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Research Article

Influence of Control Parameters during Drilling of Aluminum Reinforced with HNT Hybrid Matrix Composites

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The current paper aims to find the optimum control parameters such as weight percentage of HNT, weight percentage of boron nitride, drilling speed, and feed rate in drilling of aluminum hybrid metal matrix composites. The aluminum matrix material are reinforced with different weight percentage of HNT (3%, 5%, and 7%) and BN (2%, 3%, and 4%). The hybrid matrix are fabricated through the sir casting technique. The prediction of process parameter are optimized using Taguchi assisted grey relation analysis. Also the ANN model is developed to predict the output parameter. Through Taguchi S/N ratio method the effect of each control parameters are optimized. The results show that the weight percentage of HNT and feed rate are the most influencing parameters which affect the drilling of developed aluminum composites. The GRA results show that the optimum parameters are 3% of HNT, 4% of BN, 500 rpm drilling speed, and 20 mm/min in combination, which has minimum surface roughness, lower temperature, highest cutting force, and highest material removal rate.

1. Introduction

Aluminum metal matrix composites have become increasingly important in current industrial technology trends. Because of their unique mechanical and physical features, they had gained a lot of popularity and importance. As a result of their high strength and wear resistance, composite materials have largely replaced traditional ferrous materials in the automotive industry. Ceramic particles are commonly used to improve the mechanical strength, wear resistance, and corrosion resistance of aluminum alloys [1]. In comparison to alloys or other metals, aluminum composites offer significantly improved features such as high tensile strength, toughness, stiffness, low density, and good wear resistance. Low-density and low-cost composites have sparked a lot of attention [2]. Due to hard reinforcements in the materials, milling, turning, and drilling processes and increases in temperature are quite challenging. Finally, increased tool wear, poor surface quality, and lot of vibration occur as result of the drilling process [3]. In order to attain proper drilling quality and to find proper surface quality, the developed matrix must undergo proper optimization of control parameters [4]. The selection of proper input parameters can be achieved by selecting various optimization processes, by applying the input parameters to any one of optimization techniques, outputs such as increase in material removal rate, reduction in surface roughness, and a minimization of building process can be achieved [5]. The higher material removal rate can be achieved by increasing the spindle speed and maximizing feed rate meanwhile by increasing these process parameters increases the machining temperature and improper surface finish. So these response parameters are necessary to be optimized to achieve maximum MRR and minimum surface finish with a lower cutting force [6]. MMC's mechanical qualities are mostly determined by the degree of reinforcement and theabricateon process. The porosity increases as the reinforcing percentage increases, resulting in poor wettability. This is due to the density differential between the base alloy and the reinforcement, so proper selection of the casting process must be done [7]. Palanikumar and Muniaraj used carbide drills of various sizes to study the machinability features of SiC and graphite-reinforced aluminum matrix hybrid composites. According to them, the cutting force and feed of metal-matrix hybrid composites were the most important machinability parameters [8]. Basavarajappa et al. studied the impact of cutting settings on drilling properties of hybrid metal matrix composites (MMCs)—Al2219/15SiCp and Al2219/15SiCp–3Gris discussed in this research. The drilling characteristics of these composites are studied using the Taguchi design of experiments and analysis of variance (ANOVA). The results revealed that the ceramic reinforcement SiC + Gr exhibits better properties when compared with a single reinforcement SiC [9]. Karabulut et al. [10] investigated the milling of Al-6061/B4C MMC with 5, 10, 15, and 20% B4C. The hardness of the MMC has been seen to rise as B4C is increased, with the greatest hardness observed at 20% B4C. However, when the percentage of B4C increases, the impact resistance diminishes. At high speed, small feed rate, and dry-cutting circumstances, the best surface polish appears to correspond to 15% B4C [10]. To analyse the machining responses on WEDM done on Mg-based materials, Kavimani et al. [11] used Taguchi-based GRA coupled PCA.

Based on the results of the experiments, it can be determined that MRR and Ra are the most influencing parameters. The responses were evaluated using hybrid GRA coupled principal component analysis for multi-objective evaluation of the weighting values. In accordance with each performance, the ideal parameter was determined, and the final findings obtained based on the best combination were found to have a maximum MRR of 14.9 ml/min and a Ra of at least 2.04 m [11].

