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Experimental Analysis and Predictive Modeling of Mechanical Behavior in Epoxy Composites Reinforced with Waste Tyre Rubber Particles

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Abstract

The disposal of end-of-life tyres poses a significant environmental and resource challenge owing to their large volumes and non-biodegradable nature. In this work, we explore the incorporation of waste tyre rubber particles (WTRP) into an epoxy resin matrix to develop sustainable polymer composites and examine their mechanical behavior both experimentally and through predictive modelling. Composites with differing epoxy: WTRP ratios (80:20, 75:25, 70:30 wt.%) and varying rubber particle mesh sizes (4.85 mm, 2.36 mm, 1.18 mm, 1.00 mm) were fabricated and characterized for hardness, tensile strength, modulus and other relevant metrics measured in accordance with ASTM D638, D790, D256, and D2240 standards. The results revealed that finer rubber particles enhanced the hardness of the composite at constant loading, ascribed to improved dispersion, whereas increasing WTRP content resulted in a gradual variation in mechanical properties owing to the softer elastomeric phase. An artificial neural network (ANN)-based predictive model was developed correlating the mechanical responses to composition and particle size, demonstrating good fidelity (R > 0.9997) across the dataset. The findings suggest that optimal combinations of WTRP content and particle size can deliver improved hardness with acceptable trade-offs in rigidity, thereby offering a pathway to valorise waste tyre rubber in high-value polymer composite applications.

Keywords: Epoxy composites, Waste tyre rubber particles; Mechanical properties, Artificial neural network, Predictive modeling.

INTRODUCTION

The global accumulation of end-of-life tyres has become a critical environmental and economic concern. Each year, more than 1.5 billion tyres reach the end of their service life, contributing to millions of tons of non-biodegradable solid waste worldwide. The disposal of these tyres through landfilling or incineration poses serious threats to soil and air quality due to the release of toxic gases and leachate [1]. Therefore, effective recycling and valorization of waste tyre rubber particles (WTRP) have emerged as essential strategies for achieving sustainable material management and environmental protection. Figure 1 illustrates the industrial and commercial applications of WTRP. Epoxy resins are widely used in thermosetting polymers in coatings, adhesives, composites, and structural applications, primarily due to their high tensile strength, dimensional stability, and superior chemical resistance [2]. However, a significant limitation of pure epoxy is its brittle nature and poor impact strength, which restricts its use in dynamically loaded structures [3]. To address this

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issue, researchers have investigated the incorporation of various fillers, both synthetic and natural, such as carbon black, silica, natural fibers, and waste-derived particulates, to enhance toughness and modify other mechanical properties [4, 5].

Among these alternatives, waste tyre rubber particles have garnered significant attention due to their abundance, low cost, and elastic properties, which can potentially improve impact absorption and energy dissipation in epoxy systems. Recycled tyre rubber primarily consists of cross-linked elastomeric polymers reinforced with carbon black, providing unique mechanical and thermal properties that make it suitable for reuse in polymer composites [6]. Table 1 provides the composition of different types of tyres in weight percentages [7].

The integration of WTRP into epoxy matrices presents a sustainable solution that mitigates waste accumulation while contributing to the circular economy [8]. For instance, Valasek and Muller [9] investigated the mechanical behavior of epoxy resins filled with waste rubber powder. They reported a slight decrease in tensile strength alongside a noticeable improvement in flexibility and energy absorption. Shivamurthy et al. [10] prepared epoxy composites reinforced with 15–45 wt% WTRP, finding that the inclusion of rubber particles improved wear resistance but resulted in a decline in tensile and flexural strength at higher loadings due to weak interfacial bonding. Similarly, Tamas et al. [10] demonstrated that finer rubber particles (below 250 µm) enhanced the impact toughness of epoxy resin, which was attributed to better dispersion and stress transfer between the phases [11]. Adesina et al. [12] investigated the impact of particle size and surface treatment on the mechanical and morphological properties of rubber-modified epoxy composites. They found that silane-treated WTRP exhibited higher tensile and flexural strengths compared to untreated samples, which was attributed to improved interfacial adhesion.

Similarly, Liu et al. [13] reported that reducing the size of the rubber particles led to enhancements in hardness and surface uniformity, which linked to a denser microstructure and decreased void content. However, many of these studies primarily focused on either filler content or surface modification, without simultaneously examining the combined effects of composition and particle size on multiple mechanical properties. Kabakçı et al. [14] noted that while WTRP contributes to increased damping, toughness, and impact resistance, it often results in reduced stiffness and hardness due to the inherent softness of the elastomeric phase.

