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NEURAL NETWORK-BASED SIMULATION OF THE INFLUENCE OF WASTE TIRE RUBBER ON POLYESTER-FIBERGLASS COMPOSITES

Ahmed S. AbdelWanees, T. S. Mahmoud, I. M. Ibrahim, Ahmed O. Mosleh

Mechanical Engineering Department, Faculty of Engineering at Shoubra, Benha University, El Sahel, 11614, Cairo, Egypt

***Correspondence:** ahmed.abdallah18@feng.bu.edu.eg

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ABSTRACT

This research presents a comprehensive neural network-based simulation to delve into the intricate relationship between waste tire rubber and polyester fiberglass composites. By meticulously investigating the effects of varying mesh sizes and volume percentages of rubber particles, the fabrication process utilizes hand lay-up and vacuum degassing to ensure optimal composite quality. The study aims to accurately predict the mechanical and dynamic properties of these composites. These properties, including ultimate tensile strength (UTS), strain, impact resistance, natural frequency, and damping factor, are critical determinants of the composite's performance in various applications. A neural network model was meticulously crafted and trained using the backpropagation algorithm, with a mean squared error of 10^{-8}. This exceptional accuracy underscores the model's ability to effectively capture the complex interactions between the composite components. The model demonstrated remarkable proficiency in predicting UTS, impact resistance, natural frequency, and damping factors, achieving regression coefficients of R= 96.30%, 96.50%, 97.80%, and 97.40%, respectively. Moreover, the strain prediction accuracy was commendable, with a regression coefficient of R= 94.20%. These findings collectively underscore the immense potential of neural networks in optimizing the design of composite materials incorporating waste tire rubber. By leveraging the predictive capabilities of these models, researchers and engineers can develop sustainable materials that not only exhibit superior performance but also contribute to a more environmentally responsible future. The integration of waste tire rubber into composite materials offers a promising avenue for reducing waste and promoting circular economy principles.

KEYWORDS: Neural Networks, Recycling, Polyester-Fiberglass Composites, Waste Tire Rubber Particles, Mechanical and Dynamic Properties.

محاكاة تأثير المطاط المستخرج من الإطارات المستعملة على المواد الموتلفة من البوليستر و الألياف الزجاجية باستخدام الشبكة العصبية

أحمد سيد عبدالونيس، تامر سمير محمود، إبراهيم موسى إبراهيم، أحمد عمر مصلح

قسم الهندسة الميكانيكية، كلية الهندسة، جامعة بنها، الساحل،11614، القاهرة، مصر.

***البريد الاليكتروني للباحث الرئيسي :** ahmed.abdallah18@feng.bu.edu.eg

الملخص

هذا البحث يقدم محاكاة شاملة تعتمد على الشبكات العصبية للبحث في العلاقة المعقدة بين المطاط المستخرج من الإطارات المستعملة ومواد البوليستر-الزجاج .من خلال التحقيق الدقيق في تأثيرات الأحجام المتفاوتة للجزيئات المطاطية والنسب المئوية لحجمها،.مصنّعة باستخدام الترصيف اليدوي وإزالة الغازات في غرفة تفريغ للقضاء على فقاعات الهواء لضمان جودة التصنيع. يهدف البحث إلى التنبؤ بدقة بالخصائص الميكانيكية والديناميكية لهذه المواد المركبة .تشمل هذه الخصائص القوة القصوى للشد، والاجهاد، ومقاومة الصدم، والتردد الطبيعي، وعامل التخميد، وهي عوامل حاسمة في أداء المواد

المركبة في مختلف التطبيقات. تم إنشاء نموذج الشبكة العصبية وتدريبه باستخدام خوارزمية الانتشار العكسي، مع خطأ تربيعي متوسط قدره 10^{-8} تشير هذه الدقة الاستثنائية إلى قدرة النموذج على التقاط التفاعلات المعقدة بين مكونات المواد المركبة بشكل فعال .أظهر النموذج كفاءة رائعة في التنبؤ بمقاومة الشد ومقاومة الصدم والتردد الطبيعي وعوامل التخميد، محققًا معاملات الانحدار R = 96.30٪ و 96 ٪50.و 97 ٪80.و 97 ٪40.على التوالي .علاوة على ذلك، كانت دقة التنبؤ بالانفعال جيدة مع معامل الانحدار R = 94.20٪. تؤكد هذه النتائج مجتمعة الإمكانات الهائلة للشبكات العصبية في تحسين تصميم المواد المركبة التي تستخدم المطاط المستخرج من الإطارات المستعملة .من خلال الاستفادة من القدرات التنبؤية لهذه النماذج، يمكن للباحثين والمهندسين تطوير مواد مستدامة لا تظهر فقط أداءً متفوقًا بل تساهم أيضًا في مستقبل أكثر مراعاة للبيئة .يمثل دمج المطاط المستخرج من الإطارات المستعملة في المواد المركبة طريقًا واعدًا للحد من النفايات وتعزيز مبادئ الاقتصاد الصديق للبيئة.

