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Predicting the surface roughness and Tolerance using regression analysis while performing a boring operation in AA6061 Alloy

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Abstract*— *Aluminium alloys are widely used in aerospace applications and AA6061 is one of the popular alloy which is extensively used in spacecraft mechanical hardware. Some of the mechanical hardware of spacecraft mechanisms call for stringent tolerances in larger diameter holes. These holes are achieved through boring operation on CNC machining centre by utilizing precision boring head and boring bar. Surface roughness and tolerance of the hole plays an important role in functioning of the system. In the current work experiments are carried out to study the significant input process parameters which influence the surface roughness and tolerance of holes. This was done using ANOVA. Also, a model was developed based on linear regression analysis. It was found that optimum cutting parameters predicted by Taguchi method improved surface finish and tolerance of holes

I. INTRODUCTION

Spacecraft consists of several mechanical hardware such as mechanisms, thermal subsystems, and electronics packages. From vast experience and available resources, it is evident that to achieve geometric and dimensional tolerances, complex shapes and surface finishes required by these spacecraft mechanical hardware, machining is the best method of manufacturing. Machining is a manufacturing process where the material is removed by using different cutting tools on different machine tools to obtain close tolerances and surface finish.

Aluminium alloys are widely used in aerospace applications owing to their good specific stiffness and strength. AA6061 is one such alloy which is commonly used in several spacecraft mechanical hardware components as it can be heat treated and has good corrosion resistance properties. Also, it is easily machinable using several machining operations.

Yahya, E. et.al (2016) performed the machining experimental work on AA6061 alloy using a vertical milling machine to study the effect of tool flutes, cutting speed, depth of cut and feed rate on surface roughness and cutting force. Their work established a relationship between input parameters and output parameters using the response surface method. The tests were done using the Taguchi technique and results were analyzed using ANOVA. Their work concluded that surface roughness has only two significant parameters (tool flutes and depth of cut) which affected surface machining. Gutema, E. M. et.al (2022) explored the implications of cutting parameters like cutting speed, feed rate and cutting depth; and nose radius on surface roughness and temperature in the workpiece while turning the AA6061 work piece. Further, desirability analysis optimization was performed to find the optimum values. Their work stressed the importance of cutting speed as the most influencing parameter compared to other parameters. Sivaiah, P., & Chakradhar, D. (2018) discussed on optimum cutting conditions in turning 17-4 precipitation-hardened stainless steel using the Taguchi optimization method. Input parameters like cooling environment (cryogenic, MQL and dry) were considered apart from cutting parameters, to study their effects on surface roughness and flank wear. Aggarwal, A et.al (2008) investigated the effects of cutting parameters, nose radius and cutting environment on power consumption of a CNC turning machine while machining AISI P-20 tool steel. Their work utilized Response Surface Methodology (RSM) and Taguchi methodology. Their work discussed that cryogenic working conditions contributed more in reducing the power consumption other than the cutting speed, which remained the highest influencing parameter in power consumption. Karkalos, N. E., Efkolidis, N., Kyratsis, P., & Markopoulos, A. P. (2019) conducted a comparison study for performance of various neural network models like Multi-Layer Perceptron (MLP), the Radial Basis Function Neural Network (RBF-NN), and the Adaptive Neuro-Fuzzy Inference System (ANFIS) models with the performance of multiple regression model for drilling experiments on an AA6082-T6 workpiece. The experiment was conducted for different cutting parameters and also with three cutting tools (solid carbide drilling tools) diameters of 8mm, 10mm and 12mm. The depth of holes drilled was 30mm. The work concluded that the MLP method performed better in all cases compared to other methods. However other than