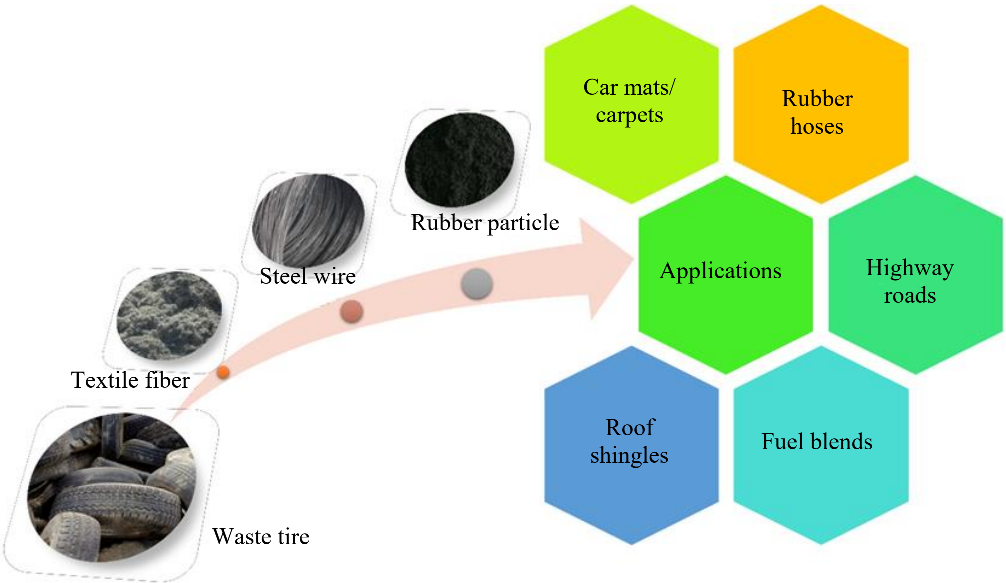

Figure 1. Industrial and commercial applications of WTRP.

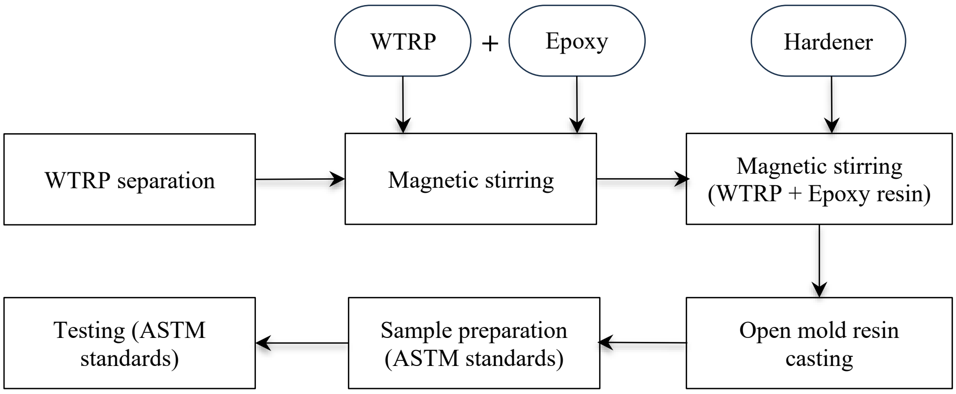

Figure 2. The schematic layout of the sample preparation process.

Table 1. Table caption in title case.

Type of tyre	Metal	Rubber/elastomers	Zinc oxide	Carbon black	Textile	Others
Passenger Car	16.5	47	1	21.5	5.5	8.5
Lorry	23	45	2	22	3	5
Off Road	12	47	2	22	10	7

Conversely, when particle dispersion and matrix bonding are effectively optimized, it is possible to maintain or even enhance hardness and strength in certain cases. Thus, a systematic experimental evaluation is essential to determine the optimal filler ratios and particle sizes that will maximize mechanical performance.

The present study aims to conduct a thorough experimental analysis and develop predictive models for the mechanical behavior of epoxy/WTRP composites. Composites were prepared with varying epoxy-to-WTRP ratios and different mesh sizes of rubber particles. The composites were assessed for tensile strength, flexural strength, impact strength, and hardness in accordance with ASTM standards. Additionally, artificial neural network (ANN)-based models were created to predict the effects of composition and mesh size on mechanical performance.

MATERIALS AND METHODS

Epoxy resin and amine hardener, supplied by Covai Seenu & Co., India, served as the polymer matrix system. WTRP were sourced from locally discarded automobile tyres. The rubber was cleaned, dried, and mechanically ground, then sieved into particle sizes of 4.85 mm, 2.36 mm, 1.18 mm, and 1.00 mm. Three composite formulations were prepared with epoxy-to-WTRP weight ratios of 80:20, 75:25, and 70:30, respectively. Figure 2 illustrates the schematic layout of the sample preparation process. Neat epoxy was used as the reference material. Composite laminates were fabricated using the hand lay-up technique, followed by compression molding. Required amounts of epoxy and WTRP were mixed with a mechanical stirrer at 1000 rpm for 30 minutes to ensure homogeneous dispersion. The hardener was added at a ratio of 10 parts per hundred resin and stirred gently to minimize air entrapment. The mixture was poured into silicone molds that had been coated with a release agent and allowed to cure at room temperature for 24 hours, followed by post-curing at 80 °C for 2 hours. The cured laminates were then cut and machined to standard dimensions in accordance with ASTM specifications.

A data-driven predictive model was developed using an artificial neural network (ANN) implemented in MATLAB R2024b Neural Network Toolbox. A feed-forward back-propagation neural network (FFBPNN) was utilized, featuring three input neurons, one hidden layer with six neurons, and four output neurons. The mathematical basis of the data training process is described in Equation (1). The tan-sigmoid (logsig) activation function was employed in the hidden layer, while a linear (purelin) function was used in the output layer [15, 16]. The transfer functions utilized in the ANN model are mathematically expressed in Equations (2) and (3). The optimal configuration of the ANN architecture was determined by systematically tuning the number of neurons in the hidden layer.

$$z_j = f\left(\sum_{i=1}^{n} m_{ij} x_j + k_i\right) \quad (1)$$

$$tansig(x) = \frac{2}{1+\exp(-2x)} - 1 \quad (2)$$

$$\text{Purelin}(x) = x \quad (3)$$

Where z_j is the ith output, f is the activation function, n is the data points number, m_{ij} is the weight coefficient, x_j is the jth input, and k_i is the bias.