الكلمات المفتاحية : الشبكات العصبية ، إعادة التدوير ، مركبات البوليستر و الالياق زجاجية ، جزيئات مطاط الإطارات المستعملة ، الخواص الميكانيكية و ديناميكية.

1. INTRODUCTION

Neural networks, inspired by the biological architecture of the human brain, have emerged as a potent computational paradigm for modeling and predicting intricate systems [1]. Within the domain of materials science and engineering, these networks have exhibited exceptional proficiency in processing voluminous datasets, discerning complex correlations, and generating precise forecasts [2,3]. By capitalizing on their data-driven learning capabilities, neural networks offer the potential to accelerate materials development, minimize costs, and expand the exploration of the design space [4].

Artificial neural networks (ANNs) have garnered significant attention as a computational paradigm capable of learning complex patterns from data. These networks are trained on datasets to establish intricate relationships among input and output variables. Once trained, ANNs can generalize their knowledge to predict or classify new, unseen data. Their adaptability and ability to handle complex, nonlinear problems have made them invaluable tools in various domains. Notably, ANNs have demonstrated efficacy in modeling and predicting the properties of materials, such as composites [5].

The escalating global waste crisis, characterized by the persistent accumulation of non-biodegradable materials, demands innovative strategies for environmental remediation and sustainable resource management [6]. Waste tires, a prominent component of this issue, pose a significant challenge owing to their recalcitrance to degradation and associated environmental risks [7,8]. Exploring the potential of repurposing waste tire rubber particles as reinforcement within polyester-fiberglass composite laminates is an approach to address this environmental concern [9], [10].

Composite materials have garnered considerable attention across diverse industries due to their exceptional strength-to-weight ratios and design flexibility. Nevertheless, the manufacturing processes of these materials often rely on non-renewable resources [11]. Polyester fiberglass composites are advanced materials comprising a matrix of thermosetting polyester resin reinforced with continuous or discontinuous glass fibers [12]. The glass fibers, typically composed of E-glass, impart exceptional tensile strength, stiffness, and dimensional stability to the composite. The polyester resin, acting as a binding medium, encapsulates the fibers, facilitating load transfer and providing corrosion resistance, chemical inertness, and dielectric properties [13]. The resulting composite exhibits a complex microstructure characterized by the interphase region between the fiber and resin, significantly influencing the material's overall mechanical behavior. This unique combination of properties renders polyester fiberglass composites as versatile engineering materials with applications spanning from automotive and aerospace to marine and construction industries [14].

The constitutive behavior of nitrile butadiene rubber under varying hardness, strain rate, and strain conditions has been studied. Results indicate a pronounced strain-dependent Young's modulus, amplified by increased hardness and strain rate. The proposed artificial neural network architecture comprising two hidden layers, with twelve and seven neurons respectively, demonstrated optimal performance in this study. A novel self-adjusting particle swarm optimization algorithm was employed to dynamically optimize the inertial and learning factors during the network training process, resulting in accelerated convergence and enhanced accuracy. The proposed model achieved a mean squared error of 1.607×10^{-4} on the testing set, corresponding to a root mean squared error of 1.268×10^{-2} and a coefficient of determination of 0.9917. Compared to traditional artificial neural networks and those optimized using standard particle swarm optimization, the proposed model exhibited significant improvements in mean squared error, with reductions of 56.5% and 26.5%, respectively. Cross-validation results corroborated the model's reliability, indicating consistent predictive performance across different data subsets [15].

A convolutional neural network (CNN) model has been developed to accurately predict the mechanical properties (modulus, strength, and toughness) of two-dimensional checkerboard composites. The model was trained on finite element data and subsequently validated on unseen data, demonstrating robust predictive capabilities. By integrating this CNN model with a genetic algorithm optimizer, optimal composite configurations for enhanced performance were identified. These findings highlight the potential of CNN-based approaches to accelerate materials design and optimization [16].

Constitutive models, including Arrhenius-type and artificial neural network (ANN), were developed based on experimental stress-strain data to investigate the superplastic deformation behavior of near-α titanium alloy (Ti-2.5Al-1.8Mn) within the temperature range of 840-890 °C and strain rate range of $2x10^{-4}$ to $8x10^{-4}$ s^{-1}. Comparative analysis revealed that the ANN model exhibited superior accuracy and efficiency in predicting the alloy's superplastic flow behavior under modeled conditions. However, the Arrhenius-type model demonstrated better predictive capabilities for unmodeled conditions, indicating potential limitations of the ANN model in extrapolating to new data regimes [17].

The efficacy of various neural network training algorithms in predicting the bending strength and hardness of particulate-reinforced (Al-Si-Mg) metal matrix composites (MMCs) has been explored. The influence of the number of neurons in the hidden layer was also assessed. Results indicate that neural networks trained using different algorithms can accurately predict these properties, offering a potential alternative to time-consuming experimental methods. Among the tested algorithms, Levenberg-Marquardt demonstrated the fastest convergence and highest prediction accuracy, suggesting its suitability for modeling the mechanical behavior of this material system [18].

