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IMPACT LOADING ANALYSIS OF PARTICULATE POLYMER COMPOSITES WITH AN EFFICIENT HYBRID MACHINE LEARNING APPROACH

Soumya A. K.[1]
Ritu Shree
Anu Sharma

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A B S T R A C T

The fracture behaviour of particle composites made of polymers under impact loading is predicted in this research using a hybrid machine learning approach dubbed Hybrid Artificial Neural Networks and Random Forest (HANN-RF), with a focus on mode-I fracture. The goal of the study is to create a model for prediction that accurately links input variables to histories of crack initiation, fracture toughness, and the intensity of the stress factor (SIF). A full dataset is created, with inputs for the composites' compositional properties and impact loading scenarios. The HANN-RF model combines a Random Forest (RF) method and an ANN (Artificial Neural Network) in order to improve robustness and accuracy in forecasting. Metrics like MAE, MAPE for short, and accuracy are used in model evaluation. The outcomes show that the HANN-RF technique successfully predicts and forecasts mode-I fracture behaviour, offering insightful information for evaluating the effect on resilience and longevity of particle polymer composites in a variety of applications.

1. INTRODUCTION

A family of materials known as "particulate polymer composites" consists of an epoxy matrix with discrete particles (Kushvaha and Sharma 2021). These composites have distinct mechanical characteristics, making them appealing for various uses in industries like airplanes, cars, and construction. For the design of particulate polymer composites to be optimized and for their structural integrity to be guaranteed under varied loading circumstances, it is essential to understand the fracture behavior of these materials.

When a crack spreads perpendicular to the applied tensile tension, it is referred to as a mode-I fracture, also known as an opening or tensile mode of fracture (Karthik et al., 2023). It is crucial to examine their mode-I fracture behavior to determine how resistant particulate polymer composites are to crack initiation, propagation, and ultimate failure. Important metrics, including the fracture toughness, crack propagation rate, and energy absorption capacity, characterize these composites' mode-I fracture behavior.

The type, size, and volume percent of the reinforcement particles and the make-up of the polymer matrix

[1] Corresponding author: Soumya A K
Email: soumya.k@jainuniversity.ac.in

influence the way fracturing in particle polymer composites behave (Ganguly 2022). The interactions between the particles and the matrix and the interactions between individual particles significantly affect the mechanisms leading to fracture and the material's overall fracture toughness.

Various experimental and computational methodologies are used to estimate how particle polymer composites may shatter in mode-I (Kushvaha et al., 2020). The crack initiation, propagation, and particle-matrix interactions can be understood using experimental methods like tensile testing, fracture toughness testing, and microscope analysis. The understanding of fracture mechanisms at various length scales and the forecasting of the fracture response of the composite material are each assisted by computational modeling methodologies like finite element analysis and molecular dynamics simulations.

In recent years, significant progress has been made in creating advanced particulate polymer composites with improved fracture resistance (Mousavi et al., 2022). Researchers want to increase the composite's fracture toughness and damage tolerance by customizing its composition, morphology, and interface characteristics. Enhancing the composite matrix's mechanical parts and fracture resistance by incorporating beneficial nanoparticles, such as carbon nanotubes or graphene, has shown encouraging results.

The research aims to develop a predictive framework that accurately captures the relationship between input variables and crack initiation, fracture toughness, and stress intensity factor (SIF) histories. By completing this goal, the researchers expect to advance knowledge of fracture behavior and make it easier for engineers and researchers to evaluate particulate polymer composites' durability and impact resistance.

The remainder of this paper is as follows: part 2 describes related works, part 3 explains the methodology, part 4 evaluates the performance of the proposed method, and Part 5 concludes the paper.

2. RELATED WORKS

By utilizing dimensional analysis and the Buckingham-pi theorem, the current study (Safaee et al., 2022) aims to examine the unpredictable fracture behavior of glass-filled epoxy composites. 0%, 5%, 10%, and 15% volume fractions of rod-like glass filler having an aspect ratio of 80 were used. For the mode-I crack-opening dynamic fracture, the study's toughness index was used to assess the cracked durability of the Particle Polymer Composites (PPCs) in various strain rate impact loading scenarios.

