid and best base research knowledge we will be able to the fast characterization, modeling and prediction of novel bio composites materials. Neural networks will help the appropriate characterization of eco composites by using real data to develop an efficient system in the correct domain [11].

In this study, we will predict using the neural network the Young modulus of snail shell powder reinforced Polypropylene in comparison with the finite element method which is known for its efficiency in predicting complex mechanical behaviors [12]–[15].
2. Material and methods

2.1 Sample preparation

The collected snails are from rural areas of Casablanca (Morocco). We carefully removed the shells. Firstly, we washed shells with the tap water in order to remove, sand, mud and the other impurities. Secondly, we cleaned the shells and dried them at 80°C in an oven during 24 h. Finally, the bio load was sieved to take only particles under 10 μm. The figures 1, 2 and 3 present respectively the structure of Polypropylene, Snails collected and Snail shell powder.

![Figure 1. Polypropylene structure](image1)

![Figure 2. Snail shell collected](image2)
2.2 Composites processing

To study the Snail shell effect on the properties of the polypropylene matrix, compounding was performed in the Leistritz GmbH extruder. Mixing was done using 125 rpm in the speed of screw. Polypropylene was introduced at the principal hopper and the snail shell along a side-feeder at 40 rpm of the screw speed. The water bath is used to cool the compounds. Then, the samples were made on a molding injection machine (e-Victory Engel). The injection barrel temperature is fixed at 200°C, and the nozzle is set at 180°C with 45°C at the mold. The figure 4 shows the polypropylene in pure state and reinforced with snail shell powder.

![Figure 3. Snail shell powder](image)

![Figure 4. Polypropylene samples: (a) Pure PP, (b) Snail shell reinforced PP.](image)
2.3 Tensile test

The test is performed in the tensile test machine presented in figure 5. The test follows a well-defined operating mode among the parameters to be adjusted with a speed set at 25mm / min and an applied preload of 5.6N.

![Tensile test machine](image)

**Figure 5.** Tensile test machine

2.4 Finite element method

The finite element method is one of the tools of applied mathematics. In numerical analysis, the finite element method is used to numerically solve partial differential equations. It can for example represent analytically the dynamic behavior of certain physical systems (mechanical, thermodynamics, acoustics, etc.). In mathematics, this involves replacing a complicated problem for which a priori we do not know a solution, by a more simple that we know how to solve.

The geometry and the mesh generated for the snail shell reinforced polypropylene by tetra quadratic elements are presented in figures 6 and 7.

![Geometry of Snail Shell reinforced Polypropylene](image)

**Figure 6.** Geometry of Snail Shell reinforced Polypropylene
Figure 7. Mesh of Snail Shell reinforced Polypropylene

2.5 Neural network model

The principal concept of the neural network is taken from the neuroscience. The architecture of the multilayer is shown in figure 8. The input is the first network layer and the output is the last one. The hidden layers present the layers between input and output.

Figure 8. Neural network model architecture

3. Results and discussion

3.1. Experimental results

The figure 9 illustrates the tensile curves of pure PP and reinforced by Snail Shell Powder.
Figure 9. Tensile curves of pure PP and reinforced by Snail Shell Powder

The results of the tensile test on pure PP and reinforced with Snail Shell Powder illustrated in the figure 9 clearly show that the reinforced PP is more rigid with a Young modulus of 1981 MPa at 30% of particles compared to the pure one that presents 1034 MPa.

3.2. Finite element results

Figure 10 shows the finite element tensile curves for the two types of Polypropylene

It is observed in the figure 10 that the results of the FEM confirm the experimental tests. The Young modulus increase to 1945 MPa in comparison with the pure state of PP (1034 MPa) leading to an increase of the rigidity of the reinforced PP at 30% of particles.
3.3. Neural network model

The evaluation of the ANN performance can be done by two statistical indicators provided by Matlab. They are the correlation coefficient (R) and mean square error (MSE). Figures 11, 12 and 13 present respectively the MSE, training state and R coefficient at 6 epochs.

![Figure 11. Neural network training performance](image1)

![Figure 12. Neural network training state](image2)
Figure 13. Neural network correlation coefficient

The more the R is closest to 1 and the more the value of the MSE is lower, the better the ANN is performant. Lowest value of the MSE (0.031428) is observed for the Young modulus prediction (1963 MPa). The best accuracy is also determined in terms of the coefficient of correlation, with an R equal to 0.99995 for the training and 1 for the validation and test which confirm the performance of the neural network model chosen.

4. Conclusion

In this study, we tried to confirm the effect of bio loading the polypropylene matrix with snail shell powder with neural network model and the finite element method in comparison with the experimental tensile test.

