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Investigation of Hardness by Experimental and Simulation Studies on Al-12.5% Si Piston Alloys Reinforced by Cu Powder

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Abstract

In this work, Aluminum composite was fabricated by using friction stir squeeze casting. Copper powder of size 5μm was stirred and later squeezed with molten Al-12.5% Si with a weight percentage ranging from 2 to 10% of the former. Hardness values from the experiments were measured and later used to determine the relationship between input parameter and output. Hardness measured was found to be good at 6% of copper. A mathematical model was developed by using Bezier equation. Neural network model was developed for further simulation. The results were predicted by using both the equation and by using neural network were on par with experimental values obtained.

Keywords: Piston alloy, Copper powder, Hardness, Bezier equation, ANN, Composite.

INTRODUCTION

Piston is primary component in any automobile industry. Depending on different automobiles pistons usually are made by three different compositions namely; Cast iron, compacted graphite iron, and cast aluminum alloys. Compacted graphite iron is a light-weight material making it very useful for diesel engines. Cast iron is best suited for the manufacturing of cylinder; Piston commonly is made by an alloy of aluminum and silicon. A major application of these alloys is in high-speed engines and aerospace industry. Piston alloy made of aluminum has major advantage; first and foremost being its weight. There are many other aspects which are to be considered in designing a piston alloy, they are; hardness, strength, wear resistance, resistance to corrosion and proper grain distribution. Aluminum-silicon alloy can be cast in the form of piston easily by the primary process, but whereas other piston alloys require secondary process and are tedious. For high-speed eutectic or hyper-eutectic pistons are employed. In order to satisfy all these conditions, piston materials must have high hardness and light-weight. Many pressurization techniques evolved in recent years to strengthen the piston alloys. However, results of these techniques are not enough to satisfy the fast-moving demand of automotive industry [1][2]. Metal matrix composites were developed to increase the strength and stiffness of Aluminum alloy. Metal matrix composite basically refers to hard reinforcement in the base metals [3-5]. Aluminum reinforced with silicon carbide resulted in good mechanical properties especially hardness. Brinell hardness was 87.5 at a percent of 10% silicon carbide, which was comparably better than compared to normal Aluminum [6].

Aluminum (AL 7075) was reinforced with silicon carbide having a particle size of 29micro meter and hardness was measured by using Vickers hardness tester for both as-cast and heat-treated condition. Hardness improved from 135VHN to 188VHN by increasing aging temperature and percentage of reinforcement respectively [7]. Micro-hardness was increased with filler addition of SiC in Al6061 and Al_2O_3 in Al 7075. Microhardness of Al 7075 with a filler of Al_2O_3 was 120VHN compared to Al 6061with SiC filler which had 80VHN [8].SiC was reinforced in Al-Zn-Mg (Al7009) to increase hardness from 90Hv to 130Hv. Hardness was improved by heat treatment to 140Hv. [9]. Hardness increased with increase in the percentage of SiC reinforcement in Al 7075 and Al 356 composites respectively [10] [11].

As the reinforcement of SiCp increased from 5 to 30 wt% there was a continuous increase of Hardness in Al-SiCp composite from 30Hv to 58Hv when measured by Rockwell hardness tester [12]. Brinell hardness was increased gradually to 95Hv with an increase in the reinforcement of SiC and gradually reduced to 70Hv with Increasing Gr particles in LM25-SiC-Gr hybrid composite [13]. Bamboo leaf ash also had the same effect as of Gr particles; the hardness was gradually decreased to 75Hv with an increase in the reinforcement of bamboo leaf ash in the Hybrid aluminum composite of Al-SiC [14]. However, hardness measured by Rockwell hardness of Al 7075/SiC/B_4C hybrid metal matrix composite (MMC) increased with reinforcement of both SiC and B_4C to 92Hv [15]. Hardness was increased from 60Hv to 90Hv as the reinforcement of SiC increased with the constant percent of fly ash in the Hybrid reinforcement of Al 6061

[16]. Hardness was found to be 95BHN, which was good in the presence of 10% SiC and 10% fly ash for a hybrid composite of Al-SiC-fly ash [17].

