MULTI OBJECTIVE OPTIMIZATION OF CNC MILLING PROCESS PARAMETERS FOR ELECTRICAL ENERGY CONSUMPTION AND PART QUALITY FOR SUSTAINABLE MANUFACTURING

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Abstract
Computer Numerical Control (CNC) machining is a widely adopted method in mechanical manufacturing systems today. Appropriate selection of process parameters can lead to substantial reduction in energy consumed for manufacturing and improved mechanical properties, ultimately facilitating production of energy-efficient, high-quality products. The aim of this paper is to study the impact of CNC machining process parameters on Aluminium alloy Al 6061, with a specific emphasis on energy consumption, microhardness, and surface roughness. Taguchi L27 Orthogonal array is employed to conduct experimental runs. Regression models for energy consumption, surface roughness, and microhardness are developed, and the relationship between cutting parameters and output responses are evaluated using analysis of variance (ANOVA). Multi objective particle swarm optimization (MOPSO) is used to find the pareto optimal solution set. Samples are manufactured using the optimized parameters in CNC to validate the algorithms.

Keywords : Computer Numerical Control, Energy consumption, L27 Orthogonal array, Analysis of Variance, Multi objective particle swarm optimization.

1. Introduction
Global industrialisation and population growth resulted in a substantial rise in worldwide demand for energy. By 2040, energy consumption is expected to surge by approximately 50.8% over present levels. As the need for energy rises, there is growing apprehension regarding carbon footprint of resources employed in the generation of energy and its accessibility [1]. The manufacturing industry has emerged as a primary contributor to global warming, owing to exhaustive energy usage and substantial carbon footprint associated with its processes [2]. Research findings suggest that 85% of the environmental impact associated with machining can be attributed to its electrical energy consumption [3]. Due to growing operational costs and environmental concerns, minimizing energy consumption in machining presents a substantial opportunity for achieving economic and environmental benefits [4]. The energy consumed in machining process is utilised for driving the cutting tool and aiding material removal [5]. Machine tool makers are increasingly developing energy-efficient motors and auxiliary systems. Nevertheless, analysing and reducing energy usage for material removal is equally critical in lowering average electrical consumption of machine tools [6].
Cutting parameter selection has significant effect on machining quality and energy consumption [7]. Various multi objective optimisation methods have been used in recent decades to examine the impact of cutting parameters on energy consumed for machining and part surface roughness [8]. Yan et al. [9] demonstrated a multi objective optimisation method using Response Surface Methodology and grey relational analysis. Minimization of energy consumption and surface roughness was the objective of this study. Lorenzini et al. [10] studied to minimise the energy consumed in milling operation

employing Response Surface Methodology with speed, feed, depth of cut as process parameters. Bhushan et al. [11] used desirability study for optimisation of parameters to attain minimal energy usage along with longest tool life. But surface finish wasn't considered a possible optimisation goal for research during this work. Mobin et al. [12] devised an adaptive optimisation algorithm using MOPSO and genetic algorithm to optimize parameters for machine scheduling. However, the algorithm was more complex and required betterment in feasibility. Bagaber and Yuso [13] used Response Surface Methodology for conducting turning tests on 316 stainless steel and multi-objective optimisation for energy usage, tool wear, and surface finish. According to the findings, there was an improvement of 14.94%, 13.98%, and 4.71% of the performance characteristics. Kant et al. [14] developed a multi-objective forecasting framework to optimise surface finish and energy usage. Grey relational analysis and Response Surface Methodology were applied for optimization and found the significant influencing factor to be feed rate. Shuo Yu et al. [15] devised a multi-objective forecast model to optimise energy usage and surface finish and the findings reveal forecast quality to be 97.5% accurate. However, research on multi-objective optimization is mostly limited to two objectives. Therefore, this work aims to perform muti-objective optimization of CNC milling process parameters to optimize three objectives i.e., energy consumption, surface roughness and microhardness. Taguchi method, ANOVA and MOPSO Matlab code is used to do the multi-objective optimization.

