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EVALUATING THE PHYSICAL CHARACTERISTICS OF LM13 ALUMINUM ALLOY BASED HYBRID COMPOSITES USING ARTIFICIAL NEURAL NETWORK

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Abstract: This research focuses on the fabrication of LM13 aluminum alloy-based Hybrid Aluminum Matrix Composites (HAMC) and the use of Artificial Neural Networks (ANN) to predict their physical properties. The objective of this study is to calculate the hardness and density of Hybrid Aluminum matrix composites (HAMC). The estimations are made using the ANN's Levenberg-Marquardt method. The stir casting technique is used to manufacture the HAMC with Graphite (Gr) and Boron carbide (B_4C) reinforcement into the LM13 aluminum alloy. The L9 orthogonal array was used to see how process variables like Graphite (Gr) reinforcement, Boron carbide (B4C) reinforcement, stirring speed, and stirring time affect the outcomes. The material's Brinell hardness number (BHN) and density were explored as output characteristics. The prediction performance of the ANN was evaluated using the determination coefficient (R^2) and mean square error (MSE). The average R^2 and MSE are 0.9944 and 0.003963, respectively, indicate that the ANN effectively fitted the experimental response variable values. The findings are also supported by the correlation coefficient (R) of 0.99721.

***Index Terms* - LM13 Aluminum Alloy, Hybrid composite, Stir Casting, Physical Characteristics, Artificial neural network**

I. INTRODUCTION

The current technologically advanced industrial system enables the manufacture of a diverse range of components in a variety of materials. Because of its great hardness and inexpensive cost, as well as its versatility, the material can be used in a wide range of applications. Metal Matrix Composites (MMC) are well-known for possessing such qualities, and researchers are exploring for materials to replace alloys and metals. Aluminum alloys display sensitive tribological and mechanical qualities when subjected to unfavorable conditions such as a lack of lubrication, a higher temperature, and so on. Aluminum Metal Matric Composites (AMCs) are limited in quantity due to their light weight, rigidity, and strength when increased with ceramic particles. A novel material with higher wear resistance and the ability to swiftly test expected mechanical and tribology characteristics are two basic criteria [1,2]. The newly produced new grade of HAMCs is the most important material in many industrial applications such as defense, aviation, automobiles, and other special-purpose applications. The usage of HAMCs has a number of advantages, including reduced weight and cost [3].

As primary reinforcements, aluminum nitride (AlN) ceramic particles, silica (SiO_2), and aluminum oxide (Al_2O_3) are used [4]. To minimize the wear rate and friction coefficient of composite materials, solid lubricant materials such as graphite can be employed in HAMCs. A small number of researchers have looked into it in a variety of applications, which has led to the addition of reinforcements and treatments that help to improve mechanical qualities. To increase the tribological properties of hybrid aluminum matrix composites, primary and secondary reinforcements are applied [5]. Secondary reinforcements are applied, such as fly ash and red mud, and graphite, such as MoS_2, is also used to boost the HAMCs [6]. Powder metallurgy and casting processes were the most prevalent methods for producing HAMCs [7]. The AMC's reinforced Silicon Carbide (SiC) is favored over ordinary aluminum alloys because of its wear resistance and high strength [8,9].

By increasing the size and volume fraction of SiC articles, the wear rate of Al6061/SiC composites was reduced [10]. By utilizing SiC particles, enhanced properties such as mechanical strength and wear resistance have been discovered with an increase in the volume fraction [11]. However, an increase in stiffness was detected, which has an impact on composite material workability. TiB_2 sliding wear properties of composites were improved when strong lubricant particles such as Molybdenum disulfide (MoS_2) and graphite (Gr) were added alongside ceramic particles such as B_4C [12,13]. Aluminum metal matrix composite of AA6061 alloy with reinforcement of carbon fiber is prepared using casting technique. The three compositions of AA6061 composite compositions mechanical properties were studied. The SEM analysis confirms that the carbon fibers uniformly distributed in the composite [14]. Furthermore, features such as mechanical strength and wear resistance have been improved by adding hard particles such as SiC, which has resulted in a decrease in frictional coefficient due to the formation of a lubricating film [15,16]

ANNs are a form of machine learning technique based on biological neurons [17]. It's used in a range of technical applications, such as extracting pectin from fruit peels [18], enhancing adsorption capacity [19], and hardening electroless nickel-boron coatings [20].

