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Experimental Investigation and Fuzzy Based Prediction of Titanium Alloy Performance During Drilling Process

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ABSTRACT

Recently, titanium and its alloys have been widely used in industry. Titanium alloys are difficult to machine due to high tool wear, cutting temperature, and edge formation. Thus, this analysis predicts how machining parameters, particularly drilling parameters, affect titanium work piece integrity. This study used Taguchi and fuzzy control software to calculate the effects of cutting parameters and drill tip angle on surface roughness maximal temperature in titanium alloy workpieces during dry drilling. Three 10 mm cutting tools have 106°, 118°, and 130° tip angles. Cutting tools are made of high-speed steel. The work piece model is a parallelogram with 100 mm width, 150 mm length, and 30 mm thickness. Cutting settings include three spindle speeds 500, 1000, and 1500 rpm with 0.1, 0.2, and 0.3 mm/rev feed rates. All simulations have the same hole depth (4 mm). We also estimated and discussed the rate of temperature change due to cutting settings. This prediction is used to diagnose and improve drilling, increase tool life, and safeguard the work piece. This reduces titanium drilling costs and effort. The machining model's work piece temperature is influenced by spindle speed and tool tip angle, but feed rate has no effect. Drillers can optimize drilling performance and obtain desired results including efficient penetration rates, shortened drilling time, and reduced equipment failure by regulating these parameters. Fuzzy Logic predicts drilling parameters on Titanium work pieces with encouraging results.

Keywords: titanium (Ti-6Al-4V), surface roughness, work piece temperature, Taguchi, fuzzy logic**,** drilling optimization.

INTRODUCTION

Because of their great fracture toughness, low density, and excellent strength-to-weight ratio, Components in the aerospace, medical, recreational, and automotive industries utilize titanium alloys [1, 2]. Numerous hundreds of holes need to be drilled for aerospace components. Since a drill is confined inside of a hole and the debris removed does not conduct heat as well as it should, heat becomes trapped and negatively impacts the tool life, the hole surface quality, and integrity [3, 4]. As a result, modeling thermal generation and distribution during drilling is crucial. for understanding the effect of drilling surface quality as well as for determining the best methods for heat dissipation.

Despite Ti drilling being widely used in industry, few research publications remain. Drilling of Ti-6Al-4V was discussed of several experiments by Sakurai et al. [5–7]. There have been studies on the effects of tool treatment of the surface, speed of cutting, and feed upon thrust force as well as torque [5], the advantages of the drill's vibratory motion [6], as well as the varying feed for chip being removed [7]. Arai and Ogawa [8] cutting fluid-assisted drilled on the high-pressure (7 MPa), Dornfeld et al. [9] upon the phenomenon of burr development, while Cantero et al. [10] upon the dry drilling tool wear, as well as work piece subsurface damage, were other researchers who studied Ti drilling. This analysis demonstrates the need for additional investigation on the drill temperature distribution during Ti drilling.

The tool temperature increases when drilling titanium. High tool temperatures are vital for tool life and have been seen in Ti drilling operations with high throughput. Extensive thermal modeling and experimental research are essential for enhancing drill design and selecting process parameters to extend tool life for Ti drilling. In order to investigate the drilling distribution of temperatures and the impact of spindle speed in drilling titanium, this study aims to construct a finite thermal finite element approach of spiral demonstrate drilling, which has proven effective for high throughput drilling for titanium [11]. The technique known as Taguchi is helpful for selecting the ideal set of variables under desired experimental circumstances. When there are more process parameters, the approach developed by Taguchi reduces the variety of experiments that would otherwise be necessary. Having the Taguchi method, a small experiments number are used to study the whole parameter space using an orthogonal array. Analysis of variance, or ANOVA, is another statistical technique utilized in the interpretation of experimental data. The primary goal of an ANOVA is to identify the design parameter that has the greatest impact [12]. A variety of engineering or other systems can now be accurately modeled using artificial intelligence techniques [13] as an effective and different approach.

Fuzzy logic is one of these methods, which employs mathematical theory to solve complex problems by fusing probabilistic reasoning with multivalued logic. Fuzzy logic is a type of method used in artificial intelligence that depends on mathematical models or equations to map as well as simulate engineering issues. It adds to our intelligence in addition to practical problem-solving abilities based on robust reasoning constrained by a minimum number of principles. Less constraining rules and multivalued logic give this method superior intelligence and reasoning capabilities [14, 15]. By using the Taguchi mathematical method in addition to grey relational analysis as a DOE technique, Kuar et al. [16] have improved the laser micro-drilling procedure. Input parameters include pulse frequency, pulse width, air pressure, and lamp current, while output parameters include hole taper and zone width. For the process of electro conductive coating, Goyal et al. [17] have devised an experimental design that utilizes an L18 orthogonal array. They discovered that the parameters ranking from greater to lower based on the level of importance from a table of ANOVA were the type of substrate, stagnation pressure, stalemate gas temperature, standoff distance, and feed arrangement of the powdered particle. According to published research, fuzzy logic modeling is used to confirm the accuracy and behavior of the machining process. To forecast hole size and roughness of the surface in multi-hole drilling, Aamir et al. used fuzzier logic [18]. The cutting pressure, surface roughness as well as tool wear were all factors that Ramesh et al. used a system of fuzzy inference to predict and validate [19]. Hashmi et al. developed a fuzzy logic choice of data for the drilling process of the AISI steel [20]. Jitesh et al. [21] developed an adaptable inductive system (ANFIS) model for the prediction of tool conditions upon hole excellence during micro-drilling. By using four carbide tools, Zeilmann and Weingaertner [21] investigated the temperature that was produced during the drilling of the titanium alloy Ti-6Al-4V. The goal was to gauge the temperature produced by MQL and determine how much lubrication affected the temperature that occurred during the drilling process of this alloy. Using thermocouples implanted on the flank face of the drilled tip, Li and Salih [22] attempted to estimate the tool temperature during titanium drilling. A 3D finite element model was employed for validating the experimental model. Wu and Han [23] used a manual thermocouple method that was placed around the workpiece to carry out an analytical model for determining the drilling temperature. The drilling tests were conducted using HSS tools. AISI 1045 and Ti-6Al-4V were employed. By insertion of thermocouples through the tool's working length's holes, Nedi and Eri [24] determined the drill bit's temperature as it was being used to drill. The same parameters for cutting were used on two different types of work piece materials: DIN 36CrNiMo4 and 9SMn28. Su et al. [25] investigation into the effects of the cutting parameters on force, torque, and maximal drill temperature paved the way for the creation of a three-dimensional finite element model (FEM) for use in the drilling of Titanium alloy using DEFORM 3D software. The distribution temperature throughout titanium drilling was studied by Patne et al. [26] using analytical, numerical, and experimental methods. In an experimental investigation, the temperature was estimated with a thermal camera, as well as the temperature of the drill bit was estimated with a thermocouple installed on the flank surface of the drill. The results of numerical and experimental investigations were then compared for validation. The findings indicated that as spindle speed increased, tool, as well as work piece temperatures, also rose. Grey-fuzzy logic was used by Shunmugesh et al. [27] to optimize the drilling characteristics of fibers of glass-reinforced polymer (GFRP). The drilling operation generated a more effective surface roughness in addition to delamination factor using the determined optimal values for parameters that were within the study's fixed ranges. Chatterjee et al. [28] investigated simulation and machining parameter optimization for drilling titanium alloys. The technique of response surfaces is used to collect data from experiments. When drilling titanium alloys using coated drill bits, the effects of different drilling parameters, including spindle speed (SS), feed rate (FR), and drill bit diameter (DB), on performance traits, including thrust force (TF), and torque (T), as well as the circularity at both ends of the holes, were examined. The author concluded that a suggested simulation framework can be used for the machining evaluation of titanium alloy drilling in order to reduce the time, expense, and resources required for experimental testing. To improve the quality of drilled holes while cortical bone drilling, Singh et al. [29] investigated an optimization of process parameters. The optimization of rotational speed (RS), feed rate (FR), and tool type (TT) in relation to output responses like roughness of the surface and rate of material removal was covered in the section above of this paper. The SEM results and magnified images had demonstrated that the twist drill produces a tiny, rounded hole.

