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Predicting mechanical properties of aluminum composite reinforced with silicon carbide using artificial neural network and multiple linear regression

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Abstract
The mechanical and physical properties of the produced Al7075-SiC composite were evaluated. Stir casting was used in the production process to obtain the following composite formulations: 0, 5, 10, 15, 20, and 25 wt.% SiC Al-SiC composites. The samples were machined and subjected to mechanical tests such as hardness, impact, and ductility. The study also involved metallographic examination and physical properties evaluation such as density. The average particle size of silicon-carbide (SiC) was 100μm. Artificial neural network and multiple linear regression (MLR) were used to predict the impact strength of the examined specimen with the composite's hardness, weight percentage of silicon carbide, and density as the independent variables. Increment in hardness, tensile strength, impact strength and the composite's density w observed as the weight percentage composition of silicon carbide in the aluminium silicon carbide composite increased. 25 weight percentage of silicon carbide content in aluminium matrix composites (AMCs) showed maximum hardness, and impact strengths of 115RH_B and 80.91KJ/m^2 respectively. 0 weight percentage silicon carbide composite formulation gave the minimum density of 2780.0 Kg/m^3 while the highest density of 2880 Kg/m^3 was obtained for the 25-weight percentage silicon carbide. The metallographic analysis of the specimens using optical microscopic process showed that stir-casting was responsible for even reinforcement distributions, which also resulted to the optimal physical and mechanical properties of the materials. The error analysis showed that compared to MLR, the ANN model gave predictions more consistent with the experimental impact strength.

Keywords: Silicon carbide (SiC); Aluminium alloy (Al7075); Stir casting process; Mechanical and physical properties; ANN; MLR

1. Introduction

Throughout human history, composite materials have been essential for everything from housing early civilizations to facilitates breakthroughs in the future. The main advantages of composites are their resistance to corrosion, flexibility in design, durability, light weight, and strength. Composite materials are employed in countless components used in building, healthcare, oil and gas, sports, transportation, and many other areas of daily life with other advantages which is the ability to meet diverse design requirements with significant weight savings as well as strength- to- weight ratio (Ovri et al., 2019). Without composite materials, some application, like rocket ships, most likely wouldn't get off the ground. Composites are combination of two materials in which one of the materials is known as the phase of reinforcement, which takes the shape of sheets, fibres or particle and is embedded in the other materials called matrix phase (Bouhfid et al., 2019)

The alloys of metals are reinforced with particulates or fibers to achieve combined properties. These properties of these materials have excellent engineering application in various areas like missiles, cutting tools, nuclear reactors and aerospace components production. Materials possessing unique combinations of characteristics that traditional metal alloys, ceramics, and polymeric materials are unable to match are mainly required in our modern technologies. Silicon Carbide particles reinforced aluminum matrix composites have been developed over past few decades due to their excellent properties like light weight, high elastic modulus, low thermal expansion coefficient, high thermal conductivity, greater strength, improved stiffness, increased wear resistance and improved damping capabilities. Thus, the silicon carbide particles reinforced aluminum matrix composites are expected to have vast applications in aerospace, aircraft, automobile, and electronic industries. When loads are carried externally to the composites, metal matrix transmits loads to reinforcements and then loads are carried by dispersed reinforcements bonded with the matrix (Rahman & Rashed, 2014a).

An economical process used for the fabrication of aluminum matrix composites is stir casting (Sahu et al., 2018). Amongst various processing routes stir casting is one of the promising liquid metallurgy techniques utilized to fabricate the composites. Its advantages lie in its simplicity, flexibility and applicability to large quantity production with cost advantage. Stir casting involves producing a melt of the selected matrix material followed by introduction of a reinforcement material into the melt to get an appropriate dispersion. To acquire the dispersion of the dispersed phase in the cast matrix, conditions such as stirring speed, stirring time, Stirrer depth, feed rate, etc. will be applied to the melt that contains suspended dispersoids after stir casting. To attain the best possible qualities for metal matrix composites, the reinforcing material must be uniformly distributed throughout the matrix alloy, the wettability or bonding between these materials must be maximized, and the porosity and chemical reaction between ingredients should also be considered (Prabu et al., 2006).

Compared to monolithic materials, aluminum-silicon carbide metal matrix composites have several advantages such as low density, light weight, high temperature strength, hardness and stiffness, high fatigue strength, and wear resistance. In a number of automotive, aerospace, and other related industries, aluminum alloys with discontinuous ceramic reinforced metal matrix composites are quickly displacing conventional materials (Ovri et al., 2019).

In this research, various weight fractions (5 wt.%, 10 wt.%, 15 wt.%, 20 wt.%, 25 wt.%) of silicon carbide particles are introduced to aluminium matrix to fabricate the Aluminum/Silicon Carbide metal matrix composite using the stir casting process. Mechanical properties such as ductility (% Elongation and % area reduction), hardness (RH_B), impact strength (KJ/m^2) tensile strength, engineering/true stress (KM/m^2)/strain conditions, physical properties like density, specific weights (Kg/m^3) including its microscopic structures are critically studied.