The research aims to address the development of a neural network model capable of predicting the dynamic and mechanical properties of polyester-fiberglass composites reinforced with varying amounts of waste tire rubber particles. By correlating material composition, processing parameters, and experimental data, this study seeks to provide valuable insights into composite properties for specific applications.

2. Materials and Methods

The materials used in this study were unsaturated polyester resin, recycled rubber particles, and fiberglass. The resin, sourced from SUNPOL in Turkey, had a 1.23 g/cm³ density. Recycled rubber particles, with sizes of 40 mesh (0.420 mm) and 20 mesh (0.841 mm), which were added in different volume percentages of 10 %, 20 %, and 30 % were obtained from HOPPEC in Egypt and exhibited an average density of 0.4 g/cm³. Fiberglass, product number E01, was supplied by Jushi Chinese-Egyptian company. That had an area weight of 300 g/m² and a roll width of 1524 mm.

Composite laminates were fabricated using a hand lay-up technique, a common method for creating custom composite parts [19]. This process involved constructing a silicone rubber mold based on standard dimensions for tensile and impact specimens. The polyester resin was then mixed with a hardener and degassed before being poured into the mold to cure. To incorporate rubber particles, the resin mixture was prepared again, with the particles added before the curing process. Finally, fiberglass was positioned within the mold, and the resin mixture was applied to create the desired composite structure [20].

The mechanical properties of the composites were determined through standardized testing procedures. Tensile strength was evaluated using a Zwick universal tensile testing machine according to ASTM D 3039 / D 3039M. Rectangular specimens with dimensions of 250x25x3 mm were subjected to a tensile load at a constant crosshead speed of 2 mm/min [21]. Impact resistance was assessed using a JB-300B impact tester following ASTM D 6110-04. Notched specimens with dimensions of 127x13x7 mm were employed for these tests.

A non-destructive free vibration test, following ASTM E756-05 guidelines, was conducted to determine the stiffness and damping properties of the composite materials. A rectangular composite beam was subjected to controlled impacts and its vibrational response was measured using specialized equipment. The data obtained was analyzed using modal analysis software to extract key dynamic parameters. These findings were then correlated with the material properties.

The simulation and modeling have been done using MATLAB software The neural network, was constructed with two input nodes, each representing a significant input variable. MATLAB 2021b's neural network toolkit was employed to train the network

3. Results and Discussion

3.1. Designing and training of neural networks.

A multilayer perceptron (MLP) is a feedforward artificial neural network model that employs multiple layers of interconnected nodes to map input data to corresponding outputs. Each node, or neuron, within a layer, is fully connected to the nodes in the subsequent layer, except for the input nodes. Non-linear activation functions are applied to each neuron to introduce complexity and enable the network to learn non-linear relationships. MLPs are typically trained using supervised learning techniques, such as backpropagation, to adjust the weights and biases of the connections. Unlike the standard linear perceptron, MLPs can effectively handle non-linearly separable data.

Artificial Neural Networks (ANNs) are trained through backpropagation (BP) is the predominant algorithm employed for training Artificial Neural Networks (ANNs), owing to its efficacy in adjusting network parameters through gradient descent optimization [22]. The process involves forward propagation of input training patterns, subsequent error calculation, backpropagation of the error, and weight adjustment [17, 23]. A single-hidden-layer ANN possesses the capability to approximate any continuous function, making it a versatile tool for addressing numerous practical problems.

The influence of the hidden layer's neuron count on network performance was investigated, corroborating findings [24]. A simple ANN architecture exhibited limitations in capturing the intricate relationship between input and target variables, leading to convergence issues and potential overfitting [25]. To optimize the model, a systematic exploration of various neuron configurations was undertaken. Commencing with a single neuron, the number of neurons was incrementally increased through a trial-and-error approach. The optimal number of hidden layer neurons was determined by minimizing the mean squared error (MSE), This analysis revealed that an architecture with 20 neurons yielded the lowest MSE, indicating superior performance.

A standard artificial neural network (ANN) architecture is typically developed through a series of sequential stages. These steps often involve (a) data acquisition and collection, (b) identification of input and output variables, (c) data analysis and preprocessing, (d) ANN training, (e) model evaluation with a testing dataset, and (f) performance assessment of the trained ANN [26].

Both input and target variables were normalized within the range from 0 to 1 before training the supposed model. It was necessary to achieve the network in the right form to be read. As a result, the initial data should be unified to make the ANN training more efficient [27]. The typical method for unifying is expressed in the following equation.

$$X' = \frac{x - 0.95\, x_{min}}{1.05\, x_{max} - 0.95\, x_{min}}$$

Define $X_{\min}$ and $X_{\max}$ as the bounds of the data variable X. The associated data corresponding to X is denoted by X'.

