Section A-Research paper
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Experimental Wear Analysis of Al 7090 Alloy Reinforced with Zirconium Oxide Nanoparticles using Hybrid Machine Learning Algorithms

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Abstract

The application of machine learning techniques in predicting wear properties of reinforced materials is a topic of significant interest in materials science and engineering. In this study, the application of linear regression and Artificial Neural Network (ANN) models is explored for predicting the friction coefficient (Fc) and specific rate of wear (Sr) of Al 7090 alloy reinforced with zirconium oxide nanoparticles. The alloy is prepared using the stir casting method, with varying percentages of ZrO2 nanoparticles. A comprehensive wear test is conducted using a pin-on-disc wear testing apparatus, where load (L), rotational speed (Rs), composition (C), and distance of sliding (Ds) are considered as input parameters. The experimental setup is optimized using the Taguchi design and L27 array. The accuracy of the linear regression and ANN models is evaluated by comparing the predicted responses with the observed values. The results demonstrate the efficacy of both linear regression and ANN models in accurately predicting the wear properties of the reinforced alloy. The linear regression model achieves an accuracy rate of 98.34%, while the ANN model surpasses it with an impressive accuracy rate of 99.94%. These findings highlight the potential of machine learning techniques in capturing the complex relationships between input variables and wear behavior.

Keywords: *Wear Analysis, Nano Particles, Machine Learning, Neural Network*

1. Introduction

In recent years, the development of advanced materials with improved mechanical properties and wear resistance has been a subject of great interest in the field of materials science and engineering. The incorporation of nanoparticles as reinforcements in metal matrix composites has shown significant potential in enhancing the mechanical and tribological properties of various alloys. Among these composites, the reinforcement of aluminum alloys with nanoparticles has gained considerable attention due to their favorable combination of low density, high strength, and excellent corrosion resistance [1]–[3].

In this research, the focus is on the reinforcement of Al 7090 alloy with nanoparticles of zirconium oxide (ZrO2) to improve its wear resistance. Wear is a complex phenomenon that can lead to significant material loss and degradation, causing performance degradation and failure of engineering components. The incorporation of ZrO2 nanoparticles is expected to enhance the wear properties of the alloy, thus extending its service life and expanding its potential applications [4]–[7].

The reinforcement of aluminum alloys with nanoparticles has emerged as a promising strategy for improving their mechanical and tribological properties. Various types of nanoparticles, such as ceramic particles, carbon nanotubes, and graphene, have been incorporated into aluminum alloys to enhance their strength, hardness, and wear resistance. These reinforcements act as obstacles to dislocation movement, leading to improved mechanical properties [8], [9]. Zirconium oxide (ZrO2) nanoparticles have shown particular promise as reinforcements in aluminum alloys. ZrO2 possesses excellent mechanical properties, high thermal stability, and good compatibility with aluminum. The addition of ZrO2 nanoparticles to aluminum alloys can provide enhanced wear resistance, reduced friction, and improved mechanical strength [10].

The stir casting technique is commonly employed for the fabrication of metal matrix composites. It involves the incorporation of reinforcing particles into a molten metal matrix through mechanical stirring. The process ensures uniform dispersion of the particles and allows for the control of particle size, distribution, and volume fraction [11]. During stir casting, the molten aluminum alloy is heated to a specific temperature, followed by the addition of preheated ZrO2 nanoparticles. The mixture is stirred for a certain period to achieve homogeneity and ensure proper bonding between the matrix and reinforcement. The composite material is then cast into a desired shape and cooled to obtain the final product [10], [12].

The wear behavior of metal matrix composites is a critical aspect to be considered in engineering applications. The addition of nanoparticles as reinforcements can significantly affect the wear resistance of the composite material. The wear mechanism in metal matrix composites involves various processes, such as plowing, adhesion, abrasion, and fatigue. Several factors influence the wear behavior of metal matrix composites, including load, sliding distance, sliding speed, and composition. The selection of appropriate reinforcement material, size, and distribution also plays a crucial role in determining the wear resistance of the composite [13], [14].