Forecasting research results more especially, the degree of impact was essential to the current study. The impact strength was predicted based on independent factors such as density, hardness, and weight % of SiC by using multiple linear regression (MLR) and artificial neural network (ANN) models (Najjar et al., 2023). This methodology is consistent with earlier studies conducted by Ndukwe et al. (2022), who used ANN and MLR to predict the compression strength of carbonized bamboo reinforced low-density polyethylene composites (Ndukwe et al., 2022). By cutting down on testing expenses and time, the use of these predictive models improves efficiency while also advancing material science and engineering by offering insightful information on the characteristics and behaviour of the composites under investigation.

In recent years, automobile parts, for instance, brake rotors, engine blocks, shaft, among others, are often made from cast iron which has good strength but constitutes weight and high fuel consumption problems. There is need to develop other materials that aid in solving problems. Aluminum metal matrix composites are commonly used but due to its low strength, wear resistance and hardness its applications are limited. To overcome this problem, material like silicon carbide is used as a reinforcement to the aluminum metal matrix composite. This tends to improve the mechanical properties of the composite. The usage of Al-SiC metal matrix composites is constantly increasing in the last years due to its unique properties.

The main aim of this research is predicting mechanical properties of aluminium composite reinforced with silicon carbide using Annual Neural Network and Multiple Linear Regression.
The specific objectives include to:

i. Study the effect of weight percentage (0%, 5%, 10%, 15%, 20%, 25%) of silicon carbide (SiC) on the mechanical behaviour of the produced Al-SiC composites.
ii. Study the microstructure of various silicon carbide weight percentaages.
iii. Predict the experimental impact strength with models driven by artificial neural network (ANN) and multiple linear regression (MLR).

2. Materials and Methods

2.1 Materials

The metal matrix used is Aluminium Alloy, 7075. Al7075 is a high-performance alloy with one of the highest strengths among aluminium grades. It is harder, has higher tensile strength than Al 6061 and can withstand prolonged period of stress. Al7075 is referred to as aircraft or aerospace alloys because of its high strength and resistance to stress.

Table 1: Chemical Composition of Al7075 Aluminum Rolling Mills, (A.R.M), Otta, Ogun State, Nig.)

Constituents	Aluminium	Zinc	Chromium	Copper	Silicon
Percentages (%)	91.07	5.6	2.5	0.23	0.6

2.2 Methods

2.2.1 Weighing of sample materials

An electronic weighing machine (available at Foundry Lab, FUTO, Owerri) was used to take the weight of aluminium with matrix masses wt.%, 90%, 85%, 80% and 70% and silicon carbide with reinforcing masses of 5 wt.%, 10 wt.%, 15 wt.%, 20 wt.% and 25 wt.%. The weighing process was carried out in order to obtain the masses of matrix and reinforcement for the silicon carbide reinforced aluminium composite.

The composite reinforcement has a total weight of 0.410kg, with reinforcement weights of 0.0205kg/5 wt.%, 0.041kg/10 wt.%, 0.0615kg/15 wt.%, 0.082kg/20 wt.% and 0.1025kgx/25 wt.%.

2.2.2 Production of samples (stir casting process)

The process used in the production of the silicon reinforced aluminium composite is stir casting process due to its cost advantage, simplicity, flexibility and applicability to large quantity production.

In this method, aluminium scrap was melted to a temperature of 650^0C, the molten metal and silicon powder is poured in and mechanically stirred so as to create an even distribution of reinforcement in the matrix metal. The mixture is poured into the sand mould. The molten composite is allowed to solidify for 48 hours before machining.

2.2.3 Machining of sample

The samples for hardness, impact and tensile tests, were machined according to the ASTM standard test dimensions.

2.3 Evaluation of mechanical properties

2.3.1 Hardness

The hardness test was done at room temperature using a monsanto hardness testing machine. For the hardness test, three readings were taken with an average value determined.

2.3.2 Impact test

Impact test is a technique that was used in this research to determine the silicon carbide reinforced aluminum composites the capacity to withstand deformation in the face of an abrupt shock or impulse load. The izod impact machine was used, this test was done at room temperature. Formula to obtain the impact strength is as follows:

$$Impact\ strength\ (I.S) = \frac{E}{A} = \frac{E}{b.d} \quad (1)$$

were,
E = Impact energy (KJ).
A = Area under notch (m^2)
b = composite length (m)
d = width below material notch (m),

2.3.3 Tensile test

Every specimen underwent tensile strength testing in accordance with ASTME 8 standards. Using a computerized Instron Testing Machine (model 3369). Three identical test specimens for each section thickness per sample were evaluated at room temperature with a strain/loading rate of 5 mm/mn. An X-Y recorder was used to create load displacement graphs, from which ultimate tensile strength, yield strength, and percentage elongation values were computed. The composites were destructively tested, and the various properties were determined.

2.4.1 Metallurgical examination

Visual examination is good enough for macro-examination but on the micro-level, there is the need for aided media. The samples under consideration were prepared for micro-examination.

2.4.2 Sample preparation

This is the primary stage involved in the metallographic examination processes. These include grinding, polishing, etching before final examination under the metallurgical microscope.