An artificial neural network (ANN) was employed to predict the influence of rubber particle content and size on the composite material's mechanical properties, including ultimate tensile strength, strain, impact resistance, and dynamic behavior characterized by damping factors and natural frequency. After trying different algorithms and settings for the designed network, the network was trained with setting parameters shown in Table 1. Using a backpropagation algorithm, optimizing weights through iterative adjustments to minimize mean squared error (MSE) to 10^{-8}. A tan-sigmoid transfer function was implemented for the two hidden layers comprising 20 neurons each, while a PURELIN function was used for the five output neurons. The network's architecture shown in Figure 1 was configured with two input neurons, corresponding to the relevant input parameters. The training was conducted with regression results shown in Figure 2, converging after approximately 8000 epochs. The model's efficacy was evaluated based on its ability to predict experimental data accurately.

Table 1. The setting of the designed ANN

Networks parameters	Settings
Network algorithms	Back-Propagation
Training function	Levenberg-Marquardt (TRAINLM)
Performance	Mean Square Error (MSE)
Epoch	8000
Goal	1×10^{-8}
The function of the hidden layer	Tan-sigmoid (TANSIG)
Function of output	PURELIN

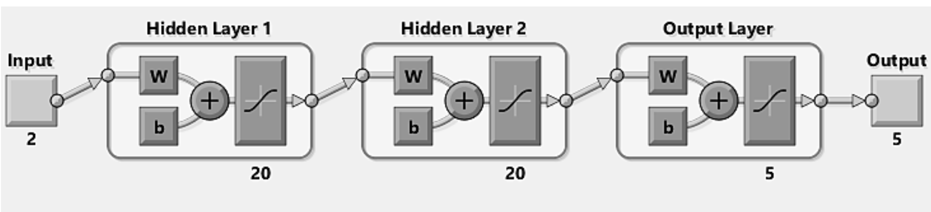

Figure 1. ANNs block diagram for mechanical and dynamic tests

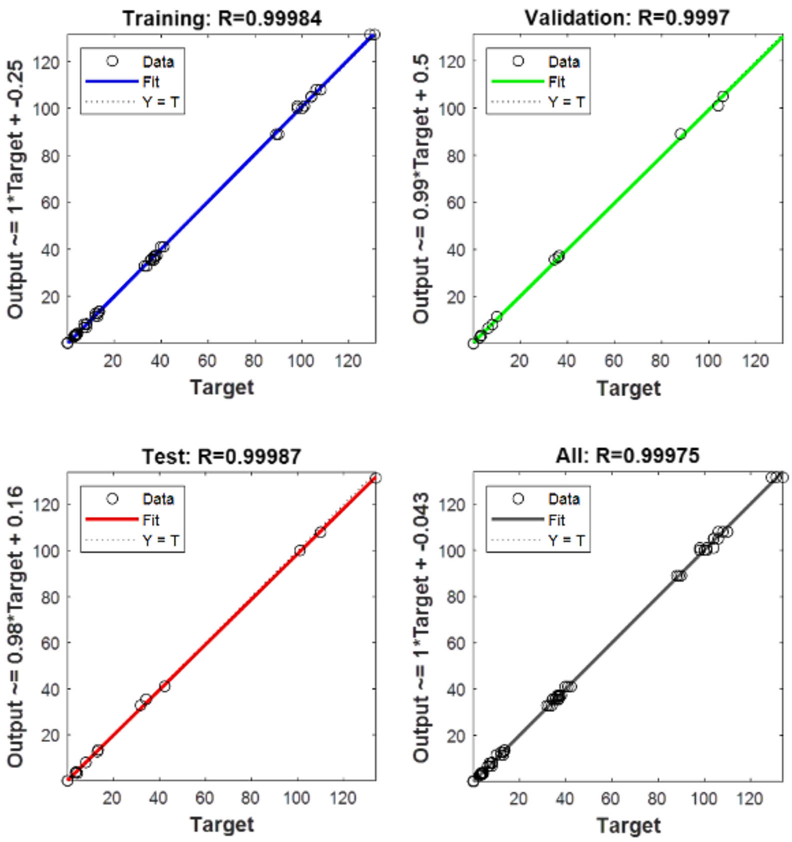

Figure 2. ANNs training regressions

3.2. Verification of ANN model.

The model's performance was assessed using standard statistical metrics, including the correlation coefficient (R), average absolute relative error (AARE), and root mean square error (RMSE) as shown in the given equations.

$$R = \frac{\sum_{i=1}^{N} (E_i - \bar{E}) - (P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N} (E_i - \bar{E})^2 \sum_{i=1}^{N} (P_i - \bar{P})^2}}$$

$$AARE = \frac{1}{N} \sum_{i=0}^{N} \left| \frac{E_i - P_i}{E_i} \right|$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=0}^{n} (E_i - P_i)^2}$$

The correlation coefficient, R, is a statistical measure that assesses the strength and direction of the linear relationship between experimental mechanical and dynamic properties results (Ei) and fitted results (Pi) derived from the modified constitutive equation. E and P represent the mean values of the experimental and fitted results, respectively. A significant number of data points (N) are essential for a reliable R-value. Insufficient data can lead to spurious relationships between experimental and predicted stresses. The average absolute relative error (AARE) is another unbiased statistical parameter that quantifies the accuracy of the equation's predictions, calculated on a term-by-term basis [28].