Percentage of ceramic particles also helped in increasing hardness by about 5% of Al 7075-SiC composite [18].The hardness of Al 7075-Al2O3 composite decreased with continuous increase in the size of reinforcement, due to the less dense distribution of Al2O3 particles in Al matrix [19].A mathematical model was developed by using response surface method and ANOVA technique based on a number of input parameters affecting the hardness and it was found that Hardness reduced initially till reinforcement was 8% and later it increased gradually to 126VHNwith an increase in reinforcement up to 15% of Al2O3 [19].An experimental investigation has its limitations, general mathematical model or prediction techniques are required so as to know the proper variation of hardness values with the number of reinforcements. Numerical methods or experimental data are required to analytically determine the mathematical equation by using a Bezier equation. Bezier curve equation it helpful in tooling, especially in fillet surfaces [20]. In high-speed machining, it is required to have a proper 5-axis tool-path, to generate these paths a Bezier equation was used to generate continuous points [21]. Bezier equation was also used in designing a wing of airplane [22]. Some other mathematical approaches are also among modern-day researchers like Response surface method and ANN. Artificial Neural Network (ANN) prediction tool, if properly trained helped researchers in predicting sufficient data. Modelling of the non-linear process and the ability of learning makes ANN advantageous over other prediction tools [23]. ANN is a non-linear statistical analysis technique which links input data to target data by a set of non-linear functions [24]. An artificial neural network was used in modeling TTT diagrams, in determining the mechanical properties of Ti alloys, corrosion resistance in Ti alloys. To investigate the effect of input parameters on material properties, and inverse models were developed to optimize these parameters. The optimum algorithm was Levenberg-Marquardt algorithm [25-27].

As per the literature, it is evident that Bezier equation can be implemented in the field of materials, to determine material properties at different points. Also, another method like ANN can be used to develop input and output relationship. Furthermore, literature presents the importance of reinforcement on hardness. Piston alloys are itself a reinforced aluminum Eutectic alloy, with 12.5% silicon which has relatively good hardness and wear-resistance. Present work aims to have application-oriented further reinforcement for the existing piston alloy to form a hybrid composite. The focus of this paper is only on hardness which can be attained by reinforcement of copper.

MATERIALS AND METHODS

Experimental Approach:

Casting process:

The piston alloy used in this study is theAl-4032 chemical composition of it is listed in Table (1) was used as a matrix material.

Table 1: Chemical composition of the matrix; (wt.%)

Elem	Si	Fe	Cu	Mg	Mn	Ni	Ti	Cr	Pb	Al
Wt. %	12.2	0.51	1.10	0.90	0.14	1.45	0.08	0.04	0.04	Bal.

Pure copper particles (Cu) of a size of 5µmwere added to the matrix and stirred well inside the furnace itself. Then the mixture was allowed to solidify inside the furnace to avoid rapid phase change and to avoid cold sluts which can occur if solidified at room temperature.

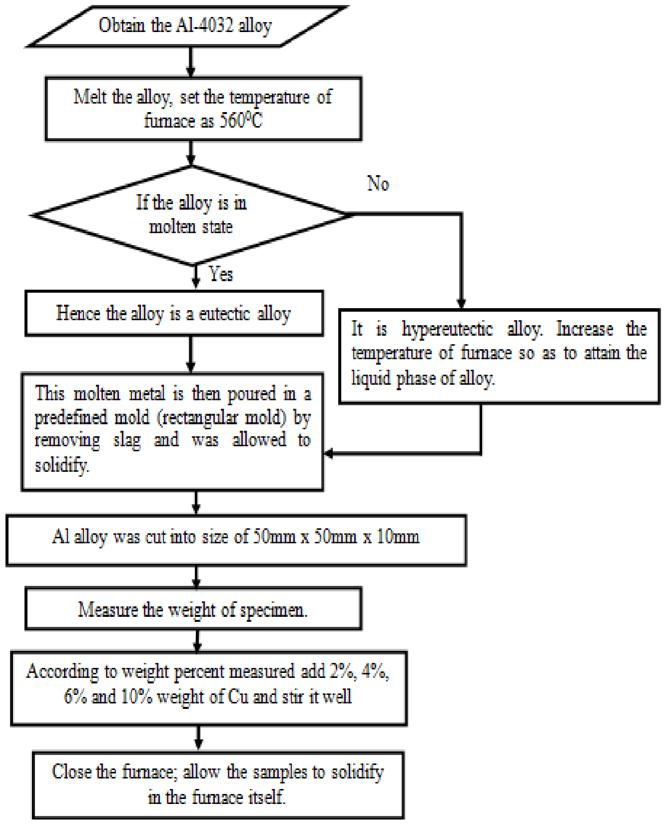

Figure 1: Flowchart showing the experimental process

This experiment was repeated 4 times with a change in 2%, 4%, 6% and 10% weight percent of Cu.

