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Manufacturing and Critical Analysis of Al/SiC/Coconut and Bagasse Ash MMC using Dimensional Analysis and Feed Forward Back–Propagation Neural Network

M. Mote[1]*, M. Phate[2] and A. Sathe[2]

[1]Mechanical Engineering Department, M.I.T Art, Design and Technology University, Pune - 412201, Maharashtra, India; mangeshmote619@gmail.com

[2]Department of Mechanical Engineering, All India Shri Shivaji Memorial Society's, College of Engineering, Pune - 412201, Maharashtra, India

[3]Mechanical Engineering Department, M.I.T Art, Design and Technology University, Pune - 412201, Maharashtra, India

Abstract

Depending on the intended usage, a composite material composed of Silicon Carbide (SIC), Aluminium (Al), and natural waste may offer a number of benefits. Sixteen combinations containing different concentrations of Silicon Carbide (SIC), aluminium, coconut, and bagasse ash were developed and tested in order to determine the ideal composition. With a strength of 161.03 MPa and a BHN of 54.3, the composite of Al:SiC: coconut ash: bagasse ash (78:6:8:8) was determined to be the best one based on testing. The Vertical Machining Centre (VMC) machine is also used to test the machining performance. A mathematical model that correlates MRR with all input parameters was developed using novel Dimensional Analysis (DA) and a feed-forward back-propagation neural network. Performance was compared to the regression, and the DA-based MRR's efficacy was examined. With a correlation coefficient (R2) of 0.9968, the experimental results indicate that DA-based MRR prediction models perform well. DA was found to be reliable and effective. Based on the current research, it is recommended that the best composite be used for the different underwater applications, like motor casing.

Major Findings: *Experimental findings show that the Al/SiC/ Ash MMC has gives good strength and quality after the machining. The MRR prediction model using DA also shows a good commitment to represent the process effectively and efficiently. The correlation of closeness is 0.9968, which shows the accuracy of the prediction model.*

Keywords: *ANN, Ash, Bagasse, Coconut, Feed Forward and Back Propagation, MRR*

1.0 Introduction

Composites made of aluminium have remarkable strength-weight ratios, which makes them useful in applications requiring strong, lightweight materials. Mechanical properties like stiffness, strength, and hardness can be greatly improved by adding reinforcing materials like carbon fibres, silicon carbide (SiC), or alumina (Al_2O_3) to aluminium matrices. Because of this, aluminium composites can be used in demanding structural applications in the automotive, aerospace, and defence sectors. When compared to pure aluminium, composites made of aluminium frequently show better corrosion resistance. The MMC has wide applications in

**Author for correspondence*

construction, chemical processing, defence and marine industries. It is also used in the underwater component preparation.

This study produces an aluminium-based composite reinforced with SiC, coconut ash, and bagasse ash; this material is important in many different industries. Both coconut ash and bagasse ash are leftovers from farming activities. By reusing waste materials and lessening their environmental impact, using them as fillers in composite materials provides value. Aluminium composites can benefit from the addition of ash fillers to improve their mechanical properties, such as stiffness, strength, and hardness. It also exhibits better thermal conductivity as compared to pure aluminium. Additionally, it shows enhanced resistance to corrosion. This is particularly advantageous in settings where corrosion is an issue, like marine applications or buildings subjected to severe weather. Coconut ash and bagasse ash-aluminium composites are made from agricultural waste materials, which lessens the environmental impact of waste and eases the strain on landfills.

While the proportion of MgO increases from 3% to 9% and the percentage of SiC decreases from 9% to 3% in the remaining 12%, the percentage of matrix aluminium AA6262 remains at 88%. In four samples, the percentage of silicon carbide increased from 3% to 12% while the percentage of aluminium decreased from 97% to 88%. The composites with 5% SiC, 7% SiC, and 7% SiC/3% Al_2O_3 by weight were prepared and their mechanical, ar properties were assessed by Chandradass *et al*[1]. Muhammad Yasir Khalid *et al*[2]., utilized in the production of materials for transportation applications such as trains, automobiles, airplanes, etc. The subject of this study is the application of natural fibres in engineering. The mechanical and wear properties of an aluminium matrix composite with an aluminium LM24 grade and reinforcing materials like silicon carbide and graphite have been investigated by Ashish Kumar *et al*[3]. Mhaske and Shirsat[4] have investigated the mechanical and microstructural characteristics of Al-SiC composites produced using various processes and under various circumstances. Several manufacturing techniques, including squeeze casting, infiltration, powder metallurgy, and stir casting, can be used to create AMCs. Using the grey relation approach, the outcomes are compared. When using the powder metallurgy method, Al metric produces better hardness and shear strength than the stir casting method[6]. As the percentage of SiC increases, the composite's hardness increases without significantly altering its density, making it appropriate for applications that call for weight reduction. Muruganandam *et al.*,[5] have investigated how variations in the mechanical characteristics of AMC are influenced by the % composition of reinforcing SiC particles. Phate *et al.*,[7-10] investigated the performance of several composites using a range of soft computing and dimensional analysis approaches. It has been shown that a composite material made of Silicon Carbide (SIC), Aluminium (Al), and natural waste offers several advantages, including strength, durability, affordability, and thermal stability. Creating a model for the pace of material removal and creating the ideal composite are the main goals of the work being presented. For industries that need high-performance materials while considering sustainability and resource efficiency, making is an excellent option[11-13].