2. Experimental Details

2.1. Materials and Methods

2.1.1. Specimen Preparation. Aluminum alloy 5052 is chosen as a matrix material due to its high fatigue strength and corrosion resistance. The chemical composition of Al5052 is shown in Table 1. HNT was chosen as a primary reinforcement with weight percentage of 3, 6, and 9. The chemical compound or the molecular chemical formula of HNT is (H4AL2O9 Si2.2H2O). HNT is a low-cost material and it is widely used in many medical fields, especially for anticancer medical aid. The material mainly contains aluminum and silica, which shows high strength-to-weight ratio, better corrosion properties, and high wear resistance. The HNT has high bonding between the surfaces of the matrix material due to its anisotropic arrangement of carbonyl groups. Al203 is the outer part of HNT, whereas the inner core material is silicon dioxide (Sio2). Mainly HNT is used as a culpableness for plastic filler agent and also for bone implants. In this current research work the composition of HNT is, Al2O3-35.4, Fe2O3-0.39, TiO2-0.15, MgO-0.16, Na2O-0.20, and SiO2-48.8. The secondary reinforcement was chosen as Boron Nitride with a weight percentage of (2, 3, and 4) due to its wettability and self-lubricant nature.

Table 1: Chemical composition of Al 5052.

Mn	Fe	Cu	Mg	Si	Zn	Cr	Ti	Zr	Bal
0.10	0.35	0.8	2.60	0.20	0.25	0.30	0.05	0.10	Al

2.1.2. Fabrication Technique. The matrix material Al 5052 was fabricated by using a combo-casting process. Initially Al5052 was heated upto 720 °C, in muffle furnace the both the reinforcement HNT and Boron Nitride (BN) are preheated. Meanwhile, the molten material was cooled down to 575 °C during that process, the preheated reinforcement material was added to the slurry and stirred at 500 rpm continuously for 10 minutes [12]. After that, the molten material is poured into a required die and cooled down. The several combinations of Aluminum hybrid matrix are shown in Table 2.

Table 2 shows the hardness value of newly developed composites. The hardness of the composites was measured using Vickers hardness test. The hardness value of 39.7 HV exhibits at 7%, and 4% of boron nitride shows high hardness value. On increase in weight, percentage of reinforcement shows higher hardness value.

2.1.3. Drilling Experimental Setup. The hybrid composites are shaped into 70 mm× 40 mm × 10 mm for the purpose machining process. In this process, optimization of drilling process parameters is chosen as the machining process. The high speed steel (HSS) is used as a drilling tool with a diameter of 8 mm. For each of the three experiments, the drill bit is changed in order to reduce the error. The tests were performed on a three-pivot CNC machining focus which has an axle speed scope of 60–6000 rpm with an 802D BMV 40 320D control framework. The surface roughness (Ra) of the processed example was estimated by the MITUTOYO SJ 210M convenient surface unpleasantness gadget [13]. The cutting power was estimated by a Kistler 9257B 3-part dynamometer, and a Kistler 5070A enhancer was utilized to intensify the signals.

2.1.4. Process Parameters. The control parameters chosen in this experiments are four factor and three levels as shown in Table 3. The weight percentage of HNT and weight percentage of BN along with feed rate and drilling speed are the process parameters. Based on the literature and expert analysis, the experiment parameters are chosen.

2.1.5. L_{27} Orthogonal Array. In this current experimental plan, it is intended to distinguish the impact of parameters like weight % of HNT, weight level of boron nitride, cutting rate and cutting feed over cutting speed, temperature, MRR, and surface roughness. To break down the cycle boundaries, the test configuration was finished utilizing Taguchi orthogonal array to limit the number of experiments [14]. In light of the Taguchi plan, L_{27} symmetrical exhibit was chosen depending on the total degrees of freedom.

2.1.6. Taguchi S/N Ratio Analysis. The deviation between input and output values, the quality of work approach, was suggested by Taguchi's design of experiments. In Taguchi

Table 2: Composition of aAluminum MMC with hardness.

HNT	3	3	3	5	5	5	7	7	7
BN (%)	2	3	4	2	3	4	2	3	4
HV	31.4	32.9	33.8	34.2	35.7	36.9	37.2	38.5	39.7

Table 3: Control parameters and corresponding levels.

S. no	Factors	Unit	Values		
			I	II	III
1	Weight percentage of HNT	%	3	5	7
2	Weight percentage of BN	%	2	3	4
3	Spindle speed	rpm	500	1000	1500
4	Feed rate	mm/min	20	40	60

strategy, the output factors are investigated as far as signal-to-noise (S/N) proportion, it is used for measuring the noise factor [15]. The legitimate S/N proportion computation standards should be picked among three measures to be specific "Larger is better," "Medium is better," and "Smaller is better." As the goal is to limit the surface roughness, temperature, and cutting force, "MRR larger is better" rules are chosen.

$$\frac{S}{N}\text{ratio} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right). \tag{1}$$

For finding the S/N ratio for MRR which has to be increased during machining process, the "larger is better" criteria is selected and the equation is as follows:

$$\frac{S}{N}\text{ratio} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right), \tag{2}$$

where "i" is the number of experiments and "y_i" is the observational results of i^{th} experiments.

