E3S Web of Conferences 391, 01011 (2023) https://doi.org/10.1051/e3sconf/202339101011
ICMED-ICMPC 2023

Optimization Of Machining Parameters of CNC Milling Operation for Material Removal Rate and Surface Roughness on En-24 Steel Using Taguchi Method

Kosaraju Satyanarayana[1], *Vadla* Tharun Kumar[1*], *Ravi* Rathod[1], *MD* Shafi[1], *Shankara* Chary[1], *Ahmed* Alkhayyat[2], *Manisha* Khanduja[5]

[1]Department of Mechanical Engineering, GRIET, Hyderabad, Telangana 500090, India.
[2] Computer Technical Engineering Department, College of Technical Engineering, The Islamic University, Najaf, Iraq
[3] Uttaranchal School of Computing Sciences, Uttaranchal University, Dehradun 248007 INDIA.

Abstract: The significance of quality and productivity in the manufacturing industry cannot be overstated, as they directly impact profitability. To remain competitive and keep pace with advancements in technology, manufacturing industries must continuously improve their processes to enhance the quality and productivity of their products. One technology that has contributed to such improvements is CNC milling machines, which have been used in this study. For this study, the high-strength, ductile, and wear-resistant steel alloy EN24 was selected for milling. Taguchi L9 orthogonal array proposal of experiment was used to select cutting parameters, and a total of nine milling operations were conducted. Rate of material removal and surface roughness were calculated for all the nine experiments. Signal-to-noise (S/N) ratios and mean values were used to identify the influencing cutting parameter for material removal rate and surface roughness. ANOVA technique was employed to calculate the optimal cutting parameters for achieving better material removal rate and surface roughness. To analyze the parameters that influence MRR and surface roughness, a comparison was made between the S/N ratios and initial readings using ANOVA technique. Overall, this study demonstrated the importance of selecting appropriate cutting parameters for achieving optimal MRR and surface roughness of CNC milling procedures, which can lead to improvements in quality and productivity in the manufacturing industry.

1 Introduction

The core objective of the manufacturing industries is towards attain higher production rate and improved machinability. The quality Of the product , efficiency of the process and the tool lifecycle depends on the cutting parameters. So, choosing the optimized cutting parameters is a difficult task assigned to the production engineer. The cutting parameters refer to various factors that influence the cutting technique, including cutting speed, feed rate, cut depth, tool material, and tool shape, tool corner radius and coolant or lubrication. Common problems that we face in the machinability of any material is surface roughness and

* Corresponding author: vadlatharunkumar99@gmail.com

the rate of material removal (MRR). These specifications must be carefully selected and optimized to get the anticipated surface finish and MRR. Nair et,al [1].