multiple regression models, MLP was observed to be competitive for smaller data sets. Sastry, M. N. P et.al (2012) investigated the effect of process parameters on MRR using RSM while machining Aluminium alloy and resin using an HSS cutting tool. A close relationship between observed and predicted values was observed. Do Duc, T et.al (2020) presented a method of predicting the surface roughness in the hole-turning operation of 3X13 steel. An experimental matrix was prepared using Central Composite Design (CCD) and RSM was used to develop a quadratic polynomial model to predict surface roughness. Apart from this SVM algorithm was also used and their study showed SVM to be a better process for predicting surface roughness. Aamir, M et.al (2021) investigated the effect of the multi-spindle drilling process on dimensional hole tolerances, such as hole size, circularity, cylindricity, and perpendicularity. In addition to this, defects during drilling operation was also studied. The materials considered for the study were AA2024, AA6061 and AA5083. Their work used an uncoated carbide twist drill of 6mm diameter. AA2024 was found to have more dimensional stability compared to other materials. Spindle speed is found to influence the most in affecting the hole size and cylindricity errors. Trinh, V. L. (2024) reviewed the methods followed in predicting the surface roughness of the machining processes. The benefits like reduced cost, improved cutting conditions and enhanced quality in predicting surface roughness, are mentioned in the work. Deshpande, A. A., & Rehman, M. A. A. (2022) reviewed the machining process modelling literature related to surface roughness. The effectiveness of different statistical and mathematical models like RSM, Fuzzy Logic, Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are discussed in the work.

Spacecraft mechanisms like solar array deployment mechanisms, solar array drive mechanisms, dual gimbal antenna, antenna pointing mechanisms etc., play a crucial role in the success of a spacecraft mission. These mechanisms comprise complex shapes, stringent tolerances and high surface finishes, critical for mechanism functioning. Some of the mechanisms call for the close tolerated holes whose dimensional accuracies are in the range of a few microns and surface finish in the range of 0.4 to 1.6 microns. For larger diameter holes and holes for which standard reamers are unavailable, a boring operation is known to be the best alternative to achieve these stringent requirements. Boring is a subtractive manufacturing technique used to enlarge a previously produced hole yet enhance its dimensional accuracy and surface finish. The process uses a single-point cutting tool to remove material parts from the interior of a workpiece.

Apart from achieving the stringent tolerances, high surface finishes and complex shapes of the components, realizing the hardware in the short lead times to meet the project schedules is also a challenging requirement. Realizing the hardware with short lead times without

Figure.1 : Boring operation on 3-Axis CNC Vertical machining Centre, DMG MORI D650V compromising the quality requires the maximum utilization of the machine and machining parameters. To achieve the correct balance among these a study has to be carried out for fixing the ideal machining parameters. Taguchi method was found to be the most popular method in Design Of Experiments and regression analysis to be most suitable if data set is small. To the best of the authors' knowledge no work related to boring of AA6061 is done.

Hence, in this work prediction of surface roughness using regression analysis is carried out while boring the AA6061 material.

II. EXPERIMENTAL METHODOLOGY

Taguchi L9 Design Of Experiments (DOEs) are used to optimize parameters for the surface roughness and tolerance of the hole on AA 6061 alloy. Depth of cut, Feed and Speed were the parameters taken in to consideration. Since three levels and three factors considered, L9 orthogonal array (OA) is used in this study. Design of experimental (DOE) has been used for reducing the number of experiments. The experimental plan having values with units, symbols and levels are listed in the Table 1.

AA6061 material with dimensions 250 mm × 150 mm × 25 mm was used for the experimental study for boring of holes with diameter of 22 mm as per experimental plan and for the confirmation tests and evaluation of the obtained models. Nine holes of each three with the diameter 21.6 mm, 21.4 mm and 21.2 mm were machined at feed of 2000 mm/min, speed of 6000 rpm and depth of cut 0.5 mm by circular pocket milling operation on DMG MORI D650V 3-Axis CNC vertical machining centre. As per the experimental plan, each hole was enlarged to the diameter of $22^{+0.021}_{+0.00}\ mm$ by boring operation in two passes with a precision digital boring head of make Microkom and carbide tool insert as shown in Fig.1 and Fig.2. The hole diameter of 22 mm with H7 tolerance was selected as the same dimension is found to repeat in several of spacecraft mechanical hardware.