Data obtained from experiments were divided into 70% training, 15% validation, and 15% testing sets. The Levenberg–Marquardt algorithm was chosen for training due to its robustness and rapid convergence in nonlinear regression problems [17]. Model performance was assessed using the coefficient of determination (R) and mean-squared error (MSE) to compare experimental and predicted results. The strong correlation between the predicted and experimental data demonstrates the reliability of the artificial neural network (ANN) in accurately capturing the nonlinear effects of composition and particle size on the performance of the composite [18].

RESULT AND DISCUSSION

Mechanical Characterization of WTRP-Reinforced Epoxy Composites

Figure 3(a–d). shows the mechanical characteristics of epoxy/WTRP composites with varying compositions and mesh sizes. Tensile, flexural, impact, and hardness were evaluated on 80:20, 75:25, and 70:30 (epoxy: WTRP) mesh sizes from 4.85 mm to 1 mm. Figure 3 (a) illustrates the tensile strength of epoxy/WTRP composites as a function of mesh size for three compositions of epoxy/WTRP. The tensile strength of all composites shows an increasing trend with decreasing mesh size, indicating that finer WTRP contribute positively to mechanical performance.

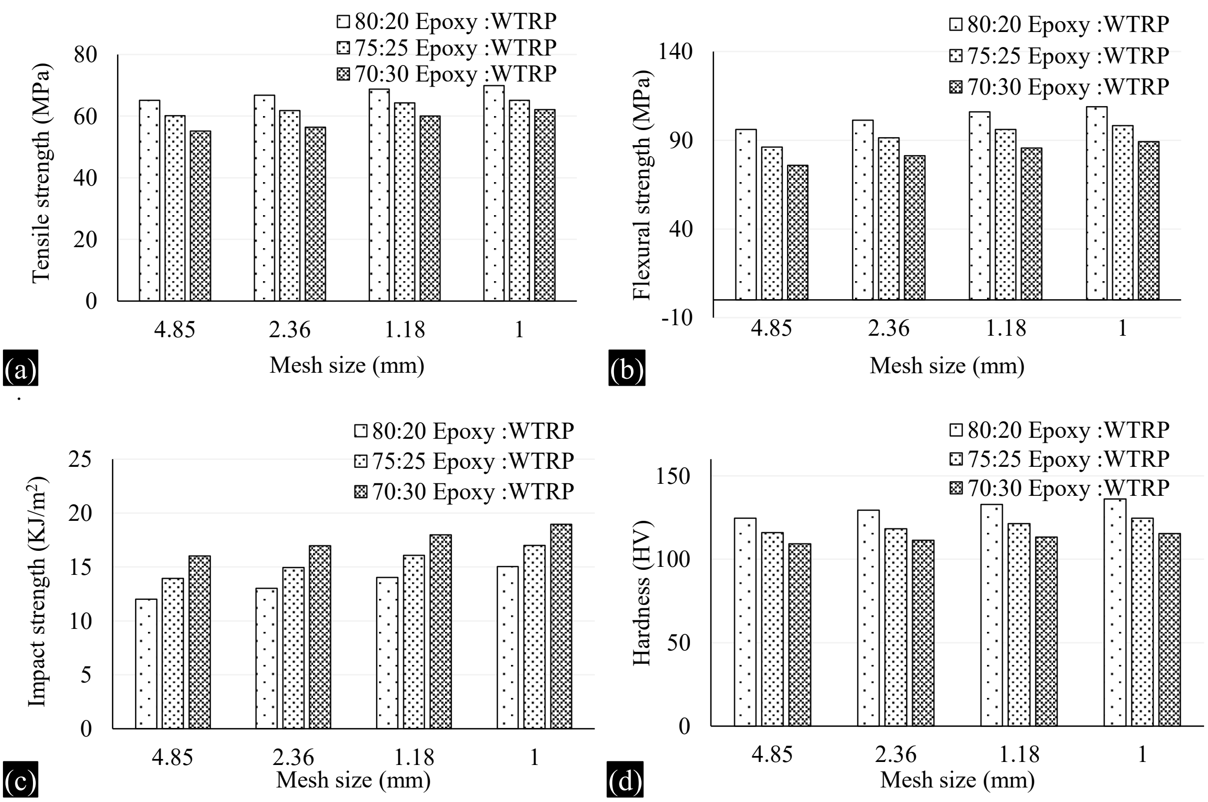

Figure 3. Effect of WTRP content and mesh size on mechanical properties of epoxy composites; (a) Tensile strength, (b) Flexural strength, (c) Impact strength, (d) Hardness