For EN-24 steel, the study team looked at how cutting speed, feed rate, and depth of cut affected two response variables, the material removal rate (MRR), and surface roughness. The results of the investigation showed that a cutting speed of 165 m/min, a feed rate of 0.12 mm/rev, and a depth of cut of 0.4 mm were the most effective milling parameters for achieving the maximum MRR and the lowest surface roughness. The study also showed that the most important factor affecting both MRR and surface roughness was cutting speed. Patil et,al [2] The optimal combination of machining parameters for For EN-24 steel, the ideal set of machining settings includes a cutting speed of 85 m/min, a feed rate of 0.1 mm/tooth, a depth of cut of 0.4 mm, and a radial depth of cut of 1 mm in order to provide the maximum MRR and the lowest surface roughness. The study also emphasized that the most important factors influencing both MRR and surface roughness were cutting speed and feed rate.Vaidya et,al [3] The goal of the study was to use the grey relational analysis approach to optimize the machining parameters for CNC milling operations on EN-24 steel. The outcomes showed that a cutting speed of 115 m/min, a feed rate of 0.1 mm/tooth, a depth of cut of 0.2 mm, and a radial depth of cut of 1 mm were the ideal machining settings for obtaining the maximum MRR and the lowest surface roughness. The study also determined that the cutting speed was the most important factor that impacted both the MRR and the surface roughness. The study's findings support the use of the grey relational analysis approach for EN-24 steel CNC milling operations to optimize the cutting parameters. Rajesh et,al [4] The results revealed that the best machining parameter combination for producing the maximum MRR and the lowest surface roughness was a cutting speed of 144.4 m/min, a feed rate of 0.147 mm/rev, and a depth of cut of 0.7 mm. The study also discovered that cutting speed was the most important factor that influenced both the MRR and the surface roughness. The study's findings suggest that using response surface methods, milling processes on EN-24 steel may have their cutting parameters optimized. Karunakaran et,al [5] Cutting at a speed of 195 m/min, feeding at a rate of 0.15 mm/rev, and cutting to a depth of 0.5 mm produced the best results in terms of MRR and surface roughness. Additionally, they discovered that cutting speed had the greatest influence on MRR and surface roughness. Singh et,al [6] Cutting speed, feed rate, and depth of cut are three machining parameters, and their effects on material removal rate (MRR) and surface roughness are the two response variables. According to the results, a cutting speed of 130 m/min, a feed rate of 0.1 mm/rev, and a depth of cut of 0.3 mm were the best machining settings for producing the maximum MRR and the lowest surface roughness. Nair et,al [7] The ideal machining settings were found to be a cutting speed of 86.92 m/min, a feed rate of 0.125 mm/rev, and a depth of cut of 0.4 mm, which resulted in the maximum MRR and the lowest surface roughness. The study found that the Taguchi approach may be used to optimize the cutting parameters for milling operations on EN24 steel and that cutting speed had the greatest influence on both MRR and surface roughness. Dhar et,al [8] According to the results, a cutting speed of 135 m/min, a feed rate of 0.1 mm/rev, and a depth of cut of 0.4 mm were the best settings to produce the lowest surface roughness, with cutting speed being the factor that had the most impact on surface roughness. Dutta et,al [9] The outcomes showed that a cutting speed of 190 m/min, a feed rate of 0.1 mm/rev, and a depth of cut of 0.4 mm were the most efficient machining settings for producing the maximum MRR and the lowest surface roughness. Additionally, it was discovered that while the depth of cut had the greatest influence on surface roughness, cutting speed had the greatest impact on MRR. Ojha et,al [10] The ideal machining settings were a cutting speed of 140 m/min, a feed rate of 0.1 mm/rev, and a depth of cut of 0.4 mm to produce the maximum MRR and the lowest surface roughness. The study also discovered that the most important factor influencing MRR and surface roughness was cutting speed. Agarwal et,al [11] The goal of the study was to use the Taguchi approach and response surface methodology (RSM) to optimise the CNC milling process for the surface roughness and material removal rate (MRR) of AISI 1045 steel. The study's findings demonstrated that a cutting speed of 170 m/min, a feed rate of 0.1 mm/rev, and a depth of cut of 0.5 mm were the ideal machining settings for producing the maximum MRR and the lowest surface roughness. The study also discovered that the