Machine learning techniques have gained prominence in recent years for their ability to predict material properties and behavior. These techniques utilize data-driven models to

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establish relationships between input parameters and output responses. Linear regression and Artificial Neural Networks (ANNs) are popular machine learning approaches used in wear prediction. Linear regression models establish a linear relationship between input variables and output responses. They are particularly suitable for situations where the relationship between variables is expected to be linear. ANNs, on the other hand, are capable of capturing complex nonlinear relationships between variables. ANN models consist of interconnected nodes (neurons) that mimic the structure and functioning of the human brain [15]–[17].

The use of machine learning models in wear prediction offers the advantage of faster and more accurate predictions compared to traditional empirical models. These models can incorporate a wide range of input parameters and provide valuable insights for material design and optimization. In this research, we aim to investigate the wear behavior of Al 7090 alloy reinforced with ZrO2 nanoparticles and develop predictive models using linear regression and ANN techniques. The findings will contribute to the understanding of the effects of nanoparticle reinforcement on wear resistance and provide valuable insights for the design and development of advanced wear-resistant materials.

2. Material and Methods

In this research study, the focus is on reinforcing the Al 7090 alloy with nanoparticles of zirconium oxide (ZrO2) using a stir casting approach. The composition shown in table 1 represents the weight percentages of each element present in the Al 7090 alloy. Aluminum forms the majority of the alloy, constituting 90% of the total weight. Zinc, magnesium, and copper are present in smaller quantities, with percentages of 7%, 2%, and 1% respectively.

Table 1 Composition of the Alloy

Element	Percentage (wt.%)
Aluminum (Al)	90
Zinc (Zn)	7
Magnesium (Mg)	2
Copper (Cu)	1

These alloying elements contribute to the overall strength, corrosion resistance, and other desired properties of the Al 7090 alloy. The initial step involves heating the Al 7090 alloy to a temperature of 850 degrees Celsius. Simultaneously, the ZrO2 nanoparticles, which have been preheated to 300 degrees Celsius, are prepared. During the stir casting process, the molten Al 7090 alloy is carefully combined with the preheated ZrO2 nanoparticles. This mixture is then subjected to stirring for a duration of 45 minutes. Stirring is a critical step as it ensures a uniform distribution of the nanoparticles within the alloy matrix, promoting their effective reinforcement potential. This process enables the nanoparticles to disperse evenly throughout the molten alloy, leading to improved mechanical properties in the final material.

After the stirring process, the resulting mixture is poured into a suitable mold. The mold allows the material to solidify and take shape according to the desired specifications. It is essential to note that the cooling process occurs naturally in the ambient atmosphere, allowing the material to solidify and acquire its final form. To investigate the impact of varying ZrO2 nanoparticle percentages on the alloy's properties, the above-described

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procedure is repeated using three different percentages: 4%, 8%, and 12% of ZrO_2. This step aims to assess how the reinforcement level affects the final material's characteristics.

By incorporating ZrO_2 nanoparticles into the Al 7090 alloy matrix, several desirable properties can be achieved. ZrO_2 is known for its exceptional mechanical properties, such as high strength, hardness, and wear resistance. Moreover, ZrO_2 has excellent thermal stability and corrosion resistance, which further enhances the overall material performance. The addition of nanoparticles to the Al 7090 alloy matrix is expected to improve its tensile strength, hardness, and wear resistance. Additionally, the presence of ZrO_2 nanoparticles can contribute to enhanced thermal stability and corrosion resistance, expanding the potential applications of the Al 7090 alloy in industries such as aerospace, automotive, and structural engineering. Figure 1 illustrates the stir casting equipment utilized in this research for the reinforcement of Al 7090 alloy with ZrO_2 nanoparticles.