Priyadarshini et al. [30] showed how to use the grey fuzzy reasoning method to optimize the laser drilling process parameters for multiple characteristics. Tej Pratap et al. [31] investigation into the modeling of cutting force during the micro-milling of titanium alloy. The primary goal of the investigation is to use a FEM model for simulating stress distribution, temperature (T) distribution, and the generation of cutting force while taking into account tool edge radius, uncut chip thickness, spindle speed, and feed rate. This paper uses the ABAQUS/Explicit finite element approach for describing the force of cutting modeling in the micro-end of the milling process of titanium alloy Ti-6Al-4V. Using the finite-element simulation of specific cutting forces, size effects in the micro-end milling process were demonstrated. Experimental findings were successfully used to validate the simulated cutting forces.

In order to find the ideal process parameters that minimize the heat-affected zone, hole roughness, and rate during CNC drilling, this paper introduces a Taguchi optimizing approach that employs fuzzy methodology. Spindle speed, feed rate, and tool angle are taken into consideration as input process parameters. The outcome demonstrated that the Taguchi methodology and desirability fuzzy algorithm are appropriate in order to improve the multi-response attributes in the drilling operation of titanium alloy Objective and Hypothesis of the study shown in Figure 1.

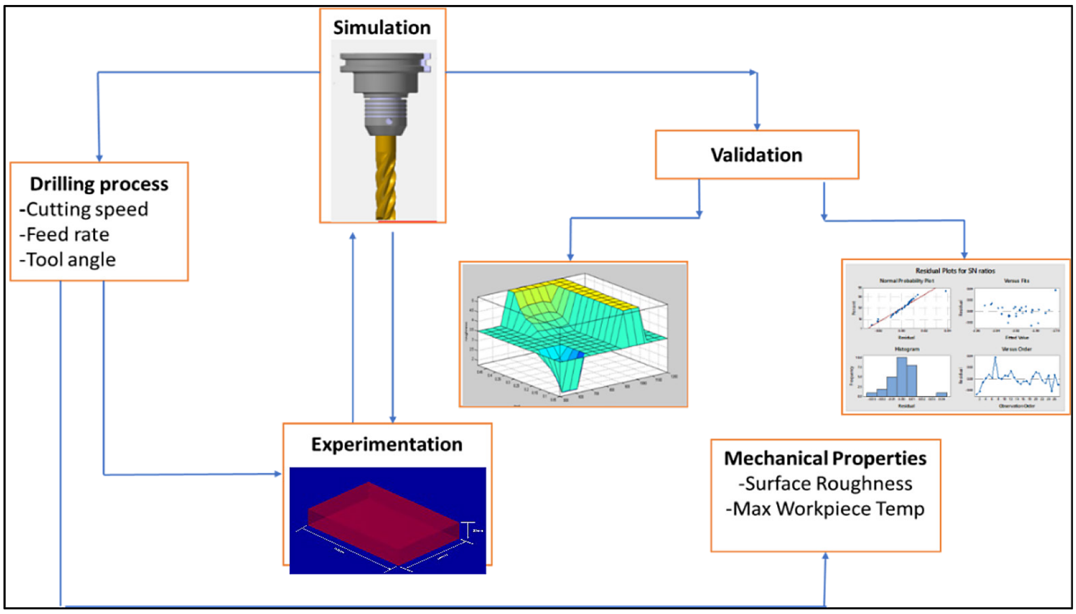

Fig. 1. Experimental diagram that analyzed and evaluated for Titanium

EXPERIMENTAL WORK

Materials and methods

Titanium is used as the experimental metal in this study, and its measurements are (100 mm, 150 mm, 30 mm), the drilling machine is used to complete the study process. Before drilling, all the pieces' surfaces are cleaned to prepare for drilling. In Table 1, combined, the mechanical and chemical-based characteristics of using metal are presented.

High-speed steel, a substance used to form cutting tools, is the subject of this study. Due to their distinct physical and mechanical characteristics, which make them perfect for producing strong, wear-resistant, difficult, and hard parts, these tools are in great demand. They can be used for a variety of tasks, including machining materials that are hard like steel made from stainless steel, titanium-based metals, and additional premium alloys as well as woodworking. A new cutting tool that contains 5% cobalt to increase surface hardness was recently created according to the German classification for metals (HSS DIN 338). This tool's chemical composition is listed in Table 2.

The production of bits for drilling, cutters for milling, saw blades, drills, taps, broaches, and various other tools frequently involves the use of high-speed steel. Compared to tools made of carbon steel.

These tools keep their sharp edges for longer, and a variety of grades and treatments for the surface are available to meet the needs of specific applications as clarified in Figure 2. The surface's roughness (Ra) has the first outputs characteristic that is assessed with a surface roughness tester (SKU: SRT-6210 Category: Automotive Testing).

For simultaneously estimating the second outputs characteristic temperature distribution across the tool and the workpiece while drilling titanium, an entirely novel, comprehensive simulation is presented in the study. Over the drill bit workpiece, The temperatures distribution of Ti-6Al-4V alloys has been determined using a thermal imaging device (Camera Model: FLIR T335). This camera provided good IR quality images of the workpiece

Table 1. Ti-6Al-4V Chemical Composition

Element % Wt.	Fe	C	Mn	P	s
Standard [21]	99.11-99.56	0.14-0.20	0.30-0.60	≤ 0.040	≤ 0.050
Measured	99.3	0.0153	0.411	0.0005	0.0010

Table 2. HSS DIN 338 Chemical Composition

Element	Si	C	S	P	Mn	Mo	Ni	V	Cr	Co	W	Fe
Percentage %	0.29	0.83	0.001	0.002	0.021	4.74	0.19	1.77	3.85	5	6.11	Remaining