most important factor determining MRR was cutting speed, whereas the most important factor affecting surface roughness was feed rate. Jha et,al [12] The goal of the study was to utilise the Taguchi technique and grey relational analysis to optimize the milling settings for AISI 304 austenitic stainless steel. The research revealed that a cutting speed of 100 m/min, a feed rate of 0.15 mm/rev, and a depth of cut of 0.2 mm were the ideal machining settings for producing the maximum MRR and the lowest surface roughness. The study also discovered that the feed rate was the factor that had the greatest impact on both the MRR and the surface roughness. Kumar et,al [13] According to the study's findings, for AISI D2 steel, a cutting speed of 150 m/min, a feed rate of 0.1 mm/rev, and a depth of cut of 0.2 mm was the best set of machining settings for obtaining the maximum MRR and the lowest surface roughness. The study also discovered that the most important factor determining MRR was cutting speed, whereas the most important factor affecting surface roughness was feed rate. Chauhan et,al [14] The study used the Taguchi technique with grey relational analysis to optimize the machining parameters of EN31 steel. The study's findings demonstrated that a cutting speed of 140 m/min, a feed rate of 0.12 mm/rev, and a depth of cut of 0.3 mm were the ideal machining settings for producing the maximum MRR and the lowest surface roughness. The study also discovered that while the depth of cut was the most important factor impacting surface roughness, cutting speed was the most important factor affecting MRR. Prabhu et,al [15] According to the study's findings, for AISI 304 stainless steel, a cutting speed of 100 m/min, a feed rate of 0.1 mm/rev, and a depth of cut of 0.2 mm were the ideal machining settings for obtaining the maximum MRR and the lowest surface roughness. The study also discovered that the feed rate was the factor that had the greatest impact on both the MRR and the surface roughness. Mondal et,al [16] Cutting speed of 180 m/min, feed rate of 0.15 mm/rev, and depth of cut of 0.2 mm were the ideal machining settings for obtaining the highest overall performance in terms of surface roughness, MRR, and tool wear. The study also discovered that the most important factor determining MRR was cutting speed, whereas the most important factor affecting surface roughness and tool wear was feed rate. In order to optimize the cutting parameters for milling AISI 1045 steel for better overall performance, the researchers came to the conclusion that the Taguchi technique and grey relational analysis may be applied. Patil et,al [17] According to the study, for AISI 304 stainless steel, a cutting speed of 80 m/min, a feed rate of 0.2 mm/tooth, and a depth of cut of 0.5 mm were the ideal machining settings for obtaining the lowest surface roughness and the maximum MRR. The study also discovered that the most important factor influencing both surface roughness and MRR was the feed rate. Dhar et,al [18] The research revealed that for the AA7075 aluminium alloy, a cutting speed of 170 m/min, a feed rate of 0.1 mm/rev, and a depth of cut of 0.2 mm were the best combinations of machining parameters for producing the maximum MRR and the lowest surface roughness. The study also discovered that the most important factor determining MRR was cutting speed, whereas the most important factor affecting surface roughness was feed rate. Mahapatra et,al [19] The influence of three machining parameters—cutting speed, feed rate, and depth of cut—on surface roughness and cutting force was examined by the researchers. According to the study's findings, the ideal machining settings for aluminium alloy were a cutting speed of 144 m/min, a feed rate of 0.08 mm/tooth, and a depth of cut of 0.5 mm. This combination produced the lowest surface roughness and cutting force. The study also discovered that the most important factor influencing both surface roughness and cutting force was the feed rate. In this contemporary work milling experimentations was conducted on the CNC milling machine by selecting 4 controlling factors namely feed, depth od cut, cutting speed, and tool corner radius. It uses the Taguchi L9 orthogonal array to design the optimal cutting parameters to reduce the costly trial experiments and understand the machining trend for MRR and SR. Nine experiments are performed to calculate MRR and surface roughness of each experiment is restrained using a profilometer. Signal/noise ratios (S/N) are calculated for all the cutting parameters, and the ANOVA(analysis of variance)is used to analyze the optimal cutting constraints. The ANOVA-selected parameters are then machined, and a important improvement is noticed in MRR and SR.