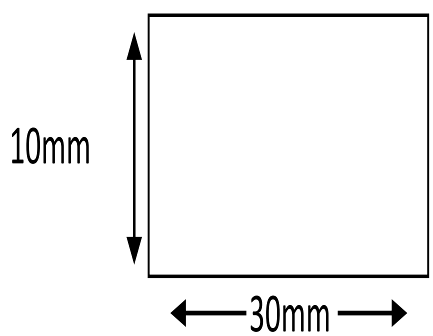

Figure 1: Microstructural specimen

2.5 Density

The density determination was carried out on the specimens by using the volume fraction and specific weights of the constituent materials by using the rule of mixtures.

2.6 Prognostic analysis motivated by data concerning the impact strength of composites using experimental measurements

To predict the impact strength of the composite under investigation, a data-driven prognostic model was developed. For this project, IBM® SPSS® software was used, utilizing the prediction capabilities of multiple linear regression (MLR) and artificial neural networks (ANN). The weight percent of silicon carbide (SiC) reinforcement, the hardness, and the density of the composite material were the three independent variables that were used to model the dependent variable of interest, which was impact strength. To determine the most accurate and dependable method for predicting the impact strength based on the provided input parameters, both ANN and MLR predictive procedures were investigated.

2.6.1 Artificial neural network

An artificial neural network (ANN) was used in this study to forecast the impact strength of the composite materials under investigation. The weight % of silicon carbide (SiC), hardness, and density of the test specimens served as the independent variables for the artificial neural network (ANN) model. For the prediction process, a multilayer perceptron (MLP) architecture was employed, which included an identity activation function for the output layer and a sigmoid activation function for the hidden layer. The following diagram was produced after the ANN model was trained using a batch training methodology.

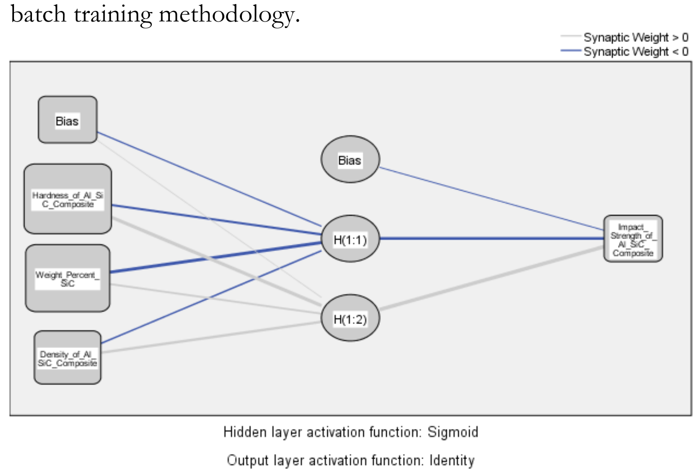

Figure 2: Artificial neural networks for the prediction of the composite's impact strength

2.6.2 Multiple linear regression (MLR)

A prediction model for the impact strength of the composites under investigation was obtained using multiple regression analysis, considering independent variables including weight % of silicon carbide (SiC), hardness, and density of the tested specimens. The impact strength was predicted by the analysis, and it also produced a predictive equation that measures the connection between the impact strength, which was the dependent variable, and the independent factors. This formula may be used to calculate the impact strength from the values of the independent components, providing a thorough grasp of the influence these factors have on the impact strength of the composites that were studied.

2.6.3 Measure of accuracy in prediction

2.6.3.1 Mean squared error (MSQ_{Error})

The mean squared error (MSQ_{Error}) is a critical statistic that evaluates how closely an estimate resembles the genuine value in order to determine how accurate projected experimental values are (Schluchter, 2014). In addition to displaying bias, which indicates how much the anticipated value consistently deviates from the real value, MSQ_{Error} also displays variance, which illustrates how much sampling variability causes the estimator to fluctuate about its expected value (Schluchter, 2014). MSQ_{Error} may be broken down into elements that, when compared to real values, expose the limitations of mathematical models, such as bias, uneven variance, and incomplete covariation, helping to enhance the model's accuracy and precision (Detmann et al., 2017). Furthermore, MSQ_{Error} is used to assess laboratories in proficiency examinations, which gives it an edge over other metrics like the z score and normalized error (Castelazo & Mitani, 2012). By taking bias and sampling error into account and concentrating on the distributional characteristics of MSQ_{Error}, the likelihood ratio test based on MSQ_{Error} enables hypothesis testing about how near a value is to a target value (Holst & Thyregod, 1999).

The mean squared error is mathematically expressed by the following relationship:

$$MSQ_{Error} = \frac{1}{N}\sum(p_v - e_v)^2 \quad (9)$$

where,

N = Total number of examined samples.
p_v = Predicted value.
e_v = Experimental value.

3.0 Result and Discussion

3.1 Mechanical properties

3.1.1 Hardness test result

The average penetration diameters of three readings were used to calculate the composites' hardness values. The comparable hardness values indicate the impact of adding silicon carbide (SiC) particles to the aluminium matrix, according to Figure 3.