Process Parameters	Unit	Symbol	Levels		
			1	2	3
Depth of Cut	mm	d	0.1	0.15	0.2
Feed	mm/min	f	100	250	500
Speed	rpm	s	4000	6000	8000

Table 1 Process parameters and their levels

A portable surface roughness tester Surtronic S-128 of make Taylor-Hobson was utilized to measure R_a (arithmetic mean surface roughness) value of holes produced by boring operation on the basis of the ISO 4287-1997 norms. Eq (1) defines R_a value. R_a value was considered for observation, as this parameter is the widely used parameter for measuring surface roughness in our organization.

$$R_a = \frac{1}{L}\int_0^L |z(x)|dx \qquad (1)$$

Where

L = Evaluation Length
z(x) = Profile height function

Average of three measurements of R_a (in µm) in each hole, measured by using portable surface roughness tester (as shown in Fig 2a) was considered. A cutoff length of 0.4 mm for each measurement was considered while taking R_a readings.

The diameter of the tolerated hole of $\emptyset 22^{+0.021}_{+0.00}\ mm$ was measured using 3-point digital bore micrometer by

(a) *(b)*

Figure 2: a). Precision Digital Boring head MicroKom – BluFlex 2 b). Boring bar with Carbide Insert

(a) *(b)*

Figure 3: a) Portable surface roughness tester Surtronic S-128 b.) 3-Point Digital Bore Micrometers by Mitutoyo

Run	Process parameters			Experimental results		S/N ratio results	
	d mm	f mm/min	s rpm	Surface roughness Ra (μm)	Tolerance of the hole (mm)	Ra (dB)	Tolerance (dB)
1.	0.1	100	4000	0.6	0.037	4.4370	28.6360
2.	0.1	250	6000	0.8	0.092	1.9382	20.7242
3.	0.1	500	8000	1.2	0.094	-1.5836	20.5374
4.	0.15	100	6000	0.4	0.089	7.9588	21.0122
5.	0.15	250	8000	0.3	0.099	10.4576	20.0873
6.	0.15	500	4000	0.8	0.046	1.9382	26.7448
7.	0.2	100	8000	0.3	0.107	10.4576	19.4123
8.	0.2	250	4000	0.4	0.056	7.9588	25.0362
9.	0.2	300	6000	1.0	0.092	0.0000	20.7242

Table 2 Experimental plan, Experimental results and S/N ratios

Mitutoyo (as shown in Fig 2b). The average of three values was taken while measuring the tolerance of the hole.

III. RESULTS AND DISCUSSIONS

The S/N ratio is defined as the ratio of mean of readings to the standard deviation of the same and is used to measure the quality characteristic deviating from the desired value by the Taguchi technique. Taguchi used the term signal for wanted value i.e mean and noise for unwanted value i.e standard deviation, which are determined for a response. Taguchi divided S/N ratio into three categories namely, higher-the-better, nominal-the-better and smaller-the-better. In the present work smaller-the-better Eqn. (2) is used for Ra and tolerance achieved. The achieved results and S/N values for Ra and tolerance, are listed in Table 2.

S/N ratio for smaller the better = $-10\log\frac{1}{n}\sum(R)^2$ (2)

