IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

PREDICTION OF MECHANICAL PROPERTIES OF ALUMINUM METAL MATRIX COMPOSITE USING ARTIFICIAL NEURAL NETWORK

[1]Mahaviradhan N, [2]Sivaganesan S

[1]Research Scholar, [2]Associate Professor
[1]Department of Mechanical Engineering,
[1]Vels Institute of Science Technology & Advanced Studies (VISTAS), Chennai, India

Abstract: Composite materials outperform conventional materials due to their superior mechanical properties, according to numerous studies in the field of materials. According to modern manufacturing trends, aluminum-based composite materials are used in a number of applications. In the aerospace and electronics industries, carbon fiber reinforced aluminum metal matrix composites (AMMC) offer a lot of potential. In this study, an open die casting procedure is used to create the AA6063-based composite material. The reinforcement is uncoated continuous long spool-type pitch-based carbon fibers, and the base metal is AA6063. The carbon fibers were laid out in a grid with eleven weight percentage levels ranging from 1% to 6% in 0.5 percent increments. A range of mechanical experiments were used to study the composite's mechanical properties.
To forecast mechanical properties, the Levenberg-Marquardt algorithm of single-input multiple-output artificial neural networks is utilized. The output characteristics of the composite are shear strength, hardness, impact strength, and tensile strength. The performance of the Artificial Neural Network (ANN) prediction was evaluated using the determination coefficient (R^2) and mean square error (MSE). The average R^2 and MSE are 0.9937 and 14.5623, respectively, indicating that the ANN effectively fitted the experimental response variable values. The findings are further supported by the correlation coefficient (R) of 0.99689.

***Index Terms* - AA6063 Aluminum alloy, Carbon fiber reinforced aluminum metal matrix composites, Open Die Casting, Artificial neural network, Levenberg-Marquardt algorithm**

I. INTRODUCTION

The demand for today's trends necessitates a diverse range of materials; the researcher's goal was to improve material quality by introducing novel reinforcements. Automotive, defense, transportation, and aerospace are just a few of the industries that use AMMCs. AMMCs are used as thermal management materials in the electronics sector. This composite's matrix phase is pure Aluminum, which can be any Al-Si alloy. Aluminum extrusions from the 6xxx series alloy are most commonly used in industrial applications. Despite the fact that the alloys are employed in a wide range of applications, from transportation to architectural construction, they have a better surface polish [1]. Metal Matrix Composites (MMCs) are made composed of a continuous metal or alloy matrix with particle, short fiber, or continuous fiber reinforcing. Metal matrices such as aluminum, titanium, copper, and magnesium alloys play an important role in MMCs. AMMCs have received the most attention in the field of lightweight metal matrix composites so far [2].

In the AA5251 aluminum matrix composites with carbon particle reinforcement, there is a noticeable increase in toughness and a rise in Brinell hardness number. Good fiber wetting results in improved mechanical properties. As a result, the fibers are distributed evenly across the matrix [3,4]. AA5251 aluminum matrix composites with a volume percentage of 5–15 percent carbon were made using the squeeze casting infiltration technique. As a result of the squeeze casting process, tensile strength is lowered [5].

Short carbon fibers wrapped with various metallic films are used in composite manufacture to adjust the interfacial reactivity of fibers with molten Al, copper, and Ni coatings, increasing the material's mechanical qualities [6]. The impact of fiber availability, alloy matrices, fiber surface coatings, manufacturing procedures, and their impact on composite properties is further explored [7,8]. The treated fibers are immediately filtered by molten aluminum alloy; particulates are uniformly scattered with carbon fibers, and the inclusion of particulates improves properties such as hardness and wear resistance. The results reveal that the strength increases as the number of carbon fibers increases [9,10]. The mechanical properties of the AA7075 aluminum metal matrix composite produced by squeeze casting for SiC reinforcement are improved [11,12].