When selecting reinforcement, factors including mechanical properties, melting point, thermal and electrical conductivity, and ultimate composite needs can all be taken into account. Al alloys with SWCNT (Single-Walled Carbon Nanotube)/MWCNT (Multi-Walled Carbon Nanotube) have been studied by Prashantha Kumar *et al*[14]. The tribological characteristics and other features of this alloy are tested. Zinc, magnesium, copper, silicon, chromium, iron, titanium, manganese, and balanced Al6061 are among the materials used for this. The material's resistance to wear is somewhat enhanced by CNT. Compared to Al 6061, Al 6060 wears more frequently. The composite of CNTs can only be in line contact. As the load on the Al6061 composite increases, so does its wear rate. The impact of several machining parameters on the response (cutting force required and the roughness) of an aluminum-based metal matrix composite has been studied by Rasagopal *et al.*,[15] Al 7075 serves as the composite matrix base, and SiC and B4C are utilized as reinforcements in percentages of 1%, 2%, and 3%, respectively. In their 2019 study, Balarami Reddy *et al.*,[16] examined the performance of Al MMC reinforced with Cu particles. Lead, zinc, copper, manganese, and aluminium are the materials used for this. Stir casting is used to distribute copper uniformly throughout the MMC. The harder the material, the higher the weight percentage of copper. Silicon carbide with percentages of 0%, 3%, and 6%, graphite at 2% constant, and aluminium

LM24 are the materials utilised. There are 500, 1500, and 2500 mm of sliding distance. The effects of silicon carbide and magnesium oxide in aluminium AA6262 composite on mechanical properties such as hardness, impact strength, tensile strength, and percentage elongation have been studied by T. Sathish *et al*[17]. An investigation of oxide-related casting defects was examined by Giulia Scampone *et al*[18]. In order to attain favourable mechanical properties and consistent mixing of reinforcement, Sijo and Jayadevan[19] investigated and optimised a number of stir casting process parameters. SiC particles were added after the temperature was raised to 750 degrees Celsius to melt the aluminium. The mixture was supplemented with magnesium to increase the wet solubility. The study comes to the conclusion that the ideal parameters for stir casting of AMC are a four-bladed stirrer, a volume fraction of 10% for SiC, a diameter ratio of 1.5, and a stirrer speed of 100 Rad/sec. Three samples of aluminium metal matrix composites with 0, 2.5, and 5% by weight of silicon carbide were created, and their wear behaviour was investigated. per Lavepreet Singh *et al.,*[20] have investigated the mechanical and microstructural properties of the workpiece with 0-5 % (SiC).VikasVerma *et al.,*[21] Since fly ash is solid and extremely damaging to the environment right now, it can be used in Al MMC. It has an impact on Al MMC's structural and functional characteristics. Al_2O_3 particles (300–400 microns) in melted aluminium and fly ash particles (10 microns) are the materials used in this experiment. All of grade 7034 is utilised due to its weight percentage chemical composition. In this study, fly ash and Al_2O_3 were combined in different ratios to create Al MMC. In this study, fly ash and Al_2O_3 were combined in different ratios to create Al MMC. After being stirred, the Al_2O_3 and fly ash mixture is poured into a heated die. Following production and testing, it was found that MMC had a 96 % density, that stirring produced a uniform particle distribution, and that during casting, reinforced particles formed a dendrite structure. Following manufacturing, MMC is tested for hardness, tensile strength, and bending strength. Fly ash and 12 weight per cent Al_2O_3 improve the mechanical characteristics of Al-based MMC. Strength, bending strength, and hardness all rise. Because it increases its hardness, a higher amount of fly ash and Al_2O_3 increases wear resistance.

Numerous aspects influencing the mechanical characteristics of Al-based MMCs have been addressed by Vijaya Ramnath *et al*[22]. Wankhade *et al*[23]. Grade 7075 aluminium and silicon carbide are employed as reinforcement. Additionally, magnesium is used as a degassing agent at a rate of 1% to 2% of its weight. The SiC weight fractions are 0%, 2.5%, and 5%, respectively. 50, 100, and 150 N of load are applied. They have also examined the impact of longer stirring times. SiCat is preheated for two hours at 200 degrees Celsius to start the manufacturing process.

From the literature review, it is observed that very few researchers are working in the MMC with natural waste, which is lightweight and can be used for the underwater component preparation[6]. Hence, the work is extended for the preparation and finding the optimal machining parameters.

2.0 Materials and Methods

2.1 Preparation of Workpiece

Depending on the application and composite composition, a composite material made of silicon carbide (SiC), Aluminum (Al), and natural waste may provide a number of advantages. Combining silicon carbide (SiC), Aluminum (Al), and natural waste materials in machining operations can produce a very effective and environmentally friendly technique that has the following benefits:

- The use of Silicon Carbide in machining, especially in composite forms or coatings, provides exceptional hardness and wear resistance. This enhances tool life and allows for more precise and consistent cutting.
- Aluminium's relatively soft and lightweight properties make it easy to machine, reducing energy consumption and tool wear. It can be paired with SiC to create high-performance composites or coatings that further improve machining outcomes.
- Both SiC and aluminium have excellent thermal conductivity properties, ensuring effective heat dissipation during machining. This prevents thermal damage to workpieces and tools, maintaining machining accuracy and extending the longevity of tools.
- Incorporating natural waste materials like recycled metals, biomass, or other byproducts

can significantly reduce environmental impact. This aligns with circular economy principles by minimising the need for virgin resources and reducing the machining industry's carbon footprint.

- Recycled natural waste materials are often more affordable than new, raw materials. By combining these with SiC and aluminium, manufacturers can create high-performance parts at a lower cost while still maintaining the required quality and functionality.
- The inclusion of natural waste in machining processes allows for the development of new composite materials. For example, adding agricultural byproducts, recycled plastics, or metal waste to aluminium can produce alloys with unique properties like increased strength, reduced weight, or improved corrosion resistance.

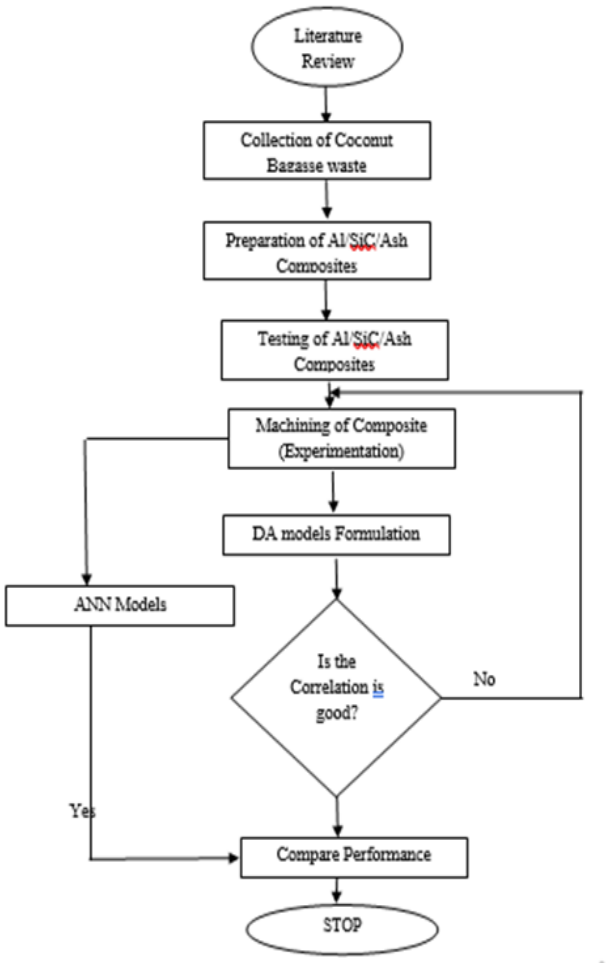


Figure 1. Flow of work.

