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Integrated Taguchi - Fuzzy Approach for Optimize the Vibration Characteristics in End Milling Parameters on Al 6061-T6

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ABSTRACT

Vibration of cutting tool and workpiece while machining of material leads to poor surface finish, low process stability and less tool life time. Therefore, it is required to optimize the cutting parameters based on vibration measurement to achieve the better surface finish and improve cutting tool life time. In present work, the cutting parameters like cutting speed, feed rate and depth of cut have been conducted on Aluminium hybrid metal matrix composite material Al 6061-T6. The experiment is designed using Taguchi L9 orthogonal array and the model development is done using Fuzzy Logic control in MATLAB software. Acceleration in Feed direction and axial direction were obtained from the Experimental vibration measurement on workpiece with different level of cutting parameters. The results obtained Vibration experiment and fuzzy predicted values are visualized

Keywords - End Milling, Vibration amplitude, Taguchi method, Fuzzy Logic.

1. INTRODUCTION

In the manufacturing industry, machining operations are quite common. It's almost always the final procedure to determine the final quality of the product. Acceleration of the tool and the workpiece actually reduces surface quality, machine instability, and tool reliability. To enhance the product condition and minimize surface finish, a measuring device is expected to forecast vibration with regard to operating conditions. Because of improvements in work and cutting structure, a broad variety of feed and speed variations, and differing depths of cut, the CNC milling center is exposed to various operating parameters [1]. The estimation of milling chatter is of considerable importance because it leads to optimizing milling efficiency. For machining processes in extremely precise manufacturing, such as milling of injection moulded and automobile parts, excellent surface quality and tool mark accuracy are required. For high-quality metal surfaces, the cutting tracks must be monitored during the milling operations. As a result, end milling monitoring is dependent on machine tool setting and on technician abilities. When a tool is clamped, cutting runout is common. Since uneven processing loads are acting on the device ends, cutting deformation causes uneven tool movement, resulting in a poor machined surface [2]. While trained engineers can minimize cutting runout with proper tightening, the runout is mostly Nano. As a result, for milling operators to plan the operating conditions in order to cut dimensions, a suitable statistical method is designed. The tool and specimen travel at a velocity defined by the device tool's normal frequency while machining. There is a lot of chatter during feed and pull back movements. Vibration is caused by the movement of the tool and the sample. Chatter [3] is a resonance frequency movement that happens as loads exerted on the tool induce it to oscillate at the device's normal frequency, wherein the magnitude is maximized with the minimal possible of oscillation. When this position is developed, the movement between the tool and sample will continue to vibrate, and continuous pressing would decrease the life of the tool and affect the machined surface, as well as affect cutting tool impact. Chatter noise [4] is caused by a number of factors; nearly every part of a cutting tool and instrument device is concerned. The dynamic model is being used in many studies to expose the impact of different operating conditions on milling efficiency. In the automotive industry, finding the best mix of operating conditions for improved milling efficiency is a big issue. To associate the input operating condition and output signal, a based on a scientific methodology may be used to determine the effects of observations. The Taguchi technique [5] is a widely used scientific methodology for performing trails. It was used to aim and improve the quantities of operating conditions for certain output variables.

2. MATERIAL AND METHODS

2.1. Material Fabrication and Properties

Aluminium hybrid composite Al 6061-T6 is a new generation of metal matrix composite. It consists of an alloying component such as Mg (0.8 %), Fe (0.7 %) is next to Al (95.85 %), which as a result of heat treatment tends to enhance greater hardness. Reinforcing particulates used for preparing samples are SiC, Al_2O_3. Specimens of Al 6061-T6 are fabricated by Stir Casting process. Aluminium alloy is melted in induction furnace at 750℃ for 2-3 hours. The silicon carbide and alumina particles in their right proportion are preheated at the temperature of 50^0C to make their surface oxidized. Then reinforcements are added to the semiliquid aluminium alloy in the furnace. Stirring of the molten metal is done by means of mechanical stirrer which rotates at a speed of 500 rpm for 10 min. Then the liquid aluminium alloy with reinforcements is poured into the die and subjected to solidification to produce required specimen. After fabrication machining operation are performed.

