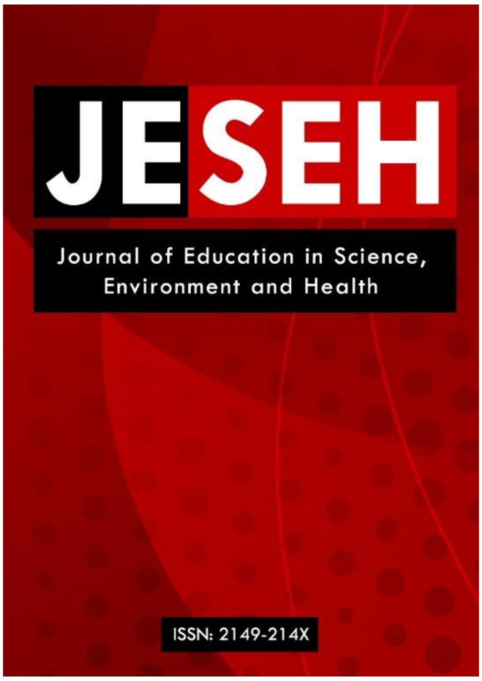

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Abstract

In this study, which focuses on selecting the material and predicting its mechanical behaviors in materials science, an Artificial Neural Network (ANN) was used to predict and simulate the low-speed impact effects of hybrid nano-doped aramid composites. There are not enough studies about open education practices in this field. Since error values below 1% were obtained with the proposed method, it has been shown that ANN results contribute to the prediction and derivation of force-time, force-displacement, and energy-time curves. It was concluded that the proposed ANN model could be useful in finding solutions to the impact responses of nanohybrid-doped aramid composites. ANN successfully predicted the prediction process for Part I and Part II, with accuracy rates of 99.4% and 99.3% for the displacement feature, 99.2% and 99.1% for the energy feature, and 97.1% and 98.3% for the force feature, respectively. This study is an applied training step that will simulate the impact strength of composite materials reinforced with nano additives and make serious contributions to important and easy-to-access technical training with a library feature that can be used as a basis for use as training material.

Introduction

The modern world is going through profound changes, and education has become the key to the development of a nation. With rapid technological development and international cooperation, competition intensifies, and economic globalization accelerates (Lin et al., 2021; Quian et al., 2018). Engineering education is the basis of national development and social development. For manufacturing enterprises to successfully enter the Industry 4.0 era and gain advantages in this new wave of the industrial revolution, they need to use internet thinking to transform manufacturing enterprises and promote the deep integration of informatics and industrialization. Research and management of risks related to the Internet strategic transformation of manufacturing enterprises directly affect the success or failure of the transformation of enterprises. This is also very important in terms of preparing the infrastructure for Industry 5.0. A risk assessment model based on a backpropagation (BP) artificial neural network was created for the Internet strategic transformation of a manufacturing organization, and a case study was conducted on an organization (Honglei et al., 2022).

In the current green environmental pressure, businesses must proactively incorporate competitive issues into their strategic plans to create innovative initiatives and gain a foothold in the highly competitive business world (Abbas, 2020). Universities strive to create an attractive classroom environment by creating a strong impression and directly influencing the perceived teaching quality of faculty members, improving overall performance (Li et al., 2017). The findings revealed that financial incentives, promotions, and performance evaluations had no impact on the faculty member's job performance. The present result is consistent with (Hee et al., 2020). However, this found that financial incentives motivate employees to perform better (Koo et al., 2020). Similarly, it has supported findings in the literature and claims that career development empowers people and promotes a sense of accomplishment, which leads to workplace satisfaction (Benson et al., 2019). Promotion is a great approach for academics to achieve job satisfaction. With the knowledge economy expanding so rapidly, informed decision-making is seen as an important tool for success and prosperity (Yang et al., 2019). To save university students from these and many similar psychological problems, digital materials, and analysis methods need to be used more widely in education and application environments. Professional behavior can be improved with the right resources available in academic environments. Here, the fact that the educational environments are interesting and business-oriented will increase the respect for the instructor and both parties will work happily and productively in a more productive educational environment. For this, educational environments need to be prepared for business life and digital content production must be supported.

Artificial intelligence technology has begun to be used in many areas of life. A person with high self-esteem is one who has better socio-emotional and cognitive functions in business life (Harun, 2017; Silverthorn, 2017). Low self-esteem appears to be associated with poor emotional adjustment in personal and social domains (Zhao et al., 2022). Therefore, teaching methods of cognitive problem-solving strategies help students improve their self-esteem (Silverthorn, 2017). Nowadays, the use of simulation-based educational materials is becoming increasingly important in the field of applied sciences, especially in complex or risky experiments that cannot be performed in laboratory environments, by taking advantage of developing technology. Simulations are radically changing educational practice in science and technology. Artificial intelligence technologies have facilitated access to data and information that were previously difficult to obtain in experimental studies in science and engineering. However, experimental studies performed in laboratory environments can be costly and time-consuming. These difficulties reveal the importance of simulations in applied training. Simulations offer students the opportunity to experiment and understand complex concepts in a digital environment.