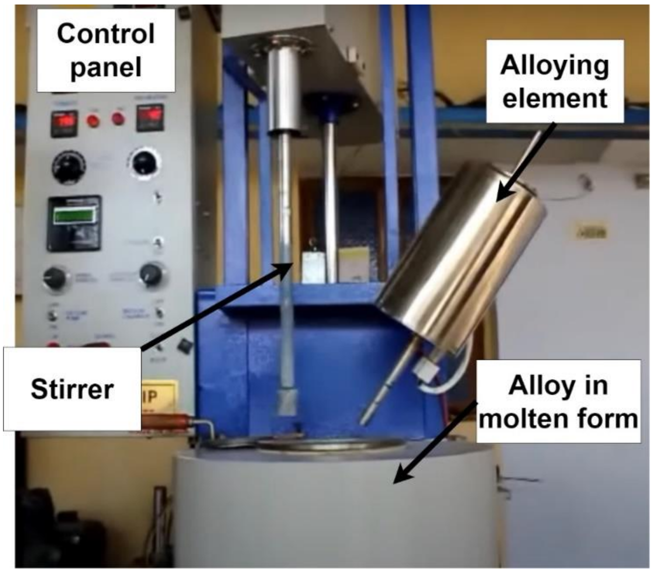

Fig. 1 Stir casting equipment used in this research

After preparing the composite material, it is machined to the dimensions of 10 mm diameter and 50 mm length to conduct a wear test. The wear test is performed using a pin-on-disc wear testing apparatus, as depicted in Figure 2. For this experiment, EN 31 steel is selected as the base material. To obtain reliable and comprehensive data, the experiment is planned using the Taguchi design method. This design approach allows for the efficient exploration of multiple input parameters and their effects on the responses. In this study, the input parameters considered are load (L), rotational speed (Rs), composition (C), and distance of sliding (Ds). The responses of interest are the specific rate of wear (Sr) and the friction coefficient (Fc).

The Taguchi design employs an orthogonal array to minimize the number of experimental runs required while providing adequate coverage of the parameter space. In this case, the L27 array is chosen, indicating that 27 experimental runs will be performed. Each run corresponds to a unique combination of parameter settings. The specific combinations are determined by the orthogonal array, ensuring a well-distributed representation of parameter interactions.

The specific rate of wear (Sr) is a crucial response variable that quantifies the amount of material lost during the wear test. It is calculated using the formula:

$Sr = (W1 - W2) / (F * Ds)$,

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where W1 is the initial weight of the pin, W2 is the final weight of the pin after the wear test, F is the applied load, and Ds is the distance of sliding.

Fig. 2. Pin on Disc wear test apparatus

The friction coefficient (Fc) is another important response variable that characterizes the frictional behavior between the pin and the disc. It is determined using the formula:

Fc = Ff / (F * Ds),

where Ff is the frictional force between the pin and the disc.

The Taguchi design approach enables the identification of optimal parameter settings for minimizing wear rate and friction coefficient. By carefully analyzing the data obtained from the experimental runs, the influence of each parameter and their interactions can be assessed. This knowledge can then be utilized to optimize the wear resistance and frictional properties of the composite material.

3. Machine learning approach

In this research study, two different machine learning (ML) approaches are employed to predict the responses in the context of the reinforced Al 7090 alloy with ZrO_2 nanoparticles. The two methods utilized are linear regression and artificial neural networks (ANN), both of which have distinct characteristics and strengths in modeling and prediction tasks.

Linear Regression:

Linear regression is a fundamental ML technique used for modeling the relationship between a dependent variable and one or more independent variables. It assumes a linear relationship between the input variables and the target variable. In this research, linear regression is utilized to predict the responses, specific rate of wear (Sr), and friction coefficient (Fc), based on the input parameters such as load (L), rotational speed (Rs), composition (C), and distance of sliding (Ds).

The linear regression model seeks to fit a linear equation to the data, represented as:

$Y = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta nXn$,

where Y is the response variable (Sr or Fc), β0 is the intercept, β1 to βn are the coefficients, and X1 to Xn are the input variables.