Among the tested samples, the 80:20 epoxy/WTRP composite exhibited the highest tensile strength, followed by the 75:25 and 70:30 composites. At a mesh size of 4.85 mm, the tensile strength values are approximately 65 MPa, 60 MPa, and 55 MPa for 80:20, 75:25, and 70:30 composites, respectively. With finer mesh sizes (1 mm), these values increase to around 70 MPa, 65 MPa, and 62 MPa, demonstrating an overall enhancement of 7–12% across the series. The intermediate composition (75:25) shows a moderate improvement in tensile strength, lying between the 80:20 and 70:30 blends at all mesh sizes. This indicates that while increasing WTRP content slightly compromises tensile strength, the 75:25 composite still maintains a balanced performance due to partial reinforcement and adequate matrix continuity. The improvement in tensile strength with decreasing particle size can be attributed to the increased surface area of finer WTRP particles, leading to improved interfacial adhesion and efficient stress transfer between the epoxy matrix and filler particles [19, 20]. Finer particles also minimize voids and stress concentrations, delaying crack propagation during loading. However, as the WTRP content increases beyond 25 wt%, the rubber particles tend to agglomerate, reducing interfacial bonding and creating weak zones that act as initiation points for fracture [21]. The rubber filler, being more flexible and less stiff than the epoxy matrix, also reduces the overall modulus and load-bearing capability at higher concentrations [22].

Overall, the 80:20 composite exhibits superior tensile strength due to the dominance of the epoxy phase and strong matrix–filler bonding, whereas the 70:30 blend shows reduced strength due to filler agglomeration and interfacial defects. The 75:25 composition provides an intermediate mechanical response, offering a trade-off between strength and filler utilization. These observations align with previous studies on particulate-filled polymer composites, which reported that optimal mechanical performance is achieved at moderate filler content and smaller particle sizes [23].

Figure 3(b) presents the variation in flexural strength of epoxy/WTRP composites with different mesh sizes for three epoxy-to-WTRP ratios. It is evident that the flexural strength increases progressively as the mesh size decreases, indicating that finer WTRP particles contribute significantly to the bending resistance of the composites. Across all mesh sizes, the 80:20 epoxy/WTRP composite exhibits the highest flexural strength, followed by 75:25 and 70:30 compositions. At a coarse mesh size of 4.85 mm, the flexural strength of the 80:20, 75:25, and 70:30 composites is approximately 95 MPa, 85 MPa, and 75 MPa, respectively. With a decrease in mesh size to 1 mm, these values increase to around 120 MPa, 100 MPa, and 90 MPa, corresponding to an enhancement of about 26%, 18%, and 20%, respectively. The intermediate composition (75:25) again shows a balanced performance, providing a moderate level of reinforcement with acceptable matrix continuity. The improvement in flexural strength with decreasing mesh size is mainly attributed to the increased surface area of finer WTRP particles, which promotes better wetting and adhesion with the epoxy matrix. This strong interfacial interaction facilitates efficient stress transfer and hinders crack propagation under bending loads [24].

Additionally, finer particles fill the micro voids more effectively, enhancing the compactness and homogeneity of the composite structure. Similar observations have been reported in epoxy composites reinforced with fine particulate fillers, where smaller particle sizes result in higher bending and impact strength [25]. On the other hand, increasing the WTRP content from 20 wt% to 30 wt% results in a decrease in flexural strength across all mesh sizes. The decline is attributed to poor matrix–filler interfacial bonding and possible agglomeration of rubber particles at higher filler loadings. Excessive rubber inclusion increases the likelihood of void formation and reduces the stiffness of the epoxy matrix, leading to early crack initiation and propagation under flexural loading. Moreover, the elastic nature of WTRP contributes less to flexural rigidity, reducing the overall resistance to bending deformation[26]. Among all compositions, the 80:20 epoxy/WTRP composite with a 1 mm mesh size demonstrates the highest flexural strength, confirming that lower particle size and moderate filler concentration lead to optimal reinforcement efficiency. These findings align well with the established behavior of particulate-filled polymer composites, where mechanical performance is maximized at intermediate filler ratios with uniform dispersion and strong interfacial adhesion [27].

Figure 3(c) shows the variation of impact strength of epoxy/WTRP composites for different mesh sizes and compositions. The experimental results reveal a consistent increase in impact strength with decreasing mesh size for all compositions. This enhancement is attributed to the improved dispersion and interfacial bonding between the finely ground WTRP and the epoxy matrix, which facilitates efficient energy dissipation under impact loading conditions. At a coarser particle size (4.85 mm), the impact strength values for 80:20, 75:25, and 70:30 compositions are approximately 12 kJ/m², 14 kJ/m², and 16 kJ/m², respectively. When the mesh size decreases to 1 mm, the impact strength rises to 15 kJ/m², 17 kJ/m², and 19 kJ/m², respectively.

This represents an increase of about 25% for 80:20, 21% for 75:25, and 19% for 70:30 compositions as the particle size is reduced from 4.85 mm to 1 mm. Moreover, when comparing different compositions at a constant mesh size (1 mm), the impact strength of the 70:30 composite is 26.6% higher than the 80:20 composition and 11.7% higher than the 75:25 composition. This progressive improvement in impact resistance with increasing WTRP content can be ascribed to the higher rubber phase, which acts as a crack arrester and enhances the energy absorption capability of the composite matrix. The elastomeric nature of WTRP contributes to plastic deformation and crack pinning, effectively reducing brittleness in the epoxy matrix. The 75:25 composition demonstrates a balanced improvement in toughness without significantly compromising stiffness, suggesting that this ratio offers an optimal trade-off between rigidity and energy absorption. The increasing trend with decreasing particle size aligns well with previous reports that finer rubber particles promote stronger matrix-particle adhesion and uniform stress transfer, leading to superior impact behavior[28]. Overall, the incorporation of WTRP, particularly at 25–30 wt.% and with fine particle sizes, significantly enhances the impact strength of epoxy composites making them promising candidates for vibration-damping and structural applications where improved toughness is required.