Accessibility means the ability to use any system or service that has been developed. In education, accessibility aims especially for individuals with disabilities to access educational materials and learning experiences easily. Open education means that learning resources and materials are freely accessible and shareable online (Adedoyin et al., 2023). Open education practices aim to ensure that everyone can access educational resources beyond traditional education. Today, artificial intelligence plays an important role in the field of education. This technology provides students with a more customized and effective learning experience (Ahmad et al., 2022). Artificial intelligence can recommend personalized learning materials to students by analyzing students' performance and learning styles. Using artificial intelligence methods, various tools and applications can be developed to increase accessibility for individuals with disabilities. For example, a better access environment can be provided to visually impaired students with some solutions such as audiobooks, speech recognition systems, or text-to-speech applications. Artificial intelligence tracks students' educational progress, helping them understand their strengths and weaknesses. Thus, it can also improve the learning process applied to students. Artificial intelligence can also promote cultural diversity and international cooperation by translating educational materials into different languages (Cantú-Ortiz et al., 2020). This technology can adapt educational materials to the needs of individuals with disabilities. For example, it can add subtitles for hearing-impaired students or make special color adjustments for colorblind students. When used in accessibility and open education applications, artificial intelligence can make education more inclusive and accessible. Thus, it can help every individual have equal access to educational opportunities.

This study aims to develop professional skills and abilities during and after university education and to find solutions to employment problems. Using modern technology and science to master students' basic socio-psychological pressure situations and analyze students' problems is the developing trend of the age. Secondly, practical deficiencies in scientific education stand out when looking at university students in terms of applied digital education factors. This study aims to outperform traditional application methods by developing an application-based ANN model to analyze current university vocational education and university students' work-life stress, and the data-matching results are successful. This study aims to predict and simulate the low-velocity impact effects of CNT and ZrO_2 reinforced aramid composite plates to predict the mechanical behavior of the material and systematic material selection in Material Analysis and Material Selection courses using the ANN method. Thus, to provide students with comprehensive educational material about material selection criteria. Thanks to the use of ANN, predicting the low-velocity impact responses of aramid composite materials with different nano-doping ratios is now more efficient and economical. This study aims to transform the practice of mechanical and materials engineering by highlighting the potential to obtain more precise and accurate results in industrial and academic fields such as material architecture and strength analysis.

Method

Mechanical Experiments

In this study, several mechanical experiments were carried out to obtain data for ANN predictions. Aramid composites are preferred materials in various industrial applications due to their high strength and lightness. However, their behavior can become complex when subjected to impact loads. This situation is determined by analyzing the data obtained because of detailed and costly mechanical experiments. For these experiments, Kevlar 29 CT736 ballistic para-aramid 410 g/m^2 density fabric reinforcement material and vinylester Polives 701 matrix were used. MWCNT and ZrO_2 were used as hybrid nano additives. MWCNT and ZrO_2 reinforcement nano additives were added into the vinylester resin at determined rates, dispersed mechanically and then in an ultrasonic mixer, then applied on a 6-layer aramid fiber fabric and placed in a vacuum environment. Then, according to the resin curing instructions, it was cured with a hot press at 70℃ under 5 bar pressure for 2 hours and left to cool naturally. In this way, the material was produced in 2 parts, with a low nano additive ratio (max. 0.5) and high nano additive ratio (max. 1.75), 6 samples for each additive ratio, for a total of 42 samples. The produced composite plate was subjected to impact tests at 10 J and 15 J energy levels and cut with a water jet according to ASTM D-7136 standard for low-speed impact tests. As a result of the tests, maximum force, displacement, and absorbed energy data were obtained.

Mechanical Experiments

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Artificial Neural Networks

ANN is a subfield of machine learning and artificial intelligence created by modeling the functioning of biological neurons. Artificial neural networks are a powerful method used to solve many problems such as data analysis, pattern recognition, classification, and regression. The simplest processing unit in ANN is a single-layer perceptron called a neuron (see Figure 1) (Demuth et al., 2014).