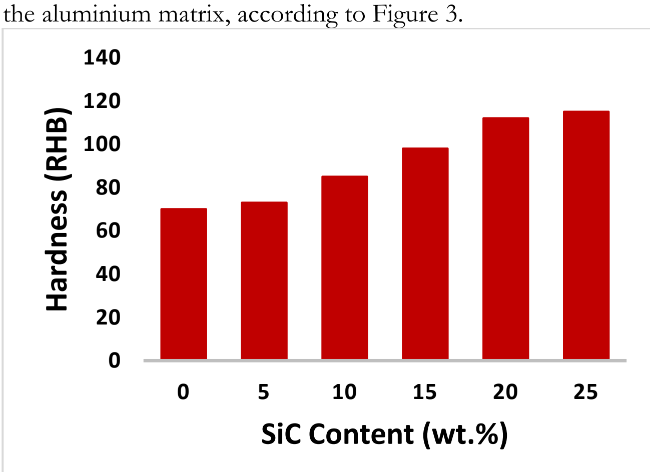

Figure 3: Effect of wt.% SiC on the hardness of the examined Al-SiC composite

As silicon carbide (SiC) was gradually added to the aluminum matrix, the hardness readings showed an increasing trend. In particular, the hardness value expanded with the inclusion of 5, 10, 15, and 20 wt.% SiC, from 70 RHB for the pure aluminum matrix to 73, 85, 98, 112, and 115 RHB, respectively. For the hardness test graph, 25 wt. % SiC reinforced aluminium matrix composites showed maximum hardness. In a similar study, Rahman & Rashed (2014) recorded a maximum hardness of 45.40 ± 1.06 at 20 wt.% of SiC. This shows that the material with 25 wt. % SiC has an enhanced wear and tear resistance in contrast to the materials with lower or no weight percentages of silicon carbide. Research on silicon carbide (SiC)-reinforced aluminum matrix composites has revealed that the hardness of these composites rises with increasing SiC weight percentages, which in turn improves wear resistance. According to research by (Şenel et al., 2018), adding SiC increases compressive strength and hardness; composites with 30 weight percent SiC showed the greatest values of these properties.

Similar findings were made by Veeresh Veeresh-Kumar et al. (2012), who discovered that increased SiC content in Al6061-SiC composites led to increase in hardness and ultimate tensile strength but decreased ductility. Additionally, it was reported by Hassan & Aigbodion (2007) that Al-Si-Fe/SiC composites' hardness values increased as the composition of SiC increased, suggesting greater wear resistance. Composites with 25 weight percent SiC generally had the maximum hardness.

3.1.2 Impact test results

One important characteristic that establishes a composite material's resistance to unexpected loads or impacts is its impact strength. The impact strength of composites made of Al7075 aluminum alloy reinforced with different proportions of silicon carbide (SiC) particles was assessed in the study under review. As shown in Figure 4, the impact energy and the area beneath the notch were used to calculate the impact strength values. As the amount of SiC reinforcement rose from 0% (pure Al7075) to 25 wt.%, the impact strength showed a linear rising trend, according to the data.

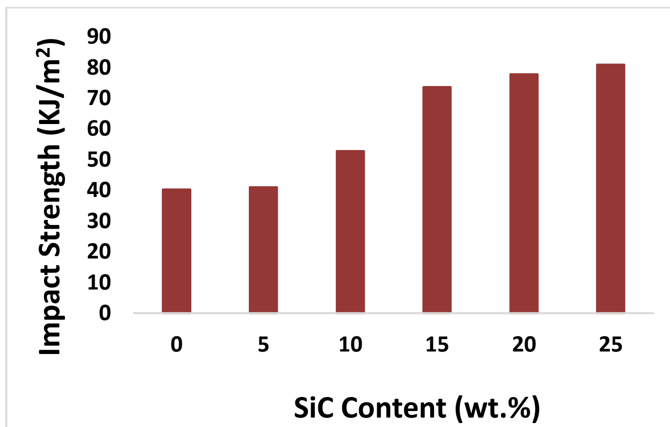

Figure 4: Effect of wt.% SiC on the impact strength of the examined Al-SiC composite

The impact strength for the unreinforced Al7075 alloy was 402.4 KJ/m², whereas the composite with 25 wt.% SiC reinforcement had 809.1 KJ/m². According to this pattern, the impact resistance of the composite material is improved when SiC particles are added to the Al7075 matrix.

The brittle and hard SiC particles scattered throughout the ductile aluminum matrix provide reinforcement, which accounts for the linear increase in impact strength that has been seen. Particle debonding, crack deflection, and matrix plastic deformation are some of the ways in which the SiC particles dissipate impact energy by acting as barriers to the spread of cracks (Ovri et al., 2019). reported that the impact test result of the silicon carbide aluminium matrix composite showed that the shock absorption strength increased from 5 wt.% to 25 wt.% silicon carbide reinforcement which aligns with the findings of the current study.

The research works by Raghuvaran et al. (2023) and Ravichandaran et al. (2023) support the observation that SiC reinforcement causes an increase in the impact strengths of Al7075-SiC composites in a linear manner. The remarkable tribological and mechanical properties of Al7075 with 12% SiC and 6% Al_2O_3 reinforcement were highlighted by Ravichandaran et al. (2023) in their study of Al7075 composites reinforced with SiC and Al_2O_3. However, M. Ravikumar et al.'s (2023) study of Al7075 composites reinforced with nano-sized SiC-Gr showed that the inclusion of SiC particles enhanced the mechanical parameters, such as ultimate tensile and compressive strength. Both investigations demonstrate the prospect of reinforcement content in regulating the mechanical characteristics of metal matrix composites, supporting the idea that increasing SiC reinforcement in Al7075 composites results in higher impact strengths.