2.2. Vibration measurement

The tests were carried out on a vertical milling machine. The tool and the workpiece components pass according to that with a frequency decided by the machine's normal frequency in the machining process. To obtain machining force results, a vibrometer was used, and the frequency range was set to 6,000 Hz to see the difference in 2,500 Hz. Oscillations in the milling machine were measured utilizing accelerometer sensors installed on head, with a frequency response of 1500 Hz. Vibration measurements [6] in response to variations, amplitude, and vectors are recorded as output waveform and radio signals. The radio signals are a plot of the amplitude of dynamic responses vs. wavelength that can be obtained from the square wave utilizing virtual FFT. The highest vibrations produced throughout the machining processes is indicated by the peak stage, as well as the maximal amplification of a machining processes is recorded for this research. Aluminium alloy Al 6061-T6 was used for the workpiece.

2.3 Experimental design

The Taguchi approach is an empirical modelling methodology used during engineering research to improve operating variables values for a desired predicted output [7-12]. Many of the tests were done in a dry environment with down machining processes. Table 3 displays the Process control parameters and their respective limits.

2.4. Fuzzy Logic Interface

Fuzzy logic interface has quickly emerged as important optimization techniques for predicting complex process control parameters. Along with its opportunity to organize with inconsistent and unscientific data, fuzzy logic (FL) was utilized in several numerical modelling conditions. Fuzzy processes make choices based upon cognitive elements for different parameters. These parameters are evaluated using IF-THEN rules, that generate several or even more outputs based on rules were declared [13].

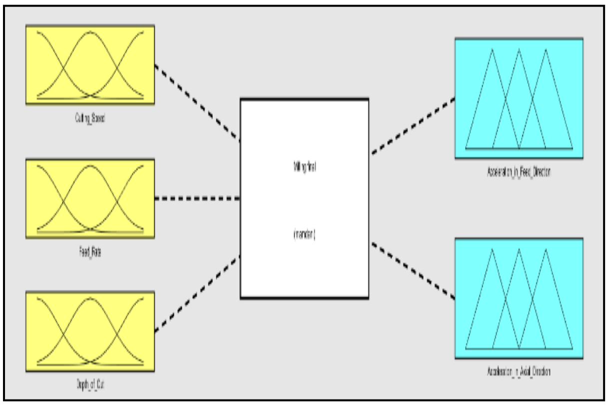

Fig. 1. Main Fuzzy logic interface engine

Figure 1 illustrates a fuzzy inference engine, often recognized as a fuzzy rule-based framework. A fuzzier, membership classifier, fuzzy rule Viewer, processing unit, and defuzzifier are all part of a fuzzy interface scheme (FIS). The fuzzification uses the membership classifier to fuzzily the SN ratio within each output variable. Following that, the processing unit (Mamdani fuzzy inference system) applies fuzzy logic to fuzzy rules to produce an expected value. Ultimately, the defuzzifier transforms the fuzzy expected value into such an Acceleration in Feed direction and axial direction output that can be used to improve the precision of the outcome of the vibration in end milling tool. The MATLAB was used to manage the fuzzy. The set of inputs is determined by the storage of the engine interface. If the input signal is greater, the time required to process the data must depend mostly on FIS. Fuzzy logic design modular for input parameters are shown in fig. 2. "Mamdani" type fuzzy interface is used to analyze optimize the output parameters with the help of some defined rules shown in Fig. 3, Fuzzy logic is a computing-based approach on "degree of truth" more than usual to "true or false". The decision making represents value between zero to one, if one indicated true value and zero value indicated false value in FIS.

