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Comparative analysis of thrust force, roughness and roundness error in drilling of aluminium composites using RSM, ANN and fuzzy logic

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ABSTRACT

Making holes without any defect in a solid product made of hybrid Aluminium composite material, is a difficult job in assembly industries. Hybrid composite of Aluminium 7075 reinforced with ceramic materials like silicon carbide, boron carbide, graphite and mica are used in automobile and structural industries due to their excellent mechanical properties. Thrust force developed during drilling, Error in the circularity and poor surface finish of the drilled holes are some of the common problems faced in the drilling process. Hence, to optimise the quality of drilling, analysing these responses under various conditions of drilling by varying the drilling factor become essential. This study discusses the development of various models to predict the thrust force developed, roughness and circularity error in the holes drilled on a hybrid metal matrix composite. Testing of drilling is conducted in CNC vertical machining centre using Titanium aluminium nitride (TiAlN) coated carbide drill tool of 5 mm diameter. Various drilling factors considered in our study are point angle of the drill tool, drilling speed and feed rate. Multiple regression equations using RSM, Artificial neural network (ANN) and Fuzzy Logic algorithms are used to develop the prediction models. The predicted values of thrust force, surface roughness and circularity error from these models are found to be matching with the observed experimental values.

1. Introduction

Hybrid metal matrix composites structure a gathering of materials that have been drawn in by number of analysts as a result of their superior properties when contrasted with monolithic materials.

More trials have been made to create mechanical parts utilizing these composite materials, but some proportion of completing ought to be done to finish the assembly cycle. Regardless, for assembly and joining, extra machining process like drilling is required. Due to hard reinforcement materials, drilling of hybrid composites turned into a difficult task in the manufacturing ventures.

Different variables of drilling process influence the nature of drilled holes. Circularity error and surface roughness in drilling hybrid metal matrix composite materials have been seen to be impacted by different boundaries like shaft speed, geometry of the twist drill, drilling speed and the tool coatings.

Our objective in this work is to conduct different drilling experiments on the prepared hybrid composite specimen of Al7075 using TiAlN coated carbide drill by varying the mentioned drilling parameters and to formulate three different predictive models using RSM, ANN and Fuzzy Logic and to compare them with the experimental values.

2. Literature review

Murthy et al. [1] analysed the impact of various factors involved in drilling like axle speed, feed rate, drill diameter, point angle, and material thickness on the roughness of the drilled hole surface in Glass Fiber Reinforced Polymer utilizing uncoated carbide tools and anticipated the relationship between the drilling force and the surface roughness. They utilized Taguchi and Surface Response Methodology. Similar to that Raviraj et al. [2] used Taguchi and Surface Roughness Methodology in to minimize Surface Roughness in their work.

Hayajneh et al. [3] anticipated the drilling force and torque during dry drilling of aluminium composites using feed forward back propagation neural network and found that the average error in the anticipated values were around 2% for drilling torque and 3.4% for drilling force when compared with the experimental values. Umesh Gowdaa et al. [4] conducted drilling experiments to estimate circularity error, surface roughness and cylindricity error

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in the holes drilled in the silicon nitride reinforced composites at different spindle speed and drill feed. They also analysed the results using artificial neural network and suggested that ANN is a reliable method for prediction.

Ahmad Mayyas et al. [5] examined the effect of various drilling factor's influence on the drilling torque and force while drilling of hybrid composites using Artificial Neural Network and Multiple Regression Analysis (MRA) and found that ANN showed better prediction than MRA. Vijaya Kumar et al, [6] focussed on minimization of tool wear in drilling of AMMC using Desirable – Fuzzy approach and the most influential factors were identified and confirmed.

Hari Singh et al. [7] conducted experiments on drilling and concluded that the optimum parameters to get better surface finish in the drilled holes can be obtained in hybrid technique by combining the Taguchi Methodology with Grey Relational Analysis.

Suman Chatterjee et al. [8] analysed the effect of drilling variables on burr height and surface quality and developed a mathematical model using RSM and found that the average error of prediction was 1.167%. Anand Babu et al. [9] experimented the impact of various drilling factors on the surface quality of drilled holes and compared with the predicted values by Fuzzy Logic and concluded that the results were close to each other. In the same manner, to optimize the drilling process in Al/SiC composites with many characteristics, Taguchi method was used by C.Dhavamani et al. in combination with fuzzy logic in [10].

Taskesan et al. [11] conducted drilling experiments on hybrid composites utilizing Titanium Aluminium Nitride (TiAlN) coated carbide tools and found that the tool material influencing more on the performance of the drilling than various parameters of drilling like feed and speed. They also proposed that the TiAlN coated drill showed the best result among the different drill tool materials.

3. Materials and methods

For the experimentation the specimen is prepared by using the Stir Casting Process. Stir Casting is a liquid state technique for the preparation of composite materials used first by A.Tony Thomas et al. [12], in which the reinforce materials are blended homogeneously with the molten aluminium (Al7075) matrix with the help of stirring by ceramic stirrer. The Al7075 alloy in the form of long bar was cut into number of small sized pieces and in a graphite crucible they are heated and softened. The reinforce materials are preheated separately and mixed thoroughly with constant motion ceramic stirrer along with a motor running at a normal speed of 300 rpm for 30 min to set up the slurry. The liquid slurry is then poured into the mould cavity and cast by conventional casting methods to prepare the specimen for our investigations.

The three different hybrid composite specimens were prepared by this method in the form of 100 × 100 × 10 mm square block and listed below in Table 1.

The drilling experiments are carried out by ARIX vertical machining centre. To record the thrust force, Kirsler dynamometer with dynaware software is used. The roughness in the surface of the drilled holes are measured using Kosaka – Surfcoder SE700. The error in Circularity is measured for all the holes using coordinate measuring machine. The specification of the drilling tools and drilling parameters used are given in Table 2.