Figure 3(d) illustrates the variation in Vickers hardness of epoxy composites reinforced with WTRP for different epoxy to WTRP ratios and different mesh sizes. The results show that the hardness of the composites increases with a decrease in WTRP particle size across all compositions. For the 80:20 epoxy/WTRP composite, hardness improved from 124 HV at 4.85 mm to 132 HV at 1 mm, corresponding to an enhancement of about 6.5%. Similarly, the 75:25 composite increased from 116 HV to 125 HV (+7.7%), while the 70:30 composite increased from 109 HV to 118 HV (+8.3%) as the mesh size decreased from 4.85 mm to 1 mm.

This increase in hardness with finer particle size can be attributed to improved particle dispersion and stronger interfacial adhesion between WTRP and the epoxy matrix, which promotes better stress transfer and limits localized deformation under indentation [29]. The finer WTRP particles (1–1.18 mm) fill the voids more effectively and contribute to a denser composite structure, thereby enhancing surface resistance. Comparatively, when the WTRP content increased from 20 wt.% to 30 wt.%, a gradual reduction in hardness was observed. The average hardness of the 80:20 composites was approximately 6–10% higher than that of the 75:25 composites and 12–15% higher than that of the 70:30 composites. This trend is mainly due to the dominance of the soft rubber phase at higher WTRP loadings, which reduces the composite's resistance to indentation and increases elasticity.

Ann Predictive Model Performance Analysis

In this modeling process, the model was developed using MATLAB (R2024b) simulation environment with the neural network fitting tool. It consists of three input parameters such as the percentage of epoxy, the percentage of WTRP, and the mesh size. The target data correspond to the experimentally measured mechanical properties of the epoxy/WTRP composites. The output parameters are hardness, tensile strength, flexural strength, and impact strength. To determine the optimal configuration of the artificial neural network (ANN), the number of neurons in the hidden layer was varied. The best performance was achieved with 6 neurons in the hidden layer, which represents the optimal ANN structure. The overall architecture of the developed ANN model is illustrated in Figure 4.

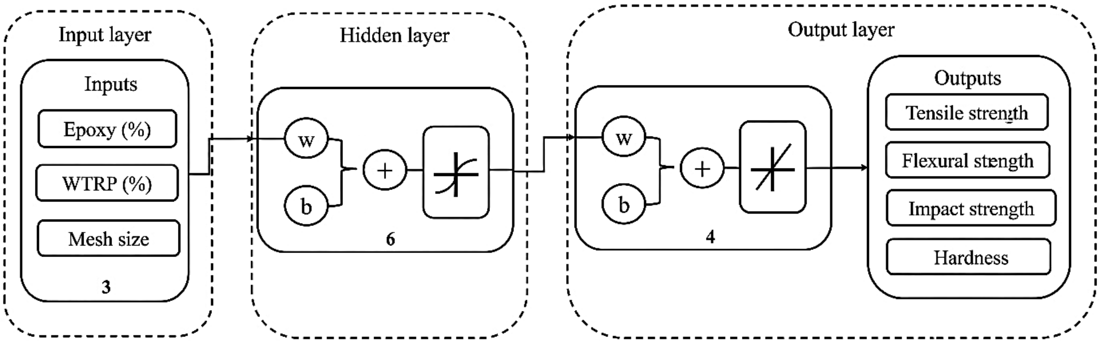

Figure 4. Overall architecture of the ANN.

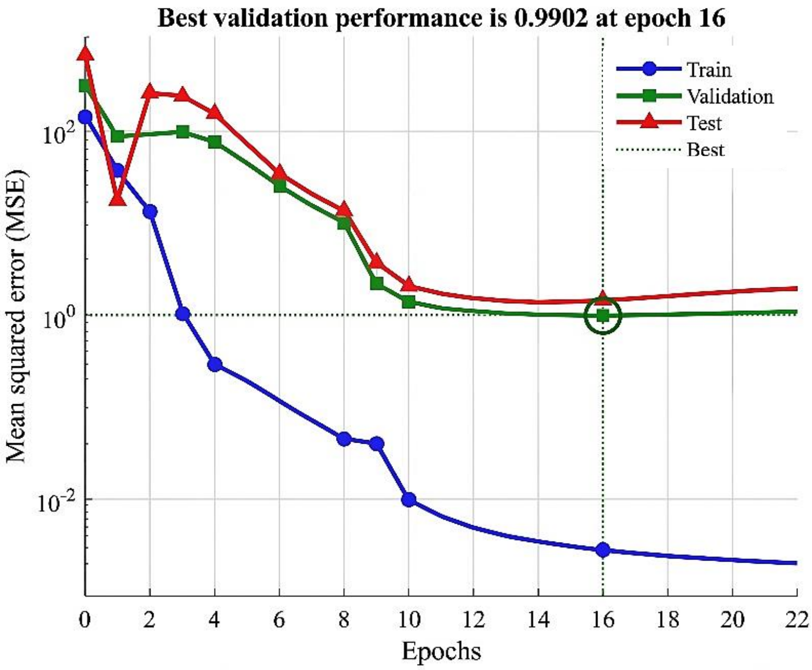

Figure 5. MSE performance curve of the ANN model.