The AARE and RMSE values with correlation coefficient (R) in Table 2. Figure 3 shows the fitting of linear relation and R-values of the tested mechanical and dynamic values.

Table 2. Standard statistical metrics of model performance.

Property	Ultimate Tensile Strength (UTS)	Strain	Impact Resistance (I.R)	Natural Frequency (N.F)	Damping Factor (D.F)
AARE	3.51%	2.46%	2.22%	1.39%	5.20%
RMSE	0.49	0.074	0.995	1.92	0.0032
R	96.30%	94.20%	96.50%	97.80%	97.40%

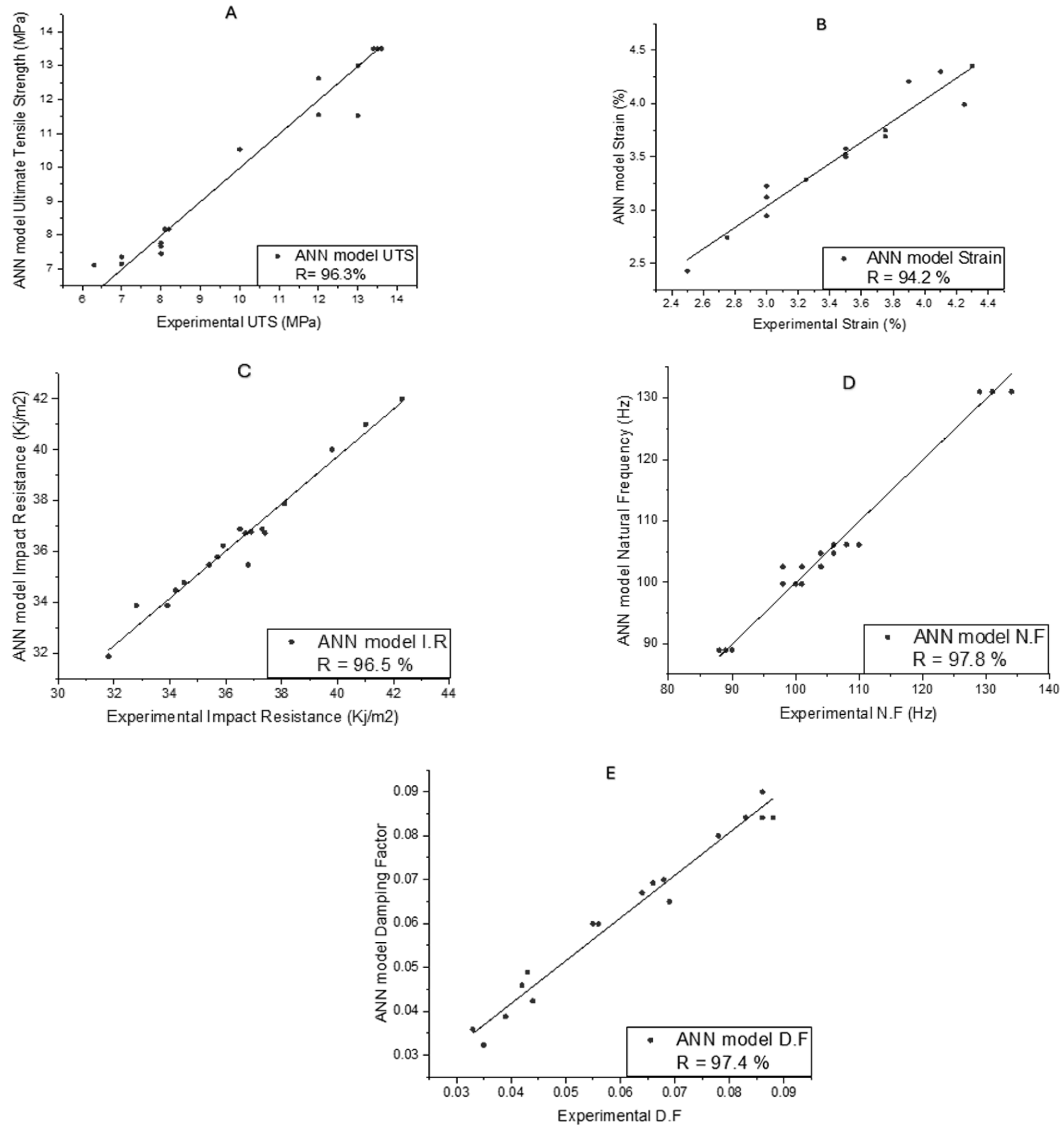

Figure 3. The linear fitting of (A) Ultimate tensile ANN predicted values (B) strain ANN predicted values (C) impact resistance ANN predicted values (D) natural frequency ANN predicted values (E) damping factor ANN predicted values.

3.3. The validation of ANN model

The following figure shows the impact of rubber particles' mesh size and volume percentages on the mechanical and dynamic properties of the investigated composite.