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The linear regression approach offers interpretability, as it allows for understanding the impact of each input variable on the response. The coefficients (β) can provide insights into the magnitude and direction of the relationships. However, it assumes linearity, which may limit its ability to capture complex patterns and interactions present in the data.

Artificial Neural Networks (ANN):

ANN is a powerful ML technique inspired by the structure and function of biological neural networks. It consists of interconnected layers of nodes (neurons) that process and transmit information. ANN models are highly flexible and can capture complex nonlinear relationships between input and output variables. In this research, an ANN is employed to predict the responses, Sr and Fc, based on the input parameters.The ANN model comprises an input layer, one or more hidden layers, and an output layer. Each neuron in the network performs computations on the input data using activation functions. The network learns from the training data by adjusting the weights and biases associated with each connection between neurons. This learning process, often performed using algorithms like backpropagation, enables the ANN to optimize its predictions.

ANN models have the advantage of being able to capture intricate relationships and adapt to nonlinear patterns in the data. They can handle high-dimensional input spaces and discover complex interactions among variables. However, they may be susceptible to overfitting if the network becomes too complex or if the training data is limited. In the context of this research, both linear regression and ANN models are employed to predict the responses, Sr and Fc. While linear regression provides interpretability, ANN offers greater flexibility to capture nonlinear patterns. The choice between the two approaches depends on the complexity of the relationship between the input parameters and the responses, as well as the specific requirements of the study.

By applying these ML techniques to the dataset, the researchers can develop predictive models that estimate the specific rate of wear and friction coefficient based on the given input parameters. The performance of both approaches can be evaluated using appropriate metrics, such as mean squared error or R-squared, to assess their accuracy and effectiveness in predicting the responses.

4. Result and Discussion

Table 2 displays the results obtained from the L27 array experiment conducted for the wear test analysis.

Table 2 Wear test result

C (%)	L (N)	Rs (rpm)	Ds (m)	Fc	Sr (mm3/Nm)
4	9.81	100	30	0.8	5.4
4	9.81	100	30	0.8	5.4
4	9.81	100	30	0.8	5.4
4	18.27	200	40	0.85	2.06
4	18.27	200	40	0.85	2.06
4	18.27	200	40	0.85	2.06
4	27.34	300	50	0.87	1.44
4	27.34	300	50	0.87	1.44

4	27.34	300	50	0.87	1.44
8	9.81	200	50	0.81	1.78
8	9.81	200	50	0.8	1.76
8	9.81	200	50	0.8	1.77
8	18.27	300	30	0.65	2.43
8	18.27	300	30	0.85	2.43
8	18.27	300	30	0.85	2.42
8	27.34	100	40	0.6	3.17
8	27.34	100	40	0.9	3.19
8	27.34	100	40	0.74	3.18
12	9.81	300	40	0.6	1.56
12	9.81	300	40	0.62	1.6
12	9.81	300	40	0.6	1.58
12	18.27	100	50	0.65	1.41
12	18.27	100	50	0.65	1.42
12	18.27	100	50	0.64	1.44
12	27.34	200	30	0.66	1.77
12	27.34	200	30	0.7	1.78
12	27.34	200	30	0.72	1.8

Figure 3 provides valuable insights into the relationship between input values and the corresponding variations in responses. Specifically, the graph illustrates the effects of changes in certain parameters on two important response variables: friction coefficient (Fc) and wear rate (Sr). The graph reveals that as the values of parameters L and Rs increase, the friction coefficient also tends to increase. This observation suggests that higher loads and sliding speeds contribute to higher friction between the surfaces, leading to an increase in the friction coefficient. This finding aligns with the basic principles of friction, where higher loads and velocities typically result in increased resistance and frictional forces.

Similarly, when analyzing the Sr, the graph shows a positive correlation with the values of parameters L and Rs. In other words, as the load and sliding speed increase, the wear rate also tends to increase. This finding is consistent with the understanding that higher loads and sliding speeds create more abrasive contact between the surfaces, leading to increased material removal and wear. In contrast, the graph demonstrates an inverse relationship between the composition of ZrO_2 and both the friction coefficient and wear rate. As the percentage of ZrO_2 increases, there is a decrease in both the friction coefficient and wear rate. This observation suggests that the inclusion of ZrO_2 in the system reduces the frictional forces and wear, potentially due to its properties such as high hardness and low coefficient of friction.