Integrating SiC, aluminium, and natural waste materials offers a multifaceted approach to machining that not only improves performance but also supports sustainability goals. This combination allows for cost-effective, eco-friendly, and high-performance solutions that can cater to various industries, from aerospace to automotive.

The prepared component is machined using a Vertical Machine Centre (VMC). The experimentation was conducted, and the mathematical model was prepared using the Dimensional Analysis (DA) approach. Feed-forward -back-propagation neural network was employed to check the reliability of the DA model. The flow of work is as shown in Figure 1. The raw material, i.e coconut



Figure 2(a). Collected coconut shells.



Figure 2(b). Dried Bagasse.



Figure 2(c). Coconut shell ash preparation.



Figure 2(e). Aluminium LM25 material.



Figure 2(d). Bagasse ash preparation.



Figure 2(f). Silicon Carbide powder.

shells & bagasse[23]were collected and dried as shown in Figure 2(a) and 2(b).

SiC is the main reinforcing material used to boost the composite's tensile strength[18]. In order to lower the final composite's overall cost, fillers like bagasse ash and coconut shell ash are utilised. The ash is prepared from the natural waste and mixed with the SiC and Al to prepare a good metal matrix composite.

After the burning, the coconut and bagasse ash was filtered to eighty microns Figure 2 (c) and Figure (d).

Al (LM25) material and SiC powder were collected as shown in Figures 2 (e) and 2 (f). The geometry and the dimensions of the prepared sample are as shown in Figure 3.

Two essential instruments for material characterisation are the microscopic structure and the X-Ray Diffraction (XRD) pattern. The arrangement of atoms, molecules, grains, or phases in a material, as seen through the use of microscopy techniques, is referred to as its microscopic structure. It offers comprehensive information about the morphology of the material. By examining how X-rays are diffracted by the crystal lattice, XRD can reveal details about a material's crystal structure. The size of the crystallites, as determined by XRD peak broadening, frequently matches the grain size seen in microscopic techniques. Phase identification in XRD is consistent with phase distributions observed in microscopy. Defects like stacking faults and dislocations

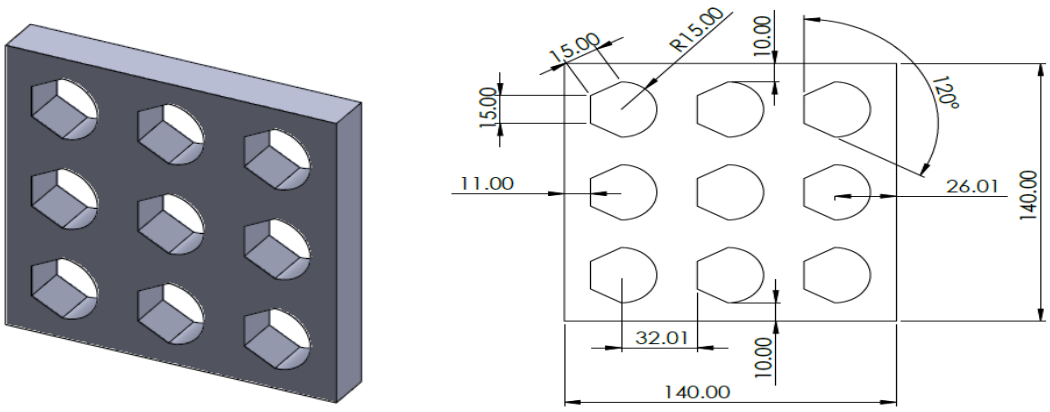


Figure 3. Composite plate and geometry of the finished work piece.

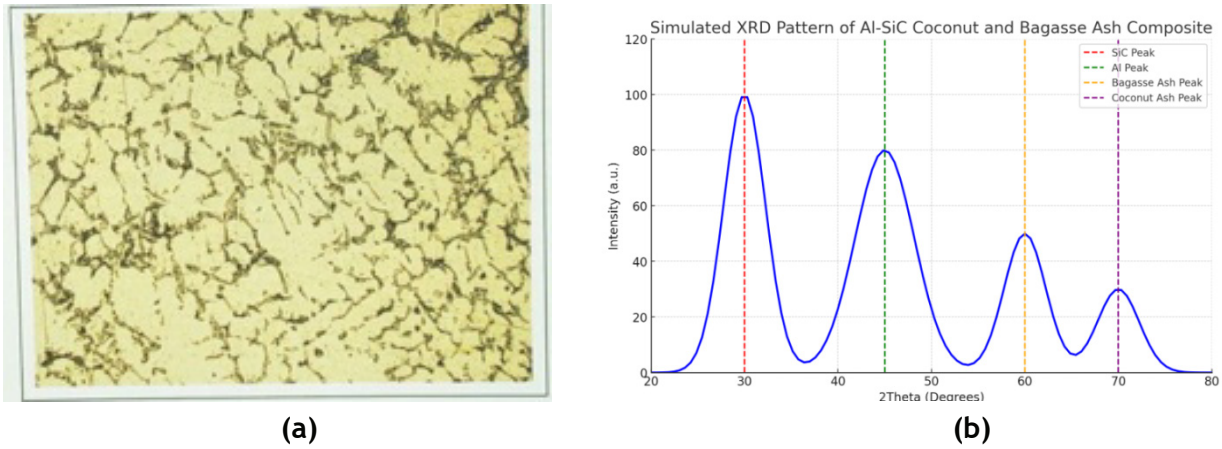


Figure 4. (**a**) Workpiece microscopic structure. (**b**) XRD pattern.

can alter the form and intensity of XRD peaks. The XRD pattern and microscopic structure of Al/SiC/Coconut & Bagasse Ash MMC are shown in Figures 4(a) and 4(b).