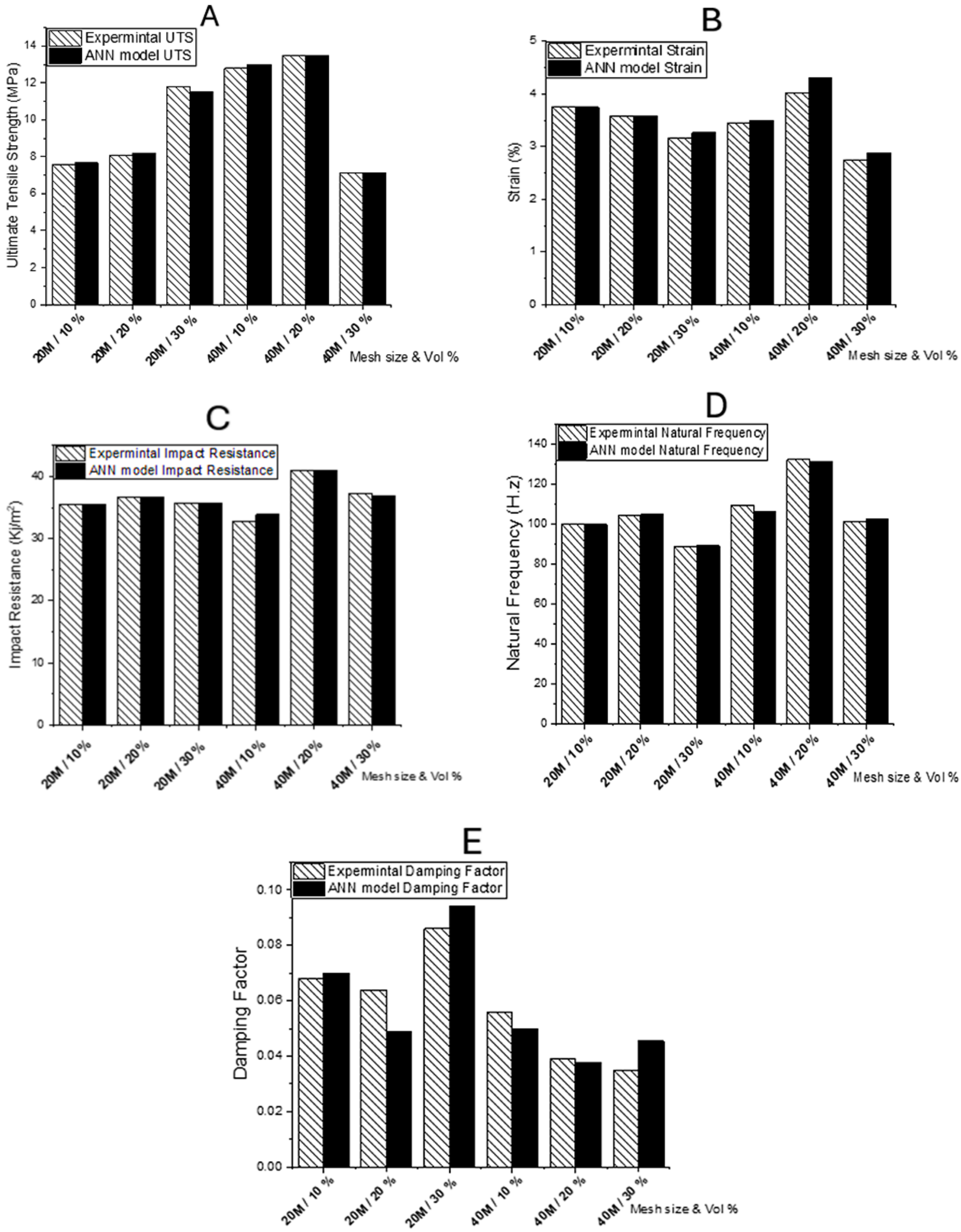

Figure 4. Comparison of results between experimental and ANN (A) Ultimate tensile values (B) strain values (C) impact resistance values (D) natural frequency values (E) damping factor values.

The neural network (NN) predictions were found to be in close alignment with the experimental results, suggesting a strong correlation between the model's output and the observed data. Results indicate that while a small amount of rubber can enhance tensile strength, excessive rubber content can weaken the composite due to disrupted stress transfer between fibers and matrix. Larger mesh sizes are more tolerant of higher rubber content, likely due to improved particle dispersion. However, an optimal balance exists between rubber content and mesh size for maximizing tensile strength.

The strain of fiberglass-polyester composites with rubber particles is influenced by particle size and volume fraction. Larger particles generally decrease strain at higher concentrations, while smaller particles can exhibit optimal strain at moderate levels. Excessive rubber content, regardless of particle size, can negatively impact strain.

Regarding impact resistance, rubber addition generally improves impact strength at low rubber contents. However, the impact decreases at higher levels, potentially due to void formation and weakened interfacial bonds. Mesh size also plays a role, with larger mesh sizes showing a more pronounced reduction in impact strength at high rubber contents. Finally, rubber inclusion consistently reduces the natural frequency and enhances the damping ratio, suggesting improved vibration absorption. The effect of mesh size on these properties is less pronounced, with some exceptions.