3.1.3 Tensile strength test result

Under tensile loading, the mechanical behavior of Al-SiC composite samples with different SiC concentrations are illustrated by the stress-strain curve shown in Figure 4.3. The baseline performance of the pure aluminum matrix was represented by the 0 wt.% SiC curve, which set the basis for the mechanical characteristics of the examined composite. The stress-strain curves were found to display different changes when the SiC composition was increased (5, 10, 15, 20, and 25 wt.%). This indicates that the SiC reinforcement gradually affected the material's load-bearing capability and deformation properties. Important information on the strength and ductility of the composite at various SiC concentrations was gained from these alterations.

The results showed that higher SiC concentration was positively correlated with increased tensile strength. This is likely because SiC particles inside the aluminum matrix had a reinforcing effect. Significantly, specimen made of 100% Al7075 (0 wt.% SiC) had the lowest tensile strength at 33,270 kN/m², but the composite with 25 weight percent SiC showed the maximum tensile strength at 146,500 kN/m².

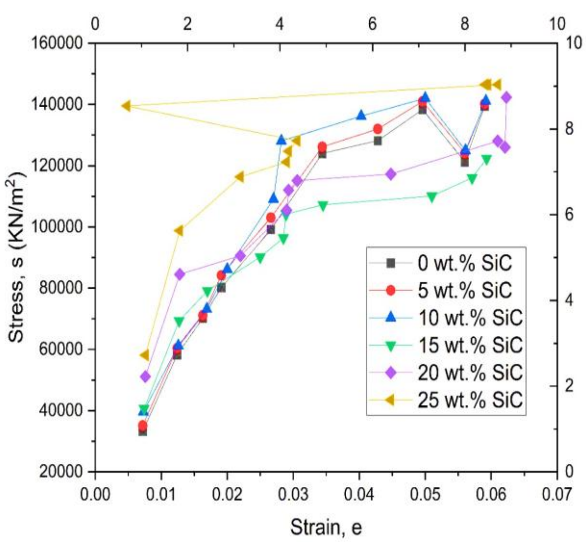

Figure 5: Effect of wt.% SiC on the tensile strength of the examined Al-SiC composite

Prior research (Pichumani et al., 2018; Sirahbizu-Yigezu et al., 2013) showed that while bend strength and elongation decreased, micro hardness, ultimate strength, and yield strength increased with a rise in Al-SiC composites with varying wt.% SiC. Furthermore, the load-bearing capacity and deformation characteristics of the material were shown to be favorably impacted by the presence of SiC particles inside the aluminum matrix. Additionally, the study on Al/SiC nano-composites shown that the strength of the nano-composites was greatly increased by the dispersion of SiC particles in the matrix, with smaller SiC particles leading to a higher augmentation of mechanical behavior (Huo et al., 2018).

With an increase in SiC content, the stress-strain curve of Al-SiC composites changes for a variety of reasons. Comparing SiC-reinforced composites to unreinforced materials, research suggests that the former are more sensitive to strain rate. At higher strains, adiabatic compression effects cause the flow stress to exhibit a non-linear trend, but it still increases strongly with strain rate (Fu et al., 2023). Furthermore, SiC volume percentage and strain rate also have a significant impact on the microstructure, with SiC cracking and interface debonding being important damage processes (Fu et al., 2023).

3.1.4 Measure of ductility of composite (Percentage elongation and percentage reduction in area)

The results of the evaluation of the composites' percentage elongation and area reduction are shown in Figure 4.4. For 0, 5, 10, 15, 20, and 25 weight percent SiC, the corresponding values were 5.94%, 5.72%, 5.41%, 5.17%, 4.43%, and 4.57%. The greatest elongation was 5.94% for the unreinforced aluminum (0 weight percent SiC), while the lowest elongation was 4.57% for the composite with 25 weight percent SiC reinforcement. The tensile properties of Al7075-SiC indicates that 25 wt.% Al7075-SiC has the better tensile toughness over lower % SiC reinforced specimen and Al7075 alloy. A higher SiC content increases strength but decreases the material's capacity to deform before failure; this loss in elongation represents a trade-off between strength and ductility in the composites (Central Environmental Lab, College of Science, Baghdad University, Baghdad-Iraq. & Abdul-Ameer, 2013). This suggests that adding more SiC to the aluminum matrix will reduce ductility (Amirkhanlou et al., 2011).

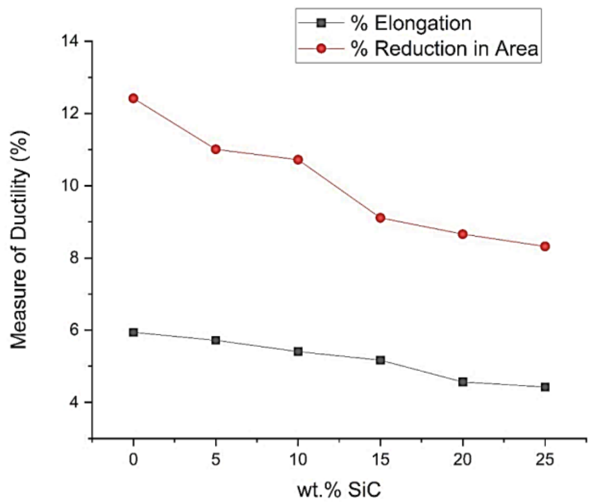

Figure 6: Effect of wt.% SiC on the ductility of the examined Al-SiC composite

The study carried out by Ovri et al. (2019) buttresses the result above, as it showed that ductility (Percentage area reduction) for Al6063 with SiC AMC reveals highest cross sectional area reduction for 5 wt.% Silicon Carbide reinforcement than that of 25 wt.%.