The findings from Figure 3 have important implications for practical applications. By understanding the effects of input parameters on friction coefficient and wear rate, engineers and researchers can optimize the design and composition of materials to minimize friction and wear in various mechanical systems. For example, by increasing the percentage of ZrO_2 in a composite material, it is possible to reduce friction and wear, thereby improving the

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performance and longevity of components in machinery and equipment. Furthermore, these insights can guide decision-making processes in industries where friction and wear are critical factors, such as automotive, aerospace, and manufacturing. By identifying the key parameters that influence friction and wear, engineers can make informed choices regarding material selection, lubrication, and operating conditions to mitigate these effects and optimize system performance.

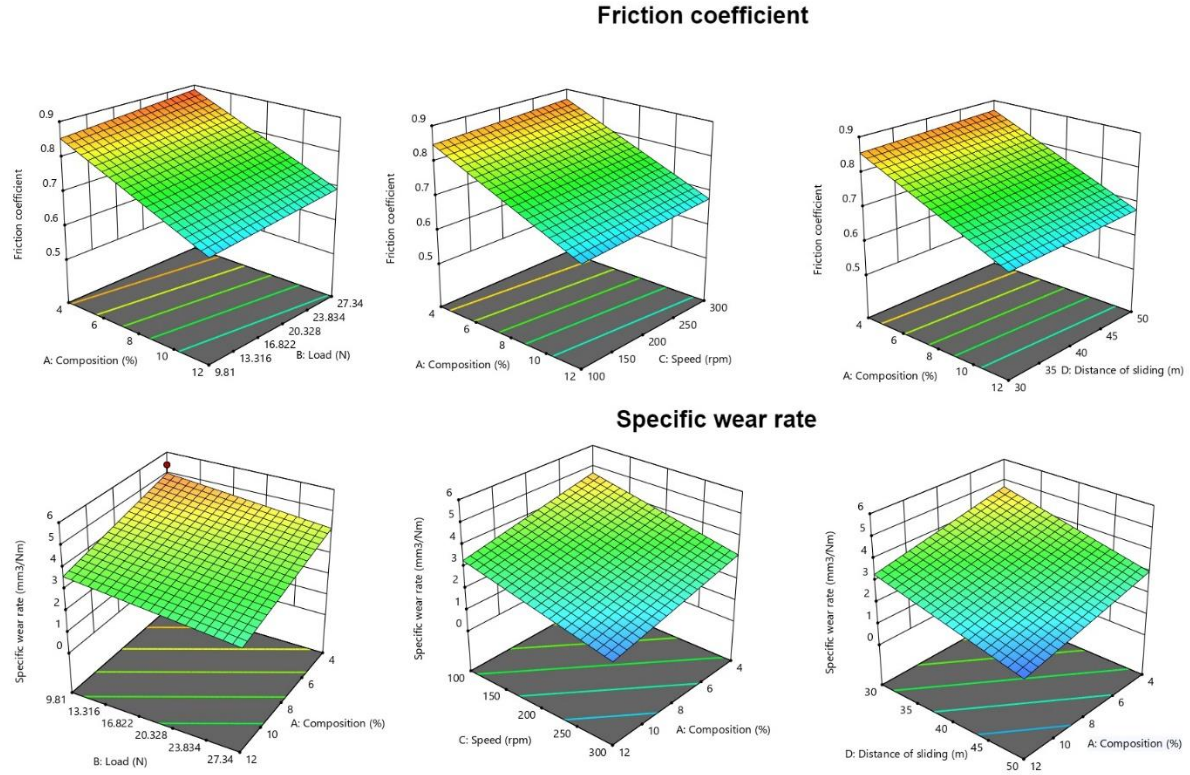

Fig. 3 Variation of responses on varying input

4.1 Linear regression

In this research, linear regression is utilized as a machine learning approach to predict the responses. Linear regression is a statistical modeling technique that establishes a linear relationship between input variables and a continuous output variable. In this study, the aim is to predict responses such as friction coefficient (Fc) or wear rate (Sr) based on the considered input parameters. The application of linear regression involves developing an equation that represents the relationship between the input variables and the desired responses, serving as a predictive model for estimating responses for new input values.