2.2 Experimentation

Machining experimentation typically involves systematically studying the effects of machining parameters and conditions on a material's performance, i.e., material removal rate. Using the capabilities of the Variable Machining Centre (VMC), experiments usually entail testing and assessing different facets of machining processes. Figure 5 depicts the setup used for the machining. Three replicates are used for each experiment, which helps to minimise the error. Care has been taken to minimise human error during the measurement.

A vertical machining Centre, or VMC, is the type of milling machine that is used to machine the prepared composite (Figure 5). Because of its vertical orientation,

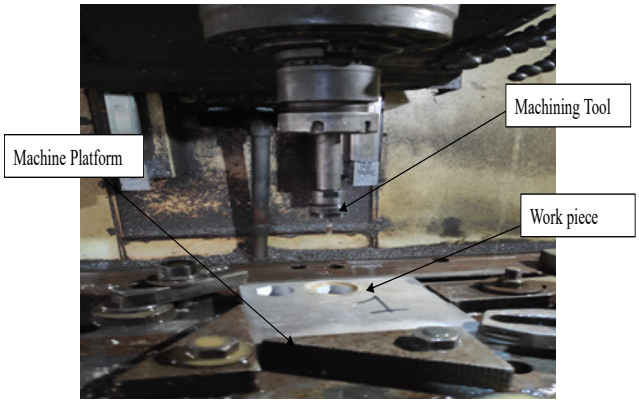


Figure 5. Machining set-up.

Table 1. Levels of various machining process signal factors

Sr No	Signal factors	Notation	(Low-1)	(Medium-2)	(High-3)
01	Spindle Speed	SP	1000 rpm	2000rpm	3000rpm
02	Feed	Frate	500	1000	1500
03	Depth of cut	DOC	0.3mm	0.5mm	0.7mm

Table 2. Taguchi L9 plan for experimentation

Composite	Input Parameters						Noise factor
	Scale (coded) Value			Actual (Un-coded) value			Material removal rate (MRR)
Hole /Exp	SP	FD	DOC	SP(A)	FD (B)	DOC (C)	
1	1	1	1	1000	500	0.3	0.65
2	1	2	2	1000	1000	0.5	1.85
3	1	3	3	1000	1500	0.7	3.68
4	2	1	2	2000	500	0.5	1.00
5	2	2	3	2000	1000	0.7	2.52
6	2	3	1	2000	1500	0.3	1.69
7	3	1	3	3000	500	0.7	1.37
8	3	2	1	3000	1000	0.3	1.14
9	3	3	2	3000	1500	0.5	2.68

it can be machined precisely. It is highly accurate and repeatable in its execution of intricate machining tasks. These are required to produce intricate components and parts with incredibly precise tolerances. Cutting operations on a VMC are influenced by process factors. In order to achieve the desired outcomes in terms of overall efficiency, surface finish, dimensional accuracy, and maximum material removal rate, they are essential. A roughness tester is used for measuring the roughness, and a digital weight machine is used for measuring the material removal from the workpiece. The procedure parameters are displayed in Table 1 below. The machining of each plate is done using the L9 plan (Table 2). The Taguchi L9 orthogonal array is used to reduce the number of experimental trials when testing multiple factors. It has some benefits such as robust design, simplicity, saving time, cost and resources.

2.3 Buckingham's Pi Theorem for Dimensional Analysis (DA) Model

In engineering, dimensional analysis (DA) is a potent technique for comprehending the intricate relationships between different factors[19,20]. Dimensional analysis is used to simplify, understand, and verify physical equations by analysing the dimensions (units) of the variables involved. It reduces the number of variables in a problem by combining them into dimensionless groups, making analysis easier. The following sections cover the methodology used to create DA models:

- Step 1: Identification of various Input and Output Parameters: In machining, input parameters and output parameters are critical for understanding and optimising the process. These are the

controllable factors that influence the machining process (listed in Tables 1 and 2).

- Step 2: Selection of Primary Dimensions (Fundamental Dimensions): The selection of primary dimensions during the formation of π terms in dimensional analysis is crucial for applying the Buckingham π theorem. This process ensures the correct grouping of variables into dimensionless terms, which simplifies the study of a physical system. In the present work, all the derived units are expressed in terms of Mass (M), Length (L), and Time (T) are the basic primary dimensions.
- Step 3: Selection of repeating variables: Choose the repeating variables that best reflect each of the process's main dimensions. In the process, they are all physically significant and independent of one another. The repeating variables should be chosen so that some of the parameters represent geometric parameters (length), mass-related parameters (density), and time-related parameters (acceleration, speed, etc.).
- Step 4: Formation of basic dimensionless (pi terms): The basic pi terms are calculated using Buckingham's pi theorem. According to this theorem, the Number of pi terms is equal to the total number of parameters involved in the process (both input and output) minus the number of primary dimensions (Phate *et al*[16-23]).
- Step 5: Formation of input pi terms (grouping): The grouping of π terms in dimensional analysis involves systematically arranging the variables into dimensionless terms, using the Buckingham π theorem. The goal is to simplify the relationships between variables, making them easier to analyse and interpret. The group of pi terms is as shown in Table 4.

The machining noise and response parameters are as tabulated in Table 3.

The final dimensionless (pi) terms are tabulated in Table 4.