Figure 5 shows the variation of MSE in the training, validation, and testing phases of an ANN model. As the number of epochs increases, the training error decreases, indicating the network effectively learns the relationship between input and output parameters. The validation and testing errors initially decrease and stabilize, demonstrating good generalization capability. The best validation performance was achieved at epoch 16, with an MSE value of 0.9902, indicating the model optimal level of learning without overfitting. The close alignment between the validation and testing curves further indicates the model robustness and reliability in predicting the mechanical properties of Epoxy/WTRP composites.

Figure 6 illustrates the error histogram of the developed ANN model, which is divided into 20 bins to depict the distribution of prediction errors across the training, validation, and testing datasets. The horizontal axis represents the error values, while the vertical axis represents the number of instances within each error range. The blue, green, and red bars indicate the training, validation, and testing datasets, respectively. The zero-error line is marked with an orange vertical line, indicating the ideal scenario in which the predicted outputs match the experimental data perfectly. As shown in the figure, most errors cluster around the zero-error line, indicating that the ANN model's predictions closely match the experimental results. The narrow and symmetric distribution of errors around zero suggests that the network has effectively generalized with minimal bias. Furthermore, the small error distribution validates the ANN model's accuracy and reliability in predicting the mechanical properties of epoxy/WTRP composites.

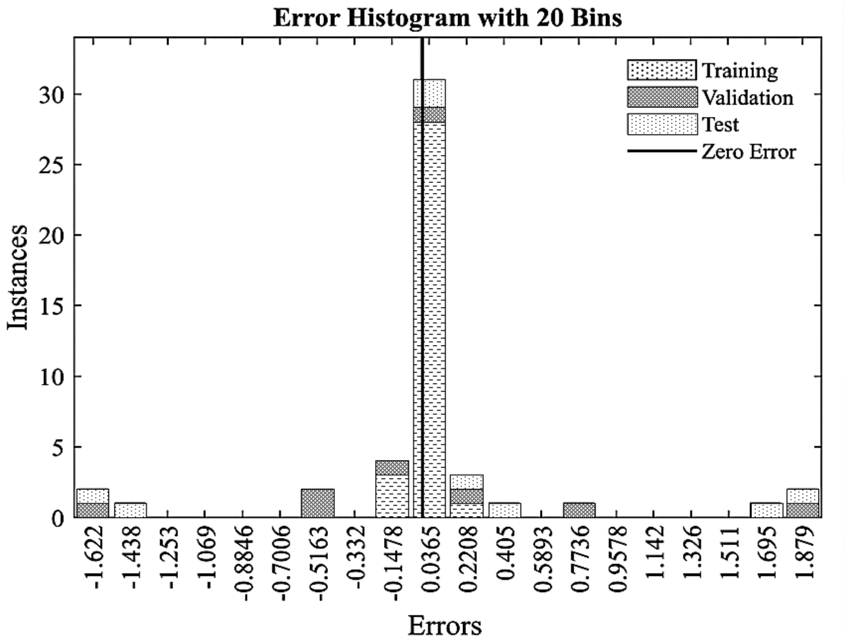

Figure 6. Error histogram of the ANN model.

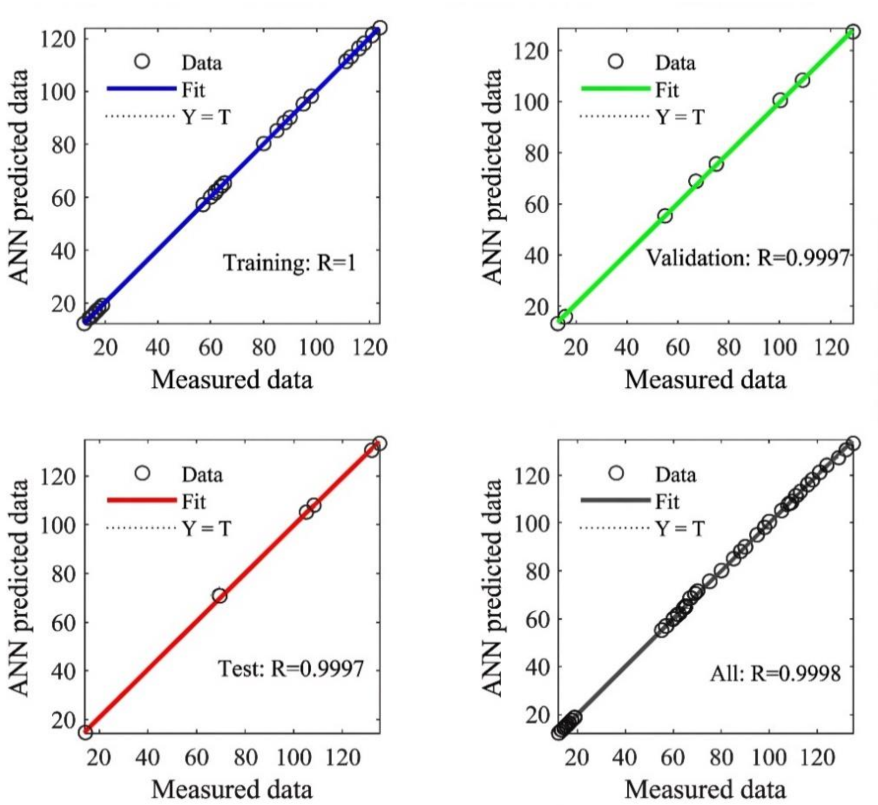

Figure 7. Regression plots of the ANN model.