Three distinct loading rates were employed in the study (Feng et al., 2022) to investigate the silica-filled polymer composites' dynamic fracture toughness in the presence of impact loading. The break-initiation hardness of the composites was projected utilizing a model of an artificial neural network; the anticipated values and results from experiments exhibited good agreement. The volume % of the fillers, the longitudinal wave speed, and the loading rate have been the three most crucial factors in the stress intensity factor's prediction were discovered to be.

A study (Gupta et al., 2022) suggested an ML method to predict the stress distribution in fiber-reinforced polymer composites using microstructural images as input. In an L2 norm less than 0.005 and a correlation score close to 0.999, the developed deep learning Convolutional neural network models (CNN) have exceptional performance in predicting stress fields for various short carbon fibers filled with epoxy. This effective method has the potential to significantly save the time and money needed to research and develop new composite materials.

Study (Hasan et al., 2022) aimed to examine how aluminum-graphite composites behaved in terms of wear and friction when they were dry and lubricated, as well as how they changed from one lubrication regime to another. In addition, five independent supervised regression models and one hybrid model were created to forecast the wear and friction of lubricated composites. The ML analysis outcomes demonstrated that the lubricant's viscosity and the lubrication level were the two distinct factors that had the most impact on how well the surfaces performed for friction and wear of the composites.

Daghigh (Daghigh et al., 2020) found out how multiple composites constructed of poly (propylene)/ethylene-propylene-diene-monomer (PP/EPDM) and low-cost bio-reinforcements affected the heat deflection temperature (HDT). To calculate HDT values based on different composite compositions, they used a K-Nearest Neighbour Regressor (KNNR) approach. Researchers looked into the use of nanoclays (NCs), short Catania fibers (SLFs), In Pistachio shell powder (PSP), and date seed powder (DSP) composites, as well as poly (propylene)/ethylene-propylene-diene-monomer (PP/EPDM) as reinforcements. This study helps create affordable, lightweight materials with better temperature resistance.

Paper (Sharma et al., 2020) was to ascertain whether the KNN algorithm can forecast the ability to fracture silicon particle-reinforced polymer composites. The Stress Intensity Factor (SIF), an indicator of fracture toughness, is estimated. To indicate how the composite might break down at various aspect ratios, the technique known as KNN is used. The work being presented focuses on examining how well the K-Nearest

Neighbour (KNN) method can predict the breaking strength of composites of polymers augmented using mica particles. With minimal experimentation, it is intended to forecast fracture toughness correctly. The Intense strain SIF, which serves as a direct measure of fracture toughness, is predicted using model parameters such as aspect ratio, duration, the capacity of the fillers, & the modulus of elasticity.

Study (Thankachan et al., 2021) predicted and assessed dry sliding wear rates of creative copper-based composite surfaces containing different boron nitride particle fractions with machine learning models and statistical approaches. The study showed that the wear rate decreases significantly when boron nitride particles are included in copper-based surface composites. After analysis, mild adhesive wear was discovered on worn-out surfaces, and abrasive wear was found on the covers in higher-stress situations.

Study (Rong et al., 2019) can use 2D cross-sectional images and two-dimensional convolution neural networks (CNNs) to predict the actual thermal conductivity of 3D composites. The thermal conductivity of composites that are both anisotropic and isotropic was successfully predicted by 2D CNNs using several cross-section pictures parallel or in the opposite direction from the fillers' preferred approach. Reducing uncertainty and increasing prediction accuracy is observed.

Study's (Nguyen and Kim 2021) objective was to build a neural learning-based model called PANN to determine the final compressive capacity of rectangle concrete-filled steel tubes (RCFST) columns and outline the corresponding uncertainties. Artificial neural networks trained through particle swarm optimization are employed in the PANN model. The findings demonstrate that it is a highly effective substitute for forecasting RCFST columns' capacity for compression. Using the Monte Carlo method and considering different sources of uncertainty, the study also examines the stochastic behavior of the compressive strength. To boost the model results' credibility and strengthen the confidence of the RCFST column, convergence studies, sensitivity analysis, and uncertainty quantifications are carried out.