2. Experiment

This work is carried out on a CNC milling machine with Aluminium alloy Al6061 as workpiece. The process parameters chosen for CNC milling are speed, feed, Depth of cut and Tool diameter as shown in Table 1. Three levels are chosen for each process parameter i.e., Level 1, Level 2, and Level 3. Experiments are conducted according to Taguchi L27 orthogonal array.

Table 1: Parameters/Levels for Design of Experiments

Parameters/Levels	Units	Level 1	Level 2	Level 3
Speed	rpm	1500	2000	2500
Feed	mm/min	1000	1500	2000
Depth of cut	mm	0.1	0.15	0.2
Tool diameter	mm	6	8	10

The experimental setup showing the workpiece and 27 cuboid samples machined from Al 6061cylindrical rods of Ø14 are shown in Figure 1. The experimental data related to performance characteristics chosen viz. energy consumption, micro hardness, and surface roughness after conducting the experimental runs are tabulated in Table 2.

Figure 1: a) Al 6061 cylindrical rod b) Machined cuboid samples

Table 2: experimental data of input and output parameters

S.No	Speed (rpm)	Feed (mm/min)	Depth of cut (mm)	Tool diameter (mm)	Energy consumption (MJ)	Surface roughness (µm)	Micro Hardness (HV)
1	1500	1000	0.1	6	0.365814	0.9566	121.1
2	1500	1000	0.15	8	0.27315	1.0066	123
3	1500	1000	0.2	10	0.235544	1.0766	125.1
4	1500	1500	0.1	8	0.359208	0.73	119.5
5	1500	1500	0.15	10	0.30419	0.756	129.6
6	1500	1500	0.2	6	0.249118	1.37	126.7
7	1500	2000	0.1	10	0.284752	0.853	126.5
8	1500	2000	0.15	6	0.252037	1.3433	134.2
9	1500	2000	0.2	8	0.313629	1.1166	127.8
10	2000	1000	0.1	6	0.398168	1.216	125.4
11	2000	1000	0.15	8	0.373743	1.0366	128.8
12	2000	1000	0.2	10	0.350491	0.71	125.8
13	2000	1500	0.1	8	0.295286	1.27	127.3
14	2000	1500	0.15	10	0.24091	0.6166	123.9
15	2000	1500	0.2	6	0.173113	1.1133	123.2
16	2000	2000	0.1	10	0.31727	0.773	129.3
17	2000	2000	0.15	6	0.197397	1.126	132.2
18	2000	2000	0.2	8	0.188092	1.0533	133.2
19	2500	1000	0.1	6	0.410503	0.6833	125.2
20	2500	1000	0.15	8	0.338782	0.576	123.8
21	2500	1000	0.2	10	0.29966	0.7233	126.3
22	2500	1500	0.1	8	0.350891	0.7066	124.3
23	2500	1500	0.15	10	0.296899	0.8533	127.3
24	2500	1500	0.2	6	0.184334	1.3333	129.5
25	2500	2000	0.1	10	0.31827	0.9166	126
26	2500	2000	0.15	6	0.248226	1.0633	124.5
27	2500	2000	0.2	8	0.206044	0.776	118.1

The energy consumption for the machined cuboid samples is calculated by connecting a three phase EVL-3 energy meter to the CNC milling machine as shown in Figure 2. The energy consumed for every sec is logged to a pen drive connected to the energy meter. The power profile generated by this data is used for calculating the energy consumed for machining each sample. The power profile generated by the three-phase energy meter EVL-3 for Sample 14 is shown in Figure 3. Power profile gives the average power consumed for each sample. The energy consumed for each sample can be calculated using the equation 1.