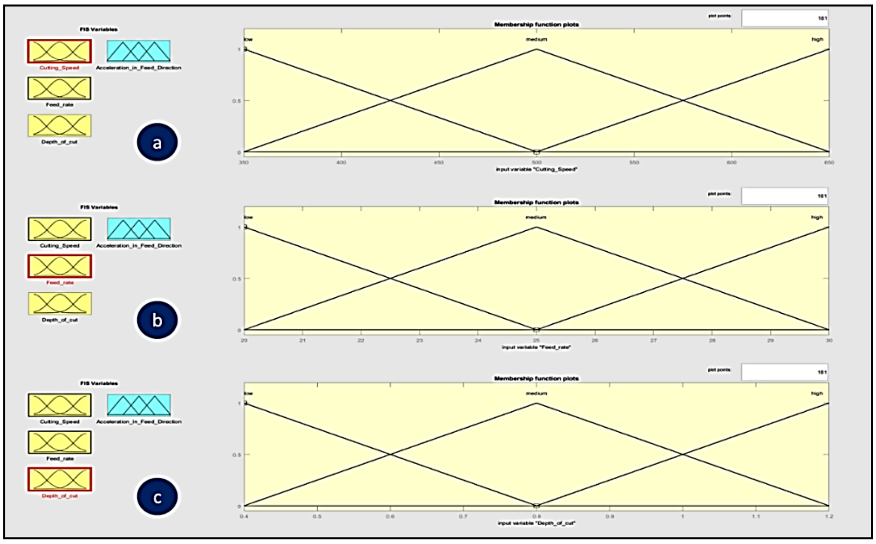

Fig. 2. Fuzzy logic design modular inputs (a) Cutting speed, (b) feed rate and (c) depth of cut

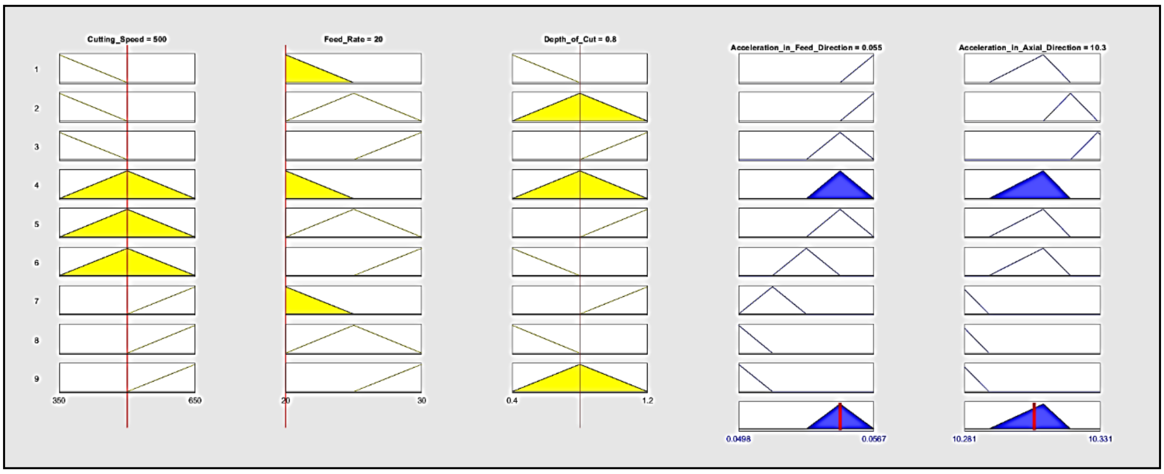

Fig. 3. Rule Viewer for input and output response

3. RESULTS AND DISCUSSIONS

3.1 Experimental Results

The milling operation is performed on a CNC vertical milling center equipped with an end mill cutter. With various levels of input parameters, the acceleration was determined in the feed and axial directions. The DYTRAN 7543A triaxial vibrometer was mounted on the workpiece and attached to a device for data analysis of the raw signal input. Table 4 shows the experimental values for acceleration in the feed and axial directions derived from the Vibrometer. When the machining speed was set to 350 m/min, the milling machine made a very loud noise and experienced intense shaking; however, the mill tool was not wearing at this time.