Study (Ayub et al., 2021) objective was to use machine learning methods to forecast multiscale properties of bio-nanocomposites' fracture toughness. The energy absorptions were determined by performing Charpy impact testing on composites with different biofilter combinations, such as nano-clays, irregular seeds of date particles, and short Catania fibers. From these results, Indicators of fracture toughness, including strain energy release rates, were then calculated. Decision tree regression and adaptive boosting regression were particularly effective at predicting and optimizing composite designs despite the limited training data provided.

3. METHODS

3.1 Dataset creation

An experiment using a gas-gun setup to assess the polymer composite's dynamic fracture was used to gather the now available data. Silica, three types of forms for the particles Cubes, flakes, and spheres were used to cast the test specimens. Aspect ratios are 1, 6, and 80 for the three types of rods, respectively. The data was split into data sets for training and testing with a proportion of 70% and 30%; respectively, data was made available..

3.2 Artificial neural network

The structure and operation of the human brain served as the inspiration for artificial neural networks (ANNs), which are computer models. They are frequently employed in several disciplines, including materials science and engineering, to examine intricate connections between input and output variables. ANNs can illuminate the relationship between the input parameters and the Crack initiation fracture toughness & stress intensity factor (SIF).

ANNs can be used to capture and learn the complex relationships and dependencies between the input factors (such as material properties, crack dimensions, loading circumstances, etc.) and the corresponding values of crack initiation fracture toughness and SIF. Interconnected nodes, called neurons, are arranged in layers in the ANN model. After passing via one or more hidden levels, the input layer receives the values of the input factors. Activation functions are applied by the neurons in the hidden layers to produce outputs while using weights and biases to the input data. The output layer provides the projected crack initiation fracture toughness and SIF values as a last step.

In the training phase, the ANN iteratively modifies the weights and biases based on the supplied training data to understand the correlations between the input parameters and the goal variables (crack initiation fracture toughness and SIF). Using methods like gradient descent and backpropagation, the model seeks to reduce the discrepancy between the predicted and actual values of the target variables. When the ANN has been trained, it can be used to forecast the crack initiation, fracture toughness, and SIF for new sets of input parameters.

They are advantageous since ANNs can handle complex data and capture nonlinear correlations. They can find hidden correlations and patterns that conventional analytical methods find difficult to identify. To effectively train the ANN and prevent overfitting, ensuring an adequate amount of high-quality training data is essential. An effective method for modeling the link between input variables, crack initiation, fracture toughness, and SIF is provided by ANNs. To make precise forecasts and gain insightful knowledge about how materials behave under varied loading circumstances, fracture dimensions, and other contributing factors, they can evaluate data and learn from it.

3.3 Random forest

Regression problems and classification using bootstrap aggregation and random forests (RF). A forest of different trees is produced using randomly selected properties drawn from randomly selected portions of the original training data. As many trees are created in classification problems, results are taken from the most prevalent class. In contrast, in regression problems, the outcome is determined as the mean of the values obtained from every one of the individual regression tree values. We concentrate on the regression kind of RF in the current work. As determined by the user, a forest may contain some trees. Assume that M represents the number of trees in the woods.

Randomize the retrieval of several subsets (y_j) from the provided dataset (Y). Make M decision trees using sampled data. Count the decision-making trees' votes and average them. The final estimate value should be the average. The random forests employ randomness at two levels: during attribute and data selection. Each leaf-node of the regression trees has a fixed estimate of X because the trees were built using random vectors taken from the training dataset S. The data points(s_1, x_1), (s_2, x_2),..., (s_n, x_n) are chosen As samples for the leaf nodes. The predicted data can be described as the mean forecasts of every single tree of regression as follows:

$$s(y_i) = \frac{1}{n}\sum_{i=0}^{n} s_n(y_i) \quad (1)$$

Such that $j = 1,2,\ldots,N$, and where $S(Y_j)$ is the anticipated outcome Tuning-parameters in RF significantly impact the model's performance.