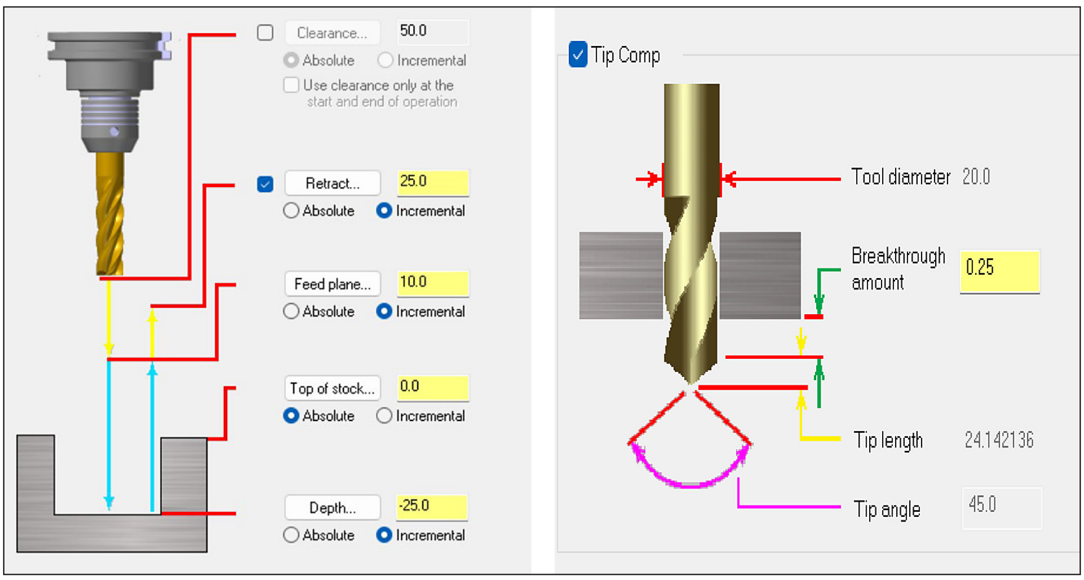

Fig. 2. Drilling tool used in the experimental work using Master Cam x5

during the drilling operation. Furthermore, the center point has been chosen to undergo testing in the exact same dimension as the workpiece.an experimental method has been created and established for determining the temperature on the piece.

Orthogonal array and fuzzy

Taguchi's statistical method was used to investigate all parameters through a limited number of experiments. It uses the S/N ratio as a measurement of the degree to which quality characteristics deviate from or approach the ideal values. During the duration of this study, machine process characteristics such as spindle speed, feed rate, and tool angle were taken into account. The L27 Taguchi orthogonal array [20] was chosen for three parameters and three levels based upon the experimental design of Taguchi. Table 3 displays the number of factors and their corresponding levels. When analyzing the S/N ratio, there are three tiers of quality: the lower the ratio, the higher the ratio, and the nominal the ratio, respectively.

The smaller number is desired according to the following equation, so a larger is preferable for this study.

$$\frac{S}{n} ratio\ (\eta) = -10 log_{10} \frac{1}{n} \sum_{i=1}^{n} 1/y\ i^2 \qquad (1)$$

For the study and computation of the optimal values for the resultant features, such as surface roughness (Ra) and distribution of temperatures (T), the smaller the value, the better. The Taguchi method was used to assess the optimization of the process parameters. Additionally, A regression analysis was conducted to associate the process with the variables and outcomes to see how closely the created model matched the experimental Ra and T values. ANOVA was also used to calculate proportions.

Effects of process variable on response output. Last but certainly not least, techniques for fuzzy logic reasoning were employed to replicate the experimental results for the best kind of drilling.

RESULTS AND DISCUSSION

Generating regression analyses model

Several regression analyses was used to create first order mathematical models for the outcome response, which included temperature distribution (T) and surface roughness (Ra). A useful, user-friendly, and precise statistical technique is multiple regression analysis. The goal of creating a model based on mathematics is to improve the machining process by connecting the resulting response to the inputs machining parameters. These models enable the use of response surface optimization techniques like multi-objective function models to address optimization problems. To determine whether the surface roughness and temperature data represent a fitness trait, a model based on linear regression is used. Minitab software is used to derive the regression model equation for Ti-6Al-4V Ra, the regression model that this research produced is provided below:

$$\begin{aligned} Ra = b_0 + b_1(SS) + b_2(FR) + b_3(TA) + \alpha = \\ -3.580 + 0.002277X1 + \\ + 6.539X2 + 0.03486X3 \end{aligned} \qquad (2)$$

$$\begin{aligned} T = b_0 + b_1(SS) + b_2(FR) + b_3(TA) + \alpha = \\ = -236.1 + 0.2316X1 + 857.2X2 + 1.787X3 \\ R^2 = 95.80\% \end{aligned} \qquad (3)$$

where: (SS, FR, TA) are the input parameters, and (Ra, T) first order output response is the measured response, b_0, b_1, are approximated using the least squares approach. Before moving on to optimization, this mathematical model's validity will be examined using F- and p-test tests. In the present investigation, R2 values greater than 80% indicate that the models are effective at predicting responses in relation to machining variables.

Figure 3 depicts normal probability diagrams of residuals for predicted responses for Ra and T, respectively. Figure 3 also demonstrates that the proposed models are adequate, as all residuals follow a nearly identical straight-line pattern, as reported by Davidson et al. Vankanti and Ganta [8] and [26]. To reduce Ra and the deviation of

Table 3. The independent levels of variables

No.	Input variables	Symbol	Level of variable		
			1	2	3
1	Spindle speed (mm/min)	SS	500	1000	1500
2	Feed Rate (mm/ rev)	FR	0.1	0.2	0.3
3	Tool angel	TA	106°	118°	130°

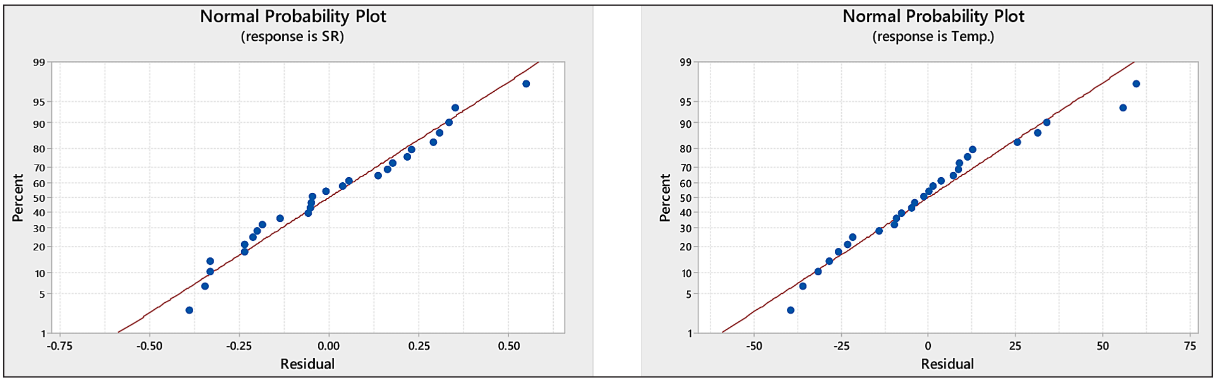

Fig. 3. Normal probability plots for (Ra) & (Temp)

T from its nominal value, this research will be beneficial for the selection of process parameters in aluminum drilling. The regression coefficient R2 (0.9172) is in good accord with the adjusted regression coefficient R2 (0.8734). The model's regression coefficient is 0.9172 and the measurement data was not scattered. The regression equation for the model is given by equation (1).