Energy consumption = Average power consumed X time taken for machining……… (1)

= 0.434526 KW X 0.154 hr

= 0.066917 KWh

= 0.2409 MJ

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Figure 2: EVL-3 energy meter connected to the CNC milling machine

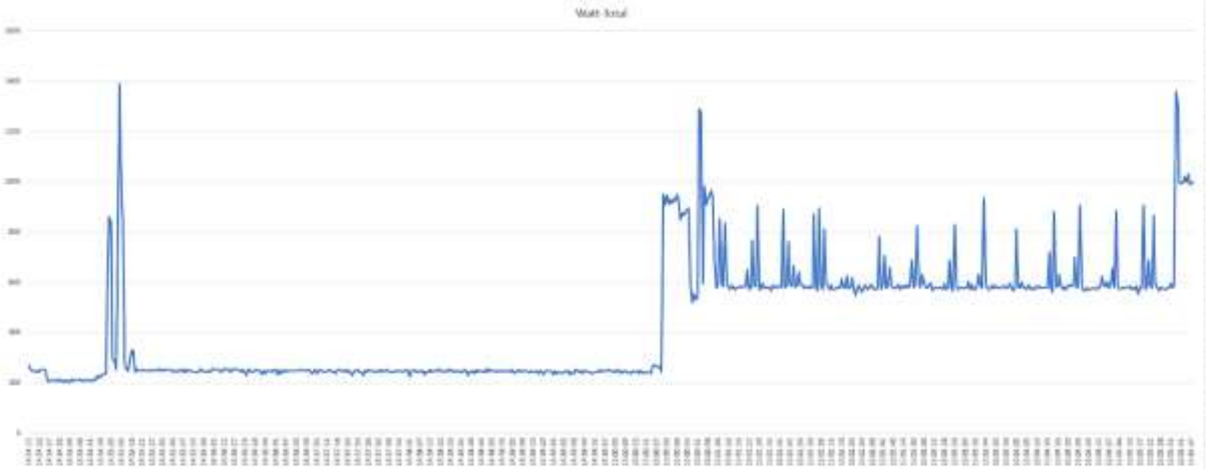

Figure 3: Power profile of Sample 14

Surface roughness is measured using Mitutoyo Surftester as shown in Figure 4. Three values of surface roughness are measured on the side faces and the average value is tabulated.

Figure 4: Mitutoyo surftester

Microhardness is tested using the Tinius Olsen FH-006 tester as shown in Figure 5. Three values of Vicker microhardness are measured with the application of a load of 500g for a duration of 15 sec on the side faces and the average value is tabulated.

Figure 5: Tinius Olsen FH-006 Microhardness tester

3. Design of Experiments

The experimental values of outcomes are transformed into S/N ratio. Microhardness to be maximized is called ‘higher the better’ and SR and EC to be minimized are called ‘lower the better’ attributes. Equations (2) and (3) are used to calculate the 'higher the better' and 'lower the better' attributes.

$$\eta_{ij} = -10\ \log(1/n\textstyle\sum_{j=1}^{n} 1/y_{ij}^{2})\ \ldots\ldots\ldots\ldots\ldots\ (2)$$

$$\eta_{ij} = -10\ \log(1/n\textstyle\sum_{j=1}^{n} y_{ij}^{2})\ \ldots\ldots\ldots\ldots\ldots\ldots\ (3)$$

Where y_{ij} is the i_{th} experiment at the j_{th} test, η is the total number of the tests.

4. Results and Discussion

4.1 Taguchi and ANOVA analysis of Energy Consumption

Signal to Noise ratios of energy consumption for the three levels of process parameters i.e., Speed, Feed, Depth of cut and Tool diameter is calculated using Minitab 19 statistical software and are presented in Table 3. According to Table 3, the ranking of the parameters according to their effect on energy consumption is Depth of cut, Feed, Speed, Tool Diameter.

Table 3: S/N ratios of energy consumption

Level	**S**	**F**	**DOC**	**TD**
1	10.758	9.536	9.320	10.715
2	11.380	11.536	11.182	10.947
3	10.856	11.922	12.492	11.332
Delta	0.622	2.386	3.173	0.617
Rank	3	2	1	4

The main effects plot for S/N ratios of energy consumption is presented in Figure 6.