3.1. Prediction models

3.1.1. Response Surface Methodology

Response Surface Methodology (RSM) is a collection of test methodologies, factual and scientific procedures that are helpful for the investigation of issues in which the response of interest is affected by different parameters and the objective is to improve the quality and to minimize the response [13–18].

Table 1
Composition of specimen.

Matrix	Reinforcement 1	Reinforcement 2
Al 7075	5% (wt) B_4C	5% (wt) SiC

Table 2
Drilling Parameters and their levels.

Drilling parameter	Level 1	Level 2	Level 3
Point angle (°)	108	118	128
Drill speed (rpm)	1000	2000	3000
Feed rate (mm/rev)	0.05	0.1	0.15

3.1.2. Artificial Neural Network

Artificial Neural Networks (ANN) mimics the brain of human being to gain the relations between the specific information sources and results as a matter of fact. The neural network contains one information layer, one hidden layers and one result layer - Back-Propagation Neural Network (BPN) model design. The quantity of hubs in the info layer rises to the quantity of boundaries in the material determination process. The result layer addresses the wellness of the applicant materials. The hidden layer addresses the communications between the information and result layers. For each input–output pair (i,y), the back propagation technique initially computes the result "y" by engendering "I" forward from the info layer to the result layer. Then the error signal |y-y'| is back spread from the result layer to the information layer to refresh the association loads [19–23]. Likewise, preparing strategy can be totally halted on the off chance that the output of the network arrives at sufficiently close to the ideal result [24–27].

3.1.3. Fuzzy Logic

Fuzzy Logic, as the name suggests has variety of meanings under different perspectives. Simply we can call it as a logical system with multiple logical values. But it is more in common with fuzzy sets. Here the classes of objects do not have a clear boundary [28–34]. Fuzzy if-then rule plays major role in the application of Fuzzy Logic. For the measurement of fuzzy calculus involving the fuzzy antecedents and consequences, the Fuzzy Dependency and Command Language (FDCL) was introduced. It developed a trend of arriving at a best solution by using the Fuzzy logic along with genetic algorithms and neuro computing. Those elements together form the soft computing [35–39]. In general soft computing makes use of the precision less, uncertain data along with partial truth to produce a tractable, robust and low cost solution. Nowadays soft computing is best used in developing a real time system with very high IQ than any other conventional system [40–42].

4. Results and discussion

The following mathematical models (1), (2) and (3) were developed using Response Surface Methodology (RSM) for Specimen 1 and the predicted values have been calculated using the coded factors of −1, 0 and 1 for the levels 1, 2 and 3 respectively and then tabulated in Table 3.

$$\begin{aligned}\text{Thrust force} = {} & 202.74 - 16.02A - 72.83B + 41.83C \\ & + 10.65AB - 22.77AC - 24.2BC - -49.66A^2 \\ & + 4.47B^2 - -6.65C^2 \end{aligned} \tag{1}$$

$$\begin{aligned}\text{Roughness} = {} & 7.17 - -0.91A - -0.7B + 0.96C + 0.19AB \\ & - -0.17AC + 0.16BC + 2.42A^2 - -0.28B^2 \\ & - -0.32C^2 \end{aligned} \tag{2}$$

Table 3
Experimental and prediction Values of various responses.

Material: Al 7075 + 5% B4C + 5% SiC
Tool Material: TiAlN Coated carbide
Drill Tool diameter – 5 mm

Expt. No	Point angle °	Feed mm/rev	Speed rpm	Thrust Force (N)				Surface Roughness (μm)				Roundness Error (mm)			
				EXPT	RSM	ANN	FUZZY	EXPT	RSM	ANN	FUZZY	EXPT	RSM	ANN	FUZZY
1	108	0.05	1000	63.77	43.027	65.353	60.746	9.54	10.352	9.572	9.193	0.0261	0.0278	0.0266	0.026
2	108	0.05	2000	98.10	97.839	107.176	87.063	8.82	10.986	8.758	9.193	0.0312	0.0313	0.0331	0.026
3	108	0.05	3000	196.20	161.588	151.44	201.105	7.48	9.658	7.946	7.427	0.0479	0.04	0.0439	0.048
4	108	0.1	1000	76.52	90.084	73.58	87.063	10.94	9.717	11.133	10.958	0.0278	0.024	0.0269	0.026
5	108	0.1	2000	147.15	169.093	153.122	163.091	10.72	10.51	10.724	10.958	0.0334	0.0312	0.0313	0.037
6	108	0.1	3000	294.30	257.041	288.475	277.133	10.01	9.341	9.825	10.076	0.0491	0.0436	0.0467	0.048
7	108	0.15	1000	93.20	123.843	153.931	87.063	11.84	10.37	11.429	11.569	0.0287	0.0316	0.0323	0.026
8	108	0.15	2000	196.20	227.050	193.081	201.105	11.02	11.322	11.259	10.958	0.0366	0.0425	0.0357	0.037
9	108	0.15	3000	343.35	339.196	344.694	341.464	10.64	10.312	10.664	10.958	0.0501	0.0586	0.0523	0.048
10	118	0.05	1000	98.10	110.091	65.498	87.063	7.27	6.996	7.672	7.427	0.0476	0.0498	0.0421	0.048
11	118	0.05	2000	117.72	154.252	134.854	125.077	7.62	7.818	7.522	7.427	0.0458	0.0531	0.0423	0.048
12	118	0.05	3000	137.34	207.350	156.985	125.077	4.78	6.678	6.125	5.051	0.0493	0.0616	0.0551	0.048
13	118	0.1	1000	156.96	134.375	85.747	163.091	8.06	6.193	8.432	8.31	0.0513	0.0547	0.0574	0.048
14	118	0.1	2000	230.54	202.734	228.099	239.119	7.93	7.174	7.674	8.31	0.0618	0.0617	0.0556	0.058
15	118	0.1	3000	250.16	280.030	255.807	239.119	6.03	6.193	5.986	5.662	0.0671	0.0739	0.0689	0.069
16	118	0.15	1000	176.58	145.361	158.198	163.091	8.97	6.678	9.157	9.193	0.0685	0.071	0.0709	0.069
17	118	0.15	2000	289.40	237.917	282.199	277.133	8.34	7.818	8.284	8.31	0.0789	0.0817	0.0765	0.079
18	118	0.15	3000	353.16	339.412	350.202	341.464	7.15	6.996	7.199	7.427	0.0996	0.0976	0.0917	0.097
19	128	0.05	1000	49.05	77.829	62.401	60.746	7.97	8.486	7.725	8.31	0.0168	0.0152	0.0222	0.019
20	128	0.05	2000	156.96	111.339	165.383	163.091	7.05	9.496	7.744	7.427	0.0247	0.0183	0.0223	0.026
21	128	0.05	3000	176.58	153.787	177.413	163.091	6.93	8.544	6.74	6.544	0.0306	0.0266	0.0263	0.026
22	128	0.1	1000	63.77	79.340	67.236	60.746	8.94	7.515	7.769	9.193	0.0268	0.0288	0.0262	0.026
23	128	0.1	2000	137.34	137.047	131.126	125.077	8.41	8.684	8.697	8.31	0.0291	0.0356	0.027	0.026
24	128	0.1	3000	196.20	203.693	198.24	201.105	8.12	7.891	7.802	8.31	0.0432	0.0476	0.0446	0.048
25	128	0.15	1000	82.40	67.552	77.346	87.063	9.41	7.832	8.981	9.193	0.0515	0.0538	0.0511	0.048
26	128	0.15	2000	112.82	149.458	110.024	125.077	9.00	9.16	9.894	9.193	0.0665	0.0643	0.0664	0.069
27	128	0.15	3000	245.25	240.302	245.275	239.119	8.75	8.526	8.372	8.31	0.0805	0.08	0.0805	0.079