Analysis of the results of the parameters in surface roughness and workpiece temperature for Ti-6Al-4V

Surface roughness (Ra) is regarded as the first response describing the quality and efficacy of the surface in this study. To determine the best level of each parameter for maximizing the reaction

Table 4. The results of the S/N ratio of surface roughness & temperature

No.	Input parameters			Output response		S/N ratios	
	Spindle speed (SS) (rpm)	Feed rate (FR) (mm/ rev)	Tool angel (TA) (degree)	Surface roughness Ra	Max. workpiece temperature (°C)	S/N ratio for RA	S/N ratio for T
1	500	0.1	106	1.67	162	-4.454	-44.1903
2	500	0.2	106	2.51	266	-7.993	-48.4976
3	500	0.3	106	3.35	335	-10.500	-50.5009
4	500	0.1	118	2.14	167	-6.608	-44.4543
5	500	0.2	118	3.27	273	-10.291	-48.7233
6	500	0.3	118	3.94	349	-11.909	-50.8565
7	500	0.1	130	2.78	176	-8.8809	-44.9103
8	500	0.2	130	3.56	296	-11.029	-49.4258
9	500	0.3	130	4.28	403	-12.628	-52.1061
10	1000	0.1	106	2.81	231	-8.974	-47.2722
11	1000	0.2	106	3.64	355	-11.222	-51.0046
12	1000	0.3	106	4.57	442	-13.198	-52.9084
13	1000	0.1	118	3.25	256	-10.237	-48.1648
14	1000	0.2	118	3.98	373	-11.997	-51.4342
15	1000	0.3	118	4.72	467	-13.478	-53.3863
16	1000	0.1	130	3.55	285	-11.004	-49.0969
17	1000	0.2	130	4.19	376	-12.444	-51.5038
18	1000	0.3	130	4.99	477	-13.962	-53.5704
19	1500	0.1	106	4.36	395	-12.789	-51.9319
20	1500	0.2	106	4.79	468	-13.606	-53.4049
21	1500	0.3	106	5.16	532	-14.253	-54.5182
22	1500	0.1	118	5.15	439	-14.236	-52.8493
23	1500	0.2	118	5.59	553	-14.948	-54.8545
24	1500	0.3	118	5.90	565	-15.417	-55.0410
25	1500	0.1	130	5.37	485	-14.599	-53.7148
26	1500	0.2	130	5.73	505	-15.163	-54.0658
27	1500	0.3	130	5.94	569	-15.475	-55.1022

Table 5. Average input response values & S/N ratio for Ra

Level	Average input response values for Ra			S/N ratio for Ra		
	X1	X2	X3	X1	X2	X3
1	3.055	3.453	3.651	-9.366	-10.198	-10.777
2	3.966	4.14	4.215	-11.836	-12.077	-12.125
3	5.332	4.761	4.487	-14.499	-13.425	-12.799

Note: Smaller is better.

Table 6. Average input response values & S/N ratio for T

Level	Average input response values for T			S/N ratio for T		
	X1	X2	X3	X1	X2	X3
1	269.666	288.444	354	-48.19	-48.51	-50.47
2	362.444	385	382.444	-50.93	-51.43	-51.08
3	501.222	459.888	396.888	-53.94	-53.11	-51.50

Note: Smaller is better.

that affects the titanium Ti-6Al-4V workpiece, the signal-to-noise ratio (S/N) is used as a measure of output quality. In general, a higher S/N ratio signifies a higher quality output. Tables 4 display the S/N ratio for surface roughness and temperature (T).

The average response value and S/N ratio for Ra and T are shown in Tables 5 and 6, respectively. Figure 4 depicts Principal results of drilling parameters on surface roughness and workpiece temperature. Signal-to-Noise ratios with greater numbers result in enhanced efficacy [32]. Despite the qualitative attribute's category. Therefore, the optimal quantity of a factor is the level with the highest S/N ratio. The optimal surface roughness is attained at X1 level 1, X2 level 1, and X3 level 1 according to Table 5. In addition, optimal drilling parameters must be selected for temperature measurement. Due to the probability of increased tool and workpiece temperature affecting the drill hole and impeding chip evacuation [33]. From Table 6 and Figure 4, the optimal parameters for temp can be found at X1 level 1, X2 level 1 and X3 level 1.

The most effective value of parameters that are based on the highest number of S/N ratio for Ra and T are (spindle speed 500 mm/min), (Feed rate 0.1 mm/rev) and (Tool angle 106). The optimum level (500, 0.1, 106) for the optimum reach of Ra.

Optimum predictive levels of Ra and temperature

The most effective levels of process parameters can be used to predict the values of Ra and T. The predicted mean under ideal process conditions [18]:

$$Ra = (X1) + (X2) + (X3) - 2(Y) = \\ = 3.055 + 3.453 + 3.651 - 2(4.118) = 1.923 \quad (4)$$

$$T = (X1) + (X2) + (X3) - 2(Y) = 269.666 + \\ + 288.444 + 354 - 2(377.78) = 156.544 \quad (5)$$

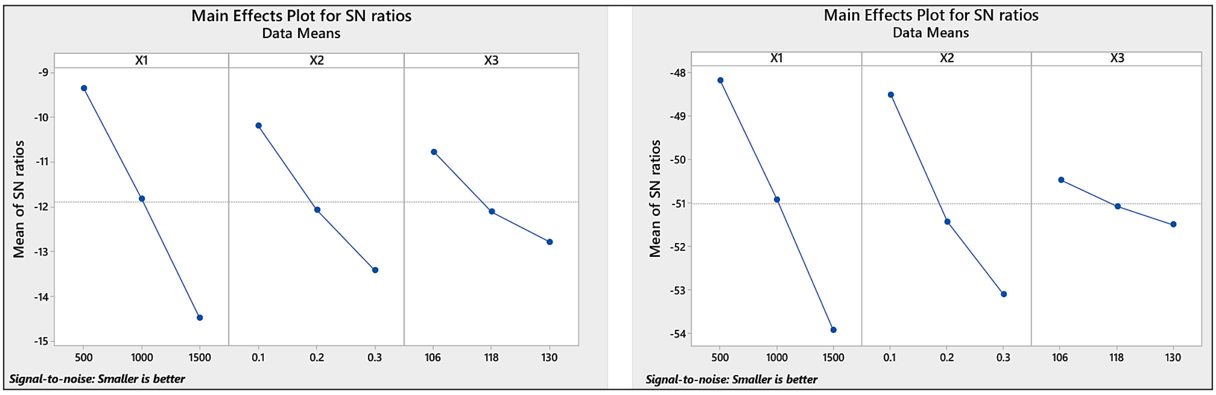

Fig. 4. Main Effects drilling parameters on (a) Ra – surface roughness (b) T – temperature

where: (X1)1,(X2)1, and (X3)1 are the optimal level quantity of T and Ra that found in Table 5 and Table 6, respectively. (Y) meaning mean for the 27 experiments for Ra and T calculated in Table 4. Similarly, It is possible to calculate the S/N ratio to determine where the Ra & T The values are appropriate. The estimated maximum S/N ratio is:

$$Ra = (S/N1) + (S/N2) + (S/N3) - 2\,(S/N)v = -9.366 + (-10.198) + (-10.777) - 2(-11.900) = -6.541 \tag{6}$$

$$T = (S/N1) + (S/N2) + (S/N3) - 2\,(S/N)v = -48.19 + (-48.51) + (-50.47) - 2(-50.861) = -45.448 \tag{7}$$

where: (S/N1), (S/N2), and (S/N3) are the maximal Signal to noise ratios of RA &T obtained from Tables 5 and Table 6, respectively, at the optimal levels. (S/N) v is the average of the Signal to noise ratios derived from Table 4.