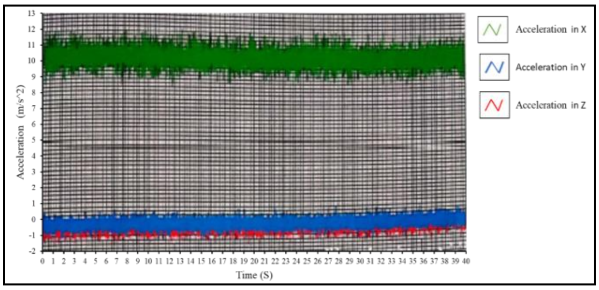

Fig. 4. Acceleration in Axial direction

When the CS is raised to 650 m/min, a comparable or even worse noise is noticed; in the meantime, the mill edge is damaged. A Time domain signal is the raw data which is directly collected from the workpiece. It is used for further analysis of vibration. This gives the variation in acceleration of the particle with respect to time. The Time domain signal for axial direction is shown in fig.4.

Table 1. Experimental values for acceleration in feed direction and acceleration in axial direction

	Factor 1	Factor 2	Factor 3	Output Responses			
Run	Cutting Speed (CS)	Feed rate (FR)	Depth of Cut (DC)	Acceleration in Feed direction		Acceleration in axial direction	
				Experimental Values	Fuzzy logic Values	Experimental Values	Fuzzy logic Values
1	350	20	0.4	0.0567	0.0561	10.306	10.306
2	350	25	0.8	0.0555	0.0561	10.314	10.319
3	350	30	1.2	0.0545	0.055	10.331	10.328
4	500	20	0.8	0.055	0.055	10.304	10.306
5	500	25	1.2	0.0546	0.055	10.306	10.306
6	500	30	0.4	0.0535	0.0532	10.308	10.306
7	650	20	1.2	0.0516	0.0515	10.281	10.284
8	650	25	0.4	0.0506	0.0504	10.282	10.284
9	650	30	0.8	0.0498	0.0504	10.283	10.284

3.2 Mathematical model

Operational parameters including CS, FR, and DC, a theoretical model was obtained to predict the output response. Equations 1 and 2 define the regression equation for acceleration in the feed and axial directions.

$$Acceleration\ in\ feed\ direction = 0.06632 - 0.000016 * cutting\ speed - 0.000183 * feed\ rate - 0.000042 * depth\ of\ cut \quad (1)$$

$$Acceleration\ in\ axial\ direction = 10.3268 - 0.000117 * cutting\ speed + 0.001033 * feed\ rate + 0.00917 * depth\ of\ cut \quad (2)$$

3.3 Statistical results for output response

The ANOVA is used to evaluate that optimum condition does have a significant influence on the overall statistics. The data in table 4 for acceleration in feed direction and acceleration in axial direction are reported to ANOVA to measure the significant values in the experimental condition, at confidence level 95%, and the statistical results for acceleration in feed direction and acceleration in axial direction are shown in Table 2 and 3, respectively.

The F-test defines that optimum condition has a major impact on the output metric. When the F value is high, changing the process parameter usually has a direct impact on the output characteristic. The influence of source terms with the minimum probability value is more important. According to Table 2 shows the essential factors are CS and FR. The cutting speed is the essential factor, as observed in Table 3. The important values for Acceleration in Feed direction are 0.004 and 0.032, respectively, and their contribution values are 88.63% and 11.36%. Similarly, the significant value for Axial Acceleration is 0.041, and the contribution values are 85.11%.

Table 2. Statistical Results for Acceleration in Feed Direction

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Cutting Speed	2	0.000039	0.000020	234.84	0.004
FR	2	0.000005	0.000003	30.28	0.032
DC	2	0.000000	0.000000	0.28	0.781
Error	2	0.000000	0.000000		
Total	8	0.000044			

Table 3. Statistical Results for Acceleration in Axial Direction

Source	DF	Adj SS	Adj MS	F-Value	P-Value
CS	2	0.001922	0.000961	23.25	0.041
FR	2	0.000165	0.000082	1.99	0.334
DC	2	0.000089	0.000044	1.07	0.482
Error	2	0.000083	0.000041		
Total	8	0.002258			

3.4 Effects of main and interaction plot

For simplicity, these results are shown in Figures 1 and 2. The unique plot features, as well as the interaction impact of the various control factors, contribute to decreasing acceleration. Several of the variables in the feed and axial cutting directions, such as the acceleration amplitude, are also critical.