Most engineering applications require lightweight materials with increased strength, as well as greater corrosion and wear resistance during operation. The squeeze casting technique was used to study the wear rate of AA024 reinforced Al_2O_3/SiC/Gr fabricates. The output factors were optimized using the Taguchi method. L27 orthogonal array was used to design the experiment. SEM with EDS was used to investigate the wear mechanism, surface morphologies, and composite composition. With the help of the, we were able to forecast optimal results. Optimized results were predicted with the artificial neural network [21].

The goal of this study is to use the Levenberg-Marquardt algorithm of a multiple-input multiple-output artificial neural network to predict the physical properties of HAMC.

II. Materials and Composite Preparation

The matrix material was LM13 alloy with reinforcing material as Gr. of 90 µm and B_4C particulate matter with a size of 45 µm. In addition, nitrogen gas is used as a corrosion and cleaning agent. In an electric furnace, ingots of the LM13 alloy are placed in a graphite crucible and melted at 850°C. In addition, the corrosion agent is used in conjunction with nitrogen gas for cleansing. The liquefied Gr mixture is then combined with the preheated B_4C powder. The molten HAMC mix is injected into the die to obtain the necessary samples. A similar procedure is used to create different composite material combinations by changing the B_4C and Gr weight proportions as well as the stirring speed and time. The test specimens are machined in CNC machine [22].

III. Modelling - Artificial Neural Network

An ANN's design is made up of three layers: input layers for input parameters, hidden layers for neurons, and output layers for response variables. The layers are connected with weights. The optional bias layers are added to the hidden and output layers in the same way as intercepts are introduced to equations. The performance of ANN modeling is evaluated using error analysis, which uses the R^2 and MSE. The minimal error might be achieved by selecting the proper network type, training, adaptation learning, performance and activation functions, number of neurons, and hidden layers.

The ANN modeling was done in MATLAB R2022a. 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, were used in this study to create a feed forward back propagation single-input multiple-output artificial neural network. R^2 and MSE were used as activation functions for the hidden and output layers, respectively, with sigmoidal tangent (TANSIG) as the activation function. With four input factors in the input layer, ten neurons in the hidden layer, and two output factors in the output layer, the system in this study uses a 4-10-2 design. A single hidden layer with 10 neurons was chosen since more than 99 percent efficiency was attained in fewer repetitions. The input data entered into the ANN tool was normalized as TANSIG processed the value from -1 to +1. In a 70:15:15 ratio, the input data was then trained, tested, and validated. The data was denormalized from -1 to +1 to obtain the final result. The intended data was then compared to the actual produced data. The flow of the process is shown in fig. 1.