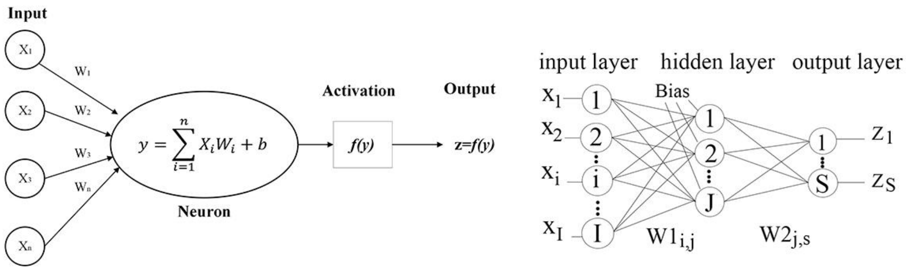


Figure 1. ANN structures

Considering *n* inputs, the linear weighted sum of the inputs of a single neuron is obtained as in Equation 1:

$$y = \sum_{i=1}^{n} X_i W_i + b \quad (1)$$

where X_i is the input value, W_i is the weight value corresponding to the input value, and *b* is the bias value. In this study, a hyperbolic tangent function in the range (-1 to +1) shown in Equation 2 was used as the activation function.

$$f(y) = \tanh(ay) \quad (2)$$

where the value of parameter *a* is 1.5. This parameter corresponds to the Tanh15 activation function, which scales the input values of ANNs by a factor of 1.5 by forcing the range of input upper values to +1 and the range of lower values to -1. This means that the activation function reaches its extremes faster, speeding up the learning rate of an ANN.

The multilayer perceptron, which is a complex and functional model, consists of multiple neurons connected on a layered architecture. The multilayer sensor model works by progressing from the input layer to the output layer, as shown in Figure 1 (Jain et al., 1996). The learning process of ANN occurs by updating the weight values of each neuron using training data and a training algorithm (Cha et al., 2023). The success of the learning process is determined using test and evaluation data. The Mean Square Error function is often used to adjust the values of weights. The Mean Square Error (MSE) function was calculated using Equation 3.

$$MSE = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (T_{ij} - Z_{ij})^2 \quad (3)$$

where Z_{ij} corresponds to the output of the activation function in the ANN, T_{ij} refers to the target values, *n* represents the total number of outputs, and *m* represents the number of training cases.

In this study, 80% of the data set was used for training the ANN, 10% for verification, and 10% for testing. In data selection processes, a randomization algorithm was applied to the data set and very good results were obtained. A splitting procedure was applied to divide the dataset into training and validation. Matlab software was used to develop and validate the ANN method. In the training of the ANN, 4 neurons were used in the input layer, 10 neurons in each of the 2 hidden layers, and 3 neurons in the output layer. An ANN structure with maximum fitness value was obtained by accepting the test coefficient as 0.001, the momentum coefficient as 1, and the learning coefficient as 1. The number of iterations and minimum error rate were accepted in the stopping criteria of the ANN. These values were chosen as the number of iterations as 20000 and the minimum error rate as 0.01. ANN architecture training and validation were obtained using a program that calculates MSE values. The program works by first training the ANN with zero neurons in the hidden layers. Then, for training and validation, the MSE value is calculated, and the neurons are incremented by one. Finally, the MSE is recalculated until the maximum number of neurons is reached according to the size of training cases (T_c) required to train. If the ANN has no hidden layer, the number of training cases required should be more than 2.5 times the number of output weights. If the ANN has a single hidden layer, the required number of training cases should be more than 2.5 times the number of hidden weights. If the ANN has two hidden layers, the required number of training cases should be greater than 2.5 times the number of hidden weights. Depending on the status of the hidden layers in the ANN, T_c is calculated with Equation 4 below.

$$T_c > 2.5[h_1(I+1) + h_2(h_1+1)] \tag{4}$$

where I is the number of neurons in the input layer of the ANN, h_1 is the number of neurons in the first hidden layer, and h_2 is the number of neurons in the second hidden layer. The coefficient of 2.5 in the equation is a parameter obtained through experiments to solve a problem using nonlinear activation functions in neurons. The R^2 coefficient of determination used to evaluate the quality and performance of the ANN model was calculated with Equation 5 below (Sabir et al., 2023).

$$R^2 = 1 - \frac{\sum_{i=1}^{k}\left(Z_i^{predicted} - t_i^{experimental}\right)^2}{\sum_{i=1}^{k}\left(t_i^{experimental} - t^{-experimental}\right)^2} \tag{5}$$

where $t^{experimental}$ corresponds to the forces obtained from experimental tests, $Z^{predicted}$ corresponds to the ANN output predicted by the ANN, $t^{-experimental}$ corresponds to the arithmetic mean of the data contained in the experimental data, and k is the size of both the predicted and experimentally obtained dataset (Zhang et al., 2023). Finally, *RMSE* was also used to calculate the performance of the ANN model and was calculated by Equation 6.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{k}\left(Z_i^{predicted} - t_i^{experimental}\right)^2}{k}} \tag{6}$$

R^2 and *RMSE* calculations were used to evaluate the overall performance of the ANN model (Elhattab et al., 2024). These do not consider error estimates at local points in the data. Therefore, the Absolute Error (AE) specified in Equation 7 was used to evaluate a more detailed local accuracy of the ANN.

$$AE = \left|Z_i^{predicted} - t_i^{experimental}\right| \tag{7}$$

Thereupon, the MAX value was calculated with Equation 8 below.

$$MAX = max\left(\left|Z_i^{predicted} - t_i^{experimental}\right|\right),\ i, \ldots, k \tag{8}$$

AE is used to visualize the error of ANN models in a plot where MAX represents the highest point in the graphs. This serves to graphically observe the evolution and maximum value of the local error.