Conclusions

In this research, the prediction of mechanical and dynamic properties resulting from changes in mesh sizes and volume percentages of rubber particles in polyester fiberglass composite laminates has been performed. The following conclusions are obtained.

- An artificial neural network was designed to predict the mechanical properties of composite materials based on rubber particle content and size. Trained using backpropagation and optimized with a mean squared error of 10^{-8}, the network accurately predicted experimental data, demonstrating its potential for optimizing composite material design.
- The model's predictive capabilities are impressive, particularly in predicting ultimate tensile strength, impact resistance, and natural frequency, as evidenced by the exceptionally low absolute average relative error (AARE) of 3.51%, 2.22 %, and 1.39 % and root mean squared error (RMSE) of 0.49, 0.995, and 1.92, and the strong correlations of R= 96.3%, 96.5 % and 97.8% respectively. The model's performance in predicting strain and damping factor is commendable, with AARE of 2.46 % and 5.20 %, low RMSE of 0.074 and 0.0032, and strong correlations of R= 94.20 % and 97.40% respectively.

The artificial neural network model demonstrated significant efficacy in predicting the mechanical and dynamic properties of the composite and provided valuable insights into the correlation between rubber particle content and size. However, the ANN model's generalizability may be constrained by factors such as the quality and quantity of training data, material composition, composite preparation conditions, and model complexity.

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References

[1] S. Schmidgall, R. Ziaei, J. Achterberg, L. Kirsch, S. P. Hajiseyedrazi, and J. Eshraghian, "Brain-inspired learning in artificial neural networks: A review," APL Mach. Learn., vol. 2, no. 2, pp. 1–14, 2024, doi: 10.1063/5.0186054.
[2] S. Badini, S. Regondi, and R. Pugliese, "Unleashing the Power of Artificial Intelligence in Materials Design," Materials (Basel)., vol. 16, no. 17, 2023, doi: 10.3390/ma16175927.
[3] B. El Said, "Predicting the non-linear response of composite materials using deep recurrent convolutional neural networks," Int. J. Solids Struct., vol. 276, no. April 2022, p. 112334, 2023, doi: 10.1016/j.ijsolstr.2023.112334.
[4] Y. Kim, Y. Kim, C. Yang, K. Park, G. X. Gu, and S. Ryu, "Deep learning framework for material design space exploration using active transfer learning and data augmentation," npj Comput. Mater., vol. 7, no. 1, 2021, doi: 10.1038/s41524-021-00609-2.
[5] N. Altinkok and R. Koker, "Use of artificial neural network for prediction of physical properties and tensile strengths in particle reinforced alüminum matrix composites," J. Mater. Sci., vol. 40, no. 7, pp. 1767–1770, Apr. 2005, doi: 10.1007/S10853-005-0689-5/METRICS.
[6] M. A. Hossain, N. Ferdous, and E. Ferdous, "Crisis-driven disruptions in global waste management: Impacts, challenges and policy responses amid COVID-19, Russia-Ukraine war, climate change, and colossal food waste," Environ. Challenges, vol. 14, p. 100807, Jan. 2024, doi: 10.1016/J.ENVC.2023.100807.
[7] B. E. Rogachuk and J. A. Okolie, "Waste tires based biorefinery for biofuels and value-added materials production," Chem. Eng. J. Adv., vol. 14, p. 100476, May 2023, doi: 10.1016/J.CEJA.2023.100476.
[8] B. H. Mousa, R. El Gamsy, and M. H. A. Latif, "Mechanical behaviour of rubber hybrid composites," Int. Conf. Aerosp. Sci. Aviat. Technol., vol. 18, no. 18, pp. 1–8, Apr. 2019, doi: 10.1088/1757-899X/610/1/012064.
[9] A. S. A. Wanees, T. S. Mahmoud, I. M. Ibrahim, and A. O. Mosleh, "Development of Eco - Friendly Composites : Lamination Configuration and Addition of Waste Tire Rubber Particles on the Mechanical Performance of Polyester - Fiberglass Composite Plates," vol. 2024, no. 9, pp. 69–79, 2024.
[10] M. Mosaad, I. Mousa, S. S. Mohamed, and M. Academy, "Drilling Performance Evaluation of Innovative Waste Tire Rubber-Reinforced Polyester-Fiberglass Laminated Composites," vol. 2024, no. 9, pp. 105–112, 2024.
[11] F. Khan et al., "Advances of composite materials in automobile applications – A review," J. Eng. Res., Feb. 2024, doi: 10.1016/J.JER.2024.02.017.
[12] F. R. Jones, "Unsaturated Polyester Resins," Brydson's Plast. Mater. Eighth Ed., pp. 743–772, 2017, doi: 10.1016/B978-0-323-35824-8.00026-8.
[13] N. T. Tuli, S. Khatun, and A. Bin Rashid, "Unlocking the future of precision manufacturing: A comprehensive exploration of 3D printing with fiber-reinforced composites in aerospace, automotive, medical, and consumer industries," Heliyon, vol. 10, no. 5, p. e27328, Mar. 2024, doi: 10.1016/J.HELIYON.2024.E27328.
[14] S. K. Georgantzinos, G. I. Giannopoulos, K. Stamoulis, and S. Markolefas, "Composites in Aerospace and Mechanical Engineering," Materials (Basel)., vol. 16, no. 22, Nov. 2023, doi: 10.3390/MA16227230.
[15] Z. Yuan et al., "Predicting mechanical behaviors of rubber materials with artificial neural networks," Int. J. Mech. Sci., vol. 249, no. February, p. 108265, 2023, doi: 10.1016/j.ijmecsci.2023.108265.
[16] D. W. Abueidda, M. Almasri, R. Ammourah, U. Ravaioli, I. M. Jasiuk, and N. A. Sobh, "Prediction and optimization of mechanical properties of composites using convolutional neural networks," Compos. Struct., vol. 227, no. August, p. 111264, 2019, doi: 10.1016/j.compstruct.2019.111264.
[17] A. Mosleh et al., "Modelling of the superplastic deformation of the near-a titanium alloy (Ti-2.5AL-1.8MN) using arrhenius-type constitutive model and artificial neural network," Metals (Basel)., vol. 7, no. 12, pp. 1–15, 2017, doi: 10.3390/met7120568.
[18] R. Koker, N. Altinkok, and A. Demir, "Neural network based prediction of mechanical properties of particulate reinforced metal matrix composites using various training algorithms," Mater. Des., vol. 28, no. 2, pp. 616–627, 2007, doi: 10.1016/j.matdes.2005.07.021.
[19] M. Davallo, H. Pasdar, and M. Mohseni, "Effects of Laminate Thickness and Ply- Stacking Sequence on the Mechanical Properties and Failure Mechanism of Unidirectional Glass-Polyester Composites," no. May 2021, 2010.
[20] A. S.Abdel-Wanees, B. Hany Mousa, I. M.Ibrahim, and T. S.Mahmoud, "Assessment Study on the Mechanical Behavior of Polyester – Fiber Composite Laminates Filled with Waste Tire Rubber Particles," Benha J. Appl. Sci., vol. 7, no. 4, pp. 21–23, 2022, doi: 10.21608/bjas.2022.251248.
[21] ASTM Committee D30, "D3039/D3039M: Standard Test Method for Tensile Properties of Polymer Matrix Composite Materials," Annu. B. ASTM Stand., vol. 15, pp. 1–13, 2017, [Online]. Available: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Standard+Test+Method+for+Tensile+Properties+of+Polymer+Matrix+Composite+Materials#1
[22] Y. Sun, W. D. Zeng, Y. Q. Zhao, Y. L. Qi, X. Ma, and Y. F. Han, "Development of constitutive relationship model of Ti600 alloy using artificial neural network," Comput. Mater. Sci., vol. 48, no. 3, pp. 686–691, May 2010, doi: 10.1016/J.COMMATSCI.2010.03.007.
[23] M. Khalefa, "Use of artificial neural network for prediction of mechanical properties of Al-Si alloys synthesized by stir casting," J. Pet. Min. Eng., vol. 21, no. 1, pp. 97–103, 2019, doi: 10.21608/jpme.2019.13857.1004.