Sample preparation and Hardness testing

All samples were polished on 80 grit SiC paper, then 120 grit SiC paper, so on to 1200 grit SiC paper. After attaining the surface finish, the sample was washed with ethanol solution and H2SO4 solution very carefully. Hardness was tested on Zwick/Roell hardness testing machine as in figure 2. It utilizes a diamond intender and is like a pyramid. Load of 1kg was applied for indentation time of 10seconds. To measure the hardness average of 5 readings were taken for every sample. The values so obtained are in terms of HV.

Figure 2: Zwick/Roell hardness tester

Mathematical Approach:

Development of equation:

Experimental results obtained were considered as a base for developing a mathematical model. In the present work, we have used Bezier equation to develop mathematical expression. As we have 4 points namely percentage of composition 2%, 4%, 6% and 10%, this is considered as 4 control points. The degree of the Bezier curve will be (n-1), so the degree of the equation will be 3. Hardness values were plotted along Y-axis and the percentage of copper along X-axis. The standard Bezier 3-degree equation is represented by:

$$P(k) = \sum_{i=0}^{n} (P_i B_i(k))$$

$$B_i^n(k) = \frac{n!}{(n-i)!\,i!}(k^i)(1-k)^{n-i}$$

Where n=3, $0 \le i \le 3$, $0 \le k \le 1$

ANN:

The simulation was carried out by taking the values obtained in the experiment. Artificial neural network tool was used to simulate and predict the values of hardness other than the experimental points. There is one input and one output figure 3 represents the network used:

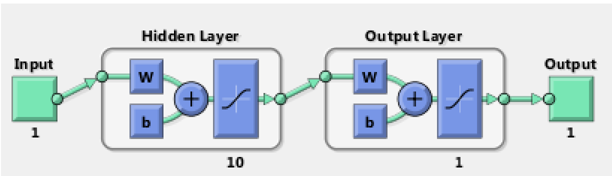

Figure 3: Network plot used in simulation

Training algorithms assessed was Levenberge Marquardt (trainlm). Two layers were used; both layers were a tangent sigmoidal hyperbolic function. ANN utilizes weights and bias of neurons in the network. During this minimum gradient of 10^{-7} and 1000 epochs were used. The training was at 70%, validation at 15% and testing at 15%. Values obtained were compared with the experimental data and as well as with the mathematical model. Mean absolute percentage error was evaluated with respect to the experimental data and also with respect to the mathematical results obtained.

Mean Absolute Percentage Error

$$\text{(MAPE)} = \left\{\frac{100}{n}\sum_{i=1}^{n}\left|\left(\frac{E_i - P_i}{E_i}\right)\right|\right\}\%$$

$$\text{Mean Square Error (MSE)} = \frac{1}{n}\left\{\sum_{i=1}^{n}(E_i - P_i)^2\right\}$$

$$\text{Regression coefficient (R)} = \sqrt{1 - \left\{\frac{\sum_{i=1}^{n}(E_i - P_i)^2}{\sum_{i=1}^{n}(P_i)^2}\right\}}$$

Where, E_i=Experimental values, P_i=ANN predicted values

The above formulations were also used to compare experimental values with a mathematical model.

Results and Discussion:

Experimental values:

The hardness of piston alloy (base metal) was 73HV; it remarkably improved with the addition of copper. As the percentage of copper increased the hardness also increased until the addition of 4% copper. The hardness measured at this point was 135HV, which is nearly twice that of the base metal. When the percentage of copper increased more than 4%, the hardness was decreased and had its least value at 10% copper. This may be due to clustering as shown in the microstructure or because of not having a homogeneous mixture. Figure 4shows the hardness values obtained experimentally.

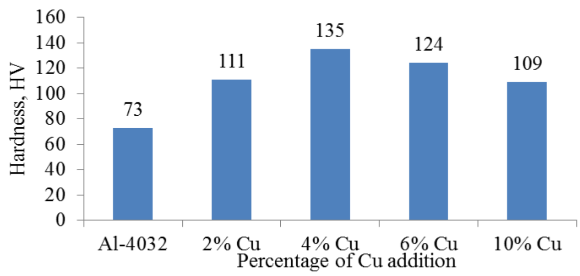

Figure 4: Average hardness values at different % of Cu

Bezier Equation:

From the experimental values available the Bezier equation is:

$$P(k) = P_0 B_0(k) + P_1 B_1(k) + P_2 B_2(k) + P_3 B_3(k)$$

$$B_0(k) = (1-k)^3 = 1 - 3k + 3k^2 - k^3$$

$$B_1(k) = 3k(1-k)^2$$

$$B_2(k) = 3k^2(1-k)$$

$$B_3(k) = k^3$$

Substituting values of $P_0 = 2, P_1 = 4, P_2 = 6, P_3 = 10$

$$P_x = 2k^3 + 6k + 2$$

Substituting values of

$P_0 = 111, P_1 = 135, P_2 = 124, P_3 = 109$

(Hardness in Y-axis) $P_y = 31k^3 - 105k^2 + 72k + 111$

At 2% Copper, $P_x = 2$, so, k = 0,

Substituting k = 0, to get $P_y = 111$, is the value of hardness

For different values of P_x ranging from 2-10(with an increment of 0.1) k is estimated and for those values of k, P_y is predicted in between the boundary 2 and 10. Mathematical model was very useful in predicting hardness at different percentages of copper, which cannot be possible experimentally. Table 2 gives the root mean square error between mathematical hardness and experimental hardness. The overall RMSE was very less. The only point where the error deviating was at 4% copper.

Table 2: MAPE and RMSE between mathematical hardness and experimental hardness

% composition of copper	Hardness, HV		MAPE	SE	RMSE
	Mathematical	Experimental			
2	111	111	0	0	0
4	124.48	135	7.79	110.63	10.51
6	123.09	124	0.72	0.81	0.90
10	109	109	0	0	0
Average			2.13	27.86	5.27

The graph in figure 5 shows that values of hardness does not have much deviation with experimental hardness values. It also states that the hardness is very good in the range of 3% to 6% copper reinforcement.

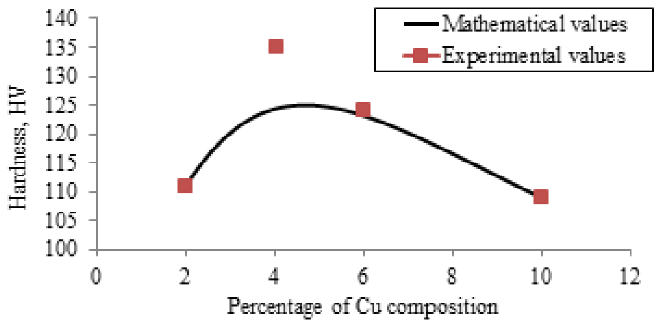

Figure 5: Experimental and mathematical values of hardness.

ANN Prediction:

ANN model was trained by Levenberg-Marquardt training algorithm with tangent sigmoid transfer function for layer-1 and layer-2 which led to best regression, MAPE and MSE. Number neurons selected were 10. The training time was 0.11secs. Training was done at 0.82275 but validation and testing showed the best result without error. The model developed had a regression of 0.84537 which is acceptable. Figure 6 shows regression values in ANN, is well within the acceptable range.