The data shown in Fig. 5a may be used to determine the best feed acceleration direction for Al 6061-T6 by examining the graph. The acceleration of the feed has a limit and is based on the CS of the blade. As the FR is increased, the number of accelerations decreases to the bare minimum. It is possible to achieve maximum feed acceleration at both lower and larger cut depths. When utilising it, the FR, CS, and DC may all influence the amount of acceleration in the feed direction. Increasing CS while maintaining a medium DC, as shown in Fig. 5b, resulted in the least amount of feed path acceleration. Increases in CS and FR are associated with a reduction in acceleration in the feed direction. It is possible to detect a very little degree of acceleration when both the FR and the DC are set to medium. Accurate Axial Direction Acceleration is depicted in Fig.6a at its most effective setting. CS has the largest influence on axial acceleration, as seen in figure 6a, which is the major effect plot of the equation. The FR and cut depth are limited to an axial acceleration that is as little as possible. Because of the quick CS, low FR, and shallow cut depth, the axial acceleration is kept to a bare minimum. As a result, the amplitude of acceleration is at its lowest (Fig. 6b). This is demonstrated by the relationship map between CS and FR, which shows that as CS increases, FR drops. The relationship map indicates that the least amount of acceleration occurs when the FR is lower and the DC is larger.

3.5 Effects of process parameters by contour plot

Process parameter acceleration in feed direction (in Al6061-T6) illustrated in Fig. 6. Surface graphs in Figure 6a demonstrate CS and FR. Six Increasing CS and FR lowers the amount of acceleration in the feed direction. Fig. 6a shows the cutting path's 3D contour effect. fig. 6b demonstrates that feed direction acceleration is lower when the DC is lowered and the CS is raised. Figure 6c shows the interaction impact of the 3D response contour plot of FR and DC. At a modest DC and a greater FR, the required feed acceleration was reached. A three-dimensional counter effect map of process parameters on the axial acceleration produced in Al 6061-T6 during end milling is depicted in Fig 7. In Figure 7a, three-dimensional contour graphs of the CS and FR are depicted. When the CS and FR are raised, it has been noticed that the axial acceleration is reduced to a bare minimum. Using the cutting rate and DC plot, Figure 7b displays the 3D contour impact of the cutting plot. When the DC is lowered while the CS is raised, as shown in Fig. 7c, the axial direction acceleration is at its lowest. Fig. 7c illustrates the interaction impact of the 3D response contour plot of FR and DC on the 3D reaction contour plot of DC. Axial direction acceleration produced in Al 6061-T6 during end milling is depicted in Fig 8.

3.6 Prediction and experimental validation

The precision of the output parameters was determined by plotting experimental vs. fuzzy logic values. The comparison of experimental and fuzzy logic values for acceleration in the feed direction is seen in Fig. 9a. Figure 9b shows a comparison of experimental and fuzzy logic values for axial acceleration. The results of this plot showed that the approximate values obtained from the fuzzy model and experiments were very similar, as shown in figure 8. Fuzzy logic concept modeler created the model for predicting acceleration in the feed and axial directions.