2.1.7. Artificial Neural Network Model. ANN is the information process that mind measures data. It comprises of countless interconnected components called neuron working in corresponding to take care of a specific issue [16]. Figure 1 shows the design of a three-layer artificial neural network (ANN). The information neurons are weight percentage of HNT, weight percentage of Boron nitride, speed, and feed rate, similarly, the yield neurons are surface roughness, temperature during machining, MRR rate, and cutting force. The information and yield estimates are prepared utilizing back propagation algorithm, and 27 exploratory variables are validated and trained.

Preparing the organization with back proliferation calculation brings about a nonstraight planning between the information and yield factors. In this manner, given the information/yield matches, the organization can have its loads changed by the back-engineering calculation to catch the nonstraight relationship [17]. It comprises the accompanying advances:

Stage 1. Instate loads and balances

Stage 2. Present Input and Desired Output variable

Stage 3. Ascertain real yields utilizing the sigmoidal nonlinearity given in condition 3.

$$f(\text{net}_i) = \frac{1}{1 - e^{-\text{net}}}. \tag{3}$$

Stage 4. Adjust loads utilizing condition 4

$$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_j x_i', \tag{4}$$

where is the yield of the hub I and η is the learning rate steady and is the affectability of the hub j. Assuming hub j is a yield hub,

$$\delta_j = f'(\text{net}_j)(d_j - y_j), \tag{5}$$

where d_j is the ideal yield of the hub j and y_j is the genuine yield and is the induction of the initiation work determined at net j. Assuming the hub j is an interior hub, the affectability is characterized as follows:

$$\delta_j = f'(\text{net}_j)\sum_k \delta_k w_{jk}, \tag{6}$$

where k aggregates over all hubs in the layer over the hub j. Refreshed conditions are determined utilizing the chain induction rule applied to the LMS preparing basis work.

Stage 5. Repeat by going to stage 2

The least difficult halting basis is to end when the adjustment of the preparation test work is more modest than some preset worth θ. A superior methodology is a cross-approval procedure to quit preparing when the mistake on a different approval set arrives at least. Subsequent to preparing, the organizations with fixed loads can give the yield to the given input.

2.1.8. Grey Relational Analysis. Taguchi S/N proportional examination is restricted to minimize number of experiments. To improve the information boundaries for multi-goals such as surface roughness, temperature, material removal rate and cutting force, a multiobjective algorithm along with Taguchi configuration is a better option [18]. Furthermore, the Taguchi plan with GRA is the strongest technique to take care of the multiobjective problems.

Three significant advances are associated with tackling multiobjective response parameters through GRA. The initial step is to standardize the deliberate yield work independently and it is basically the same as the S/N proportion estimation in Taguchi technique where various models are followed. The "smaller is better" standardization condition is chosen for minimizing surface roughness, temperature, and cutting force which the formula can be written as follows:

$$Y_{ij} = \frac{(Z_{ij} - \min(z_{ij}))}{\max(z_{ij}) - \min(z_{ij})}. \tag{7}$$

In the event of material removal rate, the used for increasing MRR is "larger is better" and the condition is as follows:

$$Y_{ij} = \frac{\left(Z_{ij} - \min\left(z_{ij}\right)\right)}{\max\left(z_{ij}\right) - \min\left(z_{ij}\right)}, \tag{8}$$

where Z_{ij} is the worth obtained from the trial information, min (Z_{ij}) is the base worth from the examination. Additionally, max (Z_{ij}) is the most extreme deserving is acquired from the test for that specific parameter.

The second step is to calculate grey relational coefficient for the normalized data using the following equation:

where $i = 1, 2, 3, \ldots, n$ $j = 1, 2, 3, \ldots, m$

where $i = 1, 2, 3, \ldots$ n $j = 1, 2, 3, \ldots$ m

GRC_{ij} is grey relational coefficients for the i^{th} try/preliminary and j^{th} subordinate variable/reaction value. δ outright unique among y_{oj} and y_{ij}, which is a distinction from the objective esteem and can be treated as a quality misfortune. It is the distinctive coefficient, which is generally fixed at 0.5.

The final step is to create grey rational grade for all experimental data. This is to find the optimum combination for the multiresponse parameters of these aluminum composites. The GRG is determined using the following equation:

$$\mathrm{GRG}_{ij} = \frac{1}{n}\sum_{i=0}^{n} \mathrm{GRC}_{ij}. \tag{9}$$

3. Results and Discussion

3.1. Signal-to-Noise Ratio Analysis. Table 4 shows L_{27} orthogonal array and experimental results for the corresponding input control parameters. The S/N ratio value is determined for each level of response parameters which suggest the optimal choice, and the most affecting parameters can be identified by S/N ratio rank order.