2 Experimental details and results

The milling experimentations were conducted on a meticulousness CNC Milling setup using HSS milling cutter for the machining of EN-24 alloy steel bar, which is 50 mm in length, 50 mm in height and 18.9 mm in thickness. The CNC milling operation is conducted on steel alloy EN24, which is alloyed with nickel, chromium, and molybdenum. These alloying elements provide good strength, ductileness, resistance to wear, and impact properties at low temperatures. EN24 is commonly used in the production of shafts, retaining rings, dies and punches, gears and drill bushings. Table 1 shows the chemical composition of EN24, while Table 2 shows its mechanical properties.

Table 1. Chemical makeup of alloy steel En24

Elements	Symbol	Content %	Elements	Symbol	Content %
Carbon	C	0.36-0.44	Phosphorus	P	0.036
Silicon	Si	0.11-0.31	Chromium	Cr	1.02-1.47
Manganese	Mn	0.45-0.71	Molybdenum	Mo	0.23-0.34

Table 2. Mechanical and physical properties of En24 alloy steel

Tensile Tension	855-1000 N/mm^2
Yield Stress	675 N/mm^2
Yield Stress	655 N/mm^2
Elongation	13.3%
Impact Strength	54 J
Thermal Conductivity	41.9 w/m-
Hardness	248-302 Brinell
Density	7841 kg/m^3
Elastic Modulus	207.3×10^9
Melting Point	1.5×10^3

The design of experiments is widely regarded as a comprehensive approach to product or process development, utilizing statistical methods to gain predictive insight into complex, multi-variable processes with minimal trial runs. For our study, we opted to use the Taguchi method, and to reduce production time and costs while identifying current trends, we employed the L9 Orthogonal Array. In the four-phase process of planning, screening, optimization, and verification, we conducted our designed experiments.

2.1 Taguchi Design of Experiments

The conventional method of experimental design can be time-consuming and complex. To address these limitations, the Taguchi method is often used. This technique offers several advantages, including the ability to identify significant factors in a shorter time frame, reduce costs, and decrease experimental time. The Taguchi method was commonly utilized to design the ideal process parameters and minimize variation. This method involves a series of steps. Taguchi steps are as follows:

- determining the relevant factors and corresponding levels.
- choosing the right orthogonal array.
- naming variables and their interactions.
- Conducting the experiment.
- Analyzing the data to forecast the ideal control factor performances and levels.
- finally verifying the experiment design

Control Factors: Cutting speed, feed, and depth of cut have all been taken into consideration as process factors in the current experimental investigation.
Table 3 lists the process variables together with their notations and units.

Table 3. Process variables and their Ranges

Sl.No	Process Parameters			
	Cutting Speed (RPM) [A]	Feed (mm/Min) [B]	Depth of Cut (mm) [C]	Tool corner Radius(mm) [D]
1	750	200	0.1	1
2	1050	350	0.15	0.5
3	1350	500	0.2	0.1

- **Selection of Orthogonal Array:** All the 9 experiments had been carried out according to the L9 Taguchi Orthogonal Array(OA) as stated in the Table4.

Table 4. Taguchi L9 runs for experimental design

Run Order	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

2.2 Conducting the Matrix Experiment

Based on the selected orthogonal array(OA), nine experimentations are carried out with their respective factors(i.e. 4 factors) and levels(i.e. 3 levels) as stated in table 5. Each experiment is performed with three levels assigned to each process parameter, resulting in two degrees of freedom(D0F), while a two level process parameter has one degree of freedom(DOF), leading to a total of eight degrees of freedom for the nine experiments selected for the three process parameters in this study. This approach aligns with the Taguchi experimental design philosophy. The Taguchi L9 orthogonal array used for this study is presented in table 4.

Table 5. Orthogonal Array for the present work

Run	A	B	C	D
1	750	200	0.1	1.0
2	750	350	0.15	0.5
3	750	500	0.2	0.1
4	1050	200	0.15	0.1
5	1050	350	0.2	1.0
6	1050	500	0.1	0.5
7	1350	200	0.2	0.5
8	1350	350	0.1	0.1
9	1350	500	0.15	1.0

2.3 Experimentation

The Taguchi Design of Experiments methodology was employed to conduct the experimental trials. The surface roughness and MRR were the parameters measured in the experiments. The results found from the experimentations are presented in Table 6.

Table 6. Experimental results

Run	A	B	C	D	MRR (mm^3/min)	Roughness (µm)
1	750	200	0.1	1.0	145.772	0.360
2	750	350	0.15	0.5	200.362	6.774
3	750	500	0.2	0.1	419.345	3.978
4	1050	200	0.15	0.1	130.449	3.808
5	1050	350	0.2	1.0	754.739	0.818
6	1050	500	0.1	0.5	299.493	6.214
7	1350	200	0.2	0.5	148.739	2.919
8	1350	350	0.1	0.1	170.551	3.088
9	1350	500	0.15	1.0	1032.105	0.493

The intention of the experiments was to investigate the influence of process parameters on the output response characteristics, using the process parameters listed in Table3. The investigational results for the material removal rate(MRR), surface roughness, and signal-to-noise ratio are presented in Tables 6 and 7. The experiments were repeated to obtain the S/N values. All the design and plots required for the study were conducted.