Where, n = No. of observations

R = Observed data for each response

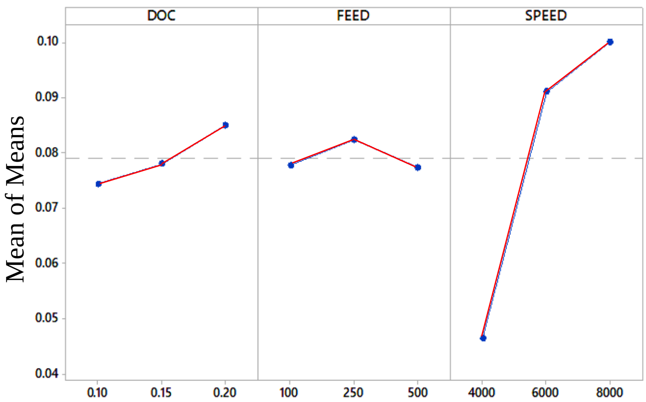

Figure 5: Effect of process parameters on tolerance of hole

a. Effect of Process parameters on Ra and tolerance of hole

Fig. 4 depicts the effect of process parameter viz. depth of cut (DOC) (d) in mm, Feed (f) in mm/min and Speed (s) in RPM, on Ra. Results show that R_a value decreased with increasing depth of cut but slightly raised with further increasing DOC. R_a value showed jump in the value with

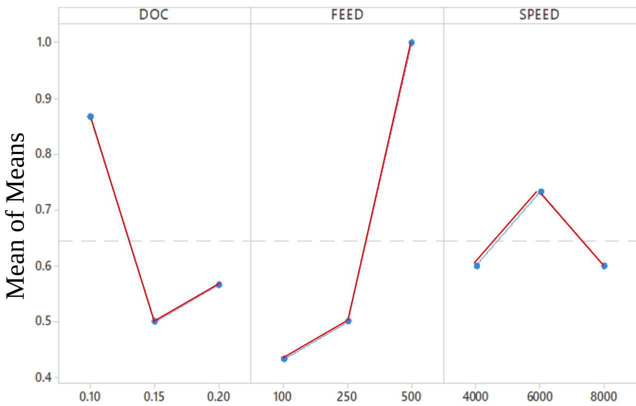

Figure 4: Effect of process parameters on R_a

increasing feed rate. With increasing the cutting speed R_a is observed to increase but reduces with further rise in the cutting speed.

Fig. 5 depicts the effect of process parameters on tolerance of holes. It is observed that increasing the DOC is affecting the tolerance of holes. Same but more significant

Effect of speed on tolerance of the holes is noticed, with sharp decline in hole quality with increase in speed. However, feed rate seems to affect the hole quality but tend to improve it with increase in its values.

Process Parameters	**Symbol**	**Mean S/N ratio**			**Rank**
		Level 1	**Level 2**	**Level 3**	
Depth of Cut (mm)	d	1.5972	**6.7849**	6.1388	2
Feed (mm/min)	f	**7.6178**	6.7849	0.1182	1
Speed (rpm)	s	4.7780	3.2990	**6.4438**	3

Table 3 Mean S/N ratio response table for R_a

Process Parameters	**Symbol**	**Mean S/N ratio**			**Rank**
		Level 1	**Level 2**	**Level 3**	
Depth of Cut (mm)	d	**23.30**	22.61	21.72	2
Feed (mm/min)	f	**23.02**	21.95	22.67	3
Speed (rpm)	s	**26.81**	20.82	20.01	1

Table 4 Mean S/N ratio response table for tolerance of holes

b. Selection of optimum cutting conditions for Ra and tolerance of hole

The obtained S/N ratio response table for R_a is shown in Table 3 and Fig. 6 depicts the mean S/N ratio graph obtained in R software. Higher S/N means there is minimum variation difference between required output and measured output. It can be seen from Fig 4 that the highest mean value of S/N ratio for R_a is obtained for DOC value of 0.15mm, federate of 100mm/min and speed value of 8000 RPM. Thus the predicted optimum cutting parameters for obtaining the best surface finish i,e least R_a value are DOC = 0.15 mm, f = 100 mm/min and N = 8000 RPM.

It can be seen from Fig. 7 that the highest mean value of S/N ratio for tolerance of hole is obtained for DOC value of 0.1 mm, federate of 100 mm/min and speed value of 4000 RPM. Thus the predicted optimum cutting parameters for obtaining the best tolerance value for hole i.e least tolerance value are DOC = 0.1 mm, f = 100 mm/min and N = 4000 RPM.

c. Conformation Test

To validate the Taguchi predicted optimum conditions conformation test needs to be conducted.