3.2. Effect of Process Parameters on Surface Roughness. Figure 2(a) shows the effect of process parameters on surface roughness between boron nitride and HNT. At 3% of HNT and 2% with the minimum feed rate, we have the minimum surface roughness value. The feed rate and percentage of HNT are the most influencing factor, which affects the surface finish. Figure 2(b) shows the influence of the control parameter on the relationship between speeds and feed rate. In the relationship between speed and feed rate, the drilling at lower feed rate and with medium speed the surface finish is better. Usually increase in hardness of the composites shows poor surface due to higher hardness in developed composites. It is difficult to machine the harder component. At 7% of HNT and 4% of BN the hardness of the composite is 39.7 HV. In this combination, the drilling and chip removal is quiet difficult [19].

3.3. Effect of Process Parameters on MRR. Figure 3(a) shows the effect of MRR along with HNT and boron nitride. It shows that minimum percentage of HNT and maximum 4% of boron nitride increases in material removal rate. From the inference, it can be relatively said that the hardness value is the main factor for MRR. The lower hardness is easily to be machined [20]. Figure 3(b) shows the effect of speed and feed over the developed composites. At 1500 rpm and 60 mm/min MRR increases.

3.4. Effect of Process Parameters on Temperature. Figure 4(a) shows the influence of process parameters on temperature. The mean effect plot shows the relation between HNT and boron nitride. Addition of HNT over 6% the hardness is increased, drilling the harder composites are challenging for machining, subsequently the increase in temperature happens at maximum percentage of HNT reinforcement and boron nitride. The feed rate is the second affecting component for increase in temperature during drilling process. Increase in feed rate above 40 mm/min results in higher volume of material is eliminated from the workpeice that requires enormous amount of force is needed to eliminate the chip which results in higher amount of material is removed results in rise in temperature [21]. The vibration of the instrument at the most extreme at the maximum depth of cut and point of contact is high at this point which increases the temperature .

3.5. Effect of Process Parameters on Cutting Force. Figure 5(a) shows the effect of process parameters on cutting force on HNT and boron nitride. The increase in weight percentage of reinforcement increases the hardness of the developed composites. While machining the harder composites, it is very difficult to drill which results in increased cutting force [22]. Figure 5(b) shows the effect of process parameters on cutting force BN and feed rate. Increased feed rate increases the cutting force due to continual chip removal from the cutting zone, which becomes tougher with time, enhancing the build-up edge and making machining more difficult [23]. In addition to increasing the cutting forces due to the hard ceramic particles present in HNT included in the aluminum alloy, the amount of reinforcement also increases the drilling process difficulty.

3.6. Grey Relational Analysis. The Taguchi S/N ratio and ANN model is used to predict only single objective function. In order to find the optimum combination of multiresponse function GRA is pursued.

Table 5 shows the normalized value for response parameters for GRA.

Figure 6 shows the overall combination of control parameter in drilling of developed aluminum composites using grey relational analysis. 3% of HNT, and 4% of boron nitride and 500 rpm of spindle speed and at 20 mm/min exhibits lower surface roughness, reducing in cutting force, lowering in the drilling temperature, and an increase in material removal rate. Table 6 shows the ANOVA results for overall

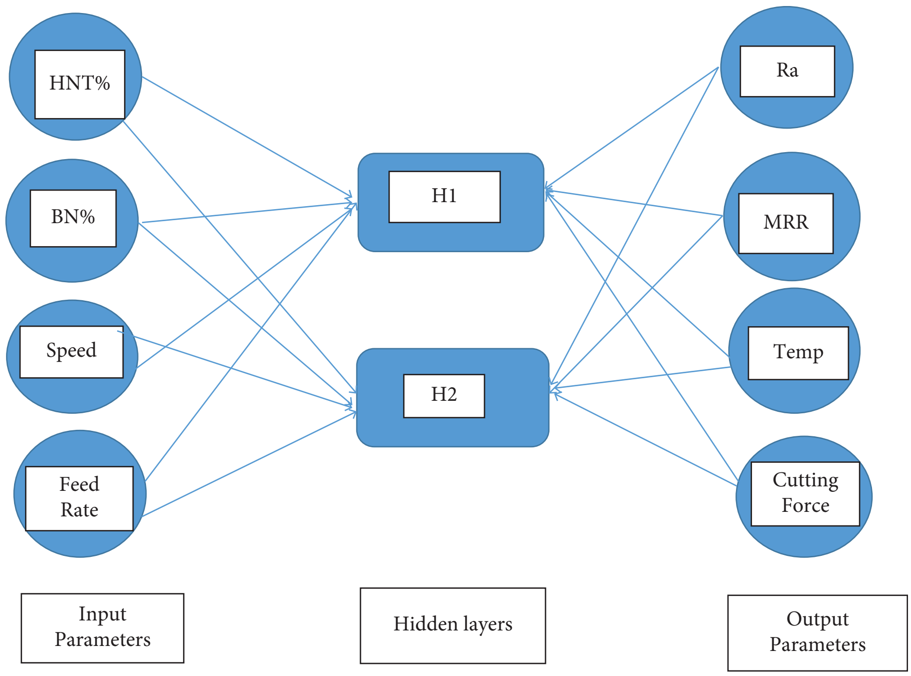
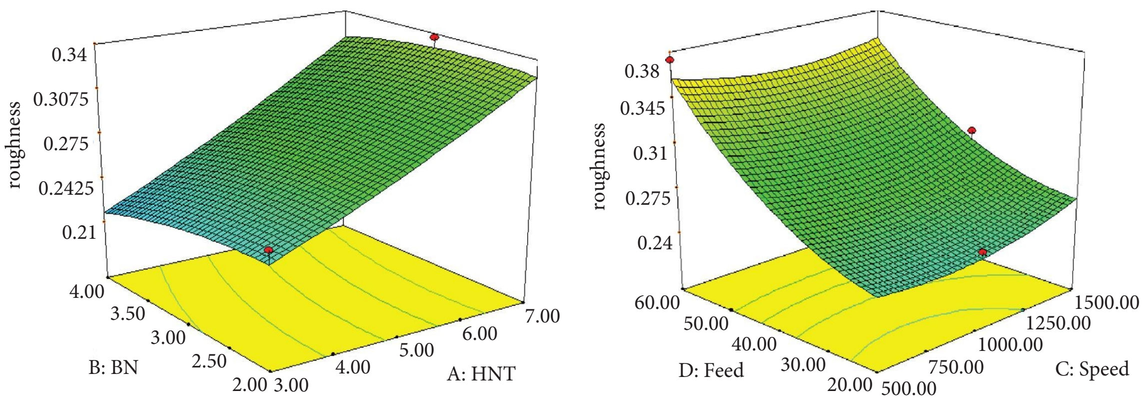