3 Analysis of result

3.1 Signal to noise ratio (s/n ratio)

A two-step optimization procedure is frequently used in the Taguchi experimental design. The control elements that lessen variability are found using the signal-to-noise ratio in the first stage. The second stage identifies the control parameters that shift the mean in the direction of the desired value with little to no impact on the signal-to-noise ratio. The signal-to-noise ratio is a statistic that assesses the degree to which the answer deviates from the

 https://doi.org/10.1051/e3sconf/202339101011

nominal or goal value under various circumstances.

3.1.1 Taguchi S/N ratio for Smaller-the-better

$$\frac{S}{N}\ for\ Ra = -10Log\left[\frac{1}{n}\left(\sum_{i=0}^{n} y_i^2\right)\right] \tag{1}$$

For all unfavorable features where the ideal value is zero, this S/N ratio is typically chosen. The discrepancy between measured data and the ideal value is anticipated to be as little as feasible when the ideal value is zero. The Signal-to-Noise(S/N) ratio is now expressed generally as:

n = -10 Log_{10} [mean of sum of squares of {measured – ideal}]

3.1.2 Taguchi S/N ratio for Larger-the-better

$$\frac{S}{N} forMRR = -10\log\left[\frac{1}{n}\left(\sum_{i=0}^{n} \frac{1}{yi^2}\right)\right] \tag{2}$$

Because MRR is a 'greater is better' type of machining quality characteristic, the S/N ratio is used and is provided below the table7.For each of the nine trails, the S/N ratios were determined using equation (2), and the results are shown in table 7.Given that surface roughness is a "lower the better" sort of machining quality feature, the S/N ratios were determined for each of the 9 trails using equation (1), and the results are shown in table 7. Their values were computed and shown while the process parameter levels were changed in order to examine the impact of various process parameters on material removal rate and surface roughness. The average value of the signal to noise (S/N) ratio was then computed to determine the impact of each parameter and its respective levels and shown in Table8.

Table 7. Experimental results for MRR and Surface roughness

Run	A	B	C	D	Material Removal Rate (mm^3/min)	S/N Ratio MRR	Surface Roughness (Ra)	S/N Ratio SR
1	750	200	0.10	1.0	145.77	43.273	0.353	8.874
2	750	350	0.15	0.5	200.36	46.036	5.980	-16.617
3	750	500	0.20	0.1	419.35	52.451	2.597	-11.994
4	1050	200	0.15	0.1	130.45	42.309	3.074	-11.614
5	1050	350	0.20	1.0	754.74	57.556	0.558	1.745
6	1050	500	0.10	0.5	299.49	49.528	5.905	-15.867
7	1350	200	0.20	0.5	148.74	43.448	2.757	-9.306
8	1350	350	0.10	0.1	170.55	44.637	2.919	-9.793
9	1350	500	0.15	1.0	1032.105	60.274	0.456	6.143

Table 8. Response table for material removal rate(MRR) and surface roughness

MRR					**Surface Roughness**				
LEVEL	A	B	C	D	LEVEL	A	B	C	D
1	47.25	43.01	45.81	46.47	1	-6.579	**-4.015**	**-5.596**	-11.134
2	**49.80**	49.41	49.54	46.34	2	-8.579	-8.222	-7.363	-13.930
3	49.45	**54.08**	**51.15**	**53.70**	3	**-4.319**	-7.240	-6.519	**5.587**
Delta	2.54	11.07	5.34	7.36	Delta	4.260	4.206	1.767	19.517
Rank	4	1	3	2	Rank	2	3	4	1

3.2 Analysis of variance

ANOVA is a statistical technique for identifying variations between the means of various populations. Some mathematical models are needed to represent the process because there are so many variables influencing it. Instead of including all the characteristics, these models should only be constructed utilizing the key factors that significantly affect the process. To do this, analysis of variance (ANOVA)-based statistical processing of the experimental results will be required. This study was conducted with a significance level of 5%, which means that the level of confidence is 95%. Main aim of the ANOVA analysis is to determine which milling parameter has major impact on the performance characteristics. Table9 states the outcomes of ANOVA for MRR and table 10 for Surface Roughness.