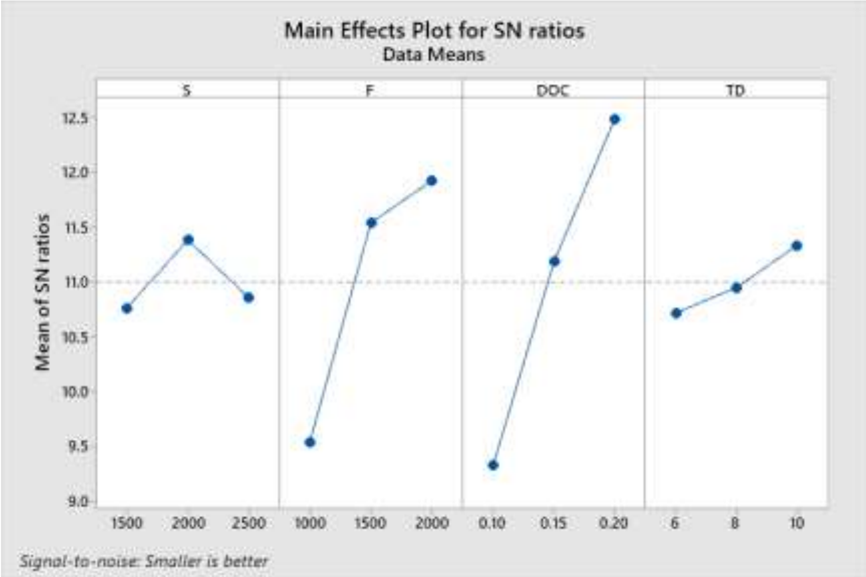

Figure 6: main effects plot for S/N ratios of energy consumption

ANOVA of energy consumption is studied considering its variation with respect to speed, feed, depth of cut, tool diameter and the interaction effects of all the process parameters as shown in Table 4. The other interaction effects are not considered as their effect was negligible.

Table 4: ANOVA of energy consumption

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
S	2	0.000928	0.79%	0.000928	0.000464	0.40	0.685
F	2	0.032792	27.94%	0.032792	0.016396	14.22	**0.005**
DOC	2	0.046167	39.33%	0.046167	0.023083	20.02	**0.002**
TD	2	0.001269	1.08%	0.001269	0.000634	0.55	0.603
S*F	4	0.020500	17.47%	0.020500	0.005125	4.44	0.052
S*DOC	4	0.003268	2.78%	0.003268	0.000817	0.71	0.615
S*TD	4	0.005529	4.71%	0.005529	0.001382	1.20	0.401
Error	6	0.006918	5.89%	0.006918	0.001153		
Total	26	0.117370	100.00%				

R2 = 94.11 %, R2 (adj) = 90 %

Where DF-Degrees of freedom; Seq SS-Sequential sum of squares; Adj SS-Adjusted sum of squares; Adj MS- Adjusted means squares

The effect of process parameters on energy consumption can be seen from the Table 4. It can be observed that depth of cut, and feed have high significant effect on the energy consumption as their P-value is less than 0.05. The interaction effect of speed and feed is significant as its % contribution to the energy consumption is 17.47% as shown in Table 4. The main effects plot of S/N ratios in Figure 6 shows that energy consumption increases with the increase in depth of cut and feed as more energy is required to remove more material per pass during machining. Similarly, the energy consumption increases with the increase in the distance the cutting tool travels during one spindle rotation. Consequently, more material is removed. Speed and tool diameter are not significant. Tool diameter is less significant because increase or decrease in tool diameter will not affect the energy consumption.

4.2 Taguchi and ANOVA analysis of Surface Roughness

Signal to Noise ratios of Surface Roughness for the three levels of process parameters i.e., Speed, Feed, Depth of cut and Tool diameter are given in Table 5. According to Table 5, the ranking of the process parameters is speed, Tool diameter, Feed and Depth of cut.

Table 5: S/N ratios of surface roughness

Level	S	F	DOC	TD
1	-0.00273	1.28490	1.11581	1.61217
2	0.32335	0.61292	0.92248	0.33386
3	1.69277	0.11558	-0.02490	0.06736
Delta	1.69550	1.16931	1.14071	1.54481
Rank	1	3	4	2

The main effects plot for S/N ratios of surface roughness is shown in Figure 7.