Figure 1: Artificial neural network model.

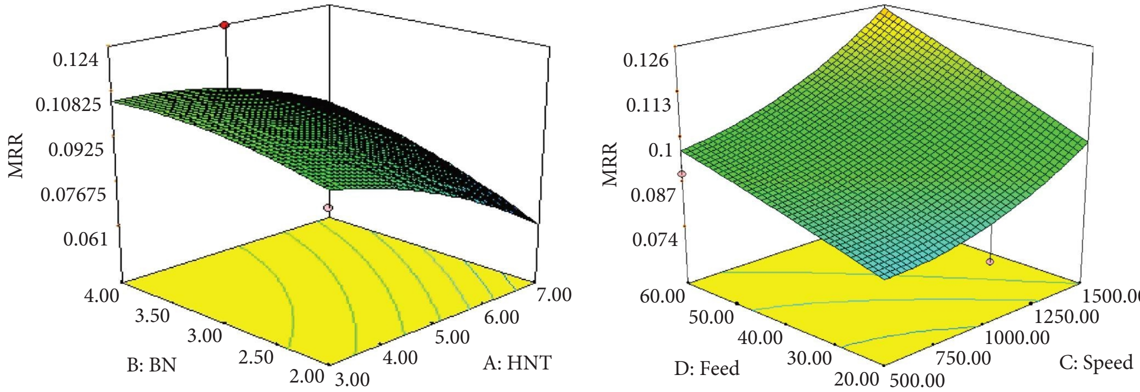
Table 4: L_{27} orthogonal array and results.

	Input parameters				Output parameters			
Sl. no	HNT %	BN %	Spindle speed (rpm)	Feed rate (mm/min)	MRR (g/min)	Surface roughness	Temperature	Cutting force
1	3	2	500	20	0.08721	0.229	41.23	109.98
2	3	2	1000	40	0.09126	0.249	54.34	219.16
3	3	2	1500	60	0.11987	0.307	63.31	290.54
4	3	3	500	40	0.10436	0.210	47.35	131.90
5	3	3	1000	60	0.11745	0.321	62.88	290.27
6	3	3	1500	20	0.11874	0.201	53.69	161.76
7	3	4	500	60	0.10098	0.304	54.87	181.85
8	3	4	1000	20	0.08634	0.168	40.17	129.76
9	3	4	1500	40	0.11975	0.263	53.77	229.17
10	5	4	500	20	0.07289	0.246	41.54	116.87
11	5	4	1000	40	0.12365	0.251	57.76	202.38
12	5	4	1500	60	0.14002	0.327	65.75	320.94
13	5	2	500	40	0.07576	0.284	54.12	201.76
14	5	2	1000	60	0.09704	0.340	75.59	290.58
15	5	2	1500	20	0.08646	0.279	57.98	239.77
16	5	3	500	60	0.08967	0.374	63.93	280.03
17	5	3	1000	20	0.07409	0.252	48.65	179.98
18	5	3	1500	40	0.10906	0.299	60.96	245.34
19	7	3	500	20	0.06956	0.301	44.62	120.98
20	7	3	1000	40	0.07006	0.337	60.67	259.89
21	7	3	1500	60	0.10702	0.412	75.90	372.18
22	7	4	500	40	0.07897	0.319	58.98	200.90
23	7	4	1000	60	0.09364	0.399	71.89	319.72
24	7	4	1500	20	0.08978	0.311	55.98	198.56
25	7	2	500	60	0.06857	0.402	74.57	288.89
26	7	2	1000	20	0.05786	0.293	63.78	190.21
27	7	2	1500	40	0.06956	0.343	72.85	289.09