- Step 6: Formation DA model

For all manufactured composites, the experiments were carried out in accordance with the DOE (L9) plan

Table 3. List of input and output parameters

Sr No	Parameters	Symbols	Nature
01	Mass of Aluminium	M_{Alu}	Independent
02	Mass SiC	M_{SiC}	Independent
03	Mass Bagasse Ash	M_{BGA}	Independent
04	Mass of Coconut Shell Ash	M_{CSA}	Independent
05	Work piece density	ρ	Independent
06	Work piece Yield strength	Syt	Independent
07	Workpiece Hardness	HBW	Independent
08	Speed during the machining	SP	Independent
09	Machining Feed Rate	F_{rate}	Independent
10	Depth of Cut during the machining	DOC	Independent
11	Removal of material during machining (Material removal Rate)	MRR	Dependent

Table 4. Grouping of basic pi terms

Sr No	Pi terms	Equation	Nature	Function
01	π_1	$\pi_1 = \frac{M_{Alu}}{\rho * DOC^3}$	Independent	Representing Parent / Base material (Aluminum) Composition
02	π_2	$\pi_2 = \frac{M_{Sic} * M_{BGA}}{M_{CSA} * \rho * DOC^3}$	Independent	Representing filler material (SiC& Ash) Composition
03	π_3	$\pi_3 = \frac{Sut * HBW}{\rho F_{rate}^2}$	Independent	Representing the Physical properties of material
04	π_4	$\pi_4 = \frac{SP * DOC}{F_{rate}}$	Independent	Representing Machining process parameters
05	πD_1	$\pi_{D1} = \frac{MRR}{F_{rate} * DOC^2}$	Dependent	Representing MRR

of experimentation. The DA-based model for the MRR is given by the Equations (1.1 to 1.7)[21,22]

$$\pi D1 = f\left(\pi_1, \pi_2, \pi_3, \pi_4\right)$$

Equation (1.1)

$$\pi D1 = K_0 {\pi_1}^a {\pi_2}^b {\pi_3}^c {\pi_4}^d$$

Equation (1.2)

$$\ln(\pi D1) = ln(K_0) + ln\left({\pi_1}^a\right) + ln\left({\pi_2}^b\right) + ln\left({\pi_3}^c\right) + ln\left({\pi_4}^d\right)$$

Equation (1.3)

$$\ln(\pi D1) = ln(K_0) + a * ln(\pi_1) + b * ln(\pi_2) + c * ln(\pi_3) + d * ln(\pi_4)$$

Equation (1.4)

A general regression is presented in by Equation 1.5

$$Z = K + a * A + b * B + c * C + d * D$$

Equation (1.5)

For a sample of 'N' data, the input matrix [X], the output matrix [Z] and the matrix of coefficients [K] is presented by

$$X = \begin{bmatrix} N & \sum A & \sum B & \sum C & \sum D \\ \sum A & \sum A*A & \sum A*B & \sum A*C & \sum A*D \\ \sum B & \sum B*A & \sum B*B & \sum B*C & \sum B*D \\ \sum C & \sum C*A & \sum C*B & \sum C*C & \sum C*D \\ \sum D & \sum D*A & \sum D*B & \sum D*C & \sum D*D \end{bmatrix}$$

$$\boldsymbol{Z} = \begin{bmatrix} \sum Z \\ \sum A*Z \\ \sum B*Z \\ \sum C*Z \\ \sum D*Z \end{bmatrix}$$

$$\boldsymbol{K} = \begin{bmatrix} \boldsymbol{ln}(K_0) \\ a \\ b \\ c \\ d \end{bmatrix}$$

Solving

$$[K] = [Z] * [X]^{-1} \qquad \text{Equation (1.6)}$$

$$\frac{\text{MRR}}{\text{F}_{\text{rate}} * \text{DOC}^2} = \text{f}\left(\frac{\text{M}_{\text{Alu}}}{\rho * \text{DOC}^3}, \frac{\text{M}_{\text{Sic}} * \text{M}_{\text{BGA}}}{\text{M}_{\text{CSA}} * \rho * \text{DOC}^3}, \frac{\text{Sut} * \text{HBW}}{\rho\ \text{F}_{\text{rate}}{}^2}, \frac{\text{SP} * \text{DOC}}{\text{F}_{\text{rate}}}\right)$$

Equation (1.7)

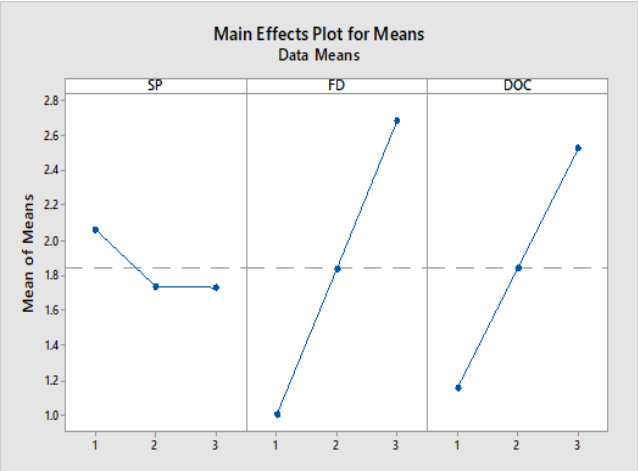


Figure 6. Machining set up.

3.0 Results and Discussion

3.1 Modelling using the DA Approach

The goal of the experiments is to measure the material removal rate that can be achieved for various composites with straight, inclined, and curvature machining under various cutting conditions. Knowing MRR makes it easier to evaluate how well machining processes work and optimise parameters for higher output. The results of this research help to improve machining efficiency, increase the capabilities of VMCs for a range of industrial applications, and advance our understanding of machining processes. Additionally, it assists us in choosing the optimal or the best composite combination. The DA model representing the MRR is given by Equation 1.8.

$$MRR = 0.0017 * \text{F}_{\text{rate}} * \text{DOC}^2 \left[\frac{\text{M}_{\text{Alu}}}{\rho * \text{DOC}^3}\right]^{0.3364} \left[\frac{\text{M}_{\text{Sic}} * \text{M}_{\text{BGA}}}{\text{M}_{\text{CSA}} * \rho * \text{DOC}^3}\right]^{0.0243} \left[\frac{\text{Sut} * \text{HBW}}{\rho\ \text{F}_{\text{rate}}{}^2}\right]^{0.0632} \left[\frac{\text{SP} * \text{DOC}}{\text{F}_{\text{rate}}}\right]^{-0.0126}$$

Equation (1.8)

The DA model for the MRR response, which takes into consideration every process parameter given in Table 2, is represented by Equation 1.8. "Al" is the parent material, "filler" is the second, "strength and hardness" are the composite's characteristics, and "machining or cutting parameters" is the fourth term. The coefficient illustrates the kind of impact that input process parameters have on the response MRR. MRR is significantly impacted by the composite's characteristics, the filler material SiC, the natural waste of coconut and bagasse ash, and the amount of parent material. Figure 6 illustrates the impact of various process factors on the final result[8-10].