Figure 7 presents a regression analysis of the developed Artificial Neural Network (ANN) model, highlighting its predictive accuracy and generalization capability. The model exhibited an almost perfect correlation between the measured and predicted outputs during the training phase, which signifies effective learning of the relationship between input and output parameters. The validation and testing datasets demonstrated excellent generalization performance, with minimal prediction errors.

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Overall, the regression analysis showed a close alignment with the experimental data across all datasets. The solid-colored lines in each subplot represent the best-fit line, while the dotted line indicates the ideal line of perfect prediction (Y = T). The close clustering of data points along the diagonal line in all subplots confirms the ANN model's effectiveness in capturing the nonlinear relationship between input variables and target outputs.

Comparison and Predictive Error Analysis

Figure 8 illustrates a comparison of the experimentally measured and ANN-predicted mechanical properties of epoxy/WTRP composites, specifically focusing on (a) tensile strength, (b) flexural strength, (c) impact strength, and (d) hardness. The plots offer insight into the predictive ability of the developed ANN model for estimating the mechanical performance of the composites. As depicted in Figure 7(a–d), the ANN-predicted values closely align with the experimentally measured values across all mechanical properties. This close correspondence between the measured and predicted data indicates that the ANN model successfully captures the nonlinear relationship between the input parameters and output responses.

Any small deviations noted between some predicted and measured points may stem from minor experimental uncertainties or inherent approximation errors within the model. Overall, the results suggest that the ANN model demonstrates high prediction accuracy and robustness, affirming its reliability for forecasting the mechanical behavior of epoxy/WTRP composites under different processing or formulation conditions.

Figure 9 depicts the percentage error between the experimentally measured and ANN-predicted mechanical properties of epoxy/WTRP composites, including tensile strength, flexural strength, impact strength, and hardness.

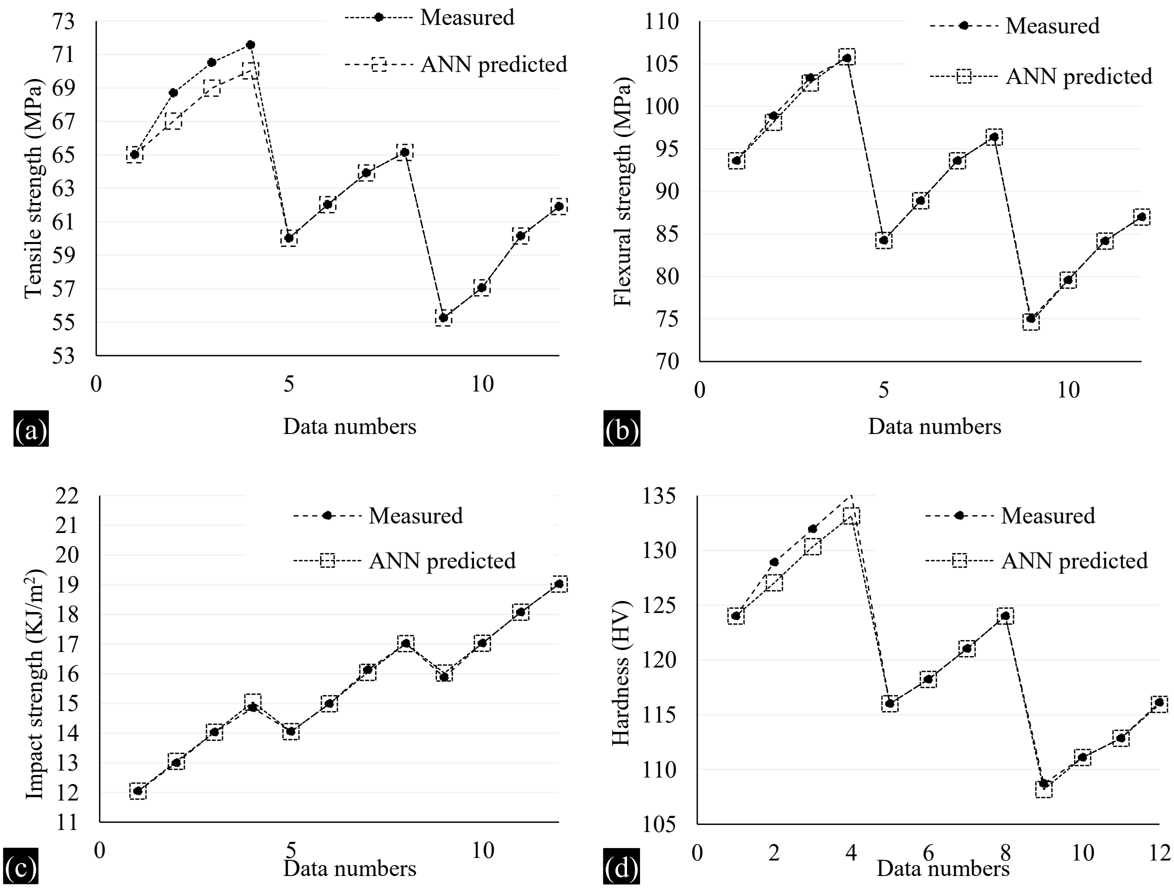

Figure 8. Comparison of measured and predicted mechanical properties of epoxy/WTRP composites; (a)Tensile strength, (b) Flexural strength, (c) Impact strength, (d) Hardness.