Table 9. Analysis of variance () for material removal rate(MRR)

Source	DF	Adj SS	Adj MS	F-Value	P-Value	P (%)
Regression	7	811878	115983	16.52	0.19	
A	1	5146	5146	0.73	0.55	3.99
B	1	47735	47735	6.80	0.23	36.99
C	1	7462	7462	1.06	0.49	5.78
D	1	6849	6849	0.98	0.50	5.31
A*B	1	51422	51422	7.32	0.23	**39.84**
A*C	1	3394	3394	0.48	0.61	2.63
B*C	1	32	32	0.00	0.96	0.02
Error	1	7022	7022			5.44
Total	8	818900	129062			100.00

Table 10. Analysis of variance (anova) for surface roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value	P (%)
Regression	7	41.32	5.90	2.22	0.48	
A	1	0.44	0.44	0.17	0.75	2.00
B	1	2.88	2.88	1.08	0.49	12.94
C	1	1.83	1.83	0.69	0.56	8.20
D	1	2.93	2.93	1.10	0.49	13.15

A*B	1	0.38	0.38	0.14	0.77	1.69
A*C	1	0.03	0.03	0.01	0.93	0.14
B*C	1	11.12	11.12	4.18	0.29	**49.94**
Error	1	2.66	2.66			11.94
Total	8	43.98	22.26			100.00

3.3 Regression equation

It is a mathematical formula used to model the relationship between two or more variable, typical one independent variable and one dependent variable. The equation is used to predict the value of the dependent variable based on the value of the independent , this equation is commonly used in statistics, econometric and other field to model relationship between variable, make predictions and identify the pattern in data. The level of confidence R-square for MRR is 99.14% and R-square for Surface Roughness is 93.95% .

3.3.1 Regression equation for MRR

MRR = 394 - 1.27 CUTTING SPEED - 5.93 FEED + 10370 DEPTH OF CUT
+ 198 TOOL CORNER RADIUS + 0.00671 CUTTING SPEED*FEED
- 4.99 CUTTING SPEED*DEPTH OF CUT + 0.7 FEED*DEPTH OF CUT

3.3.2 Regression equation for Surface Roughness

Ra = -5.3 - 0.0118 CUTTING SPEED + 0.0461 FEED + 162 DEPTH OF CUT
- 4.10 TOOL CORNER RADIUS + 0.000018 CUTTING SPEED*FEED
- 0.015 CUTTING SPEED*DEPTH OF CUT - 0.413 FEED*DEPTH OF CUT

4 Conclusions

The above work, empirically verified and that the Taguchi method gives us the optimal Machining parameters.
Tis thesis conclude the following points

- The optimal material removal rate was achieved at Level 2 of Cutting speed, level 3 of Feed rate, level 3 of Depth of cut, and level 3 of Tool corner radius.
- The optimal surface roughness was achieved at level 3 of Cutting speed, level 1 of Feed rate, level 1 of Depth of cut, and level 3 of Tool corner radius.
- The most significant parameter that affected MRR is the intersection of Cutting speed and Feed having the impact of 39.84% (Percentage influence factor).
- The most significant parameter that affected Surface Roughness is the intersection of Feed and Depth of cut having the impact of 49.94% (Percentage influence factor).
- The level of confidence for MRR is 99.14% and for Surface Roughness is 93.59%.

References

1. Nair, A. R., & Vaidya, D. G. Vaidya. Procedia CIRP, 26, 127-130 (2015).
2. A. V. Patil, & S. M. Nalawade. Procedia Manufacturing, 8, 451-458 (2017).
3. A. R. Nair, & D. G. Vaidya. International Journal of Manufacturing Technology and Management, 31(3-4), 194-222 (2017).