Analyzing variance (ANOVA) for surface roughness and temperature

In this investigation, Using ANOVA, the significance of each process parameter on Ra and T was determined. The Ra and T ANOVA results are presented in Tables 7 and 8, respectively. In ANOVA, the percent contribution is used to characterize the impact of each process parameter on the output responses parameters.

The P-value verifies the impact of process variables on responses and demonstrates that values below 0.05 are insignificant [34]. F-value is a statistical instrument used to determine the design factors have an important influence on the quality characteristic [35]. Table 7 reveals that spindle speed has the greatest statistical impact on surface roughness at 65.99%, followed by feed rate at 21.51%, meanwhile, the tool angle has the smallest effect on surface roughness. In addition, as shown in Table 8, spindle speed has the greatest impact on temperature for Titanium alloy at 61.33%, followed by feed rate at 33.36%.

Fuzzy logic model for work piece surface roughness and temperature

From Taguchi analysis, it is obvious that drilling parameters affects the characteristics of the titanium work piece, where the increment in each of the spindle speed, feed rate and tool angle lead to direct proportion in the surface roughness and temperature.

The experimental drilling data were used for fuzzy logic depended on algorithm to predict the surface roughness and maximum temperature at miscellaneous process parameters.

Fuzzy Logic modeling consists of three main processes which are: Fuzzification, Rule base making, and Defuzzification. The first process which is Fuzzification, there is converting of crisp quantities into fuzzy quantities using membership definitions.

In the second process, multi if – then rules are designed using observations and expert about inputs-outputs logical relations. Defuzzification is the last process which is the inverse of Fuzzification, here a conversion of

Table 7. ANOVA is used to analyze variances in Ra

Sources	DOF	Seq. SS	Contribution (%)	Adj. MS	Adj. SS	P-Value	F-Value
X1	2	23.634	65.99	11.8171	23.634	0.000	196.97
X2	2	7.703	21.51	3.8514	7.703	0.000	64.19
X3	2	3.278	9.15	1.6391	3.278	0.000	27.32
Error	20	1.200	3.35	0.0600	1.200		
Total	26	35.815	100.00				

Table 8. ANOVA is used to analyze variances in T

Sources	DOF	Seq. SS	Contribution (%)	Adj. MS	Adj. SS	P-Value	F-Value
X1	2	244455	61.33	122227	244455	0.000	194.25
X2	2	132974	33.36	66487	132974	0.000	105.66
X3	2	8572	2.15	4286	8572	0.006	6.81
Error	20	12585	3.16	629	12585		
Total	26	398585	100.00				

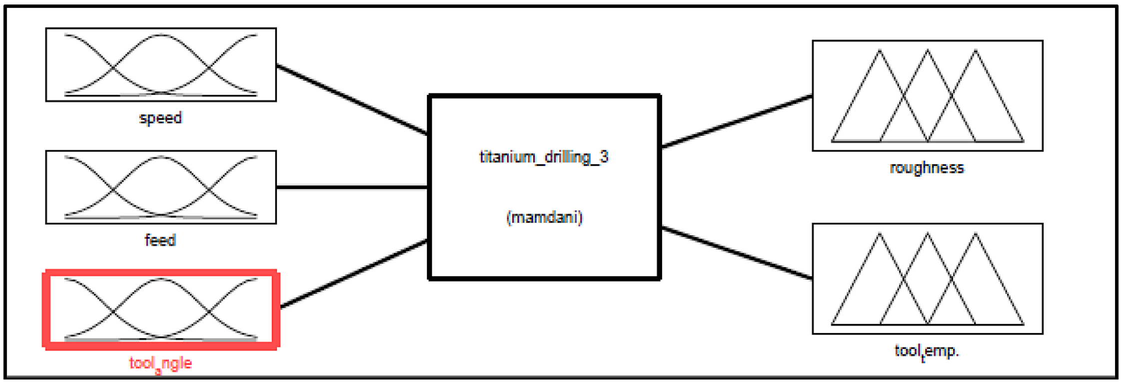

Fig. 5. The presented Fuzzy Inference System architecture

fuzzy results into crisp values is achieved [36]. MIMO FIS (Multi Input Multi Output Fuzzy Inference System) was designed where Spindle speed, feed rate and tool angle were taken as inputs of the system, on the other hand, surface roughness and maximum temperature of work piece were considered as outputs. Figure 5 shows Fuzzy Inference System architecture in MATLAB fuzzy toolbox.

A fuzzy rule for predicting surface roughness and temperature was defined using fuzzy logic. domain, where "Mamdani" was used as the fuzzy interference engine. Mamdani was chosen because of showing comparatively better results [37].

The system's outputs were calculated depending on the centroid method. In this study, triangular membership functions were considered. In the presented algorithm, inputs and outputs were fuzzified into three fuzzy sets as shown in Table 9. Figures 6 to 10 show all the membership functions of fuzzy logic system's inputs and outputs parameters.

Table 9. Fuzzy Inference System Parameters

Membership function	Variable	Input						Output			
		Spindle speed SS		Feed Rate FR		Tool Angle TA		Surface roughness (Ra)		Temperature (T)	
		Parameter	Range	Parameter	Range	Parameter	Range	Parameter	Range	Parameter	Range
Triangular	Low *(or small)*	[300 500 700]	[300 1700]	[0.05 0.1 0.15]	[0.05 0.5]	[102 106 110]	[100 134]	[1 1.75 2.5]	[1 6]	[100 175 250]	[100 600]
	Medium	[650 1000 1350]	[300 1700]	[0.125 0.2 0.275]	[0.05 0.5]	[109 118 126]	[100 134]	[2 3.5 5]	[1 6]	[200 450 500]	[100 600]
	High (or Big)	[1300 1500 1700]	[300 1700]	[1300 1500 1700]	[0.05 0.5]	[125 130 134]	[100 134]	[4.5 5.25 6]	[1 6]	[450 525 600]	[100 600]