Results and Discussion

Force-time, energy-time, and force-displacement data under 10 J and 15 J energy levels were used in the graphs obtained from mechanical experiments. The interactions of different ratios of Part I (0-0, 0.5-0.5, 0.5-0, 0-0.5) and Part II (1.75-0, 0-1.75, 1.75-1.75) CNT and ZrO_2 nano additives on the strength of the composite are discussed. Comparisons were made at 10 J and 15 J energy levels, taking the pure sample as a reference. In this study, the input data for the dataset used for training the ANN consists of CNT and ZrO_2 contribution rates, impact force duration *t* (seconds), and impact energy (Joule) values. The output data consists of displacement amount (mm), absorbed energy (Joule), and impact force (Newton) values. The data set used in this study was obtained because of mechanical experimental procedures. These data were used to adjust the weights of the ANN. Comparisons between experimental studies and ANN were made in two groups according to the proportions of additives. The first group was carried out with a low nano additive ratio (max 0.5), and the second group was realized with a high nano additive ratio (max 1.75). The purpose of performing it in two groups here is to test the performance and stability of the developed ANN method according to different contribution rates. For both data pieces (part I and part II), the experimental results and ANN predictions of the displacement feature showed a close distribution to each other. ANN predicted the displacement property with 99.4% accuracy for Part I and 99.3% for Part II. Graphical distributions of experimental and ANN prediction values of displacement values for both parts are shown in Figure 2.

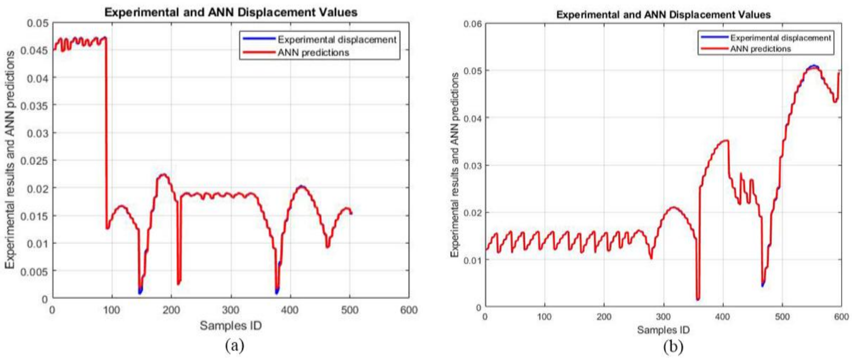


Figure 2. Experimental and ANN displacement values in part 1(a) and part 2(b)

In Part I, the best validation performance value for the displacement feature was obtained as 1.7335e-08 in the 78th period (epoch). In Part II, the best validity performance value was obtained as 2.3224e-08 in the 72nd period (epoch) (see Figure 3).

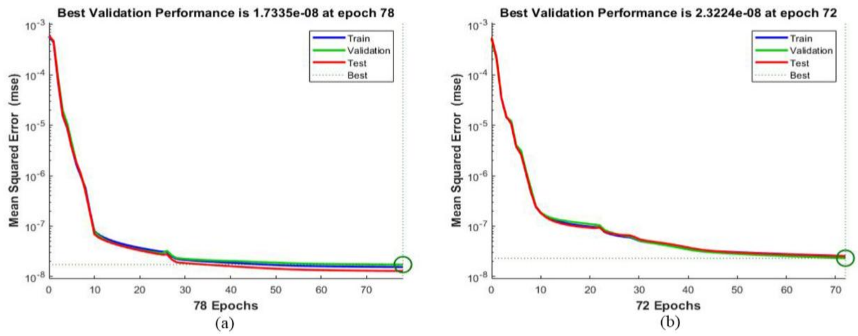


Figure 3. Best validation performance for displacement in part 1(a) and part 2(b)