$$\text{Circularity Error} = 0.062 + 2.156 \times 10^{-3}A + 9.55 \times 10^{-3}B + 0.014C - -1.893 \times 10^{-4}AB + 8.695 \times 10^{-3}AC + 3.683 \times 10^{-3}BC - -0.028A^2 + 2.583 \times 10^{-3}B^2 + 5.65 \times 10^{-3}C^2 \quad (3)$$

Table 3 contains the data collected from experiments for the Silica inclusion of the composite, and the data is extrapolated using the 3 methods-RSM, ANN and Fuzzy Logic. It is very much obvious that the data obtained by applying the fuzzy logic rather than RSM and ANN closely matches with the experimental values. Another observation is that the minimum roughness could be obtained when the point angle is 118°, speed 3000 rpm and feed 0.05 mm/rev, thus conceptually matching that the roughness is minimum when the feed is low and the speed is high. The worst case is when the point angle is 108°, speed is 1000 rpm and feed is 0.15 mm/rev. The bar charts of the above data are shown below in Figs. 1–3.

The bar chart in Fig. 3 shows that the thrust force is minimum while drilling the specimen 1 in trial number 1. That is when all the drilling parameters are at level 1. (118° point angle, 1000 rpm

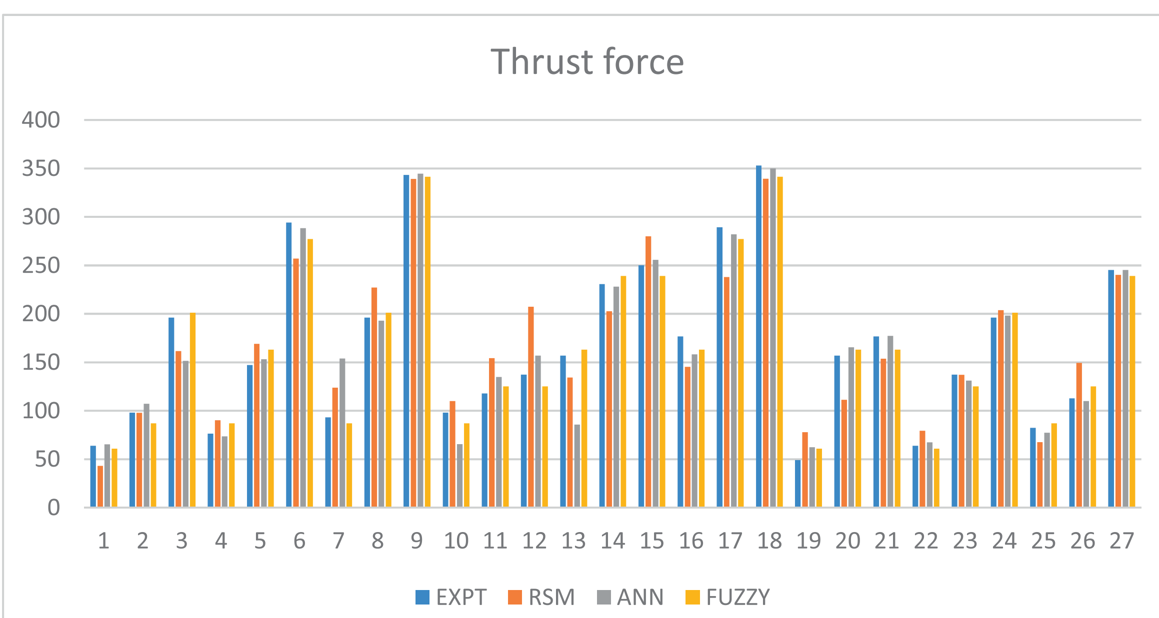

Fig. 1. Bar chart for thrust force from experiment and models.