The predicted S/N ratio is calculated based on the formula given in Eqn. (3) (Sivaiah, P., & Chakradhar, D. (2018))

$$\varepsilon_{predicted} = \varepsilon_i + \sum_{i=1}^{n}(\varepsilon_0 - \varepsilon_i) \quad (3)$$

Where

ε_i= Total mean S/N ratio
ε_0= Mean S/N ratio at an optimal level
n= No. of input process parameters

The conformation experiments were conducted at the Taguchi predicted optimum cutting conditions, and the results are tabulated in Table 5 and Table 6.

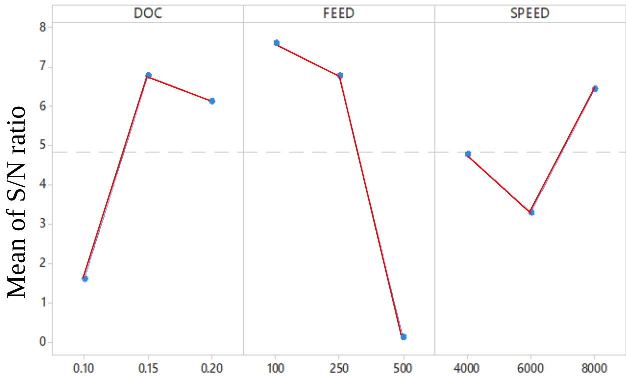

Figure 6: Mean S/N ratio of R_a

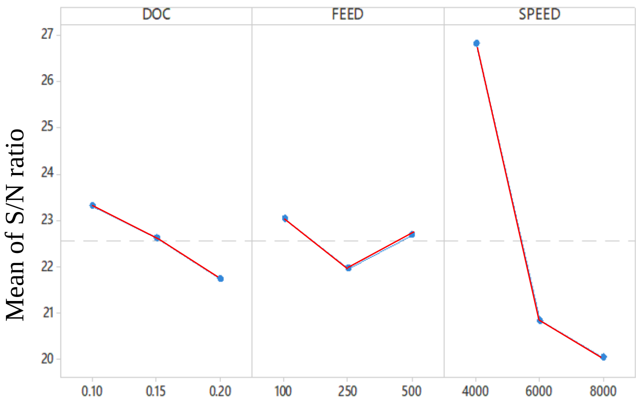

Figure 7: Mean S/N ratio of tolerance of holes

Improvement in S/N ratio for R_a and tolerance of holes is observed at the optimum cutting conditions (d2-f1-s3) when compared to the S/N ratio of initial process parameters d2-f2-s2. The S/N ratio for R_a at the optimum

	Initial process parameters	Optimal process parameters	
		Prediction	Experiment
Level	d2-f2-s2	d2-f1-s3	d2-f1-s3
Surface roughness (µm)	0.59		0.30
S/N ratio (dB)	7.188	11.165	10.45
Improvement in S/N ratio (dB)		45.38 %	
% improvement in R_a		49.15 %	

Table 5 Conformation test results for R_a

	Initial process parameters	Optimal process parameters	
		Prediction	Experiment
Level	d2-f2-s2	d1-f1-s1	d1-f1-s1
Hole tolerance (mm)	0.14		0.040
S/N ratio (dB)	20.292	28.032	27.958
Improvement in S/N ratio (dB)		34.64 %	
% improvement in hole tolerance		71.42 %	

Table 6 Conformation test results for tolerance of holes

cutting conditions is found to be 10.45 as against value at initial process parameters which is 7.188. Percentage improvement in R_a while using optimum cutting conditions when compared to initial process parameters, is found to be 49.15%. Also, for R_a the variation between predicted S/N ratio and S/N ratio obtained after conducting the experiment at optimum conditions, is found to be 6.40% with respect to the predicted value.

The S/N ratio for tolerance of holes at the optimum cutting conditions(d1-f1-s1) is found to be 27.958 as against value at initial conditions which is 20.292. Percentage improvement in hole tolerance while using optimum cutting conditions when compared to initial process parameters is observed to be 71.42%. Also, for the tolerance of holes, the variation between predicted S/N ratio and S/N ratio obtained after conducting the experiment at optimum conditions, is found to be 0.26% with respect to the predicted value.