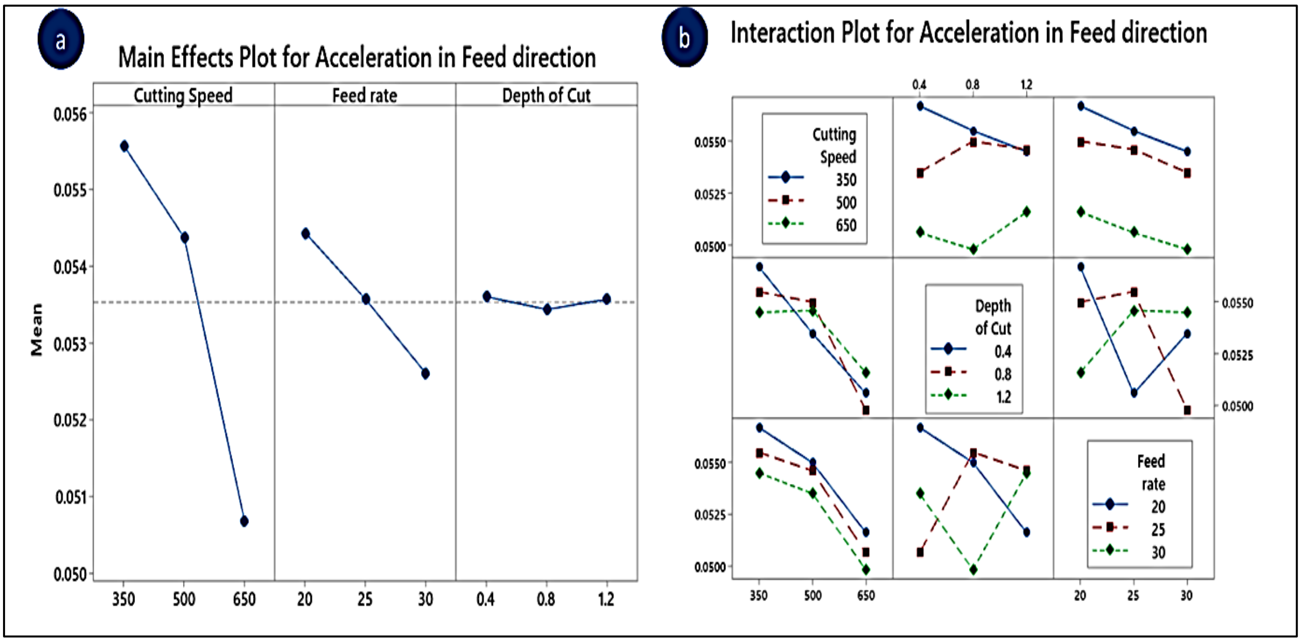

Fig. 5. Main and interaction plot for Acceleration in Feed direction

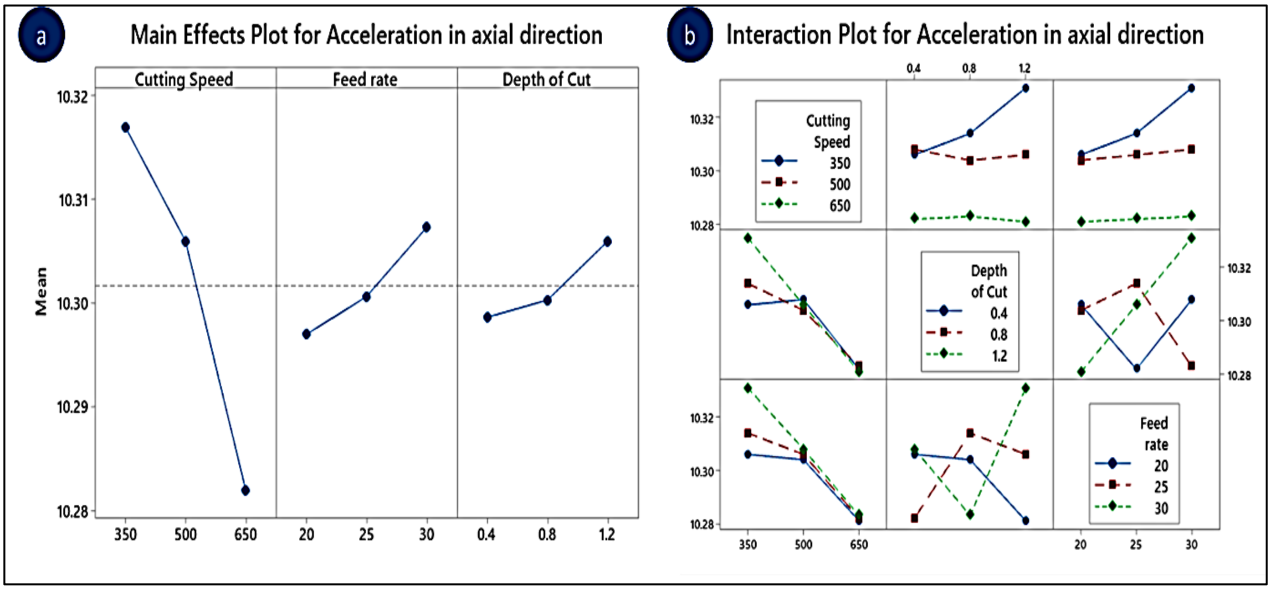

Fig. 6. Main and interaction plot for Acceleration in Axial direction