Both coated and uncoated carbon fibers were reinforced with AA7075, resulting in improved mechanical strength [13,14]. The mechanical properties of CFRASL in various applications, including as tensile, flexural, and impact strength, were investigated, and testing was carried out in accordance with ASTM standards [10]. The structural topologies of sandwich laminate composites were studied, and it was discovered that adding carbon fiber reinforcement improves the fiber's mechanical properties [15]. To regulate the optimal ratio of Nickel coated Graphite (Ni-Gr) and Silicon Carbide (SiC) for high-temperature applications, the tribological characteristics of an aluminum alloy-based HAMC were investigated [16].

ANN [17] are a sort of machine learning that is built using biological neurons as a model. It's used in a range of engineering applications, such as improving adsorption capacity [18], hardening electroless nickel-boron coatings [19], and so on. An ANN model for predicting AlSiC mechanical and electrical properties has been suggested. The greatest results were obtained using a multilayer perceptron with 20 neurons in two hidden layers [20].

The purpose of this research is to forecast the mechanical properties of carbon fiber reinforced aluminum metal matrix composites using the Levenberg-Marquardt method of a single-input multiple-output artificial neural network.

II. Materials and Methods

The reinforcement is uncoated continuous carbon fibers, and the base metal is AA6063. The carbon fibers were divided into eleven weight percentage levels, ranging from 1% to 6% in 0.5 percent increments. Aluminum alloy AA6063 is melted in an electrical furnace in a high temperature crucible at a temperature of 765°C. The molten alloy is poured into a steel mold with two carbon fiber meshes, and the sheet box is placed in the sand mold to compensate for the box's thermal deformations. In the open atmosphere, this material is gently cooled. The same method is used to make all of the required examples of various compositions [21]. To determine the mechanical qualities, a range of experiments are carried out. Brinell hardness is measured using a Brinell microhardness equipment. An impact tester is used to determine impact strength. Torsion testing is used to determine shear strength values in torsion testing machines. In a universal testing machine, a tensile test is performed to determine the tensile strength.

III. Modelling - Artificial Neural Network

The input layers for input parameters, hidden layers for neurons, and output layers for response variables make up the design of an ANN. Weights are used to connect the layers. In the same manner that intercepts are introduced to equations, the optional bias layers are added to the hidden and output layers. Error analysis, which uses the R^2 and MSE, is used to assess the performance of ANN modeling. By choosing the right network type, training, adaption learning, performance and activation functions, number of neurons, and hidden layers, the least amount of error can be obtained.

MATLAB R2022a was used to model the ANN. A feed forward back propagation single-input multiple-output artificial neural network was created in this study using the Levenberg-Marquardt algorithm and gradient descent with momentum weight and bias learning function, as well as the Levenberg-Marquardt algorithm and gradient descent with momentum weight and bias learning function. For the hidden and output layers, R^2 and MSE were employed as activation functions, using sigmoidal tangent (TANSIG) as the activation function. The system in this paper uses a 1-10-4 design, with 1 input factor in the input layer, 10 neurons in the hidden layer, and 4 output factors in the output layer. One advantage was that more than 99 percent effectiveness may be achieved in fewer iterations. It was determined to use ten neurons in a single hidden layer. As TANSIG processed the value from -1 to +1, the input data entered into the ANN tool was normalized. The input data was then trained, tested, and validated in a 70:15:15 ratio. To get the final result, the data was denormalized from -1 to +1. The data that was planned to be created was then compared to the data that was actually produced. The flow of the process is shown in **Fig.1**.