3.4 Hybrid topology

A potential method for forecasting particle polymer composites' impact loading and fracture behavior with an emphasis on mode-I fracture is called hybrid ANN-RF, which combines Artificial Neural Networks (ANN) and Random Forest (RF) algorithms.

By combining the ANN and RF models, this hybrid strategy can take advantage of each model's advantages and raise forecast accuracy. The hybrid model's ANN part identifies intricate nonlinear patterns and relationships in the data. It can handle particulate polymer composites' complex and varied fracture behavior because it can learn from big datasets and generalize from them.

While the RF component builds numerous decision trees and mixes their results, the former is an ensemble learning technique. It handles high-dimensional datasets expertly and offers robustness against noise and outliers. When attempting to understand fracture behavior, RF is particularly good at capturing interactions and the significance of features.

The hybrid technique successfully takes advantage of the benefits of both algorithms by combining the ANN and RF models. The ANN component can extract intricate features and correlations from the input data, and the RF component can then improve and validate these discoveries by looking at how the elements interact. The model's ability to forecast how particle polymer composites will behave when subjected to impact loading after this integration is improved.

The hybrid ANN-RF technique provides a powerful and comprehensive framework for forecasting mode-I fracture behavior in impact-loaded particulate polymer composites. The power of the RF in handling high-dimensional datasets and capturing feature interactions is combined with the ANN's capacity to grasp complex nonlinear relationships. In addition to improving understanding of these materials' fracture behavior and enabling breakthroughs in their design and application, this synergy makes forecasts more accurate.

4. RESULT AND DISCUSSION

In this section, we evaluate the proposed and existing methods' performance. The parameters are accuracy, MAE, and MAPE. The current process is FNN (Pashaei and Pashaei 2021), CNN (Li et al., 2018).

Accuracy is a metric for how well a model forecasts the results or labels of a specific dataset. It is computed by dividing the total number of forecasts made by the number of accurate predictions, commonly expressed as a percentage. Figure 1 depicts the accuracy outcome. The accuracy value was higher than our proposed method. By comparison, our proposed method (FNN 87.5% CNN 90.5% HANN-RF Proposed 96.5) is superior to existing methods.

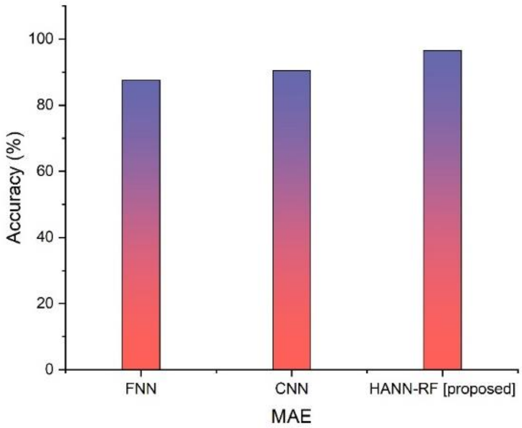

Figure 1. Accuracy result

The acronym MAE stands for Mean Absolute Error. It is a typical metric to assess a collection's average error size or deviations between expected and observed values. Without taking into account the error's direction, MAE measures how closely the predictions match the actual data. Figure 2 depicts the MAE outcome. The MAE method was lower than the accuracy value. By comparison, it shows that our proposed method (FNN, CNN HANN-RF) is better than existing methods.