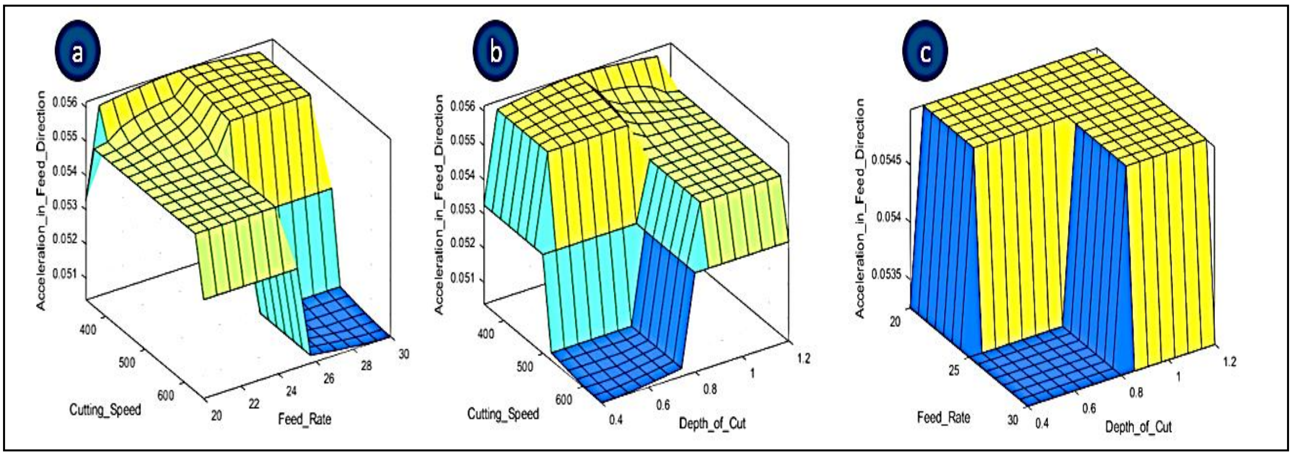

Fig. 7. Contour plot for Acceleration in Feed direction a) Cutting speed vs Feed Rate b) Cutting speed vs Depth of cut c) Feed Rate vs Depth of cut