3.2 Density of composite

The density values of composites were evaluated using the Rule of mixtures and the results are shown in Fig. 4.5. At different reinforcing levels, the densities of composite specimens made of Al7075 and Al-SiC were measured. The findings showed that density increased with the composition of SiC reinforcement. Specimens with SiC reinforcement at 5wt.%, 10wt.%, 15wt.%, 20wt.%, and 25wt.% had densities of 2790.3, 2796.0, 2840.5, 2850.0, and 2880.0 kg/m^3, in that order. At 2780.0 kg/m^3, the baseline Al7075 sample (with 0% SiC reinforcement) had the lowest density. Based on this relationship, it could be deduced that the amount of silicon carbide present has a direct impact on the density of the examined composites.

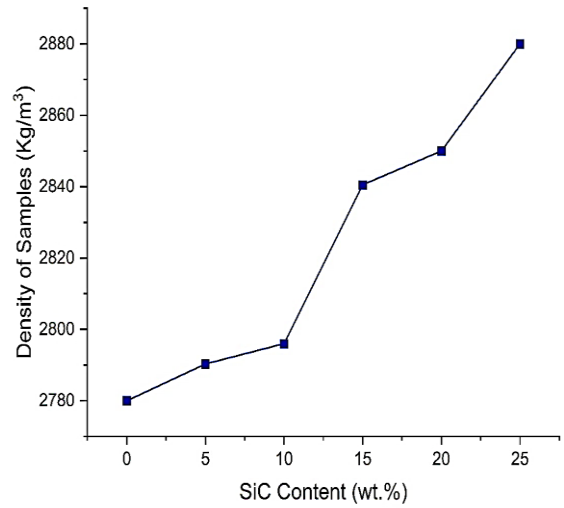

Figure 7: Effect of wt.% SiC on the density of the examined Al-SiC composite

The study carried out by Kumar et al. (2012) corroborated the results indicating that a greater density of Al-SiC composites was correlated with an increase in SiC content. Further supporting this relationship was the work of Zhiqing Zhang and Hongyu Zheng (Suresh & Poongodi, 2018), which showed that an increase in SiC content was correlated with a rise in the density of aluminum reinforced with silicon carbide particle composites.

3.2 Metallographic examination results

The metallographic test results reveal the micro-graphic composition for the Al-SiC composite material for (0 wt.%, 5 wt.%, 10 wt.%, 15 wt.%, 20 wt.% and 25 wt.%) particle reinforcements. Microstructures obtained from computerised optical microscope are shown in figure 8 for Al7075, and for the different specimen of Al-wt.% SiC.

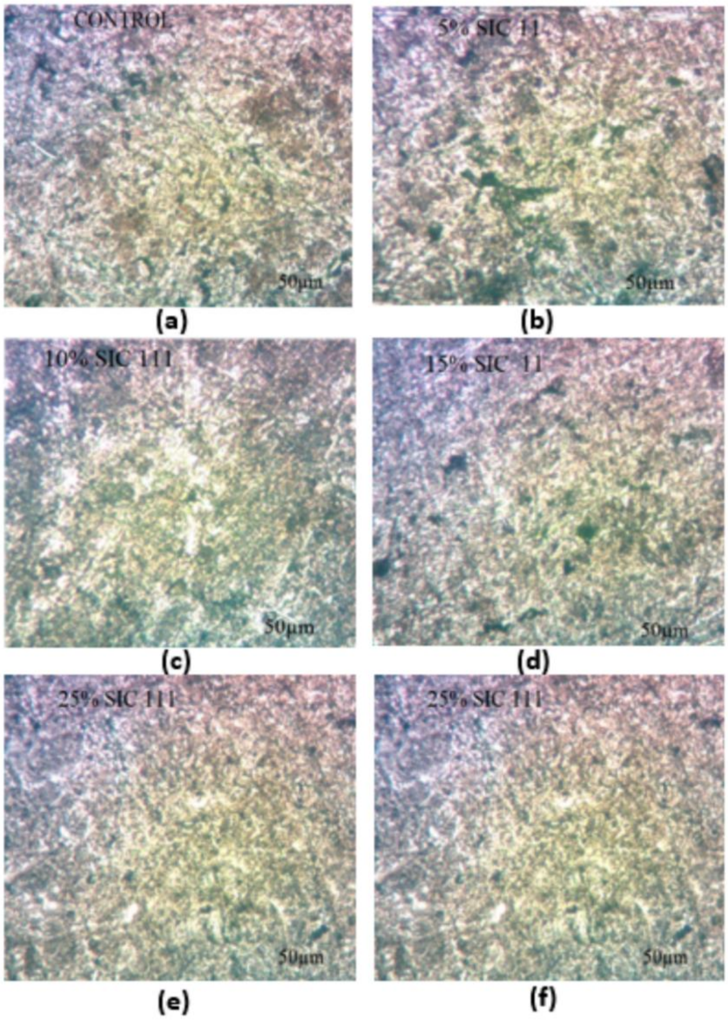

Figure 8: Micrographs of composites at 5μm (Magnification: x1000). (a) 0 wt.% SiC (b) 5 wt.% SiC (c) 10 wt.% SiC (d) 15 wt.% SiC (e) 20 wt.% SiC (f) 25 wt.% SiC.