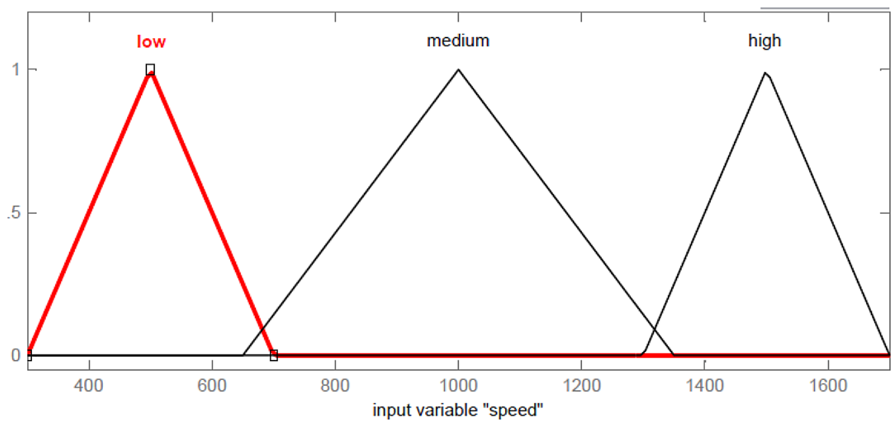

Fig. 6. Membership function of input 1 (spindle speed)

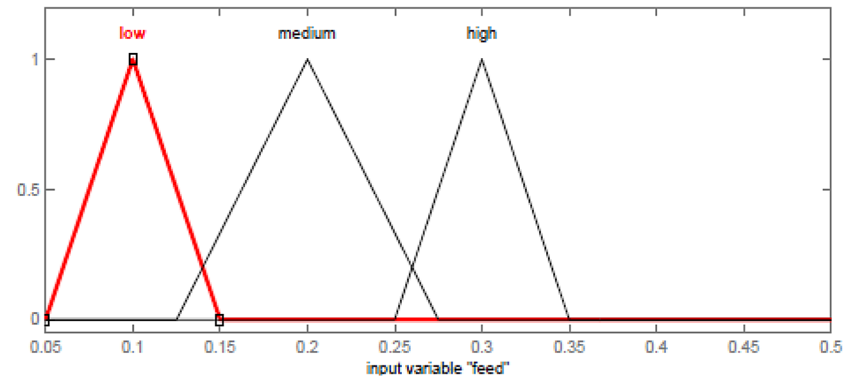

Fig. 7. Membership function of input 2 (feed rate)

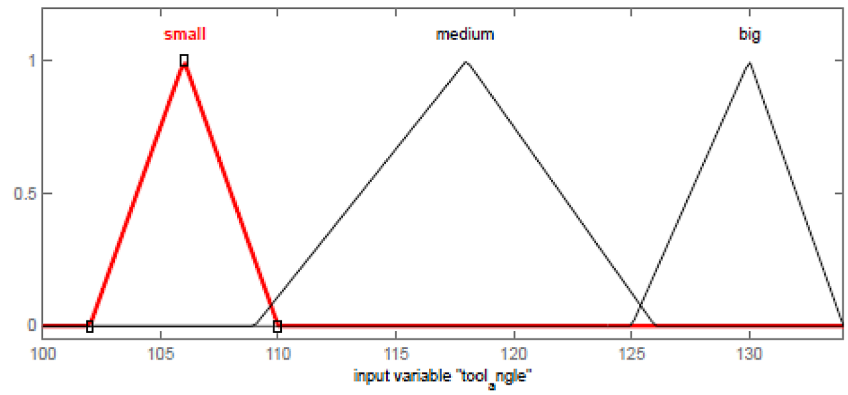

Fig. 8. Membership function of input 3 (tool angle)

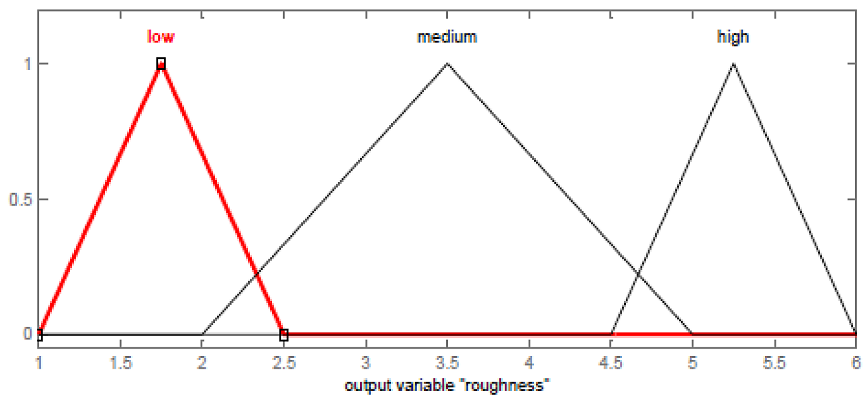

Fig. 9. Membership function of output 1 (surface roughness)

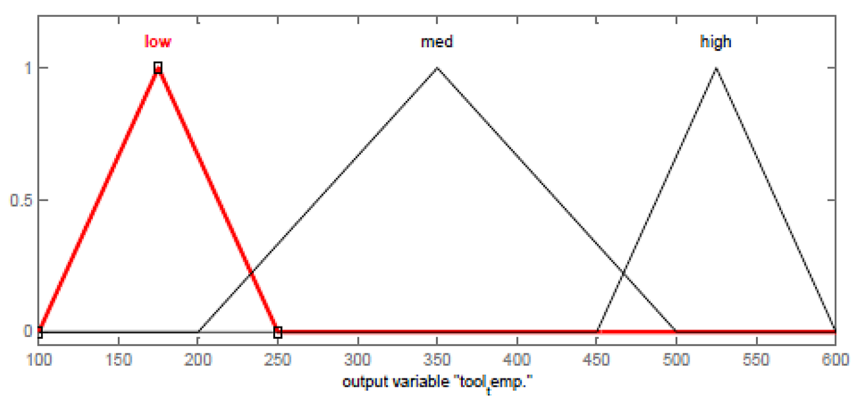

Fig. 10. Membership function of output 2 (temperature)

The presented fuzzy logic algorithm was tried for all drilling experimental data for each of surface roughness and work piece temperature. It was evident that the mentioned algorithm had the ability to predict output values for the required process parameters. Fuzzy logic set values behave in a similar manner to experimental values where the increment in the selected three drilling parameters leads into an increment in the work piece properties, where this was very compatible with Taguchi method results. Table 10 mentions that both of fuzzy results and experimental data besides Taguchi method results were harmonic with each other, values carry the same behavior for Surface Roughness and Temperature. Good agreement was noticed between experimental values and modeled values. The percentage error for both methodologies (Taguchi and Fuzzy Logic) falls within the permitted range of ten percent for both two work piece characteristics.

The excellent agreement between predicted and experimental values indicates that the acquired fuzzy logic model provided an effective and appropriate method for predicting surface roughness and maximum temperature in a titanium work piece during the drilling process.

Validation of results

It is important to make a verification for the results that obtained by (Taguchi and Fuzzy) results of the designed approach. Therefore, the results of both methods, besides the practical experiments are compared to be optimized for each of the surface roughness and maximum temperature of the titanium work piece.