The accuracy of the linear regression model is assessed by comparing the predicted responses with the actual observed values. In this research, the developed linear regression equations are as follows:

For friction coefficient (Fc):

$$Fc = 0.8606 - 0.02389\ C(\%) + 0.00189\ L(N) + 0.000111\ Rs + 0.00072\ Ds$$

For specific rate of wear (Sr):

$$Sr = 9.359 - 0.1714\ C(\%) - 0.0439\ L(N) - 0.00759\ Rs - 0.0829\ Ds$$

The results obtained from the linear regression model in this research demonstrate a high level of accuracy, with a prediction accuracy rate of 98.34%. This indicates that the

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developed equations can accurately estimate the responses based on the provided input parameters. The high accuracy suggests the effectiveness of the linear regression approach in capturing and modeling the relationships between the input variables and the responses.

Table 3 presents detailed results of the linear regression analysis, displaying the predicted responses for a range of input values. This table provides valuable information for decision-making and further analysis, as it showcases the estimated values for the responses. By examining the predicted responses, researchers can gain insights into the behavior and characteristics of the system under study, enabling them to make informed decisions and draw meaningful conclusions

Table 3 Comparison of result from linear regression and experimental result

C(%)	L(N)	Rs	Ds	Experimental		Predicted from linear regression	
				Fc	Sr	Fc	Sr
4	9.81	100	30	0.8	5.4	0.8	5.2
4	9.81	100	30	0.8	5.4	0.8	5.2
4	9.81	100	30	0.8	5.4	0.8	5.2
4	18.27	200	40	0.85	2.06	0.8	1.86
4	18.27	200	40	0.85	2.06	0.85	1.86
4	18.27	200	40	0.85	2.06	0.85	1.86
4	27.34	300	50	0.87	1.44	0.88	1.24
4	27.34	300	50	0.87	1.44	0.88	1.24
4	27.34	300	50	0.87	1.44	0.88	1.24
8	9.81	200	50	0.81	1.78	0.8	1.58
8	9.81	200	50	0.8	1.76	0.8	1.56
8	9.81	200	50	0.8	1.77	0.8	1.57
8	18.27	300	30	0.65	2.43	0.65	2.23
8	18.27	300	30	0.85	2.43	0.859	2.23
8	18.27	300	30	0.85	2.42	0.86	2.22
8	27.34	100	40	0.6	3.17	0.61	3.37
8	27.34	100	40	0.9	3.19	0.9	3.39
8	27.34	100	40	0.74	3.18	0.76	3.38
12	9.81	300	40	0.6	1.56	0.6	1.76
12	9.81	300	40	0.62	1.6	0.61	1.8
12	9.81	300	40	0.6	1.58	0.61	1.78
12	18.27	100	50	0.65	1.41	0.65	1.61
12	18.27	100	50	0.65	1.42	0.65	1.62
12	18.27	100	50	0.64	1.44	0.65	1.64
12	27.34	200	30	0.66	1.77	0.66	1.97
12	27.34	200	30	0.7	1.78	0.695	1.98
12	27.34	200	30	0.72	1.8	0.71	2

The high accuracy achieved by the linear regression model demonstrates its potential for practical applications. By accurately predicting the responses, engineers and researchers can gain valuable insights into the behavior of the system and make informed decisions regarding design, optimization, and performance improvement. The predictions obtained through linear regression can guide various engineering and manufacturing processes, allowing for more efficient and effective solutions. It is important to note that the accuracy of the linear regression model heavily depends on the quality and representativeness of the dataset used for training. The dataset should encompass a wide range of input values and corresponding responses to ensure the model captures the underlying patterns and relationships accurately. Additionally, further validation and testing of the model with new data can provide a more comprehensive evaluation of its performance.