There are other parameters which are not considered in the present work called extraneous variable. The extraneous variable such as air flow, humidity, atmospheric temperature, light intensity etc which is the influencing parameters[11-13]. The constant 0.0017 represents the impact of extraneous variable. The constant is very less which shows the minimum impact of extraneous variable.

The mean and the Signal-to-Noise Ratio (SNR) are critical for assessing the performance and robustness of a system or process. The mean represents the average performance of the system or process under the experimental conditions. It provides information about the central tendency of the output, allowing us to understand the overall level of performance. While the SNR is a key metric, it reflects the robustness of the system or process to variations. It is calculated to evaluate the quality of the response variable while minimising the impact of noise factors (uncontrollable variations). A higher SNR indicates that the system is less sensitive to noise, i.e., it is more robust. In the present work, the larger-the-better approach is used to maximise the response MRR. the mean measures the level of performance, while the SNR ensures that this performance is robust and reliable.

Table 5. Response of process parameters using the larger the better approach for MRR.

Level	Mean (Larger the better)			S/N ratio (Larger the better)		
	SP	FD	DOC	SP	FD	DOC
1	2.060	1.007	1.160	4.3062	-0.3358	0.6514
2	1.737	1.837	1.843	4.1952	4.8365	4.6354
3	1.730	2.683	2.523	4.1451	8.1458	7.3598
Delta	0.330	1.677	1.363	0.1612	8.4816	6.7084
Rank	3	1	2	3	1	2

Figure 6 shows that the feed rate is the most important element, followed by speed and depth of cut. Table 5 displays the signal-to-noise ratio and mean to maximise the MRR (the larger the better).

The MRR is negatively impacted by the input pi term associated with the machining parameters. to understand the effects of specific machining parameters. The composite is machined in accordance with the plan in Table 3 and the test environment described in Table 2. To get the best machining performance, the performance is evaluated. The cutting process parameters that have the biggest impact are feed rate, depth of cut, and speed. You can see the impact in Figure 6. While MRR somewhat declines with increasing speed, it rises with increasing feed rate.

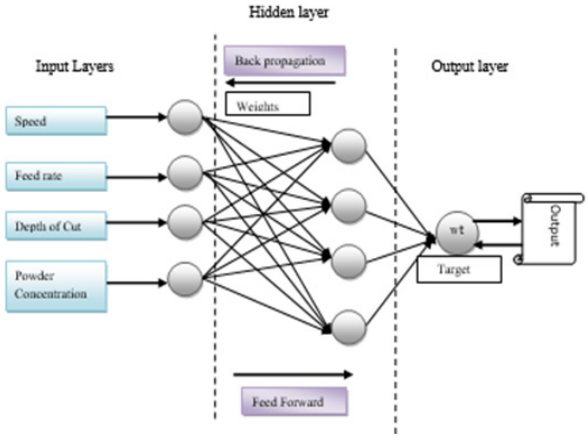


Figure 7. Basic Structure of ANN architecture.

3.2 Feed Forward Back-Propagation ANN Simulation (FFBPANN)

An Artificial Neural Network (ANN) is a type of machine learning algorithm that takes cues from the structure and functions of the human brain. A common computational model in machine learning and artificial intelligence is forward-feedback propagation. Data classification, function approximation, and prediction are all accomplished through the use of Artificial Neural Network (ANN) simulation. Its two main components for network training are feed-forward, propagation, and back-propagation. The back-propagation feed-forward method is an effective method for supervised learning tasks in ANN simulation, which strikes a balance between computational complexity and the capacity to represent complex data relationships. Figure 7 shows the basic structure of FFBPANN.

The input layer, hidden layers, and output layer make up the FFBPANN architecture. Multiple neurons (also known as nodes) make up each layer, and these are connected to neurons in neighbouring layers via weighted connections. Information moves from the input layer to the output layer (feed-forward) in a single direction via hidden layers. Feed forward involves feeding input data into the input layer, where each layer's neurons process it using an activation function to add non-linearity and a weighted sum of inputs. The network's final output is ultimately produced by using the output from one layer as the input for the subsequent layer. To determine the error (loss), it computes the expected output and contrasts it with the actual target value. Backwards pass uses the