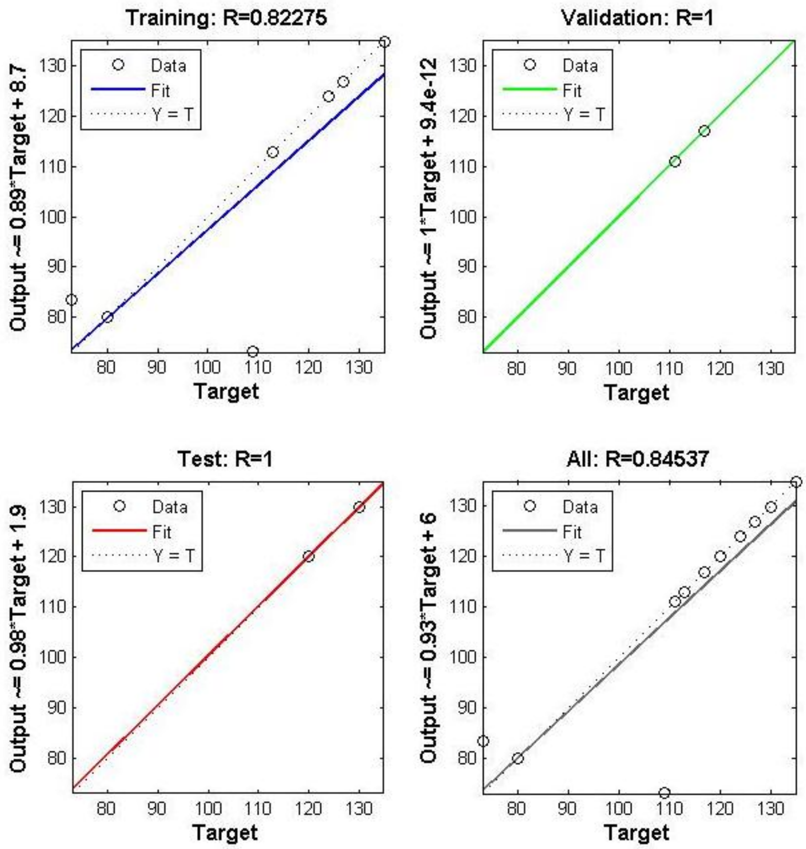

Figure 6: Training, Validation, Testing and overall regression of values in ANN

ANN prediction is useful in exploring the data obtained by experimental values. As experimentation has limitation of time and the availability of machine, it is not possible to carry out experiments at every single point. ANN model once trained can be used to obtain the data between experimental boundaries. Table 3 shows the error between the experimental and ANN predicted values. Mean Absolute Error and Root mean square error was very less. It was much better than the mathematical model developed by Bezier equation. The Average error was 2.6 which is much below the acceptable range. The only hardness value deviating was at 10% copper reinforcement. This model hence trained had overall error of 1.23%.

Table 3: MAPE and RMSE between ANN predicted hardness and experimental hardness

Percentage composition of copper	ANN Predicted hardness, HV	Experimental values of hardness, HV	MAPE	SE	RMSE
2	110.9946	111	0.004886	2.94E-05	0.005423
4	134.9872	135	0.009502	0.000165	0.012827
6	123.9772	124	0.018403	0.000521	0.022819
10	103.6384	109	4.918894	28.74669	5.361594
Average			1.237921	7.186851	2.68083

By using the experimental data ANN model predicted the hardness at different percentages of Cu reinforcement. Figure 7show the comparison of experimentally obtained values with the ANN predicted hardness values. It showed that the hardness reached maximum when percentage of Cu reinforcement was in the range of 3 to 5%.

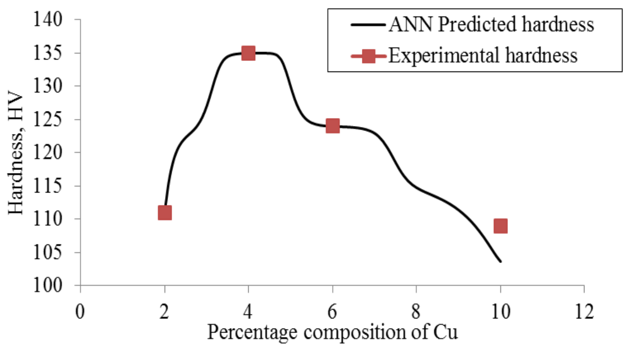

Figure 7: Experimental with ANN Predicted hardness values

Values obtained from Bezier equation is compared with ANN predicted values. This was done to know the percentage of copper which gives maximum hardness. Figure 8 shows that hardness was maximum at 3.5%Cu to 4.5%Cu.

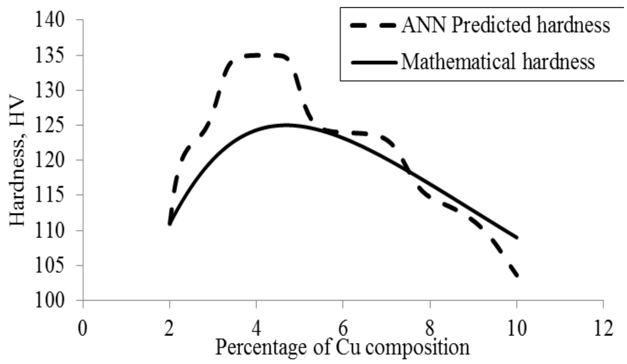

Figure 8: ANN Predicted and Mathematical hardness values.

CONCLUSIONS

Experimental investigation of hardness was carried out at 2%, 4%, 6% and 10% of copper reinforcement in Al-4032 alloy. The experimental data obtained used to generate a Bezier equation and to train the different ANN models. Percentage of Cu reinforcement was taken as input parameter and hardness was taken as target in output layer. Both the models developed are helpful for researchers to predict the hardness, As reinforcement of Cu in Aluminum alloy is time consuming and tedious. Though the hardness obtained by both models had its peak value at 4%Cu reinforcement. Hyperbolic tangent sigmoid transfer function for Levenberg-Marquardt was found to have best MPE of 1.23% with a training time of 11 seconds, when compared to MPE of Bezier equation which was 2.13%.

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