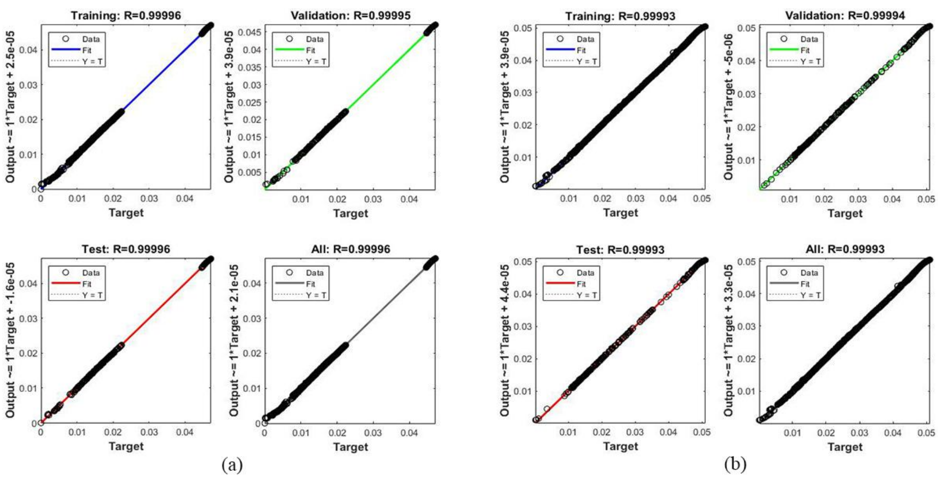


Figure 4. Training, testing, and validation regression graphs for displacement in part 1(a) and part 2(b)

The purpose of regression model estimation is to find the regression line that best represents the relationship between the dependent variable and the predictive variables. It is done to see the harmony between ANN outputs and experimental data and the level of this harmony. In other words, we can see how to approximate the results ANN can produce to the experimental output (Soares dos Santos et al., 2016). The regression (R) value for the training, testing, and validation procedures for the displacement value in Part I was calculated as 0.99996 and in Part II was calculated as 0.99993. This shows that experimental data and ANN predictions match with high accuracy (Figure 4).

Gradient, mu, and validation fail graphs for the displacement feature in Part I and Part II are shown in Figure 5. Here, Mu is the mean of the normal distribution expressed as a scaler value or series of scaler values. The gradient is the slope of the square of the error function concerning unknown weights and biases. Val fail is shown to detect validation errors at each epoch. In Part I, at the 78th epoch, the gradient value was determined as 9.6329e-08, the Mu value was 1e-09, and the validation fail value was 0. In Part II, in the 72nd epoch, the gradient value was determined as 9.8906e-08, the Mu value was 1e-08, and the validation fail value was 0.

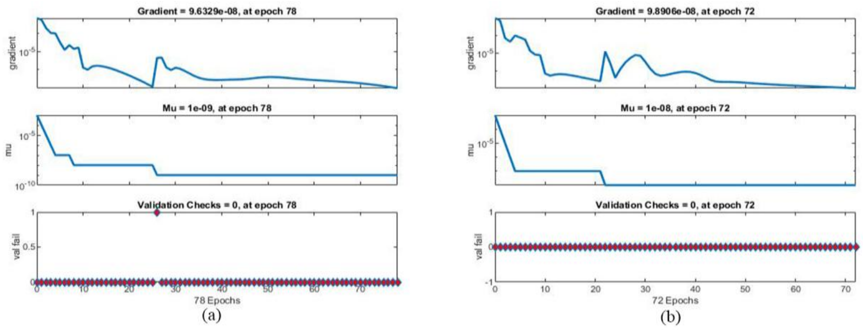


Figure 5. Gradient, mu, and validation fail graphs for displacement in part 1(a) and part 2(b)

For the energy feature, experimental results and ANN predictions showed a close distribution in both Part I and Part II. ANN predicted the energy property with 99.2% accuracy for Part I and 99.1% for Part II. Graphical distributions of experimental and ANN prediction values of displacement values for both parts are shown in Figure 6.

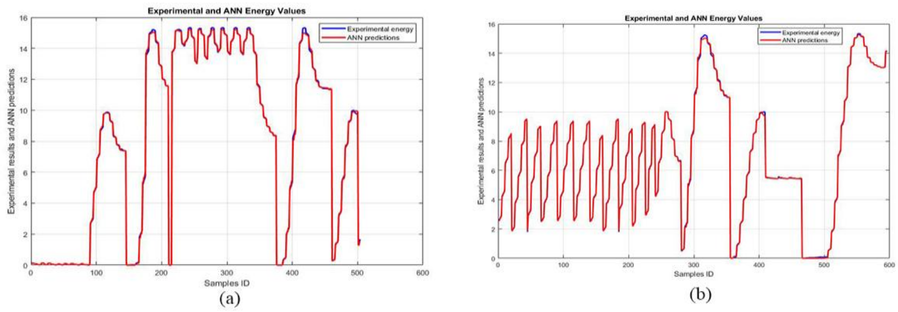


Figure 6. Experimental and ANN energy values in part 1(a) and part 2(b)

The best validation performance value for the energy feature in Part I was determined to be 0.0056 in the 288th epoch. In Part II, the best validity performance value was obtained as 0.0035 in the 316th period (epoch) (Figure 7).