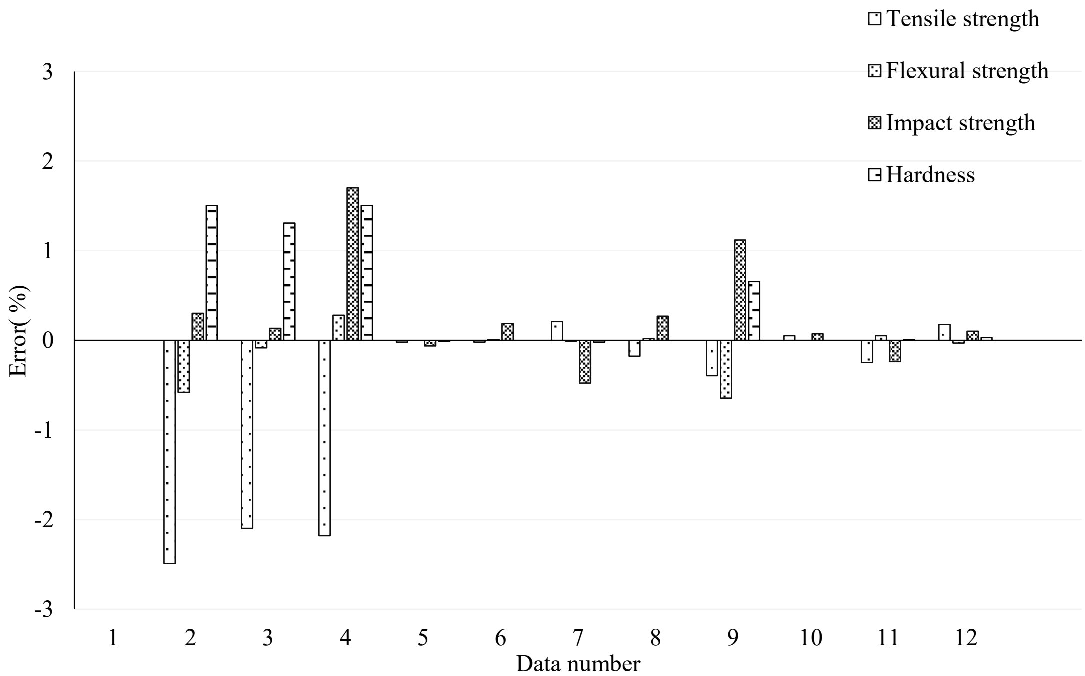

Figure 9. Predictive error percentage of the ANN model

To assess the accuracy and reliability of the developed ANN model for each mechanical property, the error percentages. Effectively captures the nonlinear relationship between the input parameters and the mechanical responses of the epoxy/WTRP composites. As indicated in the figure, the overall error values for all properties remain within a narrow range of ±3%, demonstrating excellent agreement between the measured and predicted data. The tensile strength exhibits a minimum error of approximately –2.8% and a maximum error of about +1.2%, observed for data points 2–4. The flexural strength shows errors ranging from –1.5% to +2.1%, while the impact strength presents a minimal deviation from –0.8% to +1.9%. Hardness reveals the smallest overall variation, with errors between –0.5% and +2.0%. These minor deviations indicate that the ANN model.

CONCLUSIONS

This study effectively fabricated epoxy composites reinforced with waste tyre rubber particles (WTRP) and evaluated their mechanical properties using both experimental methods and predictive modeling.

Various epoxy-to-WTRP ratios (80:20, 75:25, and 70:30 wt.%) and WTRP mesh sizes (4.85 mm, 2.36 mm, 1.18 mm, and 1.00 mm) were utilized to create the composites. Mechanical characterization, conducted in accordance with ASTM standards, demonstrated that WTRP significantly influenced the composite's tensile, flexural, impact, and hardness properties. The use of finer WTRP particles (1.00–1.18 mm) enhanced surface hardness and impact strength due to improved dispersion and interfacial adhesion within the epoxy matrix. However, because rubber is soft and elastic, and the adhesion between the filler and matrix is weak, WTRP content exceeding 25 wt.% resulted in decreased tensile and flexural strength. The 80:20 epoxy: WTRP composite incorporating 1 mm particle size exhibited the best performance, increasing hardness by 6–8% compared to pure epoxy. Additionally, the study's artificial neural network (ANN)-based predictive models demonstrated a strong correlation (R > 0.9997) between the input variables (composition and particle size) and the observed mechanical characteristics, confirming their reliability for predicting composite performance. Thus, experimental and analytical approaches work in tandem to optimize composition and particle morphology for balanced mechanical properties. This research indicates that waste tyre rubber can serve as a reinforcing phase in epoxy composites, promoting waste valorization and enhancing mechanical performance.

Future research may focus on improving interfacial bonding and load transfer efficiency in environmentally friendly composites through surface treatment of WTRP and the exploration of hybrid filler solutions.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: study conception and design: Sivakumar Sambath; Supervision, Validation, Formal analysis, Review and editing: Rajasekar Rajendran; Resources, Visualization, Software, and Assistance in data analysis and manuscript revision: Sabarish Rajagopalan. All authors reviewed the results and approved the final version of the manuscript.

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