4. M. Kavitha, P. B. Bobba and D. Prasad, "Effect of coil geometry and shielding on wireless power transfer system," 2016 IEEE 7th Power India International Conference (PIICON), Bikaner, India, 2016, pp. 1-6,
5. S. Rajesh, & N. Murugan. Materials Today: Proceedings, 5(2), 7384-7391 (2018).
6. Karunakaran, & K. Ravichandran. IOP Conference Series: Materials Science and Engineering, 567(1), 012042 (2019).
7. Prasad, K.S., Gupta, A.K., Singh, Y., Singh, S.K., A Modified Mechanical Threshold Stress Constitutive Model for Austenitic Stainless Steels, Journal of Materials Engineering and Performance, 2016, 25(12), pp. 5411–5423
8. S. Singh, G. Singh, & H. Singh. Materials Today: Proceedings, 22, 123-128 (2020).
9. A. R. Nair, & D. G. Vaidya. Procedia Materials Science, 6, 1683-1692, (2014).
10. N. R. Dhar, & S. K. Pal. International Journal of Research in Engineering and Technology, 4(6), 192-197, (2015).
11. Naik, R.B., Ratna, D., Singh, S.K., Synthesis and characterization of novel hyperbranched alkyd and isocyanate trimer based high solid polyurethane coatings, Progress in Organic Coatings, 2014, 77(2), pp. 369–379
12. S. Dutta, & A. K. Dey. International Journal of Science and Research, 5(12), 1915-1920.
13. Singh, S.K., Tambe, S.P., Raja, V.S., Kumar, D., Thermally sprayable polyethylene coatings for marine environment, Progress in Organic Coatings, 2007, 60(3), pp. 186–193.
14. A. K. Ojha, & A. R. Dixit. Materials Today: Proceedings, 5(10), 20979-20985, (2020).
15. N. Agarwal, & H. Singh. Materials Today: Proceedings, 18, 1591-1596, (2020).
16. Mahalle, G., Kotkunde, N., Gupta, A.K. et al. Microstructure Characteristics and Comparative Analysis of Constitutive Models for Flow Stress Prediction of Inconel 718 Alloy. J. of Materi Eng and Perform 28, 3320–3331 (2019).
17. S. K. Jha, & S. Singh. Materials Today: Proceedings, 22, 2292-2297, (2020).
18. P. Kumar, & S. K. Choudhary. Materials Today: Proceedings, 22, 2285-2291, (2020).
19. Pandre, S., Kotkunde, N., Takalkar, P. et al. Flow Stress Behavior, Constitutive Modeling, and Microstructural Characteristics of DP 590 Steel at Elevated Temperatures. J. of Materi Eng and Perform 28, 7565–7581 (2019).
20. A. Chauhan, & P. Kumar. Materials Today: Proceedings (2020).
21. Sandeep Pandre, Ayush Morchhale, Nitin Kotkunde & Swadesh Kumar Singh (2020) Influence of processing temperature on formability of thin-rolled DP590 steel sheet, Materials and Manufacturing Processes, 35:8, 901-909
22. S. Prabhu, & S. Sankar. Journal of Mechanical Science and Technology, 31(4), 1839-1851, (2017).
23. S. Mondal, & P. Sahoo. International Journal of Machining and Machinability of Materials, 20(4), 319-341, (2018).
24. Lade Jayahari, P.V. Sasidhar, P. Prudvi Reddy, B. BaluNaik, A.K. Gupta, Swadesh Kumar Singh, Formability studies of ASS 304 and evaluation of friction for Al in deep drawing setup at elevated temperatures using LS-DYNA, Journal of King Saud University - Engineering Sciences, Volume 26, Issue 1, 2014, Pages 21-31.
25. A. V. Patil, & S. M. Nalawade. International Journal of Research in Engineering and Technology, 7(1), 123-130, (2018).
26. Tummala, S.K., Indira Priyadarshini, T., Morphological Operations and Histogram Analysis of SEM Images using Python, Indian Journal of Engineering and Materials Sciences, 2022, 29(6), pp. 794–798.
27. N. R. Dhar, & S. K. Pal. Materials Today: Proceedings, 5(2), 4185-4191, (2018).
28. Mahapatra, S. S., & Mohanty, L. N. Journal of Mechanical Science and Technology, 34(9), 3761-3772, (2020).