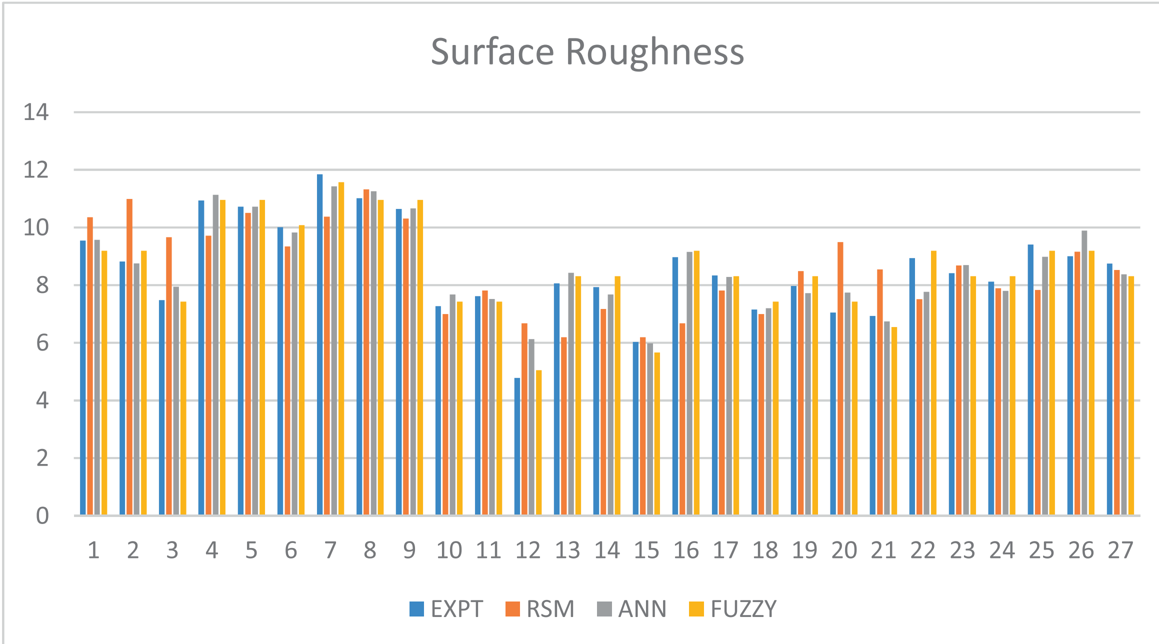

Fig. 2. Bar chart for roughness from experiment and models.

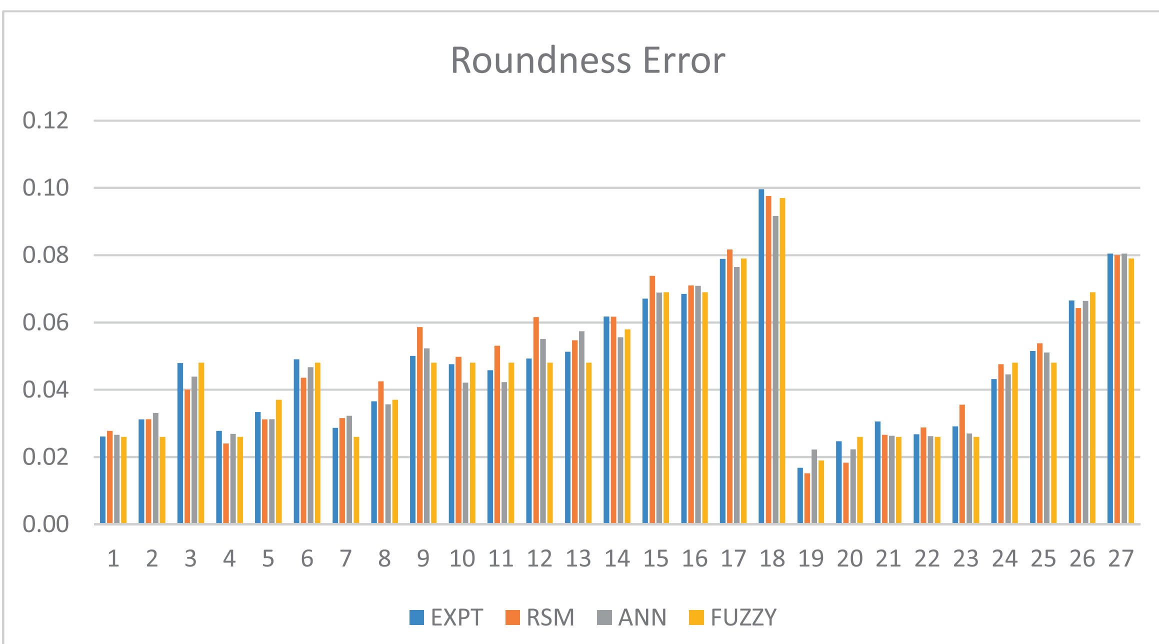

Fig. 3. Bar chart for thrust force from experiment and models.

speed and 0.05 mm/rev feed rate). It is clearly shown that the deviations in prediction values from experimental values are minimum in Fuzzy when compared with other techniques.