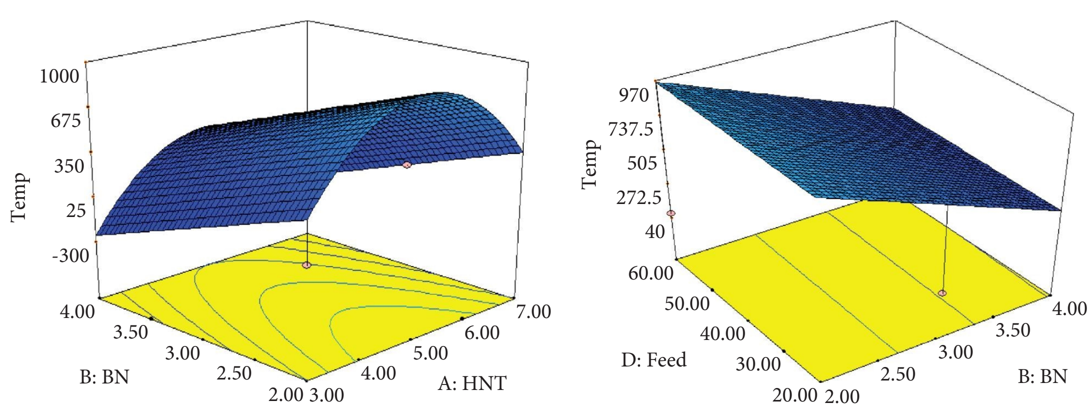
(a) (b)

Figure 2: (a) Effect on Ra on BN vs. HNT. (b) Effect on Ra on feed vs. speed.



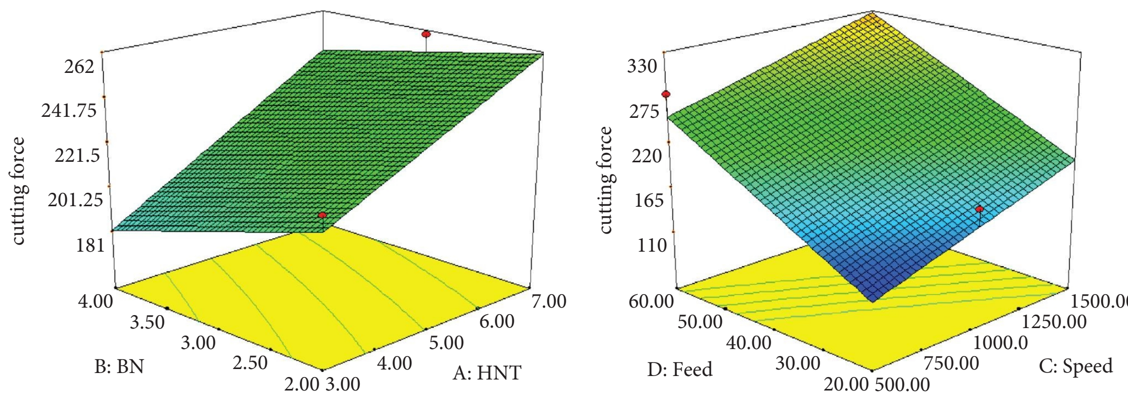
(a) (b)

Figure 3: (a) Effect of MRR on HNT vs. BN. (b) Effect of MRR on HNT vs. BN.



(a) (b)

Figure 4: (a) Effect of temperature on HNT vs. BN. (b) Effect of temperature on feed vs. BN.



(a)

(b)

Figure 5: (a) Effect of cutting force on HNT vs. BN. (b) Effect of temperature on speed vs. feed.

Table 5: Normalized value for response parameters.