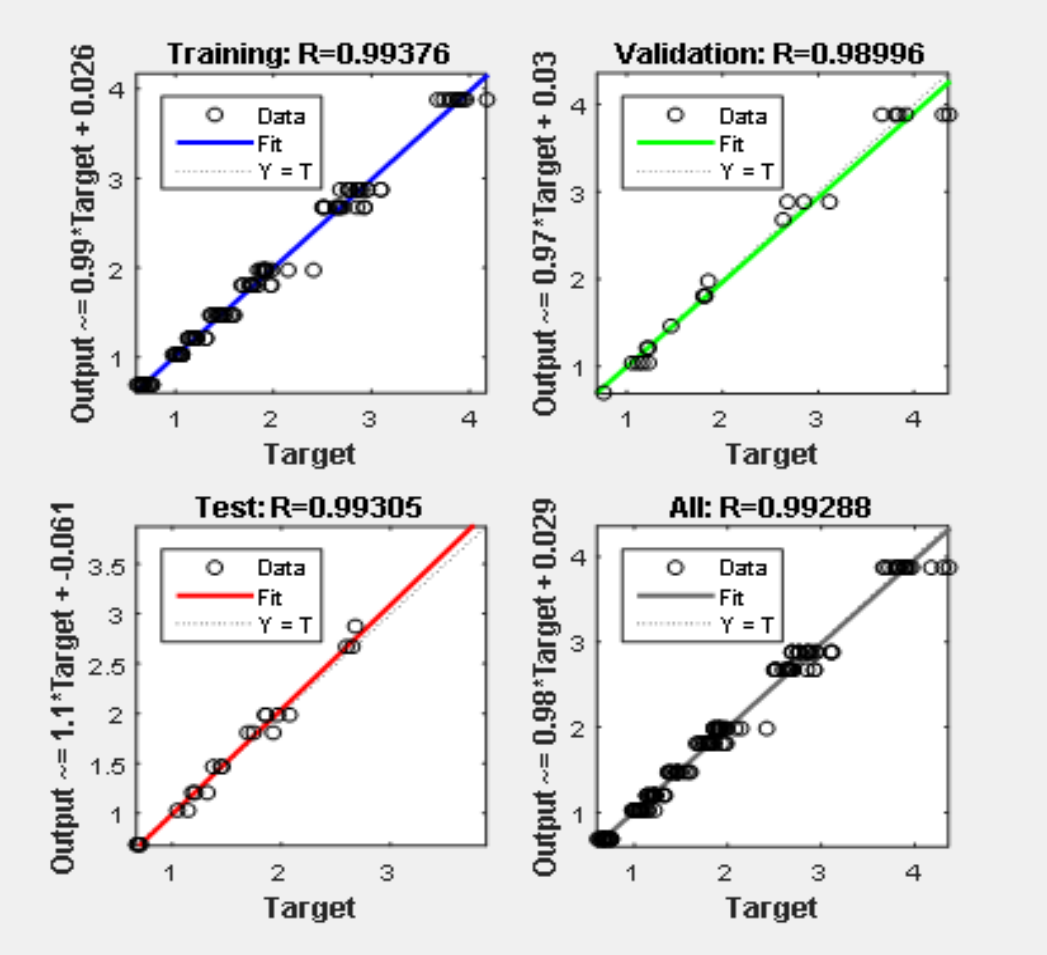


Figure 8. Regression plot for response MMR using FFBPANN.

gradient descent optimisation technique to modify the network's weights to minimise the error. Beginning at the output layer, the error spreads backwards through the network, layer by layer. The network's weights and biases are initialised either randomly or with particular techniques. The network makes predictions (forward pass) during each training iteration (epoch), and back-propagation modifies the weights to lower the error. Until the error converges to a manageable level or the maximum number of epochs is reached, this process is repeated. The simulation in this work uses the activation function (Sigmoid) and the loss function (mean squared error). In this work, we employ an optimisation technique called the Levenberg-Marquardt (LM) algorithm to minimise the error in non-linear least-squares problems.

A regression plot (Figure 8) is used to visualise the relationship between the actual output and the predicted output of the network. It is an important diagnostic tool to assess how well the ANN model is performing. The plot compares the true values (observed values from the data) with the predicted values generated by the ANN. If the model has perfect predictions, all points will lie along the diagonal (45-degree) line. This indicates that the ANN has accurately learned the mapping from inputs to outputs. If most of the points lie close to the diagonal, the model is performing well, but some deviations may indicate areas where the model could improve. If the points are scattered far from the diagonal line, this indicates that the model is not making accurate predictions, and the network needs further tuning. From Figure 8, it is observed that most of the points are nearer to the diagonal line in all training,

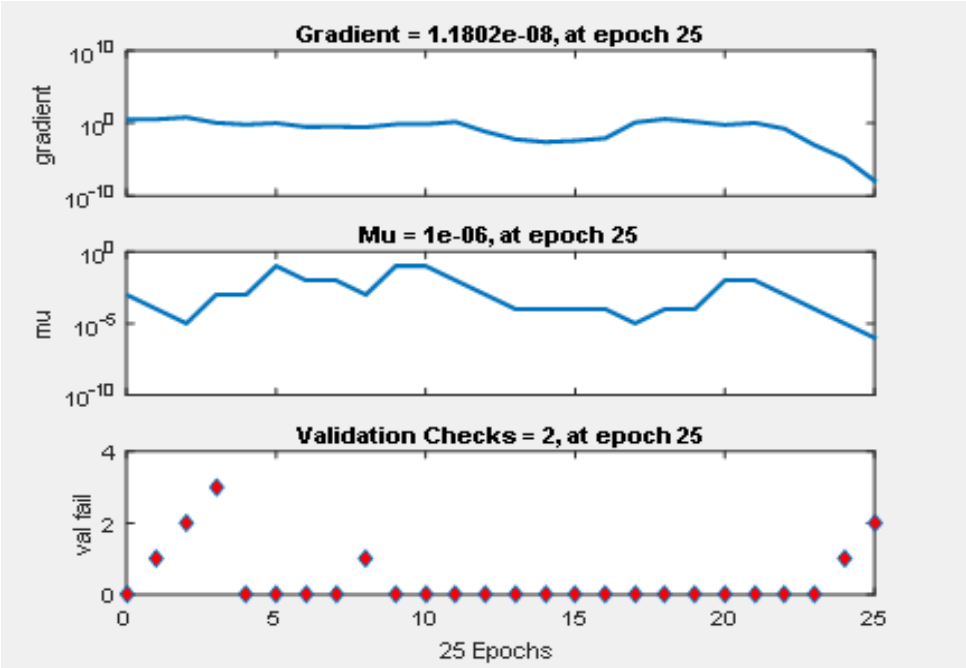


Figure 9. Training loss plot for response MMR using FFBPANN.

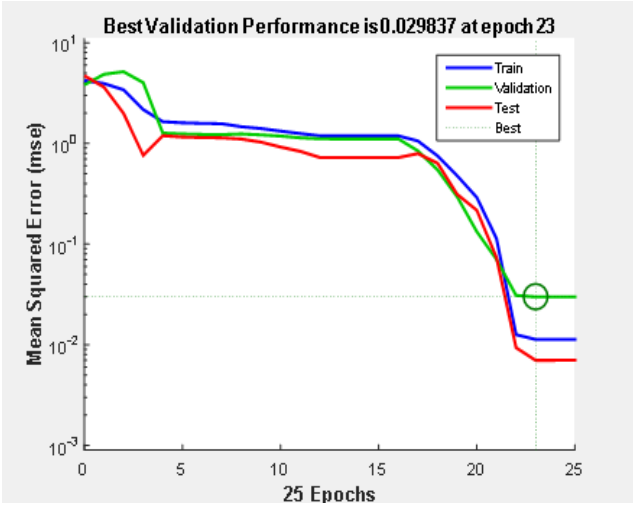


Figure 10. Validation loss plot for response MMR using FFBPANN.

testing, validation and the overall analysis. Hence good fit model is fitted for the run.

The training loss plot and the validation loss plot are as per Figures 9 and 10, respectively.