IV. ANOVA FOR R_a AND TOLERANCE OF HOLES

One of the aims of the experiment conducted is to determine the significant input parameters which affect the R_a and tolerance of holes. ANOVA is most widely used statistical tool which determines the significant input parameters that affect output parameters. Table 3 and Table 4 present the significance of input process parameters on R_a and tolerance of holes, respectively. The rank column shows the significance of an input parameter on the output parameter.

From the Table 3 it is evident that R_a was mostly influenced in the order of feed rate, DOC and speed respectively. Whereas from the Table 4, tolerance of hole was mostly influenced in the order of speed, DOC and feed respectively. From ANOVA analysis it is observed that both R_a and tolerance of holes are affected greatly by DOC which ranks 2 for both the parameters as seen in Table 3 and Table 4 respectively.

V. MODELING

Since predicting the R_a and tolerance holes for different diameters through experiments is practically difficult in nature, need for a reliable mathematical model for predicting R_a and tolerance for holes is required. From literature survey it was noticed that mathematical model developed using regression method is found to be reliable in predicting the output parameters pertaining to machining processes and in particular conventional machining processes.

Hence, in the present study most widely used statistical tool, regression analysis is used to develop a mathematical model for output parameters R_a and tolerance of holes, based on the dependent input parameters DOC, feed and speed.

The predictive equations for R_a and tolerance of holes, based on regression analysis are shown in Eqn. (3) and (4) respectively

$$R_a = 0.98 - 5.47 \times d + 0.00104 \times f - 0.00031 \times s + 0.0033 \times d \times f + 0.00026 \times d \times s \quad (R^2 = 80.25\%) \qquad (3)$$

$$Tolerance = -0.0462 + 0.261 \times d - 0.000129 \times f + 0.000024 \times s + 0.000747 \times d \times f - 0.000061 \times d \times s$$

$$(R^2 = 88.72\%) \qquad (4)$$

The co-efficient of determination (Sivaiah, P., & Chakradhar, D. (2018)) R^2 was used to check the capability of the developed models. The co-efficient of determination value varies from zero to one, closer to one better is the model in predicting the values. In the present study, the developed regression models for R_a and tolerance of holes have R^2 of 80.25% and 88.72% respectively. To validate the developed models, conformation tests were conducted and results are mentioned in Table 7 and Table 8.

For R_a from Table 7 conformation tests for performed for run numbers 2, 4 and 8 and error between predicted model and experimental values are varying from -7.5% to 11%. Similarly, for tolerance of holes mentioned Table 8, the error is varying from -2.17% to -7.86%.

Run	Ra (µm)		Error %
	Experimental	Predicted	
2	0.8	0.74	-7.5
4	0.4	0.37	-7.5
8	0.4	0.44	11

Run	Tolerance of the hole (mm)		Error %
	Experimental	Predicted	
4	0.089	0.082	-7.86
6	0.046	0.045	-2.17
9	0.092	0.088	-4.34

Table 8 Conformation results for the developed models for tolerance of holes

Further to test the modelled equations Eqn. (3) and (4), experiments were conducted for two set of process parameters as mentioned in Table 9. From the table it is observed that variation is less for R_a and slightly more for the tolerance of the holes. Percentage of variation between predicted and experiment values for R_a was found to be 7.5% and 6.67% for first and second set respectively. Whereas for tolerance of hole, percentage of variation was found to be 10% and 5% for first set and second set respectively.