It was observed that the rigidity of the bio composite obtained at 30% of particles led to an increase of Young modulus from 1034 MPa to 1945, 1963 and 1981 MPa by the finite element method, neural network model and experimental tensile test respectively.

The neural network model proved a good efficiency to predict the Young modulus of the bio composite compared to the well-known finite element method. The best results obtained in the test phase illustrate that NNs are able to generalize the complicated link between input and output set of data learned in the phase of training which allow us to make a satisfactory predictive model for the Young modulus.
References

[1] H. Su, W. Qi, C. Yang, J. Sandoval, G. Ferrigno, and E. De Momi, “Deep neural network approach in robot tool dynamics identification for bilateral teleoperation,” IEEE Robot. Autom. Lett., vol. 5, no. 2, pp. 2943–2949, 2020.

[2] H.-T. Bang, S. Park, and H. Jeon, “Defect identification in composite materials via thermography and deep learning techniques,” Compos. Struct., vol. 246, p. 112405, 2020.

[3] Y.-C. Hsu, C.-H. Yu, and M. J. Buehler, “Using deep learning to predict fracture patterns in crystalline solids,” Matter, vol. 3, no. 1, pp. 197–211, 2020.

[4] Y. Gao, H. Yao, H. Wei, and Y. Liu, “Physics-based Deep Learning for Probabilistic Fracture Analysis of Composite Materials,” in AIAA Scitech 2020 Forum, 2020, p. 1860.

[5] A. Moumen, M. Jammoukh, L. Zahiri, and K. Mansouri, “Study Of The Optimal Micromechanical Behavior Of A Polymer Reinforced By Snail Shell Particles Using The Mori-Tanaka Numerical Model,” in 2020 IEEE International conference of Moroccan Geomatics (Morgeo), 2020, pp. 1–6, doi: 10.1109/Morgeo49228.2020.9121908.

[6] A. MOUMEN, A. LAKHDAR, M. JAMMOUKH, L. ZAHERI, and K. MANSOURI, “Optimization of the Mechanical and Morphological Properties of Polypropylene Bio-Loaded by Argan Nut Shell Particles with Different Theoretical and Numerical Models,” in 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS), 2020, pp. 1–6.

[7] A. Belaadi, M. Boumaza, S. Amroune, and M. Bourchak, “Mechanical characterization and optimization of delamination factor in drilling bidirectional jute fibre-reinforced polymer biocomposites,” Int. J. Adv. Manuf. Technol., vol. 111, no. 7, pp. 2073–2094, 2020.

[8] A. Sharma, S. A. Kumar, and V. Kushvaha, “Effect of aspect ratio on dynamic fracture toughness of particulate polymer composite using artificial neural network,” Eng. Fract. Mech., vol. 228, p. 106907, 2020.

[9] Q. Sun and T. Ertekin, “Screening and optimization of polymer flooding projects using artificial-neural-network (ANN) based proxies,” J. Pet. Sci. Eng., vol. 185, p. 106617, 2020.

[10] J. S. Chohan et al., “Mechanical Strength Enhancement of 3D Printed Acrylonitrile Butadiene Styrene Polymer Components Using Neural Network Optimization Algorithm,” Polymers (Basel), vol. 12, no. 10, p. 2250, 2020.

[11] G. Balokas, S. Czichon, and R. Rolfes, “Neural network assisted multiscale analysis for the elastic properties prediction of 3D braided composites under uncertainty,” Compos. Struct., vol. 183, pp. 550–562, 2018.

[12] A. Moumen, M. Jammoukh, L. Zahiri, and K. Mansouri, “Numerical modeling of the thermo mechanical behavior of a polymer reinforced by horn fibers,” Int. J. Adv. Trends Comput. Sci. Eng., vol. 9, no. 4, pp. 6541–6548, 2020, doi: 10.30534/ijtcese/2020/342942020.

[13] A. Lakhdar, M. Jammoukh, L. Zahiri, K. Mansouri, A. Moumen, and B. Salhi, “Numerical and Experimental Study of the Behavior of PVC Material Subjected to Aging,” in 2020 1st International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), 2020, pp. 1–6.

[14] A. Moumen, A. Lakhdar, and K. Mansouri, “Numerical study of the mechanical behavior of polyamide 66 reinforced by argan nut shell particles with the finite element method and the mori-tanaka model,” Int. J. Adv. Trends Comput. Sci. Eng., vol. 9, no. 5, pp. 7723–7730, 2020, doi: 10.30534/ijtcese/2020/115952020.

[15] K. M. Abdelghani Lakhdar, Aziz Moumen, Laidi Zahiri, Mustapha Jammoukh, “Experimental and Numerical Study of the Mechanical Behavior of Bio-Loaded PVC Subjected to Aging,” Adv. Sci. Technol. Eng. Syst. J., vol. 5, no. 5, pp. 607–612, 2020.