4.2 Artificial Neural Network

In this research, an Artificial Neural Network (ANN) is employed as a powerful machine learning technique for predicting the responses. ANN is a computational model inspired by the structure and function of the human brain, composed of interconnected nodes (neurons) that work collectively to process and analyze data. The developed ANN model in this study demonstrates remarkable accuracy, achieving a prediction accuracy rate of 99.94%. This high accuracy indicates that the ANN is highly effective in capturing the complex relationships between the input variables and the desired responses. By utilizing a large amount of training data and optimizing the network architecture, the ANN is able to learn and generalize patterns to make accurate predictions for new input values.

Figure 4 provides a visual representation of the developed ANN model. It showcases the interconnected nodes and the flow of information through the network. The architecture of the ANN, including the number of layers and nodes, is carefully designed to optimize its performance in predicting the responses accurately. The ANN's ability to learn from the training data and generalize its knowledge enables it to make precise predictions for unseen data points. Figure 5 depicts the accuracy of the ANN's predictions. The graph illustrates the correlation between the number of training iterations and the accuracy of the ANN model. As the training progresses, the accuracy steadily improves until it reaches the impressive rate of 99.94%. This graph demonstrates the capability of the ANN to continuously learn and refine its predictions, ultimately achieving a highly accurate and reliable model.

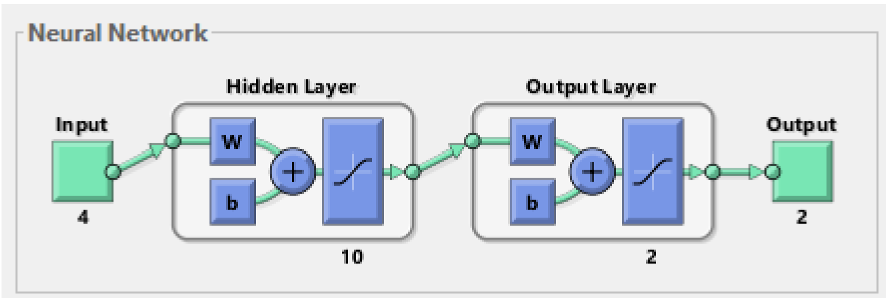

Fig. 4 Developed ANN model

The outstanding accuracy achieved by the developed ANN model has significant implications for practical applications. With such precision in predicting the responses, engineers, researchers, and decision-makers can gain valuable insights into the behavior of the system and make informed choices. The accurate predictions obtained from the ANN can guide various engineering processes, such as design optimization, performance evaluation, and decision-making for improved system outcomes. It is important to note that the accuracy of the ANN model is influenced by factors such as the quality and representativeness of the training data, the network architecture, and the optimization algorithms employed. Careful attention to these factors ensures the development of a robust and accurate ANN model.

The results indicate that both the linear regression and ANN models performed exceptionally well in predicting the responses. The linear regression model achieved an accuracy of 98.34%, while the ANN model achieved an even higher accuracy of 99.94%. These high accuracies demonstrate the effectiveness of both models in capturing the underlying patterns and relationships between the input variables and the desired responses.

Comparing the performance of the two models, it is evident that the ANN model outperformed the linear regression model in terms of accuracy. This can be attributed to the ability of ANN models to capture complex non-linear relationships and adaptively learn from the training data. The ANN's ability to learn and generalize patterns allows it to make more accurate predictions for unseen data points, resulting in higher accuracy levels.