[24] L. F. Guo, B. C. Li, Y. Xue, and Z. M. Zhang, “Constitutive relationship model of Al-W alloy using artificial neural network,” Adv. Mater. Res., vol. 1004–1005, pp. 1120–1124, 2014, doi: 10.4028/WWW.SCIENTIFIC.NET/AMR.1004-1005.1120.

[25] X. Yang et al., “Research and applications of artificial neural network in pavement engineering: A state-of-the-art review,” J. Traffic Transp. Eng. (English Ed., vol. 8, no. 6, pp. 1000–1021, Dec. 2021, doi: 10.1016/J.JTTE.2021.03.005.

[26] H. Y. Li, D. D. Wei, Y. H. Li, and X. F. Wang, “Application of artificial neural network and constitutive equations to describe the hot compressive behavior of 28CrMnMoV steel,” Mater. Des., vol. 35, pp. 557–562, Mar. 2012, doi: 10.1016/J.MATDES.2011.08.049.

[27] S. W. Wu, X. G. Zhou, G. M. Cao, Z. Y. Liu, and G. D. Wang, “The improvement on constitutive modeling of Nb-Ti micro alloyed steel by using intelligent algorithms,” Mater. Des., vol. 116, pp. 676–685, Feb. 2017, doi: 10.1016/J.MATDES.2016.12.058.

[28] A. G. Asuero, A. Sayago, and A. G. González, “The correlation coefficient: An overview,” Crit. Rev. Anal. Chem., vol. 36, no. 1, pp. 41–59, Jan. 2006, doi: 10.1080/10408340500526766.