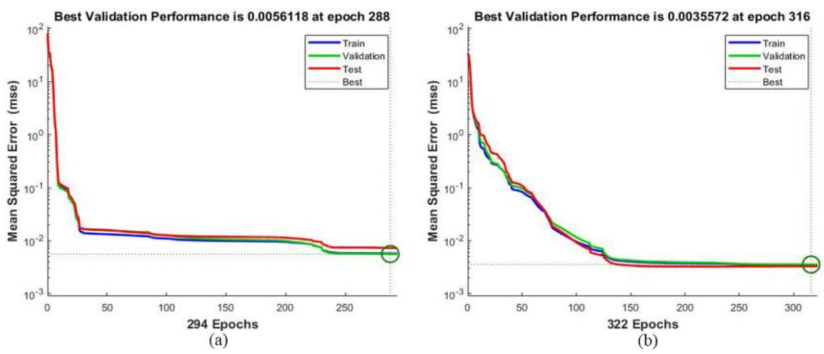


Figure 7. Best validation performance for energy in part 1(a) and part 2(b)

The regression (R) value of the training, testing, and validation processes for the energy feature in Part I was calculated as 0.99992, and in Part II, it was calculated as 0.99991. This shows that experimental data and ANN predictions match with high accuracy (Figure 8).

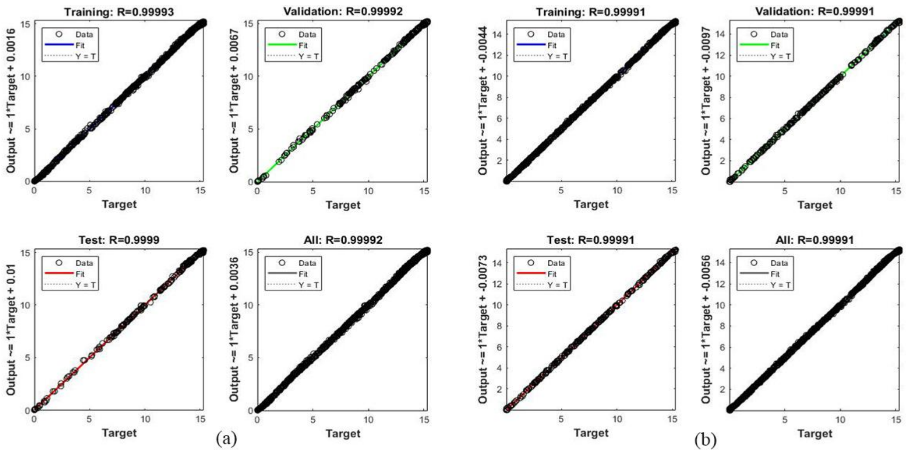
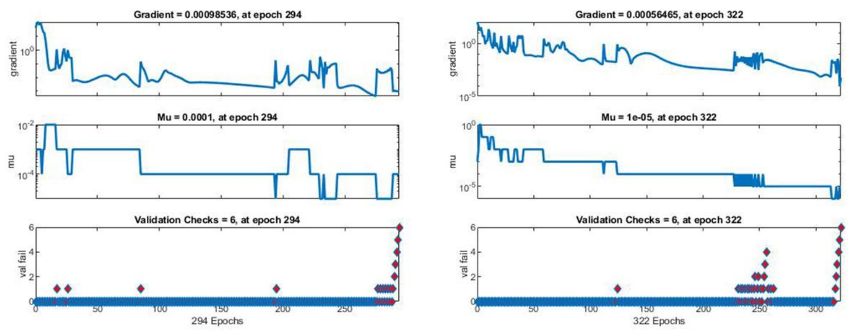


Figure 8. Training, validation, test, and regression graphs for energy in part 1(a) and part 2(b)

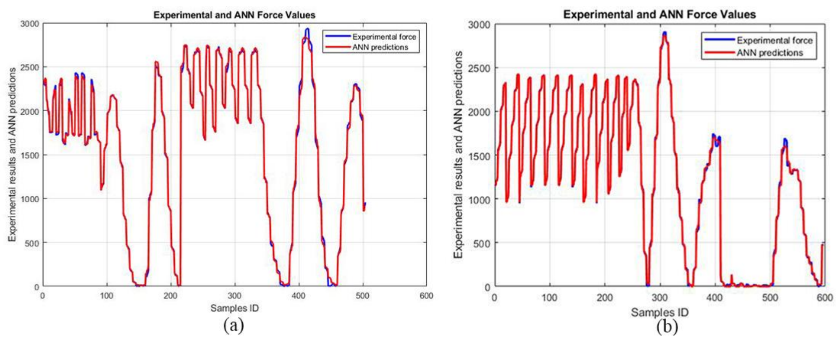
Gradient, mu, and validation fail graphs for the energy feature in Part I and Part II are shown in Figure 9. In Part I, at the 294th epoch, the gradient value was calculated as 0.0009, the Mu value was 0.0001, and the validation fail value was 6. In Part II, the gradient value was determined as 0.0005, the Mu value was 1e-05, and the validation fail value was 6 in the 322nd epoch.