A generalized explanation as to why the behaviour of the material varies with respect to feed, point angle and speed, can be given. It is well known from literature [17] that addition of boron carbide and silicon carbide to a metal matrix increases the hardenability of the material. So in this case, the specimen can harden to a depth more than just the metal. So in the machining parameters, the effect of point angle is more on the thrust, torque and roughness. As the point angle increases, the angle of friction decreases, therefore the friction force decreases. This in turn causes a reduction in the thrust force as compared to a tool with lower point angle and thus results in a lower value of roughness. The next important factor that affects the output parameters is the speed. As the speed increases, the ease with which machining can take place increases, given by Ganesan Pandi and Saravanan Muthusamy in [18]. Therefore, at higher speeds, the value of roughness is low, since the thrust force is higher. The final factor deciding the values of output parameters is the feed rate. As the feed rate is increased, more load on the tool is observed and expected, therefore the ease of machinability decreases with increase in feed rate. In the values seen

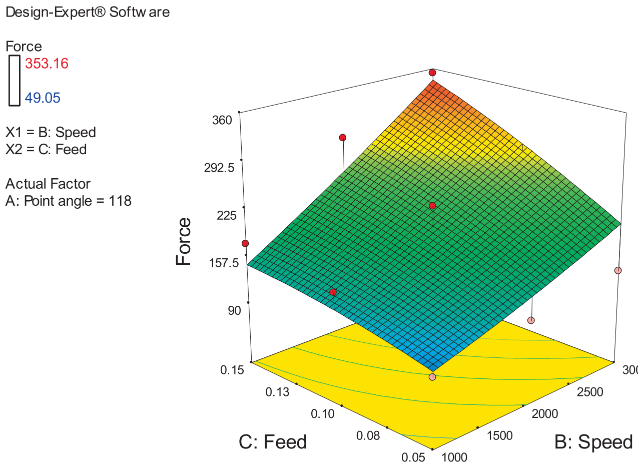

Fig. 4. Variation of thrust force at constant point angle.

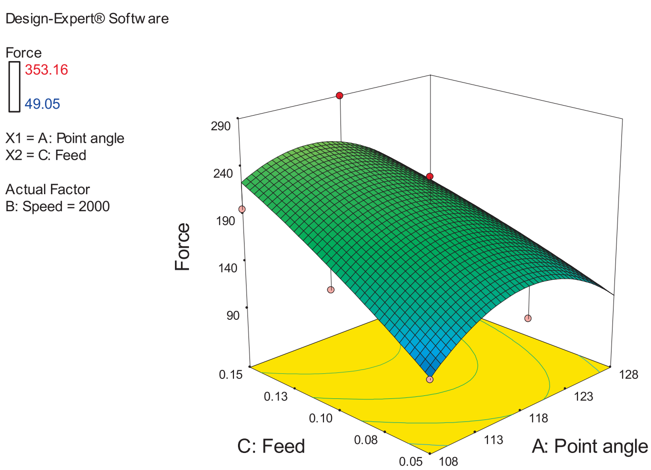

Fig. 5. Variation of thrust force at constant speed.

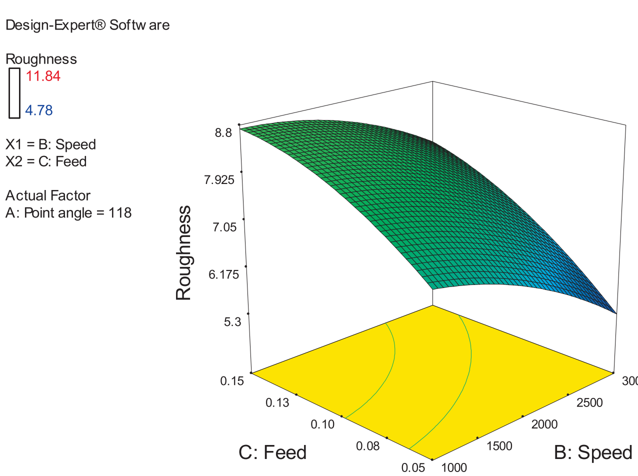

Fig. 6. Variation of roughness at constant point angle.

above, it is seen that the minimal thrust force occurs with higher point angles. Minimal roughness occurs at higher speeds, lower feed rates and higher point angles.

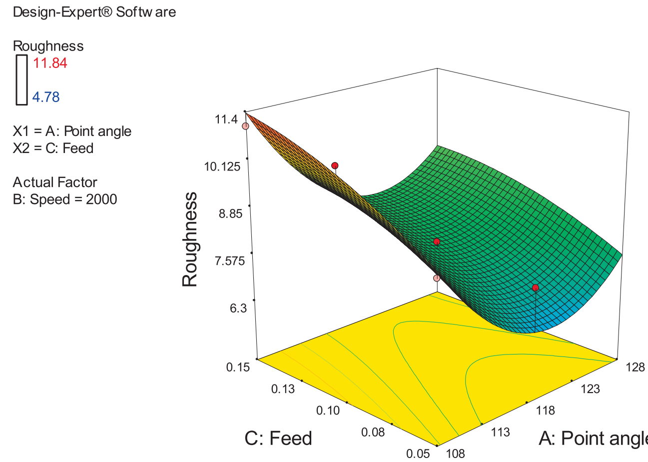

Fig. 7. Variation of roughness at constant speed.

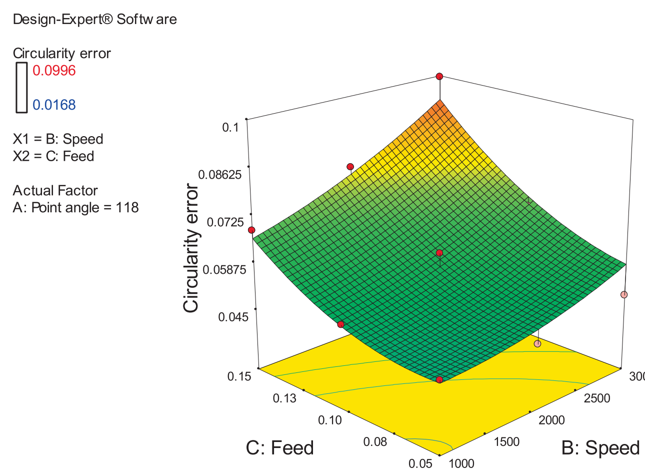

Fig. 8. Variation of circularity error at constant point angle.