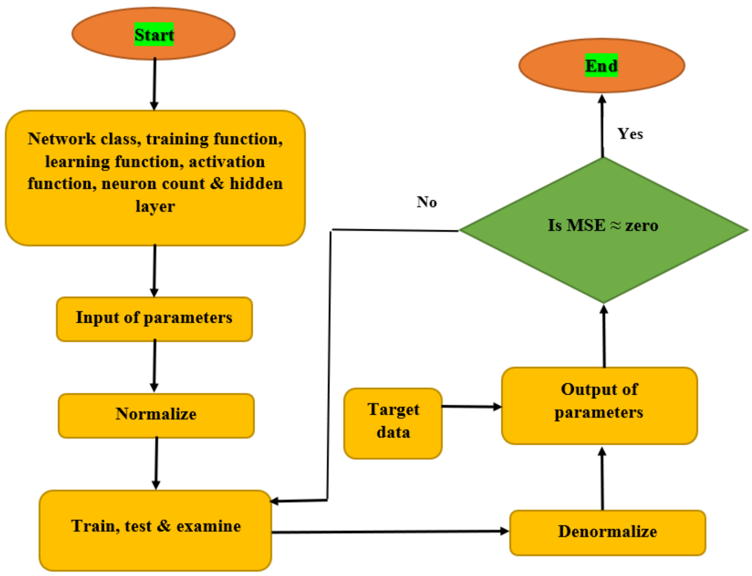

Figure 1 Flowchart for prediction of physical properties

IV. ARTIFICIAL NEURAL NETWORKS

Table 1 compares the experimental and ANN estimated values of response variables for various input parameters.

Table 1 Experimental values and estimated values of response variables

Input Data				Experimental results		ANN Estimated results	
Gr Wt %	B_4C Wt%	Stirring Speed (rpm)	Stirring time (minutes)	Brinell Hardness Number (BHN)	Density (gm/cm^3)	Brinell Hardness Number (BHN)	Density (gm/cm^3)
0.1	1	400	2	78	2.72	80.8028	2.8098
0.1	2	400	4	75	2.84	82.1803	2.8094
0.1	3	400	6	82	2.88	83.3715	2.8069
0.15	1	450	2	83	2.9	76.3841	2.8086
0.15	2	450	4	80	2.77	76.0799	2.8044
0.15	3	450	6	83	2.84	79.7147	2.7912
0.2	1	500	2	78	2.86	83.047	2.8062
0.2	2	500	4	82	2.89	82.0913	2.8011
0.2	3	500	6	84	2.71	83.6239	2.8216

Figure 2 shows the ANN architecture. Input layer is connected to hidden layer through weights, w_{1i}, where i represents input factor and j represents the neuron number of the hidden layer. b_{1j} represents bias to the jth neuron of the hidden layer. The generalized equation from input to hidden layers is written in Equation (1) as

$$H_j = \sum_{j=1}^{4} w_{1j} X_1 + b_{1j} \qquad (1)$$

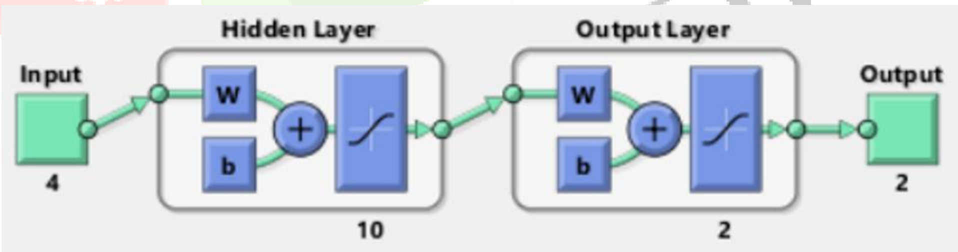

Figure 2 Architecture of 4-10-2 network for prediction of physical properties

Training was completed by using parameters as shown in Figure 3. The default settings in MATLAB are used.

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

The performance was confirmed by mean MSE. The required performance was achieved in 6 iterations. The training data set is used to generate the model, while the testing and validation dataset are used to qualify the performance of ne. The weights linking input to hidden layer was calculated as

wij = [1.1878 1.3271 -1.3247 -1.126;
-1.2313 0.2425 1.9968 0.7970;
1.4643 0.10281 2.0104 -0.0282;
-1.7294 -0.9861 1.0880 1.0250;
1.7067 -0.0440 -1.5970 0.8557;
1.0682 0.5752 -1.1043 1.8723;
-0.0614 0.9681 -0.8890 2.112;
0.7051 -0.9382 1.6136 -1.488;
-1.2871 -0.6494 -1.7806 0.9736;
-0.1662 1.9705 0.8932 -1.2202]

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 prediction. Best Validation Performance is 0.003963 at epoch 0