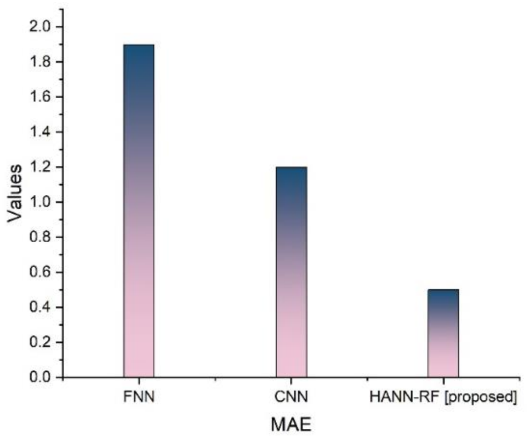

Figure 2. MAN result

By determining the typical percentage difference between the projected and actual values, MAPE, which means Mean Absolute Percentage Error, is a metric used to evaluate the accuracy of forecasting models. The MAPE method was lower than the accuracy value. By comparison, it shows that our proposed method (FNN, CNN HANN-RF) is superior to existing methods.

Finding (FNN 2, CNN 1.4, HANN-RF 0.6)

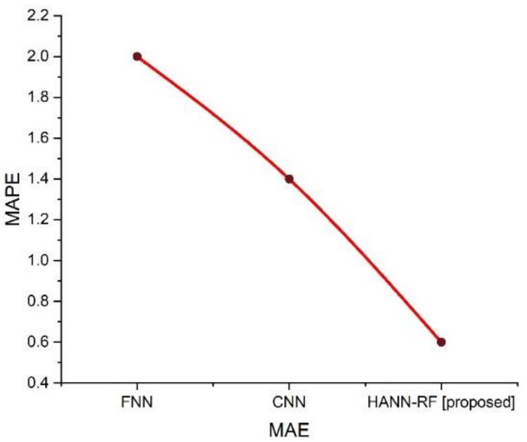

Figure 3. MAPE result

The percentage of the dependent variable's variance that can be predicted from the independent variable or variables is represented by the value of R^2, also referred to as the value of the coefficient of determination. It ranges from 0 to 1, with 0 denoting no association between the variables and 1 indicating a perfect match as the suggested model forecasts SIF histories for different augmented volume percentages of spherical, flakes, and rod fillers in pristine epoxy.

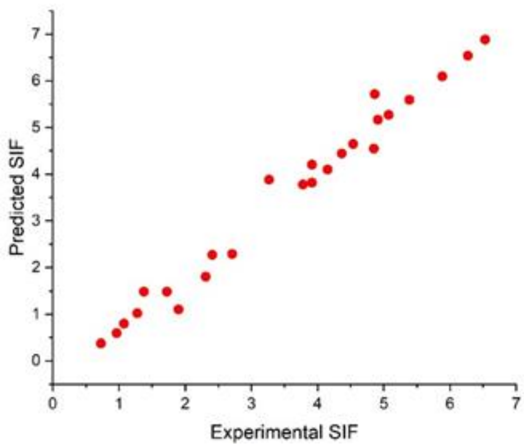

Figure 4. R^2 value

5. CONCLUSION

This paper introduces a machine learning hybrid approach called Hybridized Artificial Neural Networks and Random Forest (HANN-RF) to forecast how particle polymer composites will fracture when subjected to impact loading, emphasizing mode-I fracture in particular. The research's proposed HANN-RF model combines a random forest with artificial neural networks. The model captures complicated correlations between input elements and fracture behavior while preserving robustness and good prediction accuracy. It combines the strengths of random forest (RF) and artificial neural networks (ANN). The model's performance in precisely simulating and forecasting fracture behavior has been evaluated using metrics including MAE, MAPE, and accuracy. It shows that our proposed model is superior to other methods. With the help of this predictive model, engineers and researchers may evaluate the performance uses of particle composites of polymers in a range of applications and gain a better knowledge of their impact resistance and durability.

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Soumya A. K.
Jain (deemed to be) University,
Bangalore, India
soumya.k@jainuniversity.ac.in
ORCID 0000-0002-6657-386X

Ritu Shree
Vivekananda Global University, Jaipur,
India
ritu.shree@vgu.ac.in
ORCID 0009-0002-8705-4361

Anu Sharma
Teerthanker Mahaveer University,
Moradabad, Uttar Pradesh, India
er.anusharma18@gmail.com
ORCID 0000-0002-5164-7547