Coeff of MRR	Coeff of Ra temp	Coeff of temp	Coeff cutt force	Avg	Rank
0.43753	0.33333	0.94399	1.00000	0.679	22
0.45726	0.90372	0.55767	0.54561	0.616	16
0.67091	0.84543	0.43568	0.42065	0.593	12
0.53531	0.94765	0.71332	0.85675	0.763	25
0.64540	0.83247	0.44030	0.42102	0.585	11
0.65876	0.95840	0.56922	0.71686	0.726	23
0.51273	0.84826	0.54860	0.64591	0.639	17
0.43352	1.00000	1.00000	0.86890	0.826	27
0.66960	0.88892	0.56777	0.52379	0.663	20
0.37963	0.90695	0.92878	0.95007	0.791	26
0.71506	0.90157	0.50388	0.58658	0.677	21
1.00000	0.82704	0.41121	0.38327	0.655	19
0.38998	0.86762	0.56153	0.58821	0.602	14
0.48870	0.81550	0.33527	0.42060	0.515	5
0.43407	0.87260	0.50077	0.50251	0.577	9
0.44931	0.78681	0.42919	0.43533	0.525	6
0.38389	0.90050	0.67812	0.65191	0.654	18
0.57024	0.85302	0.46217	0.49201	0.594	13
0.36830	0.85111	0.80058	0.92259	0.736	24
0.36996	0.81814	0.46566	0.46653	0.530	7
0.55454	0.75704	0.33333	0.33333	0.495	3
0.40223	0.83430	0.48712	0.59049	0.579	10
0.46970	0.76696	0.36029	0.38464	0.495	4
0.44985	0.84169	0.53051	0.59678	0.605	15
0.36506	0.76465	0.34182	0.42289	0.474	1
0.33333	0.85880	0.43074	0.62036	0.561	8
0.36830	0.81289	0.35345	0.42262	0.489	2

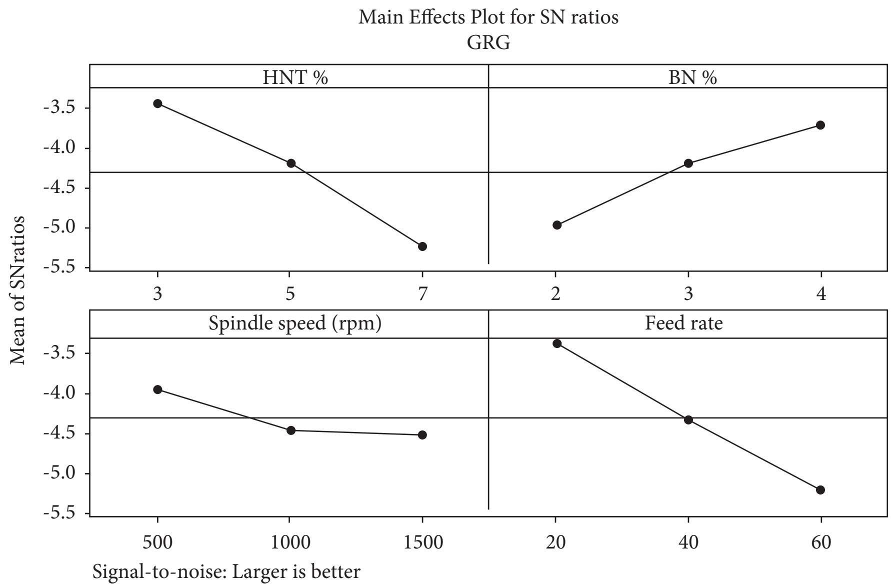


Figure 6: GRG.

Table 6: The ANOVA results of the analysis.

Source	DF	Seq SS	Adj SS	Adj MS	*F*	*P*	%
Regression	4	0.193603	0.193603	0.0484006	25.2976	0.000001	
HNT %	1	0.070460	0.070460	0.0704595	36.8272	0.0000042	29.89
BN %	1	0.037642	0.037642	0.0376418	19.6743	0.0002082	15.97
Spindle speed (rpm)	1	0.008436	0.008436	0.0084359	4.4092	0.0474359	3.57
Feed rate	1	0.077065	0.077065	0.0770653	40.2798	0.0000022	32.89
Error	22	0.042091	0.042091	0.0019132			17.85
Total	26	0.235694					