The micrographs clearly reveal composites developed with the help of manual stirring which shows minimal micro porosity in the casting. It is also observed that the distributions of reinforcement in the respective matrix are fairly uniform. While the particles may be mixed into the melt by stirring, they tended to rise to the surface again when the stirring ceased. To stay in clusters, the majority of these particles continued to adhere to one another. The reemergence of these clusters is not surprising, since one could argue that their ability to float is due to the presence of pores. The fact that individual particles also exhibited a strong tendency to return to the surface, however, suggests that the surface gas layers around the particles were primarily responsible for their buoyancy. due to poor wettability. The low wettability may be mostly caused by the gas layers. First of all, the buoyant migration of particles caused by gas layers can make it challenging to absorb the particles into the melt. Second, even while strong stirring can suspend particles in the melt, the presence of gas layers makes it difficult for the particles to get wetted by the molten metals.

Based on the study above, it was determined that high wettability required breaking the gas layers. Since individual particles and clusters of particles can move freely in a fully liquid melt, little force is imparted to the particles during agitation, which makes it extremely challenging to separate the gas layers with merely traditional stirring. For 5 wt.% SiC reinforcement there is clear distinction between grain sizes and boundaries, and increasing concentration to 10 wt.%, 15 wt.%, 20 wt.% and 25 wt.%, structural fines improve, showing better wettability from the stirring process and improved mechanical strength.

The metallographic analysis of the different materials shows that the use of stir casting method of liquid metallurgy is responsible for the even distribution of reinforcements in the micro-structures of the materials. Research done by Seshappa, Kumar, and Sankar (2016) revealed that the microstructures of the composites were observed to show the distribution of silicon carbide particles in aluminium matrix.

3.3 Prediction of the experimental impact strength of composites by ANN and MLR

The predicted values of the experimental impact strength with the model, driven by artificial neural network (ANN) and multiple linear regression (MLR) were obtained with the wt.% SiC, composite's density, and hardness as independent variables. The results are presented in Table 2.

Table 2: Prediction of the experimental impact strength of produced composite by ANN and MLR

Hardness of Al-SiC Composite	Weight Percent SiC	Density of Al-SiC Composite	Impact Strength of Al-SiC Composite	Predicted Experimental Impact Strength of Al SiC Composite			
(RH_B)	(%)	(Kg/m^3)	(KJ/m^2)	By ANN	Error	By MLR	Error
70.00	0.00	2780.00	40.25	39.35	0.90	41.93	-1.68
73.00	5.00	2790.30	41.06	42.74	-1.68	42.49	-1.43
85.00	10.00	2796.00	52.82	51.94	0.88	51.42	1.40
98.00	15.00	2840.50	73.64	71.08	2.56	67.85	5.79
112.00	20.00	2850.00	77.75	78.42	-0.67	79.44	-1.69
115.00	25.00	2880.00	80.91	80.80	0.11	83.30	-2.39

ANN network information and independent variable importance, presented in Table 2 indicated that hardness played the pivotal role in the prediction of the impact strength in the magnitude of 38.7 %, followed by wt.% SiC (36.5 %), and finally the composite's density. On the prediction of the experimental impact strength by multiple linear regression is presented in Table 3 and represented by equation (1).

The error in prediction as shown in Figure 9 reveals that the prediction made by the artificial neural network was closer to the experimental impact strength in comparison with what was obtained using multiple linear regression.

Table 3: ANN network information and independent variable importance for the prediction of the impact strength of the produced Al-SiC composite by ANN

Independent Variable Importance	
	mportance
Hardness of Al_SiC Composite	0.387
Weight_Percent_SiC	0.365
Density of Al_SiC Composite	0.249

Parameter estimates				
		Predicted		
Predictor		Hidden Layer 1		Output layer
		(1:1)	(1:2)	Impact Strength of Al-SiC Composite
Input layer	(Bias)	0.295	0.158	
	Hardness_of_Al_SiC Composite	0.745	1.238	
	Weight_Percent SiC	1.204	0.724	
	Density of Al_SiC Composite	0.587	0.763	
Hidden layer 1	(Bias)			-0.248
	H (1:1)			-0.910
	H (1:2)			1.450

Table 4: Analysis for MLR's impact strength prediction of the produced Al-SiC composites

	Model coefficients			
	Constant	**Hardness of Al-SiC Composite**	**Weight Percent SiC**	**Density of Al-SiC Composite**
Predicted Impact Strength of Al-SiC Composite	-494.401	1.015	-0.841	0.167