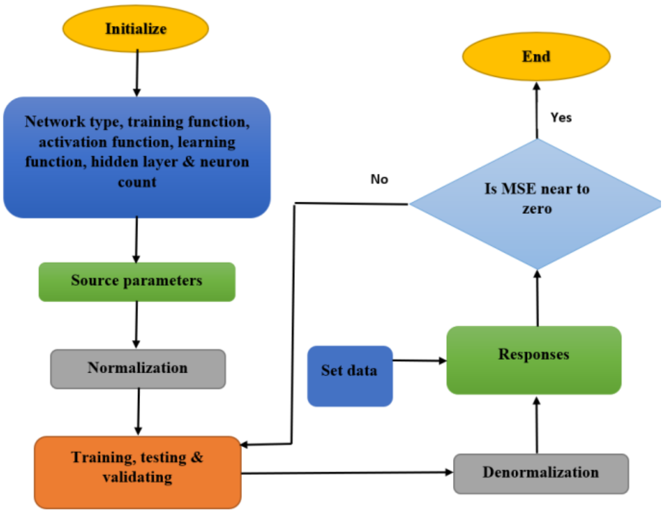

Figure 1 Flowchart for estimation of physical properties

IV. Artificial Neural Networks

For the estimation of mechanical properties, **Table 1** displays the experimental values and ANN predicted values of response variables

Table 1 Experimental values and ANN predicted values of output variables

Input Data	Experimental results				ANN Predicted results			
Carbon Wt %	Shear Strength (MPa)	Hardness (BHN)	Impact Strength (MPa)	Tensile Strength (MPa)	Shear Strength (MPa)	Hardness (BHN)	Impact Strength (MPa)	Tensile Strength (MPa)
1	134	70	9.2	275	135.2518	72.2357	9.8924	273.0153
1.5	137	72	9.3	279	135.9853	84.2358	11.8622	278.0354
2	140	75	9.4	282	142.8176	87. 0125	10.794	280.0284
2.5	141	76	9.5	285	145.7412	75.1753	10.6181	282.0181
3	143	80	9.6	290	146.2278	74.8619	11.4625	284.0652
3.5	144	82	9.8	295	148.1456	86.1546	10.727	286.9186
4	145	83	10.1	298	149.7825	79.2514	9.3343	290.1538
4.5	148	86	10.7	306	150.9574	82.4974	9.2886	285.5895
5	150	89	11.4	308	151.6523	84.3192	11.7183	309.9375
5.5	152	90	11.6	311	152.7744	86.8399	9.2365	305.4729
6	155	92	12	316	153.8526	79.0905	10.3975	311.5937

The artificial neural network architecture employed in this investigation is shown in **Fig.2**. Carbon weight percentage is used as an input factor in the input layer. Shear strength, hardness, impact strength, and tensile strength are response variables in the output layer. Weights, w_{1i}, links the input layer to the hidden layer, where i represents the input factor and j represents the count of neurons for hidden layer. Bias to the hidden layer's j^{th} neuron is represented by b_{1j}. Equation (1) represents the generalized equation from input layer to hidden layer.

$$H_j = \sum_{j=1} w_{1j} X_1 + b_{1j} \qquad (1)$$

Weights, w_{ji}, links the hidden layer to the output layer, where i means the number of neurons in the hidden layer and j signifies the number of output variables in the output layer. The bias to the i^{th} factor of the output layer is represented by b_{2i}. Equation (2) represents the generalized equation from hidden to output layers.

$$Y_i = \sum_{i=1}^{4} \tanh(Hj) * w_{ji} + b_{2i} \qquad (2)$$

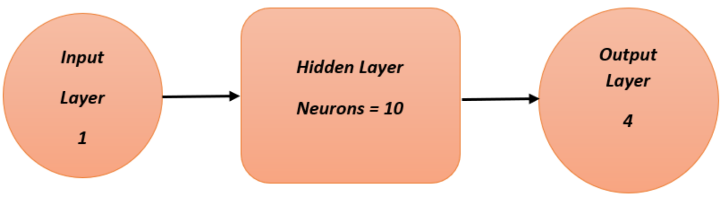

Figure 2 Architecture of 1-10-4 network for estimation of mechanical properties of Aluminum composite

Setting parameters as shown in **Fig.3** was used to train. The default MATLAB configuration parameters were used without any variations.