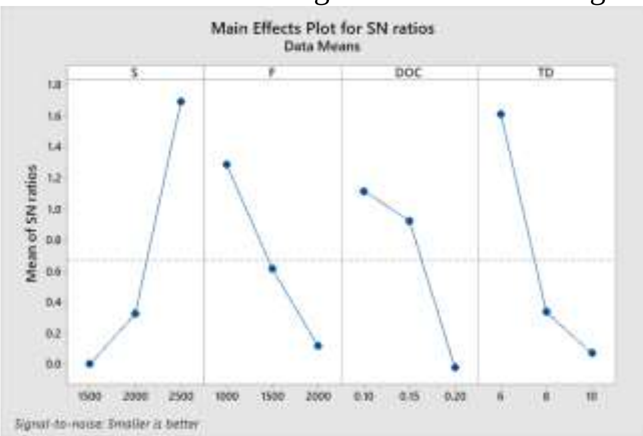

Figure 7: main effects plot for S/N ratios of surface roughness

ANOVA of surface roughness is studied considering its variation with respect to speed, feed, depth of cut, tool diameter and the interaction effects of all the process parameters as shown in Table 6. The interaction effects which are significant are considered for ANOVA analysis as indicated in Table 6.

Table 6: ANOVA of surface roughness

t	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
S	2	0.15628	10.82%	0.15628	0.07814	5.55	**0.043**
F	2	0.06412	4.44%	0.06412	0.03206	2.28	0.184
DOC	2	0.08287	5.74%	0.08287	0.04143	2.95	0.128
TD	2	0.10132	7.02%	0.10132	0.05066	3.60	0.094
S*F	4	0.13220	9.15%	0.13220	0.03305	2.35	0.168
S*DOC	4	0.18275	12.65%	0.18275	0.04569	3.25	0.096
S*TD	4	0.64040	44.34%	0.64040	0.16010	11.38	**0.006**
Error	6	0.08440	5.84%	0.08440	0.01407		
Total	26	1.44434	100.00%				

R2 = 94.16 %, R^2 (adj) = 91 %

Where DF-Degrees of freedom; Seq SS-Sequential sum of squares; Adj SS-Adjusted sum of squares; Adj MS- Adjusted means squares

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The effect of process parameters on the surface roughness can be seen from the Table 6. Table 6 indicates that the interaction effect of speed and tool diameter on surface roughness is significantly high as the P-value is less than 0.05. Increasing the cutting speed improves surface finish, especially when using smaller tool diameters. However, with larger tool diameters, the effect of cutting speed on surface roughness might not be the same. The effect of speed on surface roughness is significant as the % contribution is 10.82 % with a P-value of 0.043.

4.3 Taguchi and ANOVA analysis of Microhardness

Signal to Noise ratios of Microhardness for the three levels of process parameters i.e., Speed, Feed, Depth of cut and Tool diameter are given in Table 7.

Table 7: S/N ratios of Microhardness

Level	S	F	DOC	TD
1	42.00	41.93	41.93	41.95
2	42.12	41.98	42.10	41.98
3	41.94	42.14	42.02	42.12
Delta	0.18	0.20	0.17	0.18
Rank	2	1	4	3

The main effects plot for S/N ratios of Microhardness is shown in Figure 8.