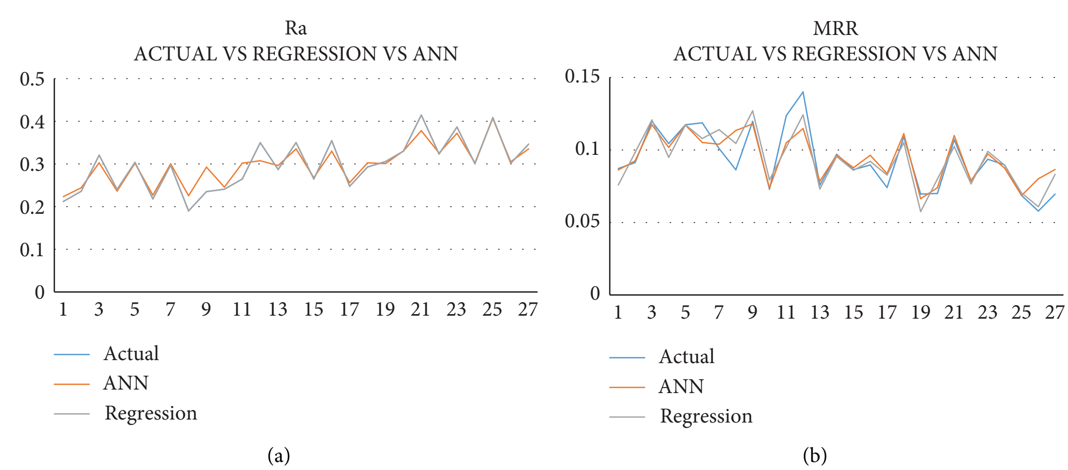
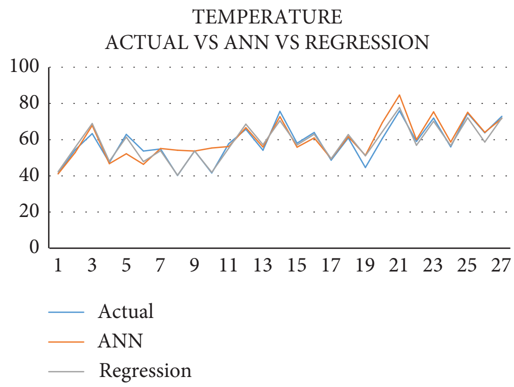
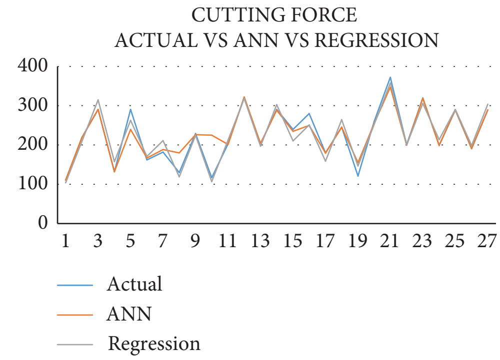


Figure 7: Continued.



(c)



(d)

Figure 7: (a) Actual vs. regression vs. ANN on Ra. (b) Actual vs. regression vs. ANN on MRR. (c) Actual vs. regression vs. ANN on temperature. (d) Actual vs. regression vs. ANN on cutting force.

combinations of input parameters. The feed rate and HNT % are most influencing parameters identified through GRG.

3.7. Regression Equation

$$\begin{aligned}
\text{MRR} &= 0.0565315 - 0.00669278\ \text{HNT}\,\% + 0.00846833\ \text{BN}\% + 2.35878e - 005\ \text{Spindle speed (rpm)} + 0.000531472\ \text{Feed},\\
\text{Ra} &= 0.0911574 + 0.0240278\ \text{HNT}\,\% - 0.00766667\ \text{BN}\,\% + 8.11111e - 006\ \text{Spindle speed (rpm)} + 0.00251667\ \text{Feed},\\
\text{Temp} &= 26.3036 + 2.98972\ \text{HNT}\,\% - 3.17\ \text{BN}\% + 0.00877556\ \text{Spindle speed (rpm)} + 0.447361\ \text{Feed},\\
\text{Cutting Force} &= -18.9769 + 13.7786\ \text{HNT}\,\% - 12.2128\ \text{BN}\,\% + 0.0793544\ \text{Spindle speed (rpm)} + 3.29758\ \text{Feed}.
\end{aligned} \tag{10}$$

Figure 7(a) shows the graph of actual experimental and predicted ANN and regression values on surface roughness. The prediction of ANN is 96.3% whereas the regression value shows 93.1%. In case of MRR Figure 7(b) shows the regression value is 92.7%, meanwhile the ANN predicted value is 95.2%.

Figure 7(c) shows the graph of actual experimental and predicted ANN and regression values on temperature measured during drilling process. The prediction of ANN is 98.1%, whereas the regression value shows 94.3%. Figure 7(d) shows the regression value of cutting force during machining is 91.9%, whereas the ANN predicted value is 95.2%. It is understood that the developed ANN model exhibits good results for estimating the surface roughness, material removal rate, temperature, and cutting force.

4. Conclusion

In this present work, Taguchi design-based grey relational analysis was used to discover the best combination of input process parameters to reduce surface roughness, cutting force, and temperature while increasing the metal removal rate of aluminum hybrid metal matrix composites in the drilling of aluminum composites.

The results show that weight percentage of HNT and feed rate are the most influencing parameters which affect the drilling of developed aluminum composites which are identified through the percentage contribution through GRA.

The GRA results show that the optimum parameters are 3% of HNT, 4% of BN, 500 rpm drilling speed, and 20 mm/min in combination which has the minimum surface roughness, lower temperature, cutting force, and increased material removal rate.

The proposed ANN model strongly implies the predicted value of observational data and outperforms the regression model for each of the response parameters in AMMC drilling.

Data Availability

All the data used in this study are provided in the manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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