Table 10. Obtained results by experiments, Taguchi, and Fuzzy Logic

CS	FR	TA	RA	Temp	Taguchi				Fuzzy			
					FITS (RA)	FITS (Temp)	Resi (RA)	Resi (Temp)	Predicted RA	Predicted temp	Residual error in RA	Residual error in temp.
500	0.1	106	1.67	162	1.923	157.111	-0.253	4.888	2.02	164	-0.35	-2
500	0.2	106	2.51	270	2.610	252.111	-0.100	17.888	3.38	278	-0.87	-8
500	0.3	106	3.35	341	3.231	326.444	0.118	14.555	3.5	343	-0.15	-2
500	0.1	118	2.14	165	2.488	182.666	-0.348	-17.666	2.02	167	0.12	-2
500	0.2	118	3.27	272	3.1748	277.666	0.095	-5.666	3.38	291	-0.11	-19
500	0.3	118	3.94	349	3.795	352	0.144	-3	3.6	361	0.34	-12
500	0.1	130	2.78	180	2.760	197.888	0.019	-17.888	2.02	184	0.76	-4
500	0.2	130	3.56	296	3.447	292.888	0.112	3.111	3.5	303	0.06	-7
500	0.3	130	4.28	371	4.068	367.222	0.211	3.777	4.79	367	-0.51	4
1000	0.1	106	2.81	242	2.834	253.888	-0.024	-11.888	2.02	239	0.79	3
1000	0.2	106	3.64	355	3.521	348.888	0.118	6.111	3.5	346	0.14	9
1000	0.3	106	4.57	442	4.142	423.222	0.427	18.777	4.79	445	-0.22	-3
1000	0.1	118	3.25	261	3.399	279.444	-0.149	-18.444	3.5	263	-0.25	-2
1000	0.2	118	3.98	371	4.085	374.444	-0.105	-3.444	4.79	360	-0.81	11
1000	0.3	118	4.72	467	4.707	448.777	0.012	18.222	4.79	452	-0.07	15
1000	0.1	130	3.55	285	3.671	294.666	-0.121	-9.666	3.6	289	-0.05	-4
1000	0.2	130	4.19	376	4.358	389.666	-0.168	-13.666	4.79	371	-0.6	5
1000	0.3	130	4.99	478	4.979	464	0.010	14	5.25	480	-0.26	-2
1500	0.1	106	4.36	393	4.200	393.666	0.159	-0.6666	4.79	407	-0.43	-14
1500	0.2	106	4.79	470	4.887	488.666	-0.097	-18.666	4.79	479	0	-9
1500	0.3	106	5.16	532	5.508	563	-0.348	-31	5.25	525	-0.09	7
1500	0.1	118	5.15	438	4.764	419.222	0.385	18.7777	4.79	432	0.36	6
1500	0.2	118	5.59	553	5.451	534.222	0.1385	28.7777	5.25	544	0.34	9
1500	0.3	118	5.9	561	6.072	588.555	-0.172	-27.5555	6	556	-0.1	5
1500	0.1	130	5.37	487	5.037	464.444	0.332	22.555	5.25	502	0.12	-15
1500	0.2	130	5.73	505	5.723	529.444	0.006	-24.444	5.25	518	0.48	-13
1500	0.3	130	5.94	596	6.344	603.777	-0.404	-7.777	6	591	-0.06	5

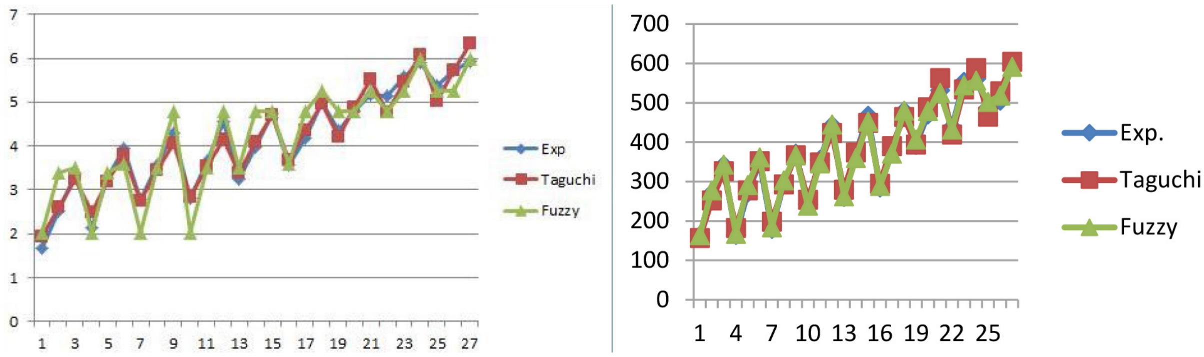

Fig. 11. Validation of results for (A) surface roughness, (B) work piece temperature results

The results that obtained by each of Taguchi, Fuzzy and practical side were compared as shown in Figure 11 for the surface roughness and for work piece temperature. There is acceptable variances among the three values. The response improvement predicts optimal conditions relatively well.

CONCLUSIONS

In this paper, CNC drilling was utilized to drill holes in titanium alloy. The quality of the workpiece surface and the amount of heat generated by the cutting tool were examined, as well as the potential influence of factors such as cutting speed, feed, and tool angle on these dependent variables in 27 tests. The experimental design was created from the experimental design. Both Taguchi method and fuzzy logic method were used for statistical processing of the collected data. For the output parameters, we create an empirical model and evaluate its suitability using analysis of variance. A summary of the survey results is as follows.

1. Monitoring tool life and surface roughness is very important to improve tool life, machining cost, and product quality. The surface roughness results from this study increase with the increase of spindle rotational speed and feed rate, but the helix angle has a less significant effect on the surface roughness.
2. Changes in spindle speed, feed rate, and tool angle were predicted at once based on the temperature distribution of the tool. As drilling speed and feed rate increase, the temperature increases significantly in both situations. Taguchi enables thorough parametric analysis and the resulting temperature distribution can be used to optimize other process variables such as feed rate, drilling speed, and tool angle.
3. The number of R2 values in the regression analysis was more than 80%, indicating that the response related to the machining parameters could be easily predicted. The built model can be used to predict the improvement in hole quality when using the drilling process. The average error between each comparison is small, allowing both Taguchi optimization and fuzzy prediction. The average S/N ratio method was used to analyze the experimental response values. From the average S/N ratio graph, it was found that the optimal drilling parameters are SS of 500 rpm, FR of 0.1 mm/rev, TA of 106°, temperature, and Ra. The predicted average response values at the optimal levels of the drilling process variables were 1.92 for Ra and 156.54 for temperature.
4. The influence of multiple variables on drilling titanium alloys is analyzed through Taguchi prediction and ANOVA. Using response graphs and ANOVA analysis, the ANOVA results show that the most important variables of Ra are drill speed and feed. Spindle speed is the second most important factor for tool temperature after drill speed. The maximum difference between the experimental results, Taguchi simulation results, and fuzzy simulation results is less than 3%, which makes it a good case for validation.
5. Additionally, the promised fuzzy logic optimization technique was applied to the same parameter set and level of detail. The results of improved response values and optimal levels of parameters of this technique are consistent with the results of Taguchi's method. Utilizing this technology improves the quality of drilled parts, opens the door to online condition monitoring, and saves time, money, and effort in tedious tasks.