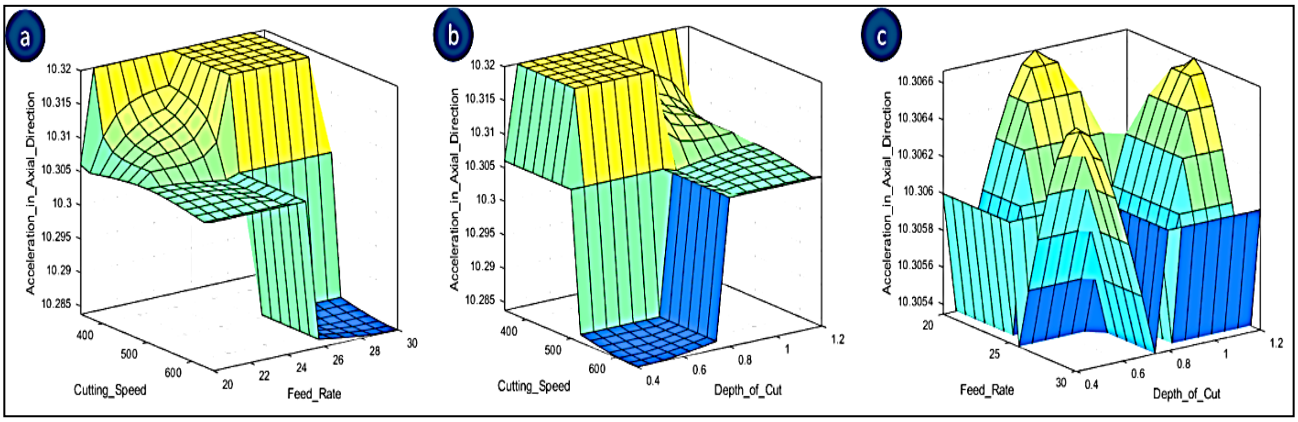

Fig. 8. Contour plot for Acceleration in Axial direction a) Cutting speed vs Feed Rate b) Cutting speed vs Depth of cut c) Feed Rate vs Depth of cut

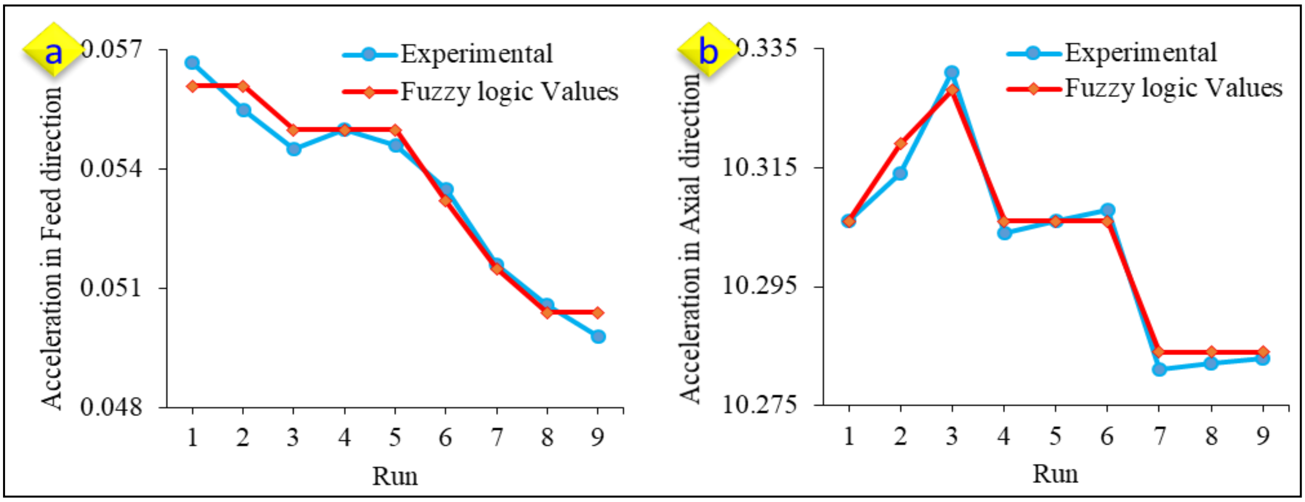

Fig. 9. Comparison of Experimental and Fuzzy logic Values for a) Acceleration in Feed direction and b) Acceleration in Feed direction

4. CONCLUSION

The specimens of aluminium hybrid composite have been prepared by stir casting technique and machined by End Milling operation. Acceleration in feed and axial direction experimental results obtained from machining are optimized through Taguchi method. According to the statistical analysis, cutting speed and feed velocity have a significant impact on acceleration in the feed and axial directions for milling parameters. Cutting speed contributes 88.63 percent to acceleration in the feed direction, while acceleration in the axial direction contributes 85.11 percent. The acceleration in the feed direction is influenced by the feed rate by 11.36 percent. Cutting speed of 650 RPM, feed rate of 30 mm/rev, and depth of cut of 0.4 mm are the best cutting parameters for Al6061-T6 material. There is a positive correlation between experimental and fuzzy logic findings.

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