(a) (b)

Figure 9. Gradient, mu, and validation fail graphs for energy in part 1(a) and part 2(b)

For the force property, experimental results and ANN predictions showed a close distribution in both Part I and Part II. ANN predicted the force property with an accuracy of 97.1% for Part I and 98.3% for Part II. Graphical distributions of experimental and ANN prediction values of displacement values for both parts are shown in Figure 10.



(a) (b)

Figure 10. Experimental and ANN force values in part 1(a) and part 2(b)

The best validation performance value for the force feature in Part I was determined as 1113.308 in the 384th period (epoch). In Part II, the best validity performance value was calculated as 370.940 in the 578th epoch (Figure 11).

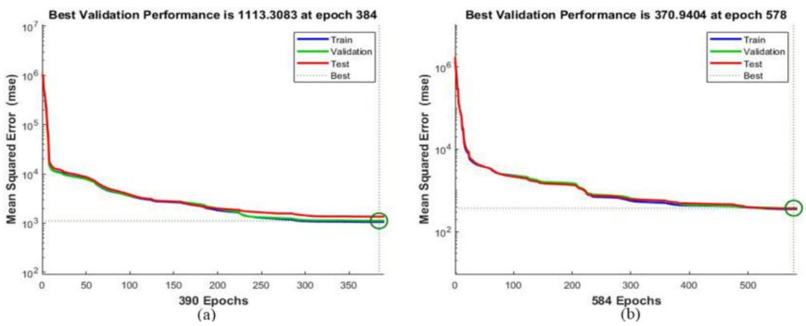


Figure 11. Best validation performance for force in part 1(a) and part 2(b)

The regression (R) value of the training, testing, and validation processes for the force feature in Part I was calculated as 0.99931, and in Part II, it was calculated as 0.99976. This shows that experimental data and ANN predictions match with high accuracy (Figure 12).

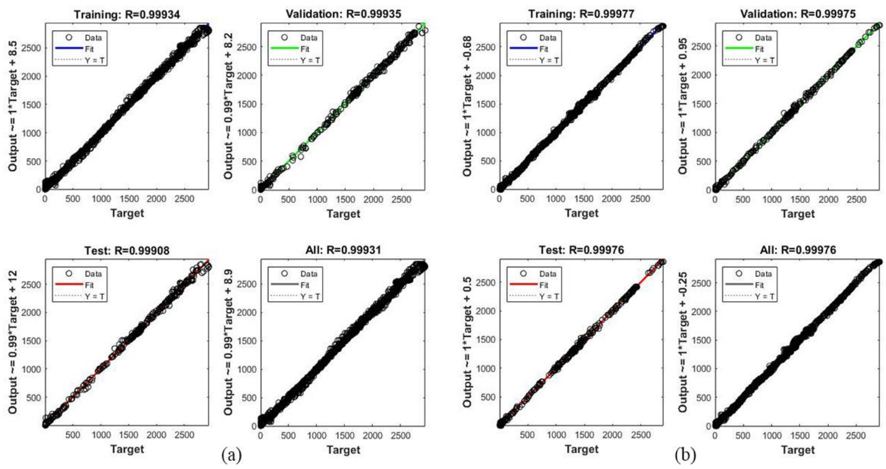


Figure 12. Training, validation, test, and regression graphs for force in part 1(a) and part 2(b)

Gradient, mu, and validation fail graphs for the force feature in Part I and Part II are shown in Figure 13. In Part I, at the 390th epoch, the gradient value was calculated as 345.694, the Mu value was 0.1, and the validation fail value was calculated as 6. In Part II, the gradient value was calculated as 197.152, the Mu value was 0.1, and the validation fail value was 6 in the 584th epoch.