Impact strength of Al-SiC composite $_{\textbf{(PREDICTED)}}$ = – 494.401+1.015 (Hardness of Al-SiC Composite) – 0.841 (wt.% SiC) + 0.167 (Density of Al-SiC Composite) (1)

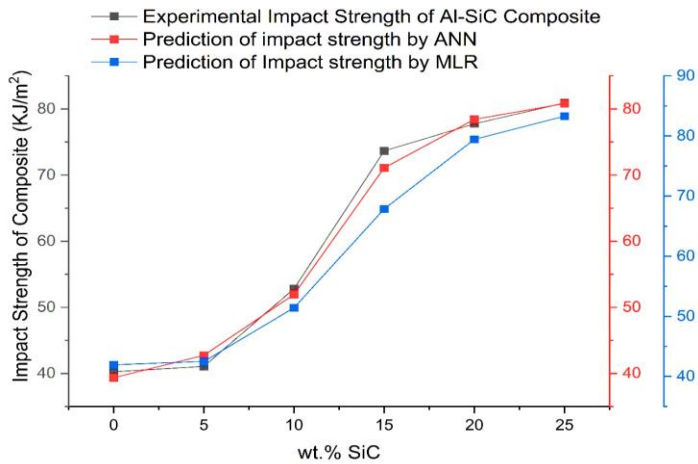

Figure 9: Effect of the number of samples on the predicted impact strength of the examined Al-SiC composites

Artificial neural networks (ANNs) were used in (Khalefa, 2019)'s study on stir-cast Al-Si alloys to predict the effect of silicon content on tensile strength, hardness, and wear loss. The results showed that the ANN predictions were closer to the experimental results, with an optimal mean square error (MSE) of 0.0335 for the tensile test (Khalefa, 2019). Furthermore, (Veeresh Kumar et al., 2017)'s work on Al6061-TiO_2 composites showed how to apply an ANN model to forecast wear characteristics. The study also revealed a strong agreement between experimental and ANN model predicted findings, underscoring the usefulness of ANNs in material property prediction (Veeresh Kumar et al., 2017). According to both studies, ANNs outperform more conventional techniques like multiple linear regression in predicting material attributes like impact strength.

4. Conclusions

From the research, the following conclusions can be made:

The addition of silicon carbide (SiC) in aluminium matrix composite increased the hardness and tensile strength of the composites when compared with unreinforced 100 % aluminium composites. 25 wt. % silicon carbide content aluminium matrix composites (AMCs) showed maximum hardness, and impact strengths of 115 and 80.91KJ/m^2 respectively.

The densities of the examined Al-SiC composites were observed to increase with increase in the wt.% SiC of the examined Al-SiC composite samples. The sample with 0 wt.% SiC gave the minimum density of 2780.0 Kg/m^3 while the highest density of 2880 Kg/m^3 was recorded for 25 wt.% SiC Al-SiC composite. On the other hand, the microscopy studies revealed that the stir casting process employed in producing the Al-SiC composite samples aided uniform particle distribution of SiC particles in the aluminium matrix.

Using artificial neural network (ANN) and multiple linear regression (MLR) models, the experimental impact strength of Al-SiC composites was predicted based on independent variables like hardness, composite density, and weight percentage SiC. Hardness was found to be the most important predictor, accounting for 38.7% of the prediction, followed by weight percentage SiC (36.5%) and composite density. The error analysis showed that compared to

MLR, the ANN model gave predictions more consistent with the experimental impact strength.

5 Recommendations

It is recommended that the Hall-Petch relationship should be used in future research on Al-SiC composites to examine how grain size affects mechanical characteristics, especially strength. It is recommended that researchers employ controlled processing settings to systematically change the aluminum matrix's grain size and investigate the resulting effects on the yield strength and hardness of the composite. The grain boundary strengthening effect may be measured using the Hall-Petch equation ($\sigma_y = \sigma_0$ + ky*d^(-1/2), where σ_y is the yield strength, σ_0 is the friction stress, ky is the strengthening coefficient, and d is the grain diameter). This research would assist clarify the relative contributions of particle reinforcement vs grain refinement to the overall strength of the composite and offer insightful information on improving the microstructure for improved mechanical performance.

Incorporating the Orowan relationship into analysis in future research is necessary to obtain a more profound comprehension of the strengthening mechanisms in Al-SiC composites. Studying how the size and distribution of SiC particles affect the yield strength and work hardening behavior of composites is a worthwhile endeavour. The Orowan strengthening effect can be measured and the optimal reinforcing parameters can be achieved by varying the SiC particle size and volume fraction in a methodical manner. A more thorough knowledge of the several strengthening mechanisms at work in Al-SiC composites would be provided by this approach, which would supplement the current findings.

Declaration Statement

The authors agreed with total interest to submit the manuscript entitled, 'Predicting mechanical properties of aluminum composite reinforced with silicon carbide using artificial neural network and multiple linear regression' for publication in your reputable Institution without conflict of interest, be it design and implementation, respect towards society, resources and research output and conduct without deceptive acts.

Conflict of Interest

The authors declare no conflict of interest.

Author Contribution

Chioma Ohanu: Writing – original draft, Methodology. J. E. O. Ovri, A. I. Ndukwe, and C. P. Egole: Supervision, Investigation, and Conceptualization. C. Onuoha: Review & editing.

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