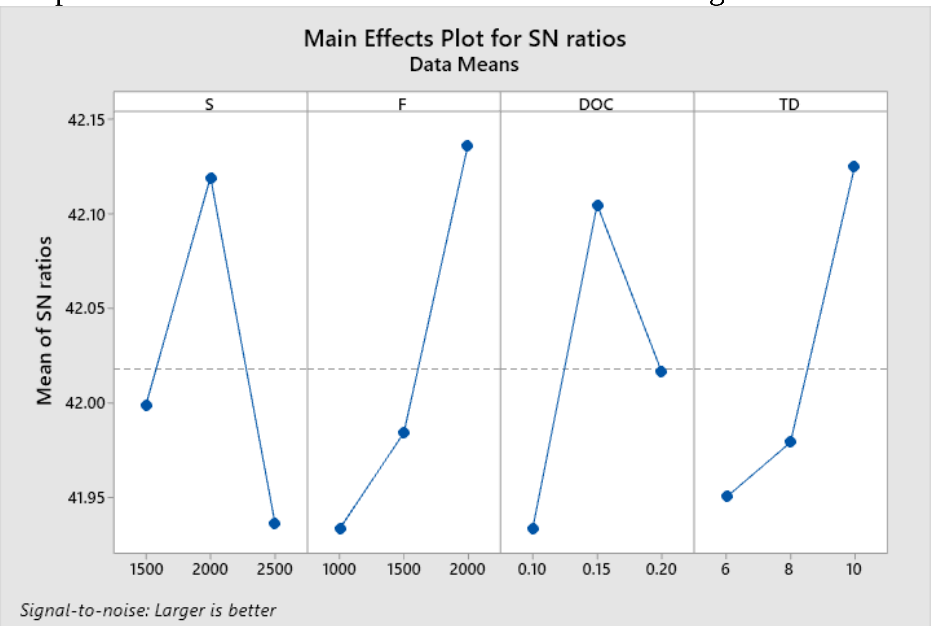

Figure 8: main effects plot for S/N ratios of Microhardness

ANOVA of Microhardness is studied considering its variation with respect to speed, feed, depth of cut, tool diameter and the interaction effects of all the process parameters as shown in Table 8. The interaction effects which are significant are also considered for ANOVA analysis as indicated in Table 8.

Table 8: ANOVA of Microhardness

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
S	2	33.20	8.99%	33.20	16.600	5.94	0.038
F	2	44.88	12.15%	44.88	22.440	8.03	**0.020**
DOC	2	28.63	7.75%	28.63	14.316	5.12	0.050
TD	2	32.57	8.82%	32.57	16.287	5.82	0.039

S*F	4	118.64	32.11%	118.64	29.659	10.61	**0.007**
S*DOC	4	39.97	10.82%	39.97	9.991	3.57	0.080
S*TD	4	54.83	14.84%	54.83	13.708	4.90	**0.042**
Error	6	16.78	4.54%	16.78	2.796		
Total	26	369.50	100.00%				

R2 = 95.46%, R2 (adj) = 91.1%

The effect of process parameters on Microhardness can be seen from the Table 8. The interaction effect of speed and feed on Microhardness is significantly high as the contribution is 32.11%. The interaction effect of speed and tool diameter is also significant with a contribution of 14.84%. Feed rate also has significant contribution as with the increase of feed rate, microhardness also increases.

4.4 Optimal levels and validation of process parameters

The main effects plots of various responses are shown in Figures 6, 7 and 8. From the analysis of these plots, the optimal parametric combinations for maximum microhardness and minimum energy consumption and surface roughness are obtained. For validation of the optimal results, experiments are conducted at optimal levels within the experimental region and the corresponding results are shown in Table 9. The predicted values (η_{pred}) for various responses at optimal levels are calculated using equation 4.

$\eta_{pred} = \eta_m + \sum_{i=1}^{4}(\eta_i - \eta_m)$ ……………………… (4)

where η_i is the mean S/N ratio of optimal level and i is the number of process parameters that affect the response. The predicted values of responses are compared with the actual values as shown in Table 9. Therefore, the experimental results confirm the validity of optimisation of process parameters for various responses satisfactorily.

Table 9: Optimal levels and validation of process parameters

Optimal levels of parameters			Validation of optimal results		
Response requirement	Optimal levels	Optimal values	Predicted value	Experimental value	% of error
Higher Microhardness	S2 F3 DOC2 TD3	2000 rpm 2000 mm/min 0.15 mm 10 mm	133.3 HV	130.1HV	2.4
Lower Energy consumption	S2 F3 DOC3 TD1	2000 rpm 2000 mm/min 0.2 mm 6 mm	0.1954 MJ	0.1861 MJ	4.76
Lower Surface Roughness	S3 F1 DOC1 TD1	2500 rpm 1000 mm/min 0.1mm 6 mm	0.6439 microns	0.6012 microns	4.27

4.5 Regression equations

Regression analysis is performed using Minitab software and the regression equations for Energy consumption, Surface roughness and Microhardness with respect to the process parameters speed, feed, depth of cut and tool diameter are given below using the equations 5, 6, 7.