REFERENCES

1. Hartman, A.D., Gerdemann S.J., Hansen J.S. Producing lower-cost titanium for automotive applications. 50 (1998): 16-19.
2. Bruni S., et al. Effects of surface treatment of Ti–6Al–4V titanium alloy on biocompatibility in cultured human umbilical vein endothelial cells. Acta biomaterialia 1.2 (2005): 223-234.
3. Arrazola P-J., et al. Machinability of titanium alloys (Ti6Al4V and Ti555. 3). Journal of materials processing technology 209.5 (2009): 2223-2230.
4. Miller S.F., P.J. Blau, A.J. Shih. Tool wear in friction drilling. International Journal of Machine Tools and Manufacture 47.10 (2007): 1636-1645.
5. Sakurai K., et al. Drilling of Ti-6Al-4V alloy. Keikinzoku 42.7 (1992): 389-394.
6. Sakurai K., Adachi K., Ogawa K. Low frequency vibratory drilling of Ti-6Al-4V alloy. Keikinzoku 42.11 (1992): 633-637.
7. Sakurai K., et al. Intermittently decelerated feed drilling of Ti-6% Al-4% V alloy. Keikinzoku 46.3 (1996): 138-143.
8. Arai M. Effects of high pressure supply of coolant in drilling of titanium alloy. Journal of Japan Institute of Light Metals 47.3 (1997): 139-144.
9. Dornfeld D.A., et al. Drilling burr formation in titanium alloy, Ti-6AI-4V. CIRP annals 48.1 (1999): 73-76.
10. Cantero J.L., et al. Dry drilling of alloy Ti–6Al–4V. International Journal of Machine Tools and Manufacture 45.11 (2005): 1246-1255.
11. Li Rui, Parag Hegde, Shih A.J. High throughput drilling of titanium alloys. International Journal of Machine Tools and Manufacture 47.1 (2007): 63-74.
12. Hanif M.I., et al. Optimization of facing process by indigenously developed force dynamometer. The International Journal of Advanced Manufacturing Technology 100 (2019): 1893-1905.
13. Vankanti V.K. and Ganta V. Optimization of process parameters in drilling of GFRP composite using Taguchi method. Journal of Materials Research and Technology 3.1 (2014): 35-41.
14. Anand G., et al. Investigation of drilling parameters on hybrid polymer composites using grey relational analysis, regression, fuzzy logic, and ANN models. Journal of the Brazilian Society of Mechanical Sciences and Engineering 40 (2018): 1-20.
15. Aamir M., et al. Fuzzy logic approach for investigation of microstructure and mechanical properties of Sn96. 5-Ag3. 0-Cu0. 5 lead free solder alloy. Soldering & Surface Mount Technology 29.4 (2017): 191-198.
16. Kuar A.S., et al. Optimization of Nd: YAG laser parameters for microdrilling of alumina with multiquality characteristics via grey–Taguchi method. Materials and manufacturing processes 27.3 (2012): 329-336.
17. Goyal T., Walia R.S., Sidhu T.S. Study of coating thickness of cold spray process using Taguchi method. Materials and Manufacturing Processes 27.2 (2012): 185-192.
18. Aamir M., et al. Optimization and modeling of process parameters in multi-hole simultaneous drilling using taguchi method and fuzzy logic approach. Materials 13.3 (2020): 680.
19. Ramesh S., Karunamoorthy L., Palanikumar K. Fuzzy modeling and analysis of machining parameters in machining titanium alloy. Materials and Manufacturing Processes 23.4 (2008): 439-447.
20. Hashmi K., Graham I.D., and Mills B. Fuzzy logic based data selection for the drilling process. Journal of Materials Processing Technology 108.1 (2000): 55-61.
21. Zeilmann R.P. and Weingaertner W.L. Analysis of temperature during drilling of Ti6Al4V with minimal quantity of lubricant. Journal of Materials Processing Technology 179.1-3 (2006): 124-127.
22. Li Rui and Shih A.J. Tool temperature in titanium drilling. (2007): 740-749.
23. Wu Jian and Rong Di Han. An analytical evaluation of drilling temperature. Key Engineering Materials 407 (2009): 400-403.
24. Nedic B. and Erić M. Cutting temperature measurement and material machinability. (2014).
25. Su Y., Chen D.D., Gong L. 3D Finite element analysis of drilling of Ti-6Al-4V Alloy. International Conference on Computer Information Systems and Industrial Applications. Atlantis press, 2015.
26. Patne H.S., et al. Modeling of temperature distribution in drilling of titanium. International Journal of Mechanical Sciences 133 (2017): 598-610.
27. Shunmugesh K., and Panneerselvam K. Grey Relational Analysis Based Optimization Of Multiple Responses in Drilling Of Carbon Fiber-Epoxy Composites. Materials Today: Proceedings 4.2 (2017): 2861-2870.
28. Suman C., Mahapatra S.S., Abhishek K. Simulation and optimization of machining parameters in drilling of titanium alloys. Simulation Modelling Practice and Theory 62 (2016): 31-48.
29. Gurmeet S., et al. Optimization of process parameters for drilled hole quality characteristics during cortical bone drilling using Taguchi method. Journal of the mechanical behavior of biomedical materials 62 (2016): 355-365.
30. Priyadarshini, M., et al. Multi characteristics optimization of laser drilling process parameter using grey fuzzy reasoning method. Materials Today: Proceedings 2.4-5 (2015): 1518-1532.

31. Tej P., Patra K., Dyakonov A.A. Modeling cutting force in micro-milling of ti-6al-4 v titanium alloy. Procedia Engineering 129 (2015): 134-139.
32. Yang, WH P., and Y.S. Tarng. Design optimization of cutting parameters for turning operations based on the Taguchi method. Journal of materials processing technology 84.1-3 (1998): 122-129.
33. Mustafa K., Kaynak Y., Bagci E. Evaluation of drilled hole quality in Al 2024 alloy. The International Journal of Advanced Manufacturing Technology 37 (2008): 1051-1060.
34. Abderrahmen Z., et al. Prediction of machining performance using RSM and ANN models in hard turning of martensitic stainless steel AISI 420. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science 233.13 (2019): 4439-4462.
35. Mustafa K., Bagci E., Kaynak Y. Application of Taguchi methods in the optimization of cutting parameters for surface finish and hole diameter accuracy in dry drilling processes. The International Journal of Advanced Manufacturing Technology 40 (2009): 458-469.
36. Vinayagamoorthy R., et al. A central composite design based fuzzy logic for optimization of drilling parameters on natural fiber reinforced composite. Journal of Mechanical Science and Technology 32 (2018): 2011-2020.
37. Pedrycz W. Fuzzy equalization in the construction of fuzzy sets. Fuzzy sets and systems 119.2 (2001): 329-335.