A good performance curve is observed in the presented work. It shows a gradual decrease in loss and/or an increase in accuracy for both training and validation datasets. The curves converge to stable values, indicating that the model has learned and generalised well. The performance curve flattens out over several epochs. It indicates the loss stops decreasing or accuracy stops improving and the model has reached the limits of its capacity for learning from the data. In the present work Levenberg- Marquardt (Training), epochs range (1 to 1000) are used. The DA model is compared with the ANN and the comparison is as shown in Figure 11.

SEM is widely used in various scientific and industrial fields to analyse surface morphology, composition, and structural details. The SEM of the machined surface is as shown in Figure 12. From Figure 12, it is observed that variations in greyscale values suggest the presence of different surface structures such as roughness, grains, or pores. Possible presence of voids, cracks, or distinct phases, depending on material composition. The SEM image reveals a textured surface with variations in contrast, indicating differences in material density and topography. The presence of bright and dark regions suggests possible variations in surface elevation, roughness, or composition. Any visible pores or voids suggest material porosity, which can impact mechanical

Table 6. Performance parameters of DA model.

Sr. No	Parameters	Notation	DA Model	ANN Regression Model
a	Closeness factor i.e. Correlation	R^2	0.997	0.999
b	Error (Absolute)	AE	0.062	0.053
c	Error (RMSE)	RMSE		0.069
d	Error (Relative)in %	RE	3.102	2.402
e	Prediction closeness (Accuracy)in %	ACE	99.94	99.95

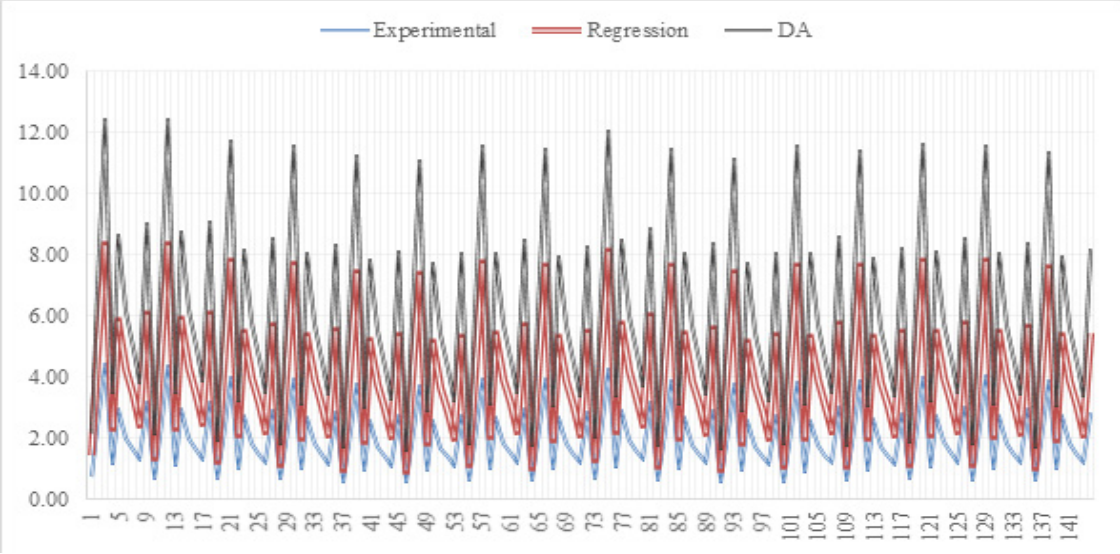


Figure 11. Comparative analysis between experimental, DA and ANN (Regression) predicted MRR

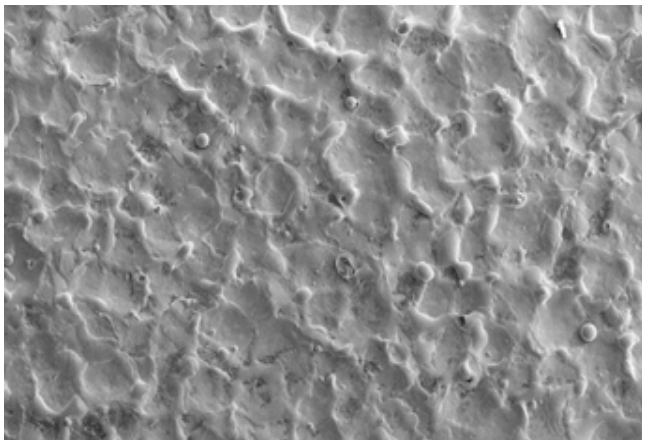


Figure 12. Surface roughness SEM image of the machining surface.

properties like strength and durability of the material. Table 6 presents a tabulation of the regression-projected MRR and DA performance. Table 5 shows that the DA model performs competently when combined with the ANN model. As a result, it can be predicted for MRR modelling.

4.0 Conclusion

Making different composites with "Al" as the parent metal and "SiC" as well as natural waste as a filler is the goal of the study that is being presented. Sixteen different composites were produced, and their hardness and strength were evaluated. The best composition of manufactured composites is provided by testing. The best one is selected

for the presented work. With strength 161.03 MPa and BHN 54.3, the composite containing Al:SiC: coconut ash: bagasse ash (78:6:8:8) was determined to be the best one based on testing. When machining composites, MRR is predicted using a Dimensional Analysis (DA) method. A chosen work component is machined using the DOE plan L9. The testing performance is used to choose the optimal composite. For the Al/SiC/Ash composite, MRR prediction models based on DA and regression were developed in the current work. The current work yielded the following significant results:

- A total of sixteen composites with various compositions were created. The optimal composition for strength and hardness tests is 78:6:8:8.
- Both the ANN model and DA can accurately forecast MRR, but DA has proven to be more adept than the ANN model.
- The composition of the parent metal has a major impact on MRR, which is followed by the composites' characteristics.
- The feed rate has a major influence during machining, followed by the depth of cut.

Thus, the presented work will help the metal industries to work in the field of Composites with Ash. The DA model will help researchers to know the impact of parameters called (extraneous), which are not considered during the research. This will help the researcher for further investigation. Hence recommended for the modelling. The outcome of the presented work is to use the natural waste in the metal preparation and its ease of machining for efficient and effective application in the machining industries. The MMC has wide applications in construction, chemical processing equipment, defence instruments and the marine industries. Both DA and ANN show good commitment to the prediction of response in an effective and efficient way.

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