Energy Consumption = 0.807245 - 0.000195636 * x - 0.000389131 * y - 2.66361 * z + 0.0649141 * a + 4.9358e-08 * x * x + 1.03039e-07 * y * y + 5.54487 * z * z - 0.00376325 * a * a……………………. (5)

Where x = Speed, y = Feed, z = Depth of cut, a = Tool Diameter

R^2 = 99.06%, R^2 (adj) = 97.89%, R^2 (pred) = 93.6%

Surface Roughness = 1.60584 + 0.000704067 * x + 0.000443189 * y - 2.85033 * z - 0.290208 * a -2.19822e-07 * x * x - 1.09356e-07 * y * y + 13.8244 * z * z + 0.0130569 *a * a……………………………………….….. (6)

R^2 = 98.03%, R^2 (adj) = 95.56%, R^2 (pred) = 87.39%

Microhardness = 104.556 + 0.0343444 * x- 0.0061 * y + 241 * z - 6.77222 * a - 8.82222e-06 * x * x + 3.04444e-06 * y * y - 762.222 * z * z + 0.419444 * a * a……………………………….……….. (7)

R^2 = 99.16%, R^2 (adj) = 98.89%, R^2 (pred) = 94.6%

As the values of Pred R-Sq (Predicted multiple correlation coefficient), R-sq (Multiple correlation coefficient), and Adj R-Sq (Adjusted multiple correlation coefficient) deviate from 1 very little, the three response models are not overfitting and demonstrate sufficient predictability. So, these models are reliable.

4.6 Multi objective optimization using MOPSO

The regression equations obtained from regression analysis are used in MOPSO Matlab code for multi objective optimization of process parameters. The optimal process parameters with MOPSO predicted values and experimental values are shown in Table 10. The results of MOPSO are validated by conducting 2 experimental runs.

Table 10: Validation of MOPSO results for CNC

S. NO	Optimal process parameters	MOPSO Predicted value			Experimental value		
		Energy Consumption	Surface Roughness	Micro Hardness	Energy Consumption	Surface Roughness	Micro Hardness
1	1500rpm, 1360mm/min, 0.118mm, 6	0.1932 MJ	0.57 µm	133 HV	0.1928 MJ	0.61 µm	131 HV
2	2100rpm, 1200mm/min, 0.12mm, 8	0.1897 MJ	0.63 µm	132 HV	0.191 MJ	0.59 µm	129 HV

5. Conclusions

Multi objective optimization of CNC milling process parameters for lower energy consumption, surface roughness and higher micro hardness is carried out in this study. The major conclusions drawn from this work are:

- Optimal levels of the parameters for single responses i.e.EC, SR and MH are S2F3DOC2TD3, S2F3DOC3TD3, S3F1DOC1TD1 respectively.
- Predicted EC, SR, MH are 0.1954 MJ, 0.6439 µm, 133.3 HV and the experimental values are 0.1861 MJ, 0.6012 µm, 130.1HV. The experimental results confirm the validity of optimal parametric combinations of various responses.
- Two optimal levels of parameters for multi-response optimisation using MOPSO are obtained.

- For 1500rpm 1360mm/min 0.118mm 6, MOPSO Predicted EC, SR, MH are 0.1932 MJ, 0.57 µm, 133 HV and the experimental values are 0.1928 MJ, 0.61 µm, 131 HV.
- For 2100rpm 1200mm/min 0.12mm 8, MOPSO Predicted EC, SR, MH are 0.1897 MJ, 0.63 µm, 132 HV and the experimental values are 0.191 MJ, 0.59 µm, 129 HV.

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