showWindow	true	mu	0.001
showCommandLine	false	mu_dec	0.1
show	25	mu_inc	10
epochs	1000	mu_max	10000000000
time	Inf		
goal	0		
min_grad	1e-07		
max_fail	6		

Figure 3 Training parameters used

MSE was used to verify the performance. In six iterations, the desirable performance was attained. The training dataset denotes to the samples that were used to build the model, whereas the testing or validation dataset is used to measure the performance. The weights connecting the input layer to the hidden layer were determined as follows:

$$w_{ij} = \begin{bmatrix} 12 \\ 12 \\ -12 \\ 12 \\ 12 \\ -12 \\ -12 \\ 12 \\ 12 \\ 12 \end{bmatrix}$$

The weights connecting hidden to output layer was calculated as

w_{j2}=[-0.7151 0.00004 0.6164 0.1793 0.4654 -0.4828 0.5888 -0.0152 0.7291 0.0008;
0.4531 -0.0373 0.2038 0.6671 0.1423 -0.4821 -0.8751 -0.6163 0.3947 -0.0535]

The bias connecting input to hidden layer was calculated as

$$b_{ij} = \begin{bmatrix} 2.4895 \\ 1.9362 \\ -1.383 \\ 0.8297 \\ -0.2765 \\ 0.2765 \\ -0.8297 \\ 1.3832 \\ -1.9362 \\ -2.4895 \end{bmatrix}$$

The bias connecting hidden to output layer was calculated as

$$b_{j2} = \begin{bmatrix} 1.5124 \\ 1.5124 \end{bmatrix}$$

Figure 4 shows the progress of MSE of the estimation. The best validation performance obtained was 14.5623 at 0^{th} epoch.

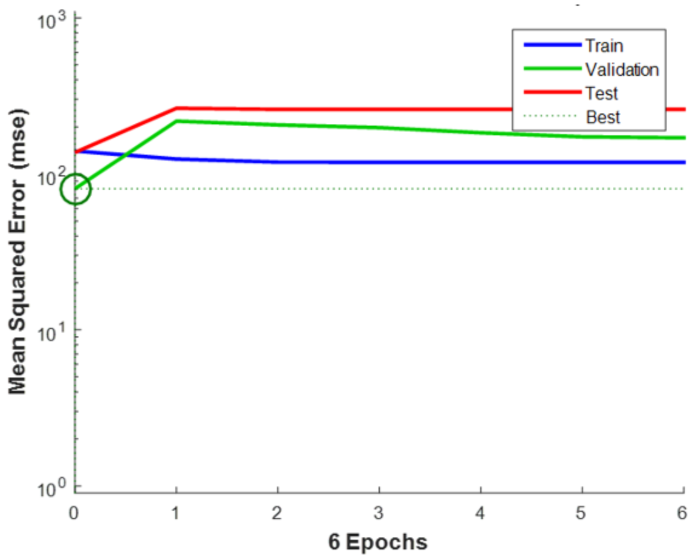

Figure 4 Progress of MSE with epochs for estimation of Aluminum composite

The error analysis of the ANN model using correlation coefficients is shown in **Fig.5**. Training, testing, and validation all had correlation coefficients of 0.99685, 0.99866, and 0.99671, respectively. In total, the value was 0.99689, representing a strong association.