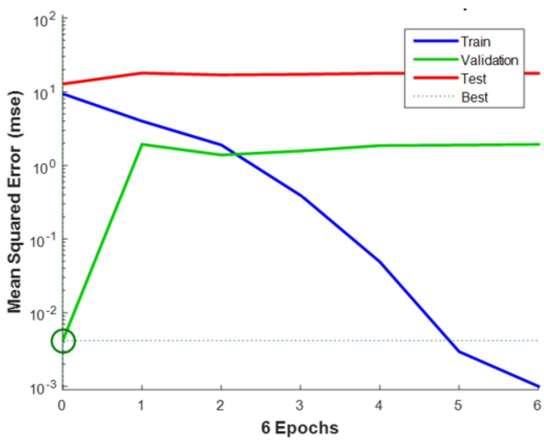

Figure 4 Progress of MSE with epochs for prediction of physical properties

Figure 5 shows the error analysis in ANN model using correlation coefficients. The correlation coefficient of training, testing, and validation were found to be 0.997, 1 and 1 respectively. In total, the value was found to be 0.99721, which shows strong correlation.

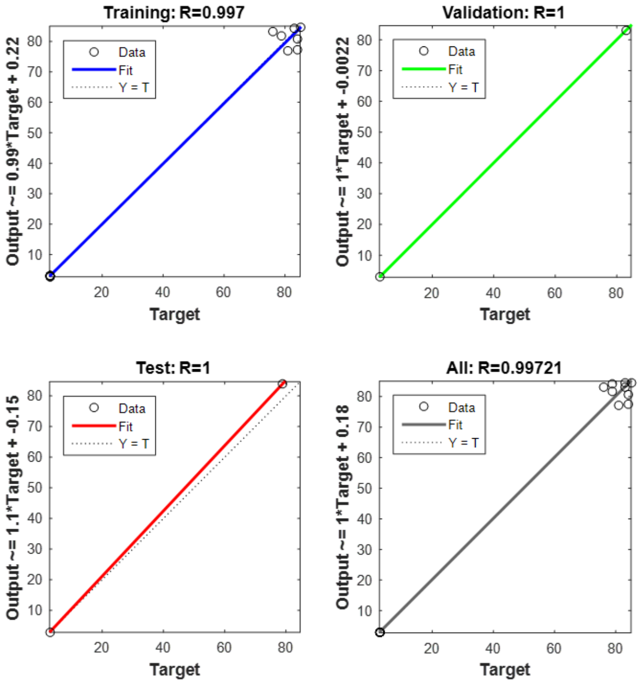

Figure 5 Correlation coefficients of training, testing, validation, and all prediction set

In Figure 6 the gradient is falling from initial value to the final value of 0.1095 at epoch 6. The gradient is declining to achieve the least error in lesser number of iterations. Gradient = 0.1095 at epoch 6

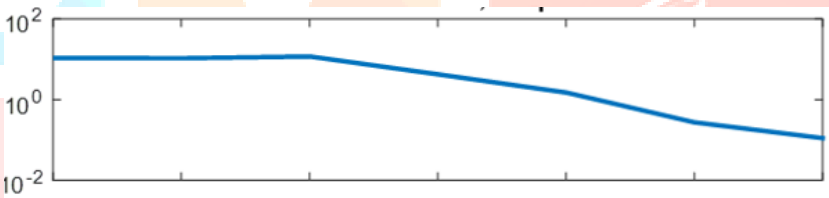

Figure 6 Training state for prediction

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

V. Conclusions

The goal is to use the stir casting technology to construct the HAMC with Graphite and Boron Carbide reinforcement into the LM13 aluminum alloy. The L9 orthogonal array was used to evaluate how process parameters like Graphite reinforcement, Boron Carbide reinforcement, stirring speed, and stirring time effect the outcomes. The material's Brinell hardness number (BHN) and density are explored as output characteristics. R^2 and MSE are used to evaluate the ANN's prediction ability. The average R^2 and MSE of 0.9944 and 0.003963, respectively, suggest that the ANN fit the experimental response variable values effectively. The correlation coefficient of 0.99721 also supported the findings.

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