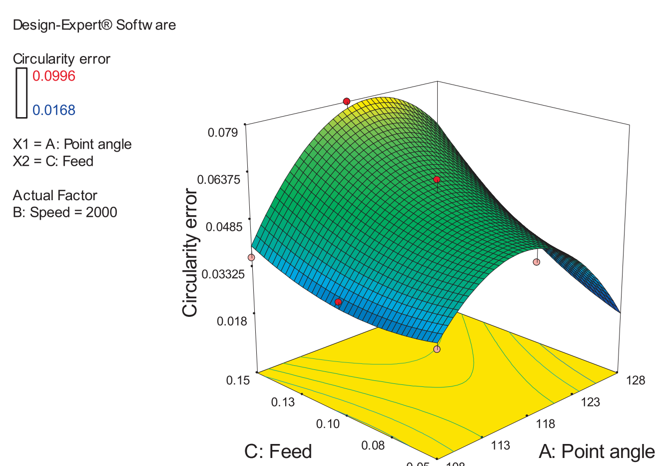

Fig. 9. Variation of circularity error at constant speed.

The following three dimensional graphs indicate the response surfaces of various parameters of the Silica inclusive specimen. Using the equations obtained earlier from Design Expert Software, the surfaces were generated, with the bottom plane as the independent variable while the Y axis indicates responses on how it varies when the two parameters on the bottom plane varies. It indicates how Speed, feed and point angle affect the Thrust force, surface roughness and circularity error.

Fig. 4 shows the variation of thrust force in the prepared specimen with different speed and feed at a particular point angle, whereas Fig. 5 indicates the variation of thrust force with different feed and point angles at constant speed. For ideal cases, the minimum points of the responses are the optimum solutions as they produce maximum quality with lesser effort. The extreme of the surfaces obtained from the responses indicates the maximum value or minimum value of a particular output parameter, and it is plotted against two input parameters in cycle. For a given speed, feed and point angle, the minimum thrust force is 49.04 N whereas the highest thrust force is 353.16 N. Minimum thrust force is achieved with lower feed rate and the thrust forces increase with increasing feed rate. Similar results found by Ravindranath et al. [19]. A model to predict the thrust forces based on drilling parameters using Response Surface Methodology was given by S.Madhavan and S.Balasivanandha Prabhu in [20]. It has been concluded that the drill geometry is the most influencing factor that affects the thrust force.

Figs. 6 and 7 show the variation of roughness of the drilled hole surface in specimen1 at constant point angle and speed by varying other parameters respectively. For ideal conditions, the minimum points of the responses are the optimum solutions as they produce good quality of smooth holes. For a given speed, feed and point angle, the minimum and maximum roughness values in specimen1 is 4.78 µm and 11.84 µm respectively. Similarly, the variations of the circularity error in the holes for specimen1 are shown in Figs. 8 and 9.

ANN is concerned with fitting of values obtained in the experiment in a line so as to train the module to know the interrelationships between the values. The trained data set is now fed with a new range of inputs, for which, it utilizes the relationships that has learnt amongst the numbers to yield a value. So a graph between the actual values and the values obtained by ANN are plotted against each other. The accuracy of the fit is given by correlation coefficient R2, which corresponds to how much deviation can be allowed. As observed above, the R2 value for which it is high, the fit is more accurate and tends to be on the line Y = T itself.

Fig. 10 shows the comparison between experimental thrust force in specimen 1 with ANN predicted thrust force. Most of the points clustering around the diagonal line, which indicates the performance of training and the R2 values greater than 0.98 indicates the accuracy of the prediction. Similarly the comparison of experimental and ANN outputs for Roughness and Circularity error are shown in Figs. 11 and 12 respectively.

Fuzzy Logic is an approach for computing based on "degrees of truth" rather than Boolean Logic. It is similar to how our brain works where there are several degrees of truth.

The graphs above indicate the value to be found out from the data set on X axis and the degree of membership i.e. probability

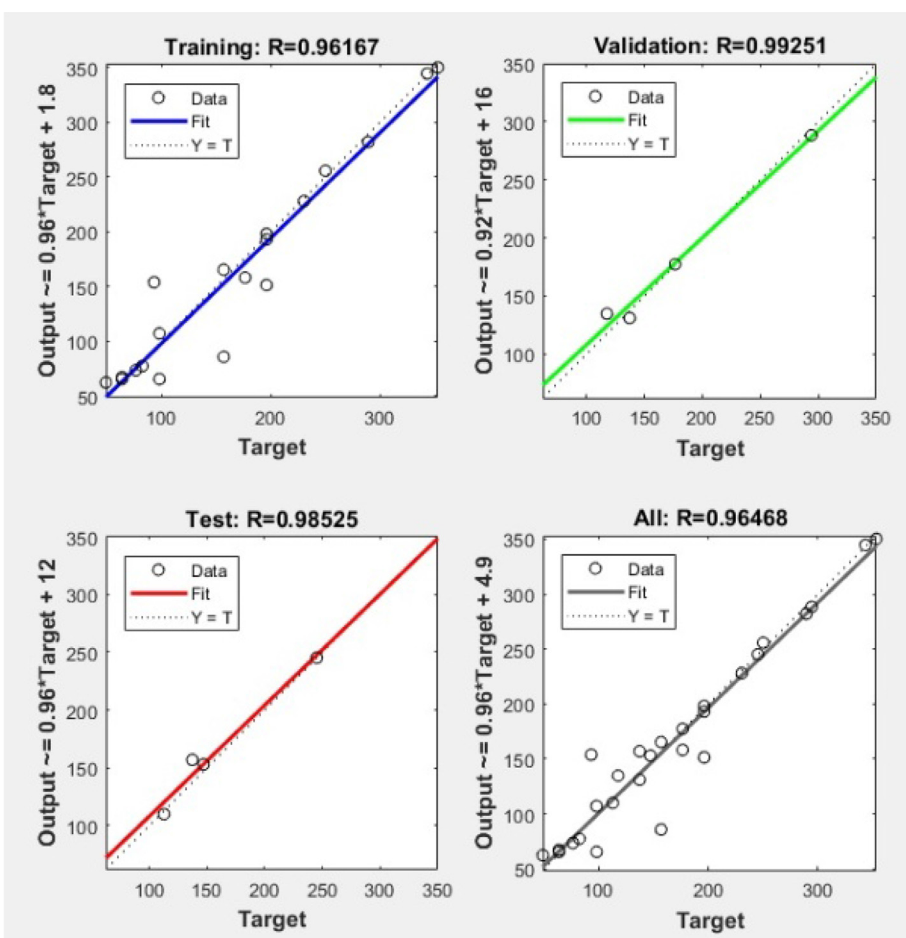

Fig. 10. Comparison of experimental & ANN output.