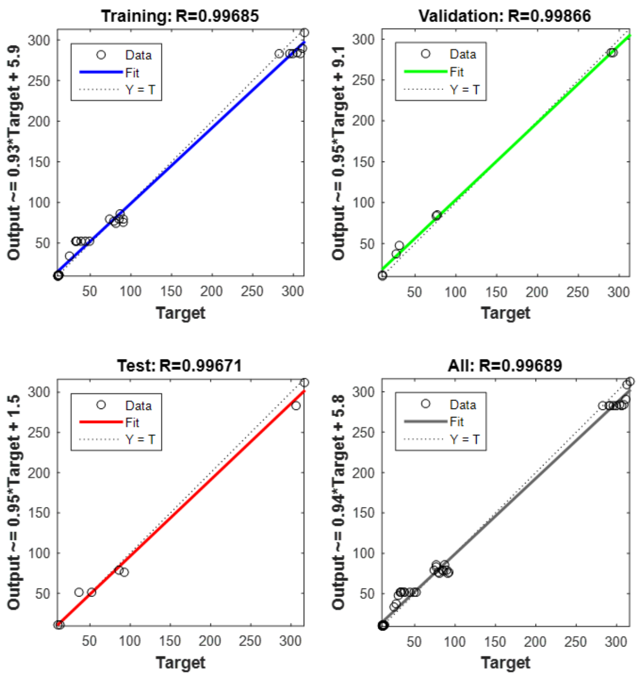

Figure 5 Correlation coefficients of training, testing, validation, and all estimation set

Figure 6 shows the estimation training state. From the origin to the end value of 0.03056, the gradient is decreasing. To attain the smallest error in the fewest number of rounds, the gradient is decreasing.

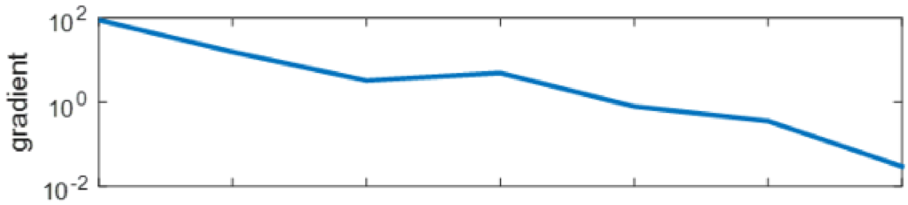

Figure 6 Training state for estimation

The MSE taken from **Fig.4** and R^2 taken from **Fig.5**, implies that the values are within the prescribed limits. Hence, the model fits well for given input conditions.

V. CONCLUSIONS

The goal of this study is to forecast the mechanical properties of AA6063 Aluminum alloy with uncoated continuous carbon fiber reinforcements, such as shear strength, hardness, impact strength, and tensile strength. Carbon weight percentages range from 1 percent to 6 percent in 0.5 percent increments. The $R^2$and MSE were used to assess the ANN's estimation performance (MSE). The average R^2 and MSE of 0.9937 and 14.5623, respectively, suggest that the ANN fit the experimental response variable values effectively. The correlation coefficient (R) of 0.99689 also supports the findings.

REFERENCES

[1] M. Deshpande, R. Gondil, S.V.S. Rahul, Waikar, T.S. Narayan, Murty and Mahata 2018 Processing and characterization of carbon fiber reinforced aluminium7075, Materials Today: Proceedings, 5(2): 7115–7122.

[2] U. Tamilarasan, L. Karunamoorthy and K. Palanikumar 2015 Mechanical properties evaluation of the carbon fibre reinforced aluminium sandwich composites., Materials Res, 18(5): 1029–1037.

[3] L.Poovazhgan, S. Vijayananth and S. Sivaganesan 2020 Optimizing ultrasonic power on fabricating aluminum nanocomposites reinforced with boron carbide nanoparticles. Mater. Sci. Forum, 979: 28–33.

[4] S. Ajith, Arul, Daniel, C. Dhanasekaran, S. Sivaganesan 2020 and R. Sridhar, Investigation on the mechanical properties of silicon carbide particulates in Al/SiC/MoS_2. Mater. Sci. Forum 979: 89–94.

[5] Madhuri Deshpande, S.V.S. Ramesh, Gondil, R.K. Narayan, Murty and Kalal 2018 Studies on 7075 aluminium alloy MMCs with milled carbon fibers as reinforcements. Trans. Indian Inst. Met, 71(4): 993–1002.

[6] S. Ajith, Arul, Daniel, S. Vijay, Ananth, A. Parthiban and S. Sivaganesan 2020 Optimization of machining parameters in electro chemical machining of Al5059/SiC/MoS_2 composites using taguchi method. Mater. Today: Proc. 21: 738–743.