VI. CONCLUSION

Following are the conclusions drawn from the experiments conducted

- The predicted optimum cutting parameters for hole diameter $22^{+0.021}_{+0.00}\ mm$, obtaining the best surface finish i.e least R_a value are d = 0.15 mm, f = 100 mm/min and s = 8000RPM. The optimum conditions are determined using Taguchi method and is represented as d2-f1-s3. The R_a value at these optimum cutting conditions was found to improve by 49.15% compared to d2-f2-s2 values. the predicted optimum cutting parameters for obtaining the best tolerance value for hole i.e least tolerance value are d = 0.1 mm, f = 100 mm/min and s = 4000 RPM. The optimum conditions determined is represented as d1-f1-s1. The tolerance of holes at these optimum conditions was found to improve by 71.42% compared to d2-f2-s2 values.
- ANOVA has shown that R_a was mostly influenced by feed rate, DOC and speed respectively. Whereas tolerance of hole was mostly influenced by speed, DOC and feed respectively.
- Experiment was further conducted for the two set of process parameters viz Set 1: d = 0.15 mm, f = 150 mm/min, s = 2000 RPM and Set 2: d = 0.15 mm, f = 280 mm/min, s = 2200 RPM, to conform the equations modelled using linear regression analysis. It was observed that percentage of variation between predicted and experiment values for R_a was found to be 7.5% and 6.67% for first and second set respectively. Whereas for tolerance of hole, percentage of variation was found to be 10% and 5% for first set and second set respectively.

Diameter of the hole (mm)	Process Parameters from models	Ra (µm)		Tolerance(mm)		% of variation w.r.t predicted	
		Predicted	Experiment	Predicted	Experiment	R_a	Tol
22	d = 0.15, f = 150, s = 2000	0.4	0.43	0.02	0.018	7.5	10
	d = 0.15, f = 280, s = 2200	0.6	0.56	0.02	0.019	6.67	5

Table 9 Conformation results for the developed model for surface roughness of hole

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REFERENCES

[1] Aamir, M., Tolouei-Rad, M., Giasin, K., Vafadar, A., Koklu, U., & Keeble, W. (2021). Evaluation of the surface defects and dimensional tolerances in multi-hole drilling of AA5083, AA6061, and AA2024. Applied Sciences, 11(9), 4285.

[2] Aggarwal, A., Singh, H., Kumar, P., & Singh, M. (2008). Optimizing power consumption for CNC turned parts using response surface methodology and Taguchi's technique—a comparative analysis. Journal of materials processing technology, 200(1-3), 373-384.

[3] Deshpande, A. A., & Rehman, M. A. A. (2022). Surface Roughness Prediction using Empirical Modelling Techniques:-A Review. SAMRIDDHI: A Journal of Physical Sciences, Engineering and Technology, 14(01 SPL), 108-117.

[4] Do Duc, T., Ba, N. N., Van, C. N., Nhu, T. N., & Tien, D. H. (2020). Surface roughness prediction in CNC hole turning of 3X13 steel using support vector machine algorithm, Tribol.

[5] Gutema, E. M., Gopal, M., & Lemu, H. G. (2022). Minimization of surface roughness and temperature during turning of aluminum 6061 using response surface methodology and desirability function analysis. Materials, 15(21), 7638.

[6] Karkalos, N. E., Efkolidis, N., Kyratsis, P., & Markopoulos, A. P. (2019). A comparative study between regression and neural networks for modeling Al6082-T6 alloy drilling. Machines, 7(1), 13.

[7] Sastry, M. N. P., Devi, K. D., & Reddy, K. M. (2012). Analysis and optimization of machining process parameters using design of experiments. Industrial Engineering Letters, 2(9), 23-32.

[8] Sivaiah, P., & Chakradhar, D. (2018). Modeling and optimization of sustainable manufacturing process in machining of 17-4 PH stainless steel. Measurement, 134, 142-152.

[9] Trinh, V. L. (2024). A Review of the Surface Roughness Prediction Methods in Finishing Machining. Engineering, Technology & Applied Science Research, 14(4).

[10] Yahya, E., Ding, G., & Qin, S. (2016). Prediction of cutting force and surface roughness using Taguchi technique for aluminum alloy AA6061. Australian Journal of Mechanical Engineering, 14(3), 151-160.