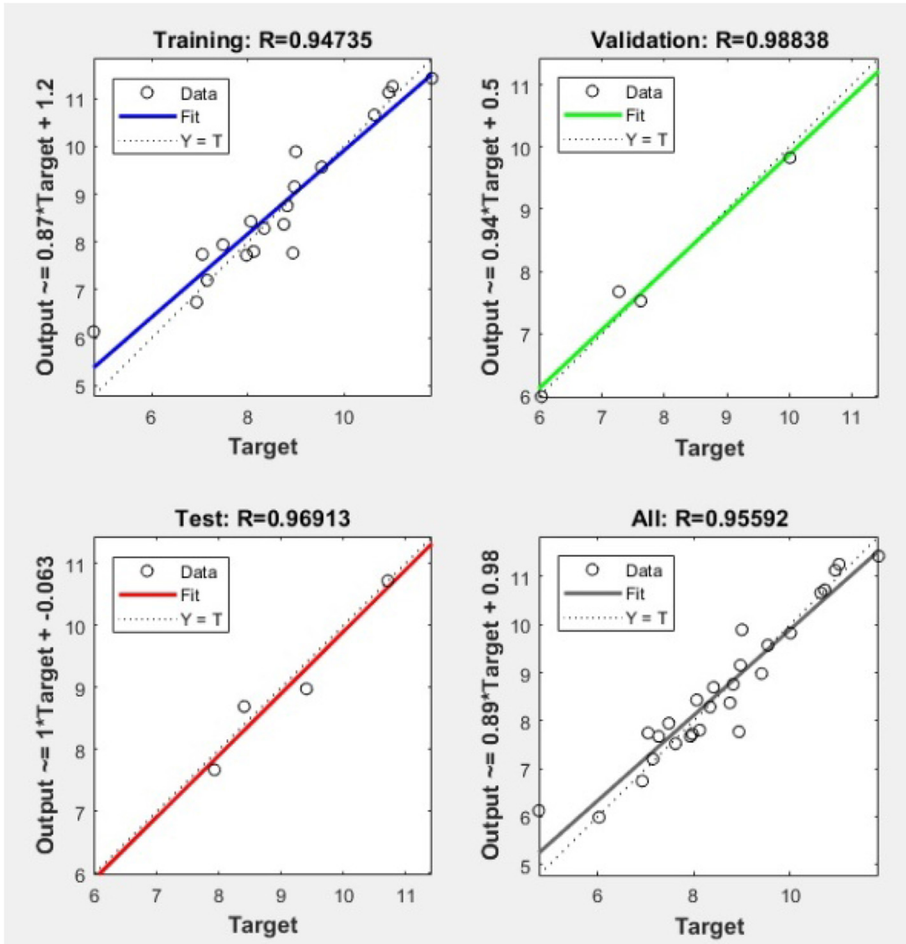

Fig. 11. Comparison of experimental & ANN output for thrust force for roughness.

on Y axis. The colours indicate the number of ranges into which a particular data set has been divided into from worst to best. The origin and the end of the lines do not contribute to the solution as it becomes asymptotic at those points and the computational domain includes all the rhombuses in the figure. The X intercept of the longer diagonal of the rhombuses give the value of thrust force or roughness value or the roundness error based on whatever is plotted on the X axis.

A rule-base is made so as to match the intercept values with that of the experimental ones. This rule-base varies with the number of ranges into which we divide the data set. The more the number of ranges, the more accurate the answer becomes. For 9 ranges, the error is only 5%. As the number of ranges into which the membership functions are divided increases, the more accurate result is obtained by Fuzzy Logic. Membership functions for thrust force, roughness and circularity error are given in Figs. 13, 14 and 15 respectively.

As the number of ranges, into which the membership functions are divided is more, the obtained fit by Fuzzy Logic is more accurate.