[7] G. Sathishkumar, S. Joseph Irudaya raja, S. Sivaganesan and M. Thuyava 2019 Synthesis and characterization of Al 7075 alloy reinforced with silicon carbide and fly ash. Int. J. Vehicle Struct. Syst, 11 (3); 273–276.

[8] A. Parthiban, R. Ravikumar, H. Abdul Zubar and M. Duraiselvam 2014 Experimental investigation of CO_2 laser cutting on AISI 316L sheet. J. Sci. Ind. Res, 73: 387–393.

[9] A. Parthiban, T. Sathish, S.S. Chandran, R. Venkatesh and V. Vijayan 2017 Optimization of CO2 laser cutting parameters on austenite stainless steel using grey relational analysis. Int. J. Mech. Eng. Technol., 10(01): 984–992.

[10] A. Parthiban, S. Sathish, M. Chandrasekaran and R. Ravikumar 2017 Optimization of CO_2 laser cutting parameters on Austenitic type Stainless steel sheet. IOP Conf. Ser.: Mater. Sci. Eng., 183.

[11] V. Vijayan and T. Karthikeyan 2014 Material selection of compliant mechanism for vibration isolation. Mech. Eng. 18(2): 121–134.

[12] A. Parthiban, R. Ravikumar, B. Suresh Kumar and N. Baskar 2014 Hybridization of response surface methodology and genetic algorithm optimization for CO_2 laser cutting parameter on AA6061 material. Int. J. Eng. Technol, 6(1): 358–373.

[13] K. Kaviyarasan, J. Pradheep, Kumar, S. Karthik, Anandh, M. Sivavishnu and S. Gokul 2020 Comparison of mechanical properties of Al6063 alloy with ceramic particles. Mater. Today: Proc., 22(4): 3067–3074.

[14] A.Devaraju 2015 Influence of fiber percentage on mechanical properties of hybrid composite materials. J. Mater. Sci. Mech. Eng. 2(13): 1–5.

[15] A. Parthiban, J.P. Prasath, P. Vivek and R. Pugazhenthi 2018 Experimental Investigation of plasma arc cutting for stainless steel sheet. Int. J. Mech. Prod. Eng. Res. Devel, 8(1): 907–914.

[16] N. Mahaviradhan, S. Sivaganesan, N. Padma Sravya and A. Parthiban 2021 Experimental investigation on mechanical properties of carbon fiber reinforced aluminum metal matrix composite. Materials Today: Proceedings, 39(1): 743-747.

[17] Vijayanand, M., Varahamoorthi, R., and Kumaradhas, P 2022 Artificial neural network modelling for average surface roughness in citrate stabilised electroless nickel boron coatings. Materials Today: Proceedings, 49: 2239-2244.

[18] Sivamani, S., Binnal, P., Roy, C., Al Khaldi, A., Al Hamar, F., Maran, J. P., and Karuppiah, P 2021 Optimization and characterization of pectin recovered from Persea americana peel using statistical and non-statistical techniques. Biomass Conversion and Biorefinery, 1-14.

[19] Sivamani, S., Prasad, B. S., Nithya, K., Sivarajasekar, N., and Hosseini-Bandegharaei, A 2021 Back-propagation neural network: Box–Behnken design modelling for optimization of copper adsorption on orange zest biochar. International Journal of Environmental Science and Technology, 1-16.

[20] Babalola Philip, Bolu Christian and Inegbenebor 2019 A. Artificial Neural Network Prediction of Aluminium Metal Matrix Composite with Silicon Carbide Particles Developed Using Stir Casting Method. International Journal of Mechanical & Mechatronics Engineering, 15:151-159.

[21] N. Mahaviradhan, and S. Sivaganesan 2021 Tribological analysis of hybrid aluminum matrix composites for high temperature applications. Materials Today: Proceedings, 3(1): 669-675.