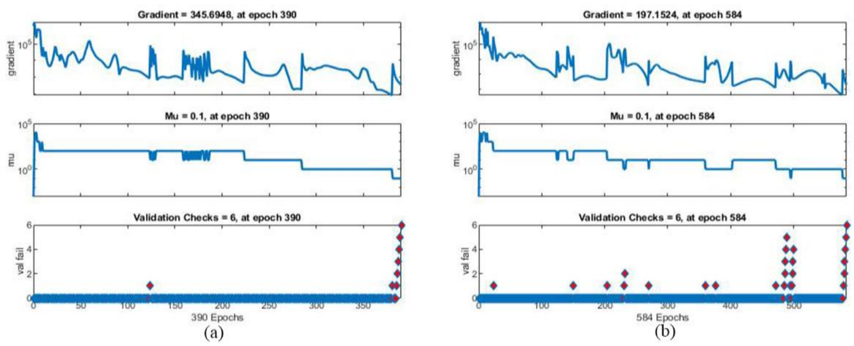


Figure 13. Gradient, mu, and validation fail graphs for force in part 1(a) and part 2(b)

Table 1. Performance values of the ANN model.

Parts	Features	Accuracy	R^2	RMSE	Max
Part I	Displacement	99.4%	0.99996	0.3715	1.1724
	Energy	99.2%	0.99992	0.4325	1.4578
	Force	97.1%	0.99931	0.4756	1.8652
Part II	Displacement	99.3%	0.99993	0.3787	1.1952
	Energy	99.1%	0.99991	0.4432	1.4697
	Force	98.3%	0.99976	0.4893	1.9641

Table 1 shows the accuracy, R^2, RMSE, and MAX performance values of the ANN model for Part I and Part II. In all cases examined, ANN prediction values showed results close to the experimental data. In this study, an educational simulation interface application was created using the developed ANN model, focusing on the need for students to systematically select materials and predict the mechanical behavior of materials in the Material Analysis and Material Selection courses from the Mechanical and Materials Engineering Department course curriculum. The main purpose of this application is to use this ANN-based application developed to provide students with a comprehensive education on material selection and prediction of mechanical behavior. This application especially allows students to gain practical experience and turn their theoretical knowledge into practice. The interface of the developed application is shown in Figure 14.

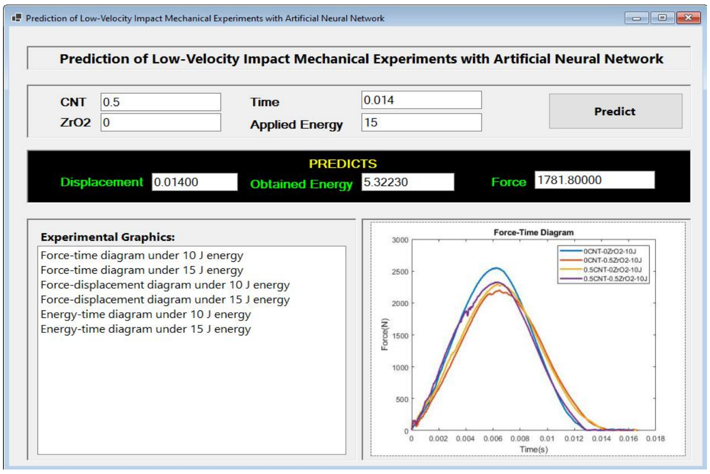


Figure 14. Prediction of low-velocity impact mechanical experiments with ANN

The developed application has an updateable library. By recording the input values entered by the students and their corresponding prediction values, the infrastructure of artificial intelligence studies is being prepared to further develop experiences. The use of ANN can be an effective method for modeling and predicting complex material behavior. It is important to evaluate whether the ANN is effective not only in low-speed impact effects but also in different application areas. For example, the usability of ANN can be investigated in other applications such as high-speed impacts and vibration analysis. Optimizing the training process and prediction time of the ANN model can make it more useful for real-time applications. This can provide faster and more effective solutions in engineering applications. These suggestions and opinions can guide future studies and research on similar topics.

Conclusion

This study provides a solution to the impact responses of nano-hybrid doped aramid composites. The proposed approach makes a significant contribution to the design of composite materials. In this study, the performance of the ANN model developed to predict the low-speed impact effects of nano hybrid-doped aramid composite sheets was examined. Experiments were carried out in two groups with different contribution rates, and the ability of the ANN to adapt to these different conditions was evaluated. A high agreement was observed between the experimental results and ANN predictions for displacement, energy, and force properties. Regression analyses also confirmed these situations. As a result, the developed ANN model successfully predicted the low-speed impact effects of different nano-doped aramid composites. This highlights the applicability of ANN as a reliable tool in engineering applications of such materials. Using this study, especially for support purposes in applied laboratory training materials, will provide students with the opportunity to put their theoretical education into practice more easily and cost-effectively. The specially developed application allows students to understand and analyze the problems they may encounter in the material selection process by using the digital environment more effectively and efficiently. As a result, this study provides students with the ability to predict material behavior and provides a practical application of the ANN approach in Mechanical and Materials Engineering education.

Recommendations

This study will be tried to be developed on different educational topics using different methods.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

Conflicts of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

Funding Declaration

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