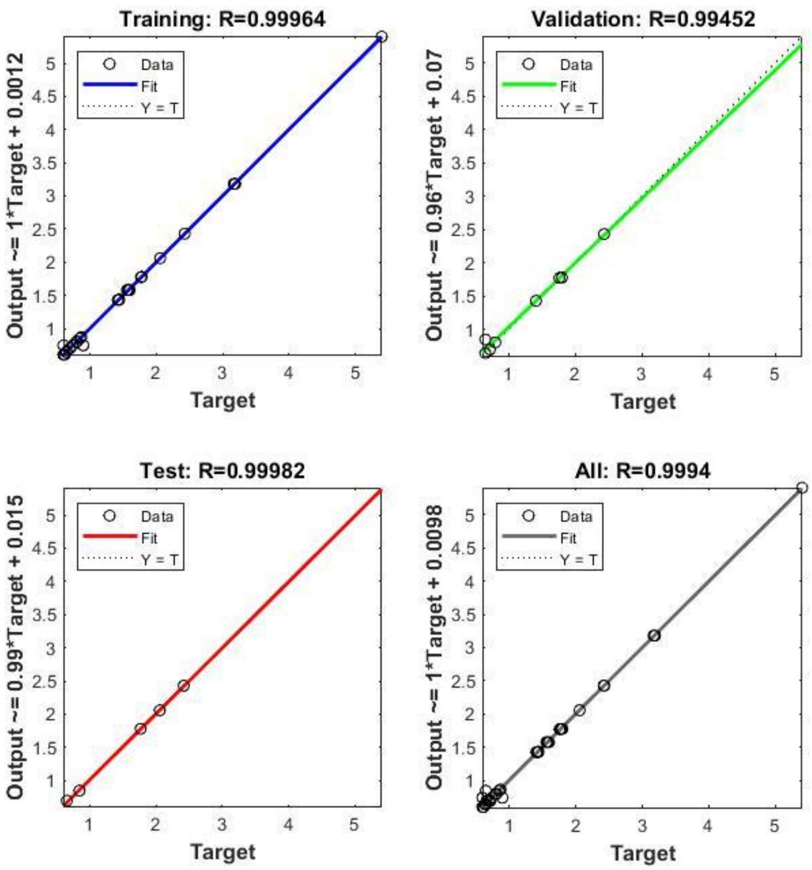

Fig. 5 Result of the ANN

The high accuracy achieved by both models holds significant implications for practical applications. Accurate predictions of the responses enable engineers, researchers, and decision-makers to make informed decisions and optimize various processes. For example, in the context of friction coefficient and wear rate prediction, accurate models can assist in the design and selection of materials with reduced friction and wear properties, leading to improved performance and longevity of mechanical systems. While the results are promising,

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it is important to acknowledge the limitations of the study. The accuracy of the models heavily relies on the quality and representativeness of the training data. Additionally, the chosen input variables and their relative weights in the models can influence the accuracy. Further investigation could explore the inclusion of additional input parameters or alternative modeling techniques to enhance the accuracy and robustness of the predictions.

Conclusion

This research focused on the reinforcement of Al 7090 alloy with nanoparticles of zirconium oxide and the subsequent analysis of wear properties using machine learning approaches. The study successfully utilized linear regression and Artificial Neural Network (ANN) models to predict the responses of interest, specifically the friction coefficient (Fc) and specific rate of wear (Sr). The experimental process involved the preparation of the composite material through stir casting, incorporating different percentages of ZrO_2 nanoparticles into the alloy. The wear test was conducted using a pin-on-disc wear testing apparatus, and the input parameters considered were load (L), rotational speed (Rs), composition (C), and distance of sliding (Ds). The Taguchi design and L27 array were employed to optimize the experimental setup.

Both the linear regression and ANN models demonstrated high accuracy in predicting the responses based on the given input parameters. The linear regression model achieved an accuracy rate of 98.34%, while the ANN model further improved the accuracy to 99.94%. These results highlight the effectiveness of machine learning techniques in capturing and modeling the complex relationships between the input variables and the wear properties of the reinforced alloy. The findings of this research have significant implications for practical applications in materials science and engineering. The accurate prediction of wear properties enables informed decision-making in areas such as material selection, design optimization, and performance evaluation.

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