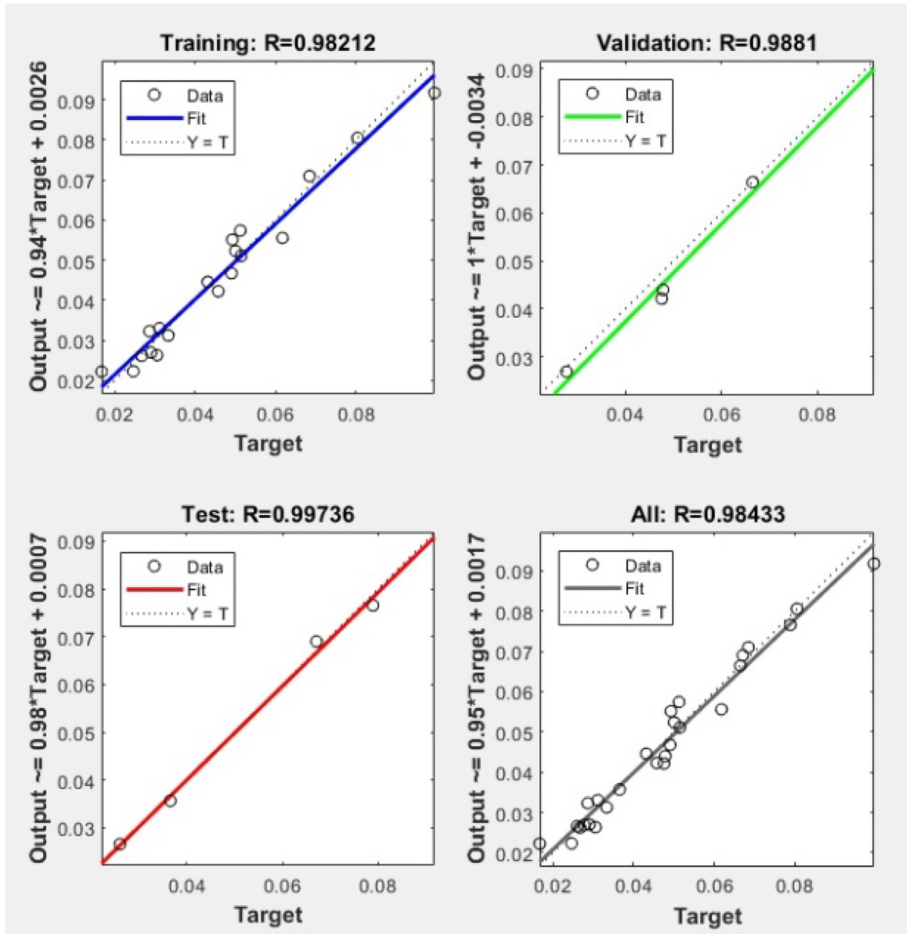

Fig. 12. Comparison of experimental & ANN output for circularity error.

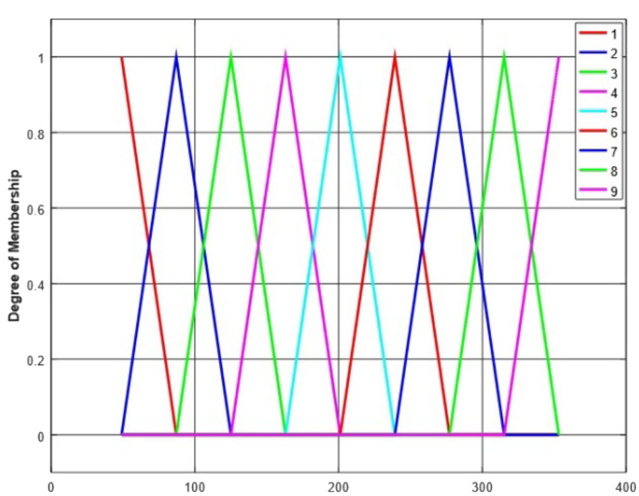

Fig. 13. Membership function for thrust force.

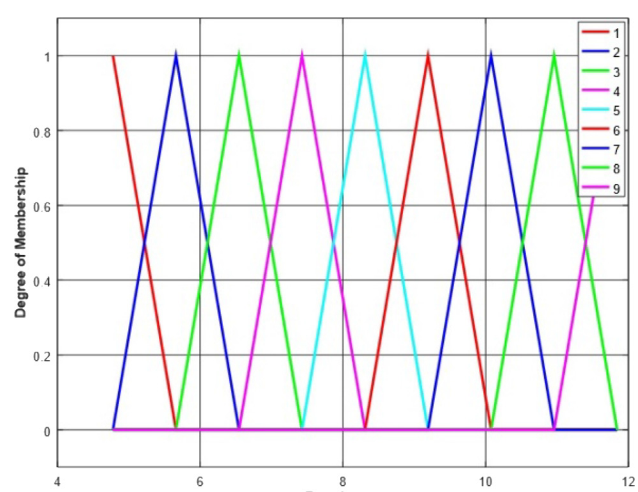

Fig. 14. Membership function for roughness.

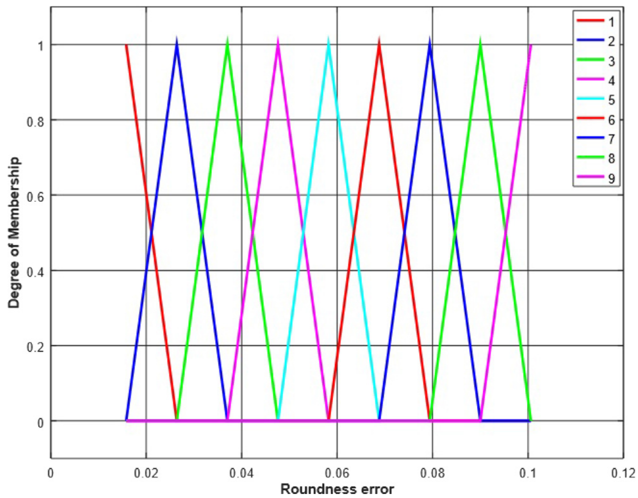

Fig. 15. Membership function for circularity error.

5. Conclusion

Various experiments are conducted to develop models for predicting the thrust force developed, roughness and circulatory error in the drilled holes on the hybrid composite of Al7075. The following conclusions are made from the developed three different prediction models. It has been found that the desirable point angle of the tool for the drilling operation taken into consideration is 118°. It can also be concluded that the responses of the composite material specimen become poor as the point angle decreases. As the point angle decreases, the values of roughness, roundness error and thrust force increase significantly, enabling to choose the desirable tool geometry for the operation. Analysis are made both on a mathematical and predictive stand point. Among the three prediction models: Response Surface Methodology (RSM), Artificial Neural Networks (ANN) and Fuzzy Logic, the Fuzzy Logic technique yields closer results with a deviation of 5% or less from that of the experimental values. Next to Fuzzy Logic, ANN method gives better results than RSM with a deviation of 5% to 10%. The accuracy of Fuzzy Logic prediction technique depends on membership function; hence, it can be improved further by increasing the number of membership functions.

CRediT authorship contribution statement

S. Senthil Babu: Conceptualization, Methodology, Investigation, Validation. **C